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The Health Returns of University Eligibility

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Abstract

This paper exploits an arbitrary university eligibility rule in Sweden combined with regression discontinuity to estimate the impact of university education on health derived demand for medical care. We find a clear jump in university attendance due to university eligibility of between 10 and 14 percentage points. For females this implies a 30-40% drop in self-harm. For males it coincides with reduced use of prescribed pain killers, implying reduced risky behaviour. Males also observe a 30% increase in mental disorders, almost exclusively related to alcohol. The spillovers of university education on to health for the marginal student are therefore significant.

Keywords: Health returns to education, demand for health, Regression Discontinuity Design

JEL Classification: *I10, I23, I26*

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1 Introduction

The expansion of university education in Sweden and most other developed countries over the past decades has led to greater opportunities for huge numbers of people. However, while the mean market returns to university education are well documented (see e.g. Card, 1999), much less research have been dedicated to the returns to university education for students at the margin of eligibility which may exhibit very different returns compared to the average university student. In this paper we exploit an arbitrary university eligibility threshold combined with Regression Discontinuity Design (RDD) in order to identify the impact of access to university on health in Sweden.

The literature on the relationship between education and health finds its theoretical origins in the demand for health model of Grossman (1972) and more recently Grossman (2000); Galama et al. (2018). 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. An education gradient in health is observed in nearly every country (Mackenbach et al., 2003; Van Doorslaer and Koolman, 2004). The concern with any association of education and health is that the relationship may be due to reverse causality or selection. 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 Bijwaard and Van Kippersluis (2016) or time preferences as suggested by Fuchs (1982).

The literature documenting the causal evidence of the impact of years education has relied on quasi-experimental evidence and remains inconclusive (see e.g. Cutler and Lleras-Muney 2012; Grossman 2015; Galama et al. 2018), with results being sensitive to methodology, sample size and source of exogenous variation but also heterogeneous across sub-groups.[1] The majority of this research however, considers changes in compulsory schooling. Cunha et al. (2010) have shown that there are potential complementarities between early and later life interventions, yet the impact of university education on health is one margin that has received little empirical attention. 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). Whilst these findings are credible, if we are to draw lessons from the compulsory schooling literature, then different margins and identifying strategies are likely to find different effects. It is therefore likely that individuals induced to university education by the Vietnam draft are different to those at the margin of eligibility to university. Using the Vietnam draft as an instrument is also limited by the fact that it only allows us to consider the impacts on males whom tend to have very different health behaviours to females.

In this paper we present new findings of the impact of university eligibility on health 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 10 to 14 percentage

[1] 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 Brunello et al. (2016) 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.

points (pp). It is this arbitrary rule that allows us to identify the impact of university eligibility on various health derived medical care use outcomes using RDD . The marginal group affected by the eligibility rule are individuals who are towards the lower end of the education distribution (46$^{\text{th}}$ percentile and 42$^{\text{nd}}$ 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 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 and on years of education and that these jumps are substantial in size relative to years of education effects found elsewhere in the causal effect of education literature (Galama et al., 2018). We find that this jump in university eligibility leads to varying effects by gender. Females observe a clear reduction in self-harm related hospital admissions suggesting an important improvement in their mental well-being. Males on the other hand observe a clear increase in admissions due to mental illness, largely due to alcohol. However, they also observe a decrease in prescriptions of opioid related medicines. Potential mechanisms for the worsening of male mental health and reduced prescriptions for pain relief include a change in peer effects leading to increased drinking for the marginal student, and reduced risky male behaviour leading to less accidents and therefore fewer prescriptions for pain relief respectively.

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 the data material we use for the analysis and in section 4 we explain our empirical approach and test the identifying assumptions we make. Section 5 presents the results for medical care use and section 6 concludes.

2 The Swedish Education System

In Sweden in order to be able to attend university a student needs to achieve eligibility by passing at least 90% of a full program at upper secondary school.[2] This is most often achieved at graduation from upper secondary school but can also be achieved later by completing complementary adult studies after upper secondary school. We define eligibility at a point in time: 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.[3] 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., 2020). Students can choose their preferred stream. A full program consists of 2500 course credits for both types of tracks.[4] 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

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

[3]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.

[4]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%.

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 the years prior.

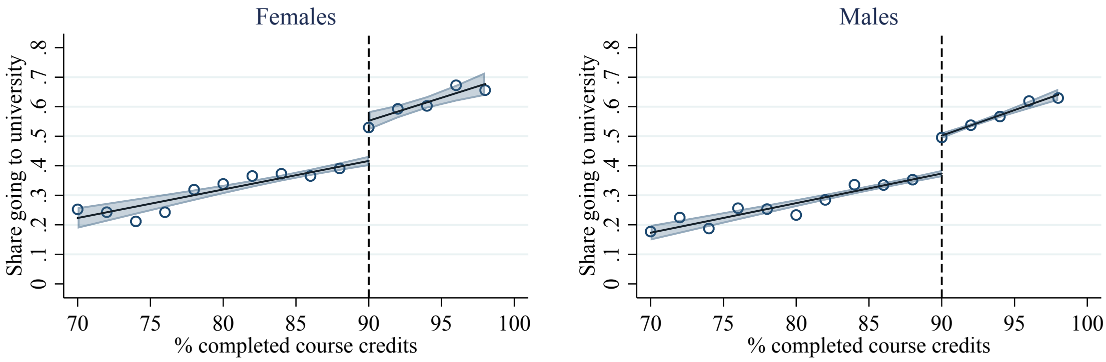

Fig. 1: Course Credit Profile of University Attendance

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 upper secondary school program (the size of the smallest course) for those graduating upper secondary school between the years 2003 and 2005. Linear regression lines are estimated either side of the cut-off with corresponding 95% confidence intervals shown by the shaded area, standard errors clustered at the running variable level. The cut-off for university eligibility is marked by the dashed vertical line at 90pp credits.

In figure 1 we show the impact of barely passing the cut-off point upon graduation from upper secondary school 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. Linear regression lines are plotted either side of the cut-off and 95% confidence intervals are indicated by the shaded area. 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.

It can be seen that the probability of enrolling in university is around 10pp higher for both females and males. Nordin et al. (2020) 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 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 RDD analysis 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 Data

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.[5] We combine education register data on final grades from compulsory school, grades from upper secondary school and data on higher education first term attendance and derive total years of schooling using highest level of education achieved. 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

[5]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.

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).[6] Keeping students who finish at age 18 or 20 has no impact on the results in this study. In our analysis we split the sample by gender because there are important differences in education patterns and labour market and health decisions between genders. This results in sample sizes of between 12,000 and 17,000 depending on the bandwidth and gender chosen.

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 diagnosis (International Classification of Diseases (ICD10 codes) and drug type (Anatomical Therapeutic Chemical (ATC) Classification System codes) that are plausibly modified by education. We define dummy variables for hospital admissions between graduation and 2013 due to: *External Causes* (ICD10 codes S,T or if coded as external and main diagnosis missing), *Mental Health* disorders (ICD10 code F) .[7] For prescriptions we consider: *Mental Health* related prescriptions that is the sum of Anti-depressives (ATC code N06A) and drugs used to treat *Anxiety, Sleep, Stress* (ATC codes N05B-C). *Opiodes* (ATC code N02A) are considered because they potentially relate to both drug abuse and recovery from severe accidents, which are both common for this age group. Finally we consider university attendance in the first term, defined as a binary variable where unitary corresponds to attendance, zero otherwise.

[6] 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.

[7] Subcategories of external are also considered: *Accidents* (ICD10 codes V and X01-X59 if external), *Self-harm* (ICD10 codes X60-X84) and *Other External* defined as all other external causes other than accidents and self-harm or child birth. Subcategories of mental ill health disorders are also considered: *Alcohol and Narcotics* related (ICD10 code F1), *Mood Affective Disorders* (ICD10 code F3), and *Neurotic, Stress Related, Somatoform Disorders* (ICD10 code F3).

Pre-determined characteristics highly correlated with our health outcomes are used and include parental income and education in 1990, age at migration and year of graduation from upper secondary school.[8] Dummies are defined for first-generation immigrant and second-generation immigrant and are region of origin specific.[9] We also define a dummy for whether the parents are of mixed origin or not and whether only one parent is an immigrant.

4 Method

4.1 Identifying the impact of university education eligibility

To estimate the effects of university eligibility on our health outcomes we use an RDD 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 easier and more immediate access to university education, and those below do not. This allows us to then assess the impact of university eligibility on educational and health outcomes. The general formulation for the regression equations we estimate is the following:

$$y_i = \alpha + \beta Eligible_i + f(\% fullprogram_i) + \varepsilon_i; \tag{1}$$

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

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

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. A low ordered polynomial is important as higher order polynomials can over fit the data (Gelman and Imbens, 2017). We find a single polynomial is sufficient in our empirical application. 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.[10] Due to the fact that we have a large sample size so close to the cut-off, we are able to have small

[10]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.

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 (Imbens and Lemieux, 2008).

When estimating equation 1, 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 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. In all our RDD analysis we cluster the standard errors at the level of the forcing variable, completed course credits.[11]

4.2 The Impact of University Eligibility on University Attendance

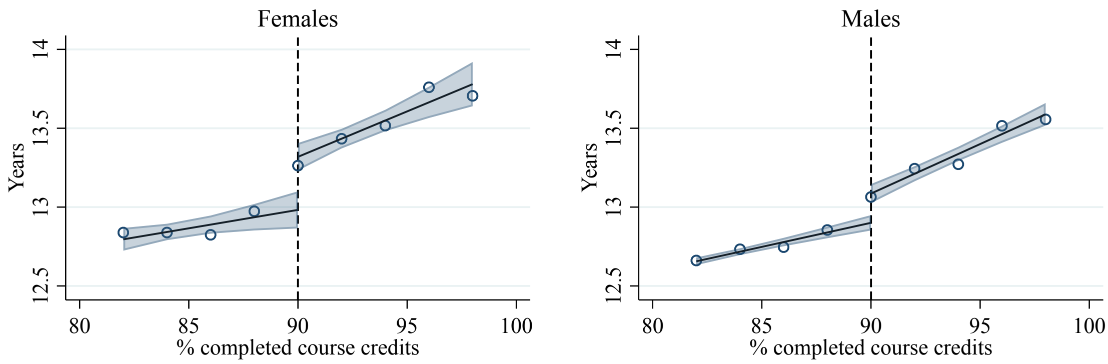

Fig. 2: Course Credit Profile of Years of Education

Notes: These figures plot mean years of education for each bin of a completed program, in bins of 2pp of a program. The dashed vertical line is the 90% cut-off for university eligibility. See notes for 1 further details.

[11] Clustering standard errors at the forcing variable level is the recommended approach for RDD analysis, but in our analysis we have a small number of clusters and this may be a problem. How standard errors behave when clustering depends not on only the number of clusters, but also amongst other things on the variance within each cluster. In testing the minimum number of clusters (see e.g. Carter et al., 2017; Lee and Steigerwald, 2018) we find the recommended minimum number of clusters to be 4.8, which is less than the number of clusters we use. We find that the standard errors of our results are in general not sensitive to whether we cluster or not.

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 and in figure 2 we can see there is also a clear jump in years of education for both females and males. The corresponding RDD results are shown in table 1. 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 RDD results using a bandwidth of 4pp and confirms there is a positive jump in the proportion attending university, 11pp for females and 13pp for males. Model (3) is as per (2) but with double the bandwidth of 8pp and corresponds to the linear regression lines in figure 1. Model (4) is as per (3) but with double the left-hand side bandwidth of 16pp. Models (5 and 6) are as per models (3 and 4) but with the addition of pre-determined covariates.[12] The results are stable to the choice of bandwidth and suggest university eligibility leads to a jump in university attendance in the range of 10pp to 13pp for females and 11pp and 12pp for males. The impact on years of education is in the range 0.14 and 0.27 years for females and 0.1 and 0.16 years for males.

[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.

Table 1: Impact of University Eligibility on Education

	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth	8pp	4pp	8pp	16pp/8pp	8pp	16pp/8pp
			Female			
1st Term Attendance	0.248***	0.113***	0.139***	0.112***	0.131***	0.098***
	(0.029)	(0.000)	(0.013)	(0.015)	(0.013)	(0.015)
Years of Schooling	0.700***	0.140***	0.265***	0.236***	0.242***	0.194***
	(0.111)	(0.000)	(0.060)	(0.049)	(0.060)	(0.048)
Observations	12,671	4,685	12,671	13,525	12,671	13,525
			Male			
1st Term Attendance	0.239***	0.125***	0.119***	0.115***	0.115***	0.112***
	(0.028)	(0.000)	(0.008)	(0.007)	(0.009)	(0.008)
Years of Schooling	0.570***	0.101***	0.161***	0.170***	0.147***	0.159***
	(0.101)	(0.000)	(0.036)	(0.034)	(0.032)	(0.033)
Observations	15,693	6,573	15,693	17,120	15,693	17,120
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 education for those graduating upper secondary school 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 our variables capturing potential manipulation mechanisms and various pre-determined covariates as a 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 1. The impact of the inclusion of these covariates is very small. The inclusion of the covariates (models 5 & 6) leads to a very small reduction in the estimated impacts 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 3 presents three visual tests of cut-off manipulation. The top panel of figure 3 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

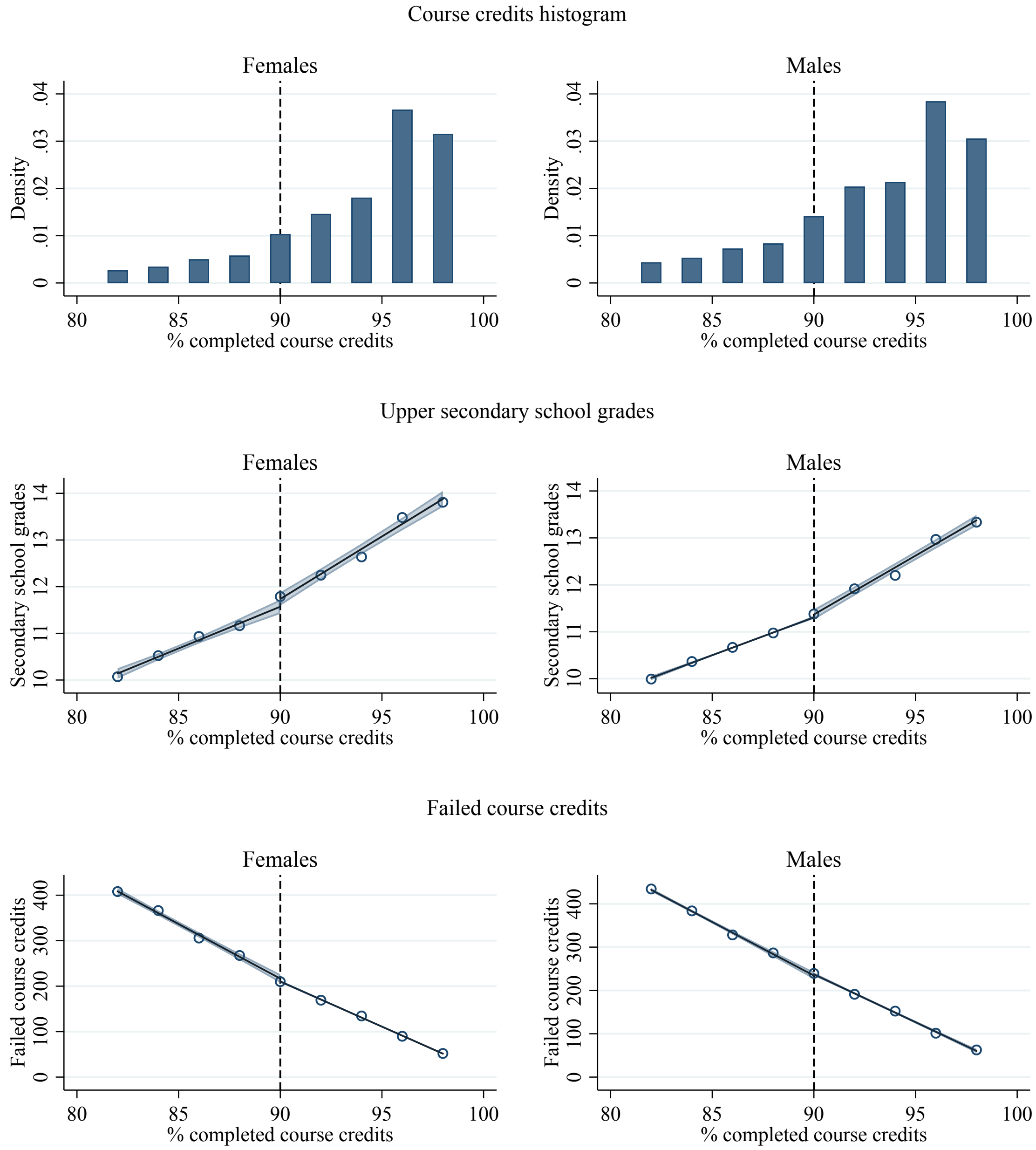

Fig. 3: Course Credit Profile of Manipulable Outcomes

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.

(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 3 shows the final grade plotted against credit score. The final (third) panel shows the number of failed courses by final achieved credit score. 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 to the left of the threshold. For the number of failed courses, if manipulation were occurring, because students can take more courses than needed for a full program, 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 2 we present results from a batch of balancing tests using RDD that assess whether our diagnostic test variables as shown in figure 3 and other pre-determined characteristics (see appendix figure A.1) 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 RDD specification to isolate the impact of university eligibility in models (2-3 and 5-6) the coefficients all substantially reduce towards zero and nearly always lose statistical significance. The first row results are a test of threshold manipulation in the spirit of (McCrary, 2008) assessing whether there is a discontinuity in the density around the cut-off and we find no evidence of this. 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 rather small in relative terms and represents a jump of less than 1pp (320 credits is the maximum). We also do not find a corresponding jump in upper secondary school grades which, a priori, we are more concerned about as it is these grades students would potentially be trying to manipulate. Our RDD results also show mother's and father's income are balanced either side of the cut-off.[13]

In sum, the fact that our estimates of the impact of university eligibility on university

[13]Balancing test figures for Compulsory school grades, mother's income and father's income are shown in figure A.1.

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 in our outcome variables 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 2: Balancing Tests

	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth	8pp	8pp	16pp/8pp	8pp	8pp	16pp/8pp
	Female			Male		
McCrary density test						
Tertiary Eligibility	0.020**	-0.001	-0.000	0.020**	0.002	0.002
	(0.007)	(0.003)	(0.003)	(0.006)	(0.002)	(0.002)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
Upper secondary grades						
Tertiary Eligibility	2.053***	0.097	0.138	1.741***	0.032	0.079
	(0.418)	(0.118)	(0.099)	(0.380)	(0.059)	(0.058)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
Number of failed credits at upper secondary school						
Tertiary Eligibility	-191.282***	-6.063	-3.966	-191.627***	4.721	3.411
	(36.038)	(4.722)	(4.433)	(39.610)	(4.374)	(3.224)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
Compulsory school grades						
Tertiary Eligibility	17.352***	1.017	2.734*	13.458***	2.227*	2.513***
	(3.717)	(1.182)	(1.437)	(2.964)	(1.006)	(0.804)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
Mother's income						
Tertiary Eligibility	50.278**	-23.454	2.018	42.992***	-11.376	-5.640
	(14.835)	(13.914)	(17.261)	(12.011)	(8.098)	(8.414)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
Father's income						
Tertiary Eligibility	114.692***	-1.930	25.995	89.767**	7.763	-13.566
	(26.648)	(17.282)	(24.844)	(27.715)	(23.488)	(20.161)
Observations	12,671	12,671	13,525	15,692	15,692	17,119
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 Results

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 4 depicts the completed credit profile of mean frequency of hospital admissions and the proportion who have had a hospital visit due to external causes or a mental disorder during the years since graduation and up to 2013, split by gender. The data indicate a slight increase in frequency of visits for females (0.5 visits). For males the data indicate a drop in the proportion who have had a hospital admissions due to external causes of 2pp, although insignificant, and an increase about 1.5pp for mental disorder related hospital admissions.

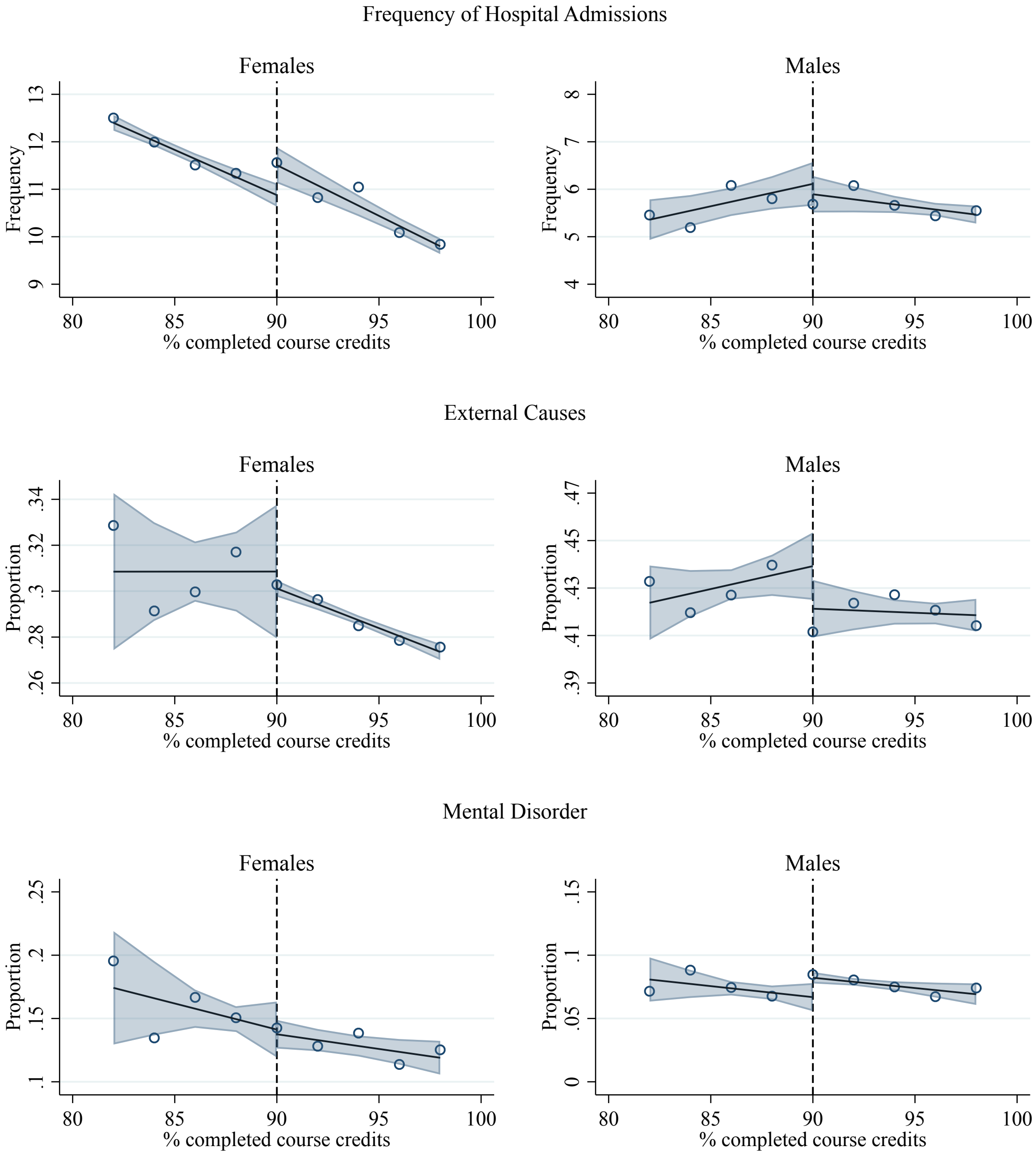

Fig. 4: Course Credit Profile of Hospital Admissions

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.

Table 3: Impact of University Eligibility on Hospital Admissions

	(1)	(2)	(3)	(4)
Model	Mean	RDD	RDD	RDD
Polynomial		1	1	1
Bandwidth		8pp	16/8pp	16/8pp
FEMALES:				
Number of admissions	11.337	0.669**	0.062	0.128
	(0.445)	(0.215)	(0.259)	(0.269)
Probability of hospital admission due to:				
External Causes	0.317	-0.005	-0.004	-0.001
	(0.017)	(0.014)	(0.010)	(0.009)
Accidents	0.110	0.001	0.017	0.017
	(0.011)	(0.007)	(0.011)	(0.010)
Self-harm	0.022	-0.007**	-0.009***	-0.009**
	(0.005)	(0.002)	(0.003)	(0.003)
Other External Causes	0.246	0.001	-0.010	-0.008
	(0.016)	(0.011)	(0.006)	(0.006)
Mental Disorder	0.151	0.002	-0.011	-0.011
	(0.013)	(0.012)	(0.009)	(0.009)
Alcohol and Narcotics	0.029	0.001	-0.003	-0.002
	(0.006)	(0.004)	(0.004)	(0.004)
Mood Affective Disorders	0.081	-0.014	-0.018*	-0.017*
	(0.010)	(0.010)	(0.009)	(0.009)
Neurotic, Stress Related Disorders	0.106	-0.001	-0.010*	-0.010*
	(0.011)	(0.008)	(0.005)	(0.005)
N	757	12,671	13,525	13,525
MALES:				
Number of admissions	5.801	-0.156	0.320	0.307
	(0.262)	(0.316)	(0.319)	(0.330)
Probability of hospital admission due to:				
External Causes	0.440	-0.021**	-0.013	-0.013
	(0.015)	(0.008)	(0.011)	(0.011)
Accidents	0.112	-0.000	0.002	0.001
	(0.010)	(0.004)	(0.005)	(0.005)
Self-harm	0.005	-0.003	-0.000	-0.000
	(0.002)	(0.004)	(0.003)	(0.003)
Other External Causes	0.395	-0.021*	-0.016	-0.015
	(0.015)	(0.010)	(0.011)	(0.011)
Mental Disorder	0.068	0.019***	0.019***	0.019***
	(0.008)	(0.005)	(0.004)	(0.004)
Alcohol and Narcotics	0.016	0.015***	0.011***	0.011***
	(0.004)	(0.002)	(0.003)	(0.003)
Mood Affective Disorders	0.031	0.003	0.006*	0.005*
	(0.005)	(0.002)	(0.003)	(0.003)
Neurotic, Stress Related Disorders	0.042	0.004	0.009***	0.010***
	(0.006)	(0.003)	(0.002)	(0.002)
N	1,094	15,692	17,119	17,119
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. Column (1) is the mean and its standard error for those 2 percentage points below the eligibility cut-off. 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 1. Robust standard errors clustered at number of credits achieved level are shown in parenthesis. Testing the null of the coefficient: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The RDD results are presented in table 3. Column (1) is the mean of the health outcome for the group of individuals with 88% of a completed program, i.e those just below the threshold of eligibility. Model (2) in table 3 is the impact of university eligibility estimated with a bandwidth of 8pp with 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.[14] Model (4) also includes covariates strongly associated with the outcome variable. The positive impact of university eligibility on hospital admissions frequency for females observed in figure 4 are not stable to modelling choice and we therefore find no evidence of university eligibility on overall frequency of admissions to hospitals for either sex.

The RDD results for the probability of hospital admission due to various causes however, reveal some significant and meaningful effects of university eligibility. Males observe a clear positive jump in hospital admissions due to a mental disorder of 2pp or 28%. This large increase is almost entirely driven by mental disorders related to alcohol and narcotics abuse.[15] Further analysis (results not shown) finds that this in turn is entirely driven by alcohol related disorders (recorded as ICD10 code F10). Females observe a negative jump in self-harm related admissions of 0.7 - 0.9pp (reduction of 33%-40%) for those just achieving eligibility.[16] Females also observe negative jumps in mood affective disorders and neurotic and stress related disorders, suggesting a mechanism behind the self-harm reductions is generally better mental health, although these are barely significant.

Turning to prescription receipt, we see in figure 5 that males who are just above the eligibility threshold observe a drop in the number of prescribed prescriptions post graduation. This drop is driven by a drop in prescriptions for opiodes for males. The corresponding RDD results are shown in table 4 and we find that the drop in number of prescriptions for males is not stable to model specification. However the drop in

[14]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.

[15]Also see corresponding figure A.3 in the appendix

[16]Also see corresponding figure A.2 in the appendix

prescriptions for opiodes is stable to RDD model specification and substantial, about 2 percentage points or a drop of about 10%. No other clear jumps are observed at the eligibility threshold.[17]

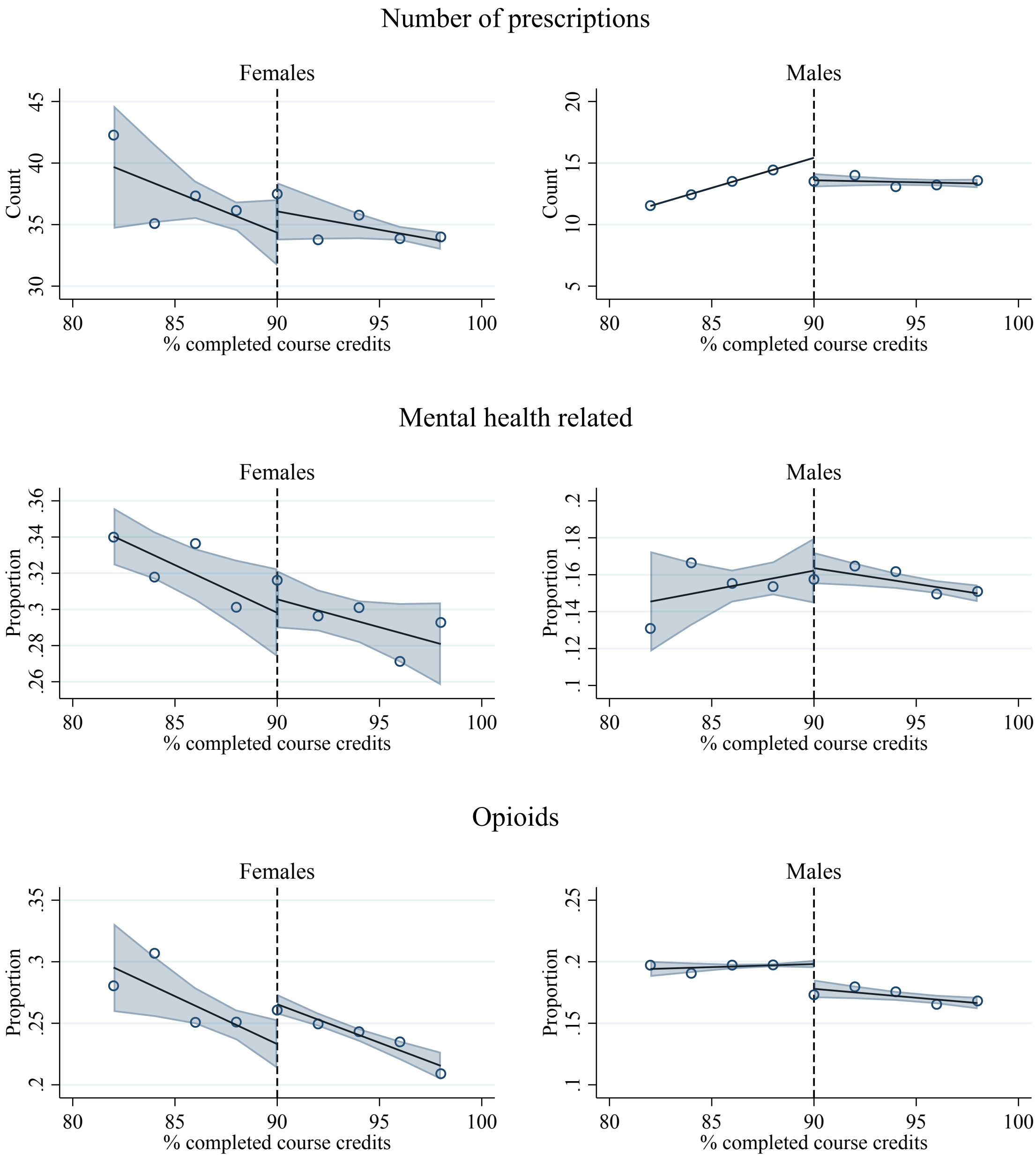

Fig. 5: Course Credit profile of Prescriptions

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

In summary, we find a large jump in university attendance due to university eligibility

[17] Also see figures for specific mental health related drug types in figure A.4 in the appendix.

Table 4: Impact of University Eligibility on Prescription Receipt

	(1)	(2)	(3)	(4)
Model	mean	RD D	RDD	RDD
Polynomial		1	1	1
Bandwidth		8pp	16/8pp	16/8pp
FEMALES:				
Number of prescriptions	36.144	2.031	-1.519	-1.497
	(1.925)	(1.775)	(1.600)	(1.623)
Probability of prescription due to:				
Mental health related	0.301	0.019	-0.000	-0.001
	(0.017)	(0.013)	(0.016)	(0.017)
Antidepressants	0.230	-0.007	-0.023**	-0.023**
	(0.015)	(0.009)	(0.008)	(0.008)
Anxiolytics, Hypnotics and Sedatives	0.243	0.014	-0.003	-0.004
	(0.016)	(0.011)	(0.011)	(0.012)
Opiodes	0.251	0.026**	0.009	0.008
	(0.016)	(0.010)	(0.010)	(0.010)
All other prescriptions	0.967	-0.000	0.007	0.007*
	(0.006)	(0.002)	(0.004)	(0.004)
N	757	12,671	13,525	13,525
MALES:				
Number of prescriptions	14.439	-1.652***	0.161	-0.157
	(1.044)	(0.297)	(0.716)	(0.584)
Probability of prescription due to:				
Mental health related	0.154	0.002	0.026**	0.025**
	(0.011)	(0.010)	(0.009)	(0.009)
Antidepressants	0.091	0.009	0.027***	0.027***
	(0.009)	(0.010)	(0.007)	(0.007)
Anxiolytics, Hypnotics and Sedatives	0.128	-0.008	0.011	0.011
	(0.010)	(0.007)	(0.008)	(0.008)
Opioids	0.197	-0.019***	-0.021***	-0.023***
	(0.012)	(0.005)	(0.005)	(0.005)
All other prescriptions	0.880	-0.009*	-0.014**	-0.015***
	(0.010)	(0.005)	(0.005)	(0.005)
N	1,094	15,692	17,119	17,119
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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

across both sexes that coincides with a clear drop in hospital admissions due to self-harm amongst females. For males a clear drop in prescriptions of opiode related drugs and a clear increase in hospital admissions for mental disorders, predominantly due to alcohol abuse are observed.

6 Conclusions

In this paper we have considered the impact of university eligibility on various health outcomes. We have utilised the robust empirical approach of RDD and subjected the results to numerous specification and diagnostic tests and made use of a large administrative dataset, altogether yielding results with high internal validity.

We have found that university eligibility leads to a sharp positive discontinuity in the proportion attending university and on years of education, in the range 0.19 and 0.27 years for females and 0.15 and 0.17 years for males. These are economically meaningful increases in years of education and lie towards the upper end of the causal effect of education on health literature (Galama et al., 2018). We have considered the health impacts of these jumps in education using medical care use as a proxy for health, with a focus on particular causes of hospitalisation and prescription that are relevant for the young adults we consider (accidents, injuries and mental health). These causes have been interpreted as causes derived from changes in individual health, not health preventative health investments, and thereby are a credible proxy for actual individual health.

We find that the discontinuous jump in university level educational attainment for females coincides with a clear drop in self-harm related hospital admissions of about 40%. This drop in self-harm corresponds with an approximate 10% drop in prescriptions for antidepressants, although this drop is not robust to specification, and with a jump in female employment of 2% as shown in Nordin et al. (2020). Increased sense of self-worth as a consequence of an increase in human capital in the form of eligibility to university, further education and greater probability of employment is therefore a potential mechanism for the observed drop in self-harm related admissions.

The corresponding results for males show a clear drop in prescriptions of opioid related medicines. In Sweden these are primarily prescribed as pain killers and are therefore related to surgery or admissions due to accidents or other external causes

(Läkemedelsverket, 2020). This drop cannot be driven by a reduction in people being treated for narcotics related admissions because in our whole sample only 35 are treated for this. We find that hospital admissions due to other external causes (which for our sample populations is predominantly injuries) drop by a similar amount as prescriptions for opioids, but that this drop in hospital admissions is not significant. The implication is however, that this drop in opioid prescriptions is due to pain relief and not narcotics treatment and therefore due to a reduction in risky behaviour. We cannot however determine what type of risky behaviour is being affected that is leading to reduced injuries. It could be that university education reduces exposure to jobs with higher risk of injury such as construction for example. It could also be that university education reduces risky behaviour during leisure time.

Males also observe an upward jump in hospital admissions for mental ill health linked to alcohol. This jump is not accompanied by any other jumps in mental ill health for males and because females actually see a mental health improvement, indicates that this jump is not driven by a mental health decline leading to changes in alcohol consumption rather that alcohol consumption has led to this decline in mental health.[18] This is perfectly plausible and potentially explained by peer effects. The margin we estimate is between eligibility and non eligibility and therefore the counter-factual peer group is very different to the treated peer group. There is a well documented drinking culture that comes with university social life. For example, college attendance in the US has been shown to increase levels of binge drinking, even after controlling for important confounding factors (Slutske et al., 2004). Kremer and Levy (2008) show that college peers who drink, influence the preferences of their peers and fraternity membership has been shown to increase the level of binge drinking (DeSimone, 2007). A meta analysis has found that drinking behaviours at universities are comparable across North America, Europe, Australasia and South America suggesting that the evidence from the US is relevant to Sweden and vice versa. Peer effects have also been

[18]It also supports our view that this is changes in health induced demand for medical care and not increased mental health investment induced by higher education.

found to be important determinants of other health behaviours such as smoking and drug use (see Sacerdote, 2011, for an overview on peer effects). This suggests that the peer group mix associated with attending university is a potential mechanism behind the mental health decline of the male marginal student.

We have found some clear and significant jumps in health care use due to eligibility to university. For the majority of the outcomes we consider there is a health improving trend with increased education, as measured using number of completed course credits. University education is therefore complementary to this health gradient in terms of female self-harm and male pain-killer related prescriptions. For male mental health however eligibility increases mental ill health which is in the opposite direction to its underlying negative course credit trend. If this jump is in-fact driven by peer effect changes influencing alcohol consumption behaviour as hypothesised above then this could also explain why eligibility has an opposing effect on health not observed in other outcomes. The health improving impacts of university eligibility fit alongside those of De Walque (2007) and Grimard and Parent (2007) who find a protective impact of university 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. Altogether this suggests that the alcohol related mental ill health impacts are unique and therefore not driven by education's impact on improved health production but by another factor, such as peer effects.

We have presented evidence supporting our view that our findings have good 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 still very limited in Sweden, unlike in the US for example where health care is predominantly private. Even so, the findings have relevance to countries without large public health care systems as we would expect changes in health to be related to education through changes in health related behaviours and through the impact of financial resources on access to a better diet and resources for increased activity and so on. It is important to understand all the channels by which education may affect health.

We conclude that university education for low ability students leads to important spillovers beyond earnings and employment. For females the picture is a positive one, observing improved health. For males it is more mixed, whilst males at the margin of eligibility appear to gain important market returns to university (Nordin et al., 2020) and reduced accidents related prescriptions of pain killers, they also observe a concerning increase in mental ill health, predominantly due to alcohol. The effects we find are the short to medium term impacts. We are unable to observe health related behaviours and long-term health impacts impacted by these potential behaviour changes. Future changes in ease of access to university will have to weigh up these impacts against the costs of providing easier access whilst acknowledging that the full health impact of eligibility remains to be investigated.

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Appendix

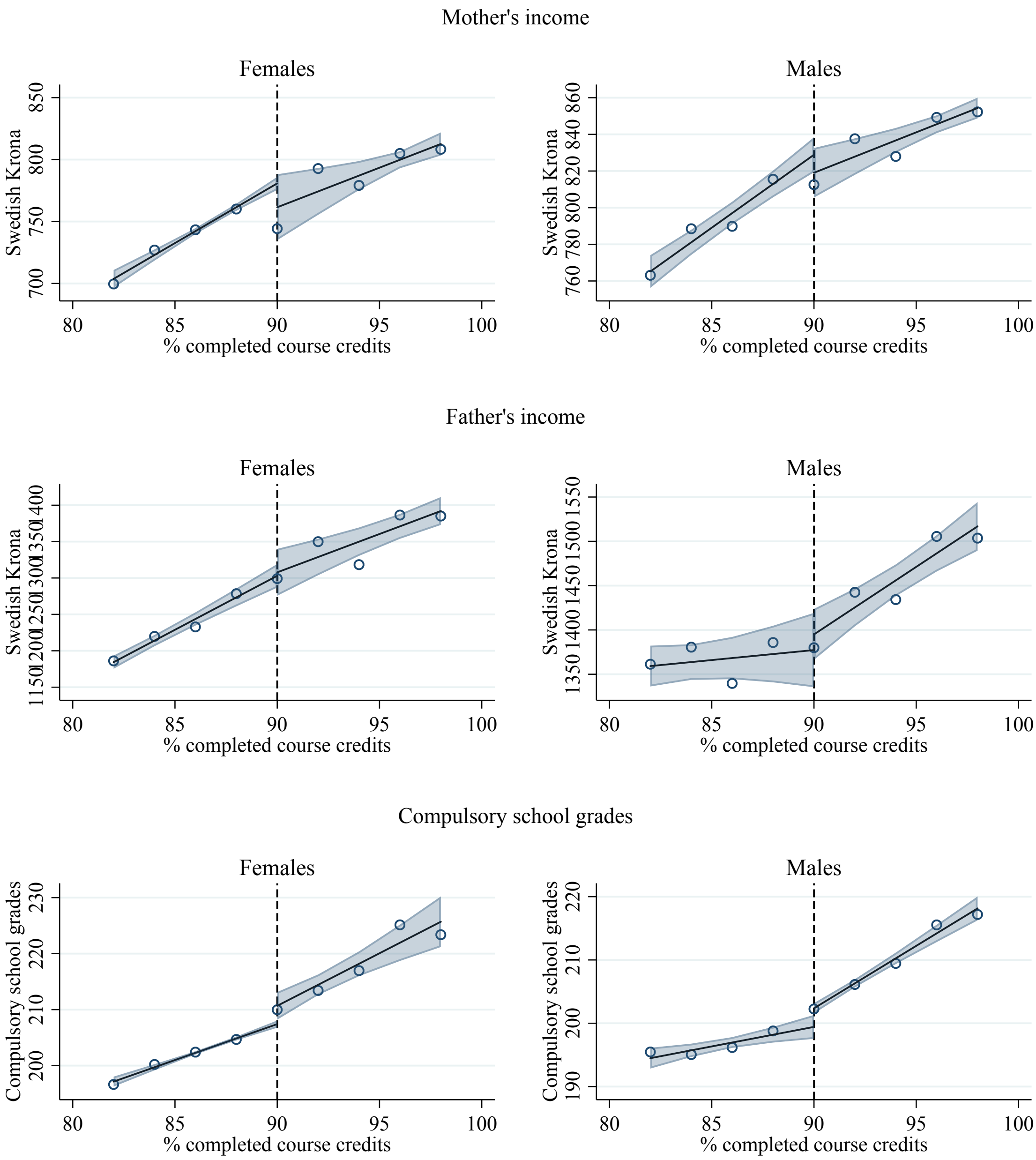

Fig. A.1: Course Credit Profile of Pre-determined Characteristics

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. In all figures we present the mean for each bin. The dashed vertical line is the 90% cut-off for university eligibility. See notes for figure 1.

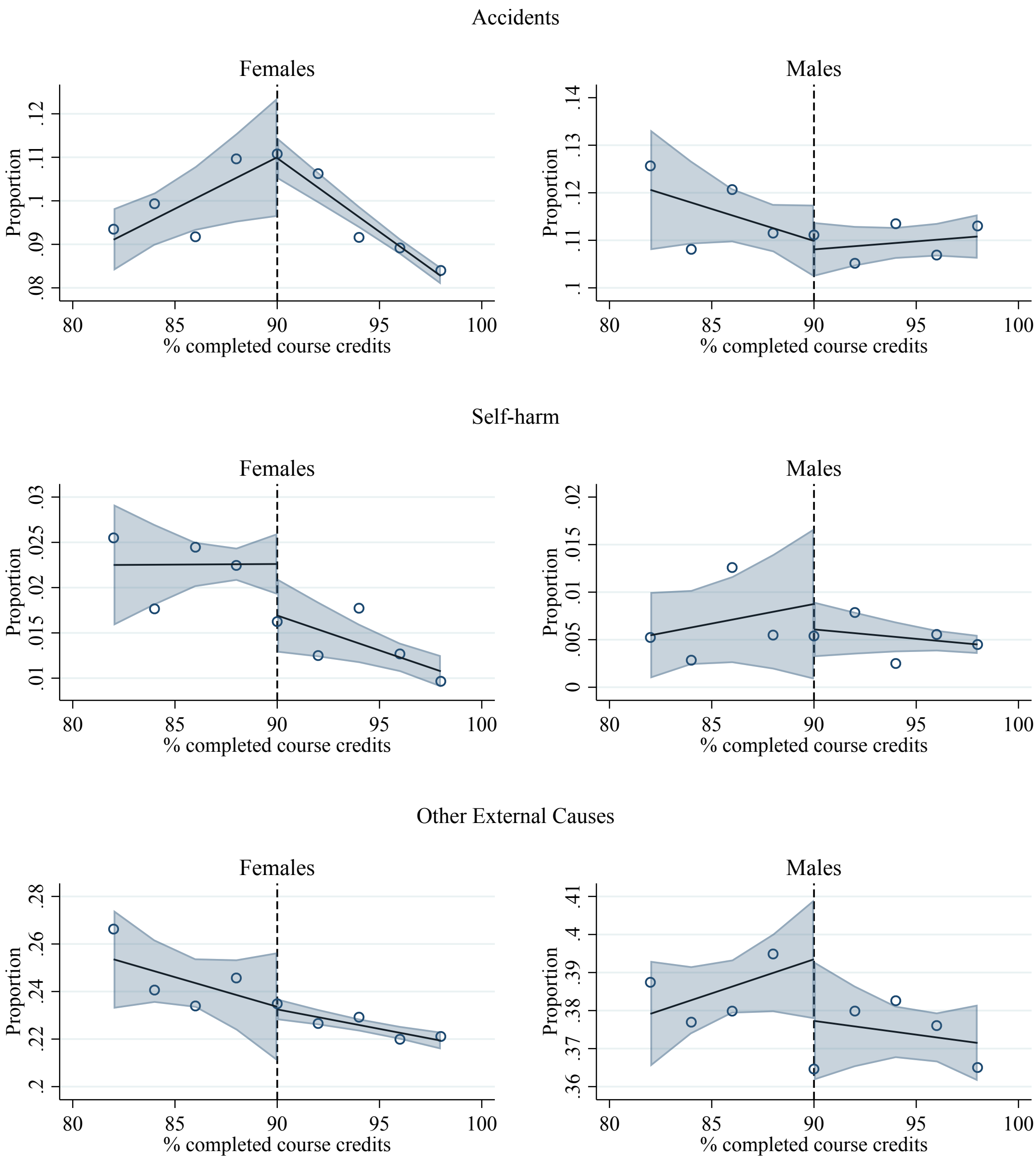

Fig. A.2: Course Credit Profile of Hospital Admissions Due to External Causes

Notes: This figure plots a scatter of the proportion diagnosed at hospital 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 for those graduating upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1 .

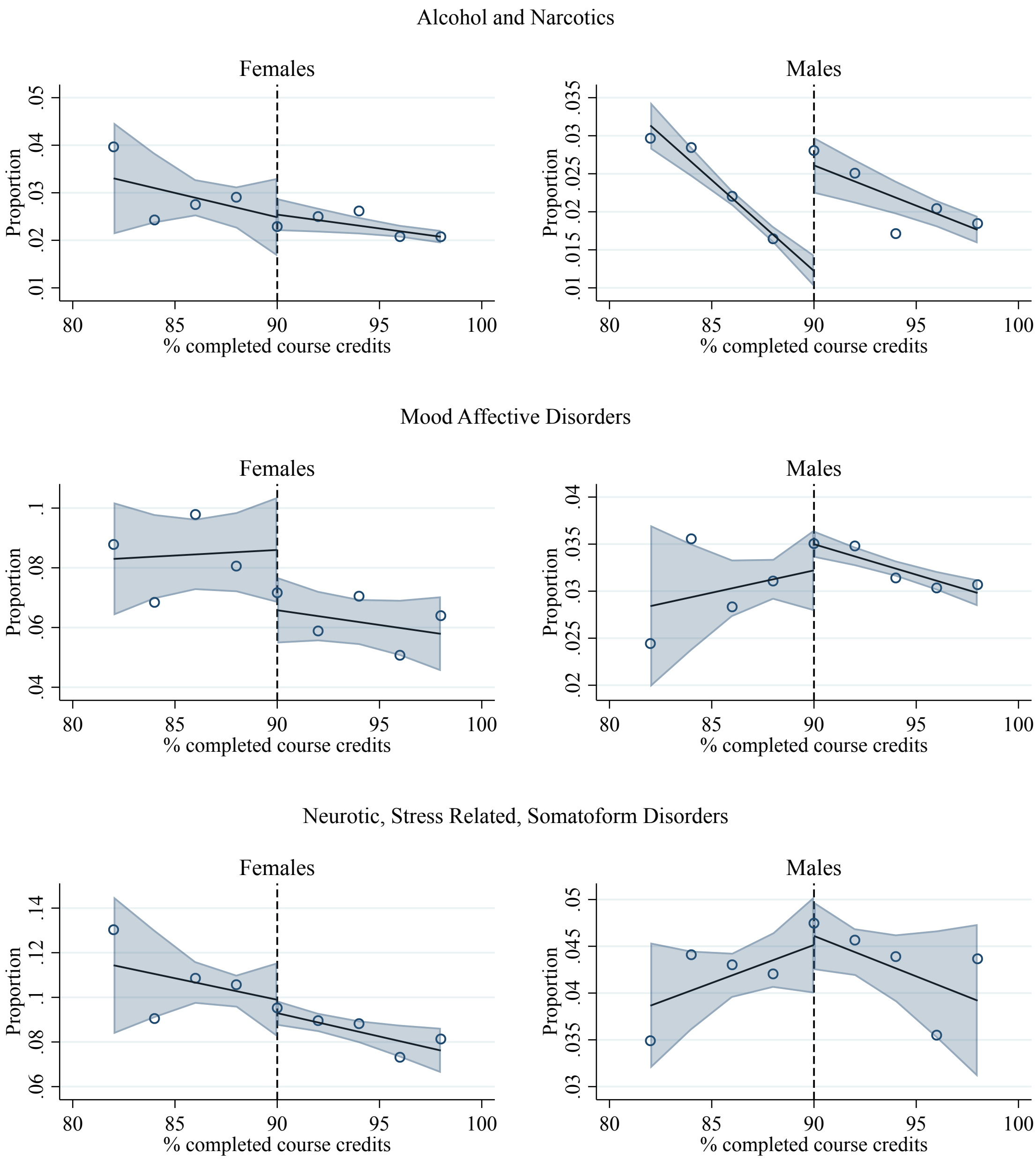

Fig. A.3: Course Credit Profile of Hospital Admissions Due to Mental Health

Notes: This figure plots a scatter of the proportion diagnosed at hospital 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 for those graduating upper secondary school between the years 2003 and 2005 (academic stream). See notes for figure 1 .

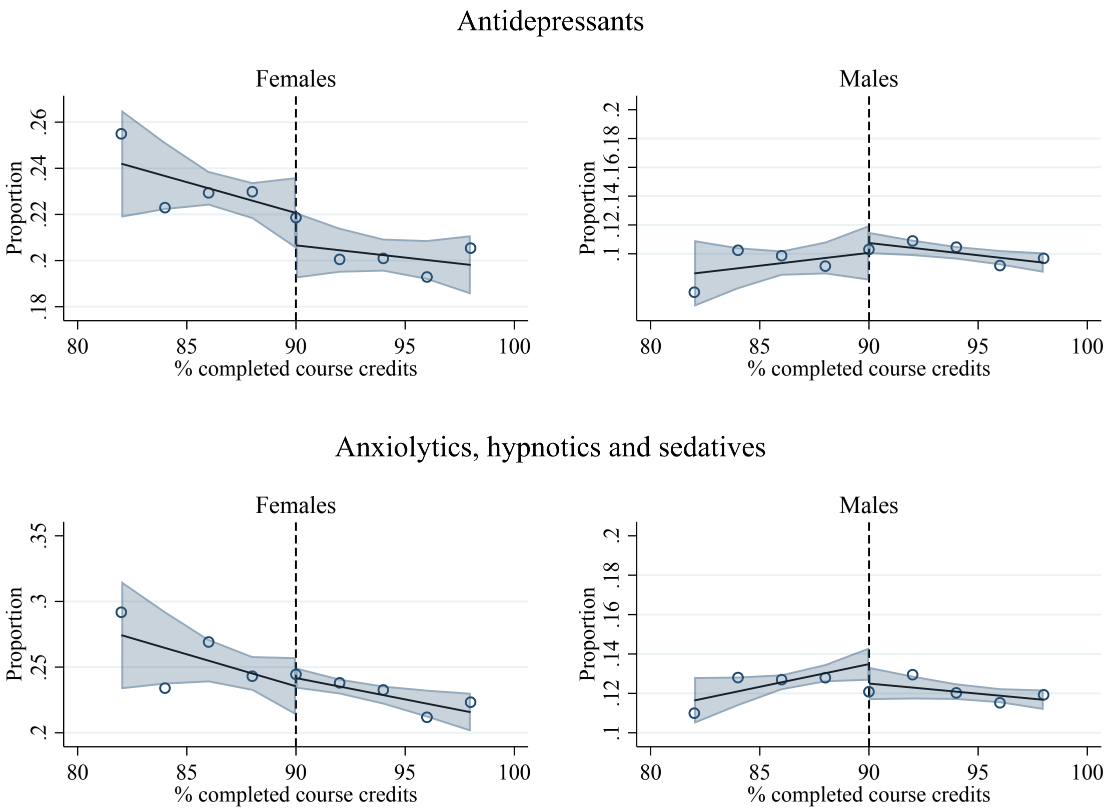

Fig. A.4: Course Credit Profile of Mental Health Related Prescription Receipt

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 for those graduating upper secondary school between the years 2003 and 2005. See notes for figure 1

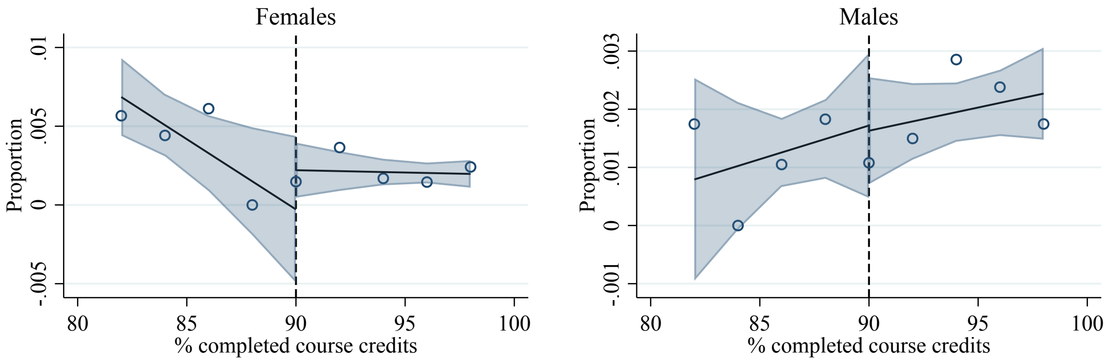

Fig. A.5: Course Credit Profile of Hospital Admissions Due to Alcohol

Notes: These figures plot a scatter of percentage completed of a full program with a bin width of 2pp against the probability of hospital admission since graduation and up to 2013 by main cause 2010-2013 for those graduating upper secondary school between the years 2003 and 2005. Alcohol related is defined as ICD codes T51, Y90, Y91, X65, X45. See notes for figure 1