

Nurses' education, employment, and heterogeneous effects of admission

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Abstract

Shortage of skilled healthcare workers is a global challenge. In this paper, we study applicants to Norwegian nursing programs. Mapping out their educational and employment trajectories, we find that a substantial share of admitted applicants never complete nursing or work as nurses, but also that many rejected applicants reapply and complete later. Thus, the effect of admitting an applicant on the applicant's completion or labor supply as a nurse is much smaller than one-to-one. Using admission discontinuities, we study the heterogeneous effects of admission on enrollment, completion, and subsequent labor market outcomes. We find indications that the effect of admission is smaller for men than for women, highlighting a possible conflict between the goals of more nurses and gender balance in nursing.

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

JEL classification: 118, 123, 128, J2

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Sammendrag

Mangel på kvalifisert helsepersonell er en internasjonal utfordring. I denne artikkelen studerer vi søkere til sykepleierutdanninger. Ved å kartlegge deres utdannings- og yrkesløp, finner vi at en betydelig andel av de som blir tatt opp aldri fullfører utdanningen eller jobber som sykepleiere, men også at mange av de som blir avvist søker på nytt og fullfører senere. Dermed er effekten av å gi opptak på hvorvidt en søker fullfører eller faktisk jobber som sykepleier langt mindre enn én-til-én. Ved å utnytte opptaksgrenser studerer vi ulike effekter av opptak på studiestart, fullføring og senere utfall i arbeidsmarkedet. Vi finner tegn til at opptak har mindre effekt for menn enn for kvinner, noe som peker på en mulig konflikt mellom målet om flere sykepleiere og målet om bedre kjønnsbalanse i yrket.

1 Introduction

The global shortage of healthcare workers has become a critical challenge, exacerbated by the COVID-19 pandemic and an aging population that demands increasingly complex care (Drennan and Ross, 2019; Scheffler and Arnold, 2019). In many countries, including Norway, education systems are struggling to keep pace with the rising demand for qualified health professionals. Although Norway has one of the highest ratios of nurses to inhabitants among OECD countries, with over 18 nurses per 1,000 inhabitants (OECD, 2023), projections suggest a potential shortfall of approximately 30,000 nurses by 2040 (Jia et al., 2023). This shortage is driven not only by demographic changes but also by systemic challenges within the educational and healthcare sectors. Healthcare professions in Norway are highly regulated, requiring formal education and licensure, which limits flexibility in addressing these shortages and places significant pressure on the education system to produce an adequate number of graduates.

This paper leverages comprehensive Norwegian administrative data to examine the educational and professional trajectories of applicants to nursing programs. Specifically, we investigate whether these applicants enroll in and complete their nursing education and whether they ultimately work as nurses or in other healthcare roles.

Despite the strategy-proof application system, which provides incentives to truthfully report preferences, many applicants do not take up offered programs. Furthermore, many admitted students drop out and do not complete their programs. On the other hand, a substantial share of applicants not initially admitted reapply and may be admitted in a later year. The detailed data allow us to trace out these complex enrollment and completion patterns. Detailed data on employment allow us to follow the applicants into the labor market, investigating to what extent they work as nurses, or in other occupations within health care, at different times after their initial applications to nursing.

A key aspect of our study is the utilization of discontinuities in the admission system to identify the causal effects of admission on subsequent enrollment, completion, and employment outcomes. The Norwegian higher education admission process provides a unique setting for this analysis, as the use of specific cutoff points for admission creates quasi-experimental conditions that allow us to credibly estimate these effects of admission. Furthermore, we explore the heterogeneity of these admission effects across various pre-determined applicant characteristics, including gender, age at the time of application, and immigrant background.

This analysis aims to uncover differential impacts that could inform targeted interventions and policies designed to support diverse groups in their educational and career pursuits within the healthcare sector. By shedding light on the factors that influence the successful transition from nursing education to employment in the healthcare field, this research contributes to the broader understanding of workforce development in a critical industry.

The analyses make three significant contributions to understanding the supply of newly-educated nurses and to inform education, healthcare and labor market policy:

- Descriptive Analyses: We provide detailed descriptive analyses of how applicants to nursing programs and nursing students move through the educational system and transition into the workforce. This allows policymakers to better understand the challenges associated with educating, recruiting and retaining healthcare workers, thereby informing strategies to address these issues effectively.
- 2. Causal Effects: By examining the causal effects of admitting marginal applicants to nursing programs, we analyze the impact of admission on enrollment, completion, and labor force participation. This aspect of the study offers valuable insights into how admission policies influence the overall supply of qualified healthcare professionals. This analysis builds on identification similar to e.g. Kirkeboen et al. (2016), however, like Öckert (2010) we estimate the effects of admission rather than completion.

3. Heterogeneous Effects: Our analysis of the heterogeneous effects of admitting different marginal applicants sheds light on the differential impacts on completion rates and workforce participation. This information is crucial for designing policies that target specific groups and efficiently allocate costly study places. Such targeted interventions can be implemented through strong policy tools within the admission system, such as quotas or extra points for certain groups (as in Semb (2024)), or through less intrusive measures like outreach programs aimed at underrepresented groups, such as men in nursing.

By shedding light on the factors that influence the successful transition from nursing education to employment in the healthcare field, this research contributes to the broader understanding of workforce development in a critical industry. Our findings have the potential to inform policymakers and educational institutions about the effectiveness of current admission practices and highlight areas for improvement to ensure a robust and well-prepared nursing workforce.

2 Data and sample selection

In this section, we describe the institutional background and the data, explain the construction of the estimation sample, and define the key terms and conventions that we use throughout our paper.

2.1 Institutional background

This analysis focuses on nurse education in Norway and the subsequent employment of nurses in healthcare. The healthcare system in Norway is primarily public, with a well-established structure of training and certification for healthcare professionals. Nursing is a licensed occupation, and to practice as a nurse, one must be licensed by a government agency. Obtaining a license requires completing a formal nursing degree.

2.1.1 Norwegian higher education

Norwegian higher education consists almost exclusively of public universities and university colleges. Students do not pay tuition and are eligible for financial support from the government, which is provided in the form of a combination of loans and grants. Historically the former have mostly 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 universities.

Norway has a centralized system of admission to higher education. Applicants submit a single application to a single organization, which handles admission for all programs and institutions. The applicants supply a rank-ordered list of up to 10 or 15 different programs, where one program is generally a combination of an institution and a detailed field (e.g. nursing).¹

Applicants are assigned to their highest-preferred program, which has a free place with a deferred acceptance algorithm. Applicants are ranked by their admission scores, which mostly reflect their high school GPAs (and some extra points, e.g. for certain high school subjects, age, and military service). The system is strategy-proof, such that applicants cannot manipulate admissions by misreporting their preferences. When programs are oversubscribed (it has more applicants than places) this creates an admission score threshold, such that applicants above the threshold will get an offer and applicants below will not. The admission is

¹The exact number of rank-ordered programs submitted by the applicants has varied over time. In addition, when an institution has more than one campus there can be different programs at different campuses, this becomes more of an issue after our observation period. Also, programs can differ in terms of form of instruction. E.g. an institution may offer both a full-time nursing program and a part-time nursing program. Programs with non-standard instruction mostly target older and currently employed students.

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. Effects of completion have previously been studied by Kirkeboen et al. (2016); Heinesen (2018), who investigated pay-offs to fields of study relative to counterfactual fields. Öckert (2010) and Ketel et al. (2016) have studied economics returns to admission for Sweden and to medicine in the Netherlands, using randomized offers.

Nursing education in Norway follows a clearly defined, standardized pathway, typically lasting three years and leading to a Bachelor's degree.² To enter the program, applicants must meet the general study competence requirement, which typically means completing three years of upper secondary education. The program is regulated by national guidelines that set the aims, scope, and content of nursing education. Half of the study time is devoted to clinical training, organized by 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 the university college meets national standards.

2.2 Data sources

Our analysis utilizes multiple data sources from Statistics Norway, which we link using unique identifiers for individuals and their parents. The primary dataset is the application records from the Norwegian Universities and Colleges Admission Service, covering nearly all applications to post-secondary education in Norway from 1998 to 2010. These records provide detailed information for each applicant, including their ranked preferences for study programs, application scores, admission cutoffs, offers received, and enrollment decisions.

We merge these application records with administrative registers that offer comprehensive demographic data, such as sex, age, immigrant status, and parental identifiers, as well as educational attainment. The educational attainment data include both the applicant's completed field of study and the parents' completed field of study when the applicant was 16 years old.

Finally, we link these records to employer-employee registers, which track employment outcomes. The employment data are available annually from 2008 to 2014 (sampled in November each year) and monthly from 2015 to 2023. To ensure consistency, we harmonize the data by using only the November observations. These employment records provide detailed information on subsequent labor market outcomes, including employment, industry and occupation.

2.3 Sample and descriptive statistics

The starting point consists of all applicants to a nursing program between 1998 and 2010. We identify all applicants on the margin between nursing and another detailed field. The sample construction follows Kirkeboen et al. (2016), except that we find applicants on margins between different detailed fields (as opposed to aggregate fields) and that we restrict the sample to applicants with nursing as their preferred detailed field. To be included in the sample, the applicant must either be predicted to get an offer to a nursing program with a binding admission cutoff, or they could have if their admission score was higher. Additionally, we restrict the sample to application scores fall within ± 1.5 standard deviations of the cutoff and exclude individuals with application scores exactly at the cutoff.

²There 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. This study focuses on registered nurses who complete a three-year Bachelor's program. For further details, see, e.g., Kyrkjebø et al. (2002), and Saunes et al. (2020).

Education panel. The above restrictions yield a balanced panel of 33,441 applicants, for whom we observe educational outcomes, including admission, enrollment, and completion within 10 years of application.

Employment panel. The employment data tracks the same set of applicants and captures employment outcomes within a window of 10 to 20 years after their initial application.³ The panel is unbalanced, with the 1998 cohort observed between 2008 and 2018 and the 2010 cohort followed from 2020 to 2023. Key employment outcomes include overall employment, employment in the health sector, employment specifically as a nurse, and employment as a full-time nurse. These measures provide a comprehensive view of how nursing graduates integrate into the workforce and their subsequent career trajectories within and beyond the healthcare sector.

Table 1 presents summary statistics. The average applicant is 25 years old and predominantly female. Regarding parental background, around 26% of applicants have a parent with a health-related degree, including 9% with a nursing degree and 1% with a medical degree. Additionally, 6% are immigrants.

Pre-det	termined characteristic	S	
Age	25.09		
Female	0.88		
At least one parent has a health degree	0.26		
At least one parent has a nurse degree	0.09		
At least one parent has a medical degree	0.01		
Immigrant	0.06		
	Education panel		
	In Application Year	Within 10 Years	
Offer Received	0.67	-	-
Enrolled	0.54	0.71	
Completed	-	0.60	
N	33441	33441	
E	Employment panel		
	After 10 Years	After 15 Years	After 20 Years
In Work	0.86	0.87	0.85
In Health Sector	0.63	0.62	0.61
Work as Nurse	0.48	0.45	0.42
Work as Full-Time Nurse	0.26	0.25	0.24
N	32036	30197	17666

Table 1: Summary statistics

Regarding admission, enrollment, and completion, 67% of applicants received an offer of admission to the nursing program in the year of application, and 54% ended up enrolling in the same year. Within a 10-year period, the enrollment rate increases to 71%, and 60% of applicants have completed the program. These figures suggest that while a majority of those who receive offers eventually enroll and complete their studies, this often occurs over an extended time horizon. This delay may partly reflect applicants with

³The employment panel in year 10 after the application has slightly fewer observations than the education panel due to missing entries in the employment register or missing information on industry or occupation.

admission scores below the cutoff who are eventually admitted in subsequent years.

Employment outcomes illustrate trends in workforce participation among this group. Ten years after application, 86% of individuals were employed, with 63% working in the health sector, 48% employed as nurses, and 26% working as full-time nurses. By 20 years after application, employment rates with 85% remained high overall, but the share working as nurses declined to 42%, and those working as full-time nurses dropped to 24%. These trends highlight a gradual transition out of nursing roles over time.

To better understand the dynamics of educational and employment outcomes, it is helpful to divide the sample into two mutually exclusive groups based on the admission cutoff: applicants with scores above the cutoff and those with scores below. This distinction sheds light on how initial admission eligibility impacts applicants' trajectories through the program and into the labor market.

Figure 1 tracks the educational trajectories of applicants scoring above and below the admission cutoff for nursing programs, focusing on enrollment, completion, and dropout rates over time. In the year of application, approximately 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. In contrast, around 14% of applicants scoring below the cutoff enroll in the same year, likely through alternative admissions channels. Over the next two years, the enrollment rate for applicants below the cutoff increases to just over 30%, suggesting that many reapply and are subsequently admitted. In the following years, the proportion of students who drop out and those who complete the program gradually rises for both groups. By the fifth year after applying, most applicants who have not dropped out have successfully completed the program.





Notes: This figure shows the educational trajectories of applicants scoring above and below the admission cutoff for nursing programs, adjusted for applicant cohort effects. We adjust for cohort effects by regressing the number of observations on a full set of dummies for each cohort and time period. The time period coefficients from this regression are used to measure the number of observations in each state, net of cohort effects, with the population mean in the application year added back to obtain an intercept that reflects the correct population average. Educational trajectories for each applicant cohort are shown in Figure A1.



Figure 2: Employment

Notes: This figure shows the employment trajectories of applicants scoring above and below the admission cutoff for nursing programs, adjusted for applicant cohort effects. We adjust for cohort effects by regressing the number of observations on a full set of dummies for each cohort and time period. The time period coefficients from this regression are used to measure the number of observations in each state, net of cohort effects, with the population mean 10 years after application added back to obtain an intercept that reflects the correct population average. Employment trajectories for individual applicant cohorts are shown in Figure A2.

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.

3 The effects of threshold crossing

We employ a Fuzzy Regression Discontinuity design (see, e.g., Lee and Lemieux (2010)) to examine educational and employment outcomes for applicants who ranked nursing as their most preferred program. Specifically, we compare applicants with admission scores just above the admission threshold to those with admission scores just below it. The underlying intuition is that applicants near the threshold are similar in both observable and unobservable characteristics that influence outcomes. However, those with admission scores slightly above the threshold are significantly more likely to be admitted (i.e., receive the treatment).

The design is considered fuzzy because some applicants with admission scroes below the threshold may still be admitted, while some with admission scroes above the threshold may not be. To estimate the effect of crossing the threshold, we first standardize and center applicants' admission scores at the cutoff. We then perform local-linear regressions on either side of the threshold to estimate the average treatment effect at the

cutoff. This analysis uses the method introduced by Calonico et al. (2014), which applies a bias-corrected estimator and an MSE-optimal bandwidth selector. The resulting estimates and their bias-corrected 95% confidence intervals (CIs) are reported in the figures below.



(c) Ever enrolled by year 10 after application



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

In Figure 3 we present reduced form estimates of the effect of being above the cutoff on receiving an offer, enrolling and completing. In sub-figure (a) we see there is a large change in the probability of getting an offer at the cutoff. Almost all applicants above the cutoff get an offer. Few applicants get an offer below the cutoff, those that do are mostly very close to the cutoff.⁴

Moving to enrollment in sub-figure (b), we see an attenuated effect compared to the effect on offers. This is mostly because only around 75% of applicants above the cutoff enroll, despite getting an offer. Very few applicants below the cutoff enroll in the application year. This however changes over time. Sub-figures (c) and (d) show that a substantial share of the applicants below the cutoff enroll later and eventually complete. For applicants just above the cutoff the share completing is about 65%, while about 55% of applicants just below also end up completing.

The shares ever enrolling and completing within 10 years decrease with the distance to the cutoff for applicants initially below the cutoff, but, unlike the share getting an offer in the application year, approximately linearly. Among applicants initially above the cutoff the shares ever enrolling and completing are

Notes: Estimates in notes are with global linear splines and local linear regressions using a triangular kernel using Calonico et al. (2014). Standard errors are reported in parentheses. Bias-corrected confidence intervals from Calonico et al. (2014) are reported in brackets. Dots represent bin means, bins are selected with the IMSE-optimal quantile-based method using polynomial regression. The lines represent fourth-degree global splines.

⁴A reason that applicants above the cutoff do not receive an offer is that may choose not to be on the waiting list in an early round, and thus miss out on an offer they would eventually have got. A reason that applicants below the cutoff get offers is that applicants may, at the time of application, request special treatment, e.g. if they due to documented illness performed below their abilities in final exams.

close to independent of the distance to the cutoff.



Figure 4: The effects of threshold crossing on employment trajectories

Notes: Estimates in notes are with global linear splines and local linear regressions using a triangular kernel using Calonico et al. (2014). Standard errors are reported in parentheses, clustering on applicant. Bias-corrected confidence intervals from Calonico et al. (2014) in brackets. Dots represent bin means, bins are selected with the IMSE-optimal quantile-based method using polynomial regression. The lines represent fourth-degree global splines.

In Figure 4 we show reduced form effects corresponding to those in Figure 3 on different employment outcomes. We see that crossing the admission threshold has no effect on the probability of working, employment is about 86% both above and below the cutoff. However, being above the admission threshold has a lasting impact on the probabilities of working in the healthcare sector, working as a nurse and as working full time as a nurse, 10 to 20 years after application.

3.1 Validity of the Regression Discontinuity Design

The Regression Discontinuity Design compares applicants just above the cutoff (who more often receive an offer, enroll and complete, cf. Figure 3) with other applicants just below the cutoff. Assuming that these applicants are ex-ante similar, we can estimate the effect of getting an offer and being admitted. This assumption is untestable but can be evaluated by looking at observable characteristics around the cutoff. Figure A3 shows that background characteristics of applicants are continuous around the cutoff. In Figure A4, we also investigate whether there is evidence of bunching—that is, a discontinuity in the distribution of applicants around the cutoff. Visual inspection does not suggest any sharp changes in density. To formally test for manipulation, we apply the density discontinuity test proposed by Cattaneo et al. (2020). The test fails to reject the null hypothesis of continuity, providing no evidence of strategic sorting around the threshold.

4 The effects of program admission

Having established a lasting effect of being above the cutoff on educational and employment outcomes in the previous section, we now move on to estimating the effect of admittance for a marginal applicant.

We estimate these by instrumenting admission with being above the cutoff. Thus, the first stage is the effect on admission in Figure 3, sub-figure (a). The exclusion restriction is that being above the cutoff only impacts later education and employment by increasing the probability of getting an offer to nursing in the application year. Unlike in Section 3, but similar to Kirkeboen et al. (2016), our main specification will be a more parametric 2SLS specification, controlling for the forcing variable and predetermined covariates. Including data further from the cutoff yields more precise estimates. In Section 4.1 we investigate the robustness of our main estimates to the choice of specification.

In Figure 5 we present 2SLS estimates of the effects of admission on educational and employment outcomes. Rescaling with the effect on admission of being above the cutoff, we find that the effect of an admission offer on enrollment in the application year is about 65 percentage points.

Following Abadie (2003), we can also estimate the levels for the treated and untreated compliers: the enrollment rates of applicants above the cutoff who get an admission offer (but who wouldn't if they were below the cutoff) and of applicants below the cutoff who don't get an offer (but who would have if they were above). Appendix Table A1 shows levels of treated and untreated compliers, in addition to the treatment effects, the difference between the levels. About 76% of treated compliers enroll, compared to 16% 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.

The effect on all-time enrollment and completion are smaller than the effect on enrollment in the application year, at 35 and 27 percentage points. From Appendix Tables A2 and A3, we learn that this is mostly because many initially unsuccessful applicants reapply and eventually enroll and complete: 50% of such applicants enroll and 42% complete within 10 years.



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

Notes: This figure shows the 2SLS estimates of admission to nursing programs on enrollment, completion, and employment outcomes. "Enrollment" refers to enrollment in the application year, while "all-time enrollment" captures enrollment observed through 2020. "Completion" refers to program completion within 10 years after application. For the employment outcomes, yearly observations are stacked, and standard errors are clustered at the applicant level. Error bars indicate 95% CI.

Figure 5 also presents effects on labor market outcomes. We find a very small effect on overall employment (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 healthcare sector. 67 % of treated compliers work in healthcare, compared to 54 % of untreated compliers, cf. Appendix Table A5.

The effect on working as a nurse is larger than the effect of working in healthcare, at 19 percentage points. Thus, being admitted to nursing slightly decreases the probability of working in healthcare 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 working as nurse works full time. Among treated compliers 53 % work as a nurse, and 30 % work full time, cf. Appendix Tables A6 and A7.

4.1 Robustness

Figure A5 presents a series of robustness checks comparing the main 2SLS estimates in Figure 5 to alternative specifications. These include (i) estimates from local linear regressions using a triangular kernel and MSE-optimal bandwidth, (ii) restricting the sample to nursing applicants under the age of 30 at the time of application, (iii) expanding the bandwidth to include observations further from the cutoff, (iv) narrowing the bandwidth to focus on applicants closer to the cutoff, and (v) including individuals located exactly at the cutoff. While the local linear specification yields somewhat different estimates for employment outcomes and is considerably less precise, the overall pattern of results remains consistent, and differences across specifications are never statistically significant.

4.2 Heterogeneity

The background data provides several predetermined characteristics of the applicants, which allows us to estimate the effects of admission for different subgroups. Specifically, we examine heterogeneous treatment effects based on gender (females/males), immigration status (two immigrant parents/at least one Norwegianborn parent), age (young/old), and GPA from upper secondary school (upper/lower part of the distribution). These groupings are useful for understanding differences in educational choices and trajectories, with some groups also being particularly relevant for policy discussions. For example, there has been ongoing debate about the extent to which males should be targeted to achieve a better gender balance in nursing, while the admission system in general until recently gave priority to older applicants.

Figure 6 presents the effects on enrolling in the nursing program during the application year. Across all subgroups, admission leads to an increase in enrollment by approximately 60 to 70 percentage points, with no statistically significant differences between the groups.



Figure 6: The effects of admission on enrollment

Notes: This figure shows the 2SLS estimates of admission to nursing programs on enrollment in the application year, disaggregated by predetermined characteristics, including gender, immigration status, age at application, and GPA from upper secondary school. Error bars indicate 95% CI.

Figure 7 shows the effect of admission on the probability of ever starting the nursing program. Here, we observe modest differences, with the most notable variation by age. Older applicants (those above the median age of 22) experience a 40 percentage point increase in the probability of ever starting the program, compared to a 30 percentage point increase for younger applicants. However, this age-related difference does not appear in enrollment rates for the application year as shown in Figure 6. In Appendix Table A2 we show treated and untreated complier levels for each group of applicants. The difference in the effect on ever starting appears to stem from the fact that older applicants, if not admitted in the application year, are less likely than younger applicants to enroll in subsequent years. Additionally, smaller gender and GPA-related differences are observed in Figure 7, with men showing a lower probability of ever starting, and those with higher grades having a higher likelihood of starting.

Next, Figure 8 examines the effects of admission on program completion. The main patterns are similar



Figure 7: The effects of admission on all-time enrollment

Notes: This figure shows the 2SLS estimates of admission to nursing programs on all-time enrollment, disaggregated by predetermined characteristics, including gender, immigration status, age at application, and GPA from upper secondary school. Error bars indicate 95% CI.



Figure 8: The effects of admission on completion

Notes: This figure shows the 2SLS estimates of admission to nursing programs on completion within 10 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.

to those in Figure 7, with lower completion rates for men, younger applicants, and those with lower grades. However, unlike the all-time enrollment results, the gender difference is particularly striking in terms of completion. An offer increases the probability of completion for women by about 30 percentage points, compared to just under 20 percentage points for men. A smaller effect of admission on completion for men relative to women may reflect either a lower completion rate among men who receive an offer or a higher completion rate among men who do not receive an offer. Appendix Table A3 shows that men complete the program less frequently than women, both when admitted (52% vs. 71%) and when not (34% vs. 43%).



Figure 9: The effects of admission on employment in health sector

Notes: This figure shows the 2SLS estimates of admission to nursing programs on employment in the health sector 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).

In Figure 9 we show effects on work in the health sector.⁵ We do not find an effect for immigrants, and there is again a striking gender difference. For women, an offer of a study place leads to an increased probability of work in the health sector, while for men there is no clear effect. 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 (56% vs. 46%).

In Figure 10 we show the effects of admission on work as a nurse (regardless of working hours). Here we see the same pattern as in Figure 9: Lower effect for men, immigrants, young people and those who do not have the best grades. The differences between the groups are nevertheless less striking, and we see that admission for men (and immigrants) has a positive effect on the probability that they will later work as a nurse. When we see an effect on work as a nurse for men in Figure 10, but not on work in the health sector in Figure 9, this suggests that the additional nurses largely come at the expense of other work in the health sector for these men. This does not apply to the same extent for women, as we see an effect on work in the health sector for women in Figure 9 that is almost as large as the effect in Figure 10.

In Figure 11 we see effects on full-time work as a nurse. These are positive for all groups, and more similar than the effects on work as a nurse regardless of working hours in Figure 10. In particular, there is

 $[\]overline{{}^{5}\text{Across all subgroups}}$, the effect on any employment is insignificant (see Figure A6).



Figure 10: The effects of admission on employment as nurse

Notes: This figure shows the 2SLS estimates of admission to nursing programs on working as a nurse 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).



Figure 11: The effects of admission on employment as full-time nurse

Notes: This figure shows the 2SLS estimates of admission to nursing programs on working as a full-time nurse 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).

no gender difference in Figure 11. This suggests that the larger effect on work as a nurse among women is largely part-time work, and that the gender difference in the effect on the number of working hours as a nurse is smaller than the differences in Figure 10 might suggest.

Overall, there are relevant differences between groups of applicants. The gender difference is particularly striking. Making an offer of a study place to a man instead of a woman makes it less likely that the person who receives the offer will complete their education and work as a nurse. It has no consequences for whether a person works full-time as a nurse, so the gender difference in the effect on total working hours as a nurse is smaller than the difference in the proportion working as a nurse. The overall effect on working as a nurse is nevertheless smaller when a man is admitted than when a woman is.

The larger effects on all-time enrollment, completion, and employment for older and high-scoring applicants mostly reflect lower levels for untreated compliers of these groups. The levels among treated compliers vary less. Older applicants may have less patience and high-scoring applicants better outside options, and thus be less inclined to wait and reapply to nursing in a later year.

4.3 Effects beyond the individual applicant

We have studied the effect of getting an offer for the preferred program on the individual applicant. Giving an offer is the fundamental treatment that the institutions (or other authorities regulating the admission) can provide, while the applicants (endogenously) either take the offered study place or not. In this subsection we briefly discuss potential spill-overs to other applicants and implications for effects beyond those on the individual applicant.

4.3.1 Supply responses

The institutions want to fill classes of a given size, not provide a given number of offers. The institutions are aware that not all offered applicants will show up and try to adjust the number of offers sent accordingly. Specifically, if men are given priority and get a larger share of a fixed amount of offers, enrollment will decline. The institutions will likely soon, if not immediately, realize and increase the total number of offers accordingly to fill the classes. However, men also have a lower propensity to complete and work as nurse conditional on enrollment in the application year.⁶

It will be harder for the institutions to adjust the amount of offers to stabilize all-time enrollment or completion, and it will be costly to increase classes to account for more students not completing. Thus, while supply responses from the institutions are likely to attenuate negative effects on completed nursing degrees or employed nurses of a reallocation of offers from women to men (or to any group with lower enrollment and completion rates), it is unlikely that the supply responses will negate such effects, especially on completion.

4.3.2 Ripple effects

Our estimates are informative of the effects of an offer on the outcomes of the applicant. Another object of interest may be the effect on the total number of nurses or on total nurse labor supply of giving an extra offer, or the effect of adding an extra slot to an oversubscribed program. As shown earlier, an important reason that the effects of an offer are not larger is that many initially unsuccessful applicants reapply in subsequent years and eventually enroll and complete. If these applicants got an offer in the initial application year they would not (or less frequently) enroll later. If the programs they eventually enroll in are oversubscribed (like

⁶As can be ascertained by instrumenting the effects of application-year enrollment instead of the effects of getting an offer, or similarly by dividing the different effect estimates by the effect on application-year enrollment.

the programs they originally applied to by construction are), this will free up places for other applicants. This may, in turn, free up new places that these previously marginally rejected applicants otherwise would have taken, and so on. Gandil (2025) shows that such ripple effects can be substantial.

To fully account for the effect of an extra place is outside the scope of this paper. However, we will consider two limiting cases, which we argue provide upper and lower bounds on the effects of an extra place, including ripple effects. The lower bound is trivial and corresponds to the treatment effects on the applicants presented above. If all initially rejected applicants that eventually enroll do so at undersubscribed programs, no places are freed up, and there are no ripple effects. The upper bound corresponds to the outcomes of treated compliers in Appendix Tables A1-A7. These are the outcomes of a marginally admitted applicant. Creating a new place means realizing these outcomes for an otherwise marginally rejected applicant. The next applicant in line, marginally lower ranked, takes the place of the original marginally rejected applicant and gets similar outcomes, and so on.

To evaluate the relevance of the lower and upper bounds, 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% percent are first observed enrolled in an oversubscribed program and year and will thus likely have displaced other marginal applicants.⁷ Thus, we expect the effect of a small expansion in the number of study places, small enough that the characteristics of the marginal applicant don't substantially change, to be closer to the upper bound than to the lower bound.

5 Conclusion

In this paper we have studied applicants to nursing programs, and to what extent they are admitted to, enroll in and complete nursing programs, and to what extent they work as nurses or other professions in healthcare.

We found that admission into a nursing program has a lasting impact on enrollment, completion and employment. However, the impact is far smaller than one-to-one. This is in part because admitted applicants not always enroll, complete or work as nurses, and in part because rejected applicants sometimes reapply, and end up enrolling later.

The heterogeneous effect estimates suggest that admission to a nursing program is less likely to shift men and top students (those with higher grades from upper secondary school) into completing a nursing degree. One concern about positive discrimination and outreach programs targeting underrepresented groups may be that such programs recruit less dedicated students, displace more motivated applicants from overrepresented groups, and thus exacerbate skill shortages.

⁷Only 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.

References

- ABADIE, A. (2003): "Semiparametric instrumental variable estimation of treatment response models," *Journal of Econometrics*, 113, 231–263.
- 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.
- DRENNAN, V. M. AND F. ROSS (2019): "Global nurse shortages—the facts, the impact and action for change," *British Medical Bulletin*, 130, 25–37.
- GANDIL, M. (2025): "Trickle down education ripple effects in college admissions," Tech. rep.
- HEINESEN, E. (2018): "Admission to higher education programmes and student educational outcomes and earnings–Evidence from Denmark," *Economics of Education Review*, 63, 1–19.
- 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.
- KIRKEBOEN, L. J., E. LEUVEN, AND M. MOGSTAD (2016): "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics*, 131, 1057–1111.
- KYRKJEBØ, J. M., T. E. MEKKI, AND B. R. HANESTAD (2002): "Nursing education in Norway," *Journal* of Advanced Nursing, 38, 296–302.
- LEE, D. S. AND T. LEMIEUX (2010): "Regression Discontinuity Designs in Economics," Journal of Economic Literature, 48, 281–355, publisher: American Economic Association.
- OECD (2023): Health at a Glance 2023: OECD Indicators, Paris: OECD Publishing.
- SAUNES, I. S., M. KARANIKOLOS, AND A. SAGAN (2020): "Norway: Health System Review." *Health* systems in transition, 22, 1–163.
- SCHEFFLER, R. M. AND D. R. ARNOLD (2019): "Projecting shortages and surpluses of doctors and nurses in the OECD: what looms ahead," *Health Economics, Policy and Law*, 14, 274–290.
- SEMB, I. M. (2024): "Affirmative Action in College Admissions: Winners, Losers, and Application Responses Applications," .
- 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

	Effect Y((1) - Y(0)	Complier	Y(1)	Complier	Y(0)
All	0.651**	(0.010)	0.758**	(0.008)	0.106**	(0.005)
Female	0.660**	(0.011)	0.767**	(0.009)	0.107**	(0.006)
Male	0.596**	(0.028)	0.695**	(0.024)	0.099**	(0.015)
Immigrant	0.700**	(0.044)	0.796**	(0.038)	0.096**	(0.022)
Non-immigrant	0.649**	(0.010)	0.756**	(0.009)	0.107**	(0.006)
Young	0.646**	(0.013)	0.746**	(0.011)	0.100**	(0.007)
Old	0.659**	(0.015)	0.774**	(0.012)	0.114**	(0.008)
Top 25%	0.671**	(0.034)	0.787**	(0.025)	0.116**	(0.023)
Bottom 75%	0.644**	(0.011)	0.747**	(0.010)	0.103**	(0.006)
Application before 2004	0.638**	(0.014)	0.767**	(0.011)	0.130**	(0.008)
Application in 2004 and beyond	0.668**	(0.014)	0.747**	(0.012)	0.079**	(0.007)
Male & application in 2004 and beyond	0.626**	(0.040)	0.723**	(0.036)	0.097**	(0.018)

Table A1: Enrollment

	Effect $Y(1) - Y(0)$		Complier $Y(1)$		Complier $Y(0)$	
All	0.348**	(0.012)	0.850**	(0.007)	0.502**	(0.009)
Female	0.351**	(0.012)	0.862**	(0.007)	0.510**	(0.010)
Male	0.327**	(0.035)	0.767**	(0.022)	0.441**	(0.027)
Immigrant	0.391**	(0.051)	0.902**	(0.033)	0.511**	(0.039)
Non-immigrant	0.346**	(0.012)	0.847**	(0.007)	0.501**	(0.010)
Young	0.295**	(0.016)	0.854**	(0.009)	0.559**	(0.013)
Old	0.413**	(0.017)	0.847**	(0.011)	0.434**	(0.013)
Top 25%	0.393**	(0.044)	0.837**	(0.020)	0.444**	(0.039)
Bottom 75%	0.340**	(0.013)	0.843**	(0.008)	0.504**	(0.010)
Application before 2004	0.349**	(0.016)	0.861**	(0.009)	0.512**	(0.013)
Application in 2004 and beyond	0.347**	(0.017)	0.837**	(0.010)	0.490**	(0.014)
Male & application in 2004 and beyond	0.321**	(0.050)	0.786**	(0.032)	0.465**	(0.037)

Table A2: All-time enrollment

	Effect Y((1) - Y(0)	Complier	Y(1)	Complier	Y(0)
All	0.265**	(0.013)	0.686**	(0.009)	0.422**	(0.009)
Female	0.278**	(0.013)	0.710**	(0.009)	0.432**	(0.010)
Male	0.173**	(0.037)	0.516**	(0.027)	0.343**	(0.025)
Immigrant	0.268**	(0.056)	0.620**	(0.043)	0.353**	(0.036)
Non-immigrant	0.265**	(0.013)	0.690**	(0.009)	0.426**	(0.009)
Young	0.216**	(0.017)	0.696**	(0.012)	0.479**	(0.013)
Old	0.322**	(0.018)	0.675**	(0.013)	0.353**	(0.013)
Тор 25%	0.328**	(0.045)	0.702**	(0.023)	0.374**	(0.038)
Bottom 75%	0.241**	(0.014)	0.663**	(0.010)	0.422**	(0.010)
Application before 2004	0.293**	(0.017)	0.726**	(0.011)	0.433**	(0.012)
Application in 2004 and beyond	0.228**	(0.019)	0.637**	(0.014)	0.409**	(0.013)
Male & application in 2004 and beyond	0.115**	(0.053)	0.457**	(0.040)	0.342**	(0.034)

Table A3: Completion

	Effect $Y(1) - Y(0)$		Complier	Y(1) Complie		er Y(0)	
All	0.017**	(0.007)	0.871**	(0.005)	0.854**	(0.005)	
Female	0.017**	(0.003)	0.874**	(0.002)	0.857**	(0.002)	
Male	0.014	(0.009)	0.851**	(0.006)	0.837**	(0.007)	
Immigrant	0.034*	(0.018)	0.784**	(0.013)	0.751**	(0.012)	
Non-immigrant	0.016**	(0.003)	0.876**	(0.002)	0.860**	(0.002)	
Young	0.013**	(0.004)	0.897**	(0.003)	0.884**	(0.003)	
Old	0.020**	(0.005)	0.841**	(0.003)	0.821**	(0.003)	
Top 25%	0.015	(0.011)	0.864**	(0.006)	0.849**	(0.009)	
Bottom 75%	0.009**	(0.003)	0.865**	(0.002)	0.856**	(0.002)	
Application before 2004	0.023**	(0.004)	0.873**	(0.003)	0.850**	(0.003)	
Application in 2004 and beyond	0.007	(0.005)	0.869**	(0.003)	0.861**	(0.004)	
Male & application in 2004 and beyond	-0.014	(0.014)	0.827**	(0.011)	0.841**	(0.009)	

Table A4: Employment

	Effect Y((1) - Y(0)	Complier	Y(1)	Complier	Y(0)
All	0.128**	(0.012)	0.672**	(0.008)	0.544**	(0.009)
Female	0.140**	(0.004)	0.695**	(0.003)	0.556**	(0.003)
Male	0.045**	(0.013)	0.503**	(0.009)	0.458**	(0.009)
Immigrant	0.042**	(0.020)	0.575**	(0.015)	0.533**	(0.014)
Non-immigrant	0.132**	(0.004)	0.678**	(0.003)	0.545**	(0.003)
Young	0.106**	(0.006)	0.671**	(0.004)	0.565**	(0.004)
Old	0.153**	(0.006)	0.675**	(0.004)	0.521**	(0.004)
Тор 25%	0.185**	(0.014)	0.681**	(0.007)	0.496**	(0.012)
Bottom 75%	0.107**	(0.005)	0.653**	(0.003)	0.546**	(0.003)
Application before 2004	0.128**	(0.005)	0.694**	(0.004)	0.565**	(0.004)
Application in 2004 and beyond	0.129**	(0.007)	0.636**	(0.005)	0.507**	(0.005)
Male & application in 2004 and beyond	0.029	(0.020)	0.458**	(0.015)	0.429**	(0.014)

Table A5: Health sector

	Effect Y((1) - Y(0)	Complier	Y(1)	Complier	Y(0)
All	0.188**	(0.012)	0.529**	(0.009)	0.340**	(0.008)
Female	0.200**	(0.004)	0.554**	(0.003)	0.353**	(0.003)
Male	0.102**	(0.011)	0.343**	(0.008)	0.241**	(0.008)
Immigrant	0.130**	(0.019)	0.436**	(0.015)	0.306**	(0.011)
Non-immigrant	0.192**	(0.004)	0.533**	(0.003)	0.342**	(0.003)
Young	0.151**	(0.006)	0.537**	(0.004)	0.386**	(0.004)
Old	0.233**	(0.006)	0.520**	(0.005)	0.287**	(0.004)
Top 25%	0.277**	(0.014)	0.561**	(0.008)	0.284**	(0.012)
Bottom 75%	0.159**	(0.005)	0.502**	(0.004)	0.343**	(0.003)
Application before 2004	0.208**	(0.005)	0.554**	(0.004)	0.346**	(0.004)
Application in 2004 and beyond	0.154**	(0.007)	0.483**	(0.005)	0.329**	(0.004)
Male & application in 2004 and beyond	0.004	(0.018)	0.262**	(0.014)	0.258**	(0.011)

Table A6: Nurse

	Effect Y	(1) - Y(0)	Complier $Y(1)$ Com		Complier	Y(0)
All	0.115**	(0.009)	0.299**	(0.007)	0.184**	(0.006)
Female	0.117**	(0.004)	0.301**	(0.003)	0.184**	(0.002)
Male	0.106**	(0.010)	0.287**	(0.008)	0.181**	(0.007)
Immigrant	0.104**	(0.016)	0.274**	(0.013)	0.169**	(0.009)
Non-immigrant	0.116**	(0.004)	0.300**	(0.003)	0.184**	(0.002)
Young	0.086**	(0.005)	0.297**	(0.004)	0.211**	(0.003)
Old	0.148**	(0.005)	0.301**	(0.004)	0.153**	(0.003)
Top 25%	0.199**	(0.012)	0.328**	(0.007)	0.129**	(0.009)
Bottom 75%	0.096**	(0.004)	0.283**	(0.003)	0.187**	(0.002)
Application before 2004	0.115**	(0.005)	0.305**	(0.004)	0.191**	(0.003)
Application in 2004 and beyond	0.115**	(0.006)	0.287**	(0.005)	0.173**	(0.004)
Male & application in 2004 and beyond	0.010	(0.016)	0.192**	(0.012)	0.183**	(0.010)

Table A7: Full-time nurse



Figure A1: 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 A2: Enrollment and completion 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.



Notes: These figures show balancing checks for various characteristics.



Figure A4: 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).





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 A6: 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).