Higher Education and Financial Behavior

The effect of studying mathematics and economics on debt behavior

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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 probability of having a loan default or delinquency, their debt-to-income ratio and their holding of liquid assets relative to their income. By combining data on admissions to post-secondary education with data on the universe of personal loans and demographic variables, I create a unique dataset, which makes it possible to identify the causal effects of different types of education on financial behavior using a fuzzy regression discontinuity design. I find that graduating from a mathematical or economic field of study decreases the probability of having a loan default or delinquency post graduation for the applicants who did not have one of these fields as their preferred field of study.

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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-in formed financial decisions it is often suggested to raise individuals' financial literacy through financial education.

This paper presents evidence on the causal effect of choice of higher education on financial outcomes. In particular, I investigate whether obtaining a degree from a study program with a mathematical or economic curriculum affects individuals' future probability of having a loan default or delinquency, their debt-to-income ratio and their holding of liquid assets relative to their income.

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. In order to identify the effect of field of study on debt 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 cut-off of 11.0. Luckily for Auguste he has a GPA of 11.1 from upper secondary school so he is offered a slot at sociology. Adam on the other hand has a GPA of 10.9 and therefore he is not offered a slot at sociology. Instead, he is offered a slot at his next-best alternative, economics, where the admission threshold is only 7.0.

I combine administrative third party reported data on applications and admissions to post-secondary education with data on GPA from upper secondary school and use being above or below the admission cut-off as an instrument for completing a particular field of study in the same way as Kirkeboen et al. (2016). I link this data with administrative data from The Danish Tax Authorities on the universe of personal loans to study the applicants debt behavior post graduation. Finally I also add administrative from Statistics Denmark on income and several demographic variables.

The main contribution of this paper is that it is the first to study how different higher education fields of study affect the students' debt behavior post graduation. Furthermore, the paper contributes to the very limited literature on the causal evidence of the effect of financial education on financial behaviour.

Firstly, I find that being above the GPA admission threshold significantly increases the probability that an applicant obtains a degree from his or her preferred field of study. Similarly, I find that being below the GPA admission threshold for the preferred field of study significantly increases the probability that an applicant obtains a degree from his or her next-best alternative field of study. These first stage results show, that I can use being above or below the threshold as an instrument for completing a certain field of study for those 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 graduating from a study program with a mathematical or economical curriculum. Here math covers several STEM educations and economics also include for instance several business majors. I find that applicants who have math or economics as their next-best alternative have a significantly smaller probability of having a loan default or delinquency post graduation if they obtain a degree from a math or economic study program. I estimate the local average treatment effects to be -8,5 %-points for graduating from a mathematical program and -15,2 %-points for graduating from economics. This effect on the compliers is very large given the baseline probability of default is 4,3 %. The estimated effect of graduating from a mathematical education is robust to different specifications, whereas the result for economic graduates are somewhat more sensitive.

Finally, I also present suggestive evidence that the estimated effects are not driven by smaller debt relative to income or a lesser degree of liquidity constraint for the individuals who obtain a math or economics degree. Furthermore, I do not find an income premium for graduating from these fields for applicants who have them as their next-best alternative. This suggests that income cannot explain the differences in probability of having a loan default or delinquency post graduation. These results indicate that studying especially math makes individuals capable of 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 in the literature (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. 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,this paper is the first to provide causal evidence on the effect of field of study and coursework in the post-secondary education system on debt behavior.

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 background and the admission process to higher education in Denmark. It also outlines the econometric methodology for identifying the effect of completing different fields of study on financial outcomes. Section 3 presents the data used for the empirical analysis which is found 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 programmes normally requires an Upper Secondary School Leaving Certificate and the admission process is administered by Coordinated Admission (KOT) under the Ministry of Higher Education and Science. The applicants can apply for and rank up to eight programmes and each program is a combination of detailed subject of study and educational institution.

Admission to these programmes 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 programmes 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 a slot 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 cut-offs which effectively shifts the probability of being admitted to 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 programme through Quota 1.

Finally, each program can have individual requirements, that the applicants are required to meet in order to get admitted. For instance, to get admitted to the economics program at the University of Copenhagen, the applicant must have studied mathematics on the highest upper secondary school level[1].

2.2 Fuzzy Regression Discontinuity Design

The Danish Quota 1 admission system and the application process generate local course rankings for the applicants with binding GPA cut-offs similar to those in the Norwegian system used by Kirkeboen et al. (2016). In the local course ranking the applicant has a preferred field of study and a next-best alternative. Whether or not the applicant is above the GPA threshold for the preferred study programme determines if the applicant will be admitted to his or her preferred programme or the next-best alternative.

A priori we would expect that being admitted to a certain study programme should increase the probability that an applicant obtains a degree from the given programme. As shown below, this is indeed the case and therefore crossing the threshold to a field of study can be used as an instrument for completing the same field of study in a fuzzy regression discontinuity design.

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

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

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

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

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 will be very flexible since I allow for different effects of the running variable of each side of the threshold. If the sample is further restricted to individuals who are within a narrow bandwidth close to the threshold it will be equivalent of a non-parametric fuzzy regression discontinuity with local linear polynomials on each side of the threshold using a rectangular kernel.

Finally, I add age, year of application and sex controls, X_i. Thereby, I allow for different levels, but restrict the slope on each side of the threshold and the jump 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 KOT I have all applications for higher education programmes in Denmark from 1993 to 2016. For each year and each applicant I have information on their applications to different programmes and how they rank their choices. From KOT I have also have information on the GPA threshold for each study program in the same period.

Statistics Denmark (DST) have several registers with information on income, assets, education and demographic variables for the Danish population and also a link between parents and children such that I have information on parental background as well. The data exists from 1986 to 2013. From these registers I obtain the applicants' GPAs from upper secondary school, current educational programs as well as completed educational program.

No direct link exists between the programmes in the KOT data and the educational data from DST. 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 of the financial behaviour I investigate in this paper. Each loan can be linked to an individual through a unique personal identifier, and therefore I can create an indicator of whether individuals are in financial trouble at a given point in time after they have finished their education.

3.2 Sample Selection

I study individuals who applied for a higher education programme between 1993 and 2004. For the oldest cohort I have loan information from 10 years after their year of application and for the youngest cohort I have data from DST until 9 years after their year of application. In this period I observe 1.363.078 applications from 709.667 individuals. I focus on first time applicants. This means that I drop applications if I observe the applicant in a previous year, if the applicant obtained a higher education prior to the year of application or was enrolled in a higher education program before the first year of application I observe in the KOT data. I also drop applicant who are more than 30 years old. This leaves me with 381.264 first time applicants.

Furthermore, some individuals have an imperfect ranking of their choices, and some individuals only apply for programmes that have a special admission system. Leaving these individuals out of the sample leaves 299.316 individuals. I also leave out individuals who only apply for one program. After this restriction the sample consists of 180.772 individuals.

In the educational data from DST, the upper secondary school GPA is only recorded for some types of upper secondary schools. Restricting the sample to individuals with a known GPA reduces the sample to 135.867 individuals.

Finally, I restrict the sample to individuals with a binding GPA cut-off in their local course ranking. For applicants with two binding cut-offs I keep the first cut-off. 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. I use the DISCED[2] classifications to divide field of study into 9 groups:

- Business, Administration and Law
- Humanities
- Arts
- Natural Sciences
- Social Sciences
- Health and Welfare
- Education
- Engineering and Technology (2 groups)
- Other (7 groups)

[2] A version of ISCED adapted for the Danish educational system

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

In order to characterize whether programmes have a mathematical content I look at the educational background of the students starting at a certain programme. 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 programme had studied in the mathematical track, I characterize the programme as having a mathematical content. For some programmes 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 we 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: Summary Statistics

	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

3.5 Outcomes

In this paper, I focus on three outcomes related to financial behaviour. The first is whether individuals are able to meet their financial obligations. I quantify this outcome by looking at a dummy variable indicating whether individuals have loan defaults or delinquencies or not. 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 programme for the first time. I measure the outcome 8 years or later after the year of application (YOA) to make sure that most students have finished their studies and are in their early labour market career. This of course means that the older YOA cohorts are more likely to experience defaults or delinquencies since I observe them for a longer period. To control for this I include YOA dummies in all estimations and also consider what happens if I restrict observations to 8-10 or 8-12 years after the YOA.

The second outcome 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 YOA cohort. I focus on financial debt[3] in this paper, since this type of debt is more likely to cause financial trouble compared to for instance mortgage debt.

The third outcome 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[4]. I define the ratio in the same way as the debt-to-income ratio and also calculate the within year of application cohort rank.

Furthermore, I also investigate whether field of study affects early labour market career earned income[5]. I do this in order to examine whether differences in income can explain my results for the three financial behaviour outcomes, and this also makes it possible 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 YOA and then find the within YOA cohort rank for each individual.

Table 2 shows how the four outcomes differ across the different fields of study. I have grouped some of the fields to get more precise estimates. The four columns are created by regressing the four outcomes on dummy variables indicating completed field of study (leaving out the dummy for Health and welfare educations), and also YOA dummies, age group dummies and a sex dummy.

The first column shows that on average 4,3 % of the sample at some

[3] bankgaeld
[4] kursakt, oblakt, pantakt and bankakt
[5] ERHVERSINDK_13

point 8 years or later after their YOA have a loan default or delinquency. There does not seem to be much variation across the different completed fields of study except for math. The probability of being in default is 1,6 %-points lower for the individuals who have completed an education with a mathematical content. This difference is significant and is a decrease of more than one third. It is of course important to stress that this is not a causal effect. We also see that the individuals who complete an education in the category "Other" have a higher probability of experiencing default or delinquency. Since this group consist of very different study programmes I will not discuss this group further.

The second column shows how the rank of the debt-to-income ratio varies across fields of study compared to the Health and welfare field of study. Here we see more pronounced differences between the fields of study. Those who complete the Arts or Humanities programmes have a higher debt-to-income ratio. This is probably due to lower income rather than higher absolute debt, based on the evidence from column four. The math graduates on average have a debt-to-income ratio very similar to the Health and Welfare graduates, but from the table we see that this is lower than all the other fields except for economics graduates who have the lowest debt-to-income ratio rank.

In the third column we see how the liquid-assets-to-income ratio differ across fields. The graduates from math and business have the highest ranks even though they also have the highest incomes, while Health and welfare and Teaching graduates have the lowest ranks. The rest of the fields have very similar ranks based on this evidence.

Finally, in the fourth column we see the income ranks for the applicants who complete the different fields. As already noted, math and business graduates have the highest incomes 8 to 10 years after the YOA, while graduates from arts and humanities have the lowest. One thing to notice is that the graduates from the Science field and Technology and engineering have surprisingly low income ranks. This is because a lot of programs from these fields are also characterized as mathematical programs. Therefore, the table shows the average income rank of graduates from science fields that are not characterized as mathematical cf. section 3.3.

Table 2: Outcomes across fields of study

	Default	Debt	Liq.ass.	Income
Art & hum.	0.007	12.053	3.049	-17.503
	(0.004)	(0.515)	(0.491)	(0.425)
Business	0.004	4.834	5.079	12.942
	(0.005)	(0.727)	(0.723)	(0.740)
Sci. & Tech.	0.005	1.560	3.703	-8.684
	(0.005)	(0.737)	(0.702)	(0.759)
Social sci.	0.003	8.671	3.977	-1.806
	(0.003)	(0.485)	(0.471)	(0.461)
Other	0.017	5.926	3.658	-6.176
	(0.006)	(0.815)	(0.789)	(0.813)
Teaching	-0.004	1.636	-0.163	8.297
	(0.003)	(0.441)	(0.440)	(0.366)
Math.	-0.016	0.906	5.151	10.313
	(0.003)	(0.499)	(0.489)	(0.505)
Econ.	0.006	-2.054	2.466	-1.809
	(0.006)	(0.781)	(0.764)	(0.819)
Observations	37993	38338	38338	38440
Average	0.043	49.651	51.212	52.289
YOA, age, sex	Yes	Yes	Yes	Yes

Robust SEs in parentheses

Baseline edu. is Health & welfare

Again, it is important to emphasize that the estimates in table 2 are only correlations and not causal estimates of the effects of graduating from different fields due to the self-selection of students into the different programs. I will discuss this problem in the next section

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 graduating from a particular field on financial outcomes. 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.

The perfect experiment to estimate the causal effect of field of study on financial outcomes would be to randomize all applicants into different fields and then study financial outcomes post graduation. It is evidently not possible to perform this experiment. As described previously a feasible way to proceed is to 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 effect of studying mathematics or economics on financial outcomes.

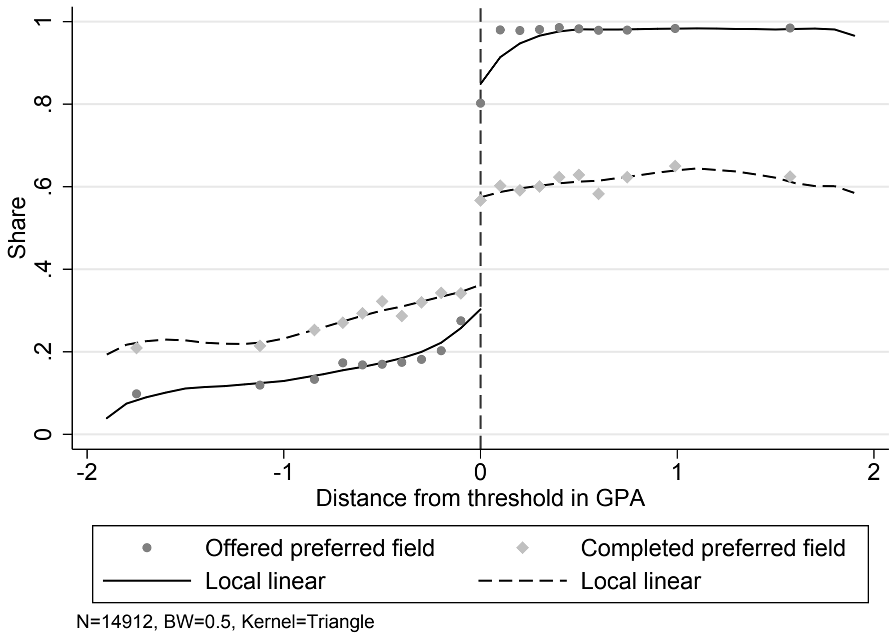
4.2 Graphical illustration of research design

Panel 1a in figure 1 illustrates how an applicants' probability of receiving an offer to enrol in his or her preferred programme changes around the GPA threshold and also the change in the probability that the applicant graduates with a degree from 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 first look at the probability of being offered 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 programme 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 are offered to enrol. The probability falls around 20 %-points for the applicants who are exactly at the cut-off. There are two explanations for this. First, the GPA is measured 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.

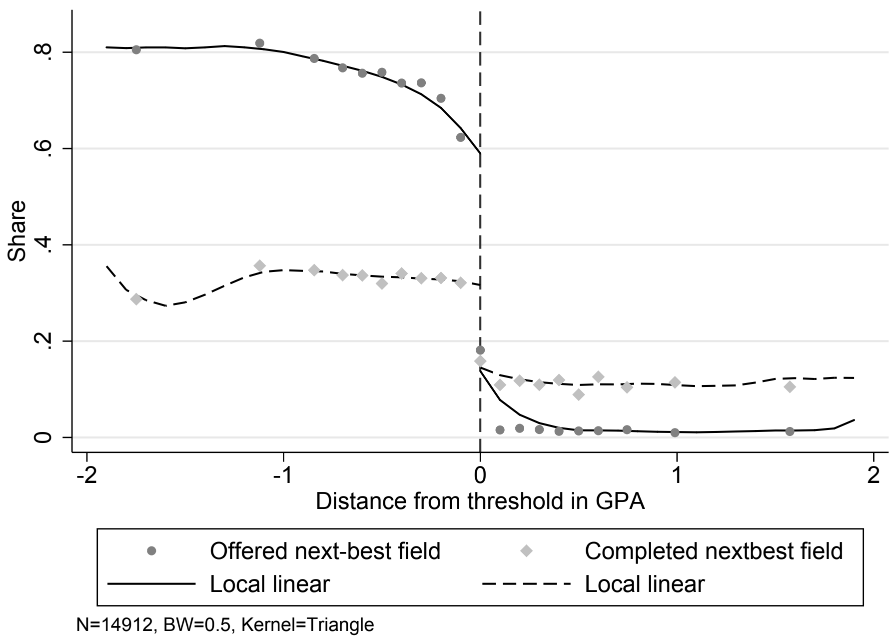
If we look at the probability that an applicant completes his or her preferred field of study we see a similar pattern. Around the threshold we see that the probability of completing a given field of study is slightly increasing with the GPA. At the cutoff the probability jumps with approximately 20 %-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 YOA. For the individuals with a GPA above the threshold the probability of completing the preferred field is less than the probability of receiving an offer. The explanation is that not all students who start at a certain programme completes it

Figure 1: Offered and completed field of study

(a) Preferred field



(b) Nex-best field

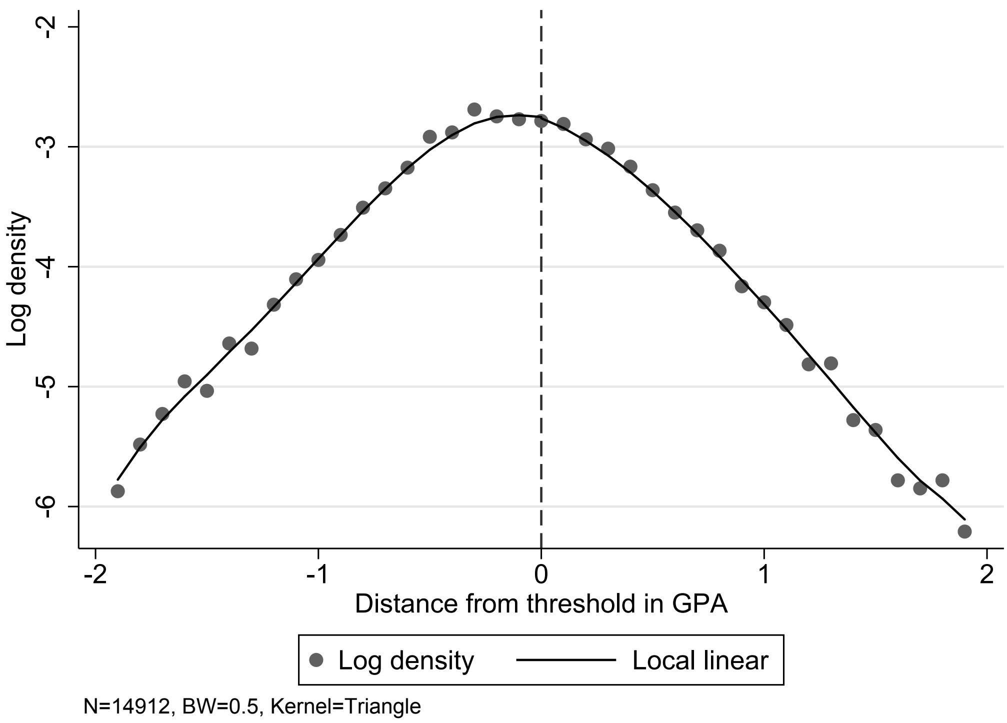


either because they drop out or because the change to a different program.

Panel 1b represents 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 1a and also shows a sharp discontinuity in the probability of obtaining a degree from 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 programme.

Both of these clear discontinuities in the probability of completing a given field of study 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 cut-off as an instrument for obtaining a degree from the preferred field or next-best alternative in a fuzzy regression discontinuity design.

Figure 2: Bunching check around the GPA threshold



It is important for the validity of the results to examine whether the individuals can manipulate the running variable. In this case it means that I have to examine whether the applicants can sort themselves above the cut-off in order to receive an offer to enrol in their preferred field. In figure 2, 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 for estimating how education affects financial behaviour.

4.3 Results

I will first look at how studying math affects the different outcomes, before I turn to the effect of studying economics.

4.3.1 Mathematics

In the left panel of figure 3 we see the first stage similar to figure 1b, but only for applicants who had a mathematical study programme as their next-best alternative (2.381 applicants). Again, we see that if applicants pass the threshold to their preferred field, the probability of obtaining a math degree sharply decreases with approximately 30 %-points. Each bin in the figures represents around 12,5 % of the sample.

In the right panel we see how the probability of having a loan default or delinquency changes with the GPA around the cut-off for applicants who have math as their next-best alternative field. The individuals to the left of the threshold are more likely to have completed an mathematical study programme, and we clearly see that just around the cut-off they are less likely to have loan defaults or delinquencies than the individuals who are offered their preferred field, which is not mathematical.

Figure 3: Completion and default for sample w. math. as next-best field

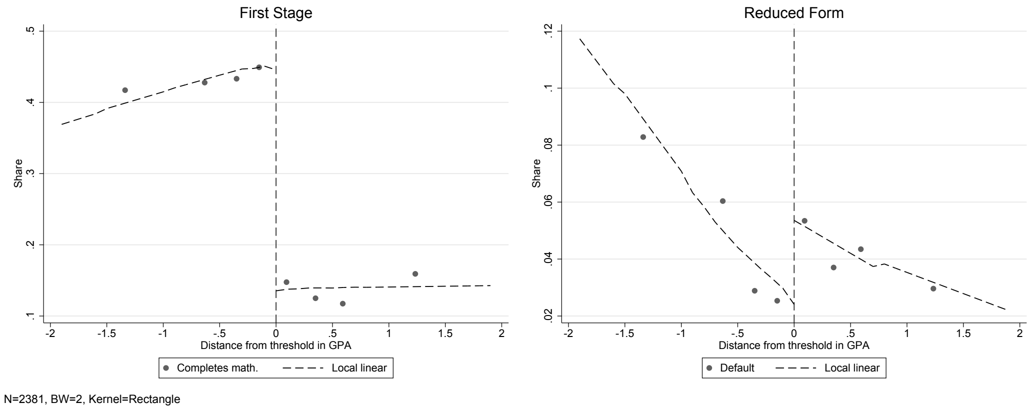


Table 3 shows the estimates of the first stage, the reduced form and the 2SLS across the three outcomes of interest. This is an estimation of equation (1) and (2), so I control for age, YOA and sex levels. In the first column we see that individuals who would prefer to study math are 27,2 %-points more likely to obtain a degree from a mathematical programme if they pass the admission threshold. At the same time the probability of having loan default or delinquency drops with 2,6 %-points at the threshold, which means that the math students are less likely to experience a loan default or delinquency later in life. 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 LATE interpretation, so it is the causal effect on the compliers - the applicants who only obtains 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 table 2), the estimated effect seems rather high.

The second column shows the estimated effect of studying math for the applicants who have math as their next-best alternative field. As expected based on figure 3 the first stage is very clear, and if an applicant crosses the threshold to the preferred field, which is not math, the probability of obtaining a math degree 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 defaults and delinquencies for math graduates, which we saw in table 2, is not merely a result of self-selection of students, but is also an indication of a causal effect of studying math on the capability of managing and servicing debt.

Table 3: Outcomes - Math

	Default		Debt		Liq.ass.	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
First Stage	0.273***	-0.316***	0.269***	-0.310***	0.269***	-0.310***
	(0.041)	(0.029)	(0.041)	(0.029)	(0.041)	(0.029)
Reduced Form	-0.026	0.027**	0.798	-0.514	-3.902	2.845
	(0.017)	(0.014)	(2.538)	(1.969)	(2.416)	(1.937)
Local Wald	-0.096	-0.085**	2.973	1.658	-14.531	-9.179
	(0.062)	(0.043)	(9.399)	(6.332)	(9.309)	(6.336)
Observations	1359	2342	1374	2364	1374	2364
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

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

In column 3 to 6 we see the same estimations for the other two outcomes, namely the debt-to-income ratio rank and the liquid-assets-to-income ratio rank. We note that the first stages are slightly different from the first stges in column 1 and 2. Since the data used to construct the loan default and delinquency 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 very small.

For the debt-to-income ratio rank we see that both 2SLS estimates are positive but insignificant. The interpretation is that those who obtain a math degree have a higher debt-to-income ratio. In table 2 we saw that the math graduates on average have a fairly low debt-to-income ratio compared to other graduates. The 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 of graduating from a mathematical education 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 a mathematical study programme decreases the probability of having a loan default or delinquency without reducing debt or increasing liquid assets relative to income. These results raise the question of what mechanism lies behind the improved credit management when it does not seem to be either lower debt or lesser degree risk of liquidity constraint.

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 their 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 do not observe a lot of applicants in the sample who have economics as their preferred field and a different field as their next-best alternative. As seen in figure A3 in the appendix this leads to a noisy first stage, which non the less is still very significant with a bandwidth of 2 as seen from table 4. Due to the low number of observations I will focus on the results from the sample with applicant who have economics as their alternative field in the local course ranking.

For the loan default and delinquency outcome we again see a significant and very large effect. As can be seen from figure A2 this sample has a larger probability of experiencing default or delinquency than the entire sample, so this can partly justify the large estimate. Furthermore, it is imprecisely estimated with a lower bound in the 95 % conficence interval of 3,6 %. Also, it should be interpreted as the local average treatment effect on the applicants who only obtain a economics degree because they did not have a GPA that was enough to get into their preferred field of study, and we do not observe their baseline probability of default, even though this it is plausible that it is lower than 15 %.

Looking at column 4 we see that studying economics has a negative effect on the relative debt. This in line with the correlation in table 2, but the effect is not significant meaning that we cannot reject that what we see in table 2 is merely a result of for instance self-selection. Finally, in column 6 we see a small, negative estimated effect, which is not significant and measured with substantial imprecision.

Table 4: Outcomes - Econ

	Default		Debt		Liq.ass.	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
First Stage	0.280***	-0.320***	0.280***	-0.320***	0.280***	-0.320***
	(0.063)	(0.034)	(0.062)	(0.034)	(0.062)	(0.034)
Reduced Form	0.013	0.049***	0.860	1.358	-3.040	0.511
	(0.026)	(0.018)	(3.881)	(2.269)	(3.883)	(2.221)
Local Wald	0.048	-0.152***	3.077	-4.242	-10.873	-1.595
	(0.091)	(0.059)	(13.733)	(7.048)	(14.218)	(6.917)
Observations	680	1735	684	1738	684	1738
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

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

4.4 Robustness

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

4.4.1 One year of completed studies

As previously mentioned the estimated 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 probability shift in the first stage I use completion of at least one year of study as the explaining variable in table 5 and drop applicants who were offered a slot via the Quota 2 system. This increases the probability shift to approximately 50 %-points. I measure completion of at least one year of study, by investigating whether the applicants are still enrolled in a program within the same field of study approximately 15 months after they started.

From the table we see that the estimated effect of studying math for at least one year on the subsequent probability of having a loan default or delinquency is similar to the estimated effects in table 3. The larger shift in the first stage has not altered this, but the effects are estimated more precisely, and here the effect of studying math, when math was the preferred field is also significant on the 5 % level. The effects on the other outcomes are smaller in absolute terms, and the improved precision also suggests that individuals who study math for at least one year have less liquid assets relative to their income.

The picture is the same for economics students. All but one of the estimates are numerically smaller than in table 4 but the estimated effect on the probability of default and delinquency is still quite large and very significant. Thus, the effects of studying math and economics are still very large compared to the baseline probability, but again it is important to stress that the estimated effects are local average treatment effects.

Table 5: One year of study

	Default		Debt		Liq.ass.	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
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)
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)
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes
N Math.	1182	2147	1197	2167	1197	2167
N Econ.	613	1596	615	1597	615	1597

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

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

4.4.2 Default and delinquency in different periods

In the previous tables the default and delinquency outcome was an indicator for whether each individual at some point more than seven years after they applied for a higher education for the first time had either a loan default or delinquency. This of course means that I observe the older cohorts for a longer period and therefore the probability that I observe them with a default or delinquency increases. I have controlled for YOA in the all the previous results, but it is important to investigate whether the specification of the outcome is driving the results.

In table 6, I estimate the effect of obtaining a math or economics degree separately on the probability of having a loan default or delinquency within a given period. In the first two columns we see the effect on default and delinquency over a 5 year period, namely 8 to 12 years after YOA. For the cohort of 1993 applicants I observe defaults over a three year period (10 to 12 years after) and for the cohort of 2004 applicants I observe four years (8 to 11 years after). Compared to table 3 we see that the estimates have changed slightly and the standard errors are smaller. For the sample with math as their alternative field the estimate is still significant and in this specification

Table 6: Default and delinquency in different periods after YOA

	8-12 y.a.		8-10 y.a.		10 y.a.	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
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)
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)
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes
Math. N	1356	2312	1333	2263	1299	2191
Math. Avg.	0.021	0.027	0.010	0.018	0.009	0.014
Econ. N	670	1716	660	1689	646	1637
Econ. Avg.	0.027	0.027	0.018	0.019	0.015	0.014

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

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

the effect is also statistically significant for the group with math as their preferred field.

For the applicants with economics as their preferred field the estimate is very similar to the estimate in table 4 but still insignificant. For the applicants with economics as their alternative field the estimated effect is approximately one third of the effect estimated in table 4 and it goes from being significant on the 1 % level to not being significant on the 10 % level. There is a small difference in the number of observations in the two estimations, but this is not causing the difference in the estimated effects. This clearly shows that the estimates for economics graduates are very sensitive to the specification of this outcome.

The remaining columns show the estimated effect if I observe loan defaults and delinquencies over a shorter period of respective 3 years or in one year. We see that completing a math programme decreases the probability of default and delinquency and has a significant effect in 3 of the 4 estimations, which indicates that this result is fairly robust to different specifications of the outcome. In all cases the effects are relatively large compared to the baseline levels that are also reported in the table, which was also the case in the estimation reported in table 3.

4.4.3 Different bandwidths

I also investigate whether the results regarding the effect on loan default and delinquency are sensitive to the selected bandwidth of 2 in table 3 and 4. Table 7 shows the estimated effects for different bandwidths. In column 1 and 2 I do not use a bandwidth. We see that the number of observations is only slightly larger than when I use a bandwidth of 2, which shows that most of the individuals in the sample have a GPA that is ±2 from the admission threshold. Therefore, the estimated effects are very similar to the effects in table 3 and 4.

In column 3 and 4 I use a smaller bandwidth of 1 which decreases the number of observations. The estimated effects for the groups who have either math or economics as their next-best alternative field are very similar to the estimates in column 2, but we see that they are less statistically significant.

Table 7: Default and delinquency with different bandwidths

	No BW		BW=1		BW=0.5	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
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)
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)
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes
Math. N	1375	2381	1217	1996	886	1369
Math. Avg.	0.053	0.064	0.053	0.064	0.053	0.064
Econ. N	692	1759	574	1504	382	1052
Econ. Avg.	0.057	0.063	0.057	0.063	0.057	0.063

Robust SEs in parentheses

Kernel=Rectangular

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

Limiting the bandwidth to 0.5 means that I loose additional observations. In this case the group with math as their alternative field still have a significantly smaller probability of having a loan default or delinquency if they obtain a math degree, but the effect for the applicants with economics as their preferred field is no longer significant despite an increase in the point estimate.

In sum, table 7 shows that the results to some extent robust to the specification of the bandwidth.

4.5 Income

One explanation for the improved debt management could be that math (and economics) educations lead to higher incomes. Kirkeboen et al. (2016) finds very different returns to different fields of study. They also show that it is important to control for the next-best alternative or preferred field of study, but due to the limited number of observations in the Danish data compared to the Norwegian, I will not use their method[6].

It is still informative to see what fields the applicants are offered to enrol in, if the do/do not cross the admission threshold. Table 8 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 alternative field. We see that in all four cases a large share of the applicants will be offered to enrol in the field of business, administration and law or the social science field, if they do (do not) cross the admission threshold for their preferred (alternative) field.

In table 2 we saw that individuals who obtain a math degree on average have a high income rank, compared to the other fields whereas this was not the case for economics. Table 9 shows how completing either the math or economics program affects income conditional on the local course ranking. We both see the effect on and the average of income and income rank 8 to 10 years after the YOA. From the table we see that the applicants who have math or economics as their preferred field benefit from completing their

[6] In a future version of this draft I will try to implement it.

Table 8: Most common preferred and nex-best alternative fields of study

	Most common	2nd most common
Econ. preferred	Humanities (37 %)	Social science (19 %)
Math. preferred	Business (37 %)	Health and welfare (23 %)
Econ. alternative	Business (40 %)	Social science (35 %)
Math. alternative	Business (34 %)	Social science (31 %)

preferred field in terms of earnings. We also see that the effects are only significant on the 10 % level. On the other hand their is no indication that completing a math or economics programme have any effect on income for the applicants who have them as their next-best alternative. As table 8 shows, a large share of these applicants have business, administration and law as their preferred field, and since graduating from this field on average leads to a very high income, this can explain why we do not see a positive effect on income.

In total, table 9 shows no evidence that the differences in the probability of having a loan default or delinquency post graduation are caused by differences in income from completing different fields of study. To some extent this suggests that the results obtained in section 4.3 are due to improved debt management for the individuals who complete a math study even though this was not their preferred field.

Table 9: Income rank and average income

	Income rank		Income	
	Pref.	Alt.	Pref.	Alt.
Math.	14.230*	-2.532	68.383*	5.039
	(7.578)	(5.042)	(40.263)	(26.137)
Econ.	26.120	-2.090	160.971*	-10.621
	(16.316)	(5.817)	(87.384)	(31.233)
YOA, age, sex	Yes	Yes	Yes	Yes
Math. N	1352	2408	1352	2408
Math. Avg.	57.483	55.666	295.829	283.761
Econ. N	716	1762	716	1762
Econ. Avg.	57.579	61.964	294.620	316.126

Robust SEs in parentheses

Bandwidth=2, Kernel=Rectangular

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

5 Conclusion

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

Using a fuzzy regression discontinuity design I estimate the effect of obtaining a degree from the field of mathematical and economic studies. I exploit that the admission system to higher education programs in Denmark creates GPA admission thresholds that effectively randomize the applicants into different fields of study.

First, I show that being above the admission cut-off significantly increases the probability that the applicant graduates from his or her preferred field of study. Thereby, I can use whether the applicant is above or below the threshold as instrument for completed field of study.

Second, I use 2SLS estimation to estimate the effect of graduating from a mathematical or economic education on financial outcomes post graduation.

I find that obtaining a math or economics degree significantly decreases the probability of having a loan default or delinquency for the applicants who have a math or economics programme as their next-best alternative in their local course ranking. I do not find a significant effect on the applicants who have these fields of study as their preferred fields. This might be due to lower sample sizes in these estimations.

I do not find any effect of field of study on the debt-to-income ratio or liquid-assets-to-income ratio, both measured as ranks. There are indications that completing a math or economic programme has an effect on income for the applicants who have these fields as their preferred fields, but I do not find any effect on income for the applicants who have them as their next-best alternative fields.

These findings suggest that the mechanisms behind the lower probability of default and delinquency are not less indebtedness, a lesser 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.

In future research, it would be of great interest to investigate if other mechanisms can explain the lower probability of default and delinquency. I would also like to investigate the importance of how I have defined mathematical and economic educations. Furthermore, I would also like to implement the estimation method used by Kirkeboen et al. (2016) to examine how the results differ when you account for the applicants' preferred and alternative fields of study in the estimations.

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Appendix

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

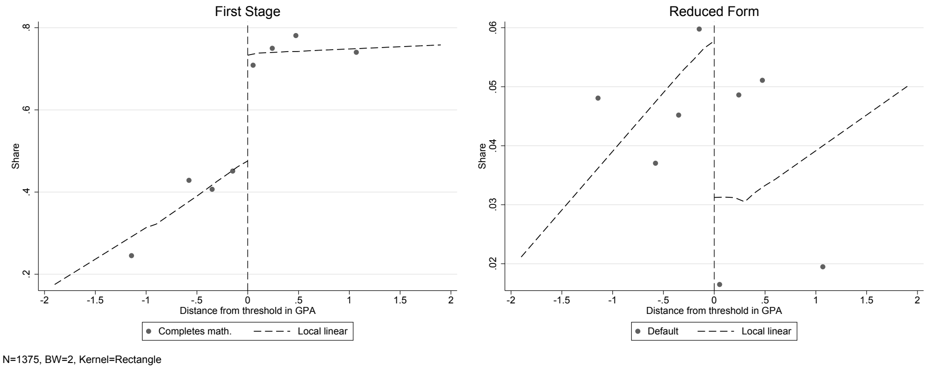

Figure A2: Completion and default for sample w. econ. as next-best field

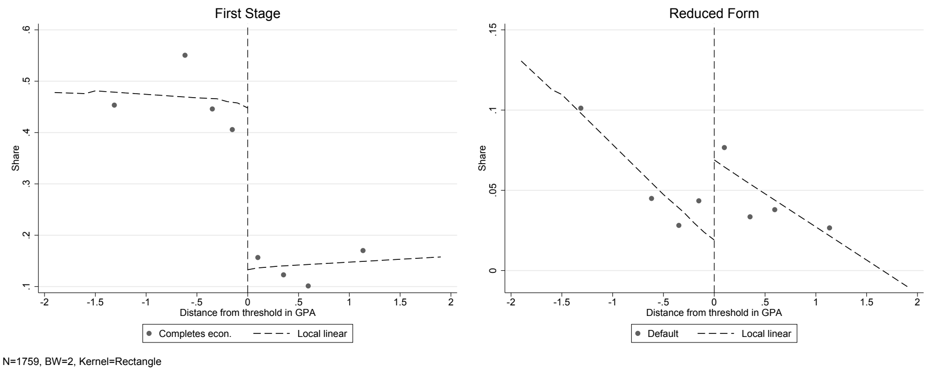

Figure A3: Completion and default for sample w. econ. as preferred field

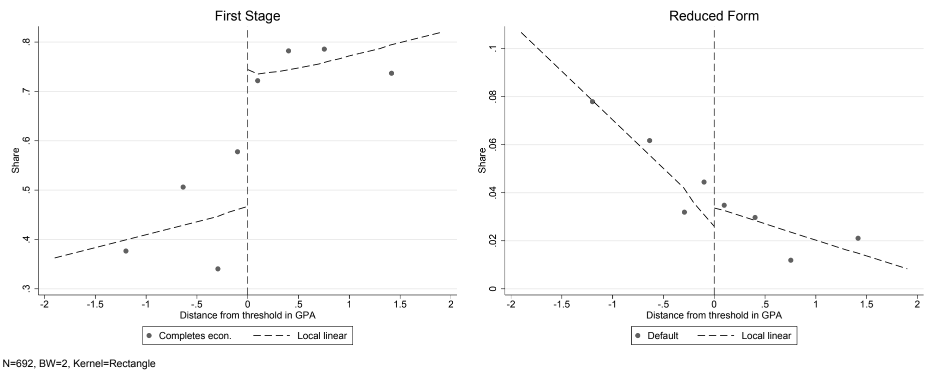

Table A1: Debt to income ratio rank with different bandwidths

	No BW		BW=1		BW=0.5	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
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)
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)
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes
Math. N	1387	2404	1227	2016	893	1383
Econ. N	696	1762	575	1510	379	1056

Robust SEs in parentheses

Kernel=Rectangular

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

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

	No BW		BW=1		BW=0.5	
	Pref.	Alt.	Pref.	Alt.	Pref.	Alt.
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)
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)
YOA, age, sex	Yes	Yes	Yes	Yes	Yes	Yes
Math. N	1387	2404	1227	2016	893	1383
Econ. N	696	1762	575	1510	379	1056

Robust SEs in parentheses

Kernel=Rectangular

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