Online appendix: Labor market returns to vocational secondary education

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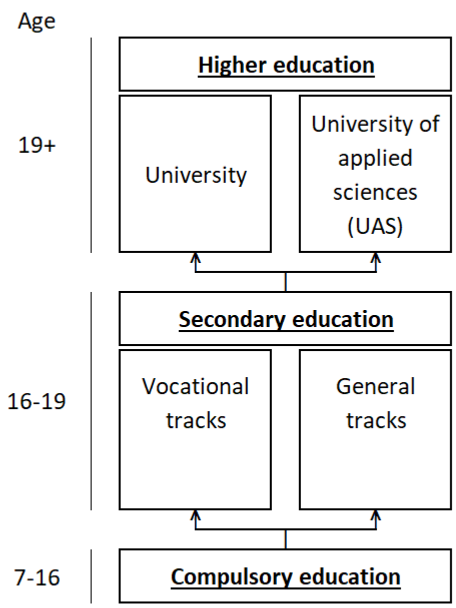
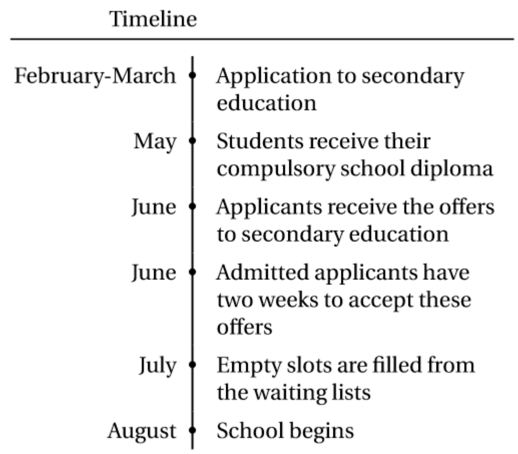
A: Institutions

Figure 1: Finnish education system

(a) Pathways through education



(b) Timeline of the application process



Notes: Figure 1a shows the possible pathways through education for students, all the way from compulsory education through higher education. Figure 1b shows the detailed timing of events from application through the beginning of school. These figures are adapted from Huttunen et al. (2019).

B: Descriptive statistics

School track broken down further

Table 1 shows the percent breakdown between secondary school tracks and vocational track subfields in our full sample, the estimation sample, as well as the two subsamples within the estimation sample: those who indicate a preference for the general and vocational tracks.

In all four samples, the most common vocational track subfield is technology and transport, admitting between 39 percent and 53 percent of applicants to the vocational track. The next most common subfield in the full sample is business and administration, making up 15 percent of admits, followed by hotel and catering, making up 20 percent of vocational admits. Due to the large number of admits to business administration in the set of students who apply to both tracks and prefer the general track, these applicants are over-represented in our pooled estimation sample. Nonetheless, the breakdown of vocational subfields amongst applicants who prefer the vocational track largely resembles the total breakdown of vocational subfields in the full sample.

Table 1: Admission to vocational subfield by application preferences

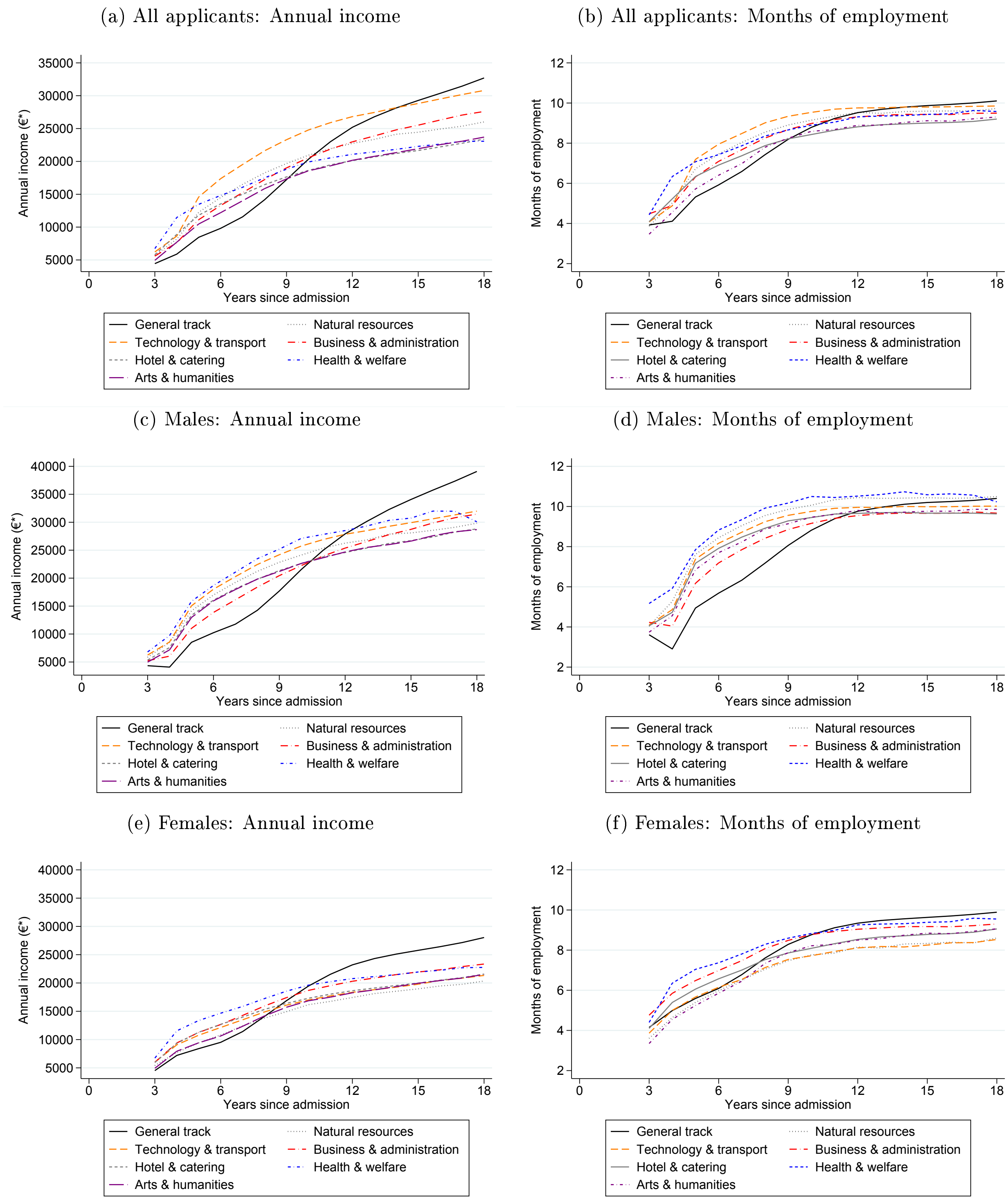
	Full sample	Estimation sample	Prefer general	Prefer vocational
General Track	175,297	15,335	14,796	539
Vocational Track	111,195	6,256	5,136	1,120
Natural resources	4.7	2.1	1.8	3.9
Technology and transport	52.8	38.8	38.2	41.6
Business and administration	14.8	35.3	38.3	21.5
Hotel and catering	19.7	16.5	18.0	9.5
Health and welfare	5.2	5.3	2.5	18.1
Arts and humanities	2.8	2.0	1.3	5.4
Total	286,492	21,591	19,932	1,659

Notes: Table 1 shows the composition of admissions and vocational subfields for people in the full sample, the estimation sample, those in the estimation sample who indicate a preference for the general track, and those in the estimation sample who indicate a preference for the vocational track. Rows 1 and 2 show raw numbers, whereas rows 3-8 indicate the percent of students admitted to each vocational subfield.

Income and employment profiles by vocational program

We explore heterogeneity in the labor market outcomes between programs within the vocational track. We divide the vocational track into seven broad programs, as defined by the Finnish Ministry of Education and Culture, and draw income and employment profiles for each track (see Figure 2). We also examine the trends in labor market outcomes by vocational subfield for men and women separately. While applicants in some subfields, noticeably "Arts and Crafts" tend to earn less than applicants in other subfields, by and large, the income and employment profiles of each subfield follow similar paths. Most interestingly, there is considerable variation in the rank order of income and employment by subfield between males, females, and the full sample. This suggests that differences between the mean returns to subfield may be largely driven by selection into the subfields, rather than something about the subfields themselves.

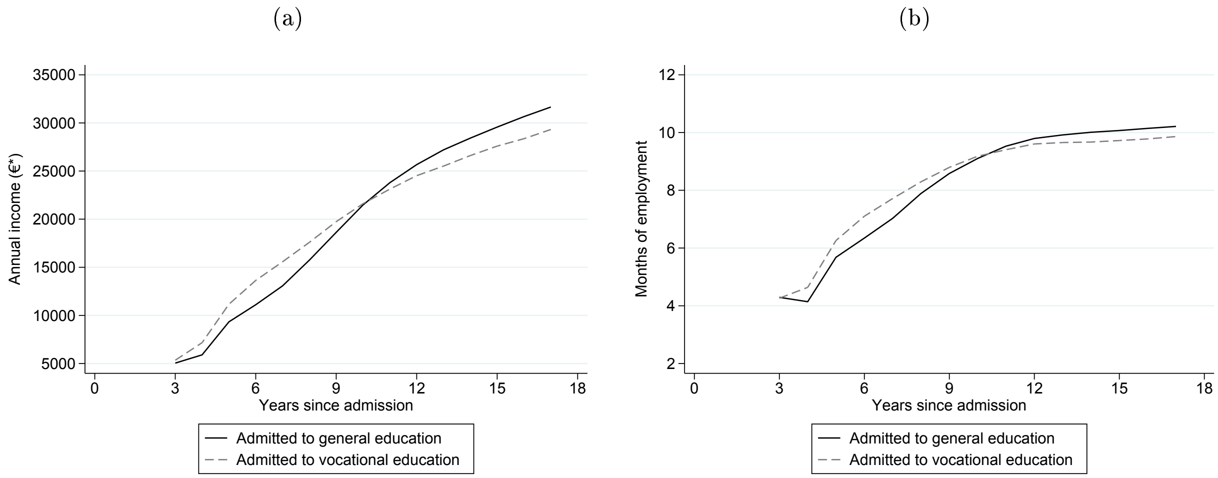
Figure 2: Time profiles by vocational subfield and gender



Notes: Figure 2 reports trends in annual income and months of employment for secondary school track and vocational subfield. Mean outcomes are shown for our full sample all together, and for males and females separately. *Incomes are indexed to 2010 euros.

Mean trends in annual incomes and employment for estimation sample

Figure 3: Time profiles in mean annual income and months of employment



Notes: Figure 3shows the mean income and employment outcomes for the cohorts of students in the RDD estimation sample applying to secondary school in the years 1996-2000 for the 17 years after admission to secondary education (~age 33). Observations with zero income and zero months of employment are included in the averages. *Incomes are indexed to 2010 euros.

Compulsory school GPA, secondary school track, and occupational task measures

The graphs in Figure 4 show mean occupational task shares measured 15 years after admission to secondary school for applicants in our full sample by compulsory school GPA and secondary school track.

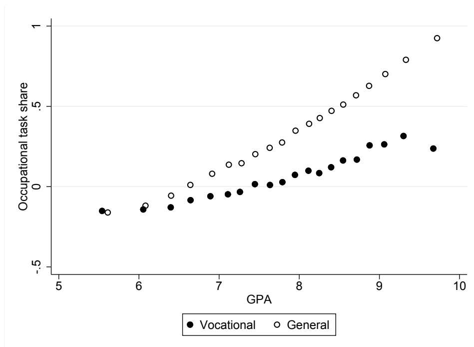
Figure 4a shows that people with low compulsory GPAs are least likely to be employed in occupations that which center around tasks involving non-routine cogntive analytic skills. For this group, secondary school track is not associated with a significant shift in the share of non-routine cognitive analytic skills on the job. In contrast, applicants admitted to the general track of secondary education are most likely to be employed in jobs requiring non-routine cognitive analytic skills. A similar trend can be seen for personal skills (Figures 4b and 4d). In contrast, the share of both routine and non-routine manual skills is greatest for applicants who are admitted to the vocational track with low GPAs (Figures 4c and 4f).

The only measure which does not suggest a linear association between compulsory school GPA and occupational task share is routine cognitive skills, measured for applicants admitted to general education. General track admits with average compulsory school GPAs are most likely to be employed in occupations requiring routine cognitive skills (Figure 4e). Interestingly, those with low GPAs are not likely to be employed in jobs requiring routine cognitive skills - perhaps because they are employed in manual skill intensive jobs; the same goes for those with high GPAs - perhaps because they are employed in jobs demanding non-routine cognitive skills.

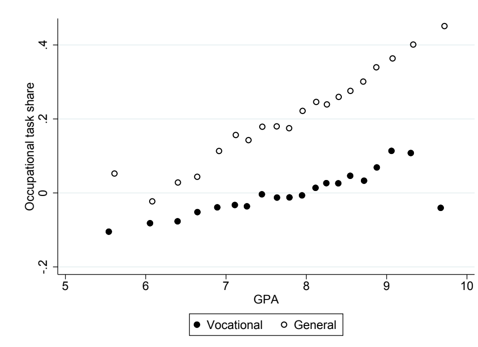
Lastly, applicants with high GPAs who are admitted to the general track of secondary education are most likely to be employed in jobs that are susceptible to offshoring (4g). This is likely due to the abstract nature of jobs requiring non-routine cognitive skills, making them less place-dependent.

Figure 4: Compulsory school GPA, secondary school track, and occupational task measures 15 years after admission

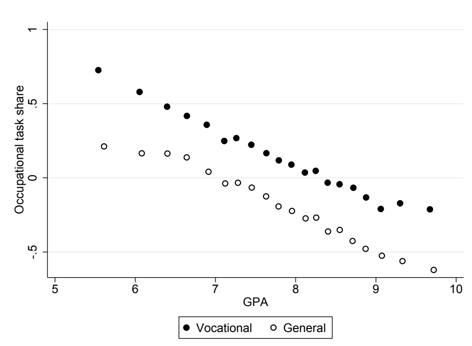
(a) Non-routine cognitive analytic



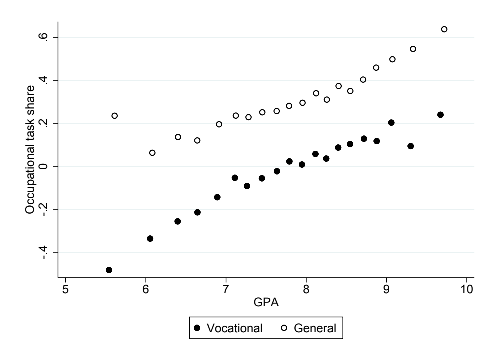
(b) Non-routine cognitive personal



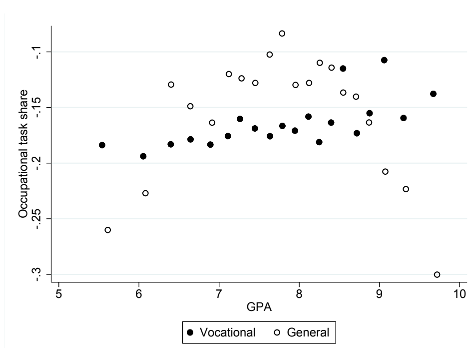
(c) Non-routine manual physical



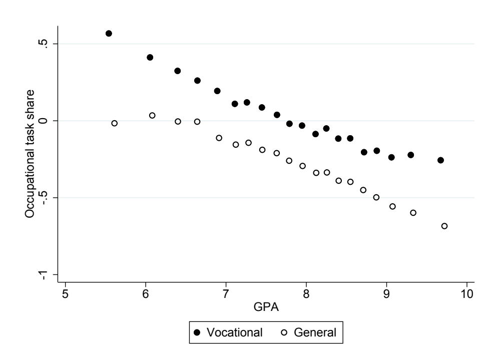
(d) Non-routine manual personal



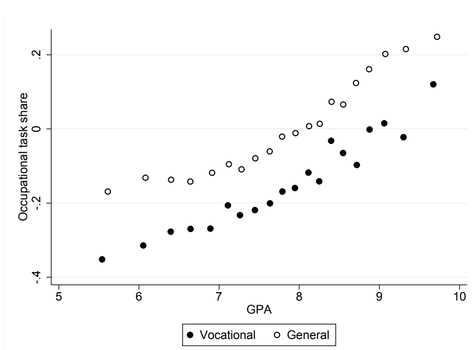
(e) Routine cognitive



(f) Routine manual



(g) Offshoreable



Notes: These graphs draw trends in occupational task shares, measured 15 years after admission, for students in vocational and general education by GPA. These graphs are drawn for all applicants for whom we observe occupational task measures in our full sample, N=230,983.

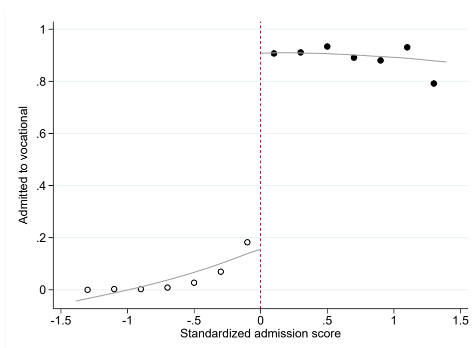
C: Data underlying the RDD estimations

Defining cutoffs for admission to the vocational track

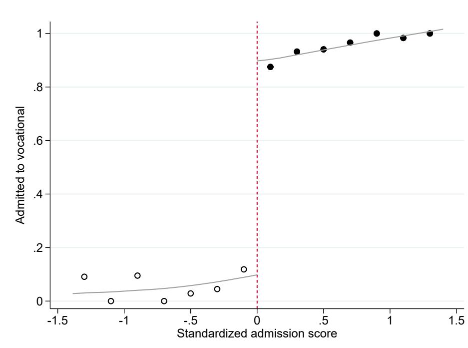
As described in Section A of the main text, the data underlying the full estimation sample discontinuity comes from pooling together two types of applicants: those who apply to both tracks but indicate a preference for the general track, and those who apply to both tracks but indicate a preference for the vocational track. The admissions outcomes for both groups of applicants separately are shown across the GPA threshold are shown in Figure 5. Enrollment outcomes for applicants with different application preferences are also depicted separately in Figure 6. These two groups of applicants are pooled together for Figure 4 in the main text.

Figure 5: Cutoffs and admission to the vocational tracks

(a) Rank general track 1st



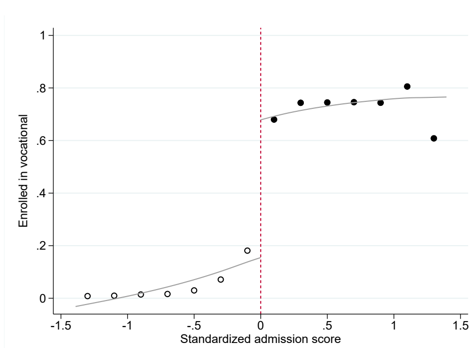
(b) Rank vocational track 1st



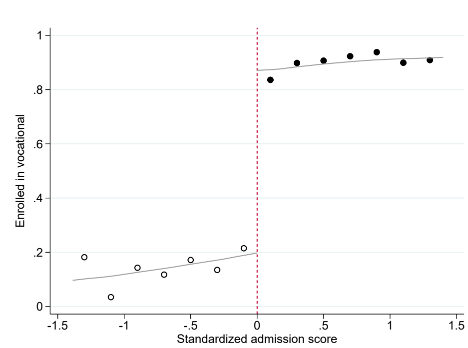
Notes: Figure 5 shows the share of applicants admitted to the vocational track for those applying to both tracks but who rank the general track first (a) or rank the vocational track first (b), plotted against program-specific standardized running variables. In both figures applicants to the right of the vertical line are more likely to be admitted to vocational education. For those who rank the general track first (a) this means that their admissions score is below the cutoff, and for those who rank the vocational track first (b) this means their admissions score is above the cutoff. The dots depict conditional means for 0.2 units wide bins. The plots also show estimates of conditional mean functions smoothed using local linear regressions, weighted using an edge kernel.

Figure 6: Cutoffs and enrollment in the vocational tracks by application preferences

(a) Rank general track 1st



(b) Rank vocational track 1st



Notes: Figure 6 shows the share of applicants enrolled to the vocational track for those applying to both tracks but who rank the general track first (a) or rank the vocational track first (b), plotted against program-specific standardized running variables. In both figures applicants to the right of the vertical line are more likely to enroll in vocational education. For those who rank the general track first (a) this means that their admissions score is below the cutoff, and for those who rank the vocational track first (b) this means their admissions score is above the cutoff. The dots depict conditional means for 0.2 units wide bins. The plots also show estimates of conditional mean functions smoothed using local linear regressions, weighted using an edge kernel.

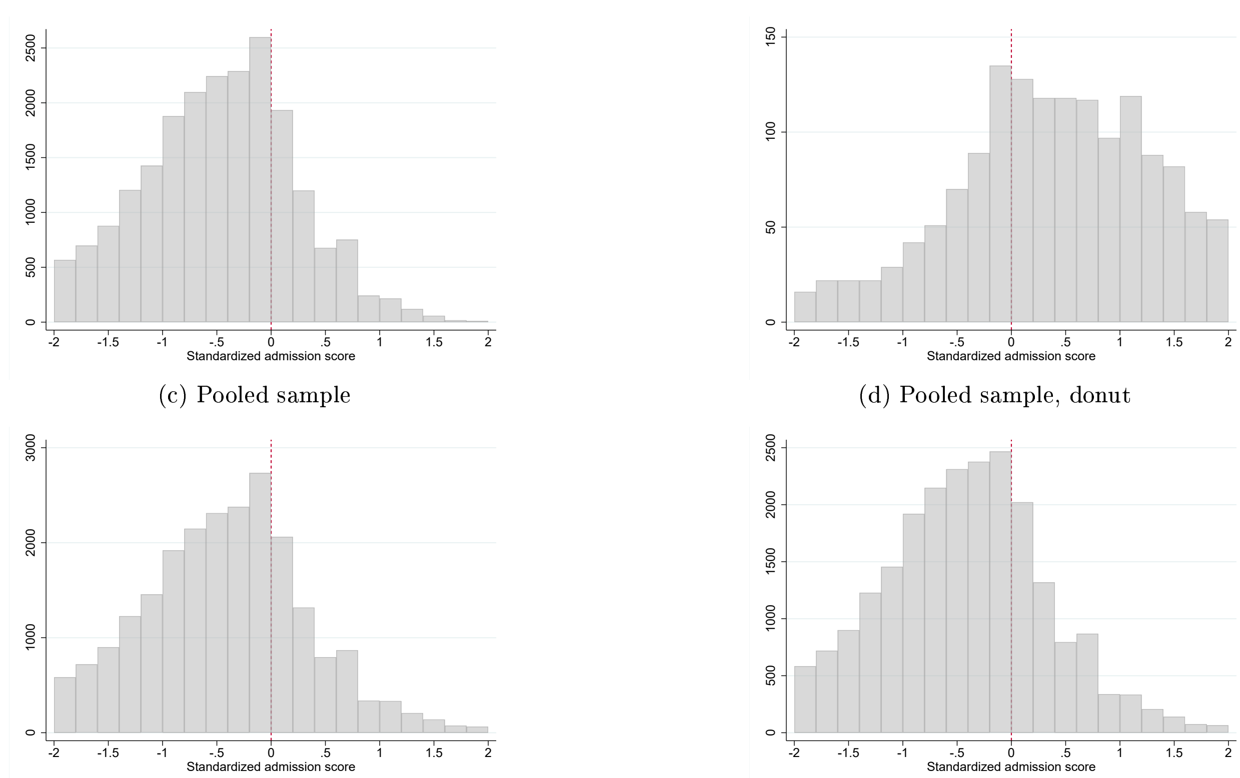
Frequencies around the cutoff

While our RDD estimation sample passes the McCrary density test, we also provide visual evidence against manipulation across the cutoff (Figure 7). Recall that applicants with high GPAs who rank the general track first have negative standardized admissions scores, while applicants with low GPAs who rank the vocational track first have negative standardized admissions scores. The cutoffs in both samples are defined by the applicant with the lowest GPA admitted to the program. Due to this definition of the cutoff, the number of applicants directly to the left of the cutoff for those who rank the general track first and the full estimation sample may appear larger than we might otherwise expect.

To account for this mechanical spiking, we also include Figure (d), where applicants used to define the admissions cutoff for each program are excluded from the sample.

Since the majority of applicants get into the track of their preference, the number of applicants with GPAs lower than required for admission is smaller than the number of applicants with GPAs that qualify for admission.

Figure 7: Density across the cutoff



(a) Rank general first

(b) Rank vocational first

(c) Pooled sample

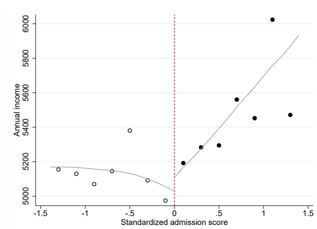
(d) Pooled sample, donut

Notes: Figure 7 shows the number of applicants in each 0.2 standardized admission unit bin across the admissions cutoff for people who indicate a preference for the general track, the vocational track, and the pooled estimation sample. Figure (d) shows a donut density graph, with applicants used to define the cutoff excluded from the sample.

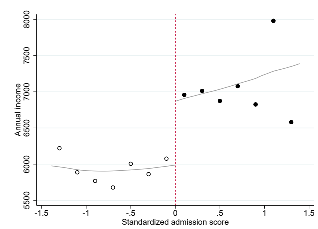
Admission cutoffs and labor market outcomes by application preferences

Figure 8: Annual Income: Rank general track first

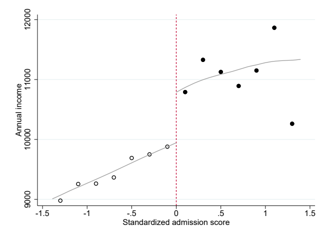
(a) 3 years after admission



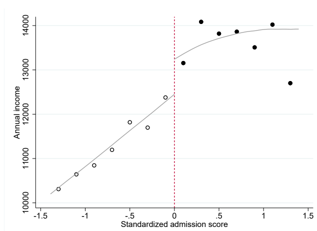
(b) 4 years after admission



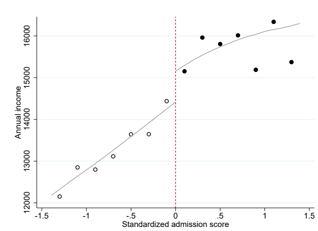
(c) 5 years after admission



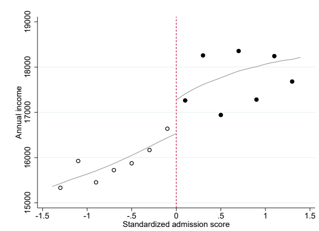
(d) 6 years after admission



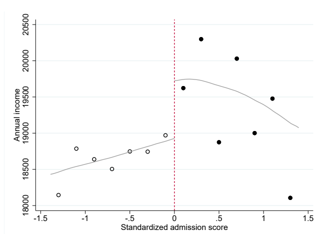
(e) 7 years after admission



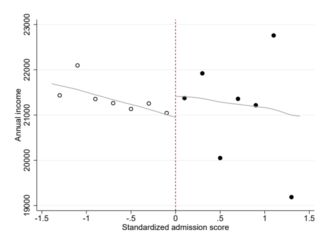
(f) 8 years after admission



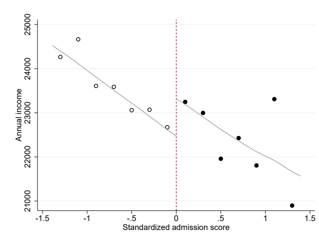
(g) 9 years after admission



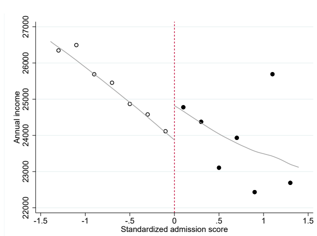
(h) 10 years after admission



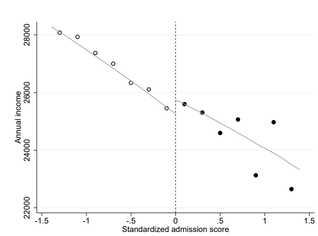
(i) 11 years after admission



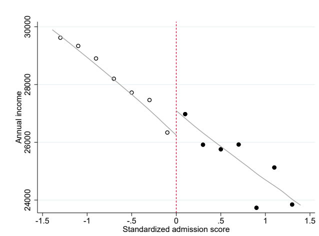
(j) 12 years after admission



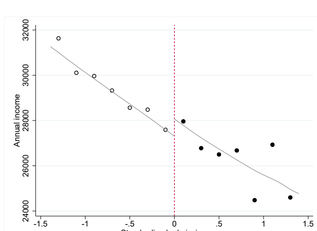
(k) 13 years after admission



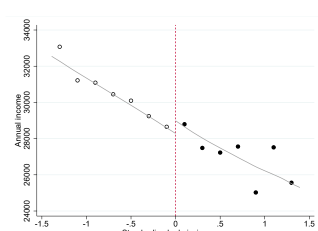
(l) 14 years after admission



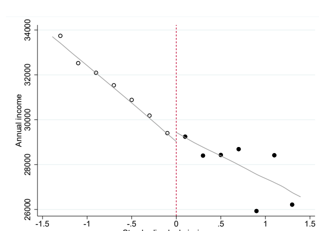
(m) 15 years after admission



(n) 16 years after admission



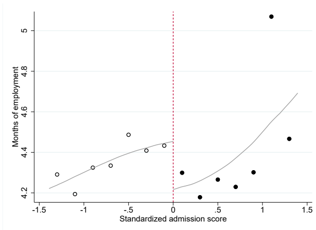
(o) 17 years after admission



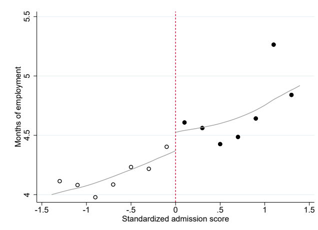
Notes: These Figures show the mean annual income 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins. The plots also show estimates of conditional mean functions smoothed using local linear regressions, weighted using an edge kernel.

Figure 9: Months of employment: Rank general track first

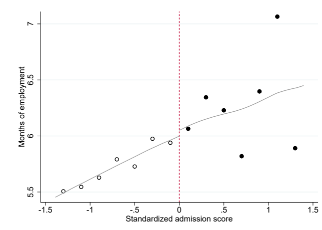
(a) 3 years after admission



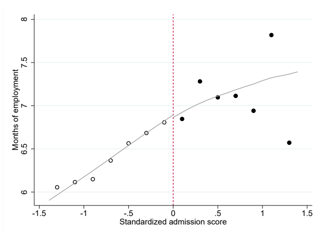
(b) 4 years after admission



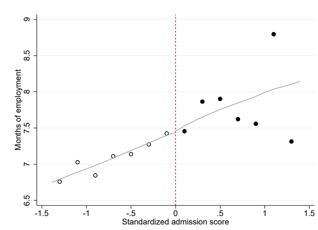
(c) 5 years after admission



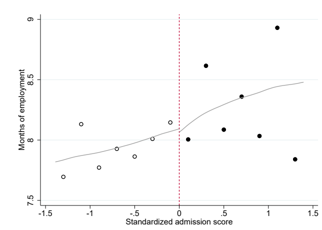
(d) 6 years after admission



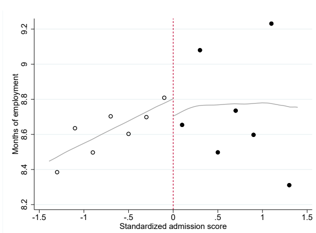
(e) 7 years after admission



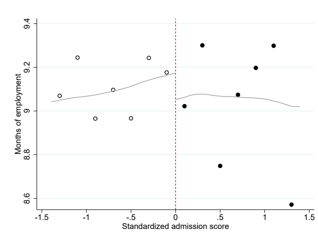
(f) 8 years after admission



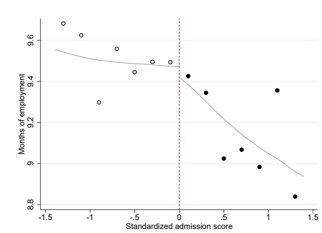
(g) 9 years after admission



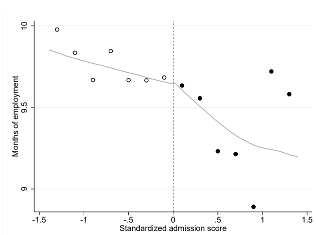
(h) 10 years after admission



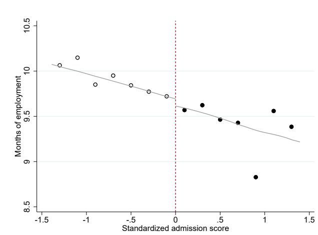
(i) 11 years after admission



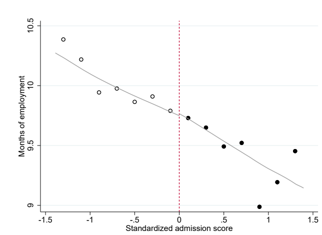
(j) 12 years after admission



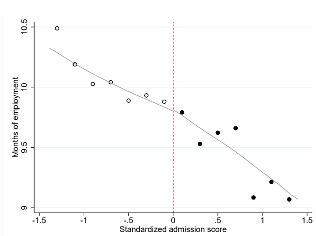
(k) 13 years after admission



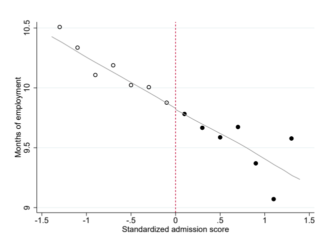
(l) 14 years after admission



(m) 15 years after admission



(n) 16 years after admission



(o) 17 years after admission

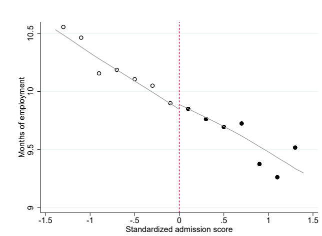


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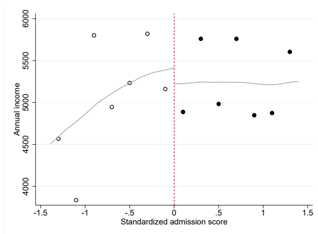
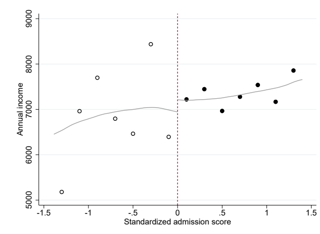
Figure 10: Annual income: Rank vocational track first

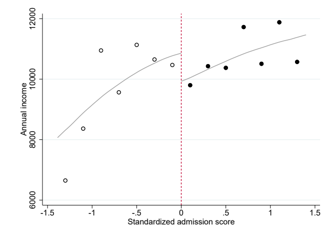
(a) 3 years after admission



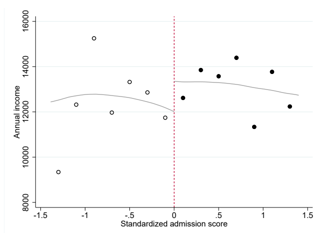
(b) 4 years after admission



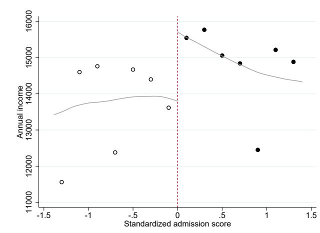
(c) 5 years after admission



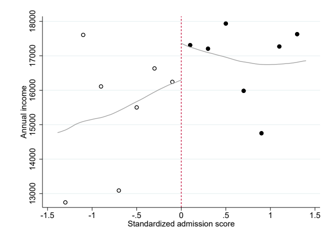
(d) 6 years after admission



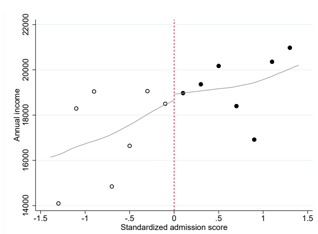
(e) 7 years after admission



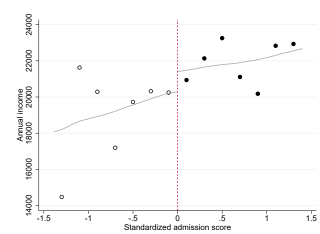
(f) 8 years after admission



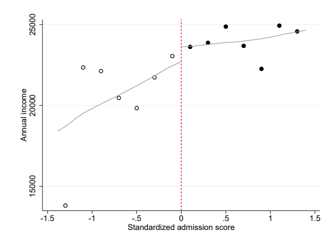
(g) 9 years after admission



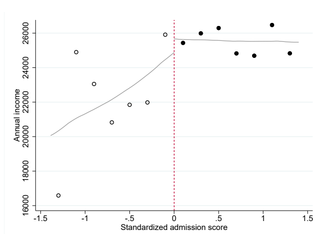
(h) 10 years after admission



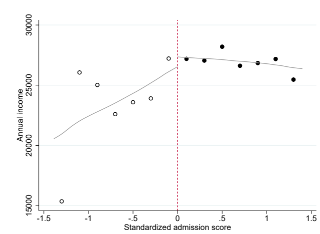
(i) 11 years after admission



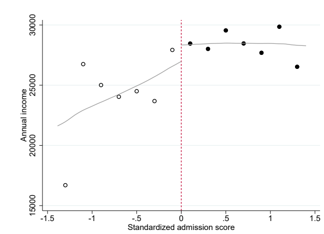
(j) 12 years after admission



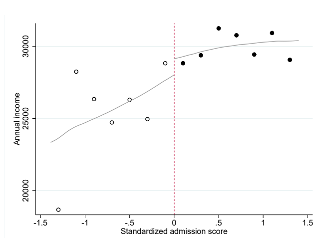
(k) Income 13 years after admission



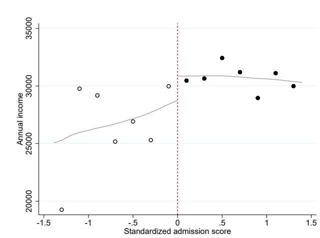
(l) 14 years after admission



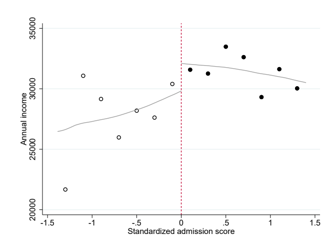
(m) 15 years after admission



(n) 16 years after admission



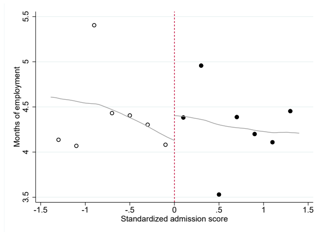
(o) 17 years after admission



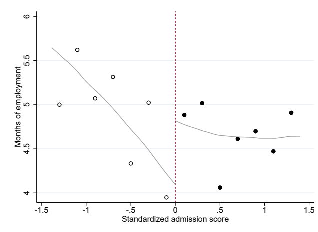
Notes: These Figures show the mean annual income 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins. The plots also show estimates of conditional mean functions smoothed using local linear regressions, weighted using an edge kernel.

Figure 11: Months of employment: Rank vocational track first

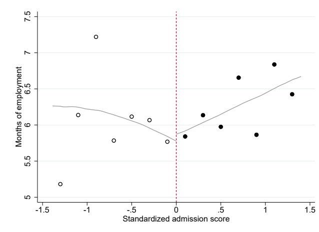
(a) 3 years after admission



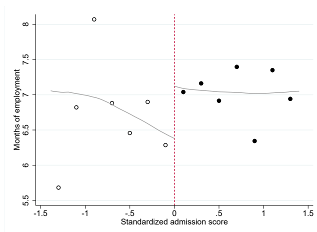
(b) 4 years after admission



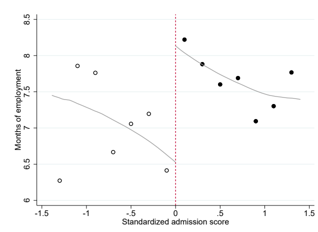
(c) 5 years after admission



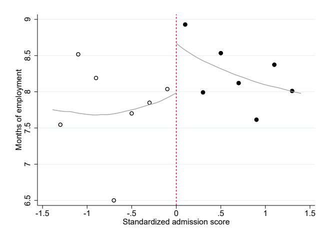
(d) 6 years after admission



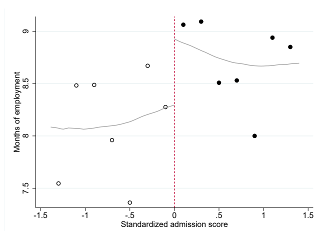
(e) 7 years after admission



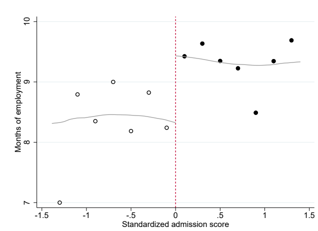
(f) 8 years after admission



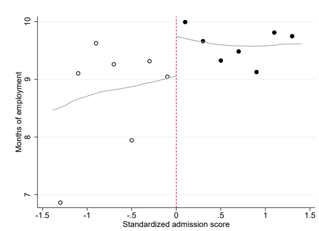
(g) 9 years after admission



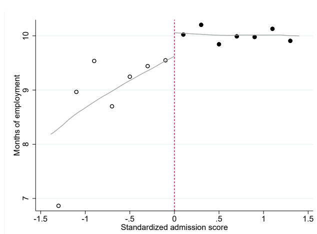
(h) 10 years after admission



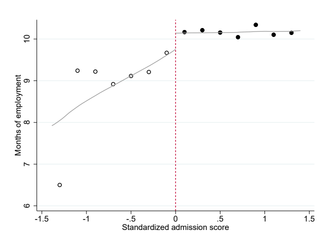
(i) 11 years after admission



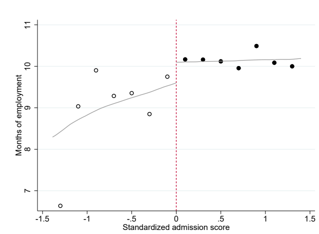
(j) 12 years after admission



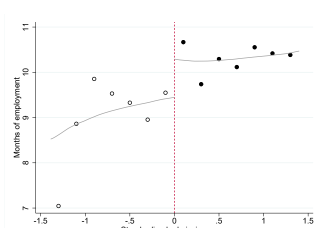
(k) 13 years after admission



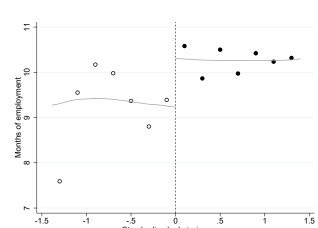
(l) 14 years after admission



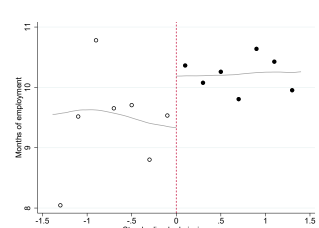
(m) 15 years after admission



(n) 16 years after admission



(o) 17 years after admission



Notes: These Figures show the mean months of employment 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins. The plots also show estimates of conditional mean functions smoothed using local linear regressions, weighted using an edge kernel.

D: Additional estimates

Specification consistency in RDD estimates: 17 years after admission

In Table 2 we provide RDD estimates of the effect of admission to the vocational track on labor market outcomes using various specifications. These results show that our estimates are not sensitive to the choice of specification.

Table 2: RDD estimates of admission to the vocational track on labor market outcomes 17 years later

(a) Annual income

	Main estimates	Donut estimation	Alternate specification	With controls
Reduced form	882	684	811	1245
	(616)	(648)	(548)	(677)
IV				
1st stage	0.481	0.467	0.488	0.473
	(0.018)	(0.019)	(0.016)	(0.020)
LATE	1,832	1,465	1,662	2,631
	(1276)	(1383)	(1118)	(1422)
Potential outcome	29,198	29,523	29,311	28,583
for compliers	(792)	(848)	(705)	(838)
Optimal bw (below/above)	1.18/1.06	1.19/0.98	1.18/1.06	1.18/1.06
N	17,661	17,223	17,661	16,041

(b) Months of employment

	Main estimates	Donut estimation	Alternate specification	With controls
Reduced form	0.153	0.073	0.155	0.177
	(0.145)	(0.150)	(0.132)	(0.155)
IV				
1st stage	0.495	0.482	0.500	0.488
	(0.017)	(0.018)	(0.015)	(0.019)
LATE	0.310	0.152	0.310	0.362
	(0.292)	(0.310)	(0.262)	(0.318)
Potential outcome	9.770	9.895	9.785	9.688
for compliers	(0.224)	(0.233)	(0.195)	(0.238)
Optimal bw (below/above)	1.36/1.16	1.37/1.06	1.36/1.16	1.36/1.16
N	19,024	18,578	19,024	17,301

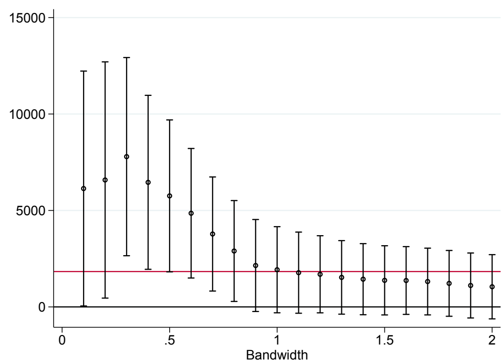
Notes: The tables show local linear estimates from four different specifications. Column 1 reports results from our most flexible specification, in which cutoff fixed effects are interacted with the running variable on both sides of the cutoff. Column 2 reports donut estimates, where students who define the cutoff are dropped from the estimation sample. Column 3 reports estimates from a specification where cutoff fixed effects are not interacted with the running variable. Column 4 reports estimates including a full set of controls. All specifications employ an edge kernel and the optimal bandwidth selection algorithm of Calonico, Cattaneo and Titiunik (2014). Standard errors (in parentheses) are clustered by cutoff.

RDD bandwidth

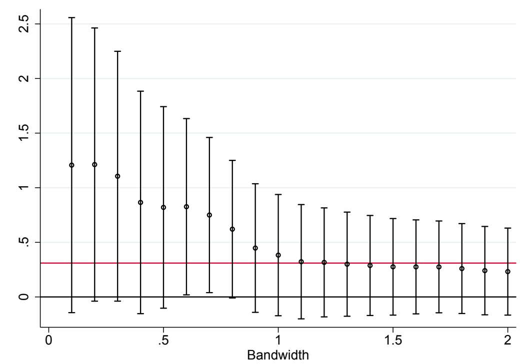
To ensure the robustness of our main estimates, we re-estimate our RDD estimates for the entire spectrum of bandwidths between 0.1 and 2 standardized admissions units below and above the cutoff (Figure 12). The red horizontal lines mark our baseline RDD estimates using optimal bandwidth selection above and below the cutoff. Our baseline RDD estimates are within the 90 percent confidence interval for all bandwidths.

Figure 12: Robustness to alternate bandwidths

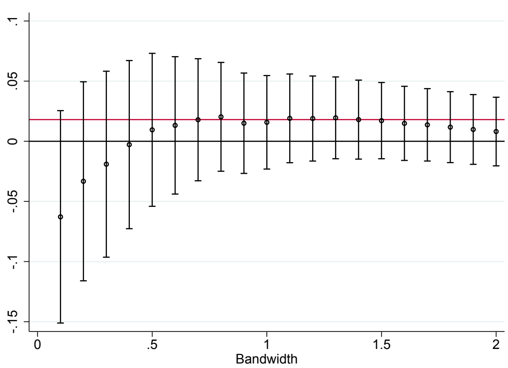
(a) Annual income



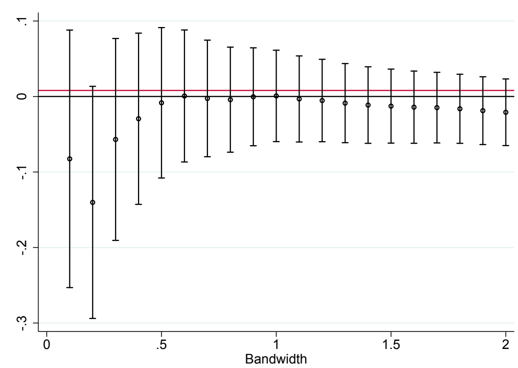
(b) Months of employment



(c) Secondary education



(d) Higher education



Notes: Figure 12 shows RDD estimates of the effects of admission to vocational education on annual income, months of employment, secondary education, and higher education estimated across the entire spectrum of bandwidths between 0.1 and 2 units to both sides of the cutoff. The graphs also show the 90 percent confidence intervals for each point estimate. These results are from our most flexible specification, in which cutoff fixed effects are interacted with the running variable on both sides of the cutoff. All specifications employ an edge kernel. Standard errors are clustered by cutoff.

Robustness to sample restrictions

In our main RDD estimates we require there to be at least two observations on either side of the cutoff. Here, we test whether or not more conservative restrictions to our estimation sample change our point estimates (Table 3). We re-run our baseline estimates, requiring 3, 4, and then 5 observations on each side of the cutoff. Restricting our sample to cutoffs with 5 observations on each side of our cutoff cuts our estimation sample in half. Nonetheless, our RDD estimates for both annual income and months of employment are remarkably stable across these changes in the estimation sample.

Table 3: Sample restrictions: Labor market outcomes 17 years after admission

(a) Annual income

	Min 2	Min 3	Min 4	Min 5
Reduced form	882	1,096	1,174	1,193
	(616)	(660)	(704)	(832)
IV				
1st stage	0.481	0.471	0.471	0.444
	(0.018)	(0.019)	(0.020)	(0.023)
LATE	1,832	2,328	2,492	2,685
	(1276)	(1398)	(1489)	(1864)
Potential outcome	29,198	29479	29137	29171
for compliers	(792)	(867)	(896)	(1149)
Optimal bw (below/above)	1.18/1.06	1.09/0.99	1.17/0.93	0.88/0.77
N	17,661	14,479	13,151	9,399

(b) Months of employment

	Min 2	Min 3	Min 4	Min5
Reduced form	0.153	0.186	0.238	0.229
	(0.145)	(0.149)	(0.156)	(0.180)
IV				
1st stage	0.495	0.494	0.491	0.462
	(0.017)	(0.018)	(0.019)	(0.022)
LATE	0.310	0.262	0.321	0.340
	(0.292)	(0.202)	(0.213)	(0.269)
Potential outcome	9.770	9.761	9.666	9.673
for compliers	(0.224)	(0.229)	(0.242)	(0.307)
Optimal bw (below/above)	1.36/1.16	1.44/1.10	1.49/0.99	1.03/0.86
N	19,024	16,541	13,151	10,470

Notes: Table 3 shows RDD estimates of the effects of admission to vocational education on annual income and months of employment for schools with at least 2-5 people on either side of the cutoff separately. These results are from our most flexible specification, in which cutoff fixed effects are interacted with the running variable on both sides of the cutoff. All specifications employ an edge kernel and an optimal bandwidth on each side of our cutoff. Standard errors (in parentheses) are clustered by cutoff.

OLS estimation

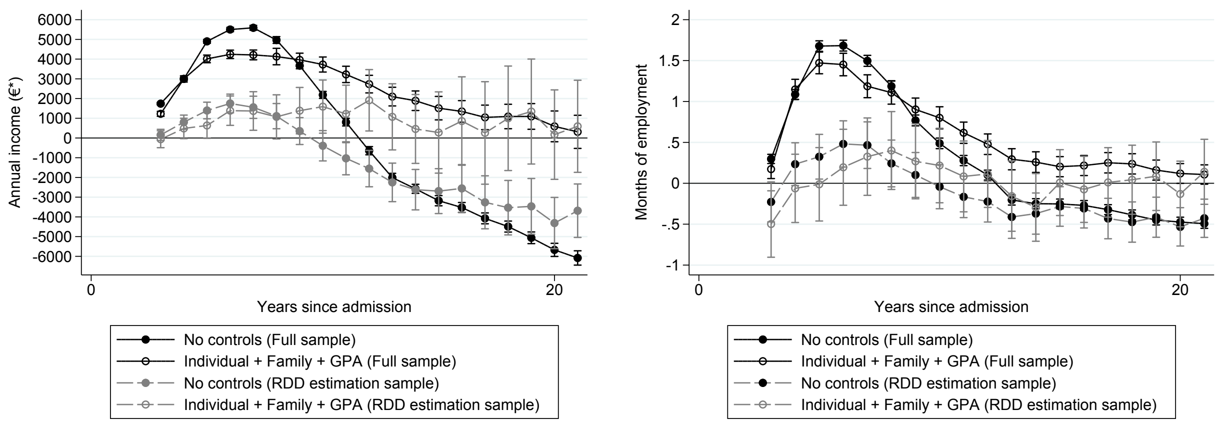
To extend our analysis to further years, we perform OLS estimation using the cohort admitted to secondary school in 1996 (See Figure 13). We specify our OLS estimation regression equation as follows:

$$y_i = b_0 + b_1 FAMILY_i + b_2 INDIVIDUAL_i + b_3 GPA_i + e_i \tag{1}$$

The vectors of family, individual, and school covariates include the variables listed in Table 1. The results reported in Figure 13 do not include fixed effects for application preferences, but including them does not change the results and we are happy to provide them if a reader would like to see them.

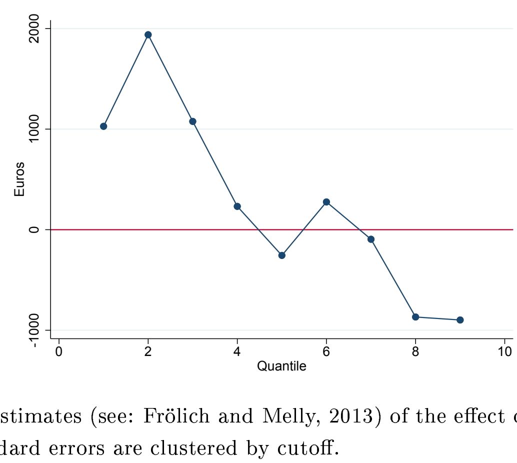
Figure 13: Estimates of labor market returns, controlling for observables

(a) Annual income | (b) Months of employment



Notes: These graphs report OLS estimates of the effect of admission to the vocational track on annual income and months of employment up through 19 years after graduation from compulsory education. These estimates are run using both the full sample and the RDD estimation sample of the cohort graduating from compulsory education in 1996 - so that they can be traced for 19 years. The controls used in this figure are the full set of covariates described in Table 1.

Figure 14: Quantile RDD estimates



Notes: Figure 14 reports quantile IV estimates (see: Frölich and Melly, 2013) of the effect of admission to the vocational track on annual income 15 years later. Standard errors are clustered by cutoff.

Table 4: RDD Estimates: School characterisation across the cutoff

	Reduced form		Potential Outcome		
	b	S.E.	b	S.E.	Observations
Estimation sample					
Average GPA among peers	-0.882	(0.043)	8.869	(0.119)	6,645
Distance to average GPA	0.980	(0.034)	-1.698	(0.090)	7,243
Percentile Rank (GPA)	0.444	(0.017)	0.260	(0.044)	6,682
School size	35	(4.4)	91.3	(5.2)	18,868
Home municipality	-0.210	(0.019)	0.929	(0.027)	10,667
Prefers general					
Average GPA among peers	-0.884	(0.051)	8.884	(0.140)	3,967
Distance to average GPA	0.905	(0.052)	-1.687	(0.142)	3,758
Percentile Rank (GPA)	0.425	(0.024)	0.263	(0.064)	3,691
School size	32	(5.5)	87.9	(7.7)	9,831
Home municipality	-0.167	(0.024)	0.932	(0.039)	7,381
Prefers vocational					
Average GPA among peers	-0.834	(0.070)	8.299	(0.046)	1,347
Distance to average GPA	0.803	(0.086)	-0.580	(0.076)	1,223
Percentile Rank (GPA)	0.309	(0.035)	0.268	(0.030)	1,177
School size	48	(11.3)	93.3	(6.1)	1,465
Home municipality	-0.280	(0.056)	0.847	(0.064)	1,050

Notes: Table 4 shows local linear estimates using our baseline specification. The LATE estimates (Columns 2 and 3) measure the mean characteristics in case of of admission to the general track on the various outcomes listed in the rows. We also estimate Potential Outcomes (Columns 4 and 5) for these students, measuring what the effects of admission to the general track would have been. All specifications employ an edge kernel and the optimal bandwidth selection algorithm of Calonico, Cattaneo, and Titiunik (2014). Standard errors (in parentheses) are clustered by cutoff.

Table 5: RDD estimates for occupational choice

	Mean occupational wage	Difference from mean
Reduced form	331	-556
	(317)	(460)
IV		
1st stage	0.476	0.504
	(0.019)	(0.018)
LATE	694	-1,103
	(666)	(911)
Potential outcome	28,087	-1,699
for compliers	(488)	(607)
Optimal bw (below/above)	1.21/0.88	1.31/1.51
N	16,068	17,351

Notes: Table 5 reports the estimates of the effect of admission to the vocational track on occupational choice and relative productivity within occupations. All estimates use our baseline specification and employ an edge kernel and the optimal bandwidth selection algorithm of Calonico, Cattaneo, and Titiunik (2014). Standard errors (in parentheses) are clustered by cutoff. We run these estimates as follows. We use data on the population of employed people aged 19-65 in the years 2011-2015 and estimate a Mincer equation with quartic age polynomials and occupation fixed effects to predict occupation specific wages. The predicted occupation specific wage is one of the outcomes we test using the main specification of our RDD design. The second outcome we test is the difference between the predicted occupation specific wage and the observed wages of people in our estimation sample.

Table 6: Post-compulsory education

	Vocational degree	General degree	Secondary degree	Tertiary degree
Reduced form	0.166	-0.208	0.006	0.004
	(0.023)	(0.027)	(0.019)	(0.020)
IV				
1st stage	0.412	0.385	0.440	0.447
	(0.020)	(0.023)	(0.018)	(0.019)
LATE	0.403	-0.539	0.014	0.008
	(0.050)	(0.062)	(0.042)	(0.044)
Potential outcome	0.440	0.754	0.254	0.279
for compliers	(0.040)	(0.048)	(0.031)	(0.034)
Optimal bw (below/above)	0.71/0.56	0.53/0.34	0.97/0.95	1.00/0.65
N	12,616	9,329	13,824	15,945

Notes: Table 6 reports the estimates of the effect of admission to the vocational track on post-compulsory educational outcomes. All estimates use our baseline specification and employ an edge kernel and the optimal bandwidth selection algorithm of Calonico, Cattaneo, and Titiunik (2014). Standard errors (in parentheses) are clustered by cutoff.

Table 7: RDD Estimates for the skill content and offshorability of occupations 15 years after application to secondary school

	Non-routine task share				Routine task share		Offshorability
	Cognitive analytic	Cognitive personality	Manual physical	Manual personality	Cognitive	Manual	
Reduced form	-0.029	0.008	0.062	-0.026	0.059	-0.002	-0.041
	(0.032)	(0.032)	(0.034)	(0.035)	(0.031)	(0.033)	(0.037)
IV							
1st stage	0.479	0.487	0.495	0.498	0.493	0.500	0.502
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)
LATE	-0.061	0.017	0.126	-0.053	0.121	-0.003	-0.081
	(0.066)	(0.065)	(0.068)	(0.071)	(0.063)	(0.067)	(0.074)
Potential outcome	0.179	0.100	0.082	0.037	-0.211	0.003	-0.140
for compliers	(0.049)	(0.049)	(0.047)	(0.049)	(0.054)	(0.047)	(0.052)
Optimal bw (below/above)	1.20/0.87	1.41/0.82	1.42/0.95	1.31/1.12	1.20/1.18	1.44/1.02	1.29/1.28
N	15,313	16,558	16,821	16,563	15,776	16962	16,480

Notes: The table shows local linear estimates using our baseline specification, the edge kernel, and the optimal bandwidth selection algorithm of Calonico, Cattaneo, and Titiunik (2014). Standard errors (in parentheses) are clustered by cutoff. Occupational task share measures are observed for 83 percent of applicants on both sides of the cutoff.

E: Present discount value calculations

Present discounted value of lifetime earnings

Our year-to-year RDD estimates suggest that for the marginal applicant, being admitted to the vocational track provides an earnings benefit through at least age thirty three, seventeen years after admission to secondary school. While we demonstrate that the premium for entering vocational education persists into a person's mid-thirties, Hanushek et al. (2017) argue that entering the vocational track might still be harmful if those admitted to the general track overtake their peers admitted to vocational education later in their careers. To test for whether or not this might be a concern given our estimates, we calculate the present discounted value of vocational education under four different scenarios, and with several discount rates.

As is common in PDV calculations, we discount all earnings to the point of time at which the individual makes the investment decision (Becker, 1964):

$$PDV = \sum_{t=0}^{n} \frac{MP_t}{(1+i)^t} \tag{2}$$

We input our RDD estimates for the vocational premium for the first seventeen years after admission, then turn to the various scenarios described below.

Scenario 1. As a benchmark, we show results assuming a vocational premium of one thousand euros persists through retirement.

Scenario 2. We show calculations assuming that immediately in the next year (age thirty four), the premium for admission to the vocational track disappears entirely, and remains at zero through retirement at age sixty-five.

Scenario 3. We assume that immediately in the next year (age thirty four), the premium for admission to the vocational track disappears entirely. In this scenario, however, we assume that after five years, the earnings of those admitted to the general track overtake their peers admitted to the vocational track, and experience a premium of one thousand euros until retirement at age sixty five.

Scenario 4. We assume that the earnings premium from our RDD estimates flips at age thirty four, and those admitted to the general track experience a premium of *one* thousand euros through retirement at age sixty five.

Scenario 5. We assume that the earnings premium from our RDD estimates flips at age thirty four, and those admitted to the general track experience a premium of *two* thousand euros through retirement at age sixty five.

Given these five scenarios, we calculate the PDV of the earnings premium of being admitted to the vocational track in Table 8a. Even if we set the discount rate to three percent, the only scenario under which those admitted to the general track at our RDD margin overtake those admitted to the vocational track is Scenario 5 - the most extreme scenario. With more realistic assumptions, our calculations suggest that it is unlikely that admission to the general track provides an earnings premium for those at our RDD margin.

As we saw in Section D, the premium experienced by applicants who indicate a preference for the general track is significantly smaller than that for indivudals who indicate a preference for the vocaitonal track. To focus on the vocational admits most at riks to be overtaken by their peers admitted to the general trac,we rerun the PDV calculations by focusing on those who rank a general track first. The results reported in Table 8b suggest that the general track is unlikely to provide a postive lifetime earnings premium (compared to vocational education) even for those marginal applicants who indicate a preference for the general track.

Table 8: Present discounted values of lifetime earnings

(a) Full estimation sample

Discount rate	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
1 percent	49,961	26,935	8,007	3,909	-19,116
3 percent	34,187	21,851	12,287	9,516	-2,819
5 percent	24,807	17,913	12,907	11,018	4,124

(b) Rank general track first

Discount rate	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
1 percent	46,714	23,688	4,760	662	-22,364
3 percent	31,659	19,323	9,758	6,987	-5,348
5 percent	22,822	15,927	10,921	9033	2,138

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