Nurses' education, employment, and heterogeneous effects of admission

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Abstract

Expanding nursing education is a common response to nurse shortages, but additional study places need not translate one-for-one into practicing nurses. We study applicants to Norwegian nursing programs using administrative register data linked to admission cutoffs from a centralized admissions system. Using a fuzzy regression discontinuity design, we estimate the effect of admission offers for applicants at the margin of admission. Admission raises enrollment in the application year by 65 percentage points, but longer-run effects are smaller: 35 percentage points for all-time enrollment, 27 percentage points for completion, and 19 percentage points for employment as a nurse. These differences reflect both incomplete take-up and completion among admitted applicants and catch-up among initially rejected applicants. We use complier outcome levels to bound the effects of adding new study places. Per 100 additional admission offers, our results imply up to 69 nursing graduates and 53 nurses; per 100 additional filled seats, up to 80 graduates and 61 nurses. Heterogeneity analyses show lower completion and nurse-employment effects for men than for women, while larger effects for older and high-GPA applicants mainly reflect less catch-up among initially rejected applicants.

JEL Classification Codes: I18, I23, I28, J2

Keywords: Nurse education, college admission, heterogeneous effects, RDD

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1 Introduction

Health systems around the world face persistent shortages of qualified nurses. Because nursing is a regulated profession that requires formal education and licensing, growth in the nursing workforce depends in part on how effectively higher education systems convert applicants into graduates and graduates into practicing nurses. According to the World Health Organization, closing the global gap by 2030 would require a substantial increase in the annual number of nurse graduates (WHO, 2020). This makes admission capacity in nursing education a central policy margin. We study this issue in Norway, a country with high nurse density by international standards (OECD, 2023) but continued excess demand for nursing study places and projected shortages in the years ahead (Jia et al., 2023).

An expansion in nursing education capacity need not translate one-for-one into a larger nursing workforce. Some admitted applicants do not enroll, some enrolled students do not complete, and some graduates do not work as nurses. At the same time, some initially rejected applicants later reapply, enroll, and eventually qualify as nurses. These patterns imply that the effect of receiving an admission offer on a marginal applicant may differ substantially from the broader effect of expanding nursing education capacity on nurse supply. Accordingly, this paper examines both the impact of admission on individual applicants' later outcomes and the extent to which expanded nursing admissions increase the long-run supply of practicing nurses.

We examine this issue using detailed administrative register data that allow us to follow applicants from their initial higher-education application to later enrollment, degree completion, and labor market outcomes. Our research design exploits admission-score cutoffs from Norway's centralized college admission system. These cutoffs generate quasi-random variation among applicants near the admission threshold for nursing programs. Comparing applicants just above and just below the cutoff allows us to estimate the causal effect of receiving an admission offer for marginal applicants in a fuzzy regression discontinuity design. Since these marginal applicants are precisely those affected by changes in admission capacity, the design provides policy-relevant estimates of the individual-level effects of expansion.

To connect these estimates to broader policy implications, we use complier outcome levels to bound the aggregate effect of increasing the number of study places. The lower bound assumes only the marginal applicant is affected. The upper bound allows for applicants who would otherwise have entered nursing later to enroll earlier, thereby freeing up places for others and generating ripple effects across programs and cohorts (Gandil, 2025). In the limiting case where this chain of displacement continues until one additional, similar applicant enters nursing, the treated-complier outcome level defines this bound.

We find that admission has a large effect on enrollment in the application year, increasing it by about 65 percentage points. The effects on longer-run outcomes are substantially smaller:

admission raises eventual enrollment by about 35 percentage points, completion by about 27 percentage points, and employment as a nurse by about 19 percentage points. These smaller long-run effects reflect substantial catch-up among applicants who are initially rejected but later reapply and complete. Using treated-complier outcome levels, we further find that an expansion of 100 study places would at most produce about 69 additional nursing graduates and 53 additional nurses in the longer run; measured per 100 additional filled seats, the corresponding upper-bound effects are about 80 graduates and 61 nurses. Finally, we document substantial heterogeneity, with both treatment effects and long-run outcome levels generally smaller for men than for women, highlighting a possible tension between the goals of expanding the nurse workforce and improving gender balance in nursing.

Our paper contributes to two strands of literature. First, it contributes to work on the causal effects of admission to higher education. Prior studies have used admission discontinuities or lotteries to estimate the effects of access to specific institutions (Hoekstra, 2009; Öckert, 2010; Cohodes and Goodman, 2014; Zimmerman, 2014; Mountjoy, 2024) or specific fields of study (Hastings et al., 2013; Kirkebøen et al., 2016; Ketel et al., 2016; Andrews et al., 2017; Heinesen, 2018; Bleemer and Mehta, 2022). We add to this literature by studying admission to a field that leads to a clearly defined occupation and by tracing not only educational attainment but also actual entry into the nursing workforce. A particularly relevant comparison is Grosz (2024), who uses lottery-based admission to oversubscribed nursing programs. Relative to that paper, we make two main contributions. First, we estimate effects for marginal applicants around admission-score cutoffs in a centralized admissions system, which makes our estimates directly informative about the applicants affected by capacity expansions at the admission margin. Second, using nationwide administrative data, we follow applicants from application to enrollment, completion, and realized employment as nurses, and use these outcomes to bound the broader effect of expanded capacity on nurse supply rather than focusing on licensure alone.

Second, we also contribute to the literature on nurse labor supply. Existing work, summarized for example by Antonazzo et al. (2003) and Shields (2004), has mainly examined the response of nurses' labor supply to wages and generally finds limited short-run responsiveness. We instead study an entirely different margin by examining the longer-run supply effects of expanding educational capacity. In doing so, we provide causal evidence on the extent to which additional nursing study places translate into additional qualified and practicing nurses.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting, the data, and descriptive trajectories in education and employment. Section 3 presents the research design and the reduced-form evidence around admission thresholds. Section 4 reports the main causal estimates and heterogeneity analyses. Section 5 concludes.

2 Institutional setting, data and sample selection

In this section, we describe the institutional background, the construction of the estimation sample, and descriptively investigate applicants' enrollment into and completion of nursing education, and subsequent employment as nurses.

2.1 Institutional background

Norway's institutional context for nursing education is characterized by a predominantly public higher education system and a largely public healthcare sector. In this setting, professional training and certification are strictly regulated. Nursing is a licensed profession in which individuals must complete a formal tertiary nursing program and obtain a license from a government authority in order to practice. This framework ensures a clearly defined pathway from education to employment in nursing.

Norwegian higher education. Norwegian higher education consists almost exclusively of public universities and university colleges. Students pay no tuition fees and are eligible for government-funded financial aid, provided as a mix of loans and grants. Historically, universities have offered broader academic educations and longer professional degrees (e.g., science, humanities, law, and medicine) while the latter have provided shorter professional degrees (e.g., engineering, nursing, and teaching). Over the past few decades, many university colleges have transitioned into or been merged into universities, blurring the distinction and resulting in more institutions offering programs at different locations.

Norway operates a centralized system of admission to higher education. Applicants submit a single application to a single organization (the Norwegian Universities and Colleges Admission Service, NUCAS), which handles admission for all programs and institutions. The applicants supply a rank-ordered list of up to 10 or 15 different programs, each typically defined by a specific field of study offered at a particular institution, such as a nursing program at a given university college.[1]

Applicants are assigned to their highest-preferred program available to them by a deferred acceptance algorithm. Applicants are ranked by their admission scores, which mostly reflect their high school GPAs, with some possibilities for extra points (e.g., for certain high school subjects, age, or military service). The system is strategy-proof, meaning applicants cannot gain advantage by misreporting their preferences. When a program is oversubscribed (i.e., it has more applicants than places), an admission score threshold is established: appli-

[1] The exact number of rank-ordered programs submitted by the applicants has varied over time. When an institution has multiple campuses, different programs may be offered at different campuses. However, this is less common in our observation period. Programs can also differ in terms of the form of instruction. For example, an institution may offer both full-time and part-time nursing programs. Programs with non-standard instruction mostly target older students or those who are currently employed.

cants above the threshold receive an offer, while those below do not. The admission is done in several rounds. In each round, an applicant can choose to accept an offer, if he or she receives any, and to stay on a waiting list for a more-preferred offer, if the current offer is not the most-preferred. If the applicant chooses to stay on the waiting list and receives another offer in the next round, the previous offer is automatically discarded. Through this process, study places are allocated in a way that reflects both applicants' preferences and their admission scores.

Nursing education in Norway. Nursing education in Norway follows a clearly defined pathway. It is offered as a three-year full-time program leading to a Bachelor's degree.[2] To gain admission into a nursing program, applicants must satisfy the general university entrance requirement, typically by completing three years of upper secondary education. The nursing curriculum is regulated by national guidelines that set the aims, scope, and content. Approximately half of the coursework is devoted to supervised clinical training, which is organized in cooperation with regional health authorities and municipalities. Upon successful completion of the program, graduates are awarded a Bachelor's degree and are authorized to practice as nurses, provided their education was completed at an accredited institution meeting the national standards. In the 2024 admissions cycle, for instance, 13 different institutions offered a total of 5384 places in 40 nursing programs at 33 different locations.[3]

2.2 Data and sample construction

We construct our estimation sample by linking multiple administrative datasets that allow us to follow individuals from their initial higher-education application through later education and labor market outcomes. The construction of the sample proceeds in three steps.

Step 1: Define the applicant pool. We start from the full population of first-time applicants to higher education in Norway between 1998 and 2010, as recorded in the NUCAS centralized application register. These records contain each applicant's ranked list of study programs, admission score, relevant program cutoffs, offers received, and enrollment decisions. Among these applicants, 72,199 submitted a valid application to at least one nursing program, corresponding to about 17% of all first-time applicants.

Step 2: Identify margins of interest. Next, we identify applicants on the margin between nursing and another field. Following Kirkebøen et al. (2016), we define each applicant's *predicted offer* as the highest-ranked field on the application list for which the applicant is above

[2] There are two types of nursing practitioners in Norway: registered nurses and licensed practical nurses. Licensed practical nurses complete vocational training at the upper secondary level and have a narrower scope of practice. We focus on applicants to registered nursing programs leading to a three-year Bachelor's degree.

[3] Two cities have more than one university or university college. Seven programs are part-time studies, in some cases offered in the same locations as a full-time program. The seven part-time programs have a total of 355 places. Source: https://www.samordnaopptak.no/info/

the admission cutoff. We then define the relevant margins as the fields that would become the predicted offer if the applicant's score were marginally higher or lower, holding all admission cutoffs fixed.[4]

Each applicant can appear on at most two such margins: one above and one below the predicted offer. For our analysis, we keep only the margin on which nursing is the preferred field, that is, cases where the applicant is just above or below the cutoff for a nursing program and ranks nursing above the relevant next-best alternative. This restriction ensures that each applicant contributes at most one observation to the estimation sample and that the relevant comparison is between nursing and the next-best non-nursing field.[5]

Applying these criteria yields 39,293 unique applicants with nursing as the preferred field on a relevant margin. We then restrict attention to applicants whose admission score lies within ± 1.5 standard deviations of the relevant cutoff and exclude observations exactly at the cutoff. This removes 4,868 applicants outside the bandwidth and 851 applicants at the cutoff.

Step 3: Linking registers and constructing analysis panels. We link the selected applicants to additional administrative registers using unique personal identifiers. These registers provide demographic characteristics such as sex, age, and immigrant background, as well as information on parental education. We exclude 133 applicants with missing demographic records. To measure outcomes over time, we use longitudinal education and employment registers that track post-secondary trajectories and labor market activity.[6]

Based on these linked data, we construct two analysis panels. The *education panel* is a balanced panel of 33,441 applicants observed for 10 years after application, capturing admission, enrollment, and degree completion. The *employment panel* follows the same individuals over a 10- to 20-year horizon.[7] It is unbalanced because later applicant cohorts cannot yet

[4] To identify these margins in practice, we process each applicant's ranked list of programs in two steps. First, we collapse consecutively ranked programs within the same field by retaining only the one with the lowest cutoff. This ensures that the cutoff reflects the lowest threshold for admission into the field, regardless of institution. Second, we remove dominated programs. These are programs that appear after a higher-ranked option with a lower cutoff and would never result in an offer.

[5] For example, consider an applicant who ranks medicine, nursing, and teaching in that order. If the applicant's score is above the cutoff for medicine, the predicted offer is medicine, placing the applicant on the margin between medicine and nursing. This case is excluded because nursing is not the preferred field. If the score is below the cutoff for medicine but above the cutoff for nursing, the predicted offer is nursing, and the applicant lies on two margins: one above (medicine vs. nursing) and one below (nursing vs. teaching). Only the latter is included in the sample, since nursing is the preferred field. If the score is below the cutoff for nursing but above the cutoff for teaching, the applicant is again included, now on the margin between nursing and teaching. If the score is below the cutoff for teaching, the applicant is excluded because there is no margin involving nursing as the preferred field.

[6] Parental education refers to the level and field of each parents' highest completed education when the applicant was age 16. Employment data are annual from 2008 to 2014 (measured in November) and monthly from 2015 to 2023. For consistency, we use November observations throughout.

[7] The employment panel includes slightly fewer individuals than the education panel due to missing records in the employment register.

Table 1: Descriptive statistics

	Applicant	Education outcomes		Employment outcomes		
	Mean	App. year	10 years	10 years	15 years	20 years
Panel A: Applicant characteristics						
Age	25.09					
Female (%)	88					
Immigrant (%)	6					
At least one parent has a health degree (%)	26					
At least one parent has a nurse degree (%)	9					
At least one parent has a medical degree (%)	1					
Panel B: Education outcomes						
Offer received (%)		67				
Enrolled (%)		54	71			
Completed (%)			60			
Panel C: Employment outcomes						
In work (%)				86	87	85
In health sector (%)				63	62	61
Work as nurse (%)				48	45	42
Work as full-time nurse (%)				26	25	24
Observations	33,441	33,441	33,441	32,036	30,197	17,665

Notes: This table reports descriptive statistics for the estimation sample described in Section 2.2. Age is reported in years. All other entries are percentages.

be observed for the full horizon: the 1998 cohort is observed from 2008 to 2018, while the 2010 cohort is observed from 2020 to 2023. Our main employment outcomes are overall employment, employment in the health sector, employment as a nurse, and employment as a full-time nurse.

2.3 Descriptive statistics

This subsection first describes the composition of the estimation sample and then compares the educational and employment trajectories of applicants above and below the admission cutoff.

Summary statistics. Table 1 presents summary statistics. The applicants in our sample are predominantly female, with an average age of 25. The age distribution is skewed, and the median applicant is 22 years old, and 23% are 30 years or older. In total, 6% of applicants are immigrants. Regarding parental background, around 26% have at least one parent with a health-related degree, including 9% with a nursing degree, and 1% with a medical degree.

With respect to admission, enrollment, and completion, 67% of applicants received an offer of admission to a nursing program in the application year, and 54% enrolled immediately. Within 10 years, the share ever enrolled rises to 71%, and 60% of applicants complete a nursing degree. The gap between immediate and eventual enrollment points to substantial delayed entry into nursing education, consistent with many applicants below the cutoff being admitted in later years.

Employment rates are high in the years following application. Ten years after applying, 86% are employed, 63% work in the health sector, 48% work as nurses, and 26% work as full-time nurses. At longer horizons, overall employment remains broadly stable, but the share working as nurses declines from 48% after 10 years to 42% after 20 years. Since health-sector employment declines much less, part of this change appears to reflect movement into other health-sector roles rather than complete exit from the sector.

To better understand these patterns, we now split the sample into two mutually exclusive groups based on the admission cutoff: applicants with scores above the cutoff and applicants with scores below. This comparison highlights how initial admission eligibility relates to later educational and labor market trajectories.

Educational trajectories. Figure 1 tracks the educational trajectories of applicants scoring above and below the admission cutoff for nursing programs, showing enrollment, completion, and dropout rates over time. In the year of application, about 75% of applicants scoring above the cutoff enroll in the program, while the remaining 25% either did not receive an offer or chose not to enroll despite being offered admission. The share ever having enrolled rises slightly over the next few years, reaching about 85% after five years. In contrast, only around 14% of applicants below the cutoff are enrolled in the application year, but this share rises quickly over the next two years to just above 30%, consistent with substantial reapplication and later admission.

In later years, the shares who drop out and complete increase gradually for both groups. By about five years after application, most applicants who have not dropped out have completed the program. Completion rates conditional on ever enrolling are very similar above and below the cutoff, suggesting that the main difference between the two groups lies in the timing and probability of entry into nursing education rather than in completion conditional on entry. This similarity is noteworthy, since applicants below the cutoff have lower admission scores on average. One possible explanation is that applicants who reapply and later enroll despite initial rejection are positively selected on motivation. At the same time, applicants below the cutoff tend to complete later than applicants above the cutoff, reflecting their later enrollment.

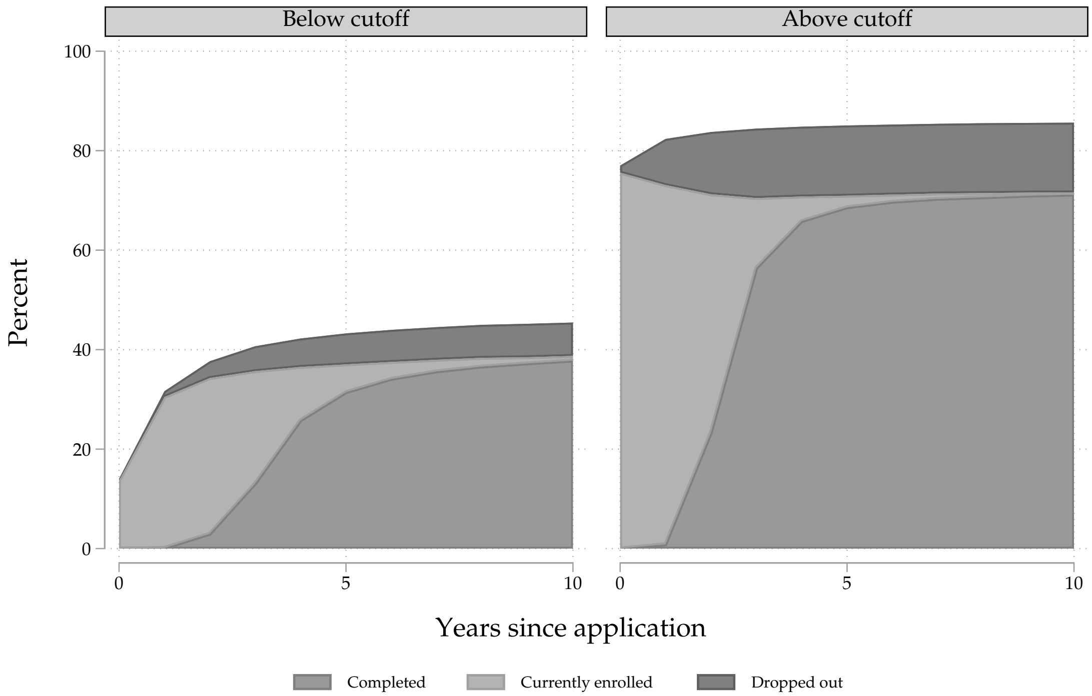


Figure 1: Enrollment and completion

Notes: This figure shows predicted educational trajectories for applicants scoring above and below the admission cutoff for nursing programs. The trajectories are obtained from separate multinomial logit models estimated for the two groups, with outcomes for never enrolled, dropped out, currently enrolled, and completed, and with fixed effects for applicant cohort and years since application. The figure reports predicted probabilities by years since application. Educational trajectories for individual applicant cohorts are shown in Figure B4.

Employment trajectories. Turning to employment outcomes, Figure 2 illustrates the employment trajectories of applicants scoring above and below the admission cutoff for nursing programs. For both groups, a substantial proportion initially transition into employment as nurses. A smaller share takes up health-related jobs outside of nursing, such as administrative or support roles in the health sector, while others are categorized as having completed the program but without any recorded employment. Over time, the figure reveals broader mobility trends, with individuals gradually shifting out of nursing roles into other forms of employment. This may reflect career shifts, preferences for less demanding work schedules, or broader structural changes in the labor market.

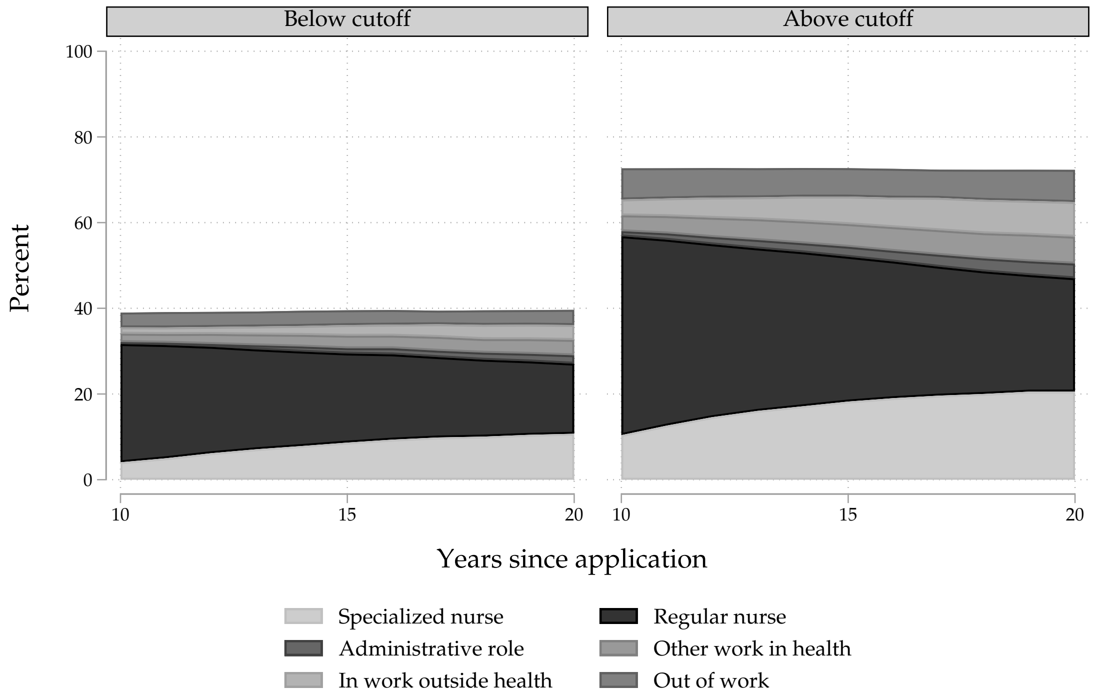


Figure 2: Employment

Notes: This figure shows predicted employment trajectories for applicants scoring above and below the admission cutoff for nursing programs. The trajectories are obtained from separate multinomial logit models estimated for the two groups, with outcomes for never enrolled, dropped out, completed but out of work, completed and working outside health, other work in health, administrative roles, regular nurse, and specialized nurse, and with fixed effects for applicant cohort and years since application. The figure reports predicted probabilities by years since application. Employment trajectories for individual applicant cohorts are shown in Figure B5.

Restricting attention to applicants above the cutoff who completed a nursing degree, the share working as nurses falls from 78% 10 years after application to 68% 20 years after application. Part of this decline is offset by increasing shares working in administrative or other health-sector roles, and by a rising share in specialist nursing roles. Even so, the share working anywhere in the health sector also declines over time.

For applicants below the cutoff who completed a nursing degree, the pattern is very similar. A slightly larger share work as nurses at a given time since application, but this difference narrows when outcomes are measured relative to enrollment or completion rather than application. For all applicants, however, the share working as nurses remains lower below the cutoff because fewer applicants in that group enroll and complete.

As noted in Section 2.2, we have an imbalanced sample for employment outcomes. However, the nearly balanced sample of applicants from 1998-2003 that we can observe until 20 years after enrollment gives very similar results. The cohort-specific trajectories in Figure B5 show very similar patterns for earlier cohorts that can be observed for longer periods, suggesting that the main employment trajectories are not driven by the imbalance in observation windows.

3 Research design

The previous section documented differences in later educational and labor market trajectories between applicants above and below the admission cutoff. In this section, we focus on local variation around the cutoff to estimate the causal effect of receiving an admission offer to nursing for marginal applicants. We then explain how these individual-level effects can be used to bound the broader effects of expanding nursing program capacity.

3.1 Identifying variation and validity

Our research design exploits the admission-score threshold for the applicant's preferred nursing margin. Applicants just above the cutoff are much more likely to receive an offer of admission to nursing than applicants just below it. Since applicants close to the same cutoff have similar admission scores and face the same institutional environment, this discontinuous change in admission provides identifying variation.

Crossing the cutoff generates a discontinuous increase in the probability of receiving an offer, but admission is not perfectly determined by the threshold. Some applicants above the cutoff do not receive an offer, and some applicants below the cutoff do receive one.[8] We therefore use a fuzzy regression discontinuity design, instrumenting admission with the indicator for being above the cutoff.

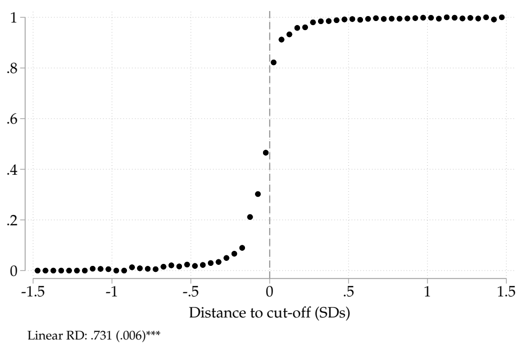
The identifying comparison is between applicants close to the same cutoff but on opposite sides of it. The key identifying assumption is that potential educational and labor market outcomes vary smoothly with admission scores at the cutoff. Under this assumption, applicants just above and just below the threshold are comparable except for the discontinuous change in their probability of receiving an offer. The IV interpretation additionally requires that crossing the threshold affects later outcomes only through its effect on admission to nursing, and that crossing the threshold does not reduce the probability of receiving an offer for applicants who would otherwise have received one. The resulting estimand is the local average treatment effect for compliers, meaning applicants whose admission status is changed by crossing the cutoff. These are the applicants most directly affected by marginal changes in admission capacity.

[8] A reason that applicants above the cutoff do not receive an offer is that applicants may choose not to remain on the waiting list in an early round and thus miss out on an offer they would eventually have received. A reason that applicants below the cutoff may receive an offer is that applicants can request special consideration, for example if documented illness reduced their exam performance.

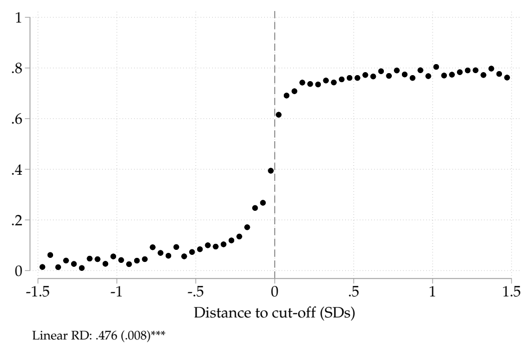
We assess the credibility of the design in two ways. First, Appendix Figure B6 shows that predetermined characteristics are smooth around the cutoff. Second, Appendix Figure B1 shows no visible discontinuity in the density of applicants at the threshold. We complement the visual density check with the manipulation test proposed by Cattaneo et al. (2020), which fails to reject continuity of the running variable. These checks provide no evidence of sorting or manipulation around the cutoff.

3.2 Reduced-form evidence around the cutoff

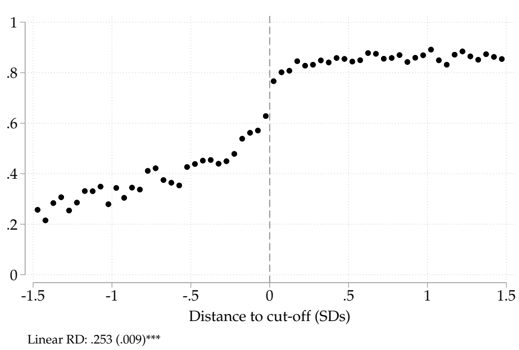
Figure 3 shows reduced-form relationships between crossing the admission cutoff and subsequent educational outcomes. Panel (a) documents the first stage, with the probability of receiving an offer increasing sharply at the cutoff. Almost all applicants above the cutoff receive an offer, while only a small share below the cutoff do.



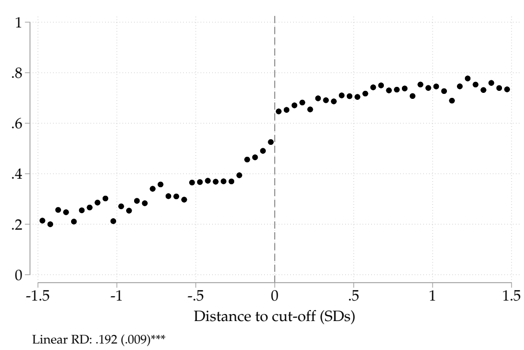
(a) Offer in the year of application



(b) Enrolled in the year of application



(c) Ever enrolled by year 10 after application



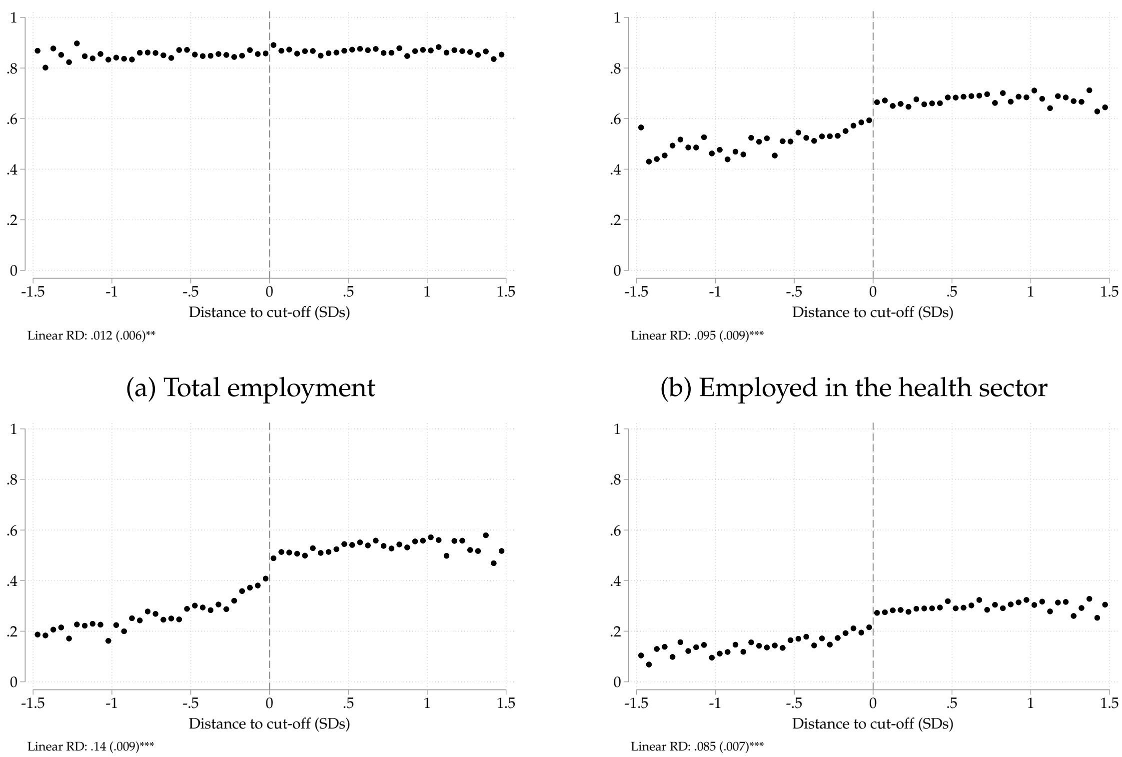
(d) Completed by year 10 after application

Figure 3: The effects of threshold crossing on admission, enrollment, and completion

Notes: The markers show average values for 30 equal-width bins, controlling for application year.

The discontinuities in enrollment and completion are smaller than the discontinuity in admission. Panel (b) shows that only about three quarters of applicants above the cutoff enroll in the application year despite receiving an offer. Applicants below the cutoff may still enroll in the application year either because they receive an offer despite being below the threshold or because they enroll in another, undersubscribed nursing program. Panels (c) and (d) show that a non-trivial share of applicants below the cutoff later catch up through reapplication and delayed entry. As a result, the discontinuity is large for immediate enrollment, smaller for ever enrollment within 10 years, and smaller still for completion. The fitted discontinuities imply that crossing the cutoff increases ever enrollment by about 25 percentage points and completion within 10 years by about 19 percentage points.

The reduced forms are also informative about the shape of the relationship away from the cutoff. The probability of receiving an offer changes sharply at the threshold, while the probabilities of later enrollment and completion vary more smoothly, especially below the cutoff. This pattern is consistent with many initially rejected applicants eventually entering nursing through later admissions rounds.



(a) Total employment

(b) Employed in the health sector

(c) Employed as nurse

(d) Employed as a full-time nurse

Figure 4: The effects of threshold crossing on employment trajectories

Notes: The markers show average values for 30 equal-width bins, controlling for application year.

Figure 4 presents the corresponding reduced-form relationships for employment outcomes 10 to 20 years after application. Crossing the admission threshold has essentially no effect on overall employment. It does, however, increase the probability of working in the health sector, working as a nurse, and working as a full-time nurse. The fitted discontinuities are about 10 percentage points for health-sector employment, 14 percentage points for nurse employment, and 9 percentage points for full-time nurse employment, while the effect on overall employment is close to zero. These effects are modest relative to the first stage, but they remain visible long after the initial admission decision.

3.3 Estimation and complier outcome levels

Our baseline estimates are obtained using a parametric 2SLS implementation of the fuzzy regression discontinuity design. Let d_i denote applicant i's admission score, measured in standard deviations relative to the relevant cutoff, and let $z_i = \mathbf{1}\{d_i > 0\}$ indicate that the applicant is above the cutoff. The treatment variable a_i equals one if the applicant receives an offer of admission to the preferred nursing program in the application year. The first-stage equation is

$$a_i = \pi z_i + \delta_1 d_i + \delta_2 z_i d_i + x_i' \theta + u_i, \tag{1}$$

where a_i is receipt of an admission offer to nursing in the application year, z_i indicates that the applicant is above the cutoff, and d_i is distance to the cutoff. The terms d_i and $z_i d_i$ form a linear spline, allowing the slope in the running variable to differ on either side of the threshold.

The second-stage equation is

$$y_i = \beta a_i + \delta_1 d_i + \delta_2 z_i d_i + x_i' \gamma + e_i, \tag{2}$$

where y_i denotes the educational or labor market outcome of interest. The coefficient β is the causal effect of receiving an admission offer for compliers within the estimation window.

The vector x_i includes fixed effects for application year, age, immigrant background, gender, parental nursing education, parental health education, parental medical education, and the specific nursing program applied to. For stacked employment outcomes, we also include fixed effects for years since application.

Although identification is based on local variation around the cutoff, the baseline specification uses the full pre-specified bandwidth rather than a narrower neighborhood around the threshold. This choice improves precision and is useful in our setting because the first stage is noisy near the cutoff, partly due to waiting-list behavior and discretionary offers. Section 4.2 therefore reports sensitivity to more local specifications and alternative bandwidth choices.

To interpret the treatment effects, we also estimate the corresponding outcome levels for treated and untreated compliers, denoted by $y(1)$ and $y(0)$. The treatment effect is the difference between these two levels. Following Abadie (2003), we recover the complier-specific levels directly from the data. We estimate $y(1)$ by replacing the dependent variable in equation

(2) with $a_i y_i$; the coefficient on a_i identifies the treated-complier outcome level. We estimate $y(0)$ by replacing the dependent variable with $-(1 - a_i)y_i$; the coefficient on a_i identifies the untreated-complier outcome level. This is algebraically equivalent to estimating the effect of non-admission on $(1 - a_i)y_i$.

Estimating these levels alongside the treatment effect is useful because a small treatment effect can arise for different reasons. For example, the effect of admission on completion may be small either because admitted applicants rarely complete or because many initially rejected applicants reapply and later catch up. Separately recovering $y(1)$ and $y(0)$ distinguishes between these explanations.

3.4 From admission effects to capacity expansions

The parameter β measures the effect of an admission offer on the marginal applicant who receives it. A capacity expansion may have broader aggregate effects. The reason is that many initially rejected applicants reapply and eventually enter nursing programs. If they would otherwise have enrolled later in oversubscribed programs, admitting them now can free scarce seats in later rounds or cohorts. These seats may then be taken by other marginal applicants, generating ripple effects across applicants and over time (Gandil, 2025).

To characterize the possible magnitude of these aggregate effects, we use two polar cases. The lower bound corresponds to a scenario in which initially rejected marginal applicants who later enroll do so only in undersubscribed programs. In that case, admitting one additional applicant today affects only that applicant, changing her expected outcome from $y(0)$ to $y(1)$. No scarce later seat is released, and the aggregate effect of an additional admission offer is therefore $\beta = y(1) - y(0)$.

The upper bound corresponds to a scenario in which initially rejected marginal applicants who would later have enrolled do so in oversubscribed programs. In that case, admitting one applicant today prevents her from occupying a scarce seat later. That later seat is then taken by another marginal applicant, who may in turn free another scarce seat. Under the assumption that this chain continues until one additional applicant enrolls who would not otherwise have done so, the aggregate effect of an additional admission offer is $y(1)$, the expected outcome of a treated complier. This upper-bound interpretation assumes a small expansion, stable applicant composition, and comparable marginal applicants across the affected programs and cohorts.

Admission versus enrollment. The estimates above use admission offers as the treatment. This is the policy margin directly shifted by the cutoff, but it is not always the margin institutions ultimately target. Institutions typically want to fill a given number of study places, and not all applicants who receive an offer enroll. The effect of an additional filled place may therefore differ from the effect of an additional offer. To capture this distinction, we also estimate specifications for completion and employment outcomes in which enrollment in the application year, rather than admission, is treated as the endogenous variable and instrumented by crossing the cutoff. These estimates describe the effects of inducing an additional marginal applicant to enroll in nursing in the application year.

4 Admission, enrollment, and nurse supply

Having established a lasting effect of being above the cutoff on educational and employment outcomes in the previous section, we now estimate the effect of an admission offer for a marginal applicant, the corresponding outcome levels of treated and untreated compliers, and the implications for filled study places and nurse supply.

4.1 Main effects and complier outcomes

Individual-level effects of admission. In Figure 5 we present 2SLS estimates of the effects of admission on educational and employment outcomes, instrumenting admission with being above the cutoff, as well as complier $y(1)$ and $y(0)$. Estimates and standard errors are also reported in Appendix Tables A1-A7. The leftmost marker and bar show the treatment effect and complier $y(1)$ and $y(0)$ for enrollment in the application year. Admission to a preferred nursing program increases the probability of enrollment by 65 percentage points. 76% of treated (admitted) compliers enroll in nursing in the application year compared to 11% of untreated compliers. Thus, the main reason that the treatment effect is substantially below one is that many applicants who get admitted still do not enroll in the application year.

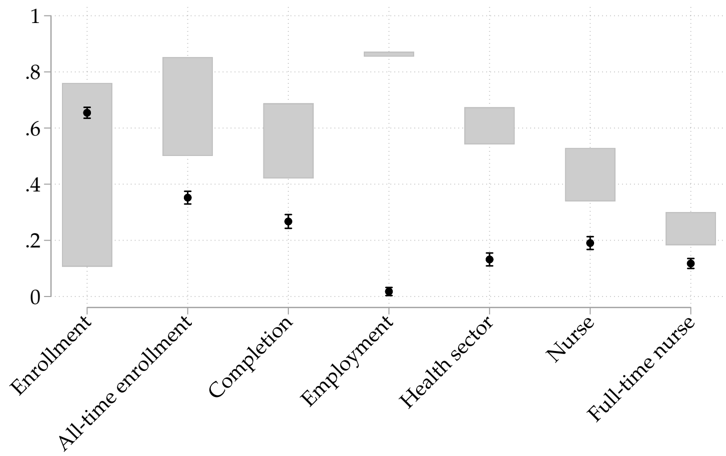


Figure 5: The effects of admission on enrollment, completion, and employment

Notes: The markers show the 2SLS estimates of admission to nursing programs on enrollment, completion, and employment outcomes. Error bars indicate 95% CI. The shaded bars indicate outcome levels of treated compliers ($y(1)$, top edge of bar) and untreated compliers ($y(0)$, bottom edge), see text for details. "Enrollment" refers to enrollment in the application year, while "all-time enrollment" measures enrollment within 10 years of application. "Completion" refers to program completion within 10 years after application. "Employment" measures any employment, "Health sector" any employment in the health sector, "Nurse" any employment as a nurse. Employment outcomes are measured 10–20 years after the application year; yearly observations over this period are stacked, and standard errors are clustered at the applicant level. Estimates and standard errors are also reported in Appendix Tables A1-A7.

The effects on all-time enrollment and completion are smaller than the effect on enrollment in the application year, at 35 and 27 percentage points, respectively. While 85% and 69% of treated compliers enroll and complete within 10 years, also many initially unsuccessful applicants reapply and eventually enroll and complete: 50% of untreated compliers enroll and 42% complete within 10 years.

Figure 5 also presents effects on labor market outcomes. We find a very small effect on overall employment of less than 2 percentage points, while the levels in Appendix Table A4 are in excess of 86%. We do, however, find an effect of 13 percentage points on the probability of working in the health sector. 67% of treated compliers work in the health sector, compared to 54% of untreated compliers.

The effect on working as a nurse is larger than the effect of working in the health sector, at 19 percentage points. Thus, being admitted to nursing slightly decreases the probability of working in the health sector outside of nursing. Finally, we find an effect on working full time as a nurse of 12 percentage points. This indicates that not all applicants shifted into nursing work as full-time nurses. Among treated compliers 53% work as a nurse, and 30% work full time.

Capacity expansions. The estimates in Figure 5 describe the individual-level effect of an admission offer. These estimates are also a lower bound on the aggregate effect of adding admission offers if initially rejected applicants who later enter nursing would otherwise have enrolled only in undersubscribed programs. On this no-ripple margin, 100 additional offers would generate 27 additional completions, 19 additional nurses, and 12 additional full-time nurses. If instead initially rejected applicants would later have used scarce seats in oversubscribed programs, the aggregate effect is larger: admitting them now frees those later seats for other marginal applicants. In the polar case where this displacement chain continues until one additional applicant enters nursing, the aggregate effect of 100 additional offers is given by the treated-complier levels: 69 completions, 53 nurses, and 30 full-time nurses.

Institutions, however, typically target filled study places rather than offers. Appendix Tables A3-A7 therefore also report estimates using application-year enrollment as the endogenous variable. These estimates can be interpreted at the filled-seat margin. Inducing 100 additional marginal applicants to enroll in the application year increases completion by at least 41, health-sector employment by 20, nurse employment by 29, and full-time nurse employment by 18. The corresponding treated-complier levels imply upper-bound effects of 80 completions, 73 health-sector workers, 61 nurses, and 34 full-time nurses per 100 additional filled seats.

To evaluate the relevance of the lower and upper bound, we follow 4503 applicants who first applied in 1998-2007 and were below the cutoff in their initial year of application but who later enrolled in nursing. 82% are first observed enrolled in an oversubscribed program and year and will thus likely have displaced other marginal applicants.[9] Thus, for a small expansion in the number of study places, small enough that the characteristics of the marginal applicant do not substantially change, we expect the aggregate effects to be larger than the no-ripple lower bound and closer to the treated-complier upper bound.

4.2 Robustness

Appendix Figure B2 presents a series of robustness checks comparing the main 2SLS estimates in Figure 5 to alternative specifications. Appendix Figure B3 shows the corresponding reduced-form estimates. The alternative specifications include (i) estimates with quadratic distance controls, (ii) estimates from local linear regressions, (iii) restricting the sample to nursing applicants under the age of 30 at the time of application, (iv) expanding the bandwidth to include observations further from the cutoff, (v) narrowing the bandwidth to focus on applicants closer to the cutoff, and (vi) including individuals located exactly at the cutoff.

[9] Only 3% are first observed enrolled in programs recorded as undersubscribed. For the remaining 15%, data on admission cutoffs is not available, or the applicants are enrolled in an institution and year that has a mix of oversubscribed and undersubscribed programs. The latter may, for example, be because nursing is taught at different campuses. While the admission data distinguish between campuses within an institution, the enrollment data do not.

The local linear specification uses a triangular kernel and the MSE-optimal bandwidth selector introduced by Calonico et al. (2014). This specification yields similar results for the education outcomes, but somewhat larger and less precise estimates for employment outcomes. The selected bandwidth varies between 0.12 and 0.18 SD across outcomes, and is thus substantially smaller than the bandwidths used in the other specifications in Figure B2.[10] Appendix Figure B3 shows that the reduced forms preserve the same qualitative pattern, but that the local and narrow-bandwidth specifications also differ in magnitude for some outcomes. At the same time, Figure 3a shows that the narrower local window substantially weakens the first stage. The local-linear IV estimates therefore reflect both reduced-form sensitivity and scaling by a smaller first stage. The overall pattern remains consistent, but the precise magnitudes from the most local specifications should be interpreted with more caution.

The remaining specifications are highly stable. Excluding the local-linear specification, the estimated effects are very similar across models for all outcomes. Admission has statistically significant effects in every specification for all outcomes except overall employment, and differences across these non-local specifications are never statistically significant.

4.3 Heterogeneity

We next examine whether admission effects differ across predetermined applicant characteristics. The motivation is not only descriptive. Admission rules and outreach policies affect which applicants are at the margin of receiving an offer, and heterogeneity therefore matters for the translation from study places to completed degrees and nurse labor supply. If marginal offers are shifted toward groups with lower completion or nurse-employment rates, the supply effect will be smaller than implied by the average treatment effect.

We focus on gender, immigrant background, age, and upper-secondary GPA. These characteristics capture dimensions along which applicants may differ in outside options, willingness to wait and reapply, and attachment to nursing. They are also policy relevant. Men remain underrepresented in nursing, and male recruitment is often discussed as a way to improve gender balance; age has also mattered directly in the Norwegian admission system, which until recently awarded priority to older applicants. The results below show modest heterogeneity in application-year enrollment but more pronounced differences in completion and later nursing work. The key distinction is between gender, where admitted male compliers complete and work as nurses less often, and age/GPA, where larger effects mainly arise because rejected older and high-scoring compliers are less likely to catch up later.

Educational progression. Figure 6a presents the effects of admission on enrolling in nursing during the application year. We observe some significant differences between groups,

[10] The triangular kernel means that the local linear specification weighs observations closer to the cutoff even more heavily.

e.g., men are 6.9 percentage points less likely to enroll than women ($p = 0.007$), and those with a high GPA are 6.9 percentage points more likely than those with average or lower GPA ($p = 0.013$). However, these differences are small relative to the effects on enrollment or the share of treated compliers enrolling. Across all subgroups, admission leads to an increase in enrollment by 60 to 71 percentage points, and 70 to 82 percent of treated compliers enroll.

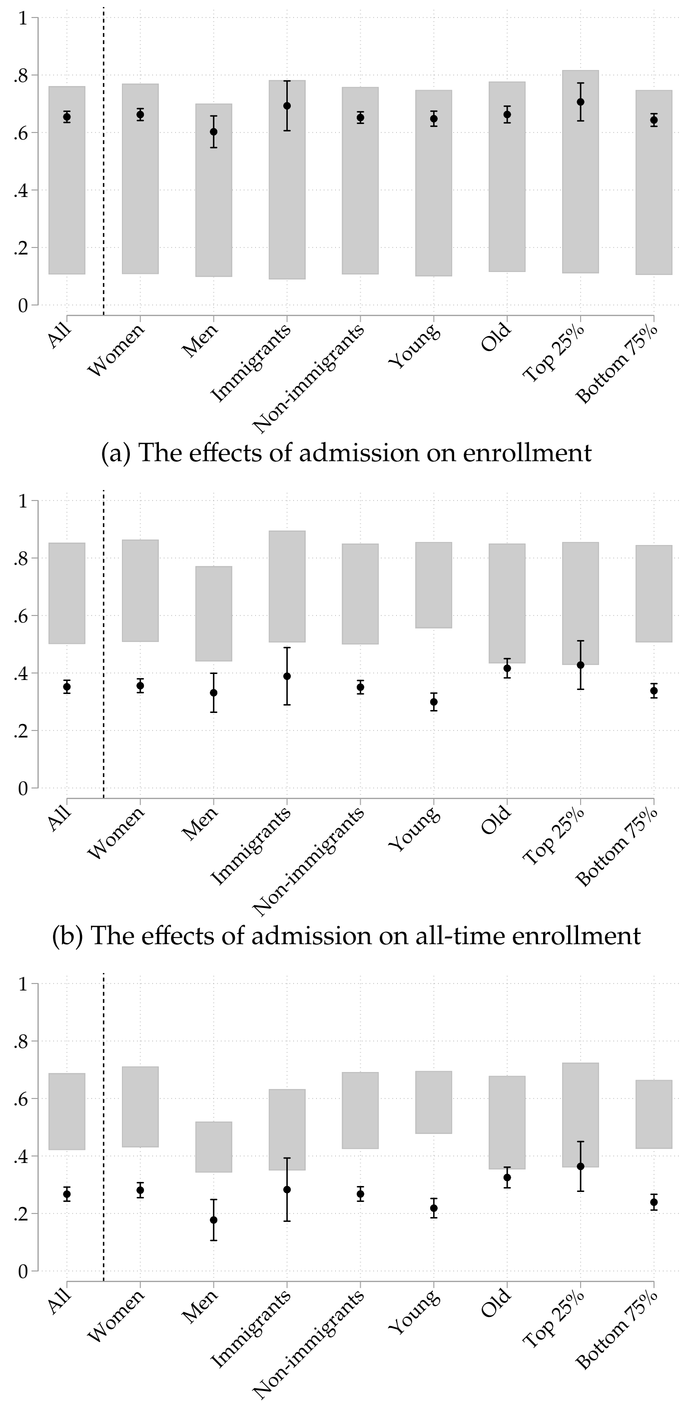
Figure 6b shows the effect of admission on the probability of ever starting a nursing program. Here, the most notable difference is by age. Older applicants (those above the median age of 22) have a 42 percentage point increase in all-time enrollment, compared to a 30 percentage point increase for younger applicants ($p < 0.001$). Because there is only a negligible corresponding age difference in application-year enrollment in Figure 6a, the larger effect for older applicants comes from later catch-up: Appendix Table A2 shows that untreated older compliers are 12 percentage points less likely than untreated younger compliers to enroll later (43% vs. 56%). There is a similar, but weaker, pattern by GPA. High-GPA applicants are more strongly affected because untreated high-GPA compliers are less likely to enroll later than untreated lower-GPA compliers (43% vs. 51%). For gender, there is no significant difference between men and women in the effect of admission on all-time enrollment, but men have lower enrollment rates both when admitted and when not.

Figure 6c examines program completion. The main patterns are similar to those in Figure 6b, with significantly smaller effects on completion for men ($p = 0.007$), younger applicants ($p < 0.001$), and those with lower GPA ($p = 0.007$). The gender difference is particularly important for nurse supply. Admission increases completion for women by 28 percentage points, compared to 18 percentage points for men. Appendix Table A3 shows that this reflects lower completion among men both when admitted (52% vs. 71% for women) and when not admitted (34% vs. 43%). By contrast, the larger completion effects for older and high-GPA applicants mostly reflect lower completion among untreated compliers. Treated-complier completion levels are similar by age (68–70%) and somewhat higher for high-GPA applicants (72% vs. 67%).

Employment outcomes. Figure 7a shows effects on work in the health sector.[11] Admission has a clear positive effect on health-sector employment for women, but not for men. Appendix Table A5 shows that women work more frequently in the health sector than men both when admitted to nursing in the application year (70% vs. 50%) and when not admitted (55% vs. 46%). The estimate for immigrants is small and imprecise, so we do not find clear evidence that admission raises their overall health-sector employment.

Figure 7b shows effects on work as a nurse, regardless of working hours. The same qualitative pattern appears: effects are smaller for men, immigrants, young applicants, and applicants outside the top GPA quartile. The differences are nevertheless less stark than for health-

[11] Across all subgroups, the effect on any employment is insignificant (see Figure B7).



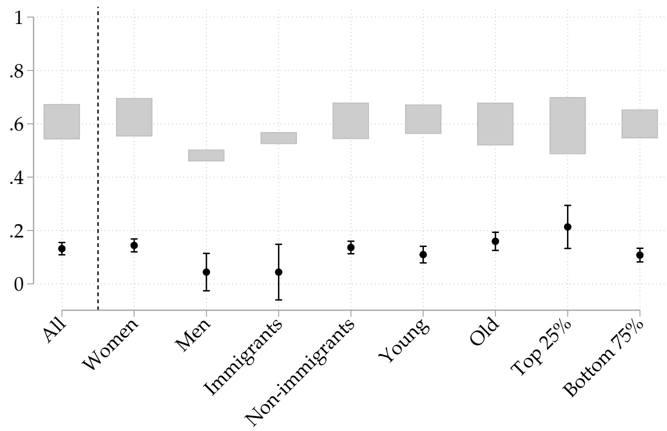
(a) The effects of admission on enrollment

(b) The effects of admission on all-time enrollment

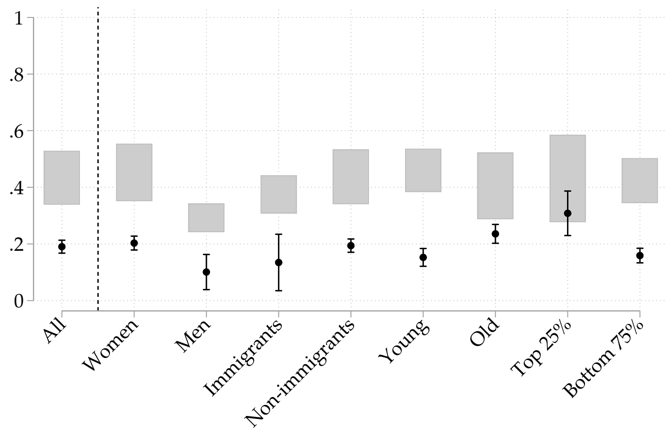
(c) The effects of admission on completion

Figure 6: Heterogeneous effects of admission on education outcomes by applicant characteristics

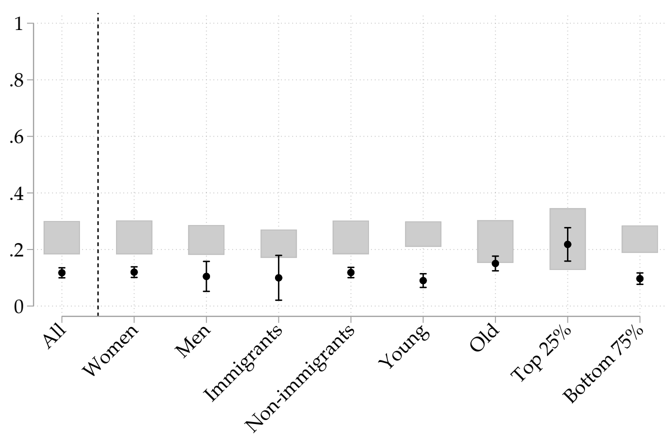
Notes: This figure shows the 2SLS estimates of admission to nursing programs on enrollment in the application year, all-time enrollment, and completion within 10 years, disaggregated by predetermined characteristics. Error bars indicate 95% CI. The shaded bars indicate complier $y(1)$ and $y(0)$, see text for details.



(a) The effects of admission on health-sector employment



(b) The effects of admission on nurse employment



(c) The effects of admission on full-time nurse employment

Figure 7: Heterogeneous effects of admission on employment outcomes by applicant characteristics

Notes: This figure shows the 2SLS estimates of admission to nursing programs on health-sector employment, nurse employment, and full-time nurse employment 10–20 years after application, disaggregated by predetermined characteristics. Error bars indicate 95% CI. The shaded bars indicate complier $y(1)$ and $y(0)$, see text for details.

sector employment, and admission has positive effects on nurse employment for both men and immigrants. For men, the positive effect on nurse employment but not on health-sector employment suggests that the additional male nurses largely come from other health-sector jobs. This is less true for women, for whom the effect on health-sector employment is almost as large as the effect on nurse employment.

Figure 7c shows effects on full-time nurse employment. These estimates are positive for all groups and more similar than the effects on nurse employment regardless of hours. In particular, the gender difference is small: admission raises full-time nurse employment by 12 percentage points for women and 11 percentage points for men. The same pattern holds on the filled-seat margin in Appendix Table A7, where the effects of application-year enrollment on full-time nurse employment are 18 percentage points for women and 17 percentage points for men. Thus, the larger gender difference in nurse employment partly reflects part-time work, while the gender difference in full-time nurse supply is smaller.

Overall, the heterogeneity results point to two distinct margins. For gender, admitting a man instead of a woman makes it less likely that the admitted applicant will complete the program and work as a nurse, although the difference is much smaller for full-time nurse employment. For age and GPA, the larger effects mostly reflect less catch-up among initially rejected applicants. Older and high-scoring applicants do not have much higher treated-complier levels; they have lower untreated-complier levels, which makes initial admission more consequential.

5 Conclusion

Expanding nursing education is a central policy response to nurse shortages, but additional study places need not translate one-for-one into additional practicing nurses. Some admitted applicants do not enroll, complete, or work as nurses, while some initially rejected applicants reapply and enter nursing later. This paper estimates how admission to nursing programs affects marginal applicants, and uses these estimates to assess what expanded capacity is likely to imply for nurse supply.

Admission has large effects on immediate enrollment, but substantially smaller effects on longer-run outcomes. An admission offer raises enrollment in the application year by 65 percentage points, but raises completion by 27 percentage points, nurse employment by 19 percentage points, and full-time nurse employment by 12 percentage points.

The effects of capacity expansions are likely larger than the individual-level treatment effects, because initially rejected applicants who later enter nursing often do so in oversubscribed programs and may displace other marginal applicants. We therefore interpret the individual-level effects as a lower-bound and the treated-complier outcome levels as an upper-bound. On the admission-offer margin, 100 additional offers would generate at most about 69 nursing graduates and 53 nurses in the longer run. On the filled-seat margin, the corresponding upper-bound effects are about 80 graduates and 61 nurses. Thus, even when accounting for potential ripple effects, expanded capacity appears to increase nurse supply substantially but less than one-for-one.

Heterogeneity matters for these supply implications. Admission is less likely to shift men into completing a nursing degree and working as nurses, although the gender difference is much smaller for full-time nurse employment. This points to a potential trade-off between increasing gender balance in nursing education and maximizing the number of completed nursing degrees or employed nurses. For age and GPA, however, the interpretation is different: larger effects for older and high-scoring applicants mostly reflect that initially rejected applicants in these groups are less likely to catch up later, not that admitted applicants in these groups have much higher completion or nurse-employment levels.

References

Abadie, A. (2003): "Semiparametric instrumental variable estimation of treatment response models," *Journal of Econometrics*, 113, 231–263.

Andrews, R. J., S. A. Imberman, and M. F. Lovenheim (2017): "Risky Business? The Effect of Majoring in Business on Earnings and Educational Attainment," *NBER Working Papers*.

Antonazzo, E., A. Scott, D. Skatun, and R. F. Elliott (2003): "The labour market for nursing: a review of the labour supply literature," *Health Economics*, 12, 465–478.

Bleemer, Z. and A. Mehta (2022): "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major," *American Economic Journal: Applied Economics*, 14, 1–22.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014): "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 82, 2295–2326.

Cattaneo, M. D., M. Jansson, and X. Ma (2020): "Simple local polynomial density estimators," *Journal of the American Statistical Association*, 115, 1449–1455.

Cohodes, S. R. and J. S. Goodman (2014): "Merit Aid, College Quality, and College Completion: Massachusetts' Adams Scholarship as an In-Kind Subsidy," *American Economic Journal: Applied Economics*, 6, 251–285.

Gandil, M. (2025): "Trickle down education - ripple effects in college admissions," Tech. rep.

Grosz, M. (2024): "Community colleges and careers: Evidence from nursing school lotteries," *Labour Economics*, 90, 102590.

Hastings, J. S., C. A. Neilson, and S. D. Zimmerman (2013): "Are Some Degrees Worth More than Others? Evidence from College Admission Cutoffs in Chile," *NBER Working Papers*.

Heinesen, E. (2018): "Admission to higher education programmes and student educational outcomes and earnings–Evidence from Denmark," *Economics of Education Review*, 63, 1–19.

Hoekstra, M. (2009): "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *The Review of Economics and Statistics*, 91, 717–724.

Jia, Z., T. Kornstad, N. M. Stølen, and G. Hjemås (2023): "Arbeidsmarkedet for helsepersonell fram mot 2040," Tech. Rep. 2, Statistics Norway.

Ketel, N., E. Leuven, H. Oosterbeek, and B. van der Klaauw (2016): "The Returns to Medical School: Evidence from Admission Lotteries," *American Economic Journal: Applied Economics*, 8, 225–54.

Kirkebøen, L. J., E. Leuven, and M. Mogstad (2016): "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics*, 131, 1057–1111.

Mountjoy, J. (2024): "Marginal Returns to Public Universities," *NBER Working Papers*.

OECD (2023): *Health at a Glance 2023: OECD Indicators*, Paris: OECD Publishing.

Shields, M. A. (2004): "Addressing nurse shortages: What can policy makers learn from the econometric evidence on nurse labour supply?" *The Economic Journal*, 114, 464–498.

WHO (2020): *State of the world's nursing 2020: investing in education, jobs and leadership*, World Health Organization.

Zimmerman, S. D. (2014): "The Returns to College Admission for Academically Marginal Students," *Journal of Labor Economics*, 32, 711–754.

Öckert, B. (2010): "What's the value of an acceptance letter? Using admissions data to estimate the return to college," *Economics of Education Review*, 29, 504–516.

Appendix A Additional tables

Table A1: Enrollment

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
All	0.654***	(0.010)	0.761***	(0.008)	0.106***	(0.005)
Women	0.662***	(0.011)	0.770***	(0.009)	0.107***	(0.006)
Men	0.603***	(0.028)	0.701***	(0.024)	0.098***	(0.015)
Immigrants	0.693***	(0.044)	0.782***	(0.039)	0.089***	(0.022)
Non-immigrants	0.652***	(0.010)	0.759***	(0.009)	0.107***	(0.006)
Young	0.648***	(0.013)	0.748***	(0.011)	0.100***	(0.007)
Old	0.663***	(0.015)	0.777***	(0.012)	0.115***	(0.008)
Top 25%	0.706***	(0.034)	0.817***	(0.026)	0.111***	(0.021)
Bottom 75%	0.643***	(0.011)	0.748***	(0.010)	0.105***	(0.006)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. The endogenous variable is admission offer. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A2: All-time enrollment

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
All	0.352***	(0.012)	0.853***	(0.007)	0.501***	(0.009)
Women	0.356***	(0.012)	0.864***	(0.007)	0.508***	(0.010)
Men	0.331***	(0.035)	0.771***	(0.022)	0.440***	(0.027)
Immigrants	0.389***	(0.051)	0.895***	(0.034)	0.506***	(0.039)
Non-immigrants	0.351***	(0.012)	0.850***	(0.007)	0.499***	(0.010)
Young	0.299***	(0.016)	0.856***	(0.009)	0.556***	(0.013)
Old	0.416***	(0.017)	0.850***	(0.011)	0.434***	(0.013)
Top 25%	0.428***	(0.043)	0.856***	(0.022)	0.428***	(0.038)
Bottom 75%	0.338***	(0.013)	0.845***	(0.008)	0.507***	(0.010)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. The endogenous variable is admission offer. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A3: Completion

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
Panel A: Endogenous variable is admission offer						
All	0.267***	(0.013)	0.688***	(0.009)	0.420***	(0.009)
Women	0.281***	(0.013)	0.712***	(0.009)	0.431***	(0.010)
Men	0.177***	(0.036)	0.519***	(0.027)	0.342***	(0.025)
Immigrants	0.283***	(0.056)	0.633***	(0.044)	0.349***	(0.036)
Non-immigrants	0.268***	(0.013)	0.692***	(0.009)	0.424***	(0.009)
Young	0.219***	(0.017)	0.696***	(0.012)	0.477***	(0.013)
Old	0.325***	(0.018)	0.679***	(0.013)	0.354***	(0.013)
Top 25%	0.364***	(0.044)	0.724***	(0.025)	0.360***	(0.037)
Bottom 75%	0.239***	(0.014)	0.665***	(0.010)	0.425***	(0.010)
Panel B: Endogenous variable is application-year enrollment						
All	0.408***	(0.018)	0.798***	(0.010)	0.390***	(0.014)
Women	0.424***	(0.018)	0.819***	(0.010)	0.395***	(0.015)
Men	0.294***	(0.056)	0.647***	(0.036)	0.352***	(0.043)
Immigrants	0.409***	(0.075)	0.687***	(0.052)	0.278***	(0.054)
Non-immigrants	0.411***	(0.018)	0.807***	(0.010)	0.396***	(0.015)
Young	0.337***	(0.025)	0.802***	(0.014)	0.465***	(0.021)
Old	0.491***	(0.025)	0.793***	(0.015)	0.303***	(0.020)
Top 25%	0.515***	(0.058)	0.856***	(0.023)	0.341***	(0.054)
Bottom 75%	0.372***	(0.020)	0.774***	(0.012)	0.402***	(0.016)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. Panel A uses admission offer as the endogenous variable. Panel B uses enrollment in the application year as the endogenous variable. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A4: Employment

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
Panel A: Endogenous variable is admission offer						
All	0.018**	(0.007)	0.872***	(0.005)	0.854***	(0.005)
Women	0.018**	(0.008)	0.875***	(0.005)	0.857***	(0.006)
Men	0.015	(0.023)	0.851***	(0.017)	0.836***	(0.017)
Immigrants	0.038	(0.044)	0.781***	(0.032)	0.743***	(0.031)
Non-immigrants	0.016**	(0.007)	0.877***	(0.005)	0.860***	(0.005)
Young	0.014	(0.009)	0.899***	(0.006)	0.885***	(0.007)
Old	0.023*	(0.012)	0.842***	(0.009)	0.819***	(0.009)
Top 25%	0.026	(0.027)	0.871***	(0.015)	0.845***	(0.023)
Bottom 75%	0.010	(0.008)	0.866***	(0.006)	0.856***	(0.006)
Panel B: Endogenous variable is application-year enrollment						
All	0.027**	(0.011)	0.881***	(0.007)	0.854***	(0.009)
Women	0.027**	(0.012)	0.883***	(0.007)	0.855***	(0.009)
Men	0.024	(0.039)	0.863***	(0.024)	0.838***	(0.031)
Immigrants	0.055	(0.064)	0.744***	(0.041)	0.690***	(0.049)
Non-immigrants	0.025**	(0.011)	0.888***	(0.007)	0.863***	(0.009)
Young	0.022	(0.014)	0.908***	(0.008)	0.886***	(0.011)
Old	0.035*	(0.018)	0.852***	(0.012)	0.817***	(0.015)
Top 25%	0.038	(0.039)	0.894***	(0.020)	0.857***	(0.034)
Bottom 75%	0.016	(0.013)	0.869***	(0.008)	0.853***	(0.010)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. Panel A uses admission offer as the endogenous variable. Panel B uses enrollment in the application year as the endogenous variable. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A5: Health sector

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
Panel A: Endogenous variable is admission offer						
All	0.132***	(0.012)	0.674***	(0.008)	0.542***	(0.009)
Women	0.144***	(0.012)	0.697***	(0.008)	0.553***	(0.009)
Men	0.044	(0.036)	0.504***	(0.025)	0.459***	(0.026)
Immigrants	0.044	(0.053)	0.568***	(0.039)	0.524***	(0.036)
Non-immigrants	0.136***	(0.012)	0.679***	(0.008)	0.543***	(0.009)
Young	0.110***	(0.016)	0.672***	(0.011)	0.563***	(0.012)
Old	0.159***	(0.017)	0.678***	(0.012)	0.519***	(0.013)
Top 25%	0.214***	(0.041)	0.699***	(0.022)	0.486***	(0.035)
Bottom 75%	0.108***	(0.013)	0.654***	(0.009)	0.546***	(0.009)
Panel B: Endogenous variable is application-year enrollment						
All	0.202***	(0.017)	0.734***	(0.010)	0.531***	(0.014)
Women	0.219***	(0.018)	0.749***	(0.010)	0.530***	(0.015)
Men	0.073	(0.059)	0.611***	(0.035)	0.537***	(0.047)
Immigrants	0.063	(0.076)	0.552***	(0.049)	0.489***	(0.058)
Non-immigrants	0.210***	(0.018)	0.744***	(0.010)	0.534***	(0.015)
Young	0.170***	(0.024)	0.724***	(0.013)	0.553***	(0.020)
Old	0.241***	(0.025)	0.747***	(0.015)	0.506***	(0.021)
Top 25%	0.303***	(0.058)	0.799***	(0.028)	0.496***	(0.052)
Bottom 75%	0.168***	(0.020)	0.705***	(0.012)	0.537***	(0.016)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. Panel A uses admission offer as the endogenous variable. Panel B uses enrollment in the application year as the endogenous variable. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A6: Nurse

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
Panel A: Endogenous variable is admission offer						
All	0.190***	(0.012)	0.529***	(0.009)	0.339***	(0.008)
Women	0.203***	(0.012)	0.554***	(0.009)	0.351***	(0.009)
Men	0.101***	(0.032)	0.343***	(0.023)	0.242***	(0.022)
Immigrants	0.135***	(0.051)	0.443***	(0.040)	0.308***	(0.031)
Non-immigrants	0.194***	(0.012)	0.534***	(0.009)	0.340***	(0.008)
Young	0.153***	(0.016)	0.537***	(0.011)	0.384***	(0.011)
Old	0.236***	(0.017)	0.523***	(0.013)	0.287***	(0.011)
Top 25%	0.308***	(0.040)	0.586***	(0.025)	0.277***	(0.032)
Bottom 75%	0.159***	(0.013)	0.504***	(0.010)	0.344***	(0.009)
Panel B: Endogenous variable is application-year enrollment						
All	0.292***	(0.017)	0.605***	(0.011)	0.313***	(0.013)
Women	0.308***	(0.018)	0.626***	(0.012)	0.318***	(0.014)
Men	0.168***	(0.051)	0.434***	(0.036)	0.267***	(0.037)
Immigrants	0.194***	(0.071)	0.434***	(0.053)	0.240***	(0.046)
Non-immigrants	0.299***	(0.018)	0.615***	(0.012)	0.317***	(0.013)
Young	0.237***	(0.024)	0.610***	(0.015)	0.373***	(0.019)
Old	0.356***	(0.024)	0.602***	(0.017)	0.245***	(0.017)
Top 25%	0.437***	(0.055)	0.694***	(0.030)	0.257***	(0.047)
Bottom 75%	0.248***	(0.020)	0.575***	(0.014)	0.327***	(0.014)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. Panel A uses admission offer as the endogenous variable. Panel B uses enrollment in the application year as the endogenous variable. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A7: Full-time nurse

	Effect (β)		Complier $y(1)$		Complier $y(0)$	
Panel A: Endogenous variable is admission offer						
All	0.118***	(0.009)	0.301***	(0.007)	0.183***	(0.006)
Women	0.120***	(0.010)	0.303***	(0.007)	0.183***	(0.006)
Men	0.105***	(0.027)	0.286***	(0.020)	0.181***	(0.018)
Immigrants	0.100**	(0.040)	0.271***	(0.033)	0.171***	(0.023)
Non-immigrants	0.119***	(0.009)	0.302***	(0.007)	0.184***	(0.006)
Young	0.090***	(0.012)	0.300***	(0.009)	0.210***	(0.008)
Old	0.151***	(0.013)	0.303***	(0.011)	0.153***	(0.008)
Top 25%	0.218***	(0.030)	0.346***	(0.020)	0.128***	(0.023)
Bottom 75%	0.097***	(0.010)	0.285***	(0.008)	0.188***	(0.006)
Panel B: Endogenous variable is application-year enrollment						
All	0.180***	(0.013)	0.344***	(0.010)	0.164***	(0.009)
Women	0.182***	(0.014)	0.343***	(0.011)	0.161***	(0.009)
Men	0.174***	(0.044)	0.357***	(0.032)	0.183***	(0.030)
Immigrants	0.144**	(0.057)	0.268***	(0.046)	0.125***	(0.034)
Non-immigrants	0.183***	(0.014)	0.348***	(0.010)	0.166***	(0.009)
Young	0.140***	(0.019)	0.341***	(0.014)	0.201***	(0.013)
Old	0.228***	(0.019)	0.349***	(0.015)	0.121***	(0.012)
Top 25%	0.309***	(0.043)	0.426***	(0.028)	0.117***	(0.032)
Bottom 75%	0.151***	(0.016)	0.323***	(0.012)	0.172***	(0.010)

Notes: This table reports two-stage least squares estimates and complier outcome levels by subgroup. Panel A uses admission offer as the endogenous variable. Panel B uses enrollment in the application year as the endogenous variable. See Section 3.3 for details on the specification and the construction of complier outcome levels. Standard errors are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix B Additional figures

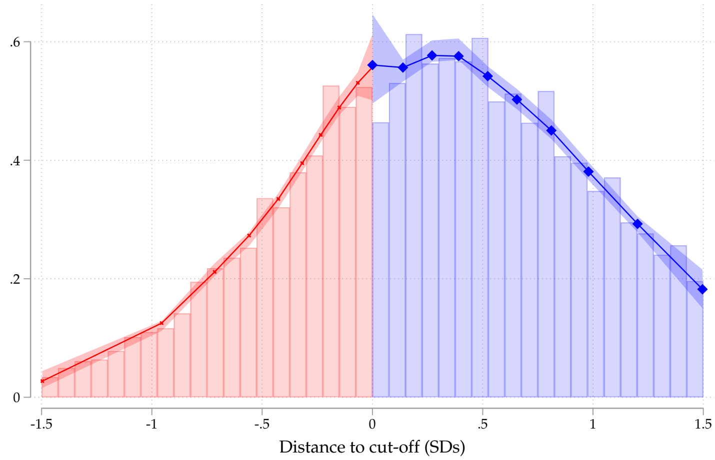


Figure B1: Validity of Regression Discontinuity Design

Notes: This figure shows the density of applicants around the admission cutoff, using the manipulation testing procedure with local polynomial density estimators as proposed by Cattaneo et al. (2020).

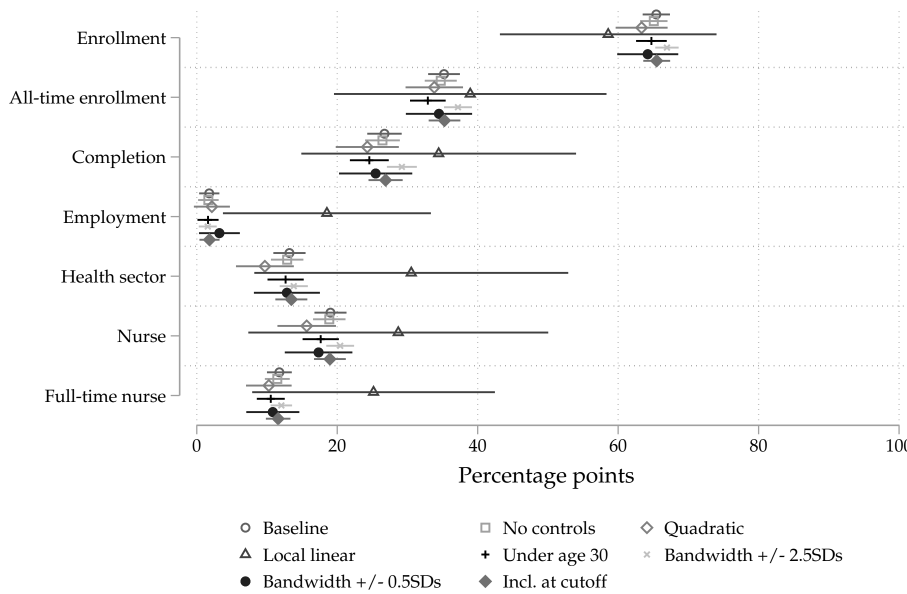


Figure B2: Robustness of IV estimates

Notes: This figure shows treatment effect estimates across five different specifications. The baseline is the 2SLS model using the estimation sample described in Section 2.2. The local linear specification applies a triangular kernel with MSE-optimal bandwidth, implemented via the rdrobust package (Calonico et al., 2014). The remaining specifications use 2SLS, but with alternative sample restrictions: limiting the sample to nursing applicants under age 30 at the time of application; including applicants with application scores up to ±2.5 SDs; focusing on applicants with scores within ±0.5 SDs of the cutoff; and including applicants located exactly at the cutoff. Standard errors for employment outcomes are clustered at the applicant level. All specifications include dummies for application year, gender, age, immigration status, and parental background. Parental background is measured when the applicant is 16 years old and includes indicators for whether at least one parent held a health-related degree, a nursing degree, or a medical degree, respectively.

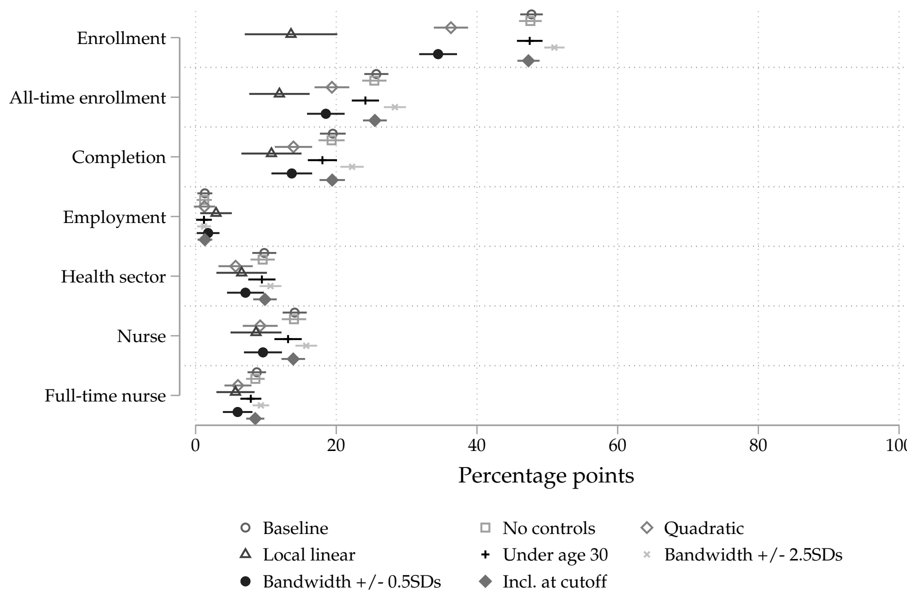


Figure B3: Robustness of reduced-form estimates

Notes: This figure shows reduced-form estimates across the same specifications as Appendix Figure B2. The markers show the effect of being above the admission cutoff on enrollment, completion, and employment outcomes. Error bars indicate 95% CI.

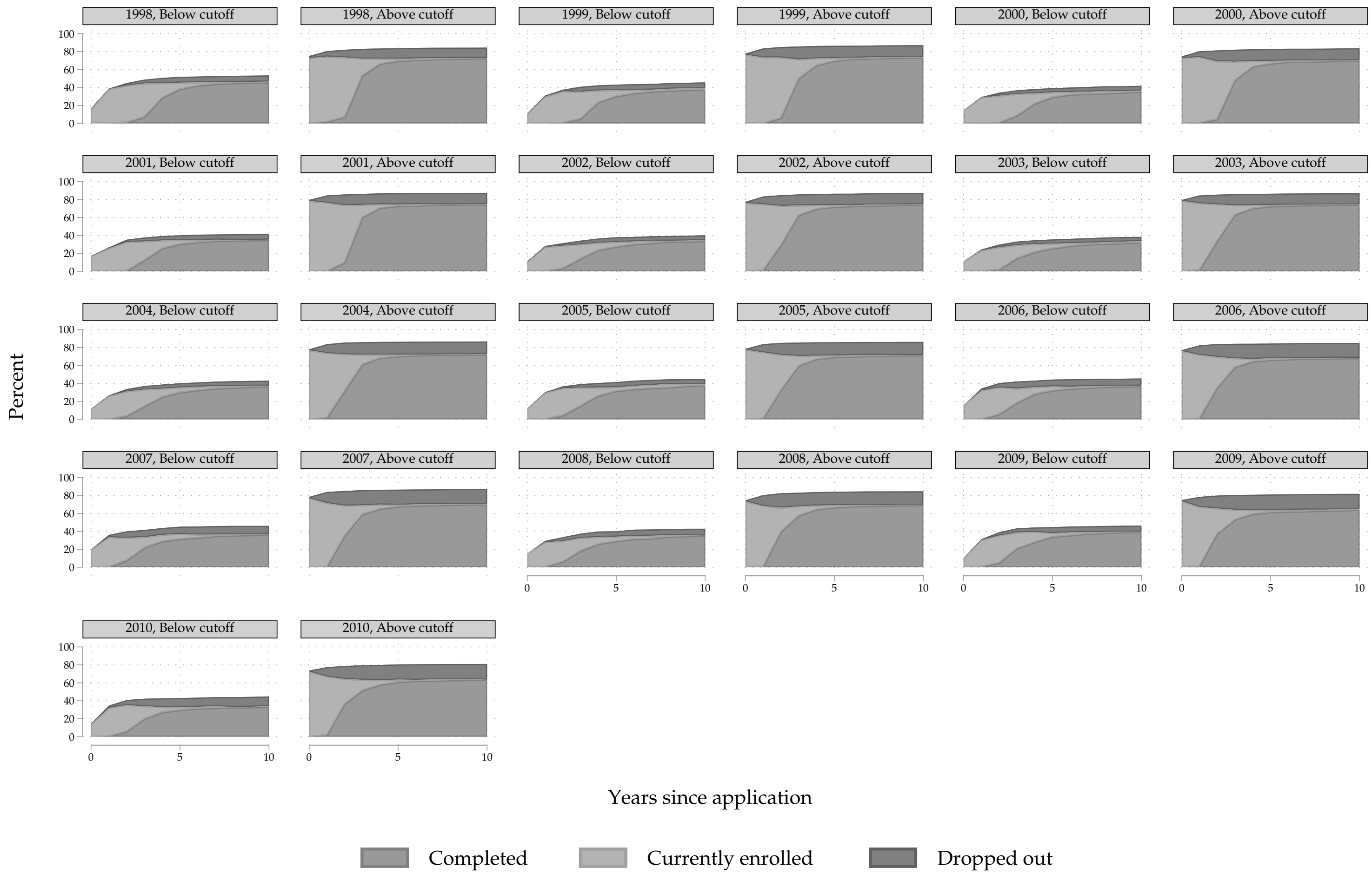


Figure B4: Enrollment and completion by applicant cohorts

Notes: This figure shows the educational trajectories of applicants scoring above and below the admission cutoff for nursing programs for application cohorts 1998-2010.

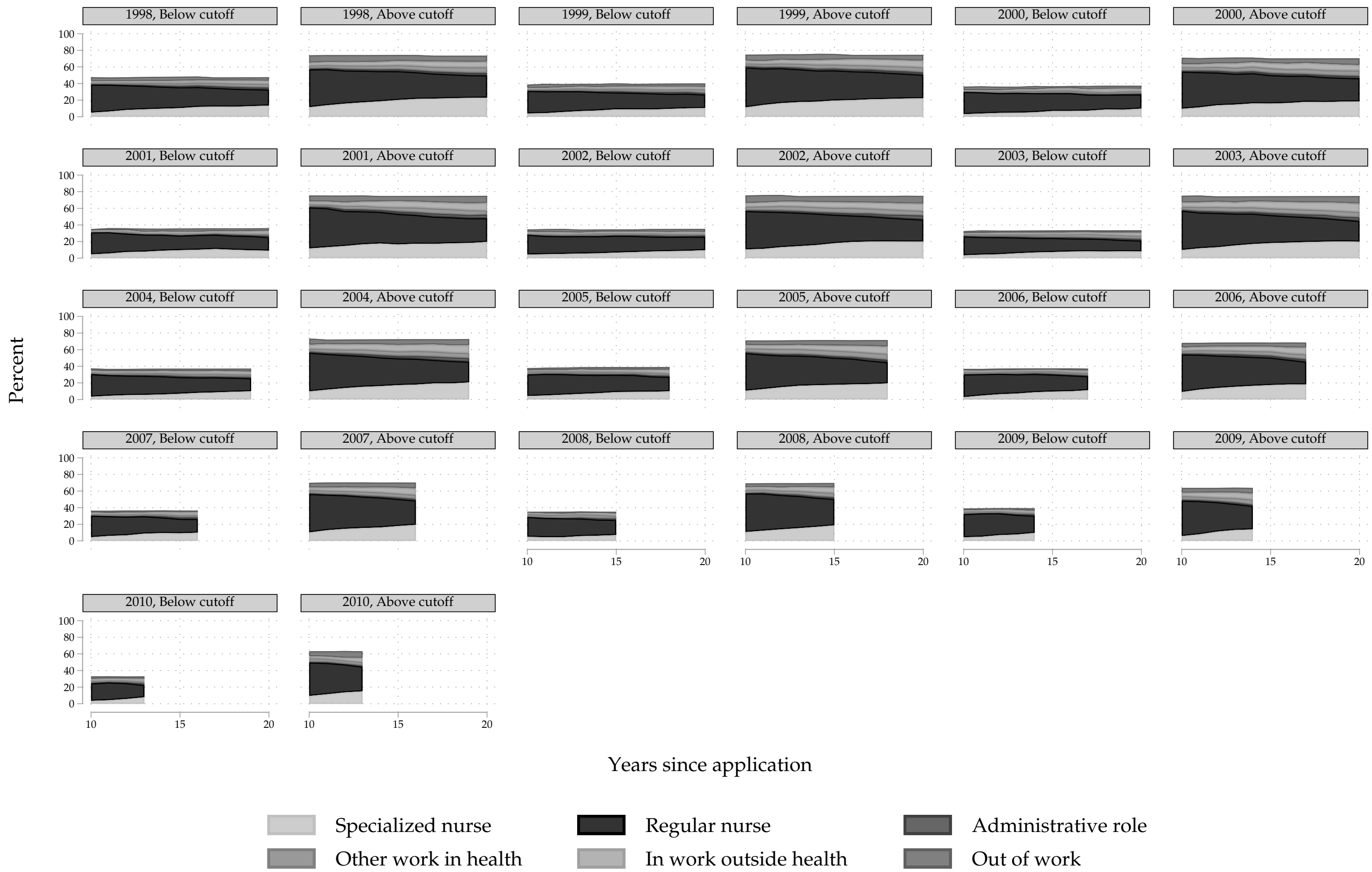
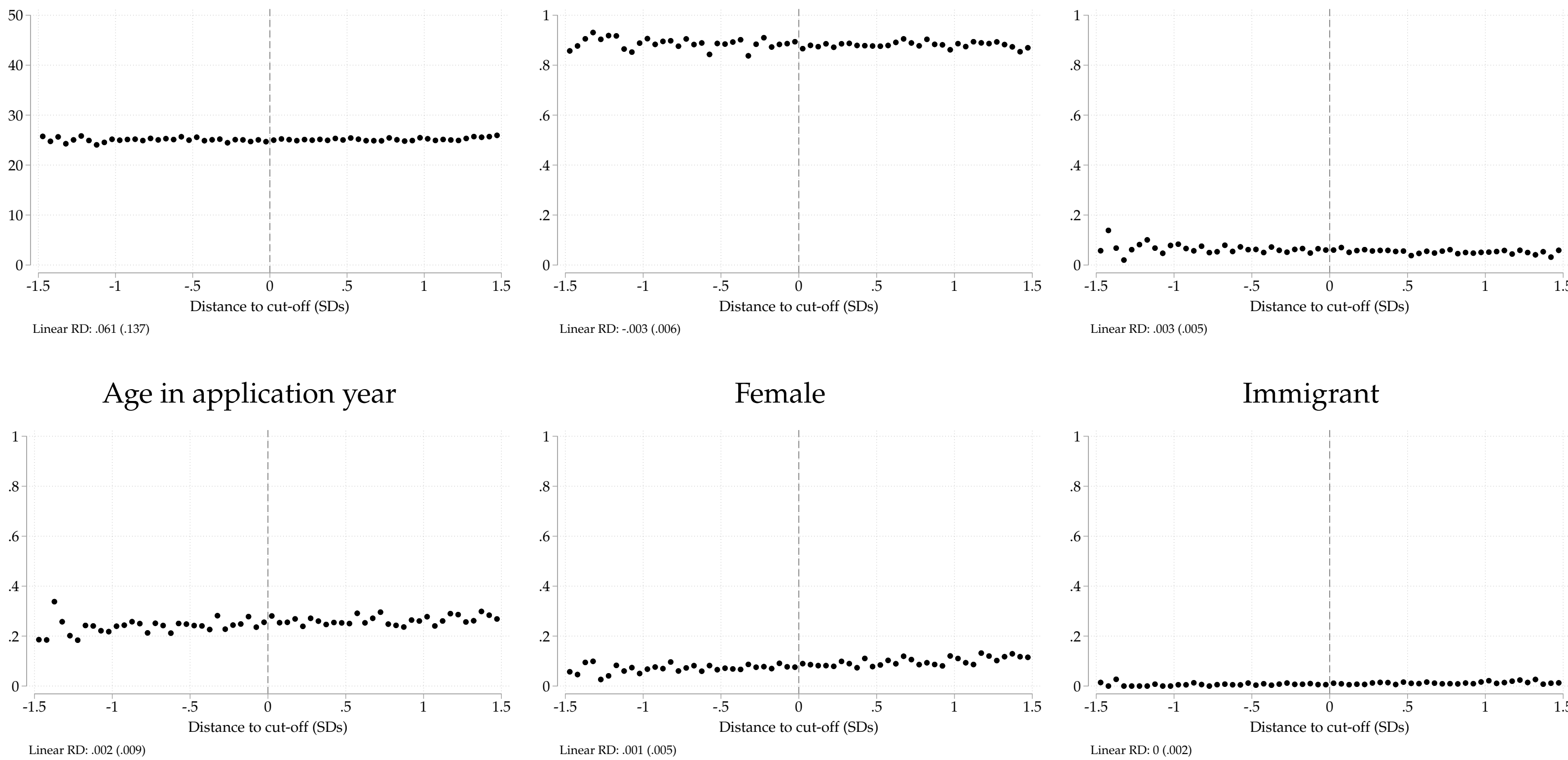


Figure B5: Employment by applicant cohorts

Notes: This figure shows the employment trajectories of applicants scoring above and below the admission cutoff for nursing programs for application cohorts 1998-2010.



Age in application year | Female | Immigrant

At least one parent has a health degree | At least one parent has a nurse degree | At least one parent has a medical degree

Figure B6: Balancing checks

Notes: These figures show balancing checks for various characteristics.

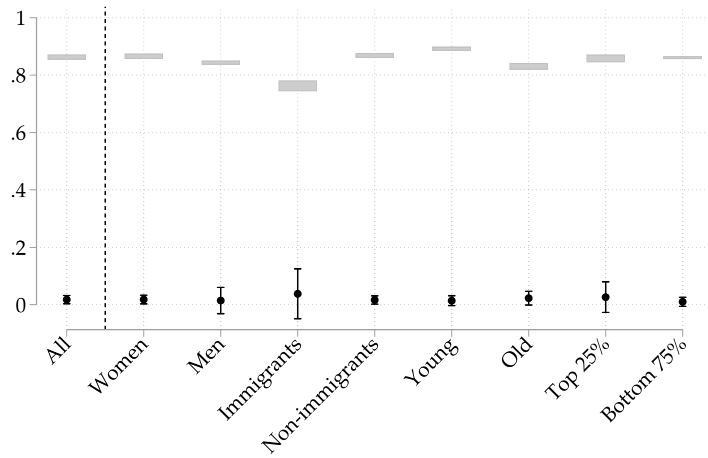


Figure B7: The effects of admission on total employment

Notes: This figure shows the 2SLS estimates of admission to nursing programs on employment between 10 and 20 years after application, disaggregated by predetermined characteristics, including gender, immigration status, age at application, and GPA from upper secondary school. Error bars indicate 95% CI (standard errors clustered at the applicant level).