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Could easier access to university improve health and reduce health inequalities?

Gawain Heckley, Martin Nordin and Ulf-G Gerdtham*†

Abstract

This paper estimates the impact of university education on medical care use and its income related inequality. We do this by exploiting an arbitrary university eligibility rule in Sweden combined with regression discontinuity design for the years 2003-2013 for students who graduated 2003-2005. We find a clear jump in university attendance due to university eligibility. This jump coincides with a positive jump in prescriptions for contraceptives for females but also a positive jump in mental health related hospital admissions for males. Analysis of the inequality impact of tertiary eligibility finds no clear impact on medical care use by socioeconomic status of the parents. The results imply that easing access to university for the lower ability student will lead to an increase in contraceptive use without increasing its socioeconomic related inequality. At the same time, the results highlight that universities may need to do more to take care of the mental health of their least able students.

Keywords: Health returns to education, demand for medical care, causes of health inequality, Regression Discontinuity Design, Concentration Index

JEL Classification: *I14, I12, I26*

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1 Introduction

The relationship between education and health is of fundamental interest and has consequently received a great deal of empirical attention. This literature finds its theoretical origins in the demand for health model of Grossman (1972) and more recently Grossman (2000). These models include health as part of an individual's human capital and they emphasise that health capital is not only determined by medical care but also potentially other factors such as knowledge capital, commonly proxied by years of education. The education gradient in health is observed in nearly every country (Mackenbach et al., 2003; Van Doorslaer and Koolman, 2004) and has prompted some to focus on education as a means of raising health levels and reducing socioeconomic related disparities in health (Marmot, 2005; Marmot et al., 2010, 2012).

In this paper we investigate whether access to university education for the student at the margin of university eligibility (and therefore of relatively low ability) shows improved health. For this group we observe a significant association between university attendance and frequency of hospital admissions and the number of prescriptions prescribed. The concern with any association of education and health is that the relationship may be due to reverse causality. In human capital models, our initial endowment of human capital affects our ability to invest further in our human capital, which means those with poor health and therefore low levels of health capital are less able to invest in their knowledge capital. As a consequence, the associations noted widely in the literature may just be due to health's impact on education. There may also be a third hard to observe variable that explains both our knowledge capital and our health capital. This could be some form of innate ability as suggested by **?** or time preferences as suggested by Fuchs (1982) where those who prefer today much more than tomorrow are more likely to consume their human capital early.

A review of the recent empirical research investigating the causal link between education and health by Grossman (2015) finds that there is either a positive impact or a zero or very small impact. This is illustrated if we consider the recent quasi-experimental evidence that uses changes to the compulsory education system as instruments. Research in the US (Lleras-Muney, 2005), in Germany (Kemptner et al., 2011; Jürges et al., 2011), in Italy (Atella and Kopinska, 2014), in the Netherlands (Van Kippersluis et al., 2011) and in France (Etilé and Jones, 2011) has found a positive impact on health. Other studies of education system changes in Britain (Clark and Royer, 2013; Braakmann, 2011), in France (Albouy and Lequien, 2009), in Germany (Pischke and Von Wachter, 2008), in Sweden (Lager and Torssander, 2012; Meghir et al., 2012) and in Denmark (Arendt, 2008) have found a small or no effect on health. Both Cutler and Lleras-Muney (2012) and **?** have suggested that the margin being estimated is very important for the interpretation of the results and is possibly the leading explanation for the large variation in results.

The impact of university education on health is one margin that has received relatively little empirical attention yet is of great potential interest. Cunha et al. (2010) have shown that there are potential complementarities between early and late life interventions. It is therefore useful to consider whether university education for low ability students can be effective in improving health outcomes. The evidence that does exist uses the Vietnam draft as a quasi-experiment and finds that university education reduces smoking initiation and increases cessation (De Walque, 2007; Grimard and Parent, 2007). It has also been found to lead to a reduction in mortality (Buckles et al., 2016).

In this paper we present new findings of the impact of university education by exploiting quasi-experimental variation caused by an arbitrary rule in Sweden that states that students must have a pass mark for at least 90% of their courses that make up a program in order to go on to university. This rule leads to a large jump in the proportion of students who go on to study at university of 8 to 9 percentage points (pp) for females and 2pp to 4pp for males. It is this arbitrary rule that allows us to identify the impact of university eligibility on various medical care use outcomes using Regression Discontinuity (RD) design. The marginal group affected by the eligibility rule are individuals who are towards the lower end of the education distribution (46th percentile and 42nd percentile for males and females respectively, who were enrolled on the academic stream at upper secondary school). The margin we estimate is therefore of particular policy interest because it captures the potential egalitarian impact of increasing access to higher education for lower ability individuals and or individuals from lower ranking socioeconomic groups.

Our results consider individuals who graduated from upper secondary school between 2003 and 2005. The data we use is based on population based administrative records of inpatient and outpatient hospital admissions (2003-2013) and prescriptions (2005-2013) linked using a personal identifier to education records. The results show that university eligibility leads to a significant and substantial jump in university attendance. Previous research using the same eligibility rule (Nordin et al., 2017) has found that the impact of university eligibility on years of education is in the region of 0.2 to 0.3 years which is similar in scale to those found for a Swedish compulsory school reform (Hjalmarsson et al., 2015). We find that this jump in university eligibility leads to no clear overall impact on hospital admissions or prescriptions. However, when we consider specific cause of hospital admission and prescription receipt we find a positive jump in the probability of prescription receipt for contraceptives for females. For males we find an increase in hospital admissions for mental disorders and a reduction in prescriptions for pain relief related medicines.

We also consider the impact of university eligibility on socioeconomic related health inequality. This analysis is complementary to our analysis of the mean using OLS. There could quite plausibly be mean preserving effects on health that are correlated with socioeconomic status or even impacts just on socioeconomic status that change the covariance of health and socioeconomic status. This analysis is a key contribution of the paper. Socioeconomic inequality in health has received a great deal of public health and political interest as witnessed by the large amount of work done by various health inequality commissions (Marmot, 2005; Marmot et al., 2010, 2012). The work of these commissions and by others (e.g., Kunst et al. (2005); Shkolnikov et al. (2011); Mackenbach et al. (2015); Hu et al. (2016)) has shown that socioeconomic related health inequalities are observed in almost every country and that not only have they persisted over time but they have even increased across most western countries.

The question we specifically address is: can we use access to university education as a policy lever to reduce the observed concentration of hospital care use or prescriptions amongst young adults from poorer or richer families? To this end we employ the novel decomposition technique of Heckley et al. (2016) and we find that university eligibility overall has no clear impact on the concentration of hospital admissions and prescriptions in young adults from either poorer or richer family backgrounds. Inequality increasing impacts are found for medical examinations at hospital amongst females but the effects are offset by males. Additionally, even though a clear impact was found for mean contraceptive prescription receipt, this jump did not coincide with a change in parental income related inequality of prescriptions for contraceptives.

Overall our findings suggest that increasing access to university should increase female contraceptive use and not have a detrimental impact on socioeconomic related health inequality. However, the increase observed in mental health hospital admissions for males just crossing the eligibility threshold suggests universities should do more to help their least able students with the pressures of university life.

The rest of the paper is structured as follows. In section 2 we introduce the Swedish education system and the eligibility rule we consider. In section 3 we introduce our measures of socioeconomic inequality. In section 4 we introduce the data material we use for the analysis and in section 5 we explain our empirical approach and test the identifying assumptions we make. Section 6 presents the results for medical care use and section 7 concludes.

2 The Swedish education system

In this section we briefly outline the Swedish educational system and the eligibility rule for university that we use to identify the impact of eligibility on medical care use.[1] In Sweden in order to be able to attend university a student needs to achieve eligibility through passing at least 90% of a full program at upper secondary school. This can also be achieved by completing complementary adult

[1] The system we describe here was in place between the years 1997 to 2010. During this period the system was slightly tweaked in 2003

studies after upper secondary school but the cut-off we consider is university eligibility as achieved at graduation from upper secondary school. We choose to use university eligibility defined at end of upper secondary school because it is a well-defined and hard to manipulate rule that leads to a jump in university attendance, as we shall show later. In general, upper secondary school is for three years and students start upper secondary school aged 16 and graduate at age 19.[2] There are two streams at upper secondary school: the academic stream with the explicit aim of going to university after graduating from upper secondary school and the vocational stream with an explicit focus of getting a job once graduated. In this paper we focus on students graduating from the academic stream because this is where the university eligibility threshold has largest bite (Nordin et al., 2017). Students can choose their preferred stream. A full program consists of 2500 course credits for both types of tracks.[3] To receive a diploma of eligibility for university a student needs to pass at least 90 percent of full program i.e. receive 2250 credits. A program is a sum of courses and courses can give either 50, 100, 150, 200 or 250 course credits (with some exceptions for even larger courses). The courses that make up a program are graded on four levels: fail, pass, pass with distinction and pass with special distinction. To receive the course credits, the student has to at least pass the course but the credits received are not impacted by how well one passes. We choose to investigate the period starting in 2003 because the diploma of eligibility for university is much more clearly defined compared to previous years.

In figure 1 we show the impact of barely passing the cut-off point on the probability of enrolling in university for cohorts graduating between 2003 to 2005. The raw data is graphed as scatter plots of the proportion who attended a first term course of university by the number of achieved credits at upper secondary school in bins of 2pp of a full program wide. The vertical dashed line represents the cut-off of university eligibility (2250=2500*0.9). Figure 1 is for men and women studying the academic track. In both figures, the probability of enrolling in university increases with the percentage completed of a full program and follows a smooth function. At the university eligibility cut-off, however, there is a positive jump in the probability of enrolling in university. From just eyeballing the data it can be seen that the probability of enrolling in university is around 10pp higher for females and there is potentially a small jump for males passing the marginal course on the academic track. Nordin et al. (2017) show that the jump for those on the vocational track is much smaller and is why we choose to focus on the academic track students. Note that the

[2]The large majority of students who complete their compulsory schooling choose to continue their studies at upper secondary school with only 1.7% of students choosing not to continue with their studies. Whilst all students are able to continue their studies at upper secondary school, there is an eligibility requirement. Those students who do not pass this eligibility requirement enter what is called an individual program with the aim to transfer to the standard upper secondary school program at some point.

[3]Whilst a large proportion of students went on to study at upper secondary school a large proportion end up dropping out: for the period under consideration in this paper the drop out rate is about 25%.

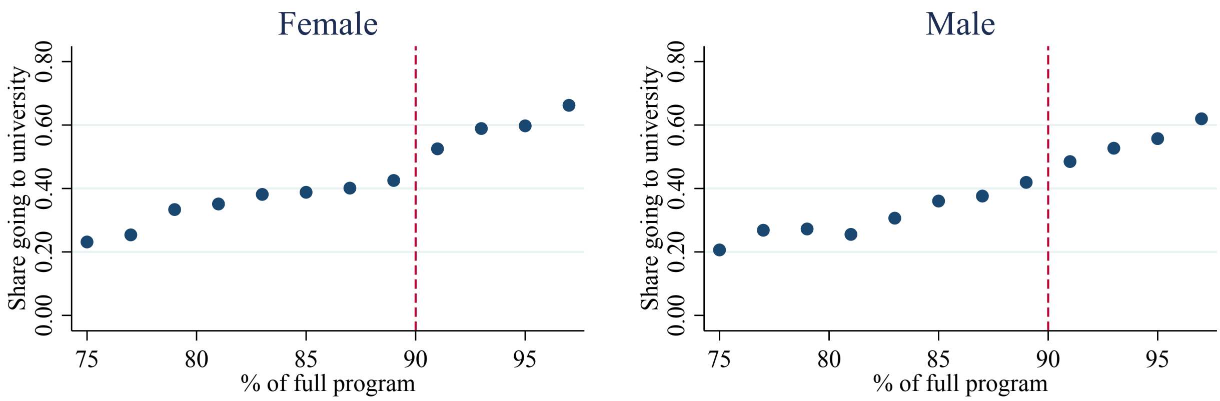

Fig. 1: Impact of university eligibility on university attendance by gender

Notes: This figure plots a scatter of the share who attended a first term of university against percentage completed of a full program with a bin width of 2pp of a full program (the size of the smallest course) in each bin for those graduating upper secondary school between the years 2003 and 2005. The cut-off for university is marked by the dashed vertical line at 90pp credits.

cut-off and forcing variable are defined at a point in time, graduation from upper secondary school. Even though students can achieve university eligibility after completing upper secondary school by complementing their studies to achieve university eligibility we still observe a jump using our definition of the cut-off. That is, students who fail to achieve university eligibility at completion of upper secondary school are less likely to go to university even though they could later on achieve eligibility by complementing their grades.

Students coming in to the final term of their upper secondary school program often have seven to eight courses of varying credit size to complete, the smallest worth just 2pp of a full program. A key identifying assumption for regression discontinuity of the eligibility threshold is that those at the margin of university eligibility will not have precise control over whether they cross the threshold. Given the typical course size is 4pp of a full program and that students often require about 32% of course credits in their final term in order to finish, a bandwidth of 4pp represents the impact on eligibility of just one course out of eight in the final term. Precise manipulation of the threshold would require the more motivated students to understand in advance how many courses they need to pass, and which particular courses they need to focus on in order to just cross the eligibility threshold, which appears quite a high stakes gamble. It would seem unlikely that students are willing to stake eligibility for university by focussing on just one or even two courses. The teachers grade the courses themselves and may also be aware that a particular student is near the eligibility threshold and mark up the grades for the marginal student so they achieve eligibility. This may happen, but for teachers to be able to manipulate the threshold *exactly* they need to know what the student is likely to achieve in the other seven or so courses they are enrolled in *and* collude with the other teachers so that the marginal student crosses the threshold exactly but no more. This form of manipulation by the teachers then has to have a link between the students and the outcomes we consider, perhaps a preference towards the students with higher ability. The information requirements seem very onerous for this degree of collusion to happen so precisely. It is this lack of precise control that allows us to identify the impact of university eligibility on health and education outcomes.

3 Measuring health inequality

An explicit aim of this paper is to study the impact of university eligibility on medical care use inequality, specifically socioeconomic related medical care use inequality. It is our view that it is important that our inequality analysis yields results based on the full distribution of socioeconomic status and that they are comparable with future work.[4] Specifically, we want to know how university eligibility increases or decreases the concentration of health amongst the richest/poorest individuals. To this end, we use the health Concentration Index (CI) as our measure of socioeconomic health inequality, a measure popular in health economics. The health CI captures the degree to which health is concentrated in higher or lower ranking socioeconomic groups (Fleurbaey et al., 2011). The health CI considers two variables: a health variable and a socioeconomic ranking variable and yields an index that can vary continuously between minus 1 and plus 1. A CI value of minus 1 would relate to a situation where all hospital admissions are concentrated in the lowest income individual, 0 would be where hospital admissions are equally distributed across the income distribution, and 1 would be where all hospital admissions are concentrated in the highest income individual. That is negative values infer a pro-poor concentration of health, positive a pro-rich concentration.

More formally, health is represented by the random variable H with corresponding mean, μ_H, and socioeconomic status is represented by the random variable Y. Socioeconomic fractional rank is given by the Cumulative Distribution Function of Y, F_Y. There are many ways to formulate the health CI: one of them is as a weighted covariance between H and F_Y yielding:

$$v_{CI} = \frac{2}{\mu_H} COV(H, F_Y); \tag{1}$$

Erreygers and Van Ourti (2011) argue that use of the health CI is appropriate if the health variable is of ratio scale, which means it does not have a finite upper bound. For health variables not of ratio scale, such as binary variables, a modified version is preferred. We are interested in relative

[4]This is in principle the same argument that has been made for using the CI to compare across countries and over time (see for e.g. Wagstaff et al. (1991)) - it produces a standardised measure. In this sense, our estimated impacts will also be comparable across future studies who look at education's impact on CI.

inequality (a proportional change in everyone's health does not impact the index) and therefore follow Kjellsson et al. (2015) and consider two variants of the health CI, the attainment relative concentration index (ARCI) and the short-fall relative concentration index (SRCI):

$$v_{ARCI} = \frac{2}{\mu_h - a_H} COV(H, F_Y); \tag{2}$$

$$v_{SRCI} = \frac{2}{b_h - \mu_H} COV(H, F_Y); \tag{3}$$

where a_H is the lower bound of H and b_H is the upper bound of H.[5] The ARCI and SRCI are relative measures of socioeconomic related health inequality that yield different measures of inequality depending on whether we measure health in terms of attainments (from the lower bound) or in terms of short-falls (from the upper bound). Which one is preferred is up to the individual reader and therefore we present both.

We can capture the impact of university eligibility on the CI using the approach of Heckley et al. (2016). The results will tell us to what extent university eligibility increases or decreases the concentration of health amongst the richest/poorest individuals. This approach means we capture the inequality aspects of university eligibility on a measure that is comparable with future studies and considers the whole socioeconomic distribution (rather than say just comparing the lowest socioeconomic status group vs the highest).

[5] As Kjellsson and Gerdtham (2013) note, the choice of socioeconomic health inequality index involves an array of value judgements. We have chosen to consider relative concentration of health inequality. We could also have considered absolute health inequality, but choose to limit our interest to relative changes.

4 Data

Table 1: Descriptive statistics

	Female	*Male*
Outcomes		
University attendance	0.580	0.521
	(0.004)	(0.004)
Frequency of hospital admissions	10.438	5.407
	(0.118)	(0.072)
Probability of being admitted to hospital due to:		
External causes	0.280	0.409
	(0.004)	(0.004)
Mental disorder	0.327	0.111
	(0.004)	(0.003)
Examinations	0.515	0.274
	(0.004)	(0.004)
All other causes	0.915	0.754
	(0.002)	(0.003)
Frequency of prescriptions	35.232	13.473
	(0.451)	(0.255)
Probability of receiving a prescription for:		
Contraceptives	0.848	0.000
	(0.003)	(0.000)
Psycholeptics	0.298	0.159
	(0.004)	(0.003)
Painkillers	0.349	0.234
	(0.004)	(0.003)
All other causes	0.966	0.873
	(0.002)	(0.003)
Years of education	13.46	13.22
	(0.01)	(0.01)
Compulsory school grades	216.18	207.40
	(0.35)	(0.28)
Father's education	10.28	10.91
	(0.04)	(0.03)
Mother's education	10.51	11.07
	(0.04)	(0.03)
Father's income	1333	1439
	(6.97)	(9.14)
Mother's income	781	827
	(3.84)	(3.70)
Observations	12652	15686

Notes: This table shows descriptive statistics for those graduating from upper secondary school between the years 2003 and 2005 and who have completed between 82% and 98% of a full program (a bandwidth of 8pp either side of the university eligibility threshold of 90%). Standard errors are shown in parenthesis

We use administrative register data on all students who graduated from upper secondary school between the years 2003 and 2005 and had previously graduated from Swedish compulsory school.[6] We combine education register data on final grades from compulsory school, grades from upper

[6]We need information on prior grades as a check and these are only available for those who attended the Swedish school system prior to starting upper secondary school. We also do not want to include individuals who have immigrated to Sweden during secondary school age. We consider the years 2003 onwards because in the years prior to 2003 it was much easier to re-take courses over the summer after graduating (from 2003 onwards, this is much less common) and as a consequence it is much harder to define whether a student achieved university education eligibility at graduation - our cut-off. We view measurement error and the potential for manipulation of the cut-off to be a significant threat to our identification strategy before the 2003 graduation year.

secondary school and data on higher education attendance and outcomes. This is then matched with administrative register data on labour market outcomes from the Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA) from Statistics Sweden (SCB) and administrative register data on hospital admissions and prescriptions is from the patient register and prescriptions register, respectively, both provided by the Swedish Board of Health (Socialstyrelsen). We also use the Multi-generational Register from Statistics Sweden that links the individuals to their parents who themselves are linked to their labour market and health outcomes. The population and housing censuses from years 1985 and 1990 provide us with parental education and income during the early childhood of the students we are following.

Our sample starts off with 128,751 students who graduated from upper secondary school between the years 2003 and 2005 and had previously graduated from Swedish compulsory school. We remove pupils who finish more than one year later (1.3 percent) or more than one year in advance (only 12 observations).[7] Keeping students who finish at age 18 or 20 has no impact on the results in this study.

Table 1 reports descriptive statistics for the sample analysed in this paper. Here we report the statistics for those with percentage of a completed program that lies within 8pp above or below the university eligibility cut-off. We split the sample by gender because there are important differences in education patterns and labour market and health decisions between genders. This leads to sample sizes of roughly 12,000 to 15,000 by gender very near to the cut-off.

Our medical care use variables are hospital admissions and prescriptions. Both the total number of hospital admissions and the total number of prescriptions since graduating and up to 2013 (our last period of observation) are considered. We also consider the probability of admission and the probability of prescription receipt by 2013 by the most common causes amongst young adults (aged 20 - 30). We consider causes of hospital admissions and prescriptions because they can be both as a consequence of a change in health status and due to investment decisions to raise current or future health levels and these two behaviours are potentially counterbalancing. We therefore consider hospital admissions and prescriptions by diagnosis (International Classification of Diseases (ICD10 codes) and drug type (Anatomical Therapeutic Chemical (ATC) Classification System codes).

Under preventative health actions we consider hospital admissions due to examinations (ICD10 code Z0-Z39) and prescriptions for contraceptives (ATC code female only). Under health consequences we have hospital admissions due to external causes (ICD10 codes S,T or if coded as external

[7]We exclude those on the individual program as they cannot gain university eligibility. Most students start upper secondary school aged 16 and graduate at age 19. It is not uncommon for students to finish upper secondary school at an older age (12.0 percent) than the typical graduation age of 19. A small share finish at a younger age (2.8 percent). There are many common and valid reasons for graduating older than 19 years of age: retaking courses, study breaks, changing programs or studying abroad. Students who graduate before the age of 19 have typically also started compulsory schooling before the mandatory starting age.

and M or main diagnosis missing), mental disorders (ICD10 code F, Z55, Z56, Z59, Z60, Z64, Z65, Z70-Z73) and for prescriptions we have psycholeptics (ATC codes N5, N6) that treat depression, anxiety and sleep disorders amongst others, and painkillers (ATC code N2).[8] Finally we consider university attendance in the first term, defined as a binary variable where unitary corresponds to attendance, zero otherwise.

The inequality outcomes we consider are the CI of frequency of hospital admissions (sum of admissions from graduation up to 2013) and the CI of frequency of prescriptions (again, the sum of prescriptions from graduation up to 2013). To measure the CI we need to rank individuals by their socioeconomic status and we choose a measure of family income as the measure of socioeconomic status for these young adults. In this way we capture a degree of intergenerational persistence. We calculate family income as the average of the income of the mother and father as reported in the 1985 and 1990 censuses. We take an average over years to remove temporal changes in income and get nearer to a measure of lifetime income of the parents. We use years 1985 and 1990 as these were defined during the childhood of the individuals we consider and therefore predetermined.

Background characteristics highly correlated with our health outcomes are used and include parental education in 1990 defined as years of education, age at migration and year of graduation from upper secondary school.[9] Dummies are defined for first-generation immigrant and second-generation immigrant and are region of origin specific.[10] We also define a dummy for whether the parents are of mixed origin or not and whether only one parent is an immigrant.

5 Method

5.1 Identifying the impact of university education eligibility

To estimate the effects of university eligibility on our health outcomes we use an RD design as our identification strategy. As shown in figure 1, the proportion going on to university is a smooth and increasing function of the percentage completed of a full program at upper secondary school. However, there is also a discontinuity caused by an arbitrarily chosen rule, the university eligibility threshold at 90% of a full program. We use individuals very close and either side of this cut-off that are just 1 or 2 completed courses apart on the assumption that they are likely to be very similar in all observable and unobservable ways except that those who are above the threshold have access to university education, and those below do not. This allows us to then assess the impact of university

[8] There are strong overlaps between the causes of hospital admissions and the causes for prescriptions. Painkillers are potentially linked to external causes related hospital admissions through the treatment of injuries requiring ongoing pain relief. Mental disorders related hospital admissions are likely to be linked in some way to psycholeptics.

[9] Where education information is not available, dummy variables are included indicating missing education information.

[10] Nordic countries, EU28, Non-EU28 countries and Russia, North America and Oceania, Africa, Asia and South America.

eligibility on educational and health outcomes. The general formulation for the regression equations we estimate is the following:

$$y_i = \alpha + \beta Eligible_i + f(\%fullprogram_i) + \varepsilon_i; \tag{4}$$

In this model y_i represents the various health outcomes we consider for individual i, $Eligible$ is a binary treatment indicator variable equal to unity for those who have passed 90% or more of a full program and therefore eligible for university, zero otherwise and $\%fullprogram$ is measured in terms of distance from the eligibility threshold in percentage points of a full program. The functional form for the forcing variable, $f(\%fullprogram)$, is a local low ordered polynomial of $\%fullprogram_i$ and an interaction of $Eligibility_i * f(\%fullprogram_i)$ so that we have different trends either side of the cut-off. We follow the standard practice and add increasingly higher order polynomials until they become insignificant but also taking special care not to have too high a polynomial as argued by Gelman and Imbens (2017) and find a single polynomial is sufficient. The coefficient β is the discontinuous effect of university eligibility on the outcome variable assuming that our functional form absorbs any potential relationship between $\%fullprogram_i$ and ε_i.

The estimated impact of university eligibility on university attendance will be an Intention To Treat (ITT) parameter. Not all students who gain university eligibility having just graduated from upper secondary school go on to higher education. Some who do not gain eligibility go on to study at adult college and gain eligibility later. Eligibility at the end of upper secondary school therefore only impacts the probability of university attendance, it does not determine it. There is also potentially a pay-off to university eligibility without even going on to higher education. It may raise the esteem of the individual and it may be seen as a valid cut-off for employers to consider given its importance to universities. Our analysis therefore focusses on the reduced form impact of university eligibility on health outcomes.

We vary the bandwidth size between 4pp, 8pp and 16/8pp of a full program. This allows us to assess the sensitivity of the results to bandwidth choice.[11] Due to the fact that we have a large sample size so close to the cut-off, we are able to have small bandwidths. The inclusion of linear trends either side of the cut-off means we are in effect modelling a Local Linear Regression (LLR) with a rectangular kernel, the recommended approach of Imbens and Lemieux (2008).

When estimated equation 4, in some specifications we will add pre-determined characteristics. There are two reasons for this. First, as we expand the bandwidth we are including more observations

[11] We model bandwidth by running our linear regressions on the sample within the bandwidth. The discrete nature of the credit score means we are unable to non-parametrically choose the optimal bandwidth as recommended in general by Imbens and Lemieux (2008). 4pp is the smallest course size so makes a natural minimum bandwidth. 8pp is the largest bandwidth on the left hand side because any larger and we would have to model 100% of a completed program which is a very large jump.

that are not close to the cut-off and the inclusion of covariates may eliminate some bias that results from the inclusion of these observations (Imbens and Lemieux, 2008). Second, it provides an additional test of our identifying assumption that the error term is a smooth function crossing over the eligibility threshold.

5.2 The impact of university eligibility on university attendance

In this section we present the estimates of the effect of university eligibility on university attendance and the results of various diagnostic tests. In figure 1 we saw that there is a jump in the proportion who attend university at the university eligibility cut-off for females. The RD results are shown in table 2. Model (1) is a simple OLS of credit score on university attendance using only those within 8pp of the university eligibility threshold. It shows a strong positive correlation between university eligibility and university attendance. Model (2) shows our RD results using a bandwidth of 4pp and confirms there is a positive jump in the proportion attending university, 8pp for females and 2pp for males. Model (3) is as per (2) but with double the bandwidth of 8pp. Model (4) is as per (3) but with double the left-hand side bandwidth of 16pp. Models (5 & 6) are as per models (3 & 4) but with the addition of predetermined covariates.[12] The results for females across models (2-4) are stable to the choice of bandwidth and suggest university eligibility leads to a jump in university attendance in the range of 8pp to 10pp. The impact is much smaller for males in the range 2pp to 4pp.

Table 2: Impact of university eligibility on university 1st term attendance

Bandwidth	(1) 8pp	(2) 4pp	(3) 8pp	(4) 16pp/8pp	(5) 8pp	(6) 16pp/8pp
Female						
Tertiary Eligibility	0.218***	0.0830***	0.0953***	0.0772***	0.0917***	0.0668***
	(0.0289)	(0.00494)	(0.0119)	(0.0130)	(0.0131)	(0.0127)
N	12652	4730	12652	13523	12652	13523
Male						
Tertiary Eligibility	0.188***	0.0175***	0.0285***	0.0415***	0.0293***	0.0429***
	(0.0318)	(0.00361)	(0.00562)	(0.00849)	(0.00646)	(0.00816)
N	15686	6644	15686	17148	15686	17148
Polynomial	0	1	1	1	1	1
Covariates	N	N	N	N	Y	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on first term university attendance for those graduating between years 2003 and 2005. Each estimate is from a separate regression. See text for details for each model (1-6). Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The final analysis of this section considers the credit score distribution of the covariates as a

[12] Upper secondary graduation year, compulsory school grades, mother's and father's education and income plus dummies for missing education and income, dummies for world region of origin for first generation migrants and dummies for origin of parents for second generation migrants, age of migration and a dummy for whether one parent is a migrant.

test of our identifying assumption. The key identifying assumption is that the students and or their teachers are not able to manipulate the final credit scores in a systematic way that is linked to other important characteristics that determine health and medical care use. Our first diagnostic test of manipulation is that we include covariates in the regression estimates in models (5 & 6) in Table 2 and the impact of the inclusion of these covariates is very small. The inclusion of the covariates (models 5 & 6) leads to a small reduction in the estimated impacts for females and a small increase for males compared to estimates from models (3 & 4). The fact that we find a small impact of these covariates suggests that unobserved characteristics are in fact a smooth function over the cut-off.

Figure 2 presents four visual tests of cut-off manipulation. The top panel of figure 2 is a histogram of the population density by credit score plotted with bins of 4pp as suggested by Lee and Lemieux (2010) as a test of manipulation in the spirit of McCrary (2008). If there is a jump in the population just above the cut-off this is a sign of individuals manipulating their position around the threshold violating our identification assumption. The discrete nature of our data means this test is not ideally suited to our data but we observe no obvious jump in the density at the university eligibility cut-off. The second panel of figure 2 shows the final grade plotted against credit score. The third panel shows compulsory grades plotted against credit score. The final (fourth) panel shows the number of failed courses by final achieved credit score. These are all visual tests of whether individuals are trying to manipulate whether they cross the university eligibility threshold. For upper secondary grades we would expect if manipulation were occurring to see a jump in overall grade just above the threshold because of students trying harder in a number of courses to ensure they do not fall the wrongside of the threshold. For compulsory school grades we would expect the more able students to find it easier to manipulate the threshold and therefore observe a jump in compulsory school grades at the threshold. Finally, we consider the number of failed courses. Students can take more courses than needed for a full program and we therefore could expect to see a jump in the number of failed courses at the threshold as a consequence of students trying to maximise their chances of crossing the threshold. We observe no clear jumps in any of our visual diagnostic tests for females or males.

In table 3 we present results from a batch of balancing tests using RD that assess whether the covariates and our diagnostic test variables are equally distributed either side of the cut-off. Models (1) and (4) are OLS of the simple association of university eligibility and the covariate and show that university eligibility is highly correlated with all our diagnostic test variables and covariates. However, using our RD specification to isolate the impact of university eligibility in models (2-3 & 5-6) the coefficients all substantially reduce towards zero and nearly always lose statistical significance. We find evidence of a small jump in compulsory school grades at the cut-off using our largest bandwidth but not the smaller bandwidth. Whilst the jump is statistically significant it is

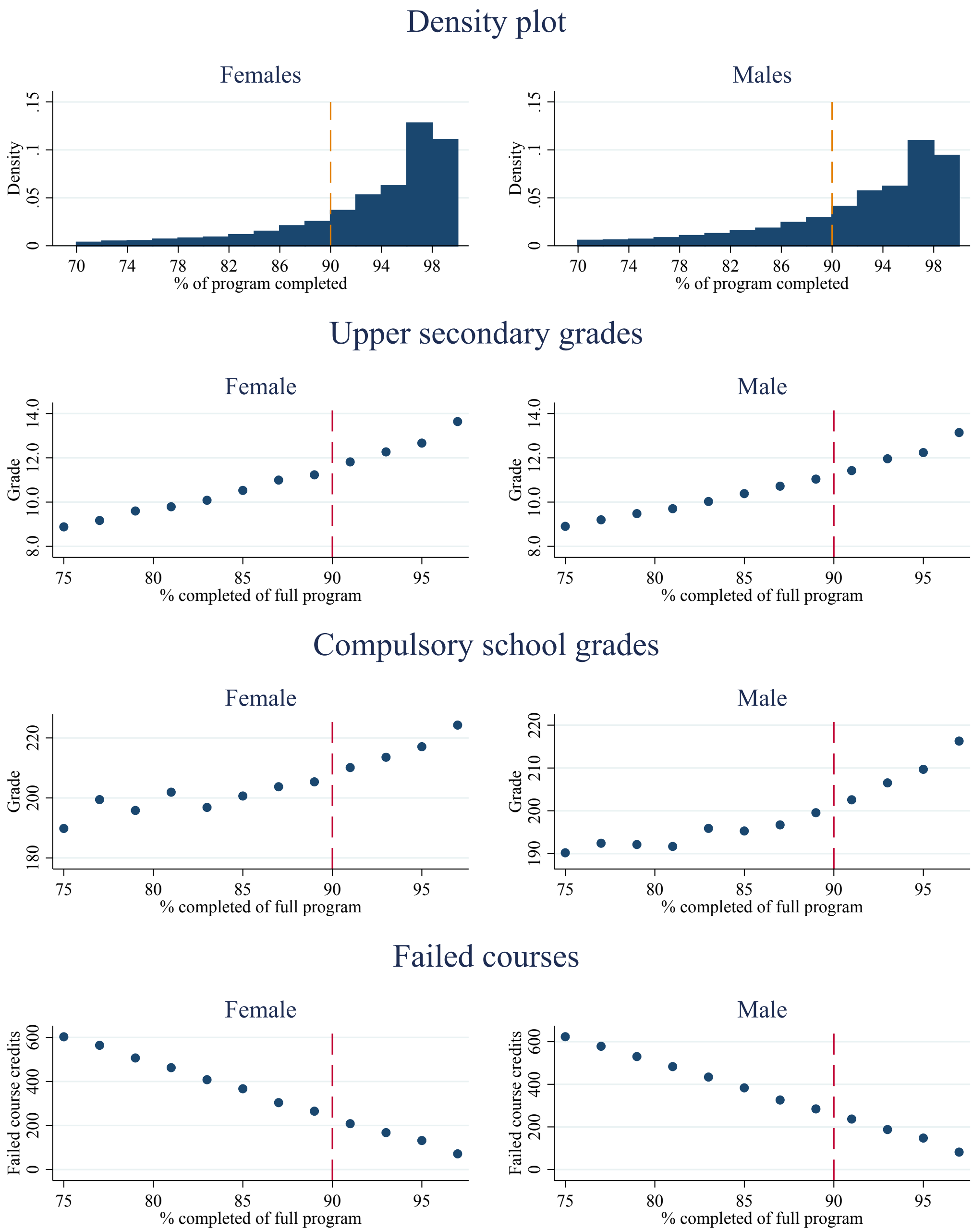

Fig. 2: Diagnostic tests

Notes: These figures plot various diagnostic tests using percentage of a completed program as the running variable shown in bins of 2pp of a program. For panels 2-4 we present the mean for each bin. The dashed vertical line is the 90% cut-off for university eligibility. See text for further details.

rather small in relative terms and represents a jump of less than 1pp (320 credits is the maximum). Our RD results also show mother's and father's education to jump significantly for males but this time for the smaller bandwidth but not the larger bandwidth. The sign has reversed compared to the naive OLS estimates of model (4). This suggests the data is very sensitive to how it is modelled for this particular variable making conclusions difficult beyond that overall the potential differences appear small and possibly insignificant. Note also we have not made any adjustment for multiple hypothesis testing here which would pull down the significance levels reported here.

In sum, the fact that our estimates of the impact of university eligibility on university attendance are stable across different model specifications and also with and without the inclusion of covariates suggests that both our observed covariates and the covariates we do not observe are a smooth function across the cut-off and that the jumps we observe are due to the policy effect. Our diagnostic tests add further evidence that we find no compelling evidence of manipulation. Altogether, this suggests that the jumps we observe in university attendance are primarily driven by the arbitrary rule and not by unobserved factors resident in the error term.

Table 3: RDD based diagnostic tests

	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth	8pp	8pp	16pp/8pp	8pp	8pp	16pp/8pp
	Female			Male		
Upper secondary school grades						
Tertiary Eligibility	2.038***	0.0723	0.158*	1.722***	0.0141	0.0677
	(0.397)	(0.0991)	(0.0820)	(0.357)	(0.0503)	(0.0532)
Failed Upper secondary school course credits						
Tertiary Eligibility	-191.5***	-5.541	-6.094	-192.2***	3.793	1.980
	(34.34)	(3.935)	(3.847)	(37.32)	(3.978)	(3.014)
Compulsory school grades						
Tertiary Eligibility	16.81***	0.503	2.589**	12.98***	1.680	1.805**
	(3.498)	(1.089)	(1.176)	(2.744)	(1.013)	(0.803)
Mother's education						
Tertiary Eligibility	0.625***	-0.116*	0.0321	0.582***	-0.277**	-0.0651
	(0.154)	(0.0647)	(0.0948)	(0.181)	(0.124)	(0.132)
Father's education						
Tertiary Eligibility	0.564***	-0.166	0.0254	0.495***	-0.275**	-0.108
	(0.174)	(0.203)	(0.144)	(0.170)	(0.136)	(0.157)
Father's income						
Tertiary Eligibility	111.5***	-8.198	19.57	88.89***	-1.721	-15.84
	(25.87)	(14.72)	(22.23)	(25.77)	(20.35)	(16.26)
Mother's income						
Tertiary Eligibility	50.77***	-20.61*	4.395	46.26***	-9.585	-0.492
	(13.81)	(11.37)	(15.93)	(12.69)	(9.977)	(7.148)
N	12652	12652	13523	15686	15686	17148
Polynomial	0	1	1	0	1	1

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on a batch of diagnostic variables and pre-determined characteristics for those graduating between years 2003 and 2005 and who were enrolled on the academic stream. Each estimate is from a separate regression. Models (1) and (4) are simple OLS associations of university eligibility and the variable being tested using a bandwidth of 8pp. Models (2) and (5) use a linear trend in course credits either side of the cut-off and bandwidth of 8pp of a full program either side of the cut-off. Models (3) and (6) are as models (2) and (5) but with a bandwidth of 16pp before the cut-off and 8pp after. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 *Estimating the distributional impact of university education*

To determine whether university eligibility increases the concentration of medical care use amongst the rich or poor we combine the concept of Recentered Influence Function (RIF) regression with RD. RIF regression allows any statistic to be linked to individual characteristics. We use the results of Firpo et al. (2009) and Heckley et al. (2016) in order to estimate the marginal effect of university eligibility on the CI, ARCI and SRCI.

We shall use linear RIF regression of the CI, which is very similar in approach to standard OLS regression. In an OLS regression we have a vector of health outcomes on the left hand side as the dependent variable and explanatory variables on the right hand side. RIF regression swaps out the vector of health outcomes and replaces these with a vector of influences on a statistic, in our case the CI. The mean of the vector of RIFs of the CI is the CI, which means under a linear setting and by the Law of Iterated Expectations (LIE) we can link each individuals characteristics to the CI using regression e.g. using OLS. The coefficients from our regression are the marginal effects. The difference between OLS of the mean and OLS of a RIF is that RIF-OLS only has a marginal interpretation - that is, we cannot calculate contributions and they are local estimates. The complication with CI marginal effects interpretation is that inequality can be concentrated amongst the rich (positive CI) or the poor (negative CI) and therefore the interpretation of the signs of the coefficients and whether the covariate is inequality increasing or decreasing depends on the value of the CI.

More precisely, we write the RIF of a statistic as RIF(v), where v represents any summary statistic of a distribution (e.g. in our case, the mean, CI, ARCI or SRCI). Firpo et al. (2009) show that the LIE can be applied to a RIF and therefore individual characteristics can be linked to the statistic of interest. This is RIF regression and it requires estimating the following:

$$E[RIF(v)|X = x] = E[\lambda(X, \epsilon)|X = x] \tag{5}$$

The choice of regression method depends on the form we want to assume for $\lambda(X, \epsilon)$ and in principle this choice is limitless. RD design lends itself very well to RIF regression because RD can essentially be thought of as a non-parametric method under certain conditions and therefore the parametrisation of the function $\lambda(X, \epsilon)$ is uncontroversial. In our analysis we are using a small bandwidth with linear regression either side of the cut-off, which is the equivalent to running the non-parametric regression technique of local linear regression with a rectangular kernel. To be precise, the RIF RD regression we estimate is the following linear regression:

$$RIF(v)_i = \alpha + \beta Eligible_i + f(\%fullprogram_i) + \epsilon_i \tag{6}$$

The parameter β from equation 6 will be the marginal effect of university eligibility on the CI, ARCI and SRCI. The functional form for the forcing variable, $f(\%fullprogram_i)$ will be as for equation 4.

6 Results

6.1 *The impact of university eligibility on hospital admissions and prescriptions*

In this section we present the estimates of the effect of university eligibility on hospital admissions and prescriptions during early adulthood (aged between 20 and 30). Figure 3 depicts completed credit profile of mean frequency of hospital admissions and prescriptions for the years since graduation up to 2013, split by gender. The data indicate no clear jumps in either hospital admissions or prescriptions at the 90% threshold.

This is confirmed in tables 4 and 5. All regression results from here on in will use regression models (1), (3), (4) and (6) from table 2. Model (1) in tables 4 and 5 is the simple association of university attendance without modelling the credit score and a bandwidth of 8pp. Model (2) is as per model (1) but now includes a linear trend estimated either side of the cut-off. Models (3) and (4) are as per model (2) but add a larger bandwidth to the left hand side.[13] Model (4) also includes covariates strongly associated with the outcome variable.

In model (1) of table 4 we can see that there is a significant negative association between university attendance and frequency of hospital admissions for females but not for males. The RD results for hospital admissions in table 4, however, show a positive jump in the frequency of hospital admissions for females according to model (2) of about 0.7 but this becomes insignificant and much smaller when increasing the bandwidth as modelled in models (3) and (4), although it remains positive. For males however the results are very sensitive to modelling choice and insignificant. Overall this suggests that university eligibility does not lead to a decrease in hospital admissions which is implied by the naive associations of model (1).

Turning to prescription receipt, we see in table 5 that the naive OLS regressions of university attendance and frequency of prescription receipt show no significant association for males or females.

[13] We cannot have a larger bandwidth on the right hand side because we would then have to model the huge jump at 100% of a completed course.

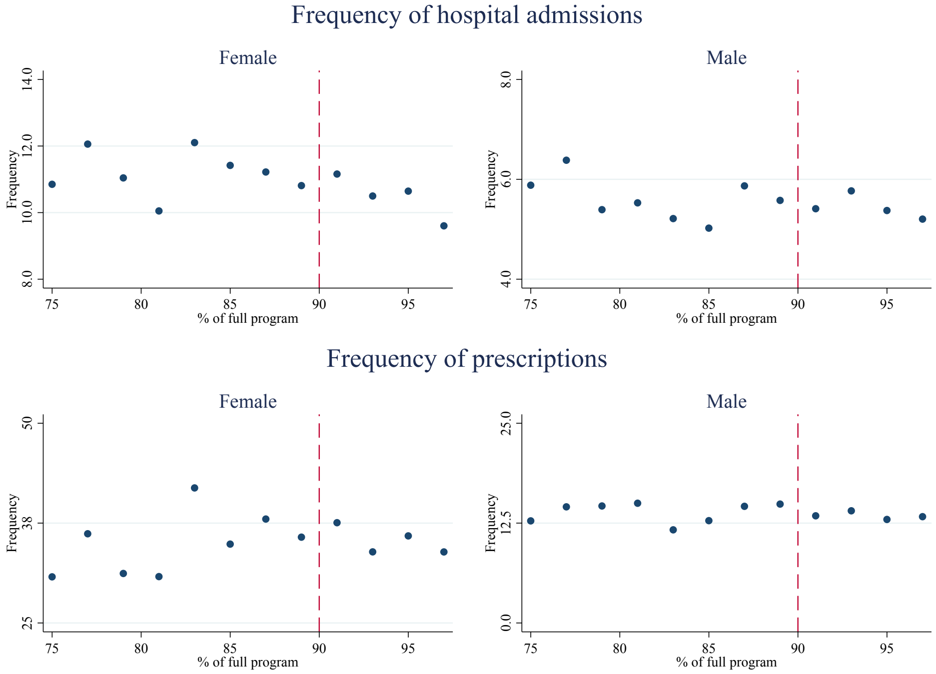

Fig. 3: Impact of university eligibility on the frequency of hospital admissions and prescriptions

Notes: These figures plot a scatter of the mean of hospital admission frequency and prescription frequency since graduation up to 2013 against percentage completed of a full program with a bin width of 2pp of a full course in each bin for those graduating upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

The RD results in table 5 are substantial in size relative to the OLS estimates of model (1) but are not at all stable to model specification and in the main not significant. As can be seen from the raw data in figure 3 there is no clear trend between frequency of prescriptions and credit score and therefore the results are sensitive to the noise in the data.

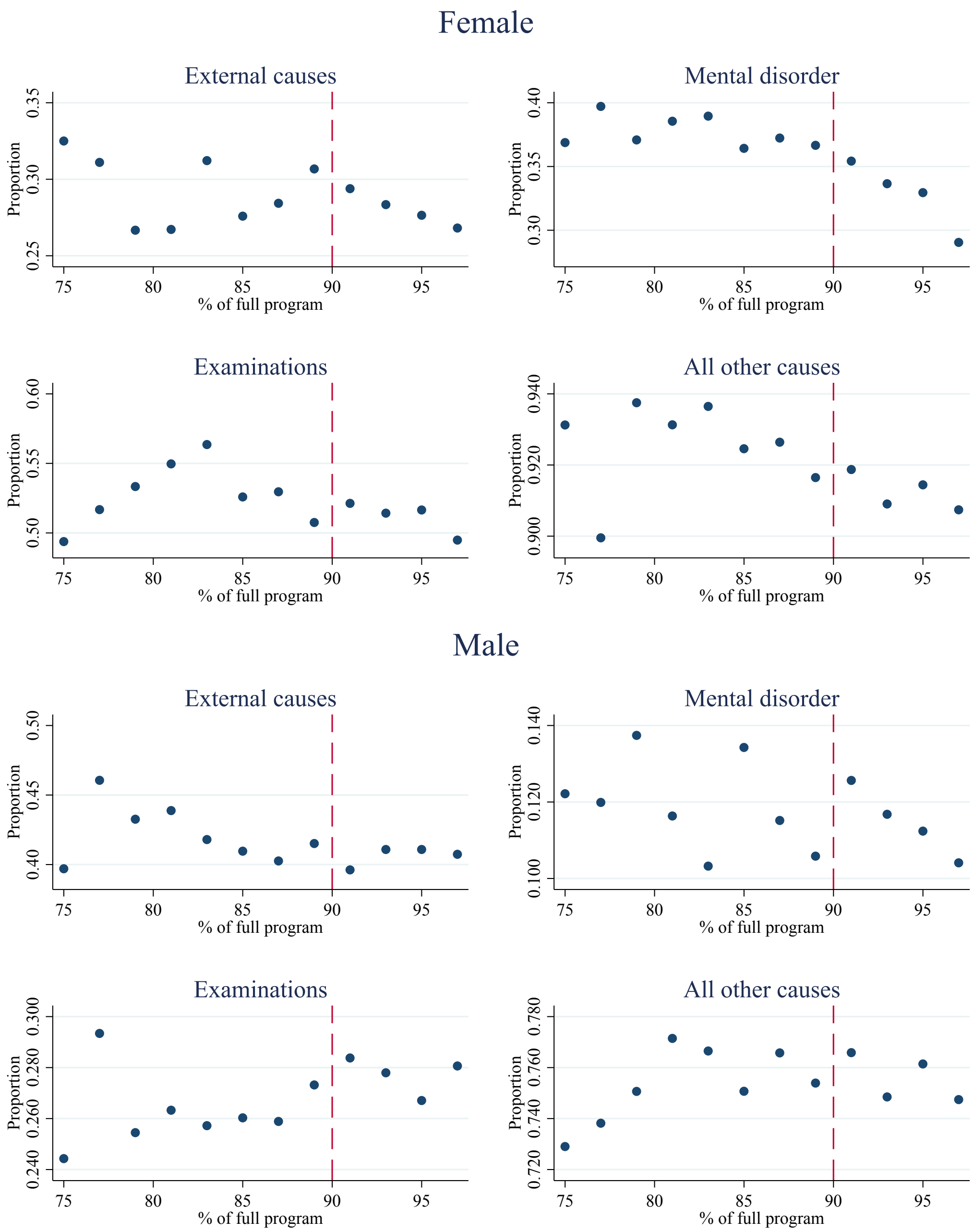

Fig. 4: Impact of university eligibility on the probability of hospital admission by diagnosis

Notes: This figure plots a scatter of average frequency of hospital admissions since graduation and up to 2013 by diagnosis against percentage completed of a full program with a bin width of 2pp of a full course in each bin for those graduating upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

Table 4: Impact of university eligibility on hospital admissions, by diagnosis

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		Females		
Number of admissions (mean: 10.44)	-0.831***	0.738***	0.120	0.209
	(0.163)	(0.159)	(0.267)	(0.281)
Probability of hospital admission due to:				
External causes (mean: 0.28)	-0.021***	-0.008	-0.001	0.001
	(0.008)	(0.013)	(0.012)	(0.011)
Mental disorder (mean: 0.33)	-0.010	-0.001	-0.007	-0.006
	(0.009)	(0.005)	(0.005)	(0.005)
Examinations (mean: 0.51)	-0.028***	0.030***	0.001	0.006
	(0.007)	(0.004)	(0.012)	(0.012)
All other causes (mean: 0.92)	-0.016***	0.003	-0.006	-0.004
	(0.003)	(0.004)	(0.006)	(0.007)
N	12652.000	12652.000	13523.000	13523.000
		Males		
Number of admissions (mean: 5.41)	-0.119	-0.239	0.188	0.185
	(0.168)	(0.276)	(0.286)	(0.294)
Probability of hospital admission due to:				
External causes (mean: 0.41)	-0.092***	-0.008	-0.004	-0.004
	(0.006)	(0.009)	(0.010)	(0.010)
Mental disorder (mean: 0.11)	0.012**	0.018*	0.017***	0.018***
	(0.006)	(0.010)	(0.005)	(0.005)
Examinations (mean: 0.27)	0.004	0.002	0.010	0.011
	(0.007)	(0.007)	(0.008)	(0.008)
All other causes (mean: 0.75)	-0.017***	0.005	-0.004	-0.004
	(0.006)	(0.008)	(0.009)	(0.008)
N	15686.000	15686.000	17148.000	17148.000
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on hospital admissions by diagnosis since graduation and up to 2013 for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression. Model (1) is a simple correlation of university attendance and health. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In figure 4 we present the credit score distribution of the *probability* of hospital admission by leading cause. In general there appears to be a downward trend in our causes of hospital admission with credit score and no clear jumps are observed for the causes we consider. The potential exception is mental disorders for males that appears to show a positive jump in cases for those reaching university eligibility, but the data appears quite noisy. In table 4 column (1) we present simple correlations of university attendance and hospital admissions by cause and in general the coefficients are negative and significant, confirming the widely documented education gradient in health and health care. The RD estimates for the probability of hospital admission by cause are found in table 4 models (2) to (4). We find that the jump in mental disorders for males is robust to model specification and lies in the range of 1.7pp to 1.8pp. These suggest a relatively large impact of university eligibility on mental disorder related admissions of about 10% (proportion who have a

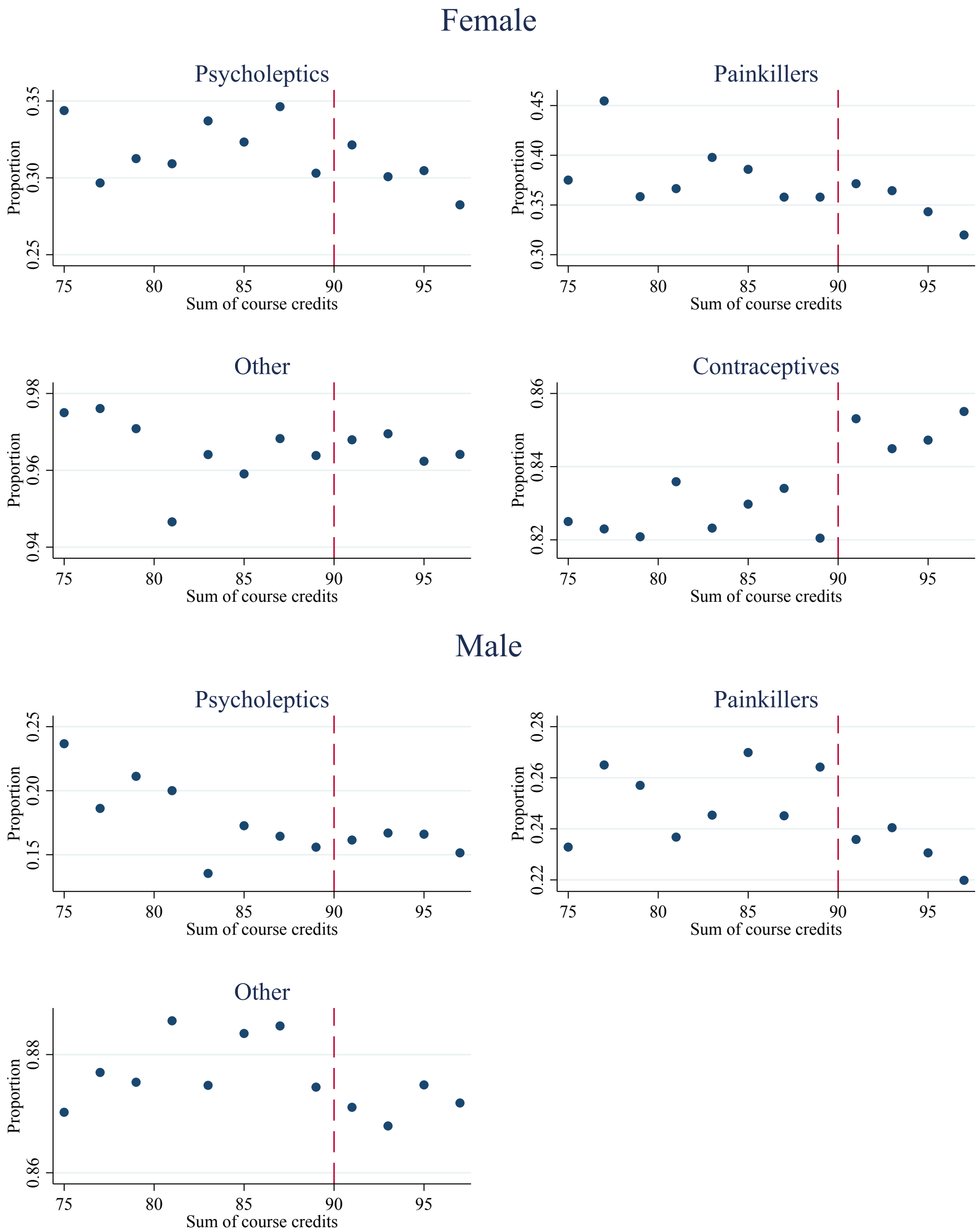

Fig. 5: Impact of university eligibility on the probability of prescription by cause

Notes: These figures plot a scatter of percentage completed of a full program with a bin width of 2pp against the probability of receiving a prescription since graduation and up to 2013 by main cause 2010-2013 in each bin for those graduating upper secondary school between the years 2003 and 2005. See notes for figure 1 mental disorder related admission is 11% for this group). No other results are robust to model choice.

Table 5: Impact of university eligibility on prescription receipt, by diagnosis

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		Females		
Frequency of prescriptions (mean: 35.23)	0.200	2.000	-1.508	-1.299
	(0.901)	(1.579)	(1.771)	(1.913)
Probability of prescription due to:				
Psycholeptics (mean: 0.3)	0.012*	0.018	0.001	0.001
	(0.006)	(0.017)	(0.018)	(0.020)
Painkillers (mean: 0.35)	-0.047***	0.032***	0.019*	0.020**
	(0.002)	(0.007)	(0.010)	(0.009)
Other (mean: 0.97)	-0.001	0.001	0.005	0.006*
	(0.004)	(0.004)	(0.003)	(0.003)
Contraceptives (mean: 0.85)	-0.023***	0.019**	0.018**	0.021**
	(0.005)	(0.008)	(0.007)	(0.009)
N	12652	12652	13523	13523
		Males		
Frequency of prescriptions (mean: 13.47)	0.763	-2.518***	-0.791	-0.814
	(0.485)	(0.495)	(0.614)	(0.601)
Probability of prescription due to:				
Psycholeptics (mean: 0.16)	0.029***	0.003	0.026***	0.027***
	(0.005)	(0.012)	(0.008)	(0.008)
Painkillers (mean: 0.23)	-0.044***	-0.021**	-0.019**	-0.019*
	(0.006)	(0.009)	(0.009)	(0.010)
Other (mean: 0.87)	-0.021***	-0.008	-0.011**	-0.011**
	(0.005)	(0.006)	(0.005)	(0.005)
N	15686	15686	17148	17148
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on frequency of prescriptions and probability of prescriptions since graduation and up to 2013 by category for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression. Model (1) is a simple correlation of university attendance and health. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We turn now to the specific causes for prescription receipt. We now consider prescriptions that are both preventative related (contraceptives (women only)) but also health outcome related in nature (psycholeptics, painkillers). We depict the credit score profile of prescriptions by cause and split by gender in figure 5. In the figure we see that females observe a clear positive jump in contraceptives and that males observe a drop in painkillers. In table 5, model (1) shows the association of university attendance with the probability of cause specific prescription receipt and we find there is in general a significant negative association between university attendance and prescription receipt. The RD results in table 5 models (2) to (4) for cause specific prescription receipt confirm that women who pass the eligibility threshold see an increase in contraceptive related prescriptions in the range 1.8pp to 2.1pp and that males see a drop in probability of receiving painkiller related prescriptions in the range of -1.9pp to -2.1pp. The results are stable across modelling strategies (2 to 4) and statistically significant suggesting that these results are robust to specification. Less stable results are also found for female painkiller prescription receipt where university eligibility is estimated to increase the probability of prescription receipt rather than reduce it as found for the OLS results.

In summary, we find that a large jump in university attendance due to university eligibility amongst females also coincides with no clear impact on hospital admissions but a clear positive impact on the proportion receiving a prescription for contraceptives. For males we find a jump in university attendance due to university eligibility but this is smaller than found for females and may also coincide with both an increase in hospital admissions due to mental disorders and a reduction in prescriptions for pain related medication.

6.2 The impact of university eligibility on health inequality

The analysis of the previous section focussed on the mean of our medical care use outcome variables. In this section we present the impact of university eligibility on the CI of parental income related medical care use inequality. We calculate the level of inequality for the whole population of students graduating upper secondary school between 2003 and 2005. The CI for parental income related frequency of hospital admission inequality is -0.012 and the CI for frequency of prescriptions is 0.021 (results shown in tables 6 and 7). That is, hospital admissions are concentrated more amongst young adults from poorer backgrounds. The opposite is the case for frequency of prescriptions. We link course credits and university eligibility to the CI using RIF regression and present the marginal effects in figure 6. There are no obvious trends in percentage completed of a full program and income related concentration of medical care use. There are also no clear jumps in income related hospital admission inequality or income related prescription inequality at the university eligibility threshold.

Model (1) of tables 6 and 7 presents the association of university attendance and parental income related medical care use inequality. These associations give us an idea as to how university attendance is linked to an increased or decreased concentration of medical care use amongst young adults with poor or rich backgrounds. The slight complication with interpretation of the coefficients in tables 6 and 7 is that a negative coefficient is only inequality reducing if the CI is positive. If the CI is negative then a negative coefficient implies a worsening of inequality, and vice versa. We see from model (1) in table 6 that university attendance is associated with a reduction in the CI for females and an increase for males but these associations are not particularly significant. For the CI of prescription frequency we find university attendance to increase inequality for females but

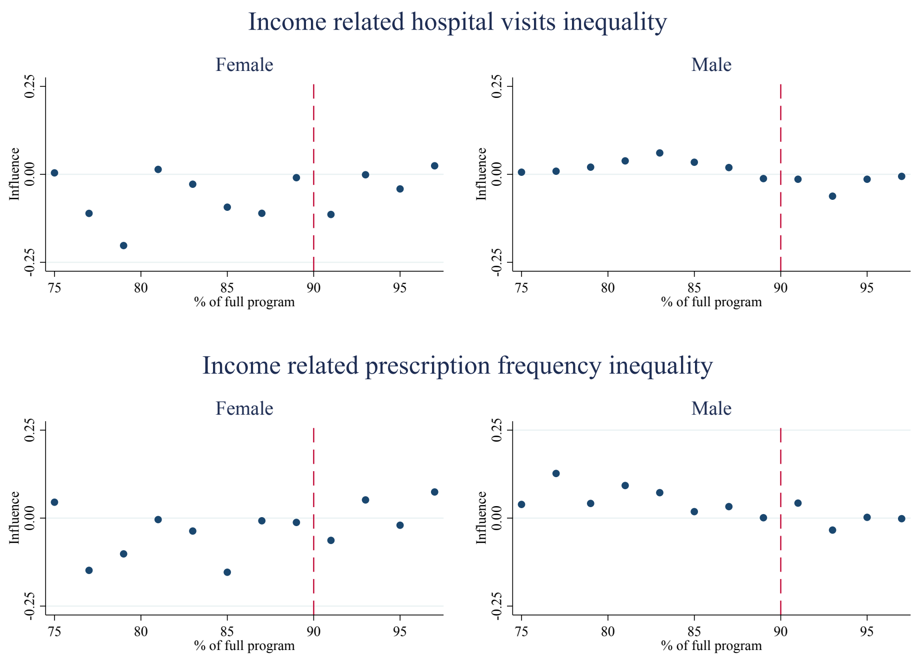

Fig. 6: Impact of university eligibility on income inequality of the probability of a hospital admission and a prescription

Notes: These figures plot a scatter of the mean frequency of hospital admissions and prescriptions (years 2010-2013) and mean (recentered) influence on the CI of hospital admissions and prescriptions against percentage completed of a full program using a bin width of 2pp of a full course for those graduating upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

reduce it for males, but again these associations are not significant. The RD estimates found in tables 6 and 7 of the impact of university eligibility on the CI confirm our observations from 6 that university eligibility leads to no clear impact on parental income related medical care use inequality.

In tables 6 and 7 we also present RD results by cause of hospital admission and cause of prescription (supporting figures are found in the appendix, A.1 and A.3). For the probability of a hospital admission we use the ARCI as our measure of relative inequality because we are interested in relative inequality but now need to account for the bounded nature of our binary health variable. We assess the sensitivity of our results to this choice of measure by also looking at the SRCI in the appendix. Just as frequency of hospital admissions inequality was found to be concentrated amongst the poor, so are the probabilities of admission due to various causes also concentrated amongst the poor. Model (1) of table 6 presents the naive associations between university attendance and ARCI and suggests the university attendance is inequality reducing for females and increasing for males, with the exception of the ARCI of external cause related and examination related hospital admissions for males. However, these associations are only statistically significant for the ARCI of examination related and mental disorder related hospital admissions for females. Examining the raw data in A.1 there appear to be small jumps for hospital admissions due to examinations. The RD results are shown in columns (2-4) in table 6 and confirm that there are jumps in the ARCI of hospital admissions for females due to examinations in the range of -0.023 to -0.033. Because the ARCI is negative (-0.013), university eligibility therefore increases the concentration of examinations amongst poor young adult females. There are also jumps in the ARCI of hospital admissions for males due to examinations in the range of 0.033 to 0.046. This suggests that university eligibility reduces the concentration of examinations amongst poor young adult males. No other stable and significant results are found for ARCI of hospital admissions.

We now turn to the particular causes of the ARCI of parental income related prescription receipt inequality. The CI of frequency of prescriptions finds a pro-rich concentration of prescriptions for young adults in Sweden. The pro-rich concentration is driven by contraceptives and *all other causes* of prescriptions whereas prescriptions for psycholeptics and painkillers are found to be more concentrated amongst the poor. In table 7 model (1) shows the association of university attendance with ARCI of cause specific prescriptions and only the ARCI for contraceptives finds a significant association (an inequality increasing association). In the appendix, figure A.3 depicts the relationship between percentage of a completed course and average effect on ARCI of prescriptions by cause. No clear trends between percentage of a completed course and the marginal impact on ARCI are observed for any cause specific prescription probability with the potential exception of contraceptives that show an increasing trend. At the 90% threshold no clear jumps are observed for females but potentially a negative jump for males for ARCI of prescriptions for other causes. This is largely confirmed in 7 models (2) to (4). Females observe no jumps at the 90% threshold that are stable to modelling specification or significant. In general this is also true for men with the exception for any other cause that sees an inequality reducing jump at the threshold that is relatively large compared to the level of ARCI and is stable to modelling specification.

Sensitivity analysis of our choice of ARCI over SRCI is found in the appendix (A.1 and A.2 and figures A.2 and A.4). The conclusions are not affected by our choice of ARCI over SRCI. To sum up, we find that there is a parental income concentration of medical care use. Hospital admissions are concentrated amongst the poor and prescriptions are more concentrated amongst the rich with the exception of psycholeptics and painkiller related prescriptions. University eligibility is found to increase hospital admission inequality through females yet reduce it through males and also reduce prescriptions for other causes inequality through males.

Table 6: Impact of university eligibility on parental income related hospital admissions, by diagnosis

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		Females		
Frequency of hospital admissions (CI=-0.012)	0.037*	-0.046	-0.033	-0.042
	(0.022)	(0.057)	(0.049)	(0.043)
Probability of admission due to:				
Mental disorders (ARCI=-0.033)	0.065***	-0.088	-0.024	-0.037
	(0.021)	(0.058)	(0.060)	(0.046)
External causes (ARCI=-0.005)	0.002	-0.021	-0.017	-0.018
	(0.019)	(0.013)	(0.017)	(0.015)
Examinations (ARCI=-0.013)	0.040**	-0.023***	-0.027***	-0.033***
	(0.020)	(0.006)	(0.010)	(0.009)
All other causes (ARCI=-0.001)	0.007*	-0.012**	0.004	0.002
	(0.004)	(0.004)	(0.007)	(0.006)
N	12652.000	12652.000	13523.000	13523.000
		Males		
Frequency of hospital admissions (CI=-0.012)	-0.005	-0.009	-0.049	-0.050*
	(0.014)	(0.025)	(0.030)	(0.028)
Probability of admission due to:				
Mental disorders (ARCI=-0.033)	-0.017	0.046*	0.007	0.002
	(0.017)	(0.025)	(0.036)	(0.033)
External causes (ARCI=-0.005)	0.012	-0.013	-0.021	-0.019
	(0.020)	(0.011)	(0.013)	(0.016)
Examinations (ARCI=-0.013)	0.001	0.046***	0.034**	0.033**
	(0.010)	(0.014)	(0.017)	(0.015)
All other causes (ARCI=-0.001)	-0.003	0.003	-0.006	-0.006
	(0.008)	(0.009)	(0.009)	(0.008)
N	15686.000	15686.000	17148.000	17148.000
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on concentration index of hospital admission frequency and the attainment relative concentration index of hospital admission probability by diagnosis since graduation and up to 2013 for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression and captures the marginal effect on the inequality index. Model (1) is a simple correlation of university attendance and health inequality. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. For simplicity of application we use empirical standard errors that do not account for the fact that the RIF is an estimated function. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Impact of university eligibility on parental income related prescription receipt admissions

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		Females		
Frequency of prescriptions (CI=0.021)	0.028	-0.047	-0.009	-0.024
	(0.023)	(0.044)	(0.047)	(0.039)
Probability of prescription due to:				
Psycholeptics (ARCI=-0.001)	0.026	-0.064***	0.008	-0.008
	(0.016)	(0.017)	(0.038)	(0.035)
Painkillers (ARCI=-0.017)	0.025	-0.034**	0.003	-0.001
	(0.019)	(0.016)	(0.022)	(0.018)
Other (ARCI=0.003)	-0.002	-0.000	-0.001	-0.001
	(0.002)	(0.005)	(0.004)	(0.004)
Contraceptives (ARCI=0.013)	0.055***	0.011	0.030	0.007
	(0.008)	(0.026)	(0.025)	(0.013)
N	12652.000	12652.000	13523.000	13523.000
		Males		
Frequency of prescriptions (CI=0.021)	-0.018*	0.025	0.009	0.006
	(0.010)	(0.030)	(0.031)	(0.027)
Probability of prescription due to:				
Psycholeptics (ARCI=-0.001)	0.007	0.074***	0.012	0.011
	(0.012)	(0.021)	(0.033)	(0.033)
Painkillers (ARCI=-0.017)	-0.020	-0.025	-0.065**	-0.065**
	(0.015)	(0.029)	(0.032)	(0.032)
Other (ARCI=0.003)	-0.002	-0.008***	-0.013***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.004)
N	15686.000	15686.000	17148.000	17148.000
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on concentration index of prescription frequency and the attainment relative concentration index of prescription probability by diagnosis since graduation and up to 2013 for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression and captures the marginal effect on the inequality index. Model (1) is a simple correlation of university attendance and health inequality. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. For simplicity of application we use empirical standard errors that do not account for the fact that the RIF is an estimated function. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Discussion

In this paper we have shown that university eligibility leads to a sharp positive discontinuity in the proportion attending university. Previous analysis using the same eligibility rule (Nordin et al., 2017) has shown that this jump in university eligibility leads to coinciding jumps in years of schooling of about 0.3 years for female and 0.2 for males and an increase in the probability of achieving 15 years of schooling (equivalent to a bachelor's degree) of about 10pp for females and 3pp for males. We find that this discontinuous jump in university level educational attainment for females coincides with no clear impact on hospital admissions but a clear positive impact on the proportion receiving a prescription for contraceptives of about 1.8pp. For males the jump in university attendance due to university eligibility is smaller than found for females and we find a possible increase in hospital admissions due to mental disorders of about 1.7pp and a reduction in prescriptions for pain related medication of about 1.9pp.

We have also considered the impact of university eligibility on socioeconomic inequality in health, specifically how university eligibility has impacted the CI of family income related health inequality. No overall impact is found on the concentration of hospital admissions or prescriptions with family income, but specific impacts were found for hospital admissions for examinations (inequality increasing for females, decreasing for males) and for prescriptions for any other reason (inequality decreasing for males only).

Our results assessing the level of health appear to fit alongside those of De Walque (2007) and Grimard and Parent (2007) who find a protective impact of education on health (reduces smoking initiation and increases likelihood of cessation), and Buckles et al. (2016) who find a negative impact on mortality, all using the Vietnam draft as an Instrumental Variable for university attendance. The jump we find in contraceptive prescriptions for females can be interpreted as a jump in health investments. This fits with the evidence showing college graduates choosing to smoke less. The jump also could be linked to a preference to delay child birth. The impacts found for males are harder to interpret because they could be either due to impacts of health on medical care use e.g. university has increased stress and anxiety so they are more likely to visit hospital, or that they are now more aware of their condition and get themselves seen to. A similar argument can be made for the results for pain-killers.

Our results looking at the socioeconomic inequality aspects of university eligibility have not yielded any clear impacts. There appear to be competing effects of university eligibility on examination related hospital admission inequality where females see an increase in inequality but males a decrease. We do not find a strong impact on contraceptive prescription inequality which suggests that increasing access to university education is unlikely to worsen contraceptive use related inequality.

The results presented in this paper are based on RD design that has a very high level of internal validity. But are the results specific to Sweden? The Swedish welfare state and health care system is very comprehensive and is similar in its coverage and provision to that of the National Health Service (NHS) in Britain. Both systems offer universal coverage and use doctors as gatekeepers to the medical system that should in theory minimise shopping for best treatments. A small difference between the NHS in Britain and Sweden's health care system is that in Sweden patients are required to pay a small out of pocket payment to visit a doctor or use any hospital service. There is therefore a financial element to the participation decision. But this is small, about 150 SEK (roughly $18 in 2018 prices) depending on where one lives in Sweden. This means that one potential channel for education to impact health, via financial resources, is more limited in Sweden. However, we would expect changes in health related behaviours to be related to education and these will independently impact the demand for health care. Financial resources can also impact health via other channels than medical care, through improved access to better diet, resources for increased activity and so on. It is important to understand all the channels by which education may affect health.

The period in which we consider the impacts on health are fairly short after the intervention, up to 8 - 10 years after graduating from upper secondary school. Early adulthood health outcomes are of interest as they allow us to understand the mechanisms by which potential changes to education could impact health immediately and later on in life. The objective health outcomes we consider, hospital admissions and prescriptions, represent health processes, behaviours and investments. The human capital models that predict the importance of education in determining our health capital do not state the timescale over which these investments might take place. It is therefore of interest to know if and how and when we see a difference in an individual's health capital investments.

A particular limitation of the data we have used is that we do not consider the impact of university eligibility on primary care use. This is because there is no national dataset that captures primary care use. Primary care use is likely to be relevant for young adults and their health investments. The impacts found for prescriptions are quite likely to be reflected in the primary care use data as the majority of prescriptions are made by the local GP and not doctors at hospitals. However, this type of analysis will remain difficult until someone manages to corral all 21 health regions in Sweden to join up and create a unified administrative system.

We conclude that university education for low ability students leads to an increase in contraceptive use amongst females. We also find that the changes in the levels of medical care use do not impact family income related medical care use and that overall any potential increases in ease of access to university are unlikely to impact overall income related medical care use amongst young adults. The results suggest caution, however, as we also find indications that male mental health issues jump for those achieving university eligibility and this suggests that universities need to take particular care of the mental health of their least able students.

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Appendix

A The impact of university eligibility on hospital admissions and prescription rates, detailed sub-group analysis

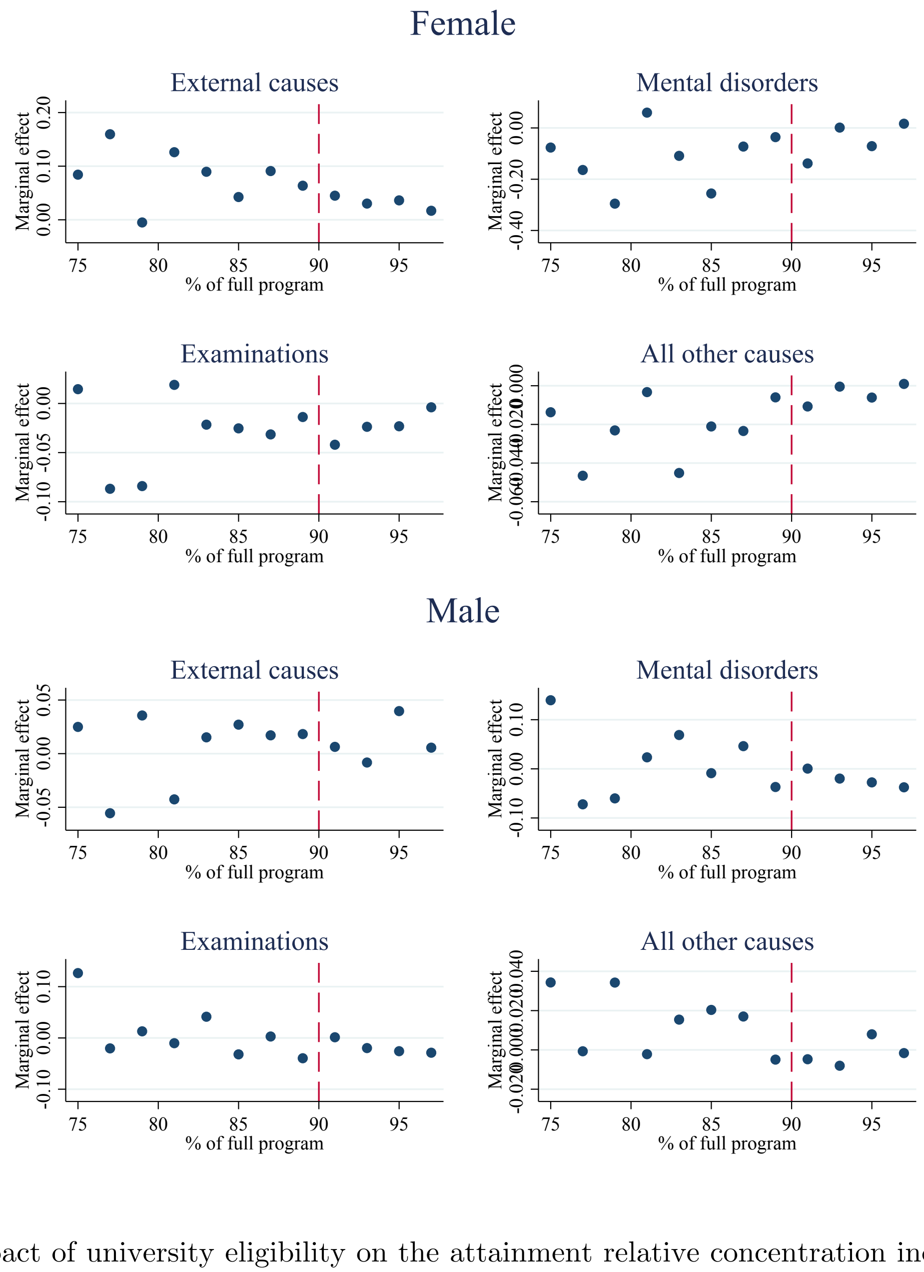

Fig. A.1: Impact of university eligibility on the attainment relative concentration index of *income related* inequality of hospital admission by diagnosis

Notes: These figures plot a scatter of the recentered influence function of attainment relative concentration index income related inequality of frequency of hospital admissions against the final achieved course credits with a bin width of 2pp of a full course in each bin for those graduating from upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

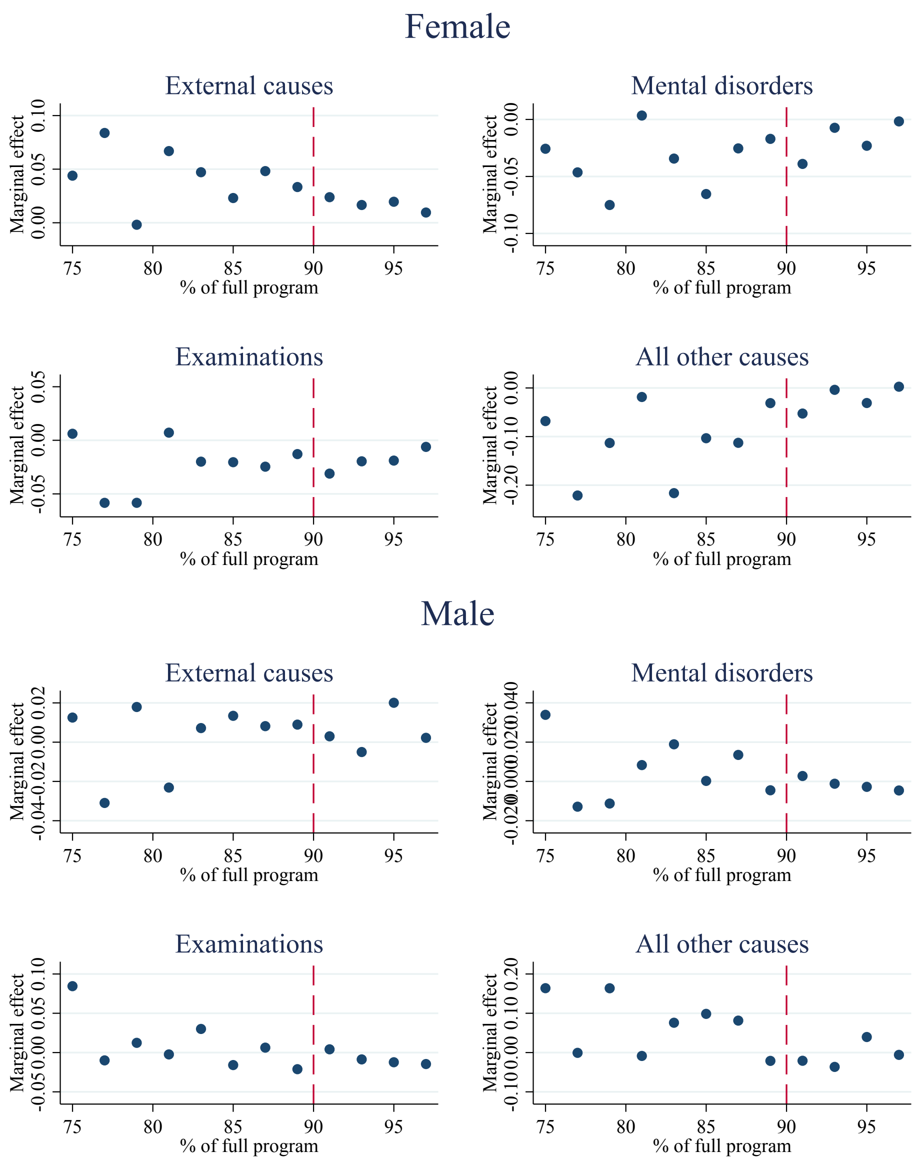

Fig. A.2: Impact of university eligibility on the short-fall relative concentration index of *income related* inequality of hospital admission by diagnosis

Notes: These figures plot a scatter of the recentered influence function of short-fall relative concentration index income related inequality of frequency of hospital admissions against the final achieved course credits with a bin width of 2pp of a full course in each bin for those graduating upper from secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

Table A.1: Impact of university eligibility on short-fall relative concentration index of parental income related hospital admission probability by cause

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		Females		
Examinations (SRCI=-0.008)	0.026**	-0.016***	-0.017***	-0.021***
	(0.012)	(0.004)	(0.006)	(0.006)
Mental disorders (SRCI=-0.007)	0.015***	-0.019	-0.005	-0.008
	(0.005)	(0.013)	(0.013)	(0.010)
External causes (SRCI=-0.002)	0.001	-0.011	-0.008	-0.009
	(0.010)	(0.007)	(0.009)	(0.008)
All other causes (SRCI=-0.003)	0.036*	-0.054**	0.019	0.010
	(0.018)	(0.020)	(0.035)	(0.028)
N	12652.000	12652.000	13523.000	13523.000
		Males		
Examinations (SRCI=-0.008)	0.000	0.029***	0.021*	0.020**
	(0.007)	(0.009)	(0.011)	(0.010)
Mental disorders (SRCI=-0.007)	-0.004	0.009*	0.001	-0.000
	(0.004)	(0.005)	(0.008)	(0.007)
External causes (SRCI=-0.002)	0.007	-0.006	-0.011	-0.010
	(0.010)	(0.006)	(0.007)	(0.008)
All other causes (SRCI=-0.003)	-0.013	0.013	-0.027	-0.029
	(0.036)	(0.042)	(0.043)	(0.039)
N	15686.000	15686.000	17148.000	17148.000
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on concentration index of prescription frequency and the attainment relative concentration index of prescription probability by diagnosis since graduation and up to 2013 for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression and captures the marginal effect on the inequality index. Model (1) is a simple correlation of university attendance and health inequality. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

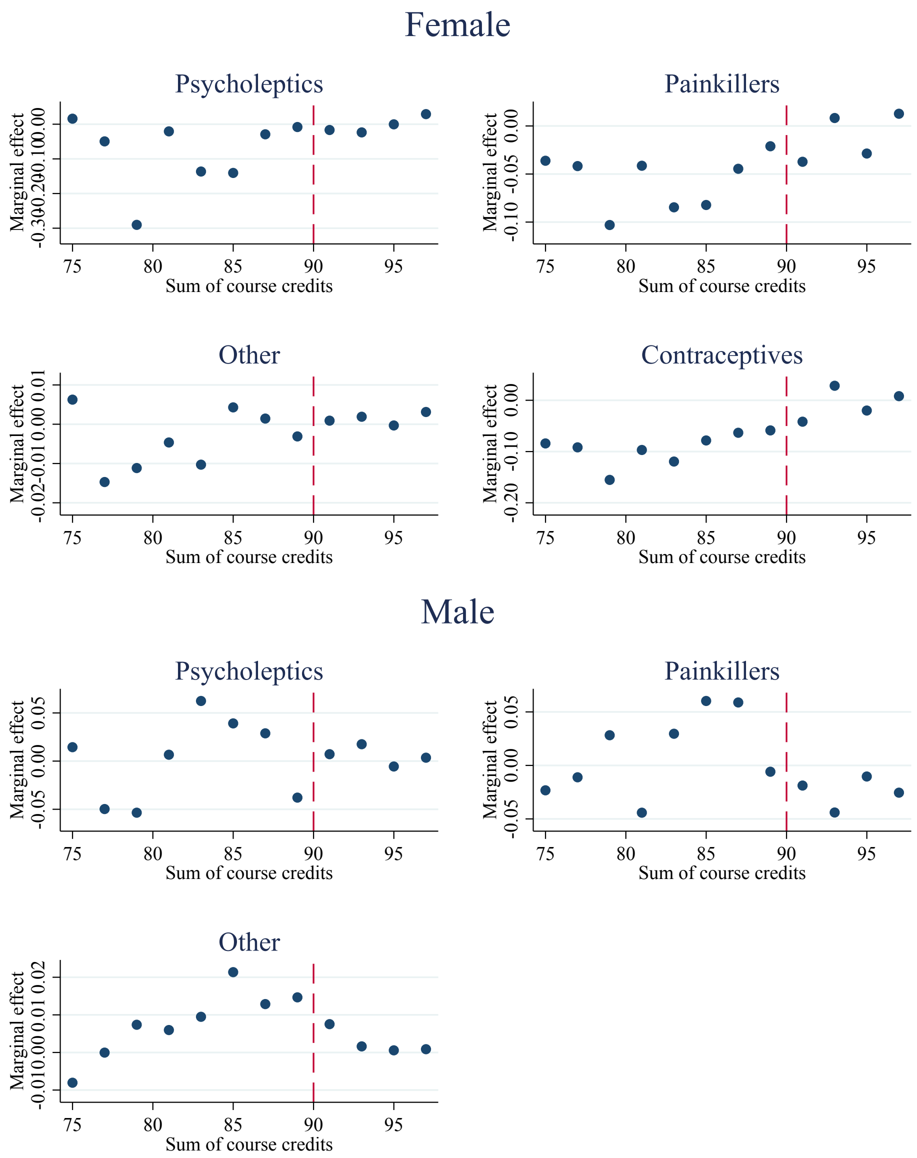

Fig. A.3: Impact of university eligibility on the attainment relative concentration index of *income inequality* of prescription receipt by cause

Notes: These figures plot a scatter of the recentered influence function of attainment relative concentration index income related inequality of frequency of prescriptions against the final achieved course credits with a bin width of 2pp of a full course in each bin for those graduating upper from secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

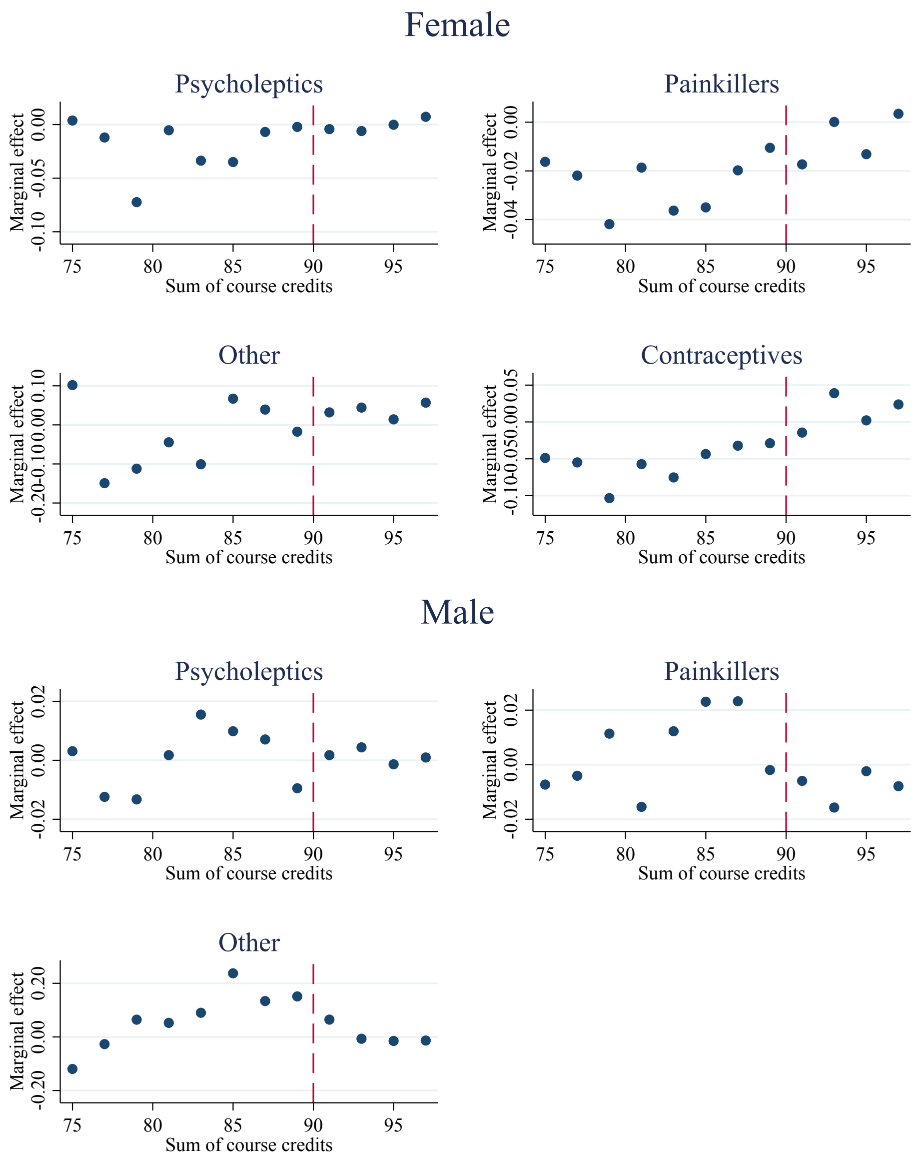

Fig. A.4: Impact of university eligibility on the short-fall relative concentration index of *income inequality* of prescription receipt by cause

Notes: These figures plot a scatter of the recentered influence function of short-fall relative concentration index income related inequality of frequency of prescriptions against the final achieved course credits with a bin width of 2pp of a full course in each bin for those graduating from upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1.

Table A.2: Impact of university eligibility on short-fall relative concentration index if parental income related prescription probability by cause

	(1)	(2)	(3)	(4)
Bandwidth	8pp	8pp	16/8pp	16/8pp
		FEMALES		
Contraceptives (SRCI=0.01)	0.041***	0.010	0.024	0.006
	(0.006)	(0.020)	(0.019)	(0.010)
Psycholeptics (SRCI=-0.000)	0.006	-0.016***	0.002	-0.002
	(0.004)	(0.004)	(0.009)	(0.009)
Painkillers (SRCI=-0.007)	0.011	-0.014**	0.001	-0.001
	(0.007)	(0.006)	(0.008)	(0.007)
Other (SRCI=0.034)	-0.022	-0.006	-0.007	-0.016
	(0.019)	(0.062)	(0.046)	(0.047)
N	12652.000	12652.000	13523.000	13523.000
		MALES		
Psycholeptics (SRCI=-0.000)	0.002	0.018***	0.003	0.003
	(0.003)	(0.005)	(0.008)	(0.008)
Painkillers (SRCI=-0.007)	-0.006	-0.009	-0.024*	-0.024*
	(0.006)	(0.011)	(0.012)	(0.012)
Other (SRCI=0.034)	-0.029	-0.103***	-0.161***	-0.162***
	(0.031)	(0.035)	(0.042)	(0.044)
N	15686.000	15686.000	17148.000	17148.000
Polynomial	0	1	1	1
Covariates	N	N	N	Y

Notes: This table shows the regression discontinuity estimates of the impact of university eligibility on concentration index of prescription frequency and the attainment relative concentration index of prescription probability by diagnosis since graduation and up to 2013 for those graduating between years 2003 and 2005, academic stream only. Each coefficient is from a separate regression and captures the marginal effect on the inequality index. Model (1) is a simple correlation of university attendance and health inequality. Models (2) and (3) use a linear trend in credits either side of the cut-off but different bandwidths. Model (4) is as model (3) and also includes covariates as outlined in table 2. Robust standard errors clustered at number of credits achieved are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$