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HIGHER EDUCATION AND FINANCIAL BEHAVIOR: THE EFFECT OF STUDYING MATHEMATICS AND ECONOMICS ON FINANCIAL OUTCOMES

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Higher Education and Financial Behavior: The effect of studying mathematics and economics on financial outcomes

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Abstract

This paper presents new evidence on the effect of education on financial behavior. In particular, I investigate whether obtaining a degree from a study program with a mathematical or economic curriculum affects individuals' future loan default probability. I identify the causal effects of different types of education on financial behavior by exploiting the GPA admission thresholds to higher education programs in a fuzzy regression discontinuity design. I compare people who have applied for the same fields of study but who are quasi-randomly allocated to different different fields of study due to small differences in their GPA from upper secondary school. I estimate the effects using a unique combination of administrative data on admissions to post-secondary education and third party reported data on the universe of personal loans. I find that completing a mathematical or economic field of study decreases the probability of default post graduation for the applicants who did not have one of these fields as their most preferred field of study.

1 Introduction

Financial decision-making in households has received growing attention among both researchers and policy-makers in recent years, especially in the wake of the financial crisis. Among others, the OECD have argued that ill-informed financial decision-making has ”tremendous adverse effects on both personal, and ultimately, global finance” (OECD, 2016). The interest often concerns the debt behaviour of households and how well individuals manage and service their debt. To prevent individuals from making ill-informed financial decisions it is often suggested to raise individuals’ financial literacy through financial education and numeric training.

This paper presents evidence on the causal effect of choice of higher education on financial outcomes. In particular, I investigate whether completing a study program with a mathematical or economic curriculum affects individuals’ future probability of loan default.

The main challenge in identifying the causal effect of financial education on financial behaviour is that the observed correlations can be driven entirely by students self-selecting into study programs. To identify the causal effect of field of study on financial behaviour, I use a fuzzy regression discontinuity design where I exploit the Danish system of admission to higher education. Imagine two applicants, Adam and Auguste. They would both prefer to study Sociology and have Economics as their next-best alternative. In the year where they both apply for admission there is an unpredictable GPA admission threshold for Sociology of 11.0. Luckily for Auguste, he has a GPA of exactly 11.0 from upper secondary school so he receives an offer to enrol in the Sociology program. Adam on the other hand has a GPA of 10.9 and therefore he does not receive an offer to enrol in the Sociology program. Instead, he is offered to enrol in his next-best alternative, Economics, where the admission threshold is only 7.0. The example illustrates how the locally unpredictable admission thresholds quasi-randomize similar applicants who are close to the threshold into different fields of study, and I exploit this variation for the identification of the causal effect of financial education and numeric training.

I combine administrative third party reported data on applications and admissions to post-secondary education with data on GPA from upper secondary school and exploit the admission thresholds to create instruments for completing a particular field of study. This method is already well established (see for instance Kirkeboen et al. (2016)) but I am the first to use it to study financial outcomes. I link the admission data with administrative data from The Danish Tax Authorities on the universe of personal loans to study the applicants financial behavior post graduation. Finally, I also add administrative data from Statistics Denmark on income and several demographic variables.

This paper is the first to study how different higher education fields of study affect financial behavior. The existing literature mainly studies short run effects of low touch interventions whereas I study the long run effects of a high touch intervention. Furthermore, the paper contributes to the scarce evidence on the causal effect of financial education and numeric training on financial behaviour.

Firstly, I show that being above the GPA admission threshold significantly increases the probability that an applicant completes his or her preferred field of study. Similarly, I show that being below the GPA admission threshold for the preferred field of study significantly increases the probability that an applicant completes his or her next-best alternative field of study. These first stage results confirm, that I can exploit the thresholds to create instruments completing a certain field of study for the applicants who have the field as their preferred or next-best alternative field of study.

Secondly, I use these instruments to estimate the causal effect of completing a field of study with a mathematical or economical curriculum. The mathematical fields of study includes several STEM educations and economics include majors in economics, accounting and finance following Chetty et al. (2014). I focus on these fields of study in order to study the effect financial knowledge and mathematical skills respectively. I find that applicants who have math or economics as their next-best alternative have a significantly smaller probability of default if they complete a mathematical or economic field of study. For the oldest application cohorts I measure this outcome 10 to 22 years after they applied for higher education. My reduced form results show that completing a mathematical field of study decreases the default probability with 2,7 %-points while completing an economic field of study decreases the default probability with 4.9 %-points. These effects are economically important since the probability of default across all the applicants in my sample who complete a field of study is 4,3 %. The estimated effect of graduating from a mathematical field of study is robust to different specifications, whereas the result for economics is sensitive to the length of period where I observe defaults.

Finally, I also present suggestive evidence that the estimated effects are not driven by smaller debt relative to income or a smaller degree of liquidity constraints for the applicants who complete the mathematical or economic field of study. Furthermore, I do not find an income premium for completing these fields for applicants who have them as their next-best alternative. This suggests that income cannot explain the differences in default probability. These results indicate that studying especially math makes individuals better at managing and servicing their debt.

Meta-analyses have tried to evaluate the impact of financial education on financial behaviour. The conclusions are mixed and the studies point out that there is a lack of causal evidence (see Fernandes et al. (2014), Miller et al. (2015) and Kaiser and Menkhoff (2017)). This paper contributes to the literature by providing such evidence.

Recent studies have provided more reliable estimates of the effects of financial education by investigating the effect of high school courses in personal finance and mathematics by using variations in state wide graduation requirements in the U.S. Brown et al. (2016)

find that both mathematics and financial education improve repayment behaviour whereas Cole et al. (2016) only find a significant effect of mathematics on credit management. In a correlational study, Allgood et al. (2011) find that taking more coursework in economics or choosing economics as an undergraduate major is associated with having fewer credit cards and full pay off of credit cards in each month. To the best of my knowledge, my paper is the first to provide causal evidence on the effect of field of study and coursework in the post-secondary education system on financial behavior. This paper confirms the previous findings that extensive treatments can have a positive impact on financial behavior and shows this is also the case for highly educated people and that the effects are potentially long-lasting.

Other studies have also investigated the effect of education on different financial outcomes. For instance, Cole et al. (2014) use variation in state compulsory schooling laws to show that additional years of education increases financial market participation and reduces the probability of having a loan default or delinquency. Another example is Christiansen et al. (2008) who show that economists are more likely to participate in the stock market.

The paper proceeds as follows. Section 2 describes the institutional setting and identification strategy. Section 3 presents the data used for the empirical analysis in section 4. Finally, section 5 concludes.

2 Institutional Background and Methodology

2.1 Admission to post-secondary education

In Denmark post-secondary education is free of charge and most students are entitled to public support from the State Educational Grant. It generally requires three to five years of study to obtain a post-secondary degree at one of the eight Danish universities, the university colleges or the academies of professional higher education.

The admission to higher education programs normally requires an Upper Secondary School Leaving Certificate and the admission process is administered by the Coordinated Admission under the Ministry of Higher Education and Science. The applicants can apply for and rank up to eight programs and each program is a combination of detailed subject of study and institution.

Admission to these programs is allocated through either Quota 1 or Quota 2. The majority of slots are allocated through Quota 1 where the applicants are ranked based on their GPA from upper secondary school. The best ranked applicant gets his or her preferred choice, the second best ranked applicant gets his or her highest available choice and so on. The number slots is limited in most programs and if the number of applicants exceeds the number of slots, admission is therefore restricted. This implies that applicants with a GPA above a certain threshold will be offered to enrol and applicants with a GPA below the threshold will be offered another program if any. It is important to notice that the applicants cannot know the specific thresholds at the time of application. Thereby, the Quota 1 admissions process creates unpredictable GPA thresholds which effectively shifts the probability of receiving an offer to enrol in a certain program.

The Quota 2 admissions are allocated by the education institutions based on criteria they select. These can be work experience, grades in particularly relevant subjects etc. If students apply for a program through the Quota 2 system, but fulfil the Quota 1 requirements, they will be admitted to the program through Quota 1.[1]

2.2 Fuzzy Regression Discontinuity Design

The institutional setting described in the previous section enables me to estimate the causal effect of field of study on outcomes such as the probability of loan default using a fuzzy regression discontinuity design. This method is already well established and has been used in other studies using Scandinavian register data (see for instance Kirkeboen et al. (2016), Heinesen (2016), Humlum et al. (2017), Öckert (2010), Daly and le Maire (2019) and Silliman and Virtanen (2019)).

Imagine we have an individual, i, with the preferred field j and the next-best alternative field k. The effect on an outcome, y, of completing field j instead of field k can then be estimated by 2SLS using the equations

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i T_{ij} + \rho_{jk} D_{ij} + \delta C_i + \varepsilon_i \tag{1}$$

$$D_{ij} = \gamma_0 + \gamma_1 x_i + \gamma_2 x_i T_{ij} + \pi_{jk} T_{ij} + \psi C_i + u_i \tag{2}$$

where (1) is the second stage and (2) is the first stage. In the equations above x_i is the running variable, in this case the distance to the GPA threshold. D_{ij} is a dummy that equals 1 if individual i completes field j and T_{ij} is a dummy indicating whether i's GPA is above the threshold for field j.

Estimating (1) and (2) on a sample of applicants who all have preferred field j and next-best alternative k will provide an estimate of ρ_{jk} which can be interpreted as the causal effect of studying j instead of k on the outcome y. This estimation allows for different effects of the running variable on either side of the threshold. In the estimations, I restrict the sample further to individuals who are within a narrow bandwidth close to the threshold. This makes my estimations equivalent of a non-parametric fuzzy regression discontinuity with local linear polynomials on each side of the threshold using a rectangular kernel.

[1] For a more detailed description of the admission process see Heinesen (2016)

Finally, I add age, year of application and sex controls, C_i. Thereby, I allow for different levels, but restrict the slope on either side of the threshold and the jump at the threshold to be the same across ages, years of application and sexes.

3 Data

In this section, I will give a brief overview of the different sources of data I combine, how I select the sample for estimations, and provide descriptive statistics for the sample.

3.1 Data Sources

I create a unique dataset for estimating the effects of choice of higher education on financial behaviour by combining third party reported Danish administrative data from three different sources.

From the Coordinated Admission, I have all applications for higher education programs in Denmark from 1993 to 2004. For each year and each applicant, I have information on their applications to different programs and how they rank their choices. From the Coordinated Admission, I have also have information on the GPA threshold for each study program in the same period.

I add data from Statistics Denmark on the applicants' GPAs from upper secondary school, current educational program as well as completed educational programs. From Statistics Denmark I also have information on income, assets, education and demographic variables.

No direct link exists between the programs in the Coordinated Admission data and the educational data from Statistics Denmark. I create this link by determining the mode of current education between applicants to a certain program six months after they enrol in the program.

Finally, I also use data from the Danish Tax Authorities on the universe of personal loans. This data contains information on loan delinquencies and defaults from 2003 to 2015. This is the main outcome I investigate in this paper. Each loan can be linked to an applicant through a unique personal identifier, and therefore I can create a proxy for whether individuals are in financial trouble at any given point in time.

3.2 Sample Selection

I study individuals who applied for a higher education program between 1993 and 2004. For the oldest cohort, I have loan information from 10 years after the year-of-application and for the youngest cohort I have data from Statistics Denmark until 9 years after the year-of-application. In this period, I observe 1.363.078 applications from 709.667 individuals. I focus on first time applicants and this leaves me with 381.264 applicants.

Some applicants have an imperfect ranking of their choices, and some only apply for programs that have a special admission system. I drop these applicants as well as applicants who only apply for one program. I also have to restrict the sample to applicants with a recorded GPA from upper secondary school. This reduces my sample to 135.867 applicants.

Finally, I restrict the sample to applicants with a binding GPA threshold in their local course ranking. For applicants with two binding thresholds, I keep the first threshold. This gives me a sample of 46.450 applicants.

3.3 Fields of study

The applicants in the sample all have a preferred field of study and a next-best alternative field in their local course ranking. I use the Danish ISCED classifications to divide field of study into eight groups: 1) Business, Administration and Law, 2) Arts and Humanities, 3) Natural Sciences, 5) Social Sciences, 6) Health and Welfare, 7) Education 2) Engineering and Technology and 8) Other.

Besides these classifications, I define two additional sub-fields: mathematics and economics. I follow Chetty et al. (2014) and define economic educations as majors within economics, accounting and finance and categorize exactly the same programs as economic educations.

In order to characterize whether programs have a mathematical content, I look at the educational background of the students enrolling in a certain program. Until 2004 the general upper secondary school was divided into a mathematical track and a linguistic track. If more than half of the students who are offered a slot at a higher education program had studied in the mathematical track, I characterize the program as having a mathematical content. For some programs this characterization is not the same from year to year. In those cases, I follow the characterization that is most predominant across the years I observe.

3.4 Summary Statistics

In table 1 we see descriptive statistics for the selected sample and the pool of all applicants. We see that the sample is younger, which is due to the fact that I only look at first time applicants. We also see that the fractions of males and immigrants are lower in the sample. The individuals in the sample have a slightly higher GPA on average, they apply for more programs and the program they are offered is slightly less preferred. Based on the parental characteristics, the sample also seems to come from a more advanced background, but eight years after they applied they have a marginally lower income.

Table 1: Comparison of Summary Statistics for All Applicants and Sample

	All			Sample		
	N	Mean	SD	N	Mean	SD
Age	693016	24.55	6.03	46450	21.35	1.81
Male	693016	0.40	0.49	46450	0.32	0.47
Immigrant/Descendant	693016	0.07	0.26	46450	0.04	0.19
GPA	484324	8.26	0.96	46450	8.60	0.87
Offered rank	530872	1.20	0.64	46450	1.61	0.97
Number of applications	709667	2.07	1.41	46450	3.27	1.40
Earnings after 8 yr.	684988	241.62	181.70	45902	234.08	156.80
Father avg. income	411392	381.60	258.32	35042	397.62	258.13
Mother avg. income	497048	231.80	135.40	40643	249.28	137.48
Father's age at birth	626216	29.93	5.57	45220	30.38	5.29
Mother's age at birth	646504	27.22	4.77	46069	27.81	4.52
Father has higher edu.	574297	0.36	0.48	43024	0.45	0.50
Mother has higher edu.	612352	0.37	0.48	44798	0.49	0.50
Observations	709667			46450		

Incomes are in 1.000 DKK (2010 prices)
The parents' incomes are measured when they are 40 to 44 years old

Table 2 shows what the most common alternative is for the applicants who have economics or math as their preferred field and what the most common preferred fields are for applicants who have economics or math as their next-best alternative field. We see that in all four cases a large share of the applicants will be offered to enrol in the fields of business or social science if they do (do not) cross the admission threshold for their preferred (next-best alternative) field. It is useful to have these counter factual fields of study in mind when we interpret the effect of being shifted into and out of the fields of mathematics and economics.

Table 2: Most common preferred and next-best alternative fields of study

Preferred field of study	**Most common next-best**	**2nd most common next-best**
Economics	Humanities (37 %)	Social science (19 %)
Mathematics	Business (37 %)	Health and welfare (23 %)
Next-best field of study	**Most common preferred**	**2nd most common prefered**
Economics	Business (40 %)	Social science (35 %)
Mathematics	Business (34 %)	Social science (31 %)

3.5 Outcomes

The main outcome I study is whether applicants are in financial trouble. As a proxy for this outcome, I use a dummy variable indicating whether the applicants have loan defaults or delinquencies. The dummy is equal to 1 if an individual have a loan default or delinquency in at least one year from eight years after he/she applied for a higher education program for the first time. I measure the outcome 8 years or later after the year-of-application to make sure that most applicants have finished their studies and are in their early labour market career. This of course means that the older year-of-application-cohorts are more likely to experience defaults since I observe them for a longer period. To control for this, I include year-of-application dummies in all estimations.

I also study three potential mechanisms to explain why the applicants get into financial trouble. The first mechanism is the debt-to-income ratio. Due to outliers in both debt and income I average both variables across year 8 to 10 after the year of application before calculating the ratio. Since there is still some extreme observations due to low incomes in the years I observe, I reduce the noise further by calculating the rank of the debt-to-income ratio for each individual within his/her year of application cohort. I focus on financial debt in this paper, since this type of debt is more likely to cause financial trouble compared to for instance mortgage debt.

The second mechanism is the liquid-assets-to-income ratio. I define liquid assets as the sum of market value of stocks, investment units, bonds and mortgage deeds, and the value of bank deposits. I define the ratio in the same way as the debt-to-income ratio and also calculate the within year-of-application cohort rank.

Finally as a third mechanism, I also investigate whether field of study affects early labour market career earned income. This also allows me to compare my results in a Danish context to those of Kirkeboen et al. (2016) in the Norwegian context. For the same reasons as mentioned above I also calculate the average income 8 to 10 years after the year of application and then find the within year-of-application cohort rank for each individual.

Figure 1 shows how the four outcomes differ across the different completed fields of study. Panel 1a shows that on average 4,3 % of the sample at some point 8 years or later after the year-of-application have a loan default. There is some variation across the different completed fields and math graduates have a particularly low probability of default. It is important to stress that this is not a causal effect.

In panel 1b we see the income ranks for the applicants who complete the different fields. Here we see that applicants who complete the business or economics fields of study have the highest incomes 8 to 10 years after the year of application, while graduates from arts and humanities have the lowest.

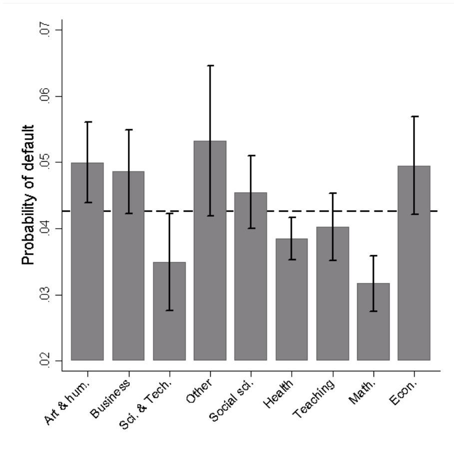
Panel 1c shows how the rank of the debt-to-income ratio varies. Here we also see clear variation between the fields of study. Those who complete the Arts or Humanities programs have a higher debt-to-income ratio. This is probably due to lower income rather than higher absolute debt, based on the evidence from panel 1b.

Finally, panel 1d we see how the liquid-assets-to-income ratio differ across fields. Math, business and economics have the highest ranks even though they also have some of the highest incomes, while Health and welfare and Teaching graduates have the lowest ranks despite having average incomes.

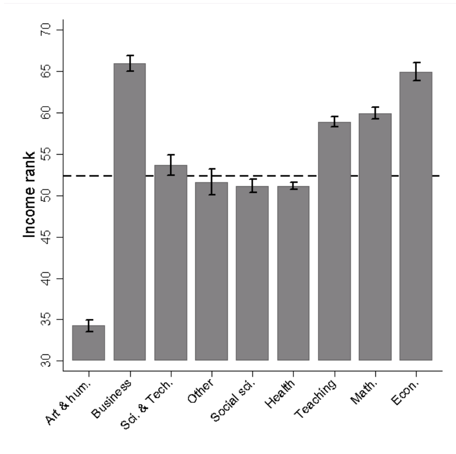
Again, it is important to emphasize that the patterns in figure 1 are only correlations and not causal estimates of the effects of completing the different fields due to the self-selection of students into the different fields. I will discuss this problem in the next section.

Figure 1: Outcomes Across Fields of Study

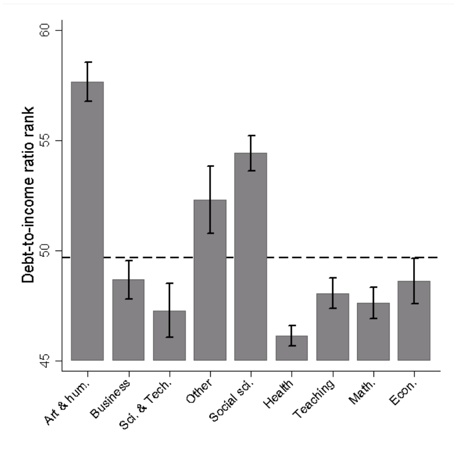
(a) Default and Delinquency



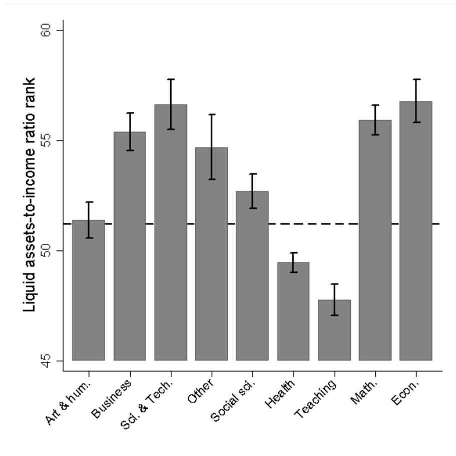
(b) Income



(c) Debt-to-income



(d) Liquid assets-to-income



Probability of default is measured from 8 years after the year of application. The debt-to-income ratio, the liquid assets-to-income ratio and income rank are within application cohort ranks measured 8 to 10 years after the year of application

4 Empirical Analysis

In this section, I will first discuss the problem of self-selection of students into different fields of study for the estimation of the causal effect of completing a particular field. I will then present a graphical illustration of the research design before presenting the main results of the paper and sensitivity analyses.

4.1 Selection problem

In section 3.5 I documented significant correlations between particular fields of study and financial outcomes. These correlations could reflect causal effects of education on financial outcomes, or could be the product of student self-selection.

The selection problem arises because the applicants select which fields of study to apply for. Arguably, the applicants who prefer to study Science differ from the applicants who would prefer to study Humanities. For instance, a factor that potentially can explain both which field of study an applicant prefers and financial outcomes is innate numeracy or numeracy acquired at an earlier educational stage. Higher numeracy would lower the ”cost” of obtaining a degree from a mathematical field of study and possibly also improve financial outcomes.

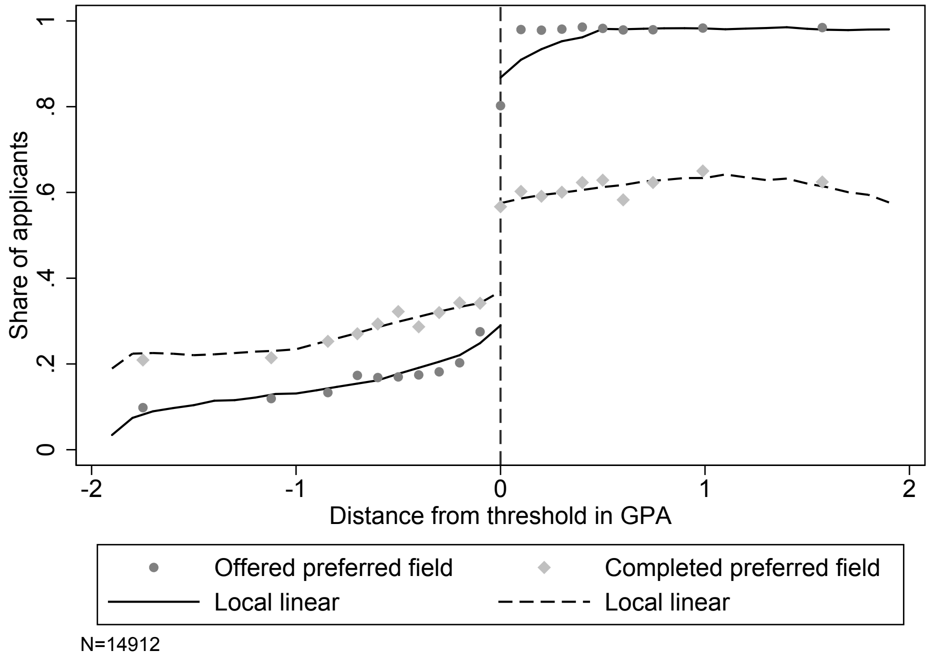
To address this selection problem, I exploit that applicants with the same local course ranking and a GPA close to the admission threshold are effectively randomized into different fields of study. In the next section, I will provide at graphical illustration of the research design applied to identify the causal effects.

4.2 Graphical illustration of research design

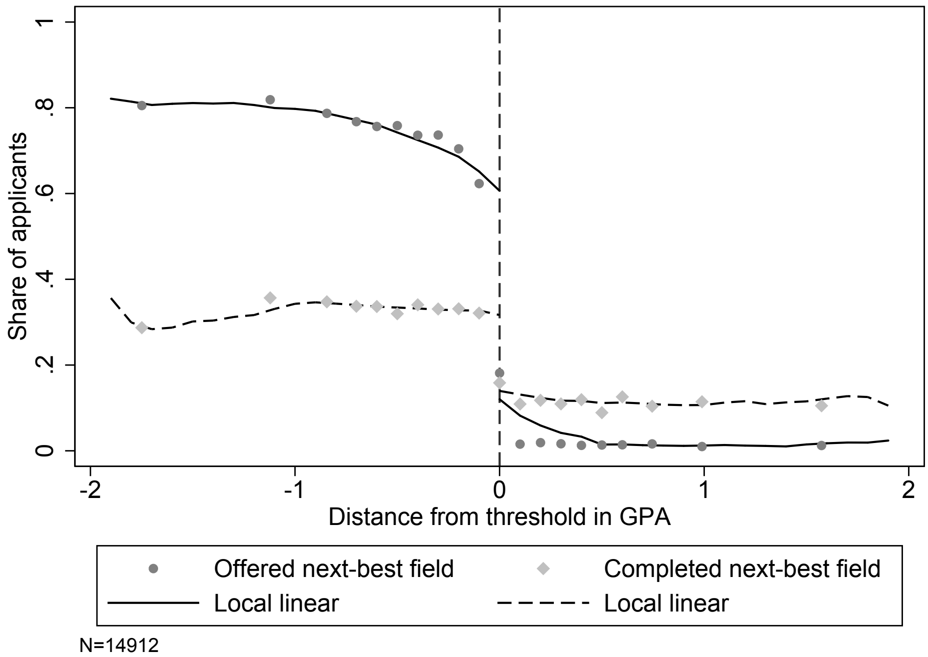
Panel 2a in figure 2 illustrates how an applicants' probability of receiving an offer to enrol in his or her preferred field of study changes around the GPA threshold and also the change in the probability that the applicant completes the preferred field. The figure is constructed by looking at the sample of applicants whose preferred field of studies differ from their next-best alternative field (14.912 applicants). Each bin of the scatter represents approximately 5% of the sample. If we look at the probability of receiving an offer to enrol in the preferred field we see that the probability is not zero if the applicants' GPAs fall below the threshold. As discussed in section 2.1 this is due to the Quota 2 system, where individuals can be admitted to a program even though their GPA is not above the threshold. We also see that the probability of receiving an offer increases with the GPA. This is because the GPA is also taken into account in the Quota 2 system. Above the threshold we see that almost all applicants with a GPA above the threshold receives an offer to enrol. The probability falls around 20 %-points for the applicants who are exactly at the threshold. There are two explanations for this. First, the GPA is mea-

Figure 2: Admission GPA threshold and the applicants' offer and completion rates

(a) Preferred field



(b) Next-best field



Panel (a) shows the share of applicants that where offered their preferred field of study and the share that completed their preferred field of study by distance to the GPA threshold. On each side of the threshold, I plot the means within bins that contain the same number of applicants and the estimated local linear regressions with rectangular kernels and a bandwidth of 0.5. Panel (b) shows the same for the applicants' next-best field.

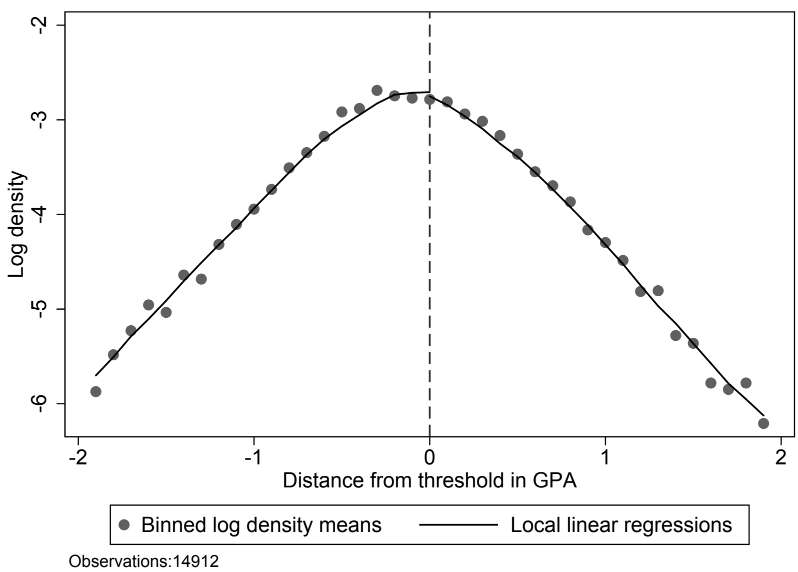
sured with one decimal's precision in the data, but the educational institutions can have more precise information than this. Second, if more than one applicant have a GPA exactly at the threshold, it is decided by lottery who will receive the offer to enrol.

If we look at the probability that an applicant completes his or her preferred field of study we see a similar pattern. Around the threshold we see that the probability of completing a given field of study is slightly increasing with the GPA. At the threshold the probability jumps with approximately 20 %-points, which is very similar to the results of Kirkeboen et al. (2016). The reason why the probability of completing is higher than the probability of receiving an offer for the individuals with a GPA below the threshold is that the students can choose to reapply in the years after their first year of application. For the applicants with a GPA above the threshold the probability of completing the preferred field is less than the probability of receiving an offer because they can drop out or change to a different field.

Panel 2b shows the other side of the story namely the probability of receiving an offer to enrol in and the probability of completing the next-best field. It clearly mirrors panel 2a and also shows a sharp discontinuity in the probability of completing the next-best field at the GPA threshold. We also see the same differences between the probability of completing a field and the probability of receiving an offer to enrol in a field.

Both of these clear discontinuities enables me to study the causal effect of studying a particular field on different outcomes. I can estimate the effect by using whether an individual is above or below the GPA threshold as an instrument for completing the preferred field or next-best alternative in a fuzzy regression discontinuity design.

Figure 3: Bunching check around the GPA threshold



The figure shows the log density of applicants by distance to the GPA threshold. The local linear regressions are estimated on each side of the threshold with a rectangular kernel with a bandwidth of 0.5.

It is important for the validity of the results to examine whether the individuals can manipulate the running variable. In this case, it means I have to examine whether the applicants can sort themselves above the threshold in order to receive an offer to enrol in their preferred field. In figure 3, I plot the log-density of applicants with different preferred and next-best alternative fields around the threshold. I also estimate the distribution using local linear polynomials separately on each side of the threshold and we see absolutely no evidence of sorting. This finding is in accordance with the features of the admission system described in section 2.1, and supports the validity of the research design.

4.3 Results

I will first look at how studying math affects the probability of default, the debt-to-income ratio and liquid asset holding, before I turn to the effect of studying economics on the same outcomes. Finally, I will study how field of study affects income.

4.3.1 Mathematics

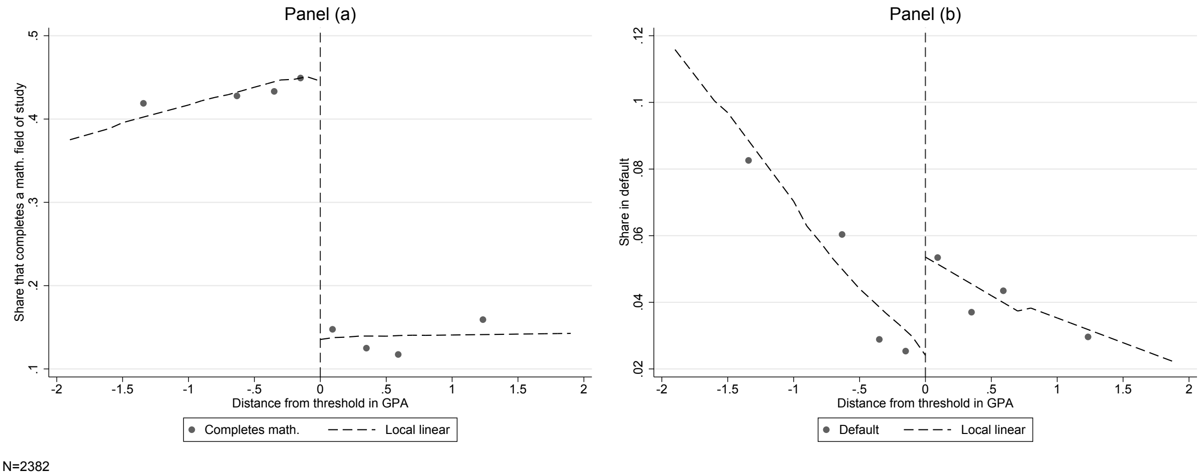
In the left panel of figure 4, we see the first stage similar to figure 2b, but only for applicants who had a mathematical study program as their next-best alternative (2.382 applicants). Again, we see a clear jump at the threshold.

In the right panel, we see how the probability loan default changes with the GPA around the threshold. The applicants to the left of the threshold are more likely to have completed the mathematical field of study, and we see that just around the threshold they are less likely to have loan defaults than the individuals who are offered their preferred field, which is not mathematics.

Table 3 shows the estimates of the first stage, the reduced form and the 2SLS across the three outcomes of interest. This is an estimation of equation (1) and (2), so I control for age, year of application and sex levels.

In the first column we see applicants who would prefer to study math are 27,2 %-points more likely to complete the mathematical field of study if they have a GPA above the threshold. At the same time the probability of default drops with 2,6 %-points at the threshold, which means that the math students are less likely to experience a loan default. Using 2SLS, I estimate the effect of studying math on the probability of default to be -9,6 %-points but the estimate is not significant on the 10 % level. This estimate has a Local Average Treatment Effect interpretation, so it is the causal effect on the compliers - the applicants who only complete a mathematical degree because they were above the threshold. Given that the average probability of experiencing loan default or delinquency is 4,3 % in the sample (see figure 1), the estimated effect on the compliers seems high.

Figure 4: Completion and default for sample w. math. as next-best field



Panel (a) shows the share of applicants with a mathematical field of study as their next-best alternative that completes a mathematical field of study by distance to the GPA threshold. On each side of the threshold, I plot the shares in bins containing the same number of applicants along with local linear regressions with rectangular kernels and a bandwidth of 2. Panel (b) shows the share of the applicants who have been in default on a loan more than 8 years after the year of application.

The second column shows the estimated effect of math for the applicants who have math as their next-best alternative field. As expected based on figure 4 the first stage is very clear, and if an applicant's GPA is above the threshold to the preferred field, which is not math, the probability of completing the mathematics field of study decreases with 31,6 %-points. The estimated reduced form effect is of the same size as for the applicants with math as preferred field, but has the opposite sign, since the applicants who have a GPA above the threshold now are less likely to study math. We also see that the effect is estimated more precisely due to the larger number of observations.

These estimates provide suggestive evidence, that the lower probability of default for math graduates we saw in figure 1, is not only a result of self-selection but also reflects a causal effect.

In column 3 to 6 we see the same estimations for the first two potential mechanisms. We note that the first stages are slightly different from the first stages in column 1 and 2. Since the data used to construct the loan default indicator and the debt and asset ratios come from different sources, there is a small discrepancy in the number of observations, but the differences are small.

For the debt-to-income ratio rank we see that both 2SLS estimates are positive but insignificant. The interpretation is that those who complete the mathematical field have a higher debt-to-income ratio. In figure 1 we saw the math graduates on average have a

Table 3: LATE on outcomes when math. is the preferred field of study or the next-best

	Probability of default		Debt-to-income ratio		Liquid assets-to-income ratio	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
GPA > threshold:	0.273***	-0.316***	0.269***	-0.310***	0.269***	-0.310***
Effect on completion	(0.041)	(0.029)	(0.041)	(0.029)	(0.041)	(0.029)
GPA > threshold:	-0.026	0.027**	0.798	-0.514	-3.902	2.845
Effect on outcome	(0.017)	(0.014)	(2.538)	(1.969)	(2.416)	(1.937)
Local Average	-0.096	-0.085**	2.973	1.658	-14.531	-9.179
Treatment Effect	(0.062)	(0.043)	(9.399)	(6.332)	(9.309)	(6.336)
Observations	1359	2342	1374	2364	1374	2364
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Probability of default is measured from 8 years after the year of application. The debt-to-income ratio and the liquid assets-to-income ratio are within application cohort ranks measured 8 to 10 years after the year of application.

fairly low debt-to-income ratio compared to other graduates. The causal estimates do not support that the correlation is based on a a causal effect of studying math.

Finally, column 5 and 6 show the estimated effect on the liquid-assets-to-income ratio rank. Again, we see that the 2SLS estimates have the same sign but are both insignificant. The estimated effects are negative and large, which indicates that if studying math has an effect it most likely reduces liquid assets relative to income.

To sum up, table 3 shows that completing an education within the mathematical field of study decreases the probability of default without reducing debt or increasing liquid assets relative to income.

4.3.2 Economics

We now turn to the effects of studying economics. Table 4 is similar to table 3 but here we look at applicants who had economics as either preferred or next-best alternative field of study. Firstly, we notice that the sample of applicants is smaller than the sample of math applicants. Particularly, we observe few applicants with economics as preferred field. As seen in figure A3 in the appendix, this leads to a noisy but still significant first stage. Due to the low number of observations, I will focus on the results from the sample of

Table 4: LATE on outcomes when econ. is the preferred field of study or the next-best

	Probability of default		Debt-to-income ratio		Liquid assets-to-income ratio	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
GPA > threshold:	0.280***	-0.320***	0.280***	-0.320***	0.280***	-0.320***
Effect on completion	(0.063)	(0.034)	(0.062)	(0.034)	(0.062)	(0.034)
GPA > threshold:	0.013	0.049***	0.860	1.358	-3.040	0.511
Effect on outcome	(0.026)	(0.018)	(3.881)	(2.269)	(3.883)	(2.221)
Local Average	0.048	-0.152***	3.077	-4.242	-10.873	-1.595
Treatment Effect	(0.091)	(0.059)	(13.733)	(7.048)	(14.218)	(6.917)
Observations	680	1735	684	1738	684	1738
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Probability of default is measured from 8 years after the year of application. The debt-to-income ratio and the liquid assets-to-income ratio are within application cohort ranks measured 8 to 10 years after the year of application.

applicants with economics as next-best alternative field in the local course ranking.

For the loan default outcome we again see a significant and large effect of -15,2 %-points. It should be interpreted as the local average treatment effect with a lower bound in the 95 % confidence interval of 3,6 %. We do not observe the baseline probability of default for the compliers, but it is plausible that it is lower than 15 %.

Looking at column 4 and 6 I do not find evidence that the two mechanisms can explain the effect on the default probability.

4.4 Income

One explanation for the improved debt management could be that math and economics educations lead to higher incomes since Kirkeboen et al. (2016) find different returns to different fields of study.

In figure 1 we saw that individuals who complete the mathematical or economic field of study on average have a high income rank, compared to some of the other fields. Table 5 shows the effect on income of completing the mathematics or economics field of study. The table shows the effect on income and income rank 8 to 10 years after the year-of-application. For the applicant who have these fields as their preferred field there is a positive effect on income, but it is only significant on the 10 % level. On the other hand there is no indication that completing the mathematical or economic fields have any effect on income for the applicants who have them as their next-best alternative. As table 2

Table 5: Income rank and average income

	Income rank		Income (1000 DKK)	
	Pref.	Next-best	Pref.	Next-best
LATE of Math.	14.230*	-2.532	68.383*	5.039
	(7.578)	(5.042)	(40.263)	(26.137)
LATE of Econ.	26.120	-2.090	160.971*	-10.621
	(16.316)	(5.817)	(87.384)	(31.233)
Age and sex dummies	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓
Observations Math.	1352	2408	1352	2408
Outcome avg. Math.	57.483	55.666	295.829	283.761
Obervations Econ.	716	1762	716	1762
Outcome avg Econ.	57.579	61.964	294.620	316.126

Robust SEs in parentheses
Bandwidth=2, Kernel=Rectangular
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Income rank is within application cohort ranks measured 8 to 10 years after the year of application. Income is the average income 8 to 10 years after the year of application.

shows, a large share of these applicants have business, administration and law as their preferred field, and since completing this field on average also leads to a high income, this can explain why we do not see a positive effect on income.

In total, table 5 shows no evidence that the differences in the probability of default are caused by differences in income from completing different fields of study. This suggests that the results in section 4.3 are due to improved debt management for the individuals who complete the mathematics or economics fields even though this was not their preferred field.

4.5 Robustness

In the following section, I will investigate how the estimates are affected if I look at applicants who complete at least one year of study and whether the results are robust to changing the bandwidths in the estimations and the time span in which I measure default.

4.5.1 One year of completed studies

As previously mentioned the estimated local average treatment effects are rather large. One explanation could be that in the first stage the instrument only shifts the probability with around 30 %-points. In order to increase the shift in probability, I use completion of at least one year of study as the explaining variable in table A3 in the appendix and drop applicants who were offered a slot via the Quota 2 system. This increases the probability shift to approximately 50 %-points.

The table shows the estimated effects are similar to the estimated effects in table 3 and 4 despite a the stronger first stage. Thus, the effects of studying math and economics are still large compared to the baseline probability, but again it is important to stress that the estimated effects are local average treatment effects.

4.5.2 Default and delinquency in different periods

In table A4 in the appendix, I estimate the effect of obtaining a math or economics degree on the probability of loan default within a given period at least eight years after application and not across all years observed. I estimate the effect on default 8-12 years after application, 10-12 years after application and 10 years after application.

The results for the mathematical field of study are robust across the different specifications. The results for economics on the other hand are sensitive to the specification.

4.5.3 Different bandwidths

I also investigate whether the results on the effect on loan default are sensitive to the selected bandwidth of 2 in table 3 and 4. Table A5 in the appendix shows the estimated effects for different bandwidths. I show the effects using no bandwidth, a bandwidth of 1 and a band width of 0.5.

The table shows that the choice of bandwidth is not driving the results, but limiting the bandwidth to 0.5 means that I loose power and therefore these results are also less significant.

5 Conclusion

This paper contributes to the scarce evidence on the causal effect of education on financial outcomes and it is the first to investigate how field of study in higher education affects financial outcomes.

Using a fuzzy regression discontinuity design, I estimate the effect of completing the mathematical or economic fields of study. I exploit that the admission system to higher education in Denmark creates GPA admission thresholds that effectively randomize the applicants into different fields of study.

First, I show that being above the admission threshold significantly increases the probability that the applicant completes his or her preferred field of study and being below the threshold increases the probability that the applicant completes his or her next-best alternative field.

Second, I use 2SLS estimation to estimate the effect of completing a mathematical or economic field of study on financial outcomes. I find that completing the mathematical or economics field of study significantly decreases the probability of loan default for the applicants who have the mathematics or economics fields of study as their next-best alternative.

I do not find any effect of field of study on the debt-to-income ratio, the liquid-assets-to-income ratio or income for the applicants who have mathematics and economics as their next-best alternative fields.

These findings suggest that the mechanisms behind the lower probability of default are not less debt, a smaller degree of liquidity constraint, or higher income. An explanation could be, that learning about economics or being better at math simply makes individuals better at managing and servicing their debt.

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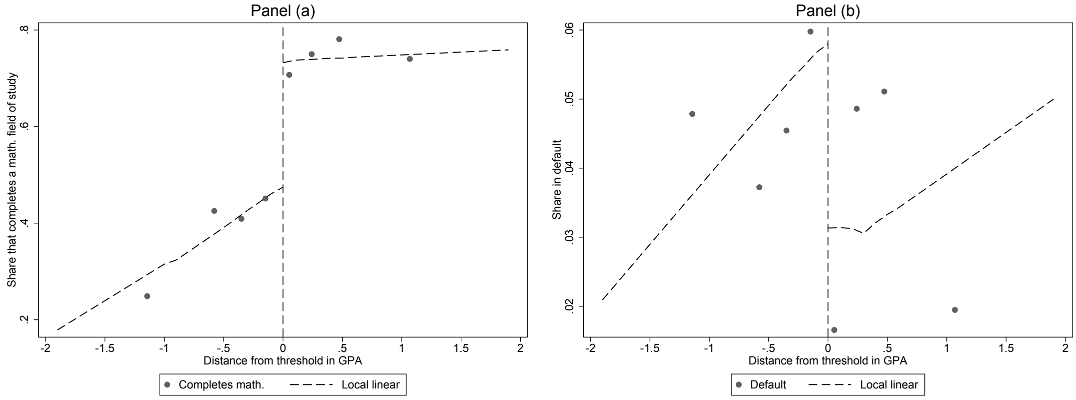
Appendix

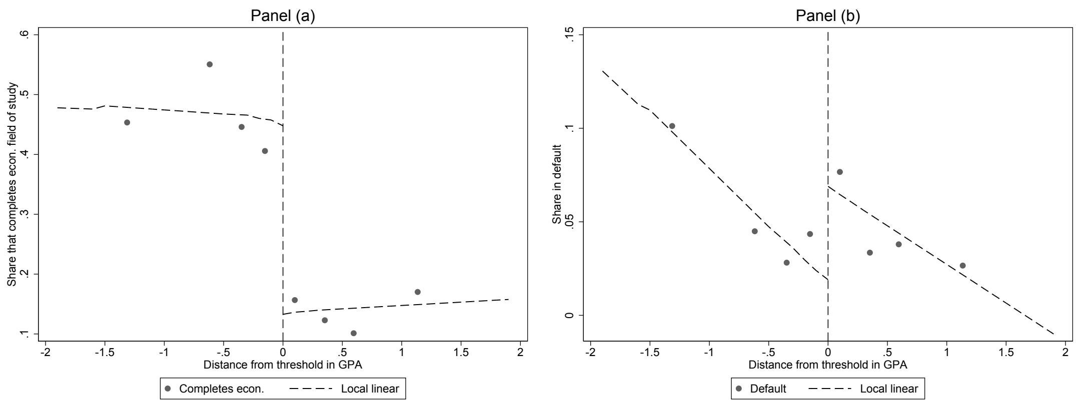
Figure A1: Completion and default for sample w. math. as preferred field



N=1373

Panel (a) shows the share of applicants with a mathematical field of study as their preferred choice that completes a mathematical field of study by distance to the GPA threshold. On each side of the threshold, I plot the shares in bins containing the same number of applicants along with local linear regressions with rectangular kernels and a bandwidth of 2. Panel (b) shows the share of the applicants who have been in default on a loan more than 8 years after the year of application.

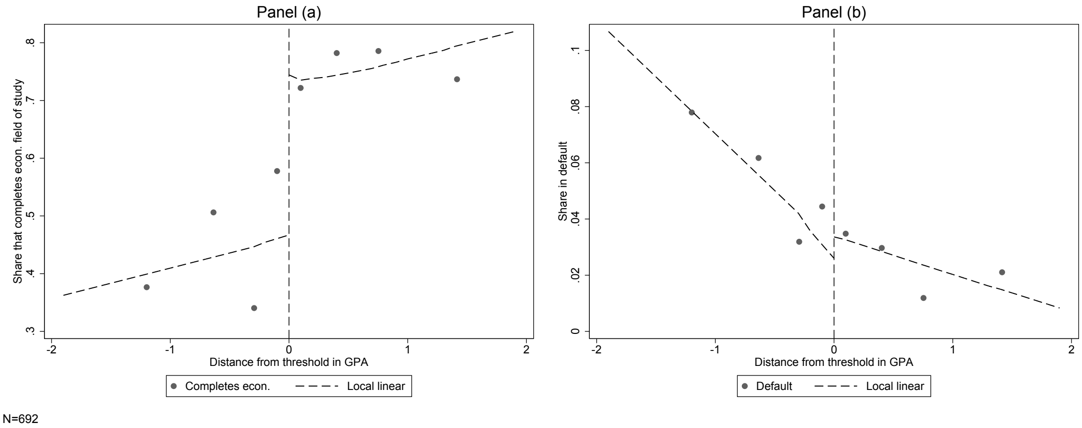
Figure A2: Completion and default for sample w. econ. as next-best field



N=1759

Panel (a) shows the share of applicants with an economic field of study as their next-best alternative that completes an economic field of study by distance to the GPA threshold. On each side of the threshold, I plot the shares in bins containing the same number of applicants along with local linear regressions with rectangular kernels and a bandwidth of 2. Panel (b) shows the share of the applicants who have been in default on a loan more than 8 years after the year of application.

Figure A3: Completion and default for sample w. econ. as preferred field



Panel (a) shows the share of applicants with an economic field of study as their preferred choice that completes an economic field of study by distance to the GPA threshold. On each side of the threshold, I plot the shares in bins containing the same number of applicants along with local linear regressions with rectangular kernels and a bandwidth of 2. Panel (b) shows the share of the applicants who have been in default on a loan more than 8 years after the year of application.

Table A1: LATE on Debt to income ratio rank with different bandwidths

	No Bandwidth		Bandwidth = 1		Bandwidth = 0.5	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
LATE of Math.	2.012	3.538	10.478	0.936	8.797	-1.768
	(8.729)	(5.854)	(12.675)	(8.074)	(19.308)	(11.251)
LATE of Econ.	4.638	-2.144	-0.953	-11.935	-14.930	-3.556
	(13.815)	(6.586)	(18.402)	(11.040)	(28.891)	(17.420)
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓
Observations Math.	1387	2404	1227	2016	893	1383
Observations Econ.	696	1762	575	1510	379	1056

Robust SEs in parentheses

Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The debt-to-income ratio is within application cohort ranks measured 8 to 10 years after the year of application.

Table A2: LATE on Liquid assets to income ratio rank with different bandwidths

	No Bandwidth		Bandwidth = 1		Bandwidth = 0.5	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
LATE of Math.	-11.487	-9.691*	-18.227	-5.015	-42.931*	-2.448
	(8.515)	(5.786)	(12.609)	(7.928)	(22.905)	(10.924)
LATE of Econ.	-13.872	-0.994	-15.385	6.104	-54.744	-5.573
	(14.754)	(6.380)	(19.188)	(10.726)	(38.402)	(17.169)
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓
Observations Math.	1387	2404	1227	2016	893	1383
Observations Econ.	696	1762	575	1510	379	1056

Robust SEs in parentheses

Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The liquid assets-to-income ratio is within application cohort ranks measured 8 to 10 years after the year of application.

Table A3: Local average treatment effect using only one year of study as treatment

	Probability of default		Debt-to-income ratio		Liquid assets-to-income ratio	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
LATE of Math.	-0.083**	-0.091***	-1.444	1.189	-9.300*	-1.107
	(0.036)	(0.029)	(5.326)	(3.952)	(5.033)	(3.975)
LATE of Econ.	0.038	-0.123***	-1.946	-3.103	-3.496	4.492
	(0.077)	(0.037)	(9.710)	(4.328)	(9.281)	(4.245)
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓
Observations Math.	1182	2147	1197	2167	1197	2167
Observations Econ.	613	1596	615	1597	615	1597

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Probability of default is measured from 8 years after the year of application. The debt-to-income ratio and the liquid assets-to-income ratio are within application cohort ranks measured 8 to 10 years after the year of application.

Table A4: LATE on probability of default in different periods after year of application

	8-12 yrs. after		8-10 yrs. after		10 yrs. after	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
LATE of Math.	-0.116***	-0.054**	-0.057**	-0.036*	-0.036	-0.038**
	(0.041)	(0.025)	(0.028)	(0.020)	(0.022)	(0.018)
LATE of Econ.	0.040	-0.049	-0.002	-0.005	-0.018	-0.008
	(0.064)	(0.035)	(0.054)	(0.030)	(0.048)	(0.026)
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓
Observations Math.	1356	2312	1333	2263	1299	2191
Avg. default rate Math.	0.021	0.027	0.010	0.018	0.009	0.014
Observations Econ.	670	1716	660	1689	646	1637
Avg. default rate Econ.	0.027	0.027	0.018	0.019	0.015	0.014

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: LATE on probability of default with different bandwidths

	No Bandwidth		Bandwidth = 1		Bandwidth = 0.5	
	Pref.	Next-best	Pref.	Next-best	Pref.	Next-best
LATE of Math.	-0.116*	-0.097**	-0.079	-0.099*	-0.215	-0.167**
	(0.059)	(0.044)	(0.083)	(0.054)	(0.143)	(0.081)
LATE of Econ.	0.036	-0.149***	0.055	-0.174*	0.107	-0.200
	(0.090)	(0.055)	(0.121)	(0.090)	(0.210)	(0.149)
Age and sex dummies	✓	✓	✓	✓	✓	✓
Yr. of appl. dummies	✓	✓	✓	✓	✓	✓
Observations Math.	1375	2381	1217	1996	886	1369
Avg. default rate Math.	0.053	0.064	0.053	0.064	0.053	0.064
Observations Econ.	692	1759	574	1504	382	1052
Avg. default rate Econ.	0.057	0.063	0.057	0.063	0.057	0.063

Robust SEs in parentheses

Kernel=Rectangular

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Probability of default is measured from 8 years after the year of application.