Labor market returns to vocational secondary education

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Abstract

We study labor-market returns to vocational versus general secondary education using a regression discontinuity design created by the centralized admissions process in Finland. Admission to the vocational track increases initial annual income and this benefit persists at least through the mid-thirties, and present discount value calculations suggest that it is unlikely that life-cycle returns will turn negative through retirement. Moreover, admission to the vocational track does not increase the likelihood of working in jobs at risk of replacement by automation or offshoring. Consistent with comparative advantage, we observe larger returns for people who express a preference for vocational education.

JEL: I26, J24, J31, C31, J23, I24

Keywords: returns to education, vocational education, technological change, application preferences, regression discontinuity, field of study

In response to recent technological changes and the worsening outcomes of non-college educated workers (Autor, 2019), governments around the world are becoming more interested in whether different types of secondary education (vocational vs. general) might play a role in providing young people the skills they need to succeed after they graduate (European Commission, 2010; United States Department of Education, 2013; 2018).[1] Yet, in stark contrast to the growing body of evidence on the impact of various fields of study in higher education (Altonji, Blom and Meghir, 2012; Hastings, Neilson and Zimmerman, 2013; Kirkeboen, Leuven, and Mogstad 2016), there exists a paucity of compelling causal evidence on the impact of secondary school curricula on labor-market outcomes (Altonji, Blom and Meghir, 2012; Hampf and Woessmann, 2017; Hanushek et al., 2017). Nonetheless, understanding the potential consequences of secondary school curricula is particularly important given that this choice takes place before higher education, and for many people is the highest level of education before entry into the labor market. Further the availability of vocational secondary education is one of the largest differences between national education systems (See Figure 1).

To examine the labor-market returns to vocational versus general secondary education, we use a regression discontinuity design (RDD) created by the centralized admissions process in Finland. Our RDD analysis focuses on applicants to secondary education who apply to both vocational and general tracks whose admission is determined by cutoffs to oversubscribed schools. The rich register data also allows us to estimate the effects of vocational secondary education separately by application preferences.

A common view suggests that there may be a trade off between benefits of vocational education in the short term and adverse impacts later on (Krueger and Kumar, 2004; Hampf and Woessmann, 2017; Hanushek

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[1] In our paper, secondary school refers to the education that takes place between ages 16 and 19, sometimes called "upper-secondary" school.

et al., 2017). According to this literature, vocational education may provide applicants with occupation specific skills that better facilitate the initial school-to-work transition. Further, vocational education may offer an important alternative for youth otherwise at risk of dropping out of secondary education. On the other hand, general education has been thought to better prepare applicants for further education - thus enhancing labor market prospects later in the career. Moreover, with changes in technology and the future of work, critics fear that vocational skills may become obsolete at a faster rate than general skills.

The trade-offs outlined above are in line with the trends in mean outcomes we see in our data on the universe of students graduating from compulsory education in Finland between the years 1996-2000. On average, applicants admitted to the vocational track experience an initial advantage, but are overtaken by their peers admitted to the general track 11-12 years after admission (ages 27-28). Seventeen years after admission to secondary education (age 33), applicants admitted to the vocational track earn 4,000 euros less annually than applicants admitted to the general track, and are employed fewer months a year. Of course, these mean differences may be driven by selection.

Empirical work aiming to identify the causal effect of vocational secondary education provides evidence that vocational education can improve short term outcomes. Recent papers exploiting randomness in admissions to oversubscribed schools from Massachussetts, Connecticut, and North Carolina suggest that vocational education can improve on-time graduation but may have mixed effects on enrollment in higher education (Dougherty, 2018; Hemelt, Lenard, and Paepelow, 2018; Brunner, Dougherty, and Ross, 2019).[2] Further, evidence from a randomized control trial targeting disadvantaged communities in the United States suggests that increasing the vocational component of secondary education boosts earnings after graduation (Kemple and Willner, 2008).

However, comparing the labor market outcomes of graduates from vocational and general programs across European countries over their life-cycles, researchers argue that the benefits of vocational education may be short-lived (Brunello and Rocco, 2017; Hanushek et al., 2017; Hampf and Woessmann, 2017). These studies find that the initial annual wage premium of vocational education disappears by the early thirties.[3] In contrast, a second approach to exploring the longer-term effects of vocational secondary education has focused on national reforms, and finds no benefits of increased exposure to general education. A study of a reform in Romania that shifted a large proportion of students from vocational training to general education suggests that while those enrolled in the general track experience improved labor-market outcomes on average, this finding is largely driven by selection (Malamud and Pop-Eleches, 2010, 2011). Other studies have looked at vocational education reforms that increased the general content in the vocational track. Studies in the Netherlands and Sweden find no benefits of additional general content on labor-market outcomes (Oosterbeek and Webbink, 2007; Hall, 2016). In Norway, Bertrand, Magne, and Mountjoy (2019) find that a similar reform also increased selection into the vocational track, and thereby lead to improved earnings for those induced into vocational education.

Our RDD strategy provides us with credible local average treatment effects (LATE) for individuals most likely to be impacted by changes in the size of the vocational education sector. Still, although we include only a subsample of applicants in our RDD estimates (those who apply to both the vocational and general tracks), our estimates include the vast majority of all secondary schools in Finland. Moreover, while other research has relied primarily on reforms that affect the educational choices of entire cohorts or cross-national

[2]This is in line with Hall (2016) who finds that expanding the general content in secondary education increases dropout.

[3]For example, Hanushek et al. (2017) estimate that the vocational income premium rapidly decreases from before age twenty through the early thirties, when the premium turns negative. Additionally, they estimate a nearly linearly decreasing employment premium that begins before age twenty and turns negative at age forty three, but then persists through retirement.

differences in secondary sectors, our design allows for cleaner inference by comparing individuals within the same age cohort and working within the same labor market. As observed by Bertrand, Magne, and Mountjoy (2019), effects estimated using vocational education reforms can be driven by compositional changes related to track choice as well as changes in the content of the vocational track. Our research design allows us to isolate the effects of vocational versus general education while keeping the content of the vocational track fixed. And, instead of restricting the analysis only to graduates, as is done in several existing studies, our estimates avoid another potential source of selection bias by focusing on differences in admission and enrollment Altonji, Blom and Meghir, (2012).

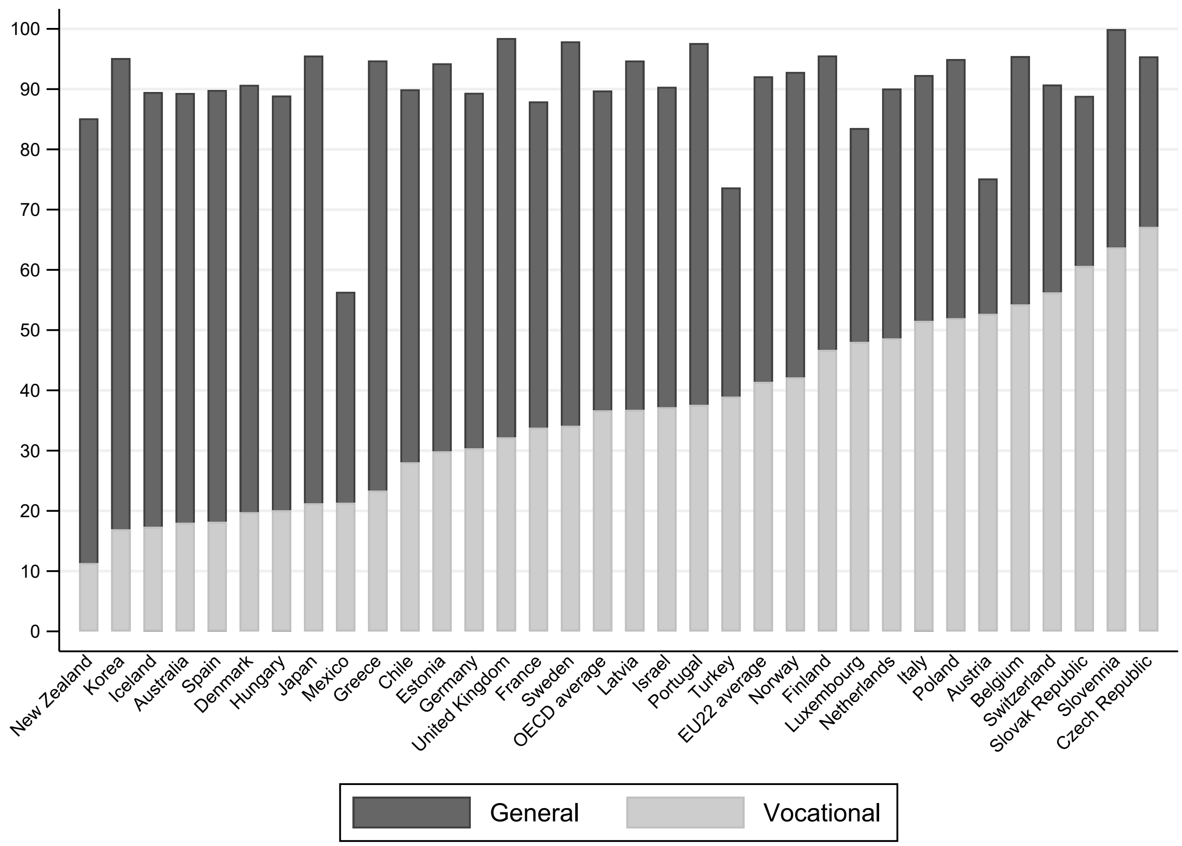
Our causal estimates suggest that enrollment in vocational secondary education increases initial annual income - and this benefit persists through age 33 (a 6 percent boost 17 years later), with no effect on months of employment, for applicants at the margin of admission to vocational versus general education. These benefits do not show a trend of going away.[4] Still, we interrogate potential mechanisms by which these benefits might turn negative. The expected benefits of general education hinge on the preparation that the general track provides for further education and adaptability to changes stemming from technological change. Both of these potential explanations suggest that the benefits of general education may increase over the life-cycle. However, we find that admission to the vocational track does not reduce the likelihood of ever graduating from higher education for the marginal applicant. Further suggesting that the benefits of vocational eduction may not be short-lived, applicants admitted to the vocational track are no more likely to be employed in occupations at risk of automation or offshoring. Results from present discount value calculations (PDV) of the lifetime return to vocational education under several scenarios suggest that it is highly unlikely that the lifetime vocational premium will turn negative through retirement.

Our results also provide insight into who is most likely to benefit from vocational secondary education. When we examine the effects by application preferences, we find that admission to the vocational track increases annual income for both sets of applicants: those who prefer the general track to the vocational and those who prefer the vocational track to the general. Nonetheless, consistent with the idea of comparative advantage, applicants who indicate a preference for vocational education experience heightened benefits. For these applicants, failing to gain admission to the vocational track reduces employment 17 years after admission by nearly 20 percent. When we situate our RDD estimates in the broader context, we see that our LATE estimates come from people near the middle of the academic ability distribution. While these are the people most likely to be impacted by changes in policies relating to secondary education, our analysis suggests that the benefits of vocational education may be even larger for people with low compulsory school GPA's who only apply to the vocational track, and that vocational education may be detrimental for people with high GPA's who apply only to the general track. These results extend recent research on the returns to higher education that observes that credible estimates of the returns to any field of study require knowledge of a person's application preferences in order to identify their counterfactual field of study (Hastings, Neilson and Zimmerman, 2013; Kirkeboen, Leuven, and Mogstad 2016).

These findings, coming from a period characterized by rapid technological change, provide new evidence that vocational education may offer an important pathway into the labor market. At first glance, these results may appear to run counter to the idea that general skills better equip people for adapting to technological change (Goldin and Katz, 2009; Acemoglu and Autor, 2011*b*; Goos, Manning, and Salomons, 2014; Deming, 2017; Deming and Noray, 2020). A more nuanced reading of this literature, however, suggests that the

[4]Not only do we see no negative trend in our RDD results, but OLS results with a rich array of controls suggest that this trend holds at least through age 37.

Figure 1: Enrollment in vocational and general secondary education in OECD countries



Notes: Figure 1 shows the share of the 17 years olds enrolled in general and vocational secondary school in OECD countries in the year 2016. The data for this graph comes from *Education at a Glance* (OECD, 2017).

classification of skills as general or vocational may fail to capture the nature of the changing demand for skills: other dimensions of skills may be more important. For example, there seems to be a growing demand for both non-routine manual and cognitive skills (Acemoglu and Autor, 2011*b*) as well as people with high levels of social skills - regardless of academic ability (Deming, 2017; Barrera-Osorio, Kugler, and Silliman, 2020). Our findings enrich this literature, suggesting that vocational education may provide valuable skills - particularly for those who are unlikely to graduate from higher education.

Last, our findings provide an important takeaway for policy-makers considering the role of vocational education. Our estimates suggest a sustained demand for vocational skills, even in Finland – where nearly half of all cohorts enroll in the vocational track. With this in mind, there may be significant room for expanding the choice of vocational education in other developed countries.

I Institutional context

Two institutional features of the Finnish secondary education system make it an attractive context for our study. First, the centralized application and admissions systems for secondary education in Finland allow us to identify applicants at the margin of admission to the vocational and general tracks. Second, the vocational sector in Finland is, in many ways, quite similar to those of other countries in the Organisation for Economic Cooperation and Development (OECD).

A Admissions to secondary education

In Finland, compulsory education consists of nine years of comprehensive schooling and it typically ends at the calendar year when the student turns sixteen.[5] Secondary education is divided into two tracks: a general track (sometimes referred to as the academic track, high school, or gymnasium) that provides basis for access to tertiary education and a vocational track that prepares students for specific occupations. The scope of the syllabus in secondary education is three years.

Application to secondary education takes place through a centralized application system maintained by the Finnish National Board of Education (FNBE). The application process is depicted in Figure 1b. The process begins in February-March during the final 9th year of compulsory education. Applicants rank their preferences for secondary school, including as many as five school and program combinations. In the cohorts we study (1996-2000), approximately 98 percent of each cohort applies to secondary education immediately after leaving compulsory education. Close to 50 percent of them apply only to programs in general education, more than 30 percent only to programs in vocational education and approximately 20 percent apply to both types of tracks. The supply of spots in each educational program is fixed and announced before the application process begins.

The allocation of spots to oversubscribed programs is based on admission scores. The general guidelines for student selection criteria are set by the Ministry of Education and Culture. For some educational programs admission is based solely on compulsory school grade point average (GPA), whereas some programs give extra points for experience and minority gender, or use aptitude tests in addition to grades. Moreover, the weights given to different grades and/or criteria vary across educational programs. As can be seen from Figure 1b, applicants only receive their compulsory school grades after submitting their applications. This is an attractive feature of the setting for our study, since applicants cannot be certain of their own admission points or thresholds at the time of application, making strategic application behavior very difficult.

Student selection follows a deferred acceptance (DA) algorithm where each applicant is considered for her preferred choice in the first round. Each program tentatively accepts applicants according to its selection criteria and rejects lower-ranking applicants in excess of its capacity. In the next rounds, the applicants rejected in the previous round are considered for their next preferred program. Each program compares these applicants to the tentatively accepted applicants from previous rounds, rejecting the lowest-ranking students in excess of its capacity. The algorithm terminates when every applicant is matched to a program or every unmatched candidate is rejected by every program she had listed in her application.

At the end of this automated admission stage, in June of the final year of compulsory school, the applicants receive an offer according to the allocation result. Admitted applicants have two weeks to accept the offers while rejected applicants are placed on a waiting list in rank order based on their admission score. During

[5]See Figure A.1a for an illustration of pathways through the education system in Finland. For reference, the description of the institutional context in this paper is based on the description in Huttunen et al. (2019), but modified to highlight features relevant to our study.

the years 1996-2000, some three percent of the offers were declined by the applicants. A potential reason for declining an offer being an unexpected event (e.g. illness, pregnancy) or the family moving to another location. After these two weeks, the schools start to fill the remaining vacant slots by calling the applicants in their waiting list in rank order. This updating of admissions offers affects roughly 10 percent of applicants in our period of study.

During the years 1996-2000, 80 percent of the applicants received an offer to their first ranked program, whereas a little more than 5 percent failed to gain any offer at all. While not all applicants enroll in and complete a degree in the track in which they receive an offer, admission to secondary school track is highly predictive of enrollment and later completion. Of those admitted to the vocational track, 90 percent enroll in vocational education immediately in the following academic year and 72 percent graduate in five years; of those admitted to the general track, 98 percent enroll in general education and 90 percent graduate in five years.

B Vocational education in Finland

Applicants to the vocational track apply to one of seven broad areas: arts and humanities, business and administration, technology and transport, natural resources, health and welfare, and hotel and catering.[6] While students specialize in areas ranging from circus arts to navigation, auto-repair, and hair-styling, all secondary vocational education includes a general education component, with courses in math, mother-tongue, Swedish, and English, with applicants able to choose further courses not specific to their area of specialization. Nonetheless, vocational coursework takes center stage, and one to two month work-placements are a key component of nearly every vocational program.[7] Still the vocational track does not foreclose the option to continue to higher education. But, in contrast to their peers from the general track who typically enter academically focused universities, graduates of the vocational track are more likely to enroll in universities of applied sciences (UAS).

All secondary education in Finland is publicly funded. Although, vocational schools employ fewer teachers per student than general secondary schools, vocational education is slightly more expensive to provide due to the equipment needs. Due in part to the slightly higher fixed costs associated with providing vocational education, there are fewer vocational schools than general secondary schools. As a result, vocational schools are often jointly governed by federations of municipalities rather than individual municipalities, and students travel a longer distance to attend these schools.

While the secondary vocational education sector in Finland is larger than the OECD average in size, it is near the European average, enrolling 46.5 percent of 17 year olds (Figure 1). Further, like many OECD countries with established vocational sectors, vocational education in Finland is largely school-based (as opposed to workplace-based). Other countries with school-based vocational sectors include Australia, France, the Netherlands, Norway, Sweden, and the United States (OECD, 2017).

When we look at the structure of secondary vocational education in Finland more closely, more similarities between the Finnish system and other vocational education systems emerge. As in most European and OECD countries, the majority of applicants in the vocational track in Finland study in programs related to business, and very few are in programs focused on subfields outside engineering, manufacturing, construction, or health and welfare (OECD, 2017).[8] And as in most school-based vocational systems, vocational programs

[6] A reform of the vocational sector in 2018 has changed the institutional context slightly. Our description focuses on the vocational system before this recent reform.

[7] The majority of the vocational programs in our sample are three years, with two year programs gradually phased out through this period.

[8] For comparability, OECD classifications are used here to define vocational programs across countries.

in Finland prepare applicants with adequate training in general skills, so they may apply for admission to higher education if they so choose.

II Data and descriptive statistics

A Data sources and outcomes

We link together population-wide Finnish administrative registers for the years 1996-2017. Our primary source of data is the Finnish National Board of Education's Application Registry (2020*a*; 2020*b*) which contains data on compulsory school performance, secondary school application preferences, and secondary school admissions results.[9] We focus on applicants who graduate from compulsory education between the years 1996-2000, and who apply to secondary education immediately upon graduation.[10]

We merge these data with the FOLK (2020*c*; 2020*d*) data sets from Statistics Finland, containing information on labor-market outcomes from the years 1996-2017. We use two primary measures of labor-market performance: annual income and months of employment. Annual income includes earnings from employment and taxable social benefits. We include observations with zero income and employment throughout our analysis. We index all income to 2010 euros using the consumer price index from the Official Statistics of Finland (2020).

In addition, the Finnish Longitudinal Employer-Employee Data (FLEED) (2020*b*) dataset provides us with socioeconomic information on the applicants and their parents.[11] Further, we combine the data from FLEED and the Application Registry to create school-level indicators. To measure educational attainment we use the Student and Degree Registers (1996-2013) (2020*f*; 2020*a*), which contain information on the year, level, and field of all post-compulsory enrolment and completed degrees.

Lastly, to examine the characteristics of the jobs that applicants in our sample find themselves in, we merge the FLEED occupational codes with occupational task data from Acemoglu and Autor (2011*a*) using a crosswalk between SOC and 4-digit ISCO occupational identifiers from the Bureau of Labor Statistics (2012). This data measures the manual and cognitive routine task-intensities of jobs, and the likelihood that jobs may be offshored. To avoid possible selection bias stemming from the fact that we can only measure the occupational content for people who are employed, we take the most recent occupation code of people not employed 15 years after compulsory school as indicative of their potential occupational task and skill content. Since, at least to our knowledge, this occupational task data has not been linked to GPA data in a nationally representative manner, we show how the occupational task measures from Acemoglu and Autor (2011*b*) relate to compulsory school grades and secondary school track in Appendix Figure 4. These graphs indicate that, on average, both educational performance in compulsory school GPA as well as secondary school track are strongly related to the tasks of occupations people are employed in much later in their lives.

B Descriptive statistics

Merging these data sources together allows us to observe the labor market outcomes of each applicant in the 1996-2000 cohorts for 17 years following admission to secondary education. We draw mean income and employment profiles for all applicants admitted to either the general or vocational track of secondary

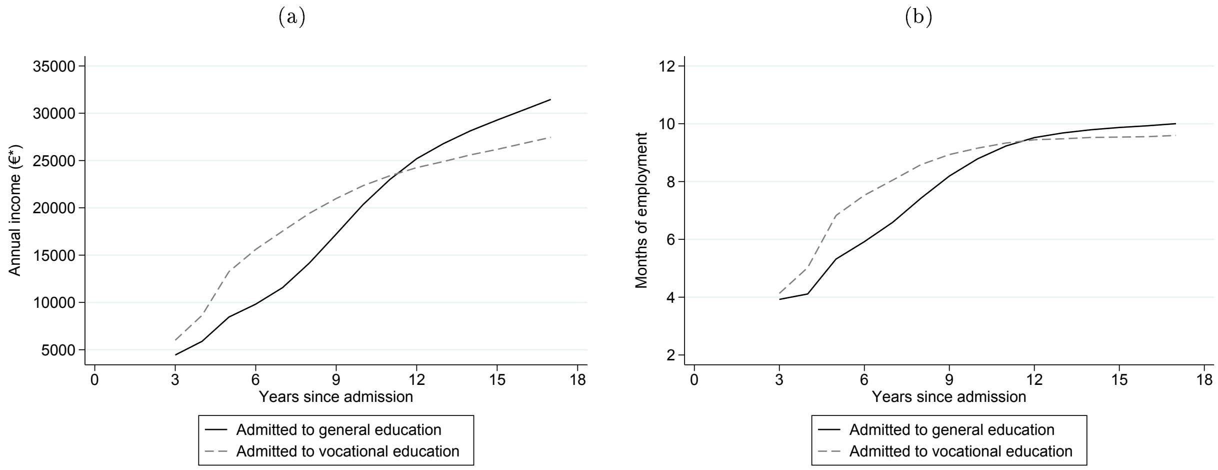
[9]This data is provided to researchers in two formats, one published by Statistics Finland, and the other by the VATT Institute for Economic Research.

[10]We are able to include data for nearly entire cohorts since each year above 98 percent of those graduating from compulsory school apply immediately to secondary education.

[11]Additional information on parent-child links is comes from Statistics Finland (2020*e*).

education (Figure 2). Although those admitted to vocational education initially outperform those admitted to general education, they are overtaken by their general track peers 12 years after admission to secondary education (typically around age 28). On average, 17 years after admission those admitted to the vocational track earn 27,500 euros annually, whereas those admitted to the general track earn 31,500 euros annually (indexed to 2010 euros). Those admitted to the vocational track are also employed on average 0.4 months less a year than those admitted to the general track. These patterns remain qualitatively similar for each of the seven vocational subfields and for both males and females (Appendix Figure 2).

Figure 2: Time profiles in mean annual income and months of employment

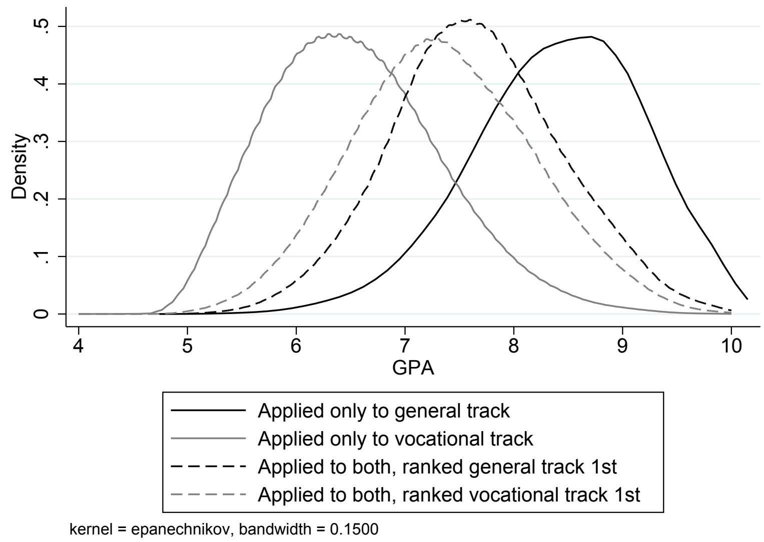


Notes: Figure 2 shows the mean income and employment outcomes for the cohorts of students applying to secondary school in the years 1996-2000 for the 17 years after admission to secondary education (~age 33). Annual income is indexed to 2010 euros, and observations with zero income and zero months of employment are included in the averages. *Incomes are indexed to 2010 euros.

As we see in Figure 3, however, these groups of applicants are already different prior to admission to secondary education. Applicants who only apply to the general track have a mean compulsory school GPA of 8.5, while applicants who only apply to the vocational track, who have a mean GPA of 6.5 (roughly 2 standard deviations lower). The mean GPA for applicants who apply to both the general and vocational tracks of secondary education is about 7.5, with only small differences by preference ordering. These graphs suggest that differences in means of longer-term outcomes of applicants are likely to be influenced by selection into secondary school track. In our RDD estimation we thereofore focus on applicants who apply to both tracks of secondary education.[12]

[12]Figure 3 in the Appendix shows time profiles for our RDD estimation sample as described in Section C.

Figure 3: Compulsory school GPA and application behavior



Notes: Figure 3 shows the distributions of applicants by compulsory school GPA for four sets of applicants: those who apply only to the general track of secondary education, the vocational track, and those who apply to both but rank the general track first as well as those who rank the vocational first.

C Estimation sample

In our estimations we focus on applicants who apply to both the general and vocational tracks, exploiting variation in admissions decisions. This is the only group of applicants for whom admissions cutoffs determine secondary school track type. This sample is also policy-relevant since they are the group most likely to be affected by changes in the size of secondary school sectors. This leaves us with just over 20 percent of each cohort. Additionally, we restrict our sample to those applicants who are above the admissions cutoff to the track not ranked first. This is to ensure that we estimate the effect of admission to vocational versus general education rather than admission to vocational (/general) compared to no offer at all. Since we restrict our estimation sample to applicants who qualify for the track not ranked first, the counterfactual for admission to the vocational track is best understood as admission to the general track. Last, our RDD design requires us to have at least two applicants to programs on each side of the admissions margin.[13] In total, our estimation sample is composed of 21,591 individuals (7.5 percent of the total data). Within this sample, roughly 90 percent (19,932) rank the general track first while 10 percent (1,659) rank the vocational track first.

Table 1 reports the mean background characteristics by secondary school admission status for the full sample (Columns 1 and 2) and estimation sample (Columns 3 and 4), as well as the mean complier characteristics estimated using our RDD strategy described in section B (Column 5). As we saw in Figure 3, applicants in our estimation sample come from the middle of the distributions of nearly all measures of background characteristics. Since our optimal RDD strategy requires secondary school programs to be oversubscribed, our compliers are also more likely to come from urban areas.

Table 1: Mean background statistics

	Full sample		Estimation sample		Complier
Track admitted	General	Vocational	General	Vocational	characteristics
Individual characteristics					
GPA	8.36	6.74	7.93	7.08	7.22
Male	0.42	0.64	0.58	0.63	0.65
Finnish nationality	0.99	0.99	0.99	0.98	0.99
Age at graduation	16.01	16.08	16.04	16.02	16.04
Native language Finnish	0.93	0.94	0.93	0.94	0.94
Native language Swedish	0.06	0.05	0.06	0.05	0.05
Non-Finnish or Swedish speaker	0.01	0.01	0.01	0.02	0.01
Urban	0.57	0.49	0.61	0.68	0.70
Semiurban	0.19	0.21	0.15	0.19	0.13
Rural	0.24	0.29	0.20	0.16	0.18
Family characteristics					
Father's income	37,268	26,301	33,251	31,703	35,392
Father in NEET	0.14	0.22	0.14	0.17	0.15
Father has secondary degree	0.35	0.47	0.39	0.42	0.44
Father has HE degree	0.40	0.13	0.32	0.27	0.26
Mother's income	24,198	18,907	22,691	21,794	21,921
Mother in NEET	0.15	0.23	0.15	0.17	0.16
Mother has secondary degree	0.37	0.49	0.42	0.43	0.47
Mother has HE degree	0.41	0.16	0.35	0.29	0.27
Observations	175,297	111,195	15,335	6,256	.

Notes: Table 1 reports mean background characteristics by admission status for the full sample (columns 1 and 2) and the estimation sample (columns 3 and 4). Additionally, the right-most column includes estimated mean complier characteristics using our RDD strategy described in section B (column 5).

Although our RDD design is limited to students who apply to both vocational and general education, most schools are included in our RDD sample. The cutoffs that applicants in our estimation sample are exposed to come from 79 percent of the vocational schools and 88 percent of the general secondary schools in Finland between the years 1996-2000.[14] We take this to suggest that our results are not driven by a handful of schools, but provide a representative estimate for marginal applicants.

III Empirical strategy

A Admissions cutoffs and the running variable

To identify the causal effect of admission to vocational secondary education we use a regression discontinuity design (RDD) created by the centralized admissions process to secondary education in Finland. We construct admissions cutoffs from the data as follows. Compulsory school GPA is the main criteria for admission in all programs. That said, schools apply slightly different scales, giving different weights to different grades, and in some cases supplement GPA with other criteria for admission. We have data on the admissions scores and rules for each cutoff and include them in our construction of the running variable.[15] The admissions cutoff to each program is defined by school and year combination (k) as the standardized admissions score of the lowest scoring applicant offered admission. The distance to cutoff k for applicant i is:

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

where τ_k is the cutoff score and c_{ik} applicant's own standardized admissions score.

For each applicant, we use the cutoff from their first-ranked application preference: for some applicants this is a cutoff for the vocational track and for others for the general track. For those who rank the general track first, we multiply their admissions score by negative one.

$$r_{ik} = \begin{cases} a_{ik}, & if\ Vocational \succ General \\ -1a_{ik}, & if\ General \succ Vocational \end{cases} \tag{2}$$

After this transformation positive values always indicate an increased likelihood of admission to the vocational track.[16] For those who rank the general track first, this means that their admissions score is below the cutoff, and for those who rank the vocational track first this means their admissions score is above the cutoff. With this transformation, we are able to pool the data (see Figure 4 for pooled bin-graphs or

[13] We test for flexibility in this requirement by modifying the number for all values from 2 to 5. Our results are not sensitive to these modifications (see Appendix Table 3).

[14] The vocational tracks represented in our estimation sample include 66 percent of the total 239 specific vocational training programs (hairdresser, acrobat, plumber, etc.). The general tracks represented in our sample include 74 percent of the 53 specific general education programs (International Baccalaureate, Performing Arts, etc.)

[15] We follow Huttunen et al. (2019) and estimate programme-specific regression models where admission scores are explained with the GPA and then divide the score with the coefficient of GPA. This way, a one unit change in GPA has the same effect on the rescaled scores in each programme.

[16] In addition to showing our full discontinuity sample, we show graphs where we separate applicants by application preferences (Figure A5) and the arguably more exogenous admissions first stage (Figure A5).

Figure A5 for separated bin-graphs).

As Figure 4a shows, crossing the admissions cutoff increases the likelihood of admission to the vocational track by roughly seventy percentage points. Still, not quite all applicants above the cutoff are observed to be admitted to the vocational track. This is due to two reasons. First, not all applicants whose admissions points were sufficient for admission could be contacted for an offer.[17] Second, for a subset of applicants we only observe offers accepted by the applicant.[18] We cannot distinguish between these two reasons for measurement error.

Crossing the admissions cutoff also increases the probability of enrolling in the vocational track (by about fifty percentage points, see Figure 4a). As we might expect, not everyone admitted to the vocational track enrolls in a vocational program: over the summer as spots in the general track (the preferred option for many of our applicants) open up, some applicants change their enrollment to the general track. Since we are interested in the effects of exposure to vocational training on labor market outcomes, we use enrollment as our first stage, and scale our reduced results by the jump in enrollment probability at the cutoff. While this scaling allows us to better gauge the magnitude of the effects of exposure - not just admission - to vocational training, it comes with additional assumptions. Primary amongst these is the exclusion restriction, which requires that admission to the vocational track cannot affect labor-market outcomes through any other channel other than enrollment.[19] Since the general track is the preferred option for most applicants in our sample, dissapointment in admission to the vocational track might cause some applicants to drop out of secondary education altogether or re-apply in the following admissions cycle in hopes of gaining admission to the general track. Both of these potential channels would likely lead to worse labor-market outcomes compared to being admitted directly to the general track. Any bias from either of these situations goes against our results (see Section IV). It is harder to come up with a plausible story biasing our results in the opposite direction.

[17] For example, during the period studied here, an offer for the waiting list could be lost by a single missed phone call.

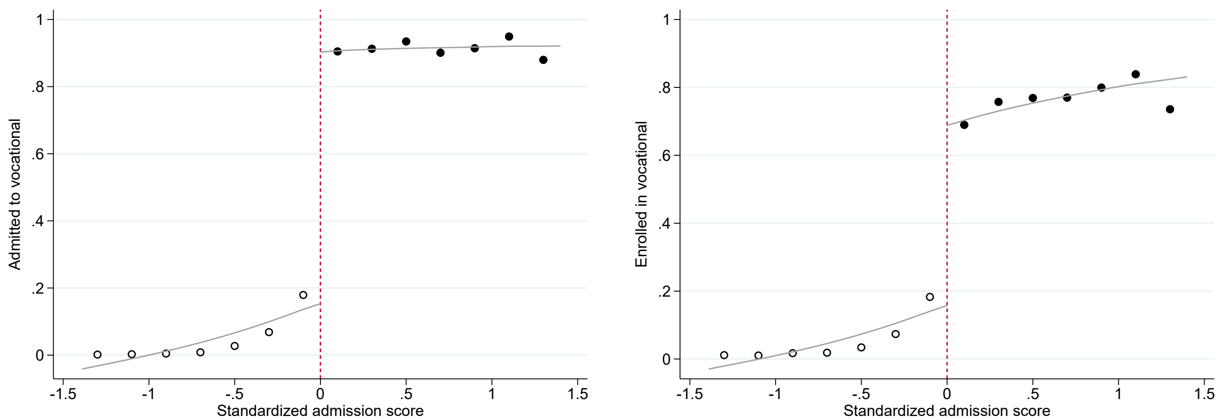
[18] We observe all offers extended during the automated stage of the admissions process; for the updating process, we only observe offers accepted by the applicant. See Section A. To account for this measurement error in the admissions process, we could use an instrument variable (IV) strategy (fuzzy RDD) where we scale by the jump in admissions probability, to estimate the local average treatment effect (LATE) of admission to vocational education.

[19] Monotonicity - the requirement that admission to the vocational track can only increase (not decrease) enrollment in the vocational track - is another assumption underlying this scaling. The institutional details of our context make this assumption unlikely to fail.

Figure 4: Cutoffs

(a) Admission

(b) Enrollment



Notes: Figure 4 shows the share of applicants admitted to and enrolled in the vocational track for those in the full estimation sample plotted against program-specific standardized running variables. As described in Section A and depicted in Figures 6 and A5, the full esitmation sample pools together those who apply to both tracks but prefer either the general or vocational track. 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.

B Specification

To eliminate selection bias, we exploit the unpredictable admissions cutoffs described above. To examine the effect of crossing the cutoff, we use the pooled data[20] and a reduced form regression specified as follows:

$$y_{ik} = b_k + \theta Z_{ik} + (1 - Z_{ik}) f_{0k}(r_{ik}) + Z_{ik} f_{1k}(r_{ik}) + w_{ik} \tag{3}$$

where y_{ik} is the outcome variable (e.g. income, employment) for applicant i to cutoff k. Z_{ik} is a dummy variable indicating being above the cutoff (a positive value of r_{ik}). We allow the slope of the running variable (f_{nk}) to differ on either side of the cutoff. For our baseline model (the most flexible model), we also allow the slope of the running variable to vary by cutoff. To reduce the dimensionality to gain statistical power, we also run our estimates without interacting our running variable with cutoff fixed-effects. Error terms (w_{ik}) are clustered at the cutoff level.

We employ a nonparametric local linear regression technique (Hahn, Todd, and Van der Klaauw, 2001;Gelman and Imbens, 2017) with edge kernel (triangular shaped) weights centered at admission cutoffs:

$$k(r_i) = 1\{|\ \frac{r_i}{h}\ | \leq 1\} * (1 - |\ \frac{r_i}{h}\ |) \tag{4}$$

h is the optimal bandwidth derived using the selection procedure in Calonico, Cattaneo, and Titiunik (2014), estimated seperately above and below the cutoff. For robustness, we use fixed bandwidths ranging from 0.1 to 2 (the optimal bandwidth being close to 1).

[20] We report RDD estimates for the two sets of application preferences separately in Section D.

Since we are interested in the effects of, not just admission, but exposure to the vocational track on later outcomes, we scale our reduced form estimates by enrollment for our main results (see Figure 4).[21] In this fuzzy RDD strategy, we define the treatment variable for these regressions, D_i, to indicate that an applicant is observed enrolling in the vocational track. The first stage regression measures how being above the admission cutoff increases the likelihood of enrollment in the vocational track and the second stage measures the effect of enrollment to the vocational track on various outcome variables.

To estimate potential outcomes for our compliers in the absence of treatment, we use our RDD strategy outlined above, but redefine the outcome and treatment variables as follows.[22] We replace the outcome variable with $y_i(1-D_i)$ and the treatment variable with $(1-D_i)$. To estimate mean complier characteristics, we use the same strategy.

C Validity of research design

The application and admission process in Finland motivates the design of our empirical strategy. First, the deferred acceptance algorithm provides no incentives for strategic behavior.[23] Second, the timing of the process (Appendix Figure 1b) makes it impossible to know one's own admissions points or the cutoffs at the time of application.

Our identifying assumption is that the potential outcomes of applicants develop smoothly across the cutoff (Lee and Lemieux, 2010). We perform two types of checks to ensure that our regression discontinuity design satisfies the identifying assumption.

First, we perform a balance check for covariates across our RD cutoff. We do this for all estimation samples by running the model in Equation 3, replacing the outcome variable with our observed background characteristics. The results in Table 2 suggest that there are a few more small statistical discontinuities than we might expect. Even though these are small and go against our results, we also run our RDD specification with a full set of controls. Adding controls does not change our results, if anything it increases their magnitude.

[21] The jump in admissions probably at the cutoff is roughly 0.7, whereas the jump in enrollment is 0.5. If the reader prefers to scale the reduced form by admissions rather than enrollment, they can divide the reduced form results by 0.7 instead of 0.5.

[22] See for example, Sarvimäki and Hämäläinen (2016), who use the same method.

[23] The literature on deferred acceptance algorithms points out that the use of finite lists can result strategic behavior if applicants leave out options to which they are unlikely to be admitted (Haeringer and Klijn, 2009; Calsamiglia, Haeringer, and Klijn, 2010). Whether or not this is the case in the Finnish context, this should not affect our estimation strategy inasmuch as the rank-order of applications is unlikely to be affected. Even if this were the case, the internal validity of our estimates would hold since any strategic behavior stemming from finite lists should also develop smoothly across admissions cutoffs.

Table 2: Covariate balance & McCrary density test

Baseline specification	Full Est. Sample Discontinuity		Prefer General Discontinuity		Prefer Vocational Discontinuity	
Individual characteristics						
Male	-0.014	(0.017)	-0.017	(0.018)	-0.019	(0.038)
Finnish nationality	-0.003	(0.003)	-0.002	(0.003)	0.000	(0.011)
Age at graduation	0.003	(0.008)	0.002	(0.008)	0.010	(0.015)
Native language Finnish	-0.007	(0.004)	-0.007	(0.004)	-0.009	(0.016)
Native language Swedish	0.001	(0.002)	0.001	(0.002)	0.003	(0.003)
Non-Finnish or Swedish Speaker	0.006	(0.003)	0.006	(0.004)	0.001	(0.014)
Urban	-0.012	(0.012)	-0.016	(0.012)	0.050	(0.046)
Semiurban	0.001	(0.008)	0.001	(0.008)	-0.000	(0.040)
Rural	0.008	(0.011)	0.015	(0.012)	-0.047	(0.037)
Prior school performance						
GPA	0.003	(0.004)	0.000	(0.000)	-0.018	(0.049)
Mothertongue	0.008	(0.027)	-0.016	(0.035)	0.006	(0.085)
Mathematics	-0.002	(0.037)	0.014	(0.040)	-0.152	(0.098)
Physics	-0.015	(0.033)	-0.016	(0.033)	-0.013	(0.100)
Biology	0.016	(0.026)	0.024	(0.029)	0.034	(0.090)
Geography	-0.002	(0.026)	-0.012	(0.031)	0.111	(0.091)
History	-0.029	(0.029)	-0.040	(0.031)	-0.085	(0.110)
Religion	0.008	(0.027)	0.002	(0.035)	-0.028	(0.099)
Physical education	0.007	(0.034)	0.006	(0.044)	-0.033	(0.125)
Music	0.043	(0.032)	0.018	(0.035)	0.144	(0.089)
Art	0.080	(0.029)	0.100	(0.034)	0.136	(0.102)
Home economics	0.007	(0.027)	0.012	(0.034)	0.037	(0.090)
Handicraft	0.004	(0.028)	0.016	(0.030)	-0.028	(0.084)
Parent characteristics						
Father's income	2,561	(2,561)	4,501	(2,955)	-786	(2,304)
Father in NEET	-0.011	(0.012)	-0.002	(0.014)	-0.014	(0.039)
Father no post-compulsory degree	0.010	(0.015)	0.011	(0.018)	0.035	(0.052)
Father has secondary degree	0.027	(0.016)	0.018	(0.019)	0.008	(0.057)
Father has short tertiary degree	-0.031	(0.015)	-0.030	(0.018)	0.042	(0.042)
Father has HE degree	-0.002	(0.009)	0.003	(0.009)	0.003	(0.010)
Mother's income	-444	(343)	-765	(441)	-562	(1188)
Mother in NEET	0.008	(0.012)	0.007	(0.013)	0.050	(0.045)
Mother no post-compulsory degree	0.001	(0.014)	-0.004	(0.017)	-0.010	(0.050)
Mother has secondary degree	0.034	(0.017)	0.040	(0.021)	0.060	(0.063)
Mother has a short tertiary degree	-0.030	(0.015)	-0.029	(0.018)	-0.010	(0.071)
Mother has HE degree	-0.007	(0.007)	-0.012	(0.008)	-0.043	(0.025)
N/McCrary density test	-128	(228)	-115	(209)	-14	(26)

Notes: The table shows local linear estimates for the jump at the cutoff using Specification 1, the edge kernel, and the optimal bandwidth selection algorithm of Calonico, Cattaneo, and Titiunik (2014). Column 1 reports estimates for our full estimation sample, while columns 2 and 3 report estimates by application preferences. Standard errors (in parentheses) are clustered by cutoff.

Second, we test for the potential manipulation of the running variable from one side of the cutoff to the other by checking for smoothness in the density of observations across the cutoff by running the McCrary bunching test. Figure 7 in the Appendix shows the distribution of applicants around the cutoff. While Figures (a)-(c) look like there may be small spikes around the cutoff, our sample passes the McCrary bunching test - suggesting there is no manipulation at the cutoff (Table 2). Moreover, since our cutoffs are defined using the last admitted applicant to each program, spiking at the cutoffs is mechanical, and when we exclude these applicants from the sample these spikes largely disappear (see Figure 7d). To complement our main estimates, we perform donut RDD estimates again excluding applicants used to identify the cutoffs from our estimation sample. The results from these donut estimates do not differ from our baseline estimates and are reported along with our main outcomes.

IV Results

A Effects over time

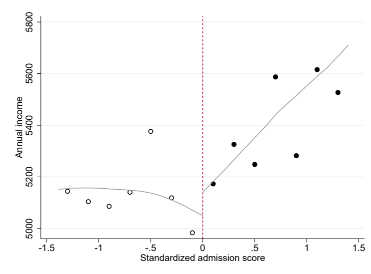
A common view suggests that applicants admitted to the general track will out-perform those admitted to the vocational track in the labor market over time (Hampf and Woessmann, 2017; Hanushek et al., 2017). To examine whether or not this is the case empirically, we use the RDD design created from the centralized application to secondary education in Finland to estimate the labor market returns to vocational secondary education for each year after admission to secondary education.

First, we show the data underlying our RDD estimates 3-17 years after admission graphically (Figures 5 and 6).[24] These figures suggest that crossing the admissions cutoff increases initial annual income (three years after graduation) and that these benefits do not disappear with time. They also suggest that there is no discernable discontinuity in months of employment at the admissions cutoff.

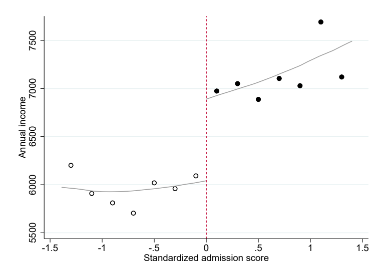
[24] Recall from Section C that the vast majority of our total estimation sample indicate a preference for the general track. As such, in large part, our main estimates come from applicants with this set of preferences. See Section D for estimates for each set of application preferences separately. In Appendix Figures 8-11 we show these same plots separated by application preferences. These figures suggest that crossing the admissions cutoff increases initial annual income (three years after graduation) for applicants with both sets of preferences and that these benefits do not disappear with time. They also suggest that there is no discontinuity in months of employment at the admissions cutoff for applicants who rank the general track first, but that there is a large discontinuity for those who rank the vocational track first.

Figure 5: Annual income: Full RDD sample

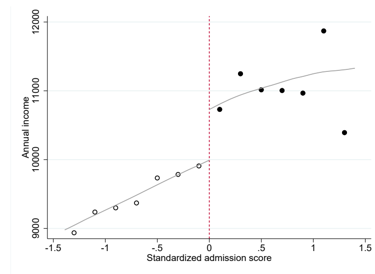
(a) 3 years after admission



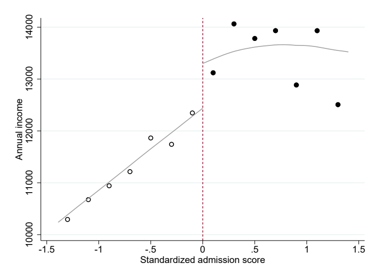
(b) 4 years after admission



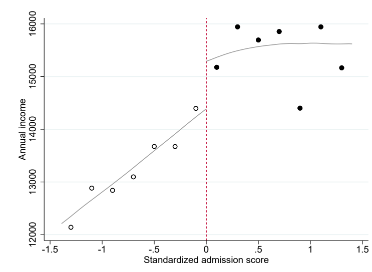
(c) 5 years after admission



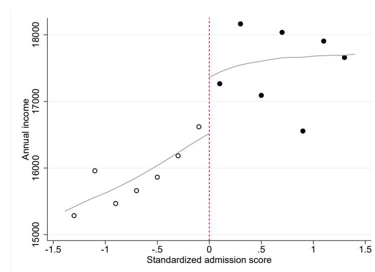
(d) 6 years after admission



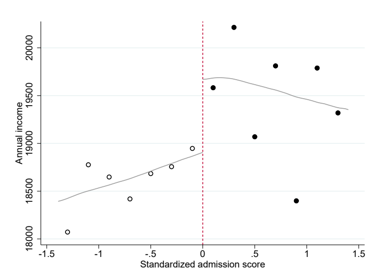
(e) 7 years after admission



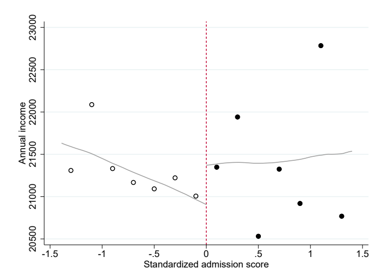
(f) 8 years after admission



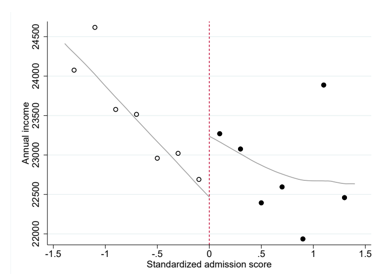
(g) 9 years after admission



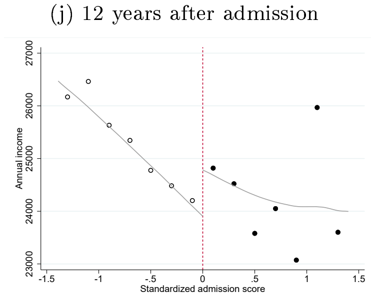
(h) 10 years after admission



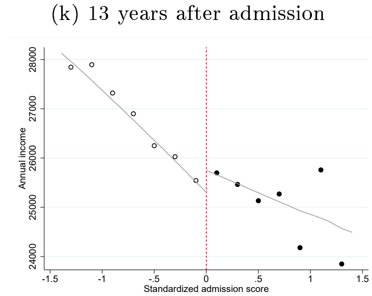
(i) 11 years after admission



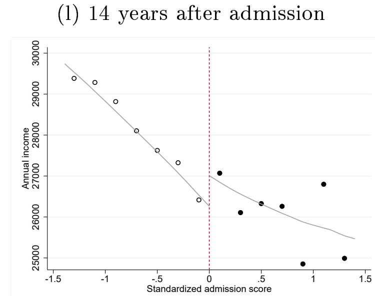
(j) 12 years after admission



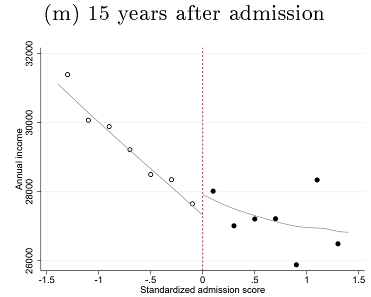
(k) 13 years after admission



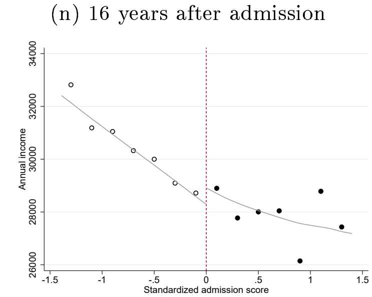
(l) 14 years after admission



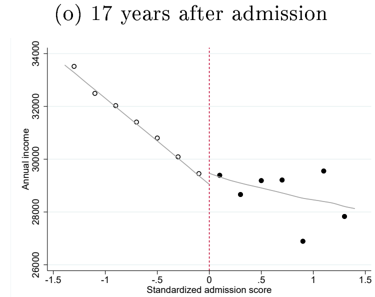
(m) 15 years after admission



(n) 16 years after admission



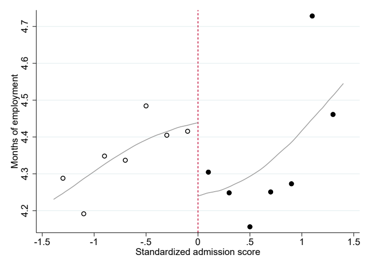
(o) 17 years after admission



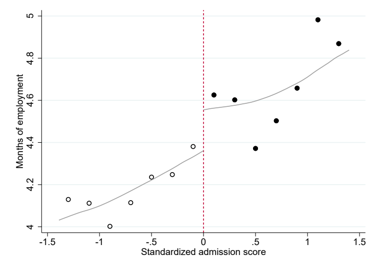
Notes: These Figures show the mean annual income 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins.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

Figure 6: Months of employment: Full RDD sample

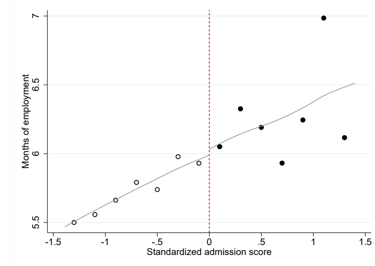
(a) 3 years after admission



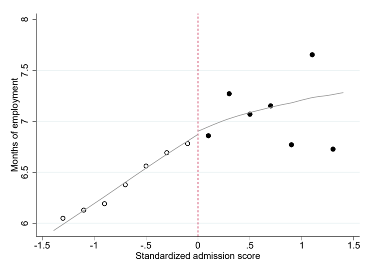
(b) 4 years after admission



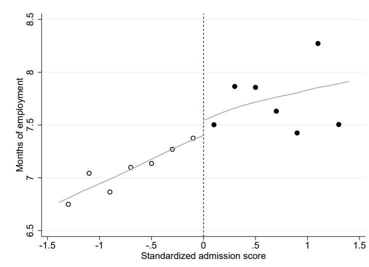
(c) 5 years after admission



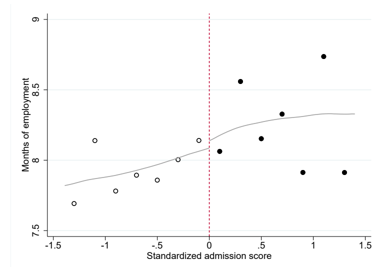
(d) 6 years after admission



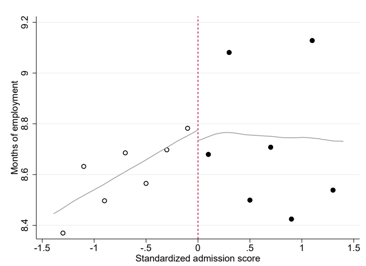
(e) 7 years after admission



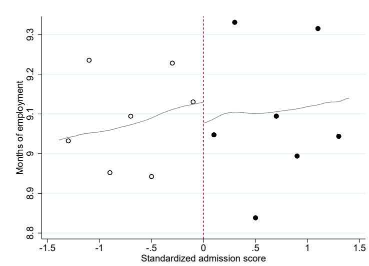
(f) 8 years after admission



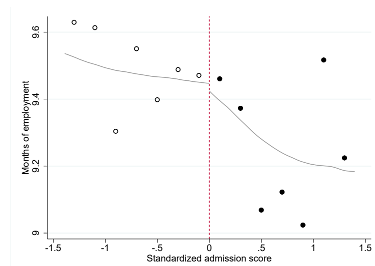
(g) 9 years after admission



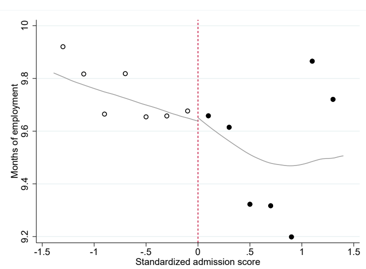
(h) 10 years after admission



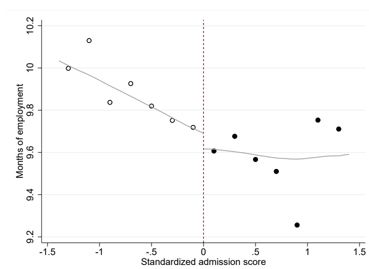
(i) 11 years after admission



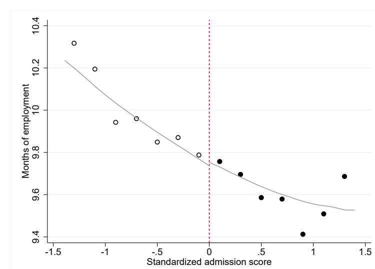
(j) 12 years after admission



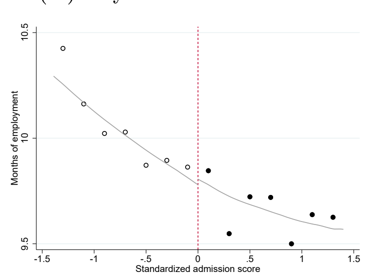
(k) 13 years after admission



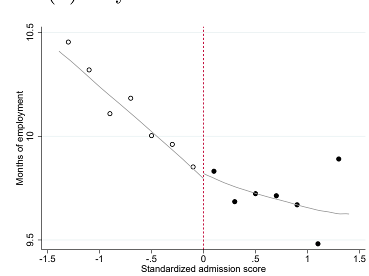
(l) 14 years after admission



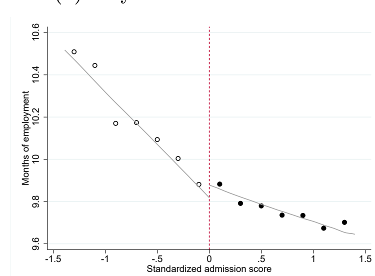
(m) 15 years after admission



(n) 16 years after admission



(o) 17 years after admission

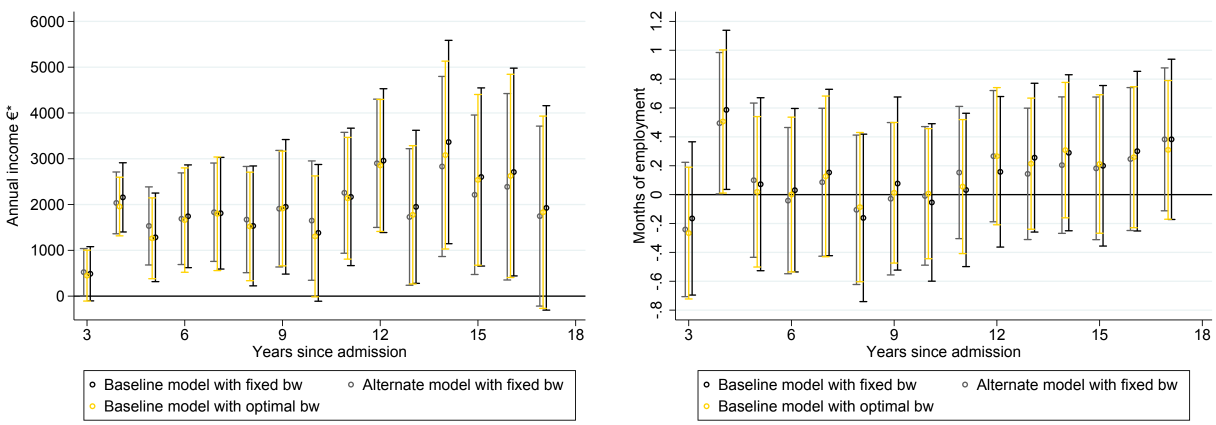


Notes: These Figures show the mean months of employment 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide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

Next, we estimate the effects for our full RDD sample. These estimates measure what would happen to the marginal applicant if they were admitted to the vocational track. In other words, these estimates provide insight into policies that expand the size of the vocational sector.[25] The first stage estimates (Appendix Table 2) show that crossing the admissions cutoff increases the rate of observed admissions to the vocational track by approximately 50 percentage points. Since we are interested in the effects of exposure - not just admission - to vocational training, we scale the reduced form estimates by our first stage, and consider our LATE estimates as our main estimates. Figure 7 reports the LATE estimates from various specifications.[26]

Figure 7: Year-by-year RDD estimates: Annual income and months of employment

(a) (b)



Notes: Figure 7 shows RDD estimates of the effects of admission to vocational education on annual income and months of employment for each of the 17 years following admission to secondary education. The graphs also show the 95 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 and a fixed bandwidth of 1 standardized admission unit on each side of our cutoff. Standard errors are clustered by cutoff. *Incomes are indexed to 2010 euros.

The initial effect of admission to vocational education on annual income is positive, and does not appear to decrease with time. Admission to the vocational track increases mean annual income by 1,800 euros 17 years after application to secondary school (age 33). The potential outcomes estimate (Appendix Table 2) indicates that without admission to vocational education these applicants would have earned 29,000 euros, suggesting that admission to the vocational track increases the mean annual income of compiers by 4 percent at age 33. These findings stand in contrast to the mean trends depicted in Figure 2, where vocational track admits are overtaken by their peers admitted to the general track already 11 years after admission to secondary education.[27] Our year-by-year estimates of the effect of admission on months of employment

[25] Our estimates measure the effect of admission to the vocational track. The treatment consists of a bundle of components, including not only admission to a vocational curriculum, but admission to a different peer group, and relative-rank within the school. On average, admission to the vocational track decreases secondary school peer quality as measured by compulsory school GPA, increases the relative rank within the school from near the bottom of the compulsory school GPA distribution to the 66th percentile, and increases the size of the school students attend (Table 4). The only thing that changes consistently across all admissions cutoffs is secondary school curriculum. Additionally, prior research from the Finnish context suggests that exposure to different peer quality in general secondary school does not have an impact on learning outcomes (Tervonen, 2016; Tervonen, Kortelainen, and Kanninen 2017). This is in line with research from the United States suggesting that admission to elite high schools does not improve learning outcomes (Abdulkadiroglu, Angrist, and Pathak, 2014; Dobbie and Fryer Jr, 2014).

[26] See section Section B.

[27] Annual income at age 33 may be relatively early in the career, particularly for women (Böhlmark and Lindquist, 2006). However, our time-profiles by gender suggest that the time gradients for males and females are qualitatively similar (Figure 2).

are near zero for most of the period we study.[28] Applicants at the admissions margin are employed for an average of 10 months a year (Appendix Table 2).[29]

To probe for the effects of admission past age 33, we limit our sample to the oldest cohort (1996) and use OLS regressions with a full set of controls (Appendix Figure 13).[30] These results suggest that no significant changes in labor market outcomes occur between 17 and 19 years (age 37) after admission to secondary education.

Finally, to assess the possibility that those admitted to the vocational track will be overtaken by their peers in lifetime earnings, we perform present discount value (PDV) calculations for several scenarios (Appendix Table 8a). Results from these calculations suggest that, the lifetime premium to the vocational track would remain positive barring an immediate drop to negative two thousand through retirement at age sixty-five combined with a discount rate of below five percent.[31] Since our RDD estimates do not suggest that the vocational premium drops to zero in the coming years, and the OLS estimates through age 37 do not suggest any changes in the trends to the vocational premium, these scenarios are highly unlikely.

B Robustness

We perform several tests to explore the robustness of our main results. Columns 2-4 of Table 2a and Table 2b show our main outcomes estimated using various specifications. First, to ensure that our results are not biased by possible endogeneity in how admissions cutoffs to programs are defined, we re-estimate our results using a donut-RDD strategy - removing applicants who determine the admissions cutoffs from our sample (Column 2). Next, we increase the precision of our results by reducing the dimensionality of our estimates through a less flexible specification in which we do not interact cutoff-specific fixed-effects with our running variable (Column 3). Further, to account for any possible discontinuities in background characteristics we add a rich set of controls (see Table 2) to our baseline specification (Column 4). Our results are robust to these modifications.

To ensure that our sample is consistent across the year-by-year estimates we fix the bandwidth to 1.0 for all outcomes. We also estimate the optimal bandwidths for each outcome measure: these range from 1.1-1.3 below the cutoff and 1.3-1.5 above (Tables 2a and 2b). The results are robust for the range of fixed bandwidths from 0.1 to 2 (Figure 12).

Last, we test whether our results are sensitive to the choice of estimation sample. In our main RDD estimates we require that there are at least two observations on either side of the cutoff. We re-run the estimates from our baseline specification by restricting our sample to cutoffs with at least 3, 4, and 5 applicants on each side of the cutoff (Table 3). Our estimation sample changes dramatically when we impose these more conservative sample restrictions. Nonetheless, our RDD point estimates remain remarkably stable across these changes in the sample design, suggesting that our estimates are not sensitive to the

When we estimate the effects separately by gender we find that both are fairly similar to our main estimates.

[28] Our results are not sensitive to alternative measures for employment, including months of unemployment and NEET status (not in employment, education, or training). We do see a positive effect of admission to the vocational track on months of employment four years after admission, possibly because these applicants are more likely to graduate on time.

[29] Apart from employment, there are two potential explanations for the positive effects on wages: 1) people may be shifted into higher-paying occupations, or 2) people get paid more within the same occupations. When we test for this, we find that, if anything, people are shifted to occupations with higher mean wages - that said our estimates are noisy (Appendix Table 5).

[30] As we see, these estimates become imprecise when we limit the sample to this cohort and our estimation sample; due to a lack of statistical power, single-cohort RDD estimates are uninformative.

[31] To focus on the applicants whose lifetime income is most likely to go negative (See Section D), these calculations are also performed exclusively for the subsample of those who indicate a preference for the general track. The results described in the body hold for this subgroup as well (see Appendix Table 8b).

specific vocational subfields or schools included in our sample.

C Post-secondary education and occupational task content

The expected benefits of general education hinge on the preparation that the general track provides for further education and adaptability to changes stemming from technological change. Both of these potential explanations suggest that the benefits of general education may increase over the life-cycle.

We examine the effect of admissions to the vocational track on later educational attainment. The descriptive statistics show that the mean likelihood of obtaining a higher educational degree for general track admits is 60 percent and only 15 percent for those admitted to the vocational track. Surprisingly, using our RDD strategy, we find that admission to the vocational track has no effect on higher educational obtainment (Appendix Table 6). At the admissions cutoff 30 percent of compliers earn a higher educational degree. The lack of difference in higher educational attainment may help to explain why we do not see a declining trend in the effect of vocational education on labor market outcomes.[32]

To further provide insight into how the effects on labor market performance may develop in later years, we examine the effect of admission to vocational education on the occupational task content of jobs 15 years after admission (Appendix Table 4). An established literature on the future of work considers automation and globalisation to represent the two major sources of labor market risks (Acemoglu and Autor, 2011*b*; Goos, Manning, and Salomons, 2014; Frey and Osborne, 2017). Workers employed in routine tasks are perceived to be at a higher risk of replacement by automation, whereas non-routine occupational tasks may safeguard workers from automation. Our RDD estimates show that, compared to general education, admission to vocational education does not increase the risk of ending up in jobs likely to be hit by automation or offshoring.

Together, our findings give no indication that the positive effects of admission to vocational education for the marginal applicant disappear over time.

D Who benefits from vocational secondary education?

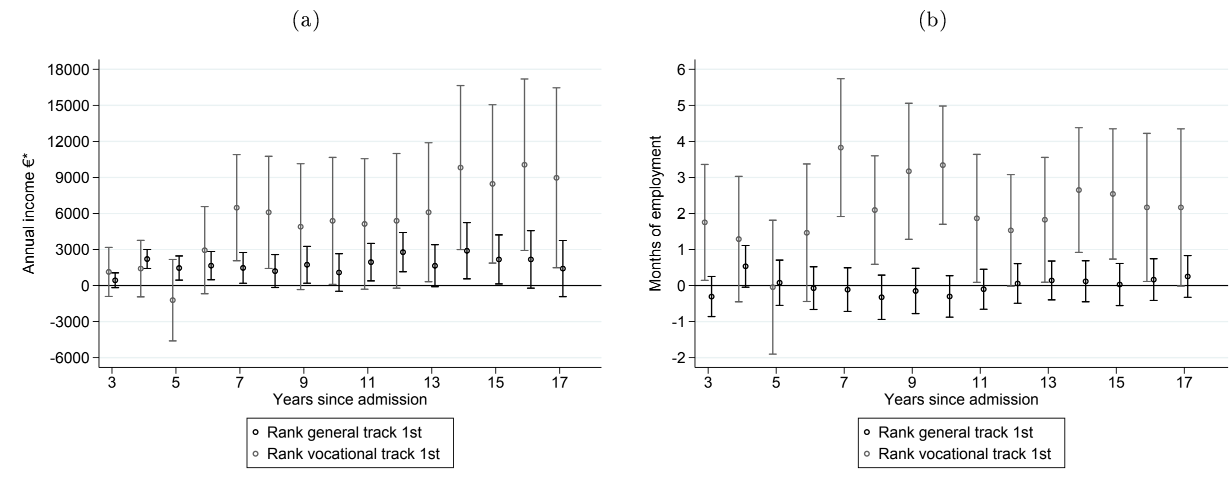
Our fuzzy RDD estimates measure the local average treatment effect of admission to vocational secondary education for applicants near the admissions cutoff who apply to both tracks. While this set of applicants is self-selected, they are also the group most likely to be affected by policies that expand or reduce the size of vocational secondary education.

Our main RDD estimates from Section A pool together applicants who rank the general track first with those who rank the vocational track first in their application preferences. Nonetheless, prior work on returns to field of study has noted that the payoffs to education type may vary according to comparative advantage and application preferences (Willis and Rosen, 1979; Kirkeboen, Leuven, and Mogstad, 2016). When we estimate the effects of admission to vocational education for applicants with each set of preferences separately, we find that both applicants who rank the general track first and those that rank the vocational track first benefit from vocational education (Figure 8). However, consistent with theory, applicants who prefer the vocational track experience heightened benefits from admission to vocational education. For those who prefer

[32]On the other hand, this may also help explain why we see a relatively small initial labor market advantage to vocational education (among our compliers, general track admits are no more likely to be enrolled in higher education).

the vocational track, admission to vocational education increases employment by almost 2 months a year 17 years after admission. Put another way, being pushed into general secondary school against someone's preferences reduces mean employment by nearly 20 percent. These large employment effects likely explain the nearly 25% increase in income at the RDD margin.

Figure 8: Year-by-year RDD estimates: Annual income and months of employment by preference group



Notes: Figure 8 shows RDD estimates of the effects of admission to vocational education on annual income and months of employment for each of the 17 years following admission to secondary education for two subsamples of applicants: those who apply to both secondary school tracks but rank the general track first and those who apply to both but rank the vocational track first. 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 and a fixed bandwidth of 1 standardized admission unit on each side of our cutoff. Standard errors (in parentheses) are clustered by cutoff. *Incomes are indexed to 2010 euros.

While we can only estimate the effects of vocational secondary education for people who apply to both secondary school tracks, others - notably those who apply only to the vocational track - are also directly affected by the size of the vocational sector (though it is less clear whether the counterfactual for them is the general track or dropping out of education altogether).[33] Imposing minimal assumptions, however, we can set bounds on the potential effects of vocational education for people outside our RDD sample. The results from our split sample RDD estimates suggest that application preferences tell us something about the potential effects of secondary school track for people with a particular set of preferences. Consistent with the notion of comparative advantage, we see that the benefits of vocational education are larger for those who indicate a preference for the vocational track in their applications to secondary school. By assuming weak monotonicity in the relationship between application preferences and labor market returns, we can interpret our RDD estimates from the subsample of applicants who rank the vocational track above the general as the lower bound for people who indicate stronger preferences for vocational secondary education (those who

[33] Other work has estimated causal effects away from the RDD cutoff in the context of education by taking advantage of alternate definitions of the running variable using data from standardized tests (Angrist and Rokkanen, 2015). Unfortunately, since standardized tests are uncommon in the Finnish context, we are unable to use a similar strategy to estimate causal effects within our RDD sample away from the admissions cutoff. Researchers have also bounded treatment effects for people not affected by treatment in instrument variable settings - "always-takers" and "never-takers" (Kowalski, 2016; Mogstad and Torgovitsky, 2018). We believe that the reason that we do not observe a sharp RDD in admissions is due to measurement error in our ability to observe admissions outcomes in the administrative data, rather than selective compliance. Instead, the people unaffected by the treatment in our setting are fundamentally different from those in our estimation sample: they have different sets of application preferences. This prevents us from using these prior strategies.

apply only to the vocational track). Conversely, we can interpret our RDD estimates from the subsample of people who prefer the general track to the vocational as an upper bound of the effects of vocational education for people with stronger preferences for general secondary education (those who apply only to the general track).

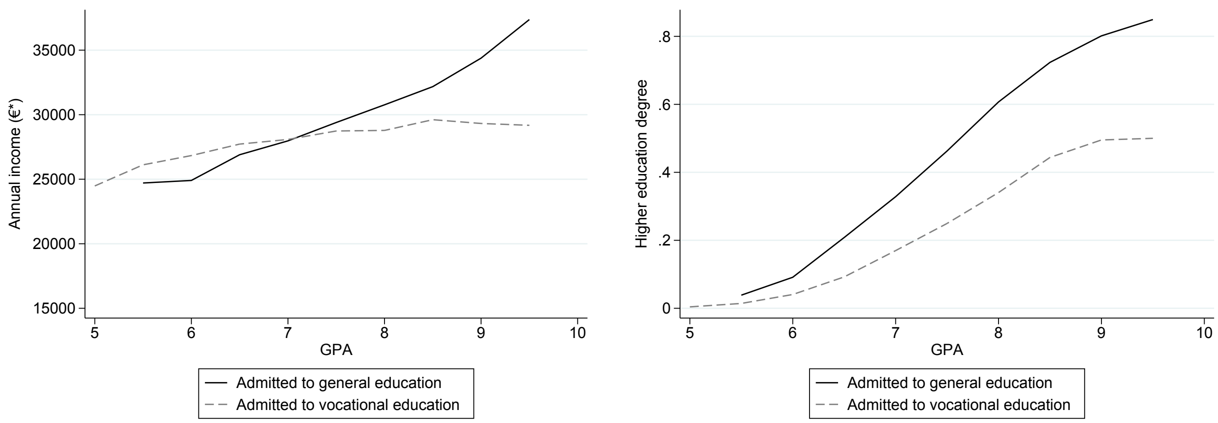
Related to preferences, another dimension by which the returns to secondary school field are likely to vary is prior skills and performance. The prior skills a person has - whether they be manual, social, analytic, etc. - will likely play a role in determining how suitable a secondary school track is for them. While we do not have measures for prior skills in each of these areas, we examine whether mean labor market outcomes for each secondary school track vary by compulsory school GPA (Figure 9). Our data tell a striking story. For people admitted to the vocational track, mean earnings are relatively flat across compulsory school GPA.[34] In sharp contrast, for those admitted to the general track, later-life earnings are strongly correlated with compulsory school GPA. The mean annual incomes between vocational and general track admits in Figure 9a cross for students with a GPA of approximately 7. Together, these observations suggest that people whose strengths lie outside of academics before secondary school may benefit from vocational education, while those who excel academically - or whose comparative advantage is academic - may benefit from general education. Given the compulsory school GPA distributions of applicants with each set of application preferences (Figure 3), this story, what we see in Figure 9 is in line with our exercise in bounding the effects of vocational education for people with different application preferences.

The potential consequences of secondary school track may also have to do with the future opportunities that a person has to develop their skills, and these opportunities may vary by academic ability. One reason the later incomes of people admitted to the general track are correlated with GPA could be that in order to realize the potential benefits of general education, general secondary school has to be followed by higher education. As we see in Figure 9b, this is most likely for people with higher compulsory school GPAs. Conversely, the correlation between GPA and earnings is weaker for people admitted to the vocational track; this may be because the returns to vocational secondary school are not as dependent on the completion of higher education.

[34] In fact, the distribution of earnings for those admitted to vocational education also seems to be narrower than that of those admitted to the general track. Extending our RDD estimates, we use a quantile instrument variable approach (Frölich and Melly, 2013) to test how admission to vocational education shifts the earnings distribution. The results from our quantile instrument variable estimates (Appendix Figure 14) suggest that admission to vocational education shifts the earnings distribution up and narrows the distribution such that the earnings differences between higher and lower earning applicants admitted to vocational education decrease.

Figure 9: Outcomes by compulsory school GPA and secondary school track

(a) Annual income 17 years after admission (b) Higher educational attainment 13 years after admission



Notes: Figure 9 shows mean annual income and higher educational attainment by compulsory school GPA for applicants admitted to the general and vocational tracks of secondary school. *Incomes are indexed to 2010 euros.

V Discussion

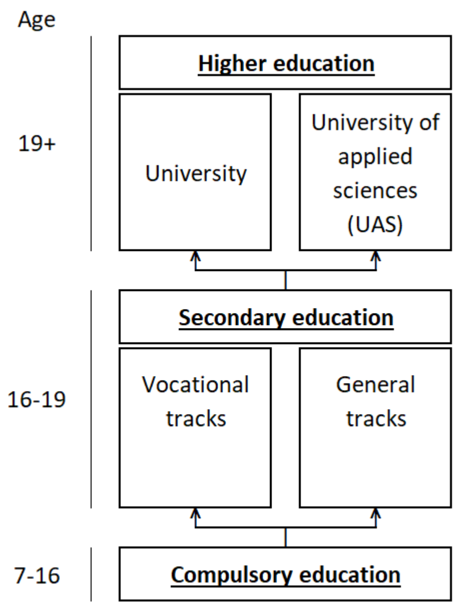
We study labor-market returns to vocational versus general secondary education using a regression discontinuity design created by the centralized admissions process in Finland. We find that admission to vocational education increases annual income by 6 percent at age 33, and that the benefits do not appear to disappear with time. These findings stand in stark contrast to much of the existing empirical and theoretical work on the long-term returns to secondary school track (Brunello and Rocco, 2017; Krueger and Kumar, 2004; Hampf and Woessmann, 2017; Hanushek et al., 2017). According to this literature, the long-term returns to vocational education should decrease with time, as technological advances makes it more difficult for individuals with narrower skill sets to adapt to changes than their peers with more general skills. Given the myriad changes to the labor-market that took place after the financial crisis of 2008-2009, we believe that the time period we study offers an attractive setting to examine how changes in the economy may affect the demand for vocational and general skills. While we find no evidence that the benefits of vocational education diminish through this time-period, we also probe for the possibility that people admitted to the vocational track may exhibit higher labor market risks due to changes in technology in the coming years. By comparing various occupational task measures, our RDD estimates suggest that people admitted to the vocational track are no more susceptible to risks of unemployment by automation and offshoring than their peers admitted to general education.

Equally important, our findings extend the prior literature on the returns to field of study in secondary education by providing insight into who is likely to benefit from vocational secondary education. Our RDD estimates measure the impact of vocational education for people most likely to be affected by changes in the size of the vocational sector. As such, these estimates come from people near the middle of the academic ability distribution, unlikely to graduate from higher education. Consistent with the idea of comparative advantage, our results suggest that applicants who express a preference for the vocational track experience heightened benefits from vocational education. For this subgroup, failing to gain access to vocational secondary education results in a 20 percent reduction in employment seventeen years after application to secondary school. Taking our RDD estimates for people who prefer the vocational track but apply to both as an lower-bound of the effects of vocational education for people with stronger preferences, our analysis suggests that the benefits of vocational education are likely to be at least as large for people who apply only to the vocational track. Since nearly half of each cohort in Finland is enrolled in the vocational track, this suggests that there may be significant room to expand vocational education in other developed countries.

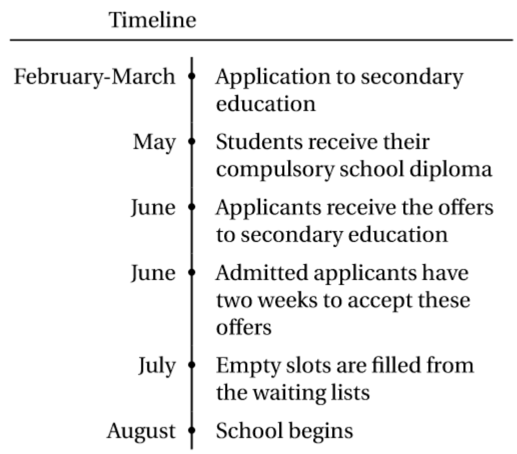
Appendix A: Institutions

Figure 1

(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).

Appendix 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

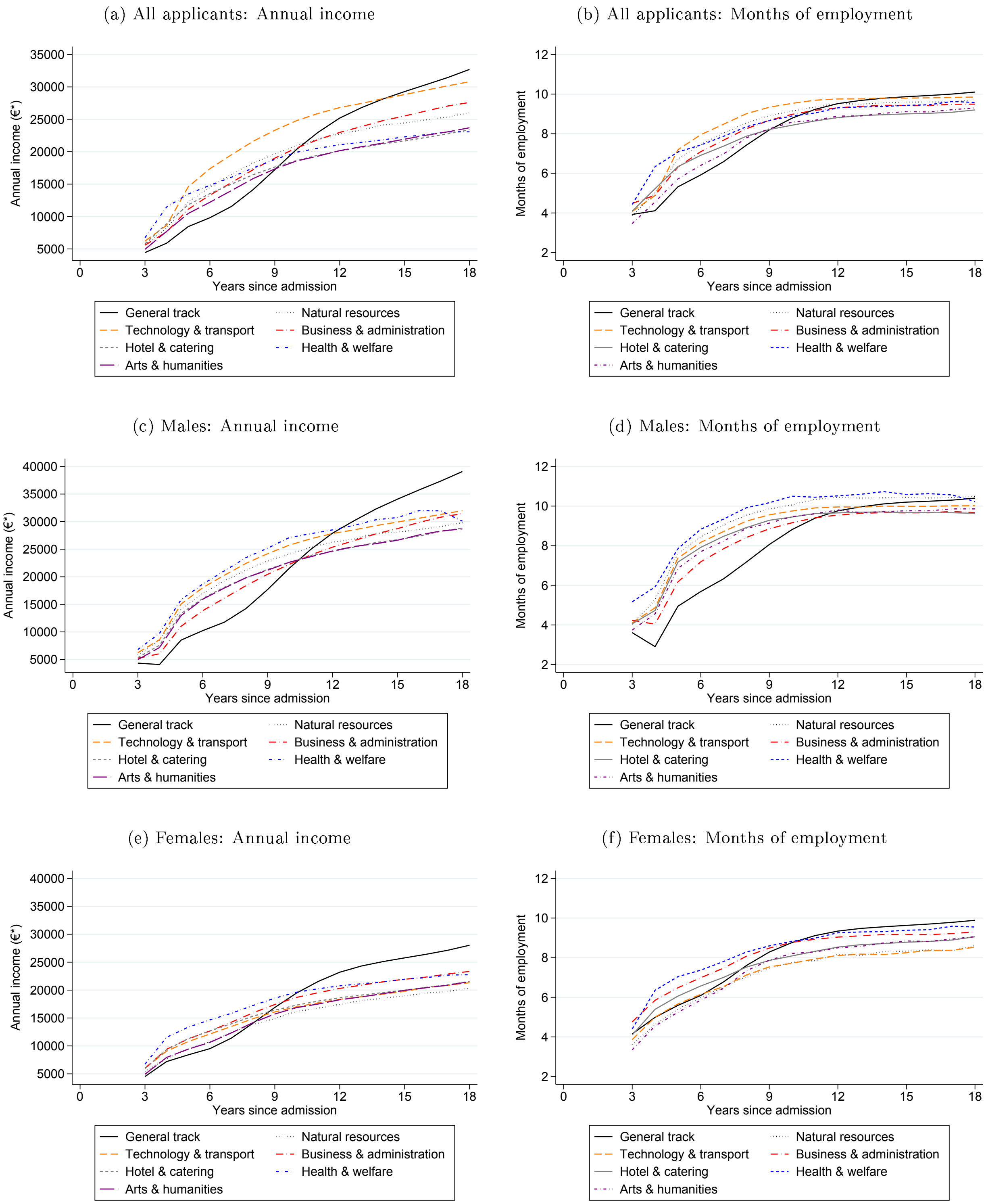
	Full sample	Estimation sample	Prefer general	Prefer vocational
General Track	175,297	15,335	14,796	539
Vocational Track	111,195	6,256	5,136	1,120
Natural resources	4.7	2.1	1.8	3.9
Technology and transport	52.8	38.8	38.2	41.6
Business and administration	14.8	35.3	38.3	21.5
Hotel and catering	19.7	16.5	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.

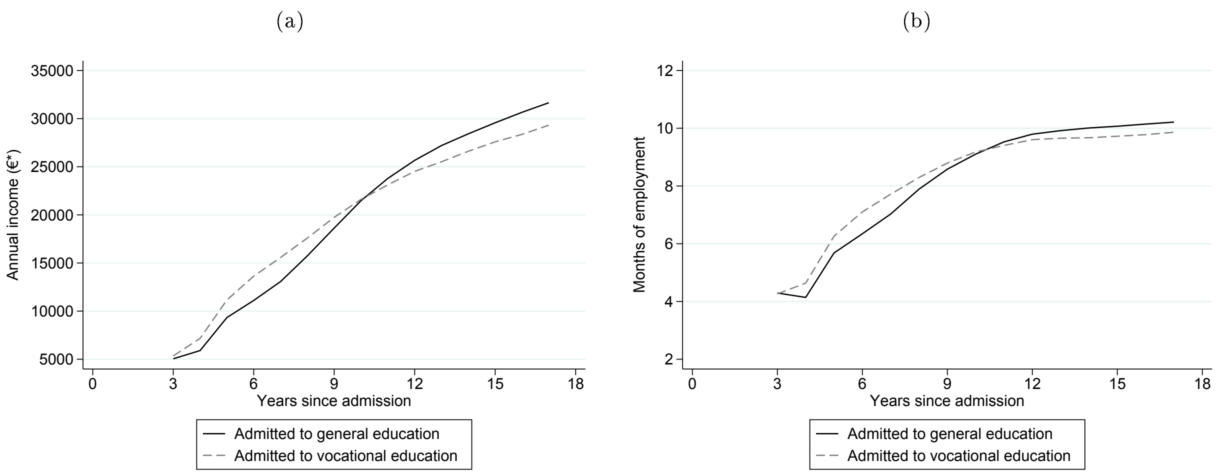
Figure 2: Time profiles by vocational subfield and gender



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.

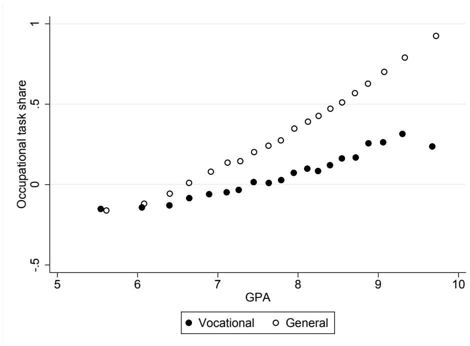
Figure 4a shows that people with low compulsory GPAs are least likely to be employed in occupations that which center around tasks involving non-routine cogntive analytic skills. For this group, secondary school track is not associated with a significant shift in the share of non-routine cognitive analytic 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.

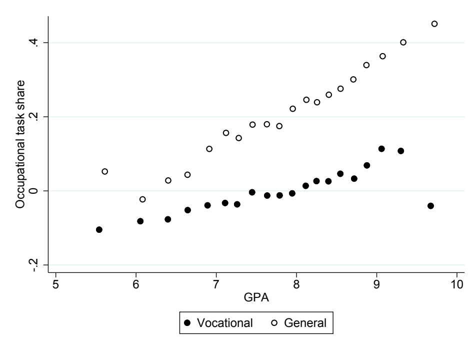
Lastly, applicants with high GPAs who are admitted to the general track of secondary education are most likely to be employed in jobs that are susceptible to offshoring (4g). This is likely due to the abstract nature of jobs requiring non-routine cognitive skills, making them less place-dependent.

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

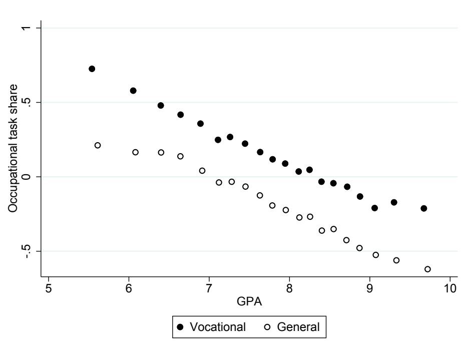
(a) Non-routine cognitive analytic



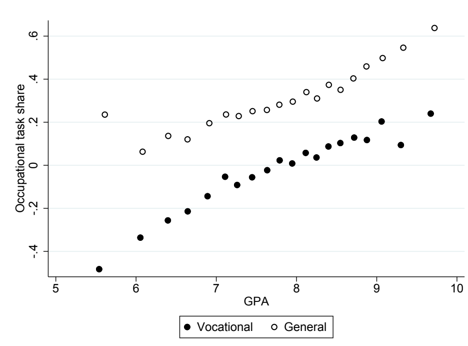
(b) Non-routine cognitive personal



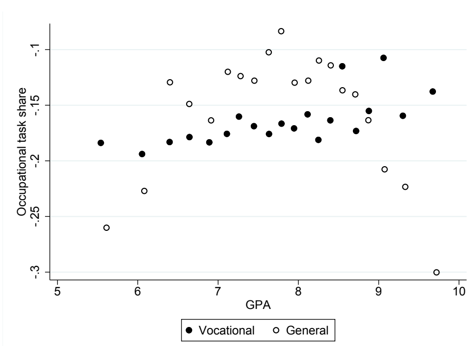
(c) Non-routine manual physical



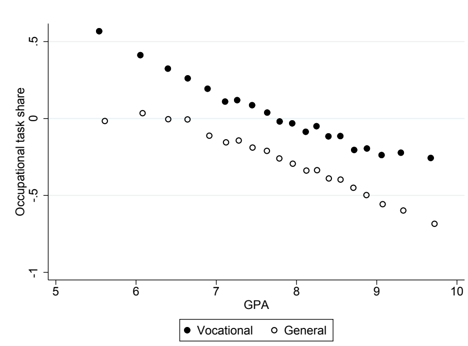
(d) Non-routine manual personal



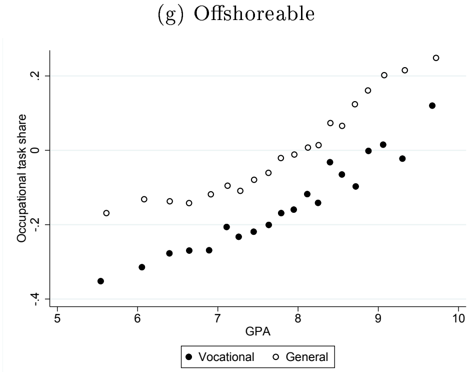
(e) Routine cognitive



(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.

Appendix C: Data underlying the RDD estimations

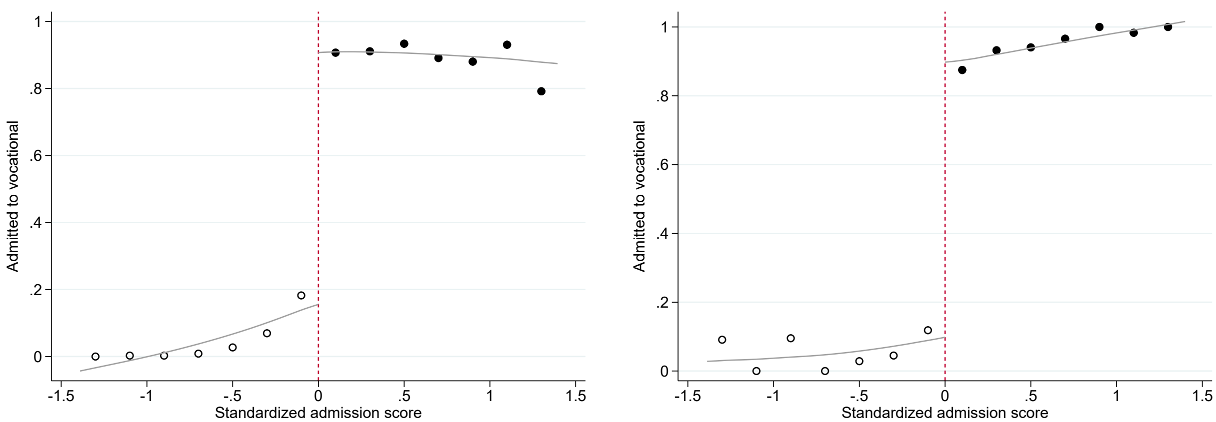
Defining cutoffs for admission to the vocational track

As described in Section A, 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

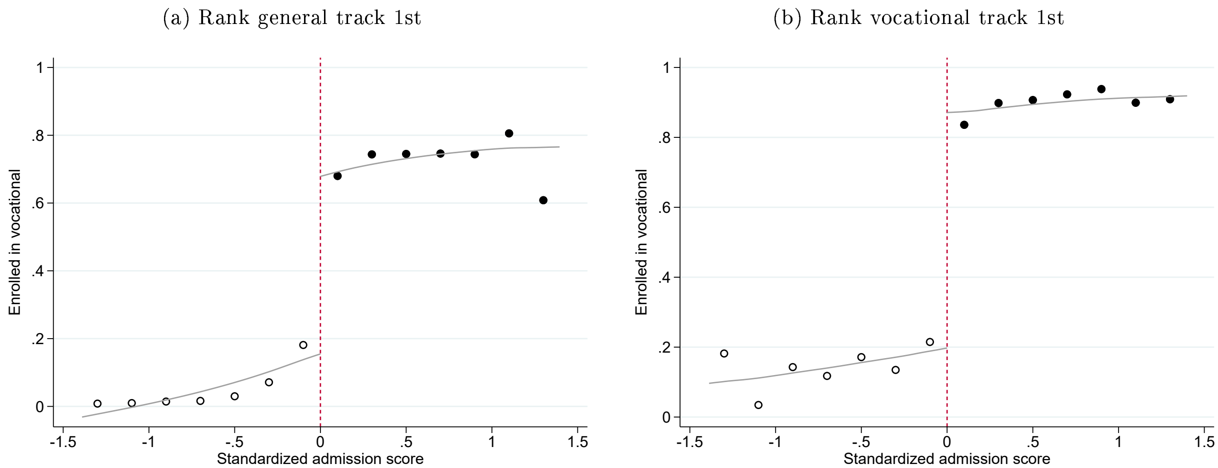
(a) Rank general track 1st

(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



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.

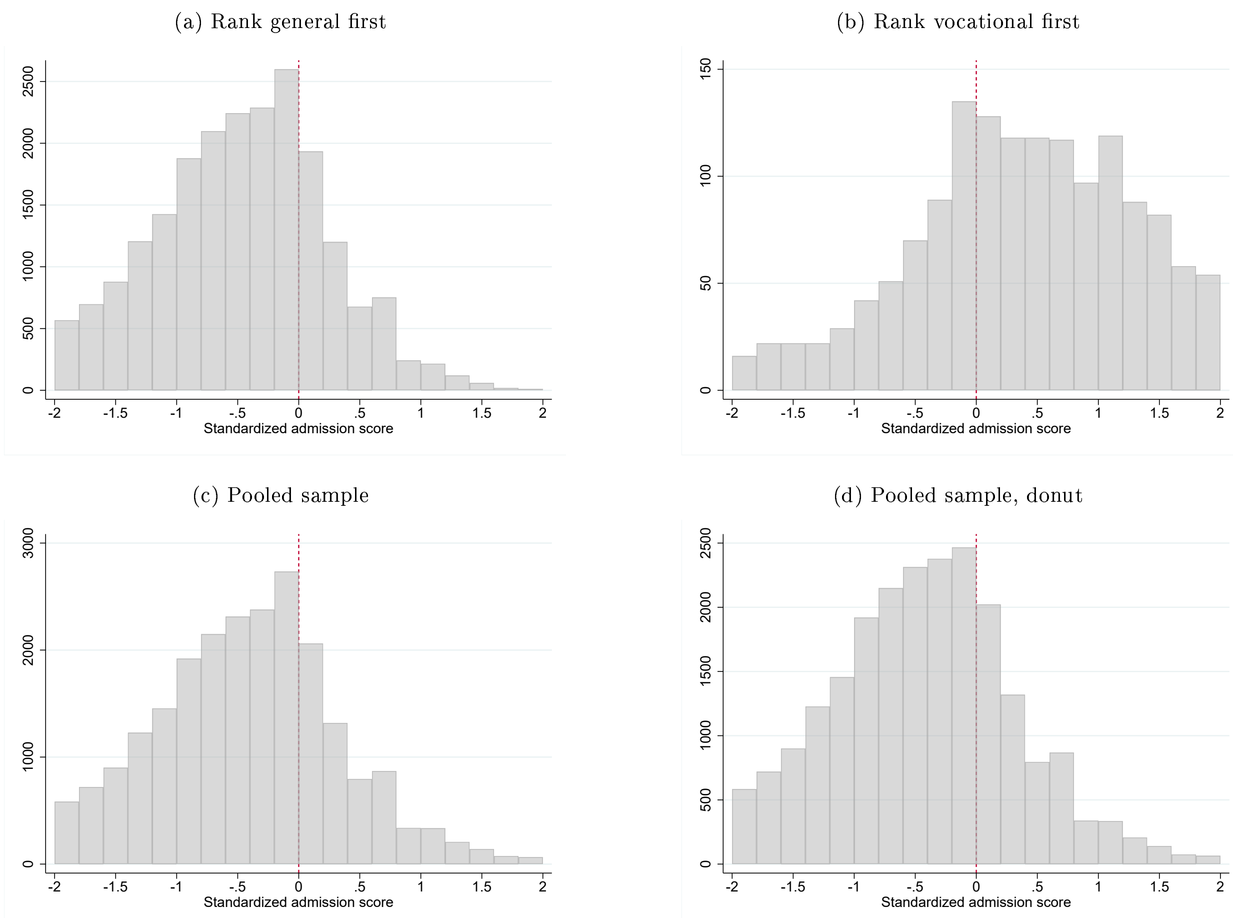
Frequencies around the cutoff

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

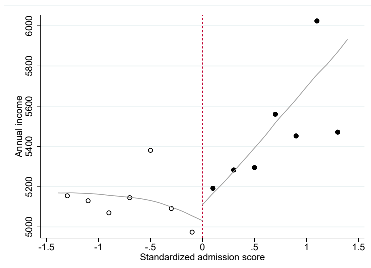


Notes: Figure 7 shows the number of applicants in each 0.2 standardized admission unit bin across the admissions cutoff for people who indicate a preference for the general track, the vocational track, and the pooled estimation sample. Figure (d) shows a donut density graph, with applicants used to define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

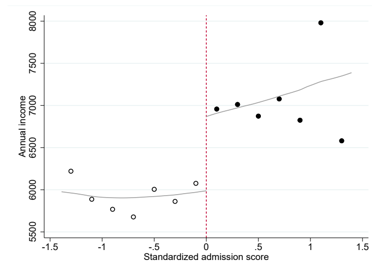
Admission cutoffs and labor market outcomes by application preferences

Figure 8: Annual Income: Rank general track first

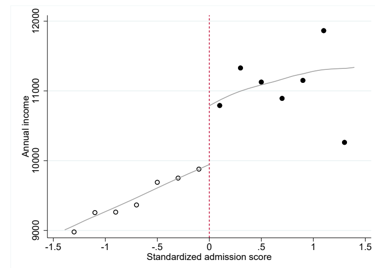
(a) 3 years after admission



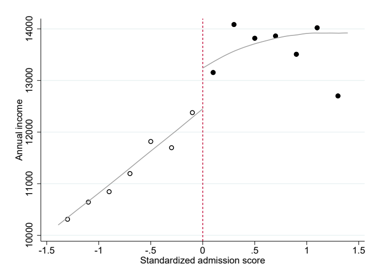
(b) 4 years after admission



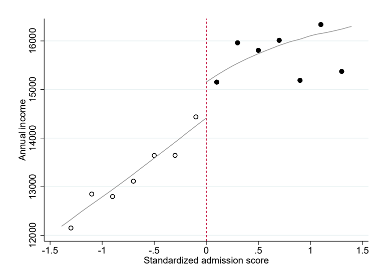
(c) 5 years after admission



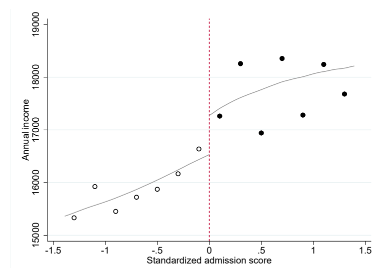
(d) 6 years after admission



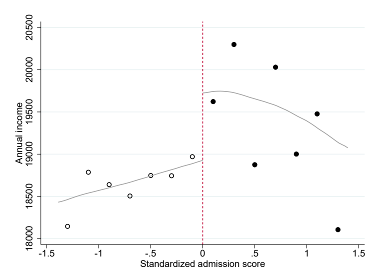
(e) 7 years after admission



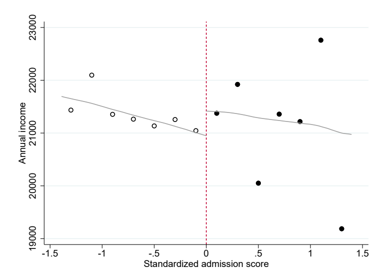
(f) 8 years after admission



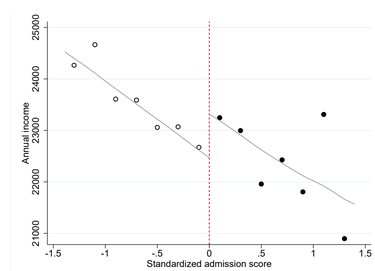
(g) 9 years after admission



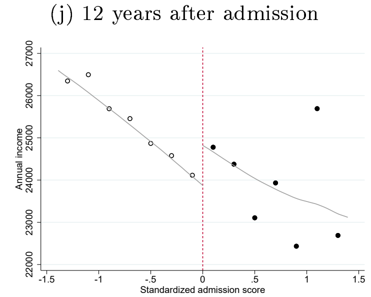
(h) 10 years after admission



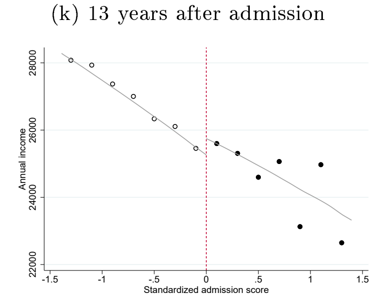
(i) 11 years after admission



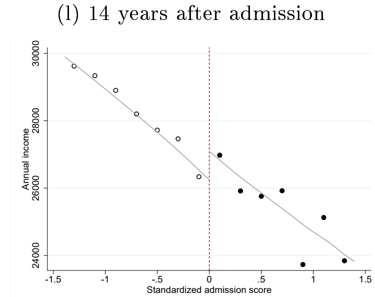
(j) 12 years after admission



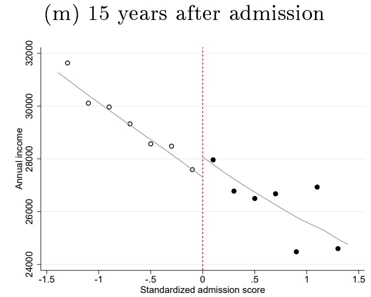
(k) 13 years after admission



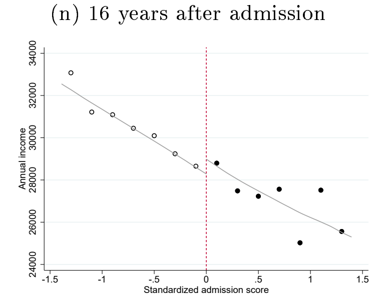
(l) 14 years after admission



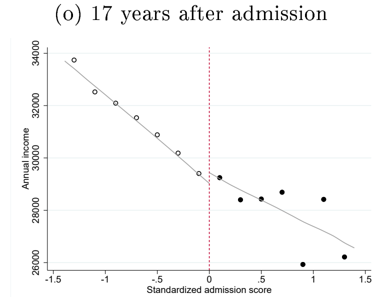
(m) 15 years after admission



(n) 16 years after admission



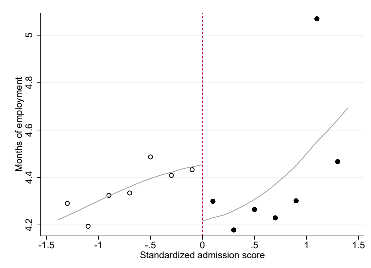
(o) 17 years after admission



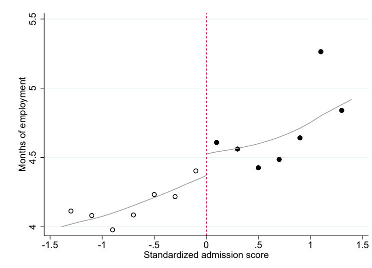
Notes: These Figures show the mean annual income 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins. 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

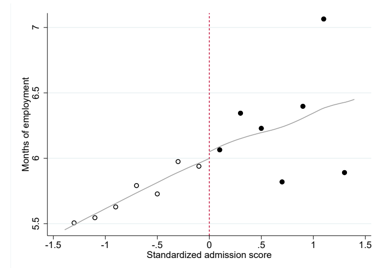
(a) 3 years after admission



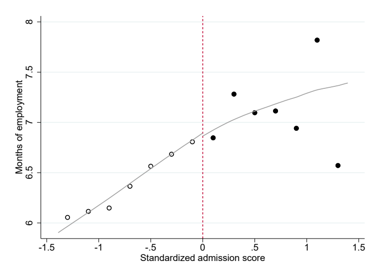
(b) 4 years after admission



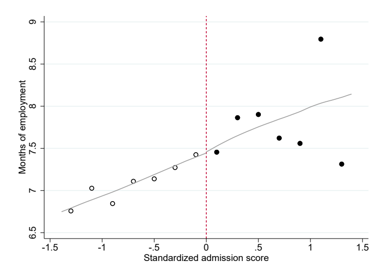
(c) 5 years after admission



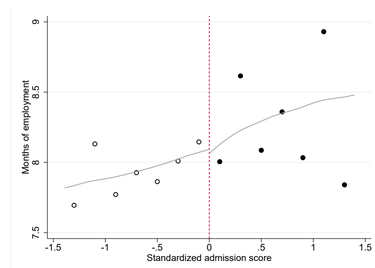
(d) 6 years after admission



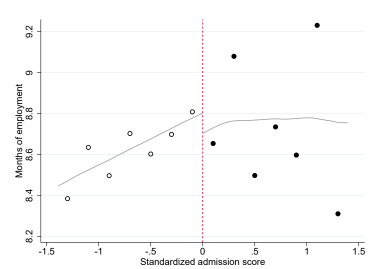
(e) 7 years after admission



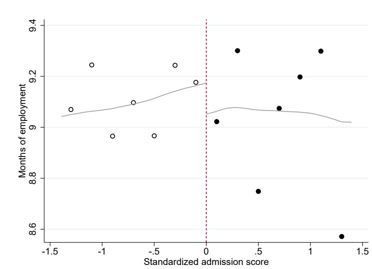
(f) 8 years after admission



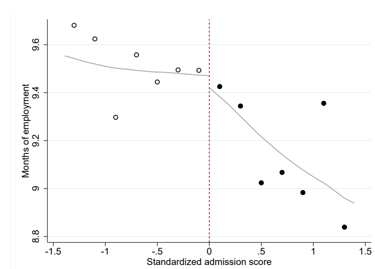
(g) 9 years after admission



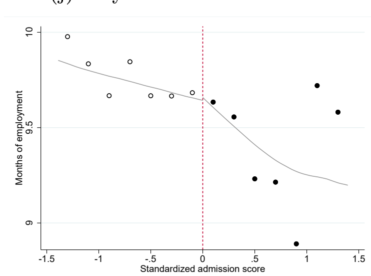
(h) 10 years after admission



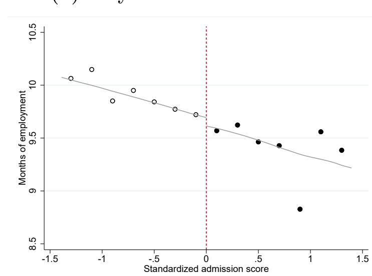
(i) 11 years after admission



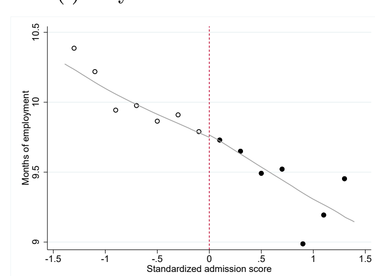
(j) 12 years after admission



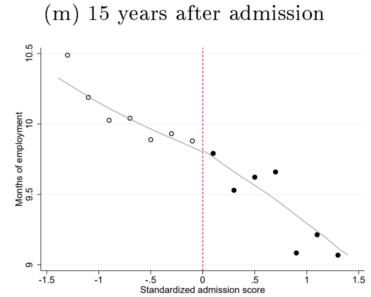
(k) 13 years after admission



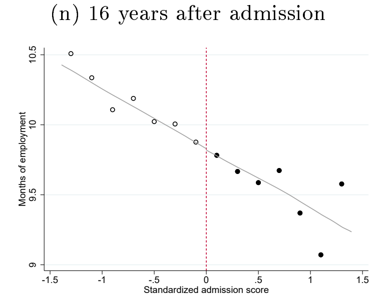
(l) 14 years after admission



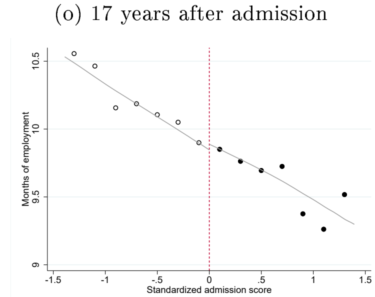
(m) 15 years after admission



(n) 16 years after admission



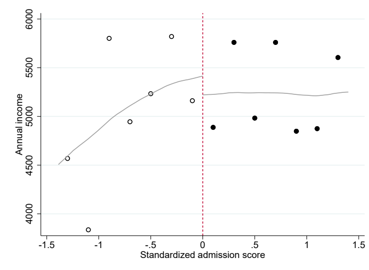
(o) 17 years after admission



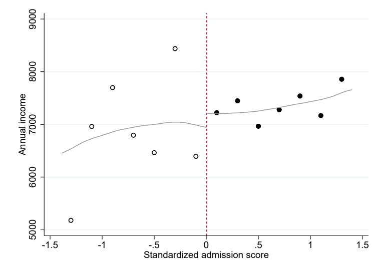
Notes: These Figures show the mean months of employment 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide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

Figure 10: Annual income: Rank vocational track first

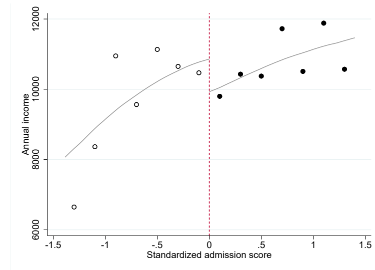
(a) 3 years after admission



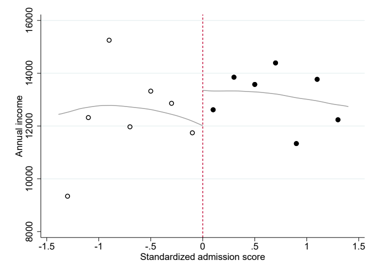
(b) 4 years after admission



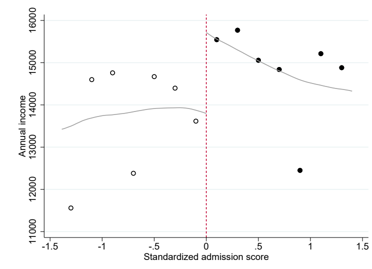
(c) 5 years after admission



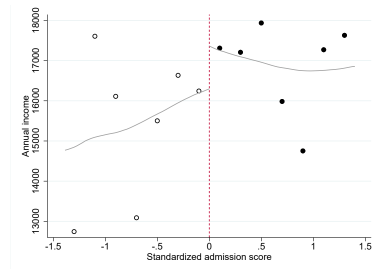
(d) 6 years after admission



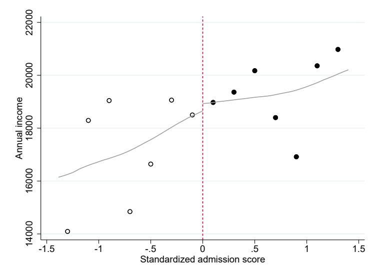
(e) 7 years after admission



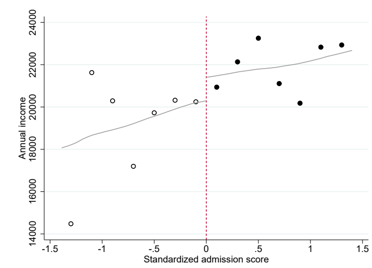
(f) 8 years after admission



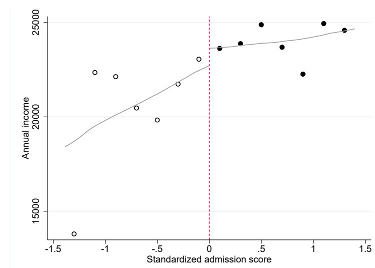
(g) 9 years after admission



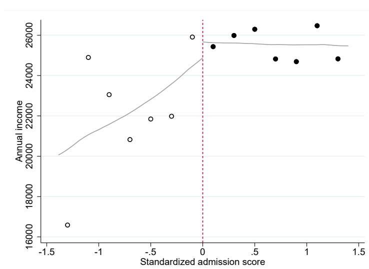
(h) 10 years after admission



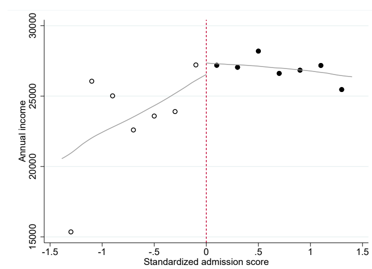
(i) 11 years after admission



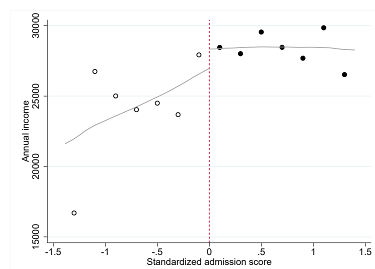
(j) 12 years after admission



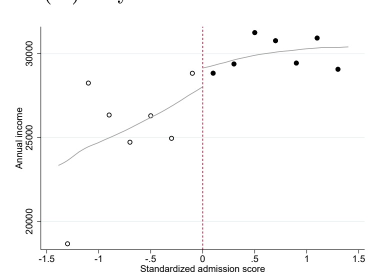
(k) Income 13 years after admission



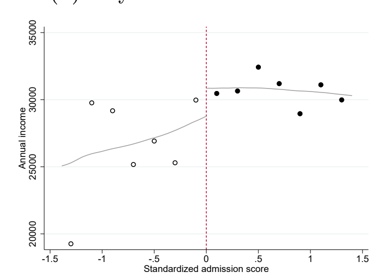
(l) 14 years after admission



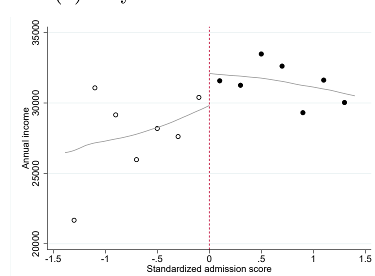
(m) 15 years after admission



(n) 16 years after admission



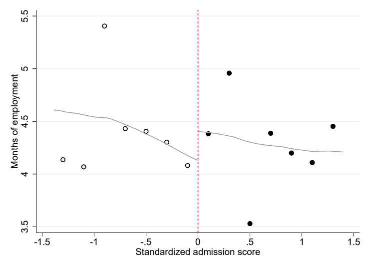
(o) 17 years after admission



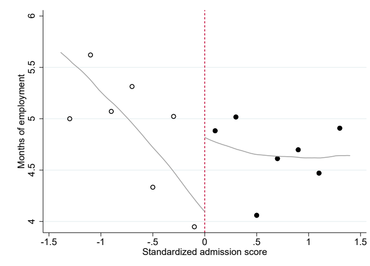
Notes: These Figures show the mean annual income 3 to 17 years after admission plotted against program-specific standardized running variables. Applicants to the right of the vertical line are more likely to be admitted to vocational education. The dots depict conditional means for 0.2 units wide bins. 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

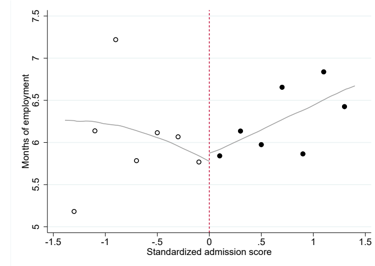
(a) 3 years after admission



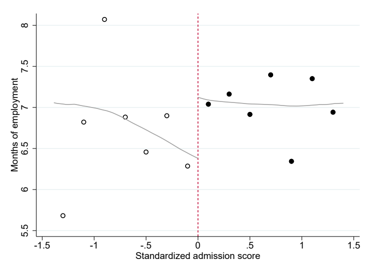
(b) 4 years after admission



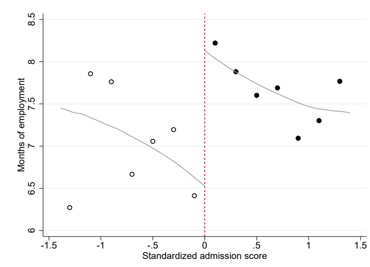
(c) 5 years after admission



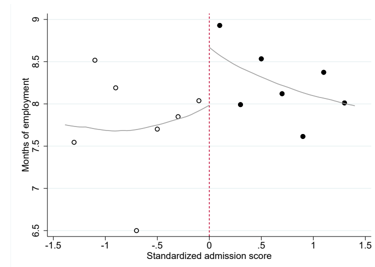
(d) 6 years after admission



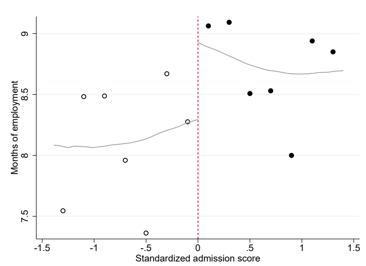
(e) 7 years after admission



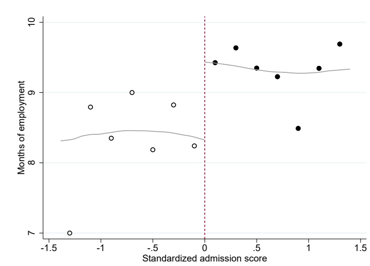
(f) 8 years after admission



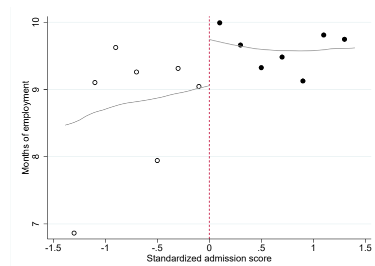
(g) 9 years after admission



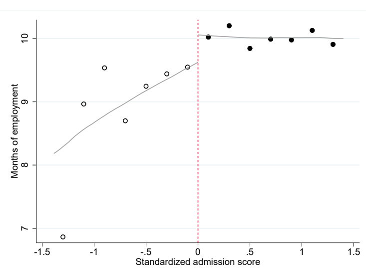
(h) 10 years after admission



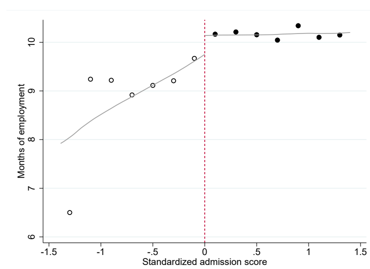
(i) 11 years after admission



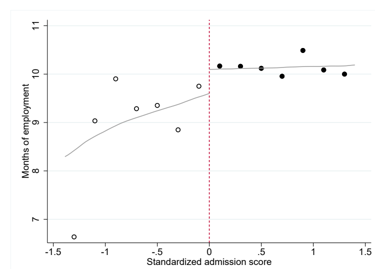
(j) 12 years after admission



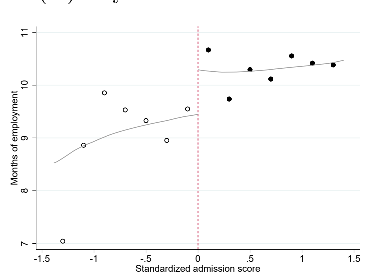
(k) 13 years after admission



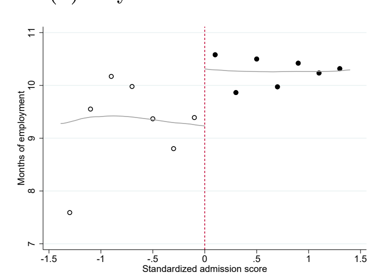
(l) 14 years after admission



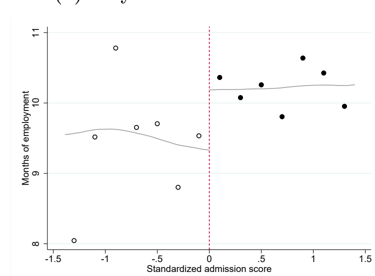
(m) 15 years after admission



(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.

Appendix 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

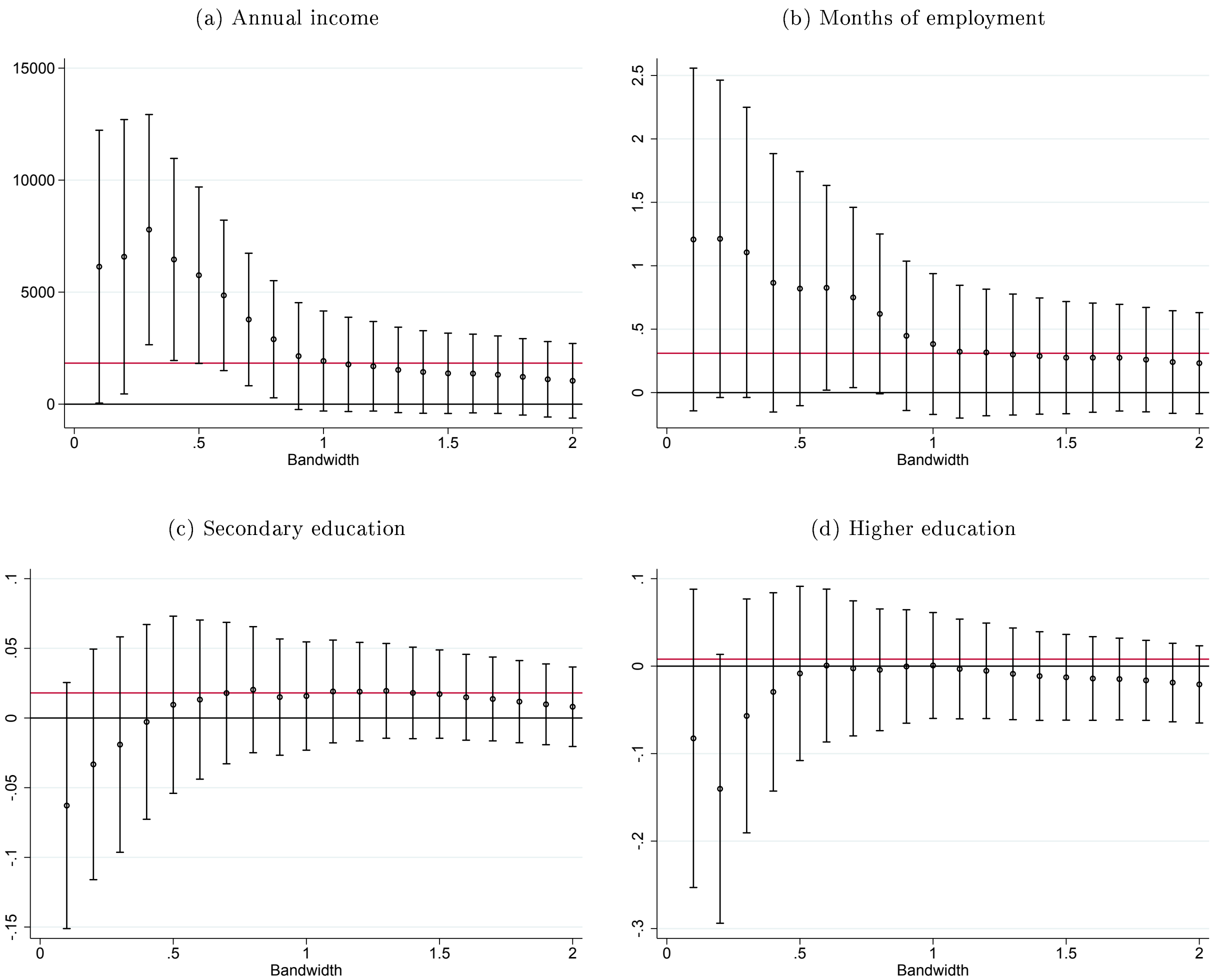
	Main estimates	Donut estimation	Alternate specification	With controls
Reduced form	0.153	0.073	0.155	0.177
	(0.145)	(0.150)	(0.132)	(0.155)
IV				
1st stage	0.495	0.482	0.500	0.488
	(0.017)	(0.018)	(0.015)	(0.019)
LATE	0.310	0.152	0.310	0.362
	(0.292)	(0.310)	(0.262)	(0.318)
Potential outcome	9.770	9.895	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



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

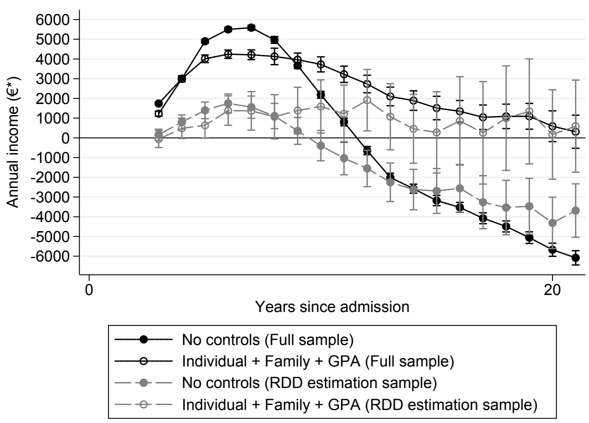
To extend our analysis to further years, we perform OLS estimation using the cohort admitted to secondary school in 1996 (See Figure 13). We specify our OLS estimation regression equation as follows:

$$y_i = b_0 + b_1 FAMILY_i + b_2 INDIVIDUAL_i + b_3 GPA_i + e_i \tag{5}$$

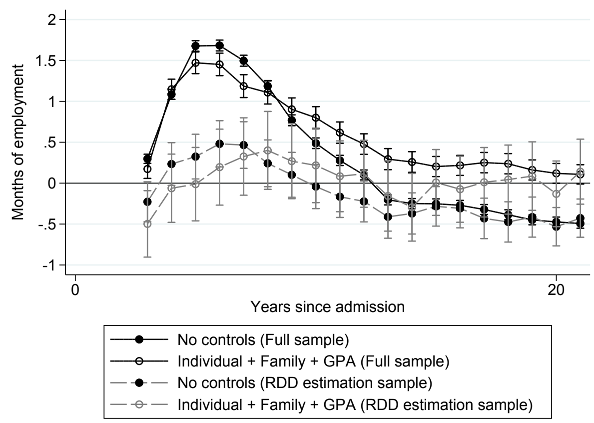
The vectors of family, individual, and school covariates include the variables listed in Table 1. The results reported in Figure 13 do not include fixed effects for application preferences, but including them does not change the results and we are happy to provide them if a reader would like to see them.

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

(a) Annual income

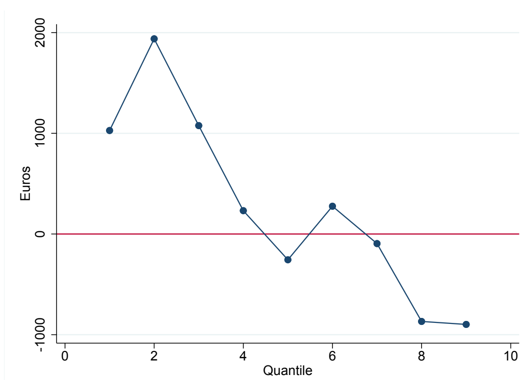


(b) Months of employment



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.

Appendix 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):

$$PDV = \sum_{t=0}^{n} \frac{MP_t}{(1+i)^t} \qquad (6)$$

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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