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Labor Market Returns to Vocational Secondary Education†

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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* D15, I21, I26, J24, J31, O33)

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 versus general) might play a role in providing young people the skills they need to succeed after they graduate (European Commission 2010; US Department of Education 2012, 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

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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.

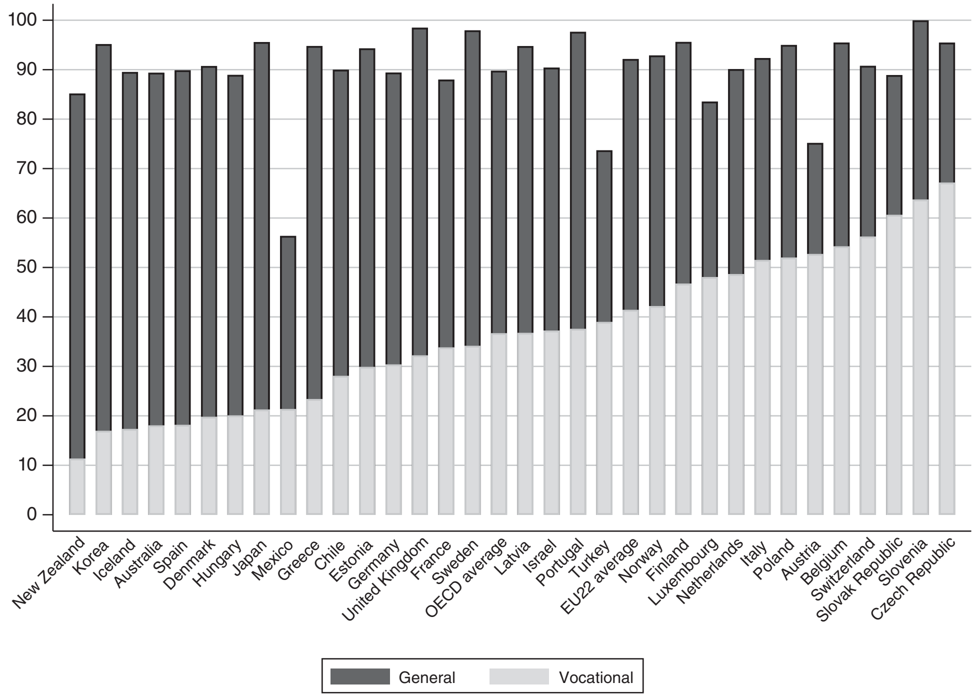

Figure 1. Enrollment in Vocational and General Secondary Education in OECD Countries

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

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 allow 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 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 and 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 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 Massachusetts, 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 led to improved earnings for those induced into vocational education.

[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 20 through the early 30s, when the premium turns negative. Additionally, they estimate a nearly linearly decreasing employment premium that begins before age 20 and turns negative at age 43 but then persists through retirement.

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 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, Mogstad, 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 education 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.

[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.

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 GPAs who only apply to the vocational track and that vocational education may be detrimental for people with high GPAs 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 2011b; Goos, Manning, and Salomons 2014; Deming 2017; Deming and Noray 2020). A more nuanced reading of this literature, however, suggests that the 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 nonroutine manual and cognitive skills (Acemoglu and Autor 2011b) 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 policymakers 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 9 years of comprehensive schooling, and it typically ends at the calendar year when the student turns 16.[5] Secondary

[5] See online Appendix Figure 1 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.

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 online Appendix Figure 1. The process begins in February–March during the final ninth 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 online Appendix Figure 1, 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 the years 1996–2000, some 3 percent of the offers were declined by the applicants. A potential reason for declining an offer is 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 5 years; of those admitted to the general track, 98 percent enroll in general education, and 90 percent graduate in 5 years.

B. *Vocational Education in Finland*

Applicants to the vocational track apply to one of six 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 hairstyling, 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 course work 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

[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.

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 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.[9] Our primary source of data is the Finnish National Board of Education's Application Registry (2020a, 2020b), which contains data on compulsory school performance, secondary school application preferences, and secondary school admissions results.[10] We focus on applicants who graduate from compulsory education between the years 1996–2000 and who apply to secondary education immediately upon graduation.[11]

We merge these data with the FOLK (2020d, 2020e) datasets 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 Statistics Finland (2020a).

In addition, the Finnish Longitudinal Employer-Employee Data (FLEED) (2020b) dataset provides us with socioeconomic information on the applicants and their parents.[12] 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) (2020f, 2020a), which contain information on the year, level, and field of all postcompulsory enrollment 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 (2011a) using a crosswalk between SOC and four-digit ISCO occupational identifiers from the Bureau of Labor Statistics (2012). These data measure 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

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

[9] See Silliman and Virtanen (2022) for replication code and instructions on accessing all data used in this project.

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

[11] 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.

[12] Additional information on parent-child links comes from Statistics Finland (2020f).

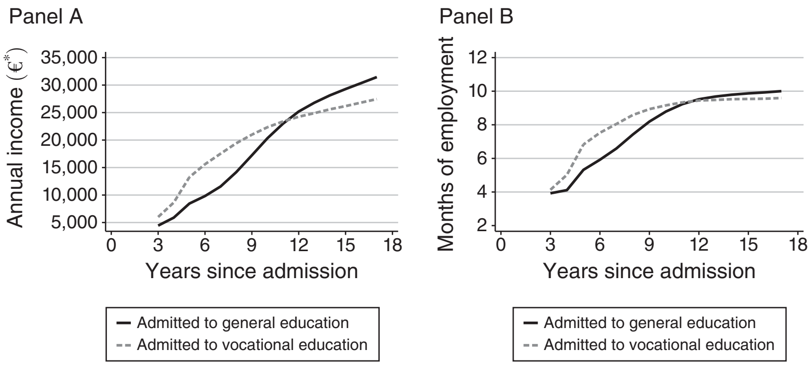

Figure 2. Time Profiles in Mean Annual Income and Months of Employment

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.

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, these occupational task data have not been linked to GPA data in a nationally representative manner, we show how the occupational task measures from Acemoglu and Autor (2011b) relate to compulsory school grades and secondary school track in online 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 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 annually, whereas those admitted to the general track earn €31,500 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 (online Appendix Figure 2).

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

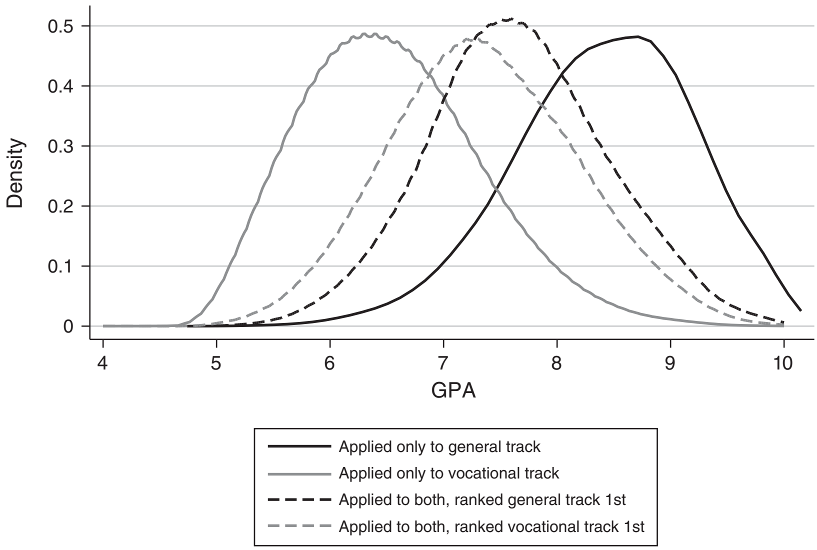

Figure 3. Compulsory School GPA and Application Behavior

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. Kernel = Epanechnikov, bandwidth = 0.1500.

apply to the vocational track 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 therefore focus on applicants who apply to both tracks of secondary education.[13]

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

[13] Figure 3 in the online Appendix shows time profiles for our RDD estimation sample as described in Section IIC.

TABLE 1—MEAN BACKGROUND STATISTICS

	Full sample		Estimation sample		
Track admitted	General	Vocational	General	Vocational	Complier 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
Semi-urban	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 rightmost column includes estimated mean complier characteristics using our RDD strategy described in Section IIB (column 5). NEET = not in employment, education, or training.

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.[14] 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 IIB (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.

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

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

between the years 1996–2000.[15] 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 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.[16] 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.

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

After this transformation, positive values always indicate an increased likelihood of admission to the vocational track.[17] 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 online Appendix Figure 5 for separated bin-graphs).

[15] 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.)

[16] We follow Huttunen et al. (2019) and estimate program-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 programs.

[17] In addition to showing our full discontinuity sample, we show graphs where we separate applicants by application preferences (online Appendix Figure 5) and the arguably more exogenous admissions first stage (online Appendix Figure 5).

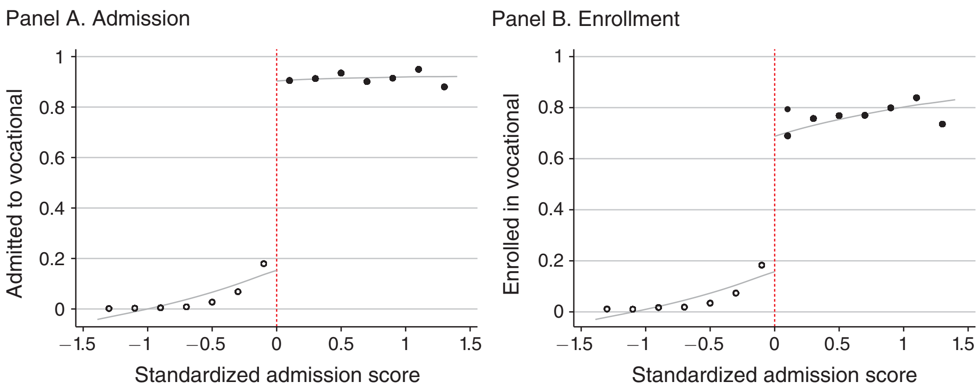

FIGURE 4. CUTOFFS

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 IIA and depicted in online Appendix Figures 5 and 6, the full estimation 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.

As panel A of Figure 4 shows, crossing the admissions cutoff increases the likelihood of admission to the vocational track by roughly 70 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.[18] Second, for a subset of applicants, we only observe offers accepted by the applicant.[19] 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 50 percentage points; see panel B of Figure 4). 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 among these is the exclusion restriction, which requires that admission to the vocational track cannot affect labor market outcomes through any other channel other

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

[19] 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 IIIA. 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.

than enrollment.[20] Since the general track is the preferred option for most applicants in our sample, disappointment in admission to the vocational track might cause some applicants to drop out of secondary education altogether or reapply 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.

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[21] 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:

$$k(r_i) = \mathbf{1}\left\{ \left|\frac{r_i}{h}\right| \leq 1 \right\} \times \left(1 - \left|\frac{r_i}{h}\right|\right). \tag{4}$$

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

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).[22] 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

[20] 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.

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

[22] 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.

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.[23] 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.[24] Second, the timing of the process (online 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.

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 online Appendix shows the distribution of applicants around the cutoff. While figures (a)–(c) of online Appendix Figure 7 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 online Appendix 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

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

[24] The literature on deferred acceptance algorithms points out that the use of finite lists can result in 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 and 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)
Semi-urban	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)
Mother tongue	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 postcompulsory 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	(1,188)
Mother in NEET	0.008	(0.012)	0.007	(0.013)	0.050	(0.045)
Mother no postcompulsory 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.

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 outperform 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).[25] 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 discernible discontinuity in months of employment at the admissions cutoff.

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.[26] The first-stage estimates (online 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.[27]

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 17 years after application to secondary school (age 33). The potential outcomes estimate (online Appendix Table 2) indicates that without admission to vocational education, these applicants would have earned €29,000, suggesting that admission to the vocational track increases the mean annual income of compliers 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

[25] Recall from Section IIC 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 IVD for estimates for each set of application preferences separately. In online 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.

[26] 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 sixty-sixth percentile, and increases the size of the school students attend (online Appendix 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 (Abdulkadiroğlu, Angrist, and Pathak 2014; Dobbie and Fryer Jr 2014).

[27] See Section IIIB.

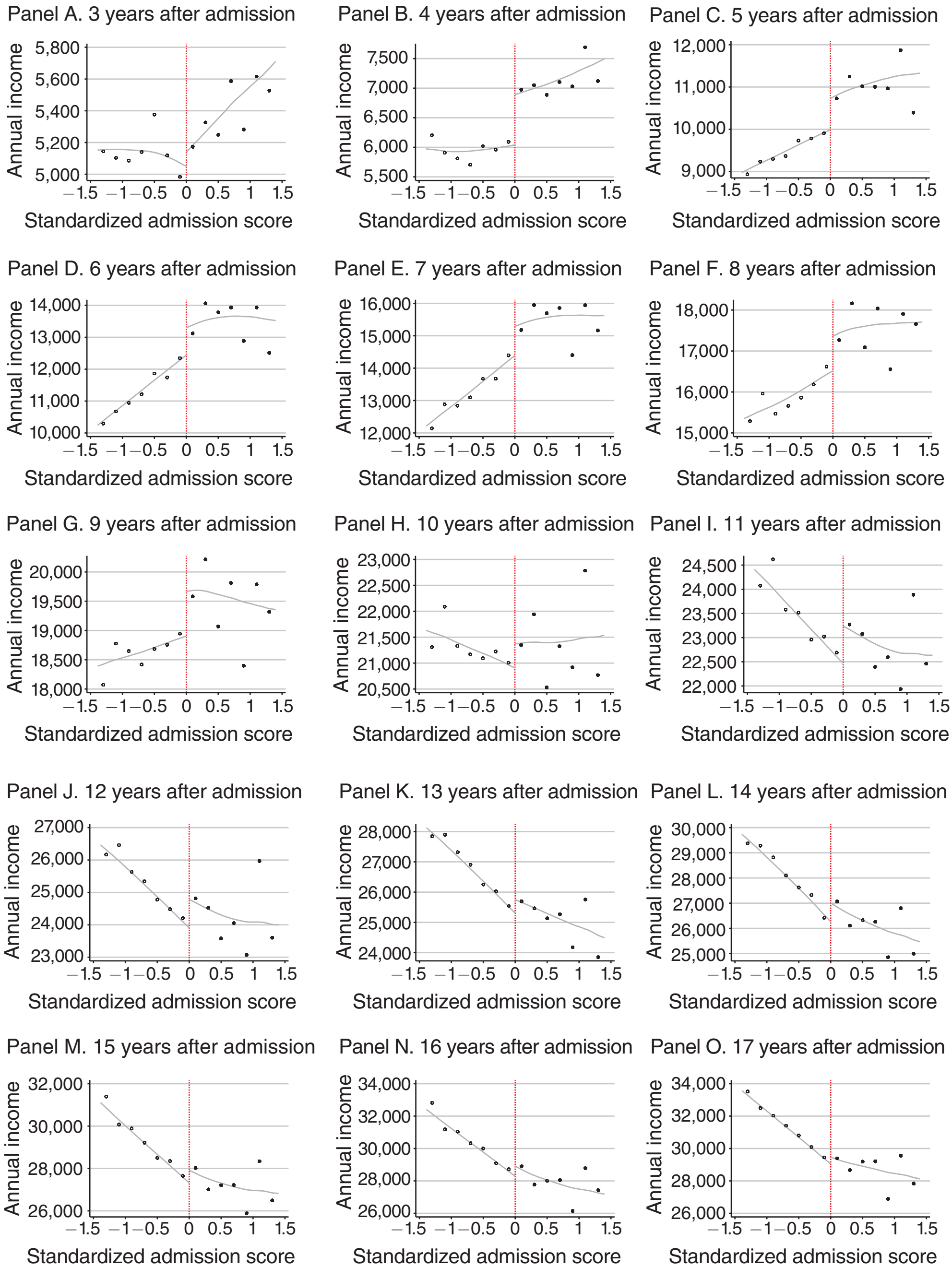

Figure 5. Annual Income: Full RDD Sample

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.

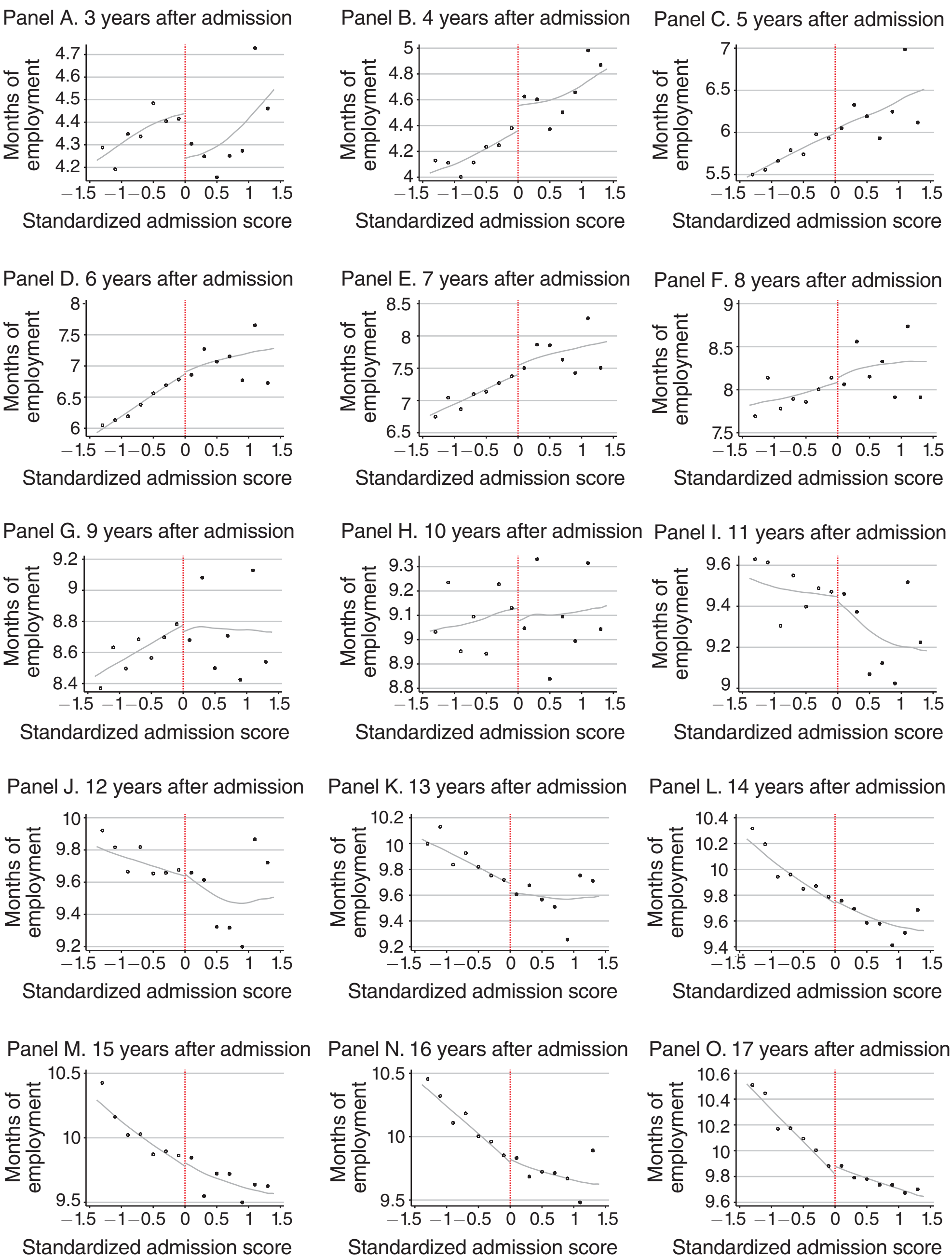

Figure 6. Months of Employment: Full RDD Sample

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.

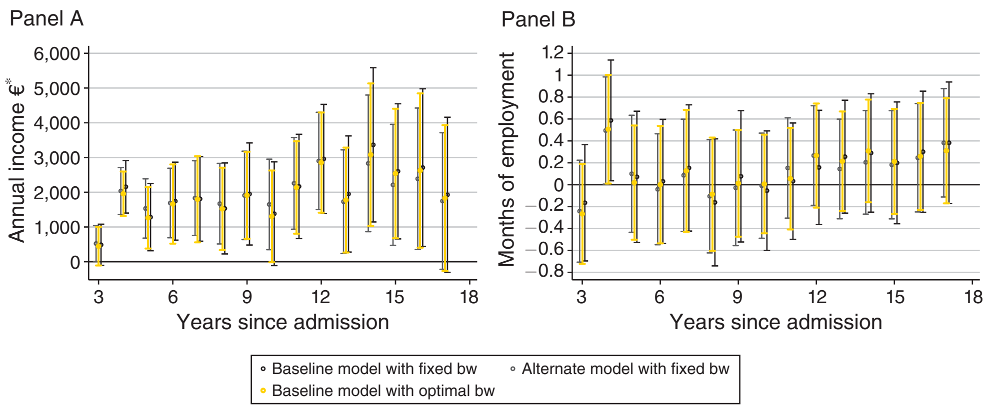

Figure 7. Year-by-Year RDD Estimates: Annual Income and Months of Employment

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 one standardized admission unit on each side of our cutoff. Standard errors are clustered by cutoff. *Incomes are indexed to 2010 euros.

to secondary education.[28] Our year-by-year estimates of the effect of admission on months of employment are near zero for most of the period we study.[29] Applicants at the admissions margin are employed for an average of 10 months a year (online Appendix Table 2).[30]

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 (online Appendix Figure 13).[31] 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 (online Appendix Table 8a). Results from these calculations suggest that the lifetime premium to the vocational track would

[28] 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). When we estimate the effects separately by gender, we find that both are fairly similar to our main estimates.

[29] 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.

[30] Apart from employment, there are two potential explanations for the positive effects on wages: (i) people may be shifted into higher-paying occupations, or (ii) 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 (online Appendix Table 5).

[31] 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.

remain positive barring an immediate drop to −2,000 through retirement at age 65 combined with a discount rate of below 5 percent.[32] Since our RDD estimates do not suggest that the vocational premium drops to 0 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 online Appendix 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 (online Appendix Tables 2a and 2b). The results are robust for the range of fixed bandwidths from 0.1 to 2 (online Appendix 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 rerun the estimates from our baseline specification by restricting our sample to cutoffs with at least three, four, and five applicants on each side of the cutoff (online Appendix 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 specific vocational subfields or schools included in our sample.

C. *Postsecondary 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.

[32] To focus on the applicants whose lifetime income is most likely to go negative (see Section IVD), 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 online Appendix Table 8b).

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 (online 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.[33]

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 (online Appendix Table 7). An established literature on the future of work considers automation and globalization to represent the two major sources of labor market risks (Acemoglu and Autor 2011b; 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 nonroutine 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 IVA 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 who 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 the vocational track, admission to vocational educa-

[33] 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).

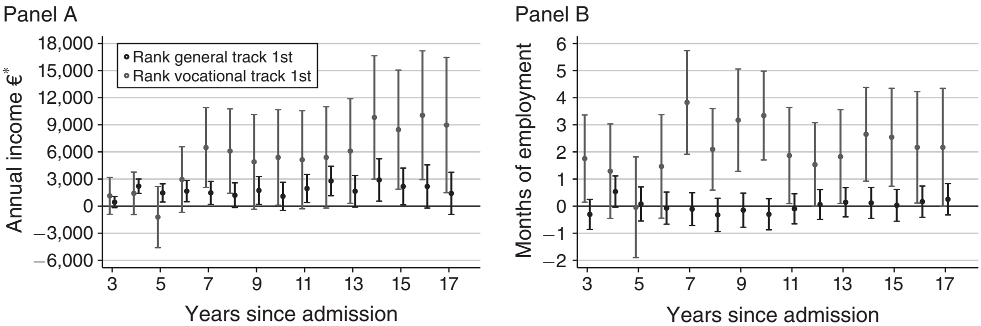

Figure 8. Year-by-Year RDD Estimates: Annual Income and Months of Employment by Preference Group

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 one standardized admission unit on each side of our cutoff. Standard errors (in parentheses) are clustered by cutoff. *Incomes are indexed to 2010 euros.

tion 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 percent increase in income at the RDD margin.

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).[34] 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

[34] 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.

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 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.[35] 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 panel A of Figure 9 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 panel B of Figure 9, 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.

V. Discussion

We study labor market returns to vocational versus general secondary education using a regression discontinuity design created by the centralized admissions pro-

[35] 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 (online 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.

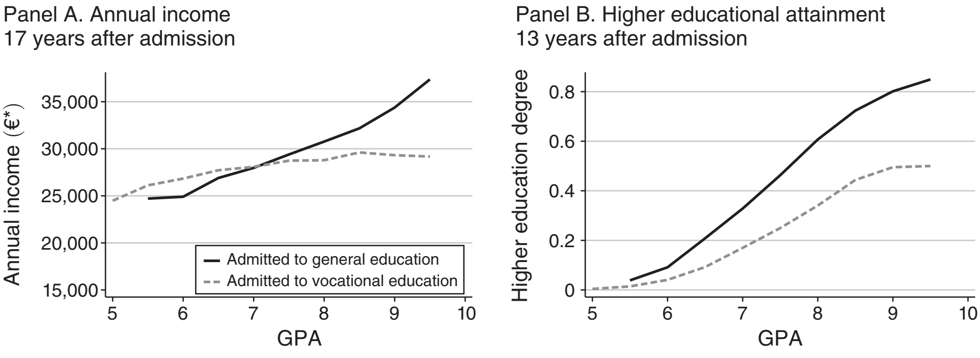

Figure 9. Outcomes by Compulsory School GPA and Secondary School Track

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.

cess 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 make 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 17 years after application to secondary school. Taking our RDD estimates for people who prefer the vocational track but apply to both as a 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.

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