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School selectivity and mental health: Evidence from regression discontinuity design

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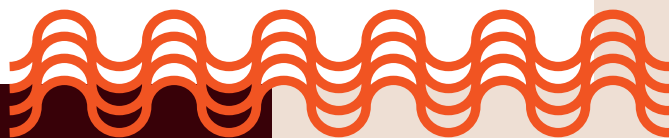
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ABSTRACT

The school environment forms a large part of adolescents' lives and can thus have a large impact on their mental health. However, fairly little is known on the specific impact of school characteristics, such as selectivity. In this paper, comprehensive Finnish register data is used to investigate how studying at a more selective, preferred upper secondary school affects students' short- and long-term mental health. A regression discontinuity design is employed for the analysis, finding that, while access to more selective school has little overall effect on individual's short- or long-term mental health, it does have positive effects during the time of matriculation examinations. Further analysis also reveals heterogeneity based on the selectivity difference between the preferred school and next-best alternative.

JEL Classification: I21, I26, I12, I31

Keywords:
education, secondary, mental health, selectivity, peers

TIIVISTELMÄ

Vaikka kouluympäristö muodostaa suuren osan nuorten elämästä ja sillä voi siten olla suuri vaikutus mielenterveyteen, varsin vähän tiedetään miten koulun ominaisuudet, kuten valikoivuus, vaikuttavat opiskelijoiden mielenterveyteen. Tässä artikkelissa tutkitaan miten selektiivisemmässä lukiossa opiskelu vaikuttaa opiskelijoiden mielenterveyteen lyhyellä ja pitkällä aikavälillä käyttäen regressio epäjatkuvuus menetelmää. Tutkimuksessa havaitaan, että vaikka selektiivisempään lukioon pääsyllä ei ole merkittäviä kokonaisvaikutuksia opiskelijoiden mielenterveyteen, vähentää se mielenterveyspalveluiden käyttöä ylioppilaskirjoitusten aikaan. Positiivisia vaikutuksia löydetään myös, kun selektiivisyysero selektiivisen ja vähemmän selektiivisen koulun välillä on suuri.

Avainsanat:
koulutus, toisen asteen koulutus, mielenterveys, selektiivisyys, vertaisryhmä

1   Introduction

Good mental health is generally considered one of the cornerstones of living a productive, well-balanced life. This has been confirmed by several studies, that have found positive effects on multiple aspects of individuals' life, from wages and job stability, all the way to marriage probability and -stability (see e.g., Goodman et al., 2011; Lundborg et al., 2014). On the other hand, mental health disorders such as depression have been widely recognized as one of the leading causes of disability among adolescents (WHO, 2020). Mental health problems also strain society, as a whole, as they not only stress the health care systems but also affect work efficiency and increase the number of sick days. According to the OECD (2018), in 2015, the average annual total cost (direct and indirect) of mental health problems within European countries was over 4% of their GDP.

One of the factors that has been found to positively affect one's mental health is education. So far, research has focused quite heavily on the effects of individuals gaining either higher levels or additional years of education, both of which have been found to result in better overall physical and mental health (see e.g., Leigh, 1983; Hartog and Oosterbeek, 1998; Crespo et al., 2014 and Avendano et al., 2017).[1]

Meanwhile, other aspects of education, such as school selectivity, have garnered less attention. Considering that school selectivity affects many aspects of students' school and social life, not least through changes in peer-group composition, its impact on mental health could be quite large. However, it is not obvious which way these effects would go: on one hand, studying with better peers could lead individuals to feel inadequate and to have negative associations with their peers (see e.g., Pop-Eleches and Urquiola, 2013 and Luthar et al., 2020), on the other hand it could invigorate individuals to study more and increase student's later life prospects, which could lessen the stress related to uncertainty later in life.

This paper contributes to the previous literature by estimating the causal effects of school selectivity on short- and long-term mental health. To study these effects, I employ regression discontinuity design (RDD), which has been widely used to study the causal effects of selective school on educational outcomes (see e.g., Öckert, 2010; Abdulkadiroglu et al., 2014; Tervonen et al., 2017). By using the same method, I am able to examine whether negative effects on one's mental health played a role in the lack of effects observed in these previous papers. In RDD papers this is a considerable possibility, since by using it, one ends up comparing

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[1]See also Lleras-Muney, 2005; Lleras-Muney (2005); Montez and Friedman (2015); Groot and van den Brink (2007); Chevalier and Feinstein (2006); McFarland and Wagner (2015) etc.

individuals who are not just at different selectivity level schools, but who are also at different points in their peer–group's ability distribution. This happens because RDD relies on comparison between individuals just above and below the selective school's admission cutoff, thus one essentially compares those at the bottom of their peer–group's ability distribution to those who were higher in their peer-group ranking (admitted to less selective school). Being at the bottom of one's peer-group's ability distribution could cause individual stress, anxiety, and depression, which could mitigate the positive educational effects that attending a better school might have and thus explain the lack of results on educational outcomes.

So far there have been few papers studying the effects of school selectivity on mental health, some were solely descriptive in nature (see e.g., Lipson et al., 2015; Coley et al., 2018; Uecker and Wilkinson, 2019), while some have been able to estimate the causal effects as well (see Pastore and Jones, 2019; Butler et al., 2020; Bütikofer et al., 2020). The descriptive evidence points mainly towards either no-effects (e.g. Uecker and Wilkinson, 2019) or positive correlation (e.g. Lipson et al., 2015) between school selectivity and better mental health. Meanwhile, the causal evidence has been less conclusive, even though all the mentioned papers used the same method, RDD. Two of these papers (Pastore and Jones (2019); Butler et al. (2020)) found negative estimates for self-reported mental health in mid-life, but due to relatively small sample sizes, the results were inconclusive. Meanwhile, the last paper by Bütikofer et al. (2020) focused on shorter-term effects and offered perhaps the most reliable estimates so far. In their paper, they were able to estimate the effects of eligibility to more selective high school with sufficient precision and found that it reduced the probability of having a mental health diagnosis within the first six years by around 1.7 percentage points.

The rich register data on both Finnish high school application and mental health, allows me to not only use RDD for my analysis, but also to overcome the problems and challenges faced by previous studies on this subject. For one, I am able to obtain quite a large sample, due to the fact that the application data comprise all students in Finland who applied to any high school schools between 1996 and 2003. As the data also contains information on applied schools, their preference order, the admission scores and the enrolment decisions, I am able to form strong first stage for selective school enrolment and thus estimate these results with sufficient precision. Additionally, as the mental health data comes from annual, individual-level registers covering years 1995–2016, I am able to study the effects on mental health for up to 13 years after admission and can thus offer a comprehensive overview on mental health effects during individuals' teen years and early adult life.

Based on my results, eligibility, and enrolment to a more selective general school do not, on average, lead to any significant effects on one's overall short- or long-term mental health. Thus it seems unlikely that the effects, or rather the lack thereof, on educational outcomes reported are due to those at the bottom of the ability distribution having more mental health related issues. In fact, if anything the estimates point towards selective school having positive effect on one's mental health for the first 10 years. The effects are largest and statistically significant during matriculation examinations, at which point those eligible to more selective school were around two percentage points less likely to have any mental health issues. It is also fascinating to see that the annual estimates turn positive (more mental health issues), although not statistically significant, during the last few years examined in this paper. This timing coincides somewhat with graduation from higher education and is could therefore be caused by variation in the early labour market outcomes. Further analysis reveals some heterogeneity based on school characteristics. The largest (and statistically significant) effects are found when the sample consists of schools where the selectivity difference to the next best option is above the median.

The remainder of the paper is organized as follows: Chapter 2 gives a brief introduction to the Finnish schooling system, while Chapter 3 introduces the data sets used in this paper, as well as the final samples used in the analysis. It also offers a descriptive analysis of the data. The empirical strategy used in this paper is covered in Chapter 4, while the validity of the design is discussed in Chapter 5. The results, together with a heterogeneity analysis, are presented in Chapter 6. Chapter 7 concludes.

2   Institutional background

In Finland, it is compulsory for all children aged seven to go to comprehensive school for nine years. Education is free of charge and maintained by local authorities as well as other education providers.[2] Typically, students finish their compulsory schooling at the age of 16 and continue their studies in either general upper secondary education (lukio in Finnish) or vocational education. The chart depicting Finland's education system is presented in appendix B.1.

General upper secondary education does not qualify students for any particular occupation, but instead focuses on preparing students for their further education. These schools can be further divided into regular

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[2]Less than two percent of students go to private or state schools.

and specialised general schools. The main difference between the two is that specialised schools offer wider selection of certain courses or put more emphasis on certain subjects.[3] In any case, these schools usually lasts three years, at the end of which students take the matriculation examination, where the grading is standardized at the country level. Those who pass the exam are then eligible to apply to universities and universities of applied sciences, entry of which is typically based on matriculation examination grades as well as on school grades in the field of relevant subjects and/or entry examination. Meanwhile vocational education provides the basic skills required in the field of ones choosing. Similar to general upper secondary school, the education lasts typically three years, but one graduates with either upper secondary qualification, further qualification, or specialist qualification, depending on their track and institution. The individual then typically either enters the job market or applies to universities of applied sciences.

Application to secondary education is a centralized process, maintained by the Finnish National Board of Education (FNBE), which begins by students submitting a form consisting of up to five program-school combinations (hereafter referred to as tracks) they wish to study at. These tracks/schools need to be in ranked in their preference order, the first one being their most preferred option and the fifth their least favorite track (from their top fie options) they would wish to study at. Admission to each track is based on admission scores, which in the case of general school, are based mainly on the student's Grade-point average (GPA) in their last year of compulsory schooling.[45] Admission points in the case of vocational tracks are also somewhat based on GPA but far less so than compared to general schools. For this reason, I will focus on general schools, as these schools are far more straightforward, comparable, and transparent to order in terms of selectivity. To gain precision, I will pool all general schools, but for a robustness check I have also conducted some analysis using only the "regular" general schools, as their admission score is based solely on primary school GPA.[6]

The selection regime in each school was based on the DA algorithm. This means that students are at first considered for their most preferred option and then, based on the admission scores and the capacity of the school, either preliminary accepted or rejected to the school in question. In the following rounds, the schools next in line (in terms of preference order) consider applicants who have been rejected by their

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[3]Such as languages, sports or arts.

[4]Specialised schools also give points for experience, minority status or according to aptitude tests.

[5]Students do not know their final grades at the time of application, which, combined with always moving admission cutoffs, makes it unlikely that students would have been able to strategize themselves just above any school cutoff.

[6]These estimates are presented in Table 4.

previous options and compare them to the applicants who have been accepted in the previous rounds. After their capacity has been filled, the school rejects the excessive applicants who have obtained the lowest scores. The process goes on, until all applicants have either been matched to a school or all they have been rejected by all of their applied schools. After this automated algorithm has stopped, admission letters are sent and applicants are given two weeks to either accept or reject the offer. There also exists a waiting list for each school, because typically not all admitted students accept the offer. In practice, if someone rejects the offer, the place is offered to the next best, previously rejected, applicant based on their admission scores.[7]

3 Data

3.1 Data sources

3.1.1 Application and supplementary data

The data used in the analysis originates from multiple sources. The main data set used to create the RD design is created by linking together population-wide Finnish administrative registers for the years 1996–2003. The main source for this data is the Finnish National Board of Education's Application Registry. The data set consists of information on individuals' primary school grades, applied secondary school education schools, as well as the preference order individuals listed the tracks in. It also includes all additional points that were used to make the offer decisions to different schools, as well as the actual admission decisions.[8]

In this study I focus on first time applicants, who finished compulsory school that year[9] and applied through regular format.[10] Using social security numbers encrypted by Statistics Finland, I merge these data with the information on applicants' and their parents socioeconomic background from Finnish Longitudinal Employer-Employee Data (FLEED),[11] enrolment from the Student register, completed degrees from the Register on Degrees and Examinations, and information on mental health that originates from multiple registers, further described in the following subsection.

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[7]During 1996–2003 these "waiting/substitution list" offers were made on phone, and a missed phone call was all it took for the potential applicant to lose their chance to be admitted to that school.

[8]Note: admission=individual is observed to have received an offer in the data.

[9]Around 98% individuals apply straight after graduation.

[10]As opposed to flexible/adaptive format (around 4.5% of applicants)

[11]Merged using Parent data.

3.1.2 Health data

To address the effects of school selectivity on mental health, I rely on data from two sources: the Care Registers for Social Welfare and Health Care and the Social Insurance Institution of Finland (KELA). The care registers consist of variables concerning inpatient and outpatient care at public sector specialised mental health care facilities.[12] For outpatient care visits the data starts from 1998, while the data on inpatient care is already available from 1996. In both both cases, the data covers until 2016 and also contains information on the reason for hospitalization, the date the visit/spell took place and the related ICD-10 classification (International Classification of Diseases). The ones I use to determine whether individual had mental health related visits/spells consist of codes F0–F9 (Mental and behavioural disorders) and also codes that correspond to other unspecified psychiatric illness, problems with mental coping/wellness, suicide attempts, sleep disorders etc.[13] The ICD-10 codes are further explained in Appendix A, Table 1.

The data set from KELA contains information on mental health related pharmaceutical/ medicine purchases that have been reimbursed under a comprehensive national health insurance scheme between 1995 and 2016. These pharmaceuticals include Antipsychotics (ATC code N05A)[14], Anxiolytics (N05B), Hypnotics and sedatives (N05C), Antidepressants (N06A), Psycho-stimulants (N06B) as well as Psycholeptics and psychoanaleptics in combination (N06C).[15] In Finland all permanent residents fall automatically under the national health insurance and are thus eligible for the benefits, such as the reimbursement of medicine, the amount of which depends on the medicine and can be up to 100% of the price. KELA typically reimburses pharmaceuticals related to mental health illnesses quite comprehensively: for example, in 2019, around 92 percent of all available antidepressant-related pharmaceuticals were reimbursable by KELA.

The reimbursed medicine data set complements the inpatient/outpatient data, since it allows the identification of milder mental health-related issues that do not require hospitalization (in the case of inpatient care) as well as observing individuals who use private health care instead of public ones. Additionally, it offers a more reliable source of information on individuals' mental health post upper secondary graduation

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[12]This data does not include private visits, but due to Finland's national health insurance system, the public system is widely used by everyone without a full-time job. Thus, it should be sufficient for studying high school-aged children but should be used with caution after individuals graduate from upper secondary school.

[13]Additional ICD-10 codes are: Z00.4, Z03.2, Z04.6, Z50.4, Z73, Z86.5, Z91.5, G47.0, G47.2, G47.8, G47.9

[14]ATC code = Anatomical Therapeutic Chemical code = Unique code for medicine. It is based on organ/system it works on. This classification system maintained by WHO.

[15]See Appendix Table 2.

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compared to the care registers. On the other hand, during the early years, the care register complements the KELA-data, as some visits might, for example, not require the prescription of medicine, and also because the medicine used by hospitals is not included in the KELA-data. Together, these data sets offer a broad, reliable overview on individuals' mental health between 1995–2016 and are more than sufficient for my analysis.

3.2 Estimation sample

My aim in this paper is to use RDD to estimate the causal effects of studying at a more selective general school. For this purpose, a few restrictions are needed. First, I restrict the sample to those who had a more selective general school as their preferred option and a less selective general school, at which they were above the admission cutoff, as their later alternative (the next best alternative thereafter). To ascertain that they did not get admission to any other type of school, I also require that schools before their next best alternative were all general schools. For a similar reason, I require that individuals were above the automated algorithm-based admission cutoff at the next best general school.[16]

In this paper, I have opted to use not only the most preferred school, but all schools up until the admission, as long as they are less selective than previous school and had a next best alternative (as well as preferences) that fulfilled the requirements listed in the previous paragraph. This means that individuals can be observed up to four times in my sample.[17][18] However, in practice, only around 8% of individuals are observed more than once in the sample.

To reduce "fuzziness" (see section 4) on enrolment at the cutoff, I continue by excluding individuals who got offers despite not exceeding the admission cutoff (around 9% of the remaining sample).[19]

I also exclude individuals right at the cutoff, both because I am unable to discern compliers from never takers (at the cutoff) and also because the cutoffs are defined using the last admitted applicant at each track, which could lead to cutoffs being endogenous in the applicant pool. Also, as I do not observe the exact points

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[16]By requiring that individual was above the automated algorithm-based admission cutoff to their next best alternative, I ensure that those below the cutoff at their preferred school gained admission to their next best alternative.

[17]For example if individual applied to five general schools, and was admitted to the fifth school (by being above the automated cutoff), he/she could be present up to four times in the sample, if the previous preferences had same preference and selectivity order (i.e. first preference was most selective, second was a bit easier etc.).

[18]I.e. I am using all general schools individual had possibility to gain admission at, as long as they had the next best alternative.

[19]My results are robust to this exclusion.

used to determine admission in case of ties, I exclude individuals right at the cutoff, as otherwise compliers could be mistaken as never takers. Another reason for this is the fact that the cutoffs are defined using the last admitted applicant at each school, which could lead to cutoffs being endogenous in the applicant pool.[20]

Lastly, to ensure that there is a sufficient amount of mass on both sides of the threshold to conduct RDD analysis, I exclude the schools that do not have at least two individuals on either side of the cutoff within one grade in either direction. After making all of the above mentioned restrictions I am left with 36 983 observations (35 461 individuals) for my analysis.

3.3   Descriptive statistics

Table 1 offers some descriptive statistics for the observed background characteristics as well as some outcomes, namely for the probability of graduating from general school, from higher education within 13 years since application, and for the probabilities of having mental health issues within three and 13 years after application. The background characteristics include age, gender, whether the individual was a native Finnish speaker, Swedish speaker, or had some other native language. They also include indicators for whether individual resided in the top 15 biggest (in terms of number of inhabitants) cities in Finland a year prior to application, whether individual had bought mental health-related medicine a year prior to application, and whether an individual's mother or father had at least a bachelor's degree.

The Table reports the means and standard errors for the whole estimation sample, as well as separately for those who were not eligible to their preferred/more selective school and for those eligible to their preferred/more selective school. As one can observe from the first column of this Table, the whole sample consists mainly of around 16 year old Finnish speakers without any mental health related issues prior to applying. Around half of the individuals also resided in cities prior to application. It also appears, that nearly everyone graduates from general school within 13 years after application, while around 65% graduate from higher education during that time. Lastly, around 6 percent have some mental health related issues within the first 3 years since application, while after 13 years this figure already exceeds 26 percent.

The following two columns report these estimates based on their eligibility to a more selective school. According to these estimates, those eligible to the selective school are more likely to be female, Finnish

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[20]The results are robust to this exclusion and presented without it in Table 4. This exclusion leads to an RDD setup typically known as "donut" RDD.

Table 1: Mean background characteristics and probability of mental health issues 13 years since admission

	All	Not eligible to selective school	Eligible to selective school
Age	16.004	16.016	16.002
	(0.001)	(0.003)	(0.001)
Male	0.379	0.444	0.367
	(0.003)	(0.007)	(0.003)
Native language Finnish	0.913	0.898	0.916
	(0.001)	(0.004	(0.002)
Native language Swedish	0.072	0.071	0.072
	(0.001)	(0.003)	(0.001)
Non-Finnish or Swedish speaker	0.015	0.030	0.012
	(0.001)	(0.002)	(0.001)
Living in city	0.457	0.498	0.449
	(0.003)	(0.007)	(0.003)
Father has HE	0.323	0.289	0.33
	(0.002)	(0.006)	(0.003)
Mother has HE	0.246	0.209	0.253
	(0.002)	(0.005)	(0.003)
Mental health issues year prior	0.005	0.007	0.005
	(0.000)	(0.001)	(0.000)
Graduation within 13 years	0.934	0.830	0.953
	(0.001)	(0.005)	(0.001)
Has HE degree within 13 years	0.651	0.463	0.686
	(0.003)	(0.007)	(0.003)
Mental health issues within 3 years	0.061	0.068	0.06
	(0.001)	(0.003)	(0.001)
Mental health issues within 13 years	0.266	0.292	0.261
	(0.002)	(0.006)	(0.003)
Observations	35 461	5 524	29 937

Note: City is defined as belonging in top 15 of biggest cities in Finland. He education degree implies bachelors degree or higher. Standard errors in parenthesis.

speakers and have highly educated parents. They are also more likely to graduate from general school and higher education. On the other hand, they are a bit less likely to have lived in the city, have mental health issues within the first three and 13 years since admission.

4 Empirical strategy

As mentioned earlier, I employ RDD for my analysis as it is one of the most internally valid methods available for causal estimation. RDD relies on the existence of a so-called running variable and, in it, a cutoff, which determines whether an individual received a treatment or not. The idea is that individuals just above and below this cutoff are, on average, exactly the same prior to treatment. Therefore, any differences observed in outcomes of interest at the cutoff should only be due to the treatment and not some unobservable characteristics.

For this reason, in order to use RDD, I need to create a running variable as well as determine the admission cutoffs. Within general schools, the admissions rely heavily on GPA, although some schools use different scale some grades differently (value certain grades more etc.), and some also use some extra criteria for admission. Due to this, I follow Huttunen et al. (2019) and re-scale the admission scores to GPA units.[21]

Using these re-scaled admission scores, I then assign the admission cutoffs for each school as the scores of the lowest scoring applicant, who received an offer from the school in question.[22] These cutoffs, together with re-scaled admission scores, now enable me to create the standardized admission score, which will henceforth be known as (centralized) running variable. It can be expressed as follows:

$$r_{ik} = (c_{ik} - \tau_k), \tag{1}$$

where c_{ik} individual i's admission score in school k, and τ_k is the school's cutoff admission score. Therefore if $r_{ik} >= 0$, individual was above the cutoff into more selective school, while if it is < 0, he/she was below the more selective cutoff and admitted into a less selective school.

Now, the used model (in reduced form) can be written as:

$$Y_{ik} = \delta_k + \alpha Z_{ik} + (1 - Z_{ik})f_0(r_{ik}) + Z_{ik}f_1(r_{ik}) + \epsilon_{ik}, \tag{2}$$

where Y_{ik} represents the outcome variable for applicant i at cutoff k. Meanwhile, δ_k controls for the

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[21]In practice this means estimating program specific regression models, where admission scores are explained with the GPA. The existing score is then divided with he obtained coefficient. Now, a one unit change in the GPA has the same effect on the re-scaled scores for each school.

[22]Note: The cutoffs as well as the re-scaling are done before the sample restrictions.

cutoff specific fixed effects; Z_{ik} is an indicator taking a value of 1 if the applicant was above the cutoff to the more selective school, and 0 otherwise. The terms f_0 and f_1 identify the slope of the running variable on either side of each cutoff separately.[23] Finally the ϵ_{ik} are the error terms clustered at the cutoff and individual level. Equation is estimated using non-parametric local linear regression with triangular kernel weights that are calculated using optimal bandwidths obtained using CCT optimal bandwidth selector proposed by Calonico et al. (2017).

Also, as one can see from sub-figure B.3b, which reports the enrolment probability to more selective school, the discontinuity at the cutoff is only around 70%, instead of 100%. The main reason for this is the waiting list, which creates "fuzziness" into the admission probability above the cutoff [24] To take this into account, I utilize fuzzy RDD when estimating the effects of selective school enrolment. In practice this is done by instrumenting enrolment to a more selective school (I denote this as D_{ik}) with Z_{ik}. The use of a fuzzy RDD means that the estimated effects must now be interpreted as local average treatment effects (LATE) and apply only to compliers.

However, as pointed out by Bütikofer et al. (2020), there is also a chance that eligibility (in itself) affects mental health outcomes (e.g. individuals might gain self confidence from being eligible), which would violate the exclusion restriction assumption in fuzzy RDD. For this reason, my main analysis presents both treatments (eligibility and enrolment) and the figures etc. focus on the sharp sample estimates (eligibility).[25]

5   Validity of the research design

The internal validity of the RDD design relies on the assumption that covariates and the distribution of observations evolve smoothly across the cutoff (Lee and Lemieux, 2010). To test the covariate balance around the cutoff, I substitute the outcome variable in equation 2 with the covariate in question and estimate the model. The estimates and their standard errors are reported in Table 1. According to these results, only one of the covariates has a slightly significant discontinuity at the cutoff, thus indicating that the background characteristics are quite well balanced around the cutoff. I also include these background characteristics into

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[23]I.e. Slopes are interacted with cutoff-dummies.

[24]See figure B.3a and also section 2 for more information.

[25]Note that in here sharp sample estimates present eligibility rather then admission, as to some individuals are not being offered an admission, even though they are above the cutoff, due to missed phone call etc.

Table 2: Estimated discontinuities at the background characteristics, means below the cutoff and McCrary's test

	Mean below	Discontinuities	se
Covariate			
GPA	8.071	0.032	(0.020)
Age	16.008	0.003	(0.010)
Male	0.451	-0.011	(0.023)
Native language Finnish	0.912	-0.003	(0.007)
Native language Swedish	0.068	-0.001	(0.004)
Non-Finnish or Swedish speaker	0.018	0.004	(0.006)
Living in city	0.622	-0.021	(0.017)
Father has HE	0.330	-0.026	(0.019)
Mother has HE	0.233	0.010	(0.020)
Father has secondary degree	0.300	0.035*	(0.021)
Mother has secondary degree	0.339	0.007	(0.021)
Mental health issues year prior	0.007	-0.004	(0.004)
McCrary's density test		-0.0427	(0.0418)

The estimates are computed using equation 2 (sharp) and the CCT optimal bandwidths. Standard errors clustered at cutoff and individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

my main analysis as controls. The results of this are reported in the top part of Table 3. As one can see, the results are almost identical to those reported in the next section's Table 3, thus giving further support to the validity of the RDD design.

The last row of Table 2 reports the McCrary's density test (McCrary, 2008), which tests for bunching/manipulation at the vicinity of the cutoff. In addition, Figure B.2 depicts the distribution of individuals around the cutoff. Neither of these show any sign of bunching, and the density appears to evolve quite smoothly around the cutoff, adding evidence to the validity of the design.

6 Results

6.1 Main results

I begin my analysis by showing how the peer-group changes due to admission to a more preferred, selective school. These estimates are reported in the first two columns of Table 3, starting with the selectivity

Table 3: Effects of eligibility and enrolment to more selective school

	peer-group			Matriculation grade in	
	Min GPA (1)	Relative Rank (2)	Enrolment in general school (3)	Mother language (4)	Mathematics (5)
Eligibility	0.535***	-30.715***	0.014	-0.007	-0.132
	(0.044)	(3.189)	(0.013)	(0.085)	(0.145)
Enrolment	0.890***	-51.106***	0.023	-0.011	-0.172
	(0.059)	(4.121)	(0.021)	(0.139)	(0.192)
Mean below	7.121	43.081	0.956	3.026	2.919
Bandwidth	0.369	0.356	0.593	0.392	0.710
Observations	8 604	8 976	11 931	8 301	4 327
	Graduation by 3rd year (6)	HE graduation by 13th year (7)	HE graduation time (8)	Mental health issues by 3rd year (9)	Mental health issues by 13th year (10)
Eligibility	-0.019	-0.014	0.021	-0.009	0.003
	(0.030)	(0.024)	(0.125)	(0.013)	(0.020)
Enrolment	-0.031	-0.011	0.030	-0.013	0.004
	(0.050)	(0.039)	(0.184)	(0.020)	(0.032)
Mean below	0.735	0.536	9.553	0.075	0.274
Bandwidth	0.400	0.532	0.540	0.586	0.593
Observations	9 537	13 250	7 186	14 469	14 589

*The estimates are computed using equation 2 and optimal CCT bandwidths. Standard errors clustered at cutoff and individual level are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

differences between the more and less selective schools in terms of minimum GPA, which on average is around 0.5–0.9 grades. Meanwhile, the next column shows how one's relative ability ranking at the school they were admitted into changes at the cutoff.[26] According to these results, eligibility into a more selective school appears to reduce one's ranking by around 31 placements.

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[26]The ranking begins from one and increases as one's relative ability increases. Note that the ranking does not go to one at the cutoff, due to donut RDD estimation as well as the fact that not all eligible students gain admission.

I then move on to estimate the effects on educational outcomes, as they offer context to the mental health effects and ease with the interpretation of these effects. These results are presented in columns 3–8 in Table 3, starting from the effects on enrolment in any general school and ending on the higher degree timing estimates. The results show little to no effects regarding educational outcomes: nearly all (96%) enroll to secondary education in the application year and around 74% graduate within three years. There are also no significant effects on the matriculation exam grades, which are near the population mean.[27] Individuals on both sides of the cutoff also have equal likelihood (around 54%) to graduate with higher education degree and do so in average 9.6 years after the application to upper secondary education.

My results on mental health are reported in the last two columns of Table 3, which present the effects on the cumulative probability of individual having mental health issues within the first three and 13 years after application. According to these estimates, the short-term effects are around 0.9 to 1.3 percentage points on the negative side, although these estimates are statistically insignificant. The same is true for the long-term estimates, which are only slightly above zero.

The results presented, especially the estimates for mental health outcomes, are quite robust to the choice of bandwidth. This is evident from the sub-figures in B.5, reporting the effects of eligibility with different bandwidths for mental health as well as educational outcomes.[28] The estimates are also robust in terms of model specification as well as on the definition of mental health issue. The first can be seen by comparing the main mental health estimates to those presented int the lower part of Table 3, which reports the effects using a model without a cutoff and running variable interaction. Meanwhile, the latter is clear from Tables 5 and 6, which report the estimates by the type of mental health outcome.[29]

6.2   Timing of the effects

To get as comprehensive a picture of the mental health effects as possible, I turn my focus on the time variation of the effects. In practice, I do this by estimating the annual and cumulative effects separately for years 1–13 since the application.[30] These effects, together with their 90 percent confidence intervals are

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[27]The scale of matriculation grades is from 0 to 6, and follows normal distribution, with grade mean of 3.

[28]The educational and mental health effects are also presented as bingraphs in figure B.4.

[29]By medicine purchases, inpatient and outpatient visits, purchase of antidepressant, other medicine purchases, inpatient/outpatient visits due to mood disorders and visits for other reasons.

[30]The estimates are obtained using equation 2 and bandwidth of 0.8, which is slightly larger than the optimal ones reported in previous Table. The use of slightly larger bandwidth is sensible due to rareness of mental health issues in
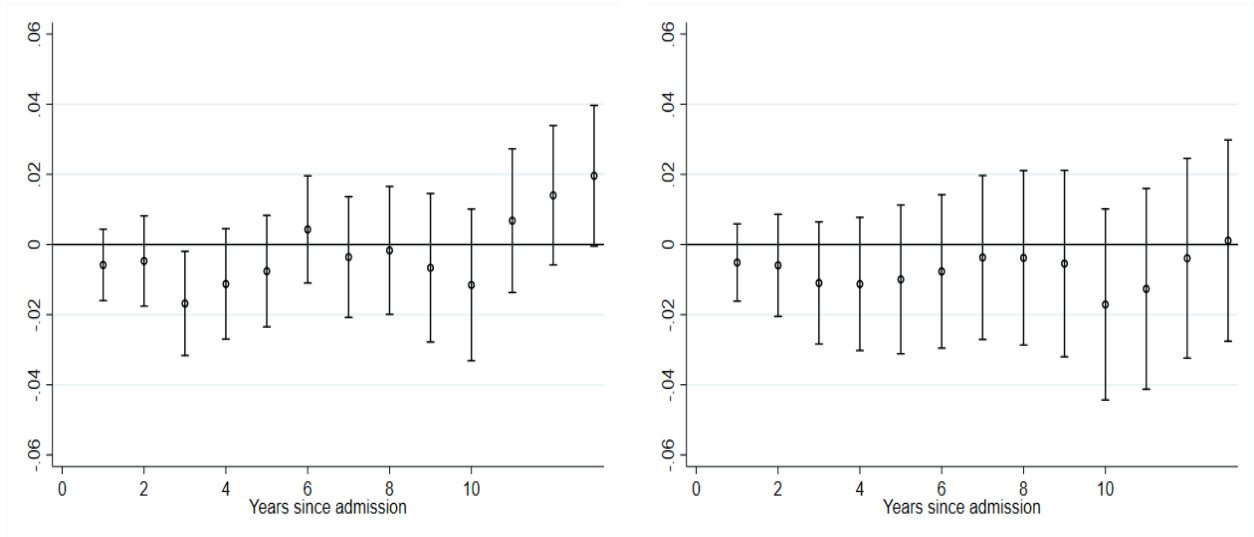
(a) Annual mental health issues   (b) Cumulative mental health issues

Notes: The estimates are computed using equation 2 and fixed bandwidth of 0.8, the line present 90% confidence intervals of the estimates.

Figure 1: Year-by-year estimates of being eligible to more selective school on the probability of having any annual or cumulative mental health issues

Table 4: Effects of eligibility and enrolment to more selective school on the probability of having any annual and semiannual mental health issues in 3rd year.

	Mental health issues in		
	3rd year (1)	first half of 3rd year (2)	seconds half of 3rd year (3)
Eligibility	-0.017*	-0.018**	-0.010
	(0.009)	(0.008)	(0.008)
Enrolment	-0.025*	-0.033**	-0.015
	(0.013)	(0.012)	(0.012)
Mean below	0.053	0.042	0.040
Observations	19 743	19 743	19 743

The estimates are computed using equation 2 and fixed bandwidth of 0.8. Standard errors clustered at cutoff and individual level are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

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annual data as well as early years in cumulative data.

reported in sub-figures 1b and 1a. The sub-figure on the right-hand side shows the cumulative effects, which are consistently near zero and statistically insignificant. Meanwhile, the annual effects on the left-hand side show more variability: the effects are negative for the first 10 years, after of which they become positive (although statistically insignificant). The figure also shows that effects are at their most negative during students' third year and are also slightly statistically significant (at 10% risk level).

The fact that the estimates are largest on third year is interesting, considering that students take most of their matriculation examinations in the spring of that year. In order to get better comprehension what happens in the third year, I study the mental effects semiannually during the year in question.[31] These results, together with the estimates for the overall third year, are presented in Table 4. According to them, the mental health effects are largest and statistically significant during the first half of 3rd year, thus coinciding with matriculation examinations. During this time, those eligible to a more selective school are around 1.8 percentage points less likely to have any mental health issues. These effects are substantial, considering the counterfactual of 4.2 percent.[32]

6.3   Heterogeneity and Mechanisms

I continue my analysis by studying the heterogeneity and mechanisms behind my mental health results. I start by estimating the effects separately for sub-samples based on the more preferred/selective school's characteristics. This is done in sub-figures 2a and 2b which show the effects separately for school that are either below or above the median in terms of the characteristic in question.[33] In these figures, the characteristic upon which this deviation is done is reported in the y-axis. Figure 2a reports the effects of eligibility to a more selective school on the probability of having mental health issues during the first three years, while figure 2b does the same for the first 13 years.

As can be seen from these figures, the estimates are nearly always more negative when using sub-samples comprising schools that are above the median in terms of the characteristic in question. The only exception for this are the long-term estimates in sub-samples separated by the median in terms of the number of students. In this case, the estimates are positive when selective schools have at least median amount of

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[31]I used June to separate the year into two parts.

[32]Appendix also reports the robustness of these results to bandwidth (see last figures in B.5 and functional form (see Table 3).

[33]Medians are calculated using selective schools' characteristics.

(a) By 3rd year   (b) By 13th year
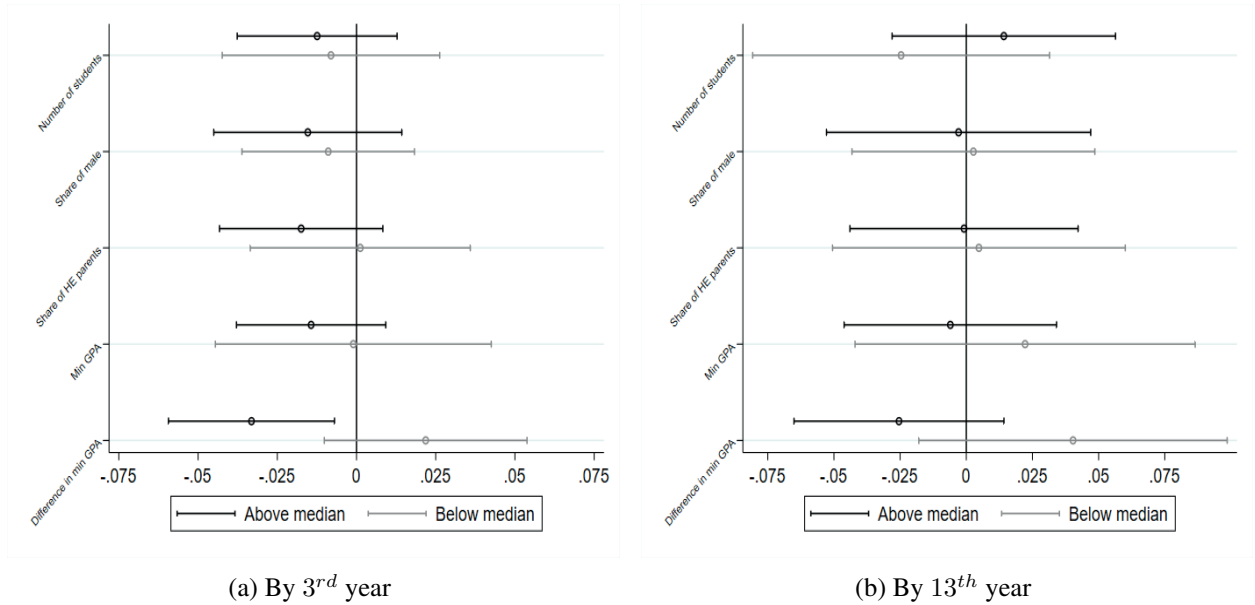
Notes: The estimates are computed using equation 2 and a fixed bandwidth of 0.8, the line present 95% confidence intervals of the estimates.

Figure 2: Effects of eligibility to a more selective school on the cumulative probability of having any mental health issues by school characteristics.

students, and negative (less mental health issues) when using schools with less then median amount of students.

The estimates are also typically not statistically significant in both the short- and long-term, although they are more on the negative side during the short-term. In fact, the only statistically significant estimates are the ones reporting the short-term effects using a sample consisting on schools at which the selectivity difference (in terms of minimum GPA needed for admission) to the next-best option was larger than median. According to these results, those eligible to a more selective school within this sub-sample were around 3.3 percentage points less likely to have mental health issues within the first three years since application.

Further insight to how school characteristics affect the results is provided by columns 5 and 6 in Table 4, reporting the effects using sub-samples where the individual's preferred, selective school and the next best alternative both belonged to the same municipality or the same type.[34] These estimates are close to the main estimates, and thus, it seems unlikely that school type or location drives my results.

Lastly, I try to gain some insight into the role that preferences might play in my analysis. To study this I first restrict my sample to schools that are present on both sides of the cutoff, and then remove the school

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[34]Regular general track.

related effects, add controls for the admitted school. In other words, I then have a sample in which each school has (admitted) some individuals who preferred that school and some who missed the cutoff of their preferred school and had this school as their next-best alternative. It should be noticed that this means that I have now removed both, the most selective schools (as they only accept individuals who preferred them), and the least selective schools (as they are present only as next-best alternatives in my sample). With this remaining sample, I thus estimate a function:

$$Y_i = \alpha_1 Adm_i + \alpha_2 X_i + \alpha_3 Pref_i + \epsilon_i, \tag{3}$$

where Y_i represents the outcome variable for applicant i. Adm_i controls for the school the individual was admitted to, while the X_i presents a set of background characteristics presented in Table 2. The main interest of this analysis is the dummy variable $Pref_i$, gaining value 1 if the school individual was admitted to was first in their preference order and 0 otherwise. ϵ_i is the error term.

Estimates reflecting Equation 3 are reported in Table 5 on short- and long-term mental health. Columns 1 and 3 report the estimates obtained from the regression without the inclusion of background characteristics,

Table 5: Effects of admission to a preferred school on short- and long-term mental health.

	(1)	(2)	(3)	(4)
		Mental health issues		
	by 3rd year	by 3rd year	by 13th year	by 13th year
Admitted to preferred	-0.00306	-0.00100	-0.0162	-0.0128
	(0.00585)	(0.00593)	(0.0108)	(0.0109)
Observations	16 088	16 088	16 088	16 088
Added background characteristics		X		X

Robust standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

while columns 2 and 4 have them included in the regression. As one can see from these results, the part that could be explained through preferences is quite modest in the short-term, especially so after inclusion of background characteristics, and does not statistically significantly differ from zero. The long-term results are similar, even though the estimates are larger.

7 Conclusions

In this paper, I studied whether attending a more selective, preferred general upper secondary school had causal effects on individuals' short- and long-term mental health. By using a rich administrative data on the centralized admission system in Finland, I was able to uncover the causal effects by employing RDD. An additional perk of having used the RDD for my analysis is that it allows me to examine whether the lack of results in previous RDD papers, regarding the educational effects of school selectivity, could be due to negative effects on one's mental health. This could be the case if, for example, those barely admitted to a more selective school experienced increased stress and feelings of inadequacy by being at the bottom of their peer-group, which could then be reflected in their schoolwork. The presence of such effects could then mitigate/mask some positive effects that selective school might have on their educational outcomes.

However, based on my results, those eligible or enrolled to more selective school did not, on average, have any additional mental health related inpatient/outpatient visits or mental health related medicine purchases within the next three or 13 years since application. In fact, my estimates were on the negative side (less mental health issues) in the short-term, and stayed that way for the first 10 years since the application and were even statistically significant during the time of matriculation examinations, at which point, those eligible were around two percentage points less likely to have had mental health issues. Further heterogeneity analysis revealed some variation based on the selective school's characteristics, with the largest positive effects reported when selectivity difference between preferred and next-best alternative schools were above median.

The supplementary analysis on the effects of preferences suggests that preferences did not play a major role in explaining the effects, although the analysis only applied to mid-tier schools (selectivity wise). A possible reason, outside of preferences, for my positive short-term effects could be that selective schools might be better at recognising early signs of stress and intervene before problems evolve into ones requiring mental health related doctor visits/medicine purchases.

My short-term results are in line with the positive findings on one's mental health during the early years by Bütikofer et al. (2020), while my estimates after 10th year coincide with the negative (although imprecise) mid-life estimates found by Pastore and Jones (2019) and Butler et al. (2020). An interesting future alley of research would be to study how other aspects outside school selectivity (such as teacher turnover, class

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composition etc.) affect students' and teachers' mental health.

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Appendices

A   tables

Table 1: ICD-10 codes and their meaning

ICD-10 code	Meaning	Example
F0	Mental disorders due to known physiological conditions	Dementia
F1	Mental and behavioral disorders due to psychoactive substance use	Alcohol abuse
F2	Schizophrenia, schizotypal, delusional, and other non-mood psychotic disorders	Schizophrenia
F3	Mood [affective] disorders	Depression
F4	Anxiety, dissociative, stress-related, somatoform and other nonpsychotic mental disorders	Anxiety disorder
F5	Behavioral syndromes associated with physiological disturbances and physical factors	Eating disorder
F6	Disorders of adult personality and behavior	Paranoid personality disorder
F7	Intellectual disabilities	Moderate intellectual disabilities
F8	Pervasive and specific developmental disorders	Specific developmental disorders of scholastic skills
F9	Behavioral and emotional disorders with onset usually occurring in childhood and adolescence	ADHD
Few specific codes:		
Z00.4	Unclassified general psychiatric examination	
Z03.2	Monitoring for suspected psychiatric disorder	
Z04.6	Encounter for general psychiatric examinations	
Z50.4	Psychotherapy, not elsewhere classified	
Z73	Burn-out	
Z86.5	Personal history of mental and behavioral disorders	
Z91.5	Personal history of self-harm	
G47.0, G47.2, G47.4, G47.8, G47.9	Sleep disorder related	

Source: Terveyden ja hyvinvoinnin laitos

Table 2: Mental Health Medication Classification

N06= Depression Medication and Central Nervous System Stimulants			N05=Psychosis Medication		
N06A=Depression Medication	N06B=Central Nervous System Stimulants	N06C=Aldazine Drug Combinations	N05A= Antipsychotics	N05B= Anxiolytics	N05C=Hypnotics & sedatives

Source:Fimea, https://www.fimea.fi/web/en/databases_and_registers/atc-codes

Table 3: Effects of eligibility and enrolment to more selective school on mental health with different model variations.

	Mental health issues				
	by 3rd year	by 13th year	in 3rd year	in first half of 3rd year	in second half of 3rd year
Added background characteristics					
Eligibility	-0.008	0.003	-0.016*	-0.017**	-0.00
	(0.012)	(0.020)	(0.009)	(0.008)	(0.008)
Enrolment	-0.013	0.005	-0.024*	-0.026**	-0.014
	(0.020)	(0.031)	(0.013)	(0.012)	(0.012)
Mean below	0.074	0.273	0.052	0.042	0.039
Observations	14 469	14 589	19 743	19 743	19 743
No cutoff interactions					
Eligibility	-0.009	0.004	-0.015*	-0.016**	-0.006
	(0.011)	(0.018)	(0.008)	(0.007)	(0.007)
Enrolment	-0.002	0.030	-0.023*	-0.026**	-0.010
	(0.018)	(0.030)	(0.013)	(0.011)	(0.012)
Mean below	0.078	0.274	0.057	0.044	0.042
Observations	14 469	14 589	19 743	19 743	19 743

The estimates in first two columns are computed using equation 2. The cumulative estimates are estimated with CCT optimal bandwidths, while the annual ones have fixed bandwidth of 0.8. Standard errors clustered at cutoff and individual level in parenthesis *** p<0.01, ** p<0.05, * p<0.1..

Table 4: Effects of eligibility and enrolment to more selective school on mental health with different sample restrictions.

	Mental health issues					
	by 3rd year (1)	by 13th year (2)	by 3rd year (3)	by 13th year (4)	by 3rd year (5)	by 13th year (6)
	Regular schools		**Cutoff observations included**		**Same municipality**	
Eligibility	-0.022	0.011	-0.008	0.010	-0.016	0.019
	(0.014)	(0.020)	(0.011)	(0.017)	(0.014)	(0.024)
Enrolment	-0.033	0.016	-0.014	0.016	-0.022	0.026
	(0.020)	(0.030)	(0.017)	(0.027)	(0.019)	(0.032)
Mean below	0.076	0.241	0.077	0.271	0.070	0.238
Observations	13 936	13 936	20 567	20 567	11 130	11 130

The estimates are computed using equation 2 and the bandwidth 0.8. Same municipality sample refers to sample where selective and next best option were in the same municipality. Standard errors clustered at cutoff and individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effects of eligibility and enrolment to more selective school on mental health medicine purchases and inpatient/outpatient care visits in short- and long-term.

	By 3rd year			By 13th year		
	Medicine purchases (1)	Inpatient spells (2)	Outpatient visits (3)	Medicine purchases (4)	Inpatient spells (5)	Outpatient visits (6)
Eligibility	-0.010	-0.003	0.007	0.003	0.004	0.015
	(0.009)	(0.004)	(0.008)	(0.017)	(0.008)	(0.013)
Enrolment	-0.015	-0.005	0.010	0.005	0.006	0.022
	(0.014)	(0.006)	(0.013)	(0.025)	(0.012)	(0.020)
Mean below	0.055	0.011	0.042	0.244	0.037	0.110
Observations	19 743	19 743	19 743	19 743	19 743	19 743

The estimates are computed using equation 2 and the bandwidth 0.8. Standard errors clustered at cutoff and individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effects of eligibility and enrolment to more selective school on mental health medicine purchases and inpatient/outpatient care visits in short- and long-term.

	Mental health related medicine purchases			
	By 3rd year		By 13th year	
	Antidepressants	Other	Antidepressants	Other
	(1)	(2)	(3)	(4)
Eligibility	-0.002	-0.003	0.004	0.006
	(0.007)	(0.004)	(0.014)	(0.013)
Enrolment	-0.004	-0.005	0.006	0.009
	(0.011)	(0.007)	(0.022)	(0.020)
Mean below	0.045	0.014	0.194	0.130
Observations	19743	19743	19743	19743

	Mental health related inpatient/outpatient care visits			
	By 3rd year		By 13th year	
	Mood disorder	Other	Mood disorder	Other
	(5)	(6)	(7)	(8)
Eligibility	-0.005	-0.006	0.008	0.007
	(0.004)	(0.006)	(0.010)	(0.010)
Enrolment	-0.008	-0.009	0.012	0.010
	(0.007)	(0.010)	(0.015)	(0.016)
Mean below	0.018	0.036	0.061	0.088
Observations	19743	19743	19743	19743

The estimates are computed using equation 2 and the bandwidth 0.8. Standard errors clustered at cutoff and individual level in parenthesis. Effects on antidepressants and mood disorder visits/spells are presented separately, due to them being the most common ones in the data. *** p<0.01, ** p<0.05, * p<0.1.

B Figures
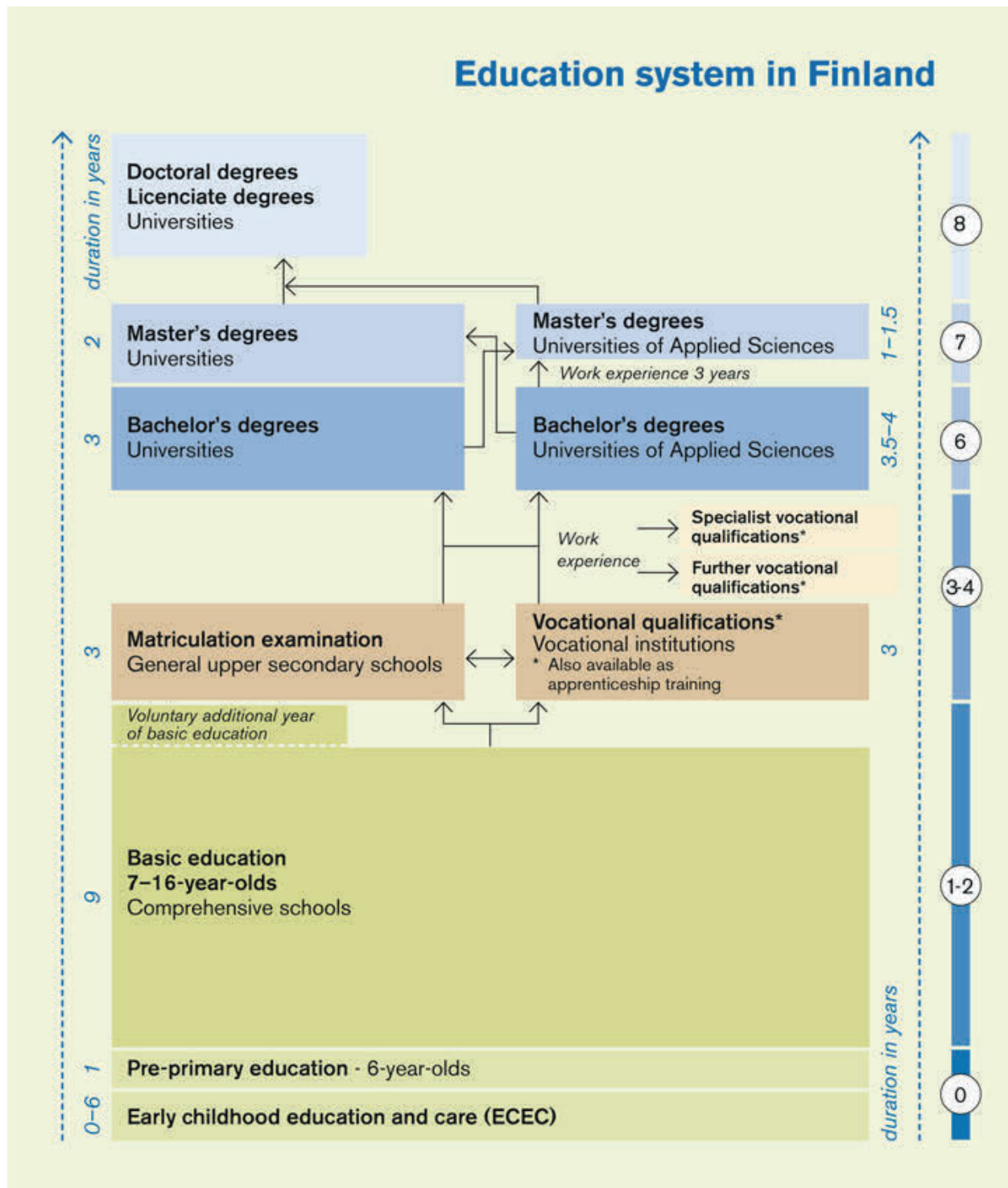
Figure B.1: Education System in Finland
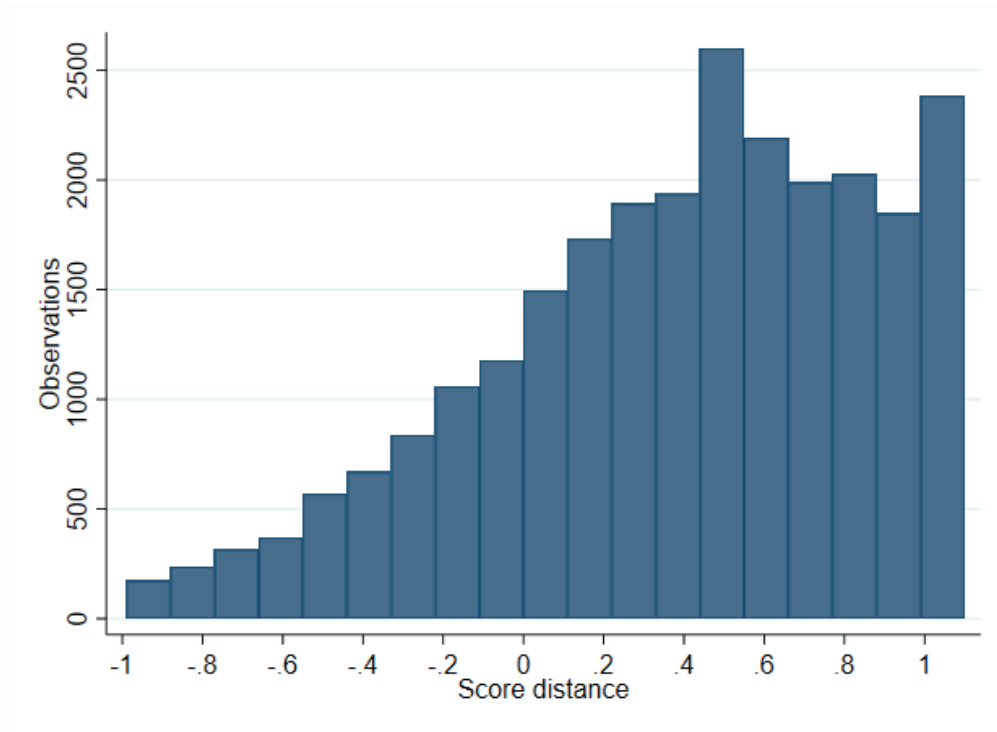
Figure B.2: Histogram for the density of observations within 1 point from cutoffs.
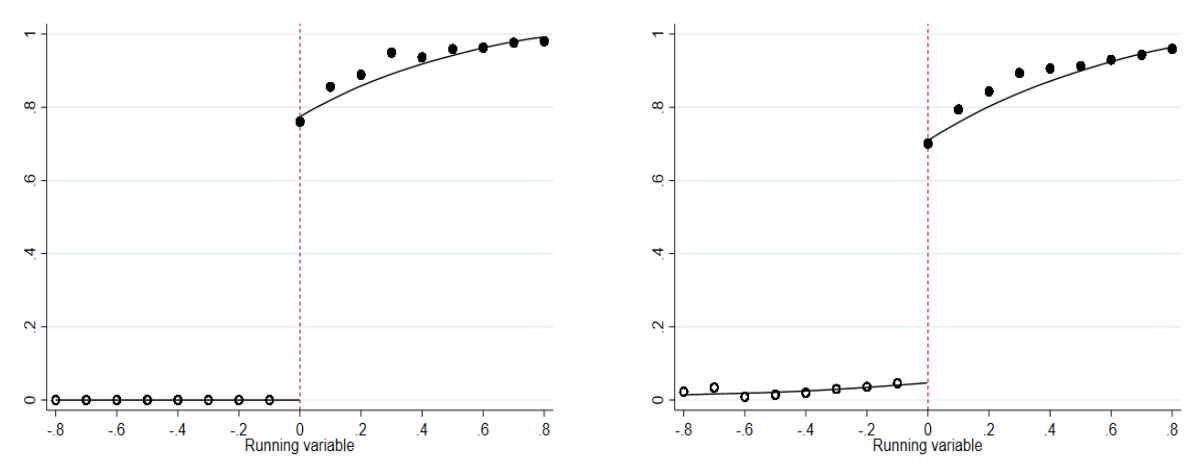
(a) Admission to selective school

(b) Enrolment to selective school

Figure B.3: Admission and enrolment discontinuities to more selective school.
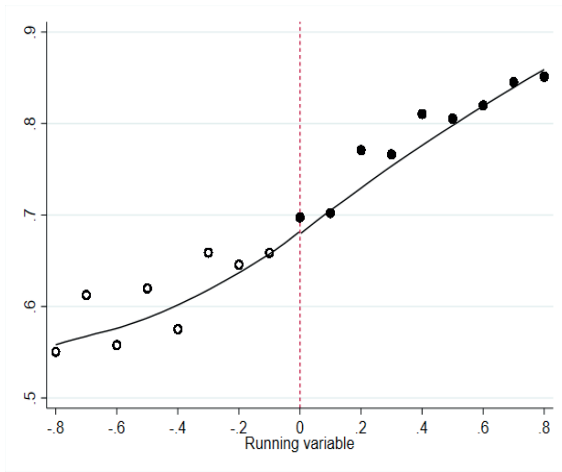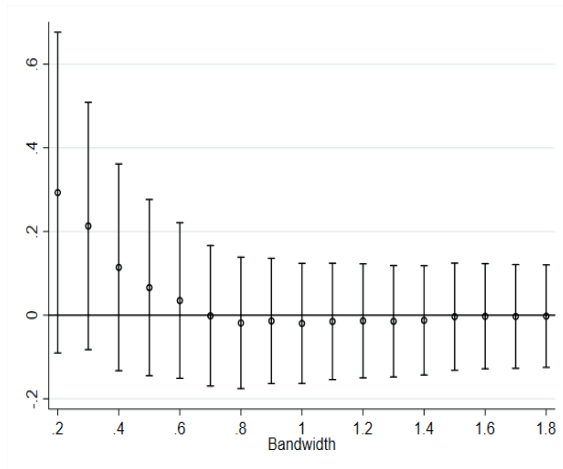
(a) general school graduation by 3rd year
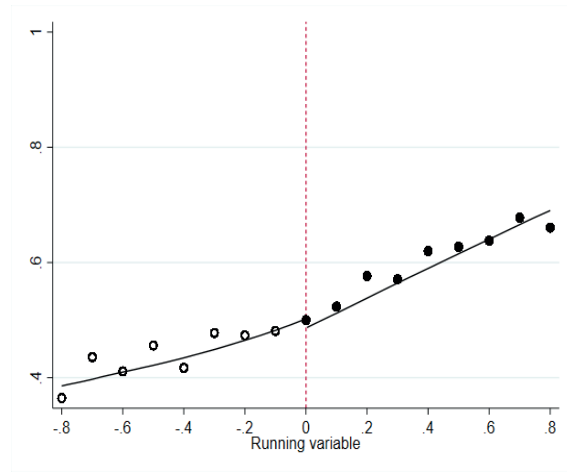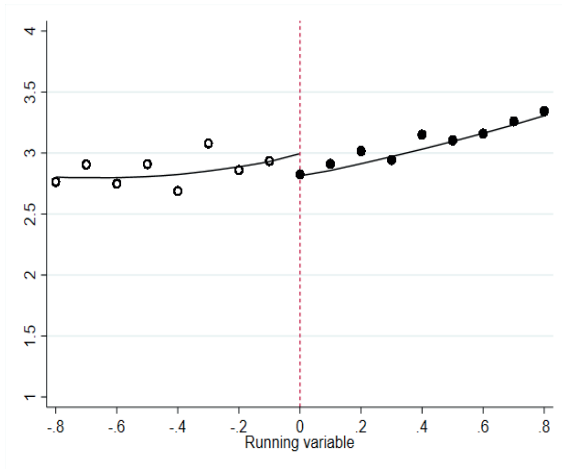
(b) HE graduation by 13th year

(c) Matriculation exam score motherlanguage
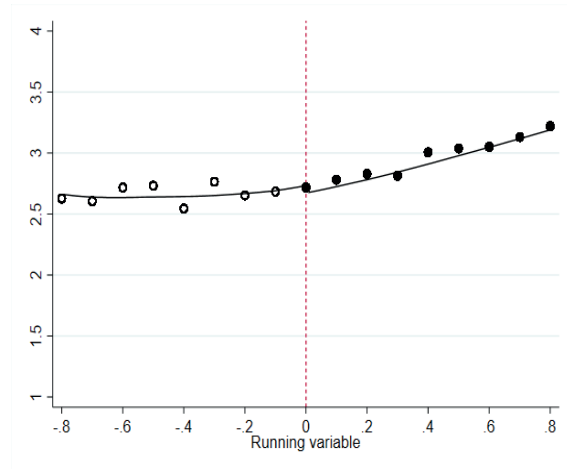
(d) Matriculation exam score mathematics
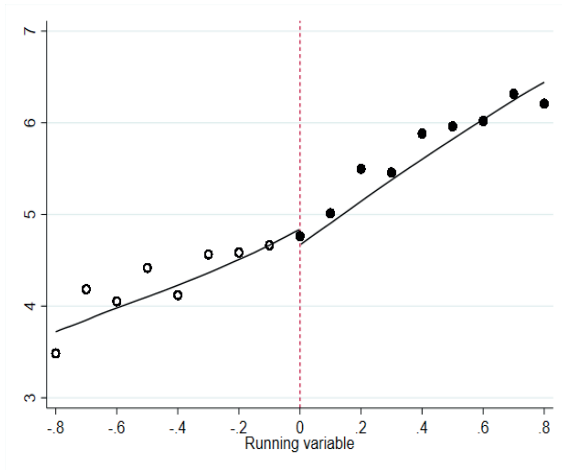
(e) He graduation speed
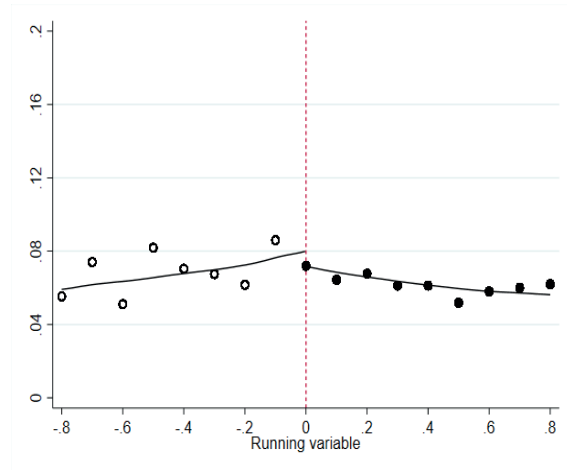
(f) Cumulative mental health issues by 3rd year

Figure B.4: Effects of exceeding the cutoff to more selective school to graduation and mental health outcomes
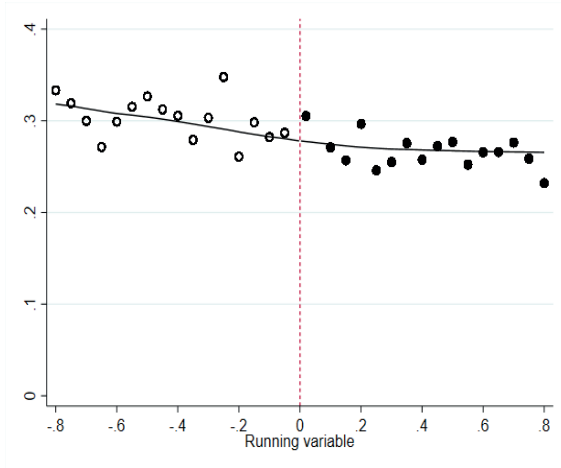
(g) Cumulative mental health issues by 13th year
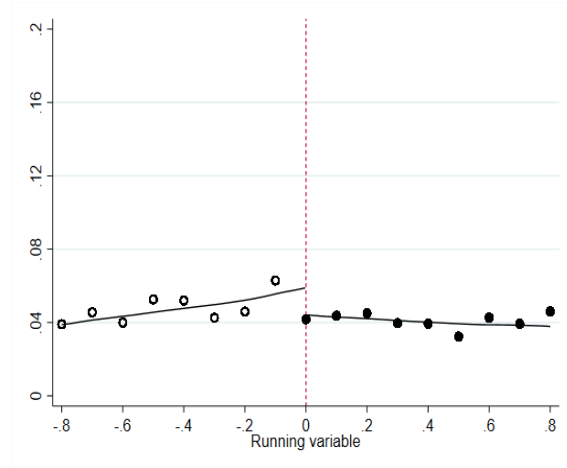
(h) Cumulative mental health issues by 3rd year
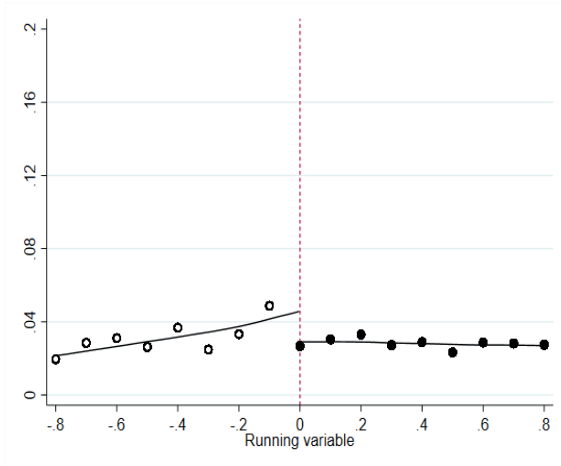
(i) Cumulative mental health issues by 13th year
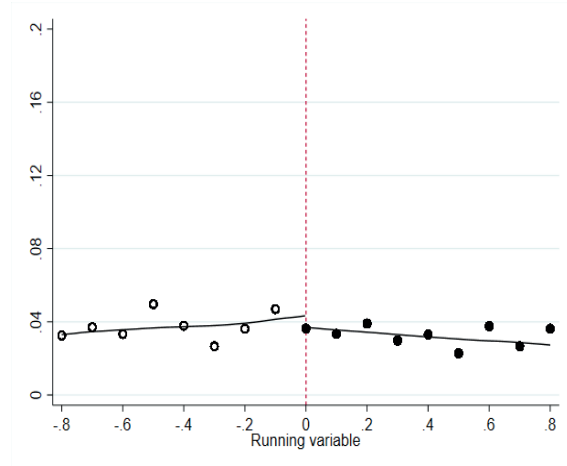
(j) Annual mental health issues in 3rd year

Notes: The dots present sample means with bin width of 0.1. The lines are local linear regressions smoothed using kernel weights and bandwidth of 0.8.

Figure B.4: Effects of exceeding the cutoff to more selective school to graduation and mental health outcome
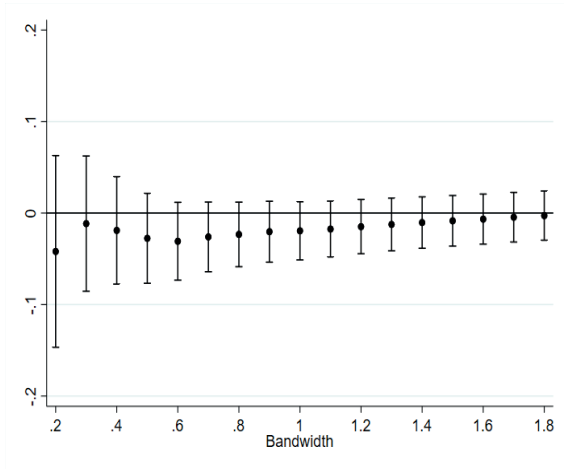
(a) Graduation by 3rd year
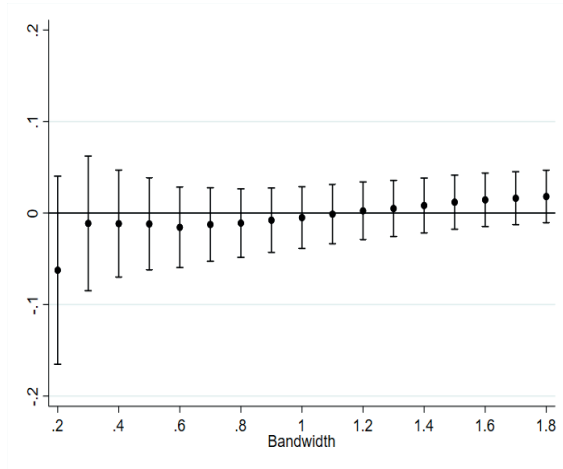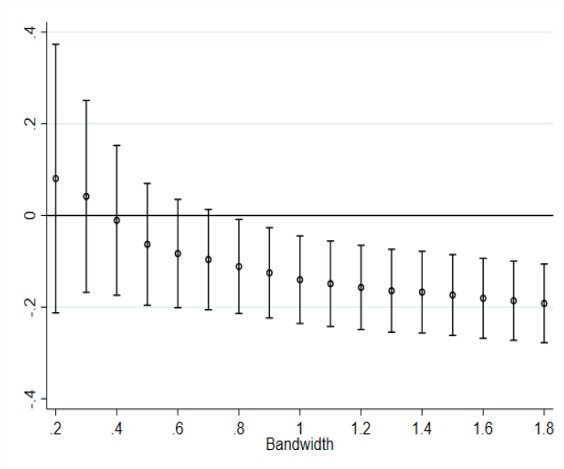
(b) HE graduation by 13th year

(c) Matriculation exam score motherlanguage

(d) Matriculation exam score mathematics
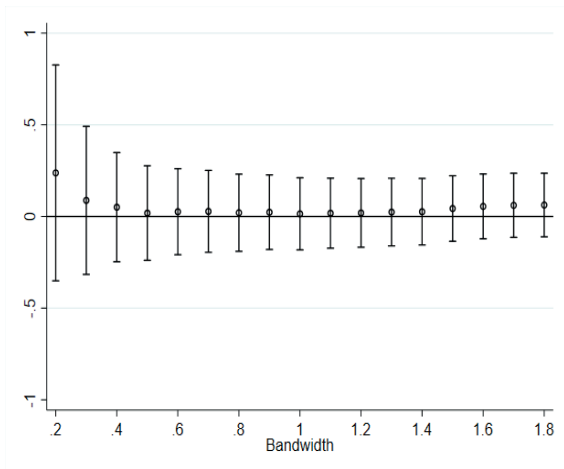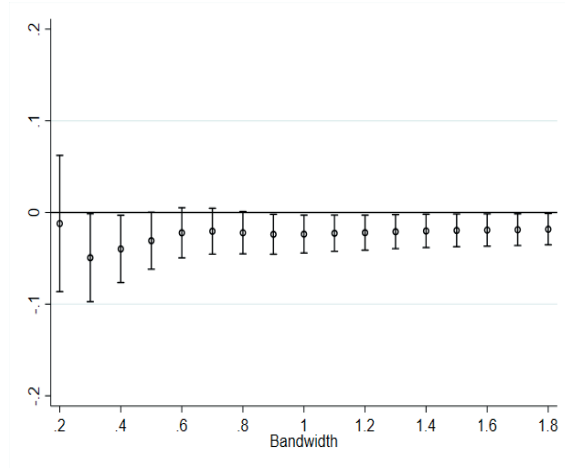
(e) He graduation speed
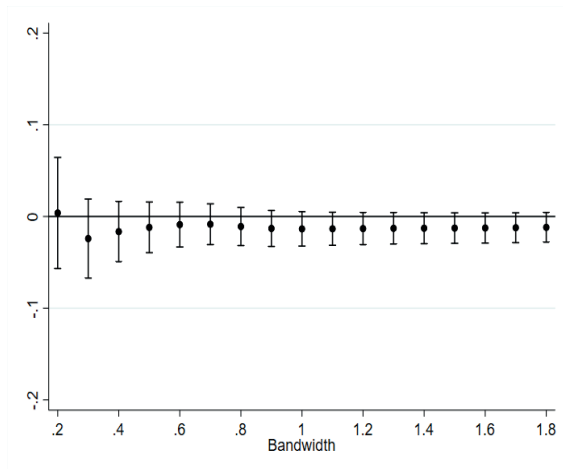
(f) Cumulative mental health issues by 3rd year

Notes: Each point and 95% confidence intervals are derived separately from regressions with bandwidth specified in x-axis.
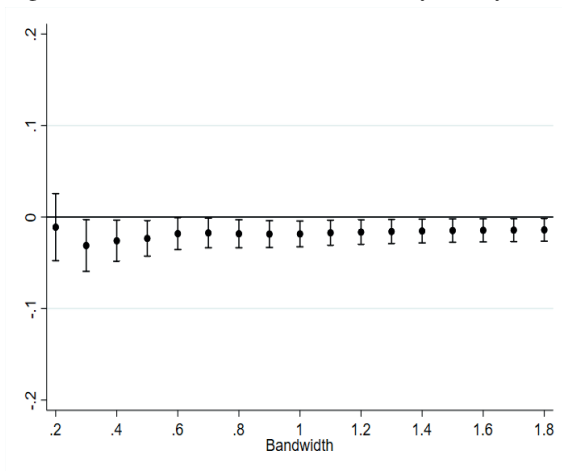
Figure B.5: Effects of exceeding the cutoff to more selective school using different bandwidths and 95% confidence interval.
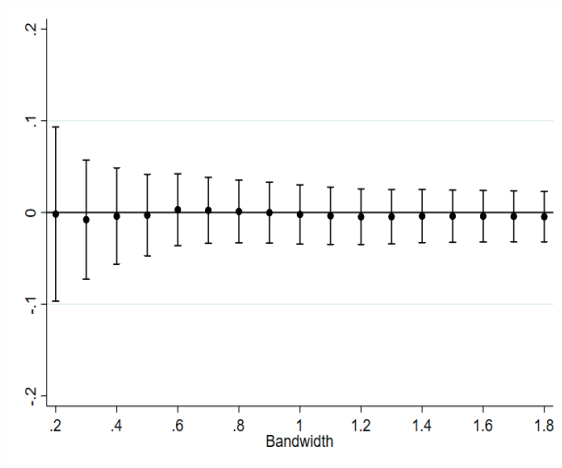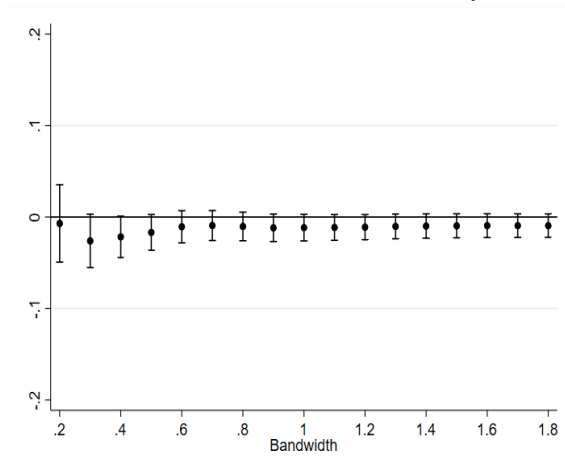
(g) Cumulative mental health issues by 13th year

(h) Annual mental health issues in 3rd year

(i) Mental health issues in first half of 3rd year

(j) Mental health issues in second half of 3rd year

Notes: Each point and 95% confidence intervals are derived separately from regressions with bandwidth specified in x-axis.

Figure B.5: Effects of exceeding the cutoff to more selective school using different bandwidths and 95% confidence interval.

LABORE

on vuonna 1971 perustettu itsenäinen ja voittoa tavoit-
telematon kansantalouden asiantuntijayksikkö. Laitok-
sessa tehdään taloustieteellist tutkimusta ja laaditaan
suhdanne-ennusteita. Lisäksi laitoksen tutkijat toimiva-
tulkopuolisissa asiantuntijatehtävissä sekä osallistuvat
aktiivisesti julkiseen talouspoliittiseen keskusteluun.
Palkansaajien tutkimuslaitoksen toiminnan tavoitteena
on tarjota tutkimustietoa yhteiskunnallisen keskustelun
sekä päätöksenteon tueksi.

Palkansaajien tutkimuslaitoksessa tehtävän tut-
kimustyön painopiste on tilastollisiin aineistoihin
perustuvassa empiirisessä tutkimuksessa. Sen taustalla
on vahva teoreettinen näkemys ja tieteellisten me-
netelmien asiantuntemus.