Short- and long-term effects of vocational vs. general schooling: Evidence from Sweden*

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Abstract

In this paper, we estimate the relative earnings returns for Swedish upper secondary schooling programs with vocational and general content for individuals born 1955-76. These data contain detailed information from applications about students' choices which allows us to address two important sources of endogeneity. First, we use GPA admission cutoffs to generate a random element in program assignment. Second, we control for students' first best and second best choice combinations to proxy for students' comparative advantages. Combining these two strategies and merging data with annual earnings information from 1978-2011, we estimate the marginal returns to vocational schooling relative to general schooling. For men, our results indicate that vocational schooling has an earnings advantage over general schooling up and until the age of 27, with estimates thereafter close to zero. For women, we observe a similar earnings advantage for vocational schooling up and until the age of 23.

JEL-codes: J24, J31, I24
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1 Introduction

There are large differences in how educational systems in different countries prioritize and mix vocational and general educational contents. Despite an enormous literature on the returns to years of schooling, and despite the widely accepted view that educational content is also important, there are only a few studies that address the long-run impact of educational content on labor market outcomes.[1] For a given number of schooling years, vocational and general schooling are typically linked with the following short-term and long-term predictions concerning earnings and employment.[2] First, since the aim of vocational education is to prepare for specific occupations, it should lead to a better school to work transition, and possibly to lower unemployment and/or higher labor earnings in the short run. Second, since general education is assumed to generate knowledge that enhances workers' ability to learn, this may create a skill multiplier effect that allows workers to adapt more readily to new technologies during their working career. In the long run, general education may therefore be associated with a relative earnings advantage. This suggests that the earnings of individuals with general education could catch up and then later exceed the earnings of those with vocational education as both types progress in their careers.

The aim of this article is to test these two predictions, regarding the short-term and the long-term effects of vocational schooling relative to general schooling. We use Swedish register data of individuals born between 1955 and 1976. The outcome variable is annual earnings as measured between 1978 and 2011, when individuals in our sample are between 18 and 56 years old. To causally identify the relative effect of vocational versus general schooling on earnings, we exploit data from applications to upper secondary school. At age 15, individuals can apply for various 2-year upper secondary programs, which only differ in their degree to which they contain vocational and general contents. To account for endogeneity of track choice, we employ a regression discontinuity (RD)

[1] See, e.g., Malamud and Pop-Eleches (2010); Dustmann et al. (2016); Hanushek et al. (2016).

[2] See Brunello (2001); Hanushek et al. (2016); Korpi et al. (2003); Krueger and Kumar (2004a,b); Rosenbaum (2001); Shavit and Müller (1998); Wolter and Ryan (2011).

design based on grade point average (GPA)-cutoffs, which decide whether an individual gets into a program, or not (see, e.g. Abdulkadiroğlu et al., 2014; Kaufmann et al., 2015). In addition, we control for choice combinations as a proxy for individuals' comparative advantages (Kirkebøen et al., 2016). Our estimates are then identified by the assignment to program type via the GPA cutoff (RD), within groups of individuals with identical first-best and second-best choices.

Regarding long-term evidence of educational contents, studies analyzing the expansion of comprehensive schooling typically find positive effects on labor market outcomes, whereas studies analyzing the expansion of vocational schooling have reported no statistically significant effects.[3] This may suggest that earnings impacts of schooling differ depending on educational contents.[4] To date, Malamud and Pop-Eleches (2010) provide the perhaps most effective set-up to evaluate the relative labor market impacts of vocational and general education. They analyze the variation in educational contents which arose in Romania following an educational reform in 1973. After the reform, individuals were required to study an additional two years of general education before entering vocational schools. The later cohorts therefore received more general, and less vocational education. Comparing adjacent cohorts from census data (1992, 2002) and household survey data (1995, 2000), when individuals were 33-44 years old, the occupational composition changed, with less manual workers and craftsmen in the later cohort, but they found no statistically significant differences in family income or wages. An attractive feature of

[3]For effects on comprehensive schooling, see Angrist and Krueger (1991), Harmon and Walker (1995), Meghir and Palme (2005), and Aakvik et al. (2010), and for expansions of vocational schooling see Oosterbeek and Webbink (2007), Pischke and von Wachter (2008) and Hall (2012).

[4]Hall (2012) analyzes a pilot scheme in Sweden from 1987 to 1991, where 2-year vocational programs at upper secondary school in some regions were extended to three years. In relation to the present study, the 2-year vocational programs are identical to those studied here, with about 2-4 hours of general subjects per week, and the majority of hours devoted to vocational in-class training (no apprenticeships). The difference is that we compare these with general programs, where there is no vocational training and general subjects amount to 22 hours per week (see Table 1). Hall (2012) instead compare the 2-year vocational programs with pilot programs which extended the vocational programs to 3 years. The extensions in the pilot scheme also involved changes in curricula which saw the number of hours of general subjects increase to 6-7 hours per week, and the third year included 60 % apprenticeship training. The insignificant results reported may be interpreted as the effects of an additional schooling year, but the design of the pilot scheme makes it difficult to set it in direct relation to the question of educational contents, since both general and vocational education was increased.

their study is that the framework allows for a comparison between individuals who could not choose between different regimes. The authors are therefore able to compare average outcomes of comparable individuals exposed to a different mix of educational contents, providing a very clear setting. As for any study, a limitation is its context. The case of Romania may not generalize to other countries if, e.g., the compressed wage structure of the communist regime also affected wage setting in the following decade. Also, a relative long-term advantage of general education may be that it enhances learning capabilities and increases the likelihood of receiving on-the-job training. According to OECD (2004), Romania had the lowest incidence of on-the-job training in Europe, on average seven hours per year. The corresponding number for Sweden was 33 hours per year, which was one of the highest in Europe.

Hanushek et al. (2016) also evaluate an average impact on labor market outcomes, using data from 11 countries included in the International Literacy Survey (IALS). Controlling for cognitive skills, country fixed effects, years of schooling and parental background, their findings indicate an initial advantage in employment probabilities for individuals with vocational education, which diminishes with age. These results imply a short-term advantage which gradually declines. They confirm their findings using the German Mikrozensus and Austrian administrative data. This is an important contribution in relation to Malamud and Pop-Eleches (2010), who estimated earnings for males aged at least 33 years old, and thereby could hide short-term differences in outcomes, e.g. with an initial advantage of vocational education. Importantly, the analyses in both Malamud and Pop-Eleches (2010) and Hanushek et al. (2016) are limited to males. The validity of the findings may not extend to females, especially since women tend to choose educational paths and working careers that are different from those of men.

Dustmann et al. (2016) study individuals, born in West Germany 1961-1976, who enrolled into tracks with different amounts of vocational and general education. They exploit information on birth dates to compare individuals born around the cutoff date of school cohorts. Their evidence suggests that the built-in flexibility of the tracking

system allowed individuals to correct initial choices, so that high (low) performing individuals switched to more (less) advanced tracks after the initial tracking. They report no statistically significant differences in educational achievement or labor market outcomes until 2006, when individuals were aged between 30 and 45. Their findings highlight the importance of taking the flexibility of an educational system into account, since different earnings impacts of educational contents could work through the possibilities attending further education. Although including both men and women, Dustmann et al. (2016) do not present results on gender-specific labor market outcomes.

We contribute to this literature by providing causal evidence of the relative returns of vocational and general schooling, with data covering a large part of the individuals' working lives. Our estimates test if there is evidence of the alleged trade-off between school to work transitions and long-term outcomes. To the best of our knowledge, we provide the first causal evidence of this issue which is based on uninterrupted earnings trajectories, for both males and females. Our study also complements the earlier studies by reporting results from a different context, with the diversity in the tracking system greater than in the US, the UK or southern Europe, but smaller than in Germany and many other European countries. We find that both males and females who have followed vocational schooling, as opposed to general schooling, have an earnings advantage up to age 27 (men), and 23 (women). This is in line with the results of Hanushek et al. (2016). We show that these results are not due to differences in educational choices after upper secondary schooling. In the long term, we find no statistically significant earnings differences between the two types of schooling for men. For women, in contrast, individuals with vocational schooling experience a renewed earnings advantage from age 43 and onwards. We find suggestive evidence that this can be explained by further education completed in adulthood.

This paper is structured as follows. In the following section, we explain the institutional setting and application process in detail and the data used in this study. Section

3 describes challenges in identifying the relative effects of different programs and shows our estimation framework. Section 4 presents results. Section 5 concludes.

2 Institutional setting and data

This study relies on two types of data: first, we use data containing information on all applications for upper secondary schooling programs in Sweden from 1971 to 1991. These data is used to identify application choice, GPA cutoffs and track assignment. Second, we use data on earnings from 1978 to 2011 to estimate the effects of schooling on labor market outcomes.

2.1 Applications to upper secondary schooling and program types

The individuals included in our study, born 1955-1976, attended a schooling system which was then relatively newly implemented, and which, in large parts, is still in place today.[5] First, compulsory (primary) school starts from the year the child turns 7 years old, and lasts for nine years. During ninth grade, individuals can apply for 2- or 3-year programs in upper secondary school, i.e. grades 10 to 11 or 10 to 12.[6] The *new gymnasium*, launched in 1971, merged three different forms of schooling (*fackskola, yrkesskola and gymnasieskola*) into a cohesive institution which offered 14 different 2-year vocational programs (e.g., Nursing, Electronics or Construction), three different 2-year general programs (Social studies, Business, Engineering) and five general 3-year programs.[7] Whereas the completion of 3-year programs qualified individuals for university, both vocational and general 2-years programs only provide eligibility for short college educations, classified as tertiary level schooling, in fields such as physiotherapy, nursing and pre-school teaching. Another

[5]The compulsory school reform was fully implemented in 1962 and the new upper secondary school was in place from 1971.

[6]About 25 % of each cohort does not apply during ninth grade. These individuals have the possibility to apply in later years.

[7]For vocational schooling, 3-year programs were only introduced via a pilot scheme in 1987 (cf. Hall, 2012), before being more broadly implemented from 1992.

possibility to return to school is adult education (*komvux*), with which individuals can qualify for tertiary education. Adults returning to formal education is relatively common in Sweden. Municipalities are obliged by law to offer upper secondary schooling for adults. This would be of interest for drop outs or individuals who wished to complement or change directions of their schooling.

In this paper, we are interested in the relative importance of vocational versus general skills. To analyze the difference in schooling contents, we put our focus on 2-year programs only. This allows us to identify the effects of the contents rather than the length of schooling. Curricula from some of the most popular programs are presented in Table 1. There is a clear distinction between vocational and general programs in that the majority of hours at vocational programs are directed to a particular profession. Such subjects constitute zero hours in the general programs.

2.2 Assignment to programs

When applying for upper secondary programs during ninth grade, individuals make up to six choices for specific programs in a specific region. Individuals can apply for the same program in different regions, or for different programs in the same region. 90 % of the individuals, however, applied within the same region where they also went to primary school, i.e. usually in the region of residence.[8] In Sweden, there are 102 high-school regions (*gymnasieregion*) with an average of 1,700 applicants per cohort. On average, individuals applied for 2.6 programs (Figure 1).

For each program offered in a region in a specific year, individuals compete for slots with their GPA, which are based on centrally graded exams. The assignment follows an iterative process. In a first step of the assignment process, individuals are assigned to the program of their first choice and are ranked according to their application GPA. If the number of applicants is smaller or equal to the number of slots available, all applicants

[8]There are two main reasons for applications outside the home region. First, a common pattern is that individuals apply in neighbouring regions. Second, individuals apply for highly specialized schools.

are accepted. If the number of applicants exceeds the number of slots, a threshold cutoff is defined. All individuals with a GPA below this threshold are moved to their second choice, whereas individuals above the threshold are placed in this choice. After moving individuals below the GPA cutoff to their second choice, individuals in each program-region combination are again ranked according to their GPA and assigned to their third choice if the GPA is lower than the adjusted GPA cutoff. This process is repeated until all options are exhausted. Individuals are subsequently sent a letter of acceptance, which they need to confirm, or they will lose their slot.[9]

2.3 Information on GPA cutoffs

GPA thresholds, i.e. the minimum GPA which is required to get into a specific program, are not systematically collected, but need to be constructed from the data at hand. In a clean allocation process where everybody above the GPA threshold is admitted to the program, and everybody below the threshold is not, the threshold could be simply defined based on the lowest accepted GPA. For several reasons, however, the cutoff in our setting between applicants being accepted and not accepted is rather fuzzy. First, information on applicants' GPA is measured with error. Although the data contain a measure of GPA, students could also earn bonus points, e.g. for repeat applicants, or if applying for programs where they would be in the minority (e.g., male applicants in female programs). Second, headmasters have some discretion in assigning additional students to programs. Third, we do not observe which individuals are accepted at a program, but rather who starts in a program.

The algorithm used to determine the threshold GPA is based on a simple rule. GPA is defined on a scale from 1 (lowest possible) to 5 (highest possible), and is measured with increments of 0.1. For each decimal GPA unit k from $k = 1, 1.1, \ldots, 4.9, 5$, the algorithm first calculates the number of individuals accepted above this hypothetical threshold k,

[9] When handing in the first application to upper secondary schooling, individuals apply with a preliminary GPA, which is based on grades from mid-term exams. This information is used by the administration to make a preliminary assignment which is later refined.

$\sum_{k=k+.1}^{5.0} I_{i,GPA=k}^{acc}$, and divides it by the total number of individuals who applied with a GPA above the threshold $\sum_{k=k+.1}^{5.0} I_{i,GPA=k}$. In a perfect case, in which everybody above a threshold would be accepted, this share would be equal to one. In the same manner, the algorithm calculates the number of individuals below this threshold k, $\sum_{k=1.0}^{k-.1} I_{i,GPA=k}^{non}$, and divides this number by the number of individuals who applied with a GPA below this threshold. In a perfect setting, this share would be 0 below the true threshold. The GPA unit k with the greatest difference between these two shares constitutes the threshold GPA^{Th}, k^*:

$$k^* = argmax(k) = \frac{\sum_{k=k+.1}^{5.0} I_{i,GPA=k}^{acc}}{\sum_{k=k+.1}^{5.0} I_{i,GPA=k}} - \frac{\sum_{k=1.0}^{k-.1} I_{i,GPA=k}^{non}}{\sum_{k=1.0}^{k-.1} I_{i,GPA=k}} \quad (1)$$

In a setting in which all individuals above (below) the threshold would (not) be accepted, this difference would be 1 at the true threshold level k^*.

Figure 2 shows the share of accepted individuals, relative to the GPA threshold (=0). Around 18 % of the individuals with a GPA below the threshold are actually accepted in the program. Out of those individuals, who apply with a GPA higher than the threshold, the average acceptance varies but converges to about 95 percent.

2.4 Earnings data and post-schooling outcomes

The main outcome variable to estimate the effects of vocational versus general schooling is annual earnings, which we observe from 1978 to 2011. The earnings information includes all earnings from labor, without transfers, and are expressed in 2011 values. To explore whether mediating outcomes, such as unemployment or tertiary education, play a role, we use additional information on these variables. In addition, the data also contain information on parental background, such as migration background, parental income, and parental education.

3 Estimation strategy

The effects on outcomes of vocational schooling, relative to general schooling, can be estimated by a regression of an outcome variable y_i, e.g. earnings, on a dummy for wether an individual attended vocational schooling, or not (voc_i):

$$y_i = \alpha + \beta \cdot voc_i + \varepsilon_i \tag{2}$$

The estimated $\widehat{\beta}$ is likely to be biased due to unobserved characteristics. To address selection into tracks, we employ an RD design where GPA thresholds create a random element in whether individuals are accepted to a program, or not. Within this framework, we approximate for individuals' comparative advantages by controlling for different choice combinations, i.e. by field-type combinations.

3.1 GPA cutoffs to identify causal effects of track choice

GPA thresholds have been used to identify the returns to education in a wide range of studies, from effects of school choice (Clark, 2010; Jackson, 2010; Duflo et al., 2011; Pop-Eleches and Urquiola, 2013; Abdulkadiroğlu et al., 2014), the effects of tertiary education on wages, marriage market outcomes, and political participation (Kaufmann et al., 2015; Solis, 2015). The basic idea of this approach is that two individuals with the same combination of track choices are compared. One of the two individuals is admitted to the track, whereas the other individual has a slightly lower GPA and is not admitted to the track. At least close to the GPA threshold, the cutoff creates a random element in the track admission. This setting thus creates a discontinuity in the running variable, i.e. GPA, whereas predetermined variables should be smooth around the threshold (Imbens and Lemieux, 2008).

In this study, students apply for different types of programs in different municipalities. In each year available, each combination of program and municipality constitutes

one competition. In each of these competitions, individuals are ranked according to their GPA. The cutoff defines whether an individual is accepted, i.e. if their GPA exceeds threshold, or not, i.e. if their GPA is lower than threshold.

3.2 Differences in preferences

Endogeneity of program enrolment is particularly challenging when aiming at estimating the payoff to educational contents. Even with a valid instrument for a specific education, one still needs to control for individuals' comparative advantages. This type of bias has been less analyzed in the literature, most likely due to the often missing information of data on actual applications and choice sets.

In this study, we follow the approach by Kirkebøen et al. (2016) who analyze the wage returns to university programs by way of exploring admission cutoffs in combination with information on individuals' ranking of educational fields. Given the availability of choices made by applicants, we define preferred fields ("first best choice"), and the next best alternative ("second best choices"). The specific program combinations of the preferred field and next best alternative are then used as a control in the estimation framework.

More than 90 % of the applicants were accepted to either the first or second choice. For these cases, we define the preferred field as the first choice, irrespective of whether they are accepted at their first or their second choice. If an applicant is accepted at the third choice, the second choice becomes the preferred field. If an individual gets into the fourth choice, the third choice becomes the preferred field, etc. In either case, the next best alternative is the choice which is following the preferred field.

3.3 Sample restrictions

To achieve a clean identification of the effect of vocational schooling, relative to general schooling, we limit the sample in several ways. First, we limit our sample to those who have either chosen a vocational program as their first choice and a general program as a

second choice, or vice versa. Table 2 displays the program combinations observed in our data. In total, 7.9 % choose program combinations which are either vocational-general (4.5 percent) or general-vocational (3.5 percent).[10] Out of 1,749,290 applicants spanning over 21 years, we retain 148,003 observations with program combinations vocational-general or general-vocational.

For our RD design, we need to compare individuals at the margin of becoming accepted to their preferred choice. We therefore need to condition that there is a threshold defined for the individuals' applied first choice. Our algorithm described above defines thresholds, some of which are of low quality, if, e.g., a high share of accepted below the threshold or a low share of not accepted below the threshold, or if the demand for a track only slightly exceeds its supply. We remove a quarter of the thresholds with the lowest quality, resulting in 107,043 remaining observations. Table 3 presents descriptive mean statistics of the estimation sample by gender and program type.[11]

3.4 Econometric model

The running variable is based on the distance $dist_i^{Th}$ which is the difference between the GPA cutoff (GPA^{Th}) and an individual's own GPA. For individuals with values around zero, we expect to see an increased probability in being accepted to their first choice. A value above zero will increase the probability of being accepted to a vocational track if a vocational program is the first choice. If general program is first choice, the running variable is -$dist_i^{Th}$, to make the running variable express the probability of being accepted to vocational track. Figure 3 illustrates the share of individuals in vocational studies across different vales of the running variable. The discontinuity is fuzzy and we will use the variation around zero as an instrumental variable.

[10] 58 % state the same type of educations as first and second choice (general-general, or vocational-vocational), and 27 % do not state a second choice, presumably as they were certain of being accepted to their first choice.

[11] For completeness, and to give an idea about what kind of selection these marginal individuals constitute, the averages of the same variables are also shown in Table 4 for the total sample as well as a sample consisting of only participants in 2-year programs.

The model we estimate is a two stage least squares:

$$voc_{i,t} = \alpha_1 + \alpha_2 \cdot D_I(x_i^{Th} > 0) + \alpha_3 \cdot W_i + \theta_{j1,j2} + \gamma_r + \lambda_t + \varepsilon_{i,t} \tag{3}$$

$$y_{i,t} = \ beta_1 + \beta_2 \cdot \widehat{voc_i} + \beta_3 \cdot f(x_i^{Th}) + \beta_4 \cdot W_i + \theta_{j1,j2} + \gamma_r + \lambda_t + \nu_{i,t} \tag{4}$$

The main outcome variable is annual earnings, $y_{i,t}$, where ($voc_i = 1$) indicates a vocational program or a general program ($voc_i = 0$). Our estimation strategy identifies the local average treatment effect (LATE) of $\widehat{\beta}_2$. The variable x_i^{Th} is the running variable. Further, the matrix W_i contains controls for individual time-invariant characteristics, including GPA level, year of birth, whether being adopted, foreign born, father's and mother's education, whether father is foreign born or mother is foreign born. $\theta_{j1,j2}$ indicates a fixed effects dummy for each combinations of first- and second-best program choices, whereas fixed effects for region and cohort-specific effects are indicated by γ_r and λ_t. All regressions are run separately by gender.

3.5 Tests for exogeneity

One issue with the construction of thresholds is that individuals may be aware of the threshold in advance, and only perform sufficiently to be accepted into their program of choice. Alternatively, the choice itself may be affected by expectations about the GPA cutoff. This could mean that the GPA value is misleading as a predictor of ability. Figure 4 shows the individuals' GPA, relative to the GPA threshold. More individuals appear to be just right of the threshold, suggesting selection plays a role here. Following the test proposed by McCrary (2008), there is indeed significant evidence for heaping.

As a test for whether the program assignment is endogenous, we ran regressions on enrolment in vocational education against pre-determined variables, to see whether they are significantly correlated with the type of program assignment.

$$voc_i = \alpha + \beta_1 \cdot dist_i^{Th} + \beta_3 \cdot X_i + \theta_{j1,j2} + \gamma_r + \lambda_t + \varepsilon_{i,t} \tag{5}$$

In total, there are 16 different pre-determined variables. For each of these 16 variables, Equation (5) is estimated for both males and females and also varying the sample condition on distance to threshold, from a maximum distance from the GPA threshold of .50, .40, .30, .20 and .10, respectively. In total, this yields 160 coefficients ($5 \cdot 2 \cdot 16 = 160$). In addition, we also switched places to test pre-determined variables on the left hand side of the equation.

$$x_{i,t} = \alpha + \beta_1 \cdot voc_i + \beta_2 \cdot dist_i^{Th} + \beta_3 \cdot X_i + \theta_{j1,j2} + \gamma_r + \lambda_t + \varepsilon_{i,t} \tag{6}$$

We then did the tests with and without controls for other predetermined variables. Each set of estimates yield significant estimates in about 5 % of the cases. In all, these exogeneity tests yield in total 480 parameters of which 23 (4.8 percent) are statistically significant from zero at the five % level.

4 Results

4.1 Main results

Figures 5 and 6 show the main estimation results for the sample of marginal individuals. Each point of the lines shown represents one estimation of Equation (4) for individuals at specific ages, from 19 to 52. The figures illustrate the coefficient value with standard errors associated with the indicator variable of an individual attending a vocational program. Panels (a) through (c) show the returns on annual earnings for different model

specification: (a) shows the estimation results from an OLS model without control variables. Panel (b) is a reduced for model. Panel (c) is based on estimates from the full model, as shown in Equation (4). Panel (d) uses the same empirical specification as in (c), but shows estimates, which are translated into percentages of the samples' average earnings.

The pattern emerging is very clear in one sense, that vocational education generates a short-term earnings advantage. For males, the estimates without controls display higher earnings for vocational studies, but the long-term difference gradually disappears as we add controls. The remaining short-term earnings advantage of vocational studies is at around 2 % and statistically significant for the first ten years.

For females, the descriptive estimates without controls form a U-shaped pattern with higher earnings for those with vocational studies both initially and at the end of our observations window. Again, the short-term earnings advantage remains as we add controls. Compared with males, the initial advantage is shorter for females, about five years, until the age of about 23. Later in life, there are another five estimates at ages 43-47 which are positive and significantly different from zero. This last set of estimates is somewhat unexpected, possible explanations include later educational decisions.

4.2 Mechanisms

It is important to note that the results may reflect other things than educational contents. For instance, if initial educational choices are linked to differences in further education, our results may merely reflect years of schooling or, for the short-term, locking in effects of registrations in education. Panels (a) and (b) Figure 7 show descriptive statistics of college registrations for men and women; Panels (c) and (d) provide causal estimates of type of upper secondary schooling on accumulated college exams. The latter panels are based on a regression of Equation (4) with accumulated college exams as the outcome variable.

There are only very small differences in the shares registered in education, except for males at age 18. On the other hand, the proportions with college exams show large differences especially among females. Our linear probability models also indicate that an important share of the difference among females is causal, so that vocational courses more commonly provide paths to further education. Individuals who completed 2-year upper secondary programs only had limited eligibility for higher education. The typical exams are in areas such as physiotherapists, pre-school teacher. Exam types are divided into eight categories by statistics Sweden, 80 % of the women got their exam in the categories "teaching" (27 percent) or "health" (53). Nursing is the vocational program that primarily drives these patterns.

Given the higher likelihood of attaining a college exam, it may be that the later earnings advantage is driven by further education. This is difficult to formally investigate. However, a rudimentary check is to exclude individuals who registered in further education. The significant differences above age 40 then disappear, with point estimates interchangeably above and below zero (results not displayed). The same exercise for men does not alter the main implications from the main estimates.

4.3 Bandwidth around threshold

One concern in studies using RD designs is the choice of the bandwidth. Throughout this paper, we applied a bandwidth of 0.5 GPA-points for setting the estimation sample.

Figures **??** show the same estimates as Panel (c) of Figures 5 and 6, with the only difference being the weights attached for values of the running variable. We use a narrow sample where triangular weights are applied if the GPA of the individuals are within .50 of the threshold (panels (a) and (c)). In panels (b) and (d), triangular weights are set for individuals within 1.5 of the threshold.

applied for around zero bandwidth which is used to limit the sample. For both men and women, the results show that the patterns, i.e. early advantages of vocational

education which diminish around 23 (women) and around 30 (men). Only for women, the significant advantages of vocational schooling in later life become insignificant when reducing the bandwidth to 0.2 or less.

5 Conclusion

While vocational schooling is preparing individuals for specific occupations, general schooling enhances general knowledge and might improve later learning, e.g. through learning on-the-job. In this paper, we exploit GPA-cutoffs to test whether vocational and general schooling differ in their impact on labor earnings. If there is a true causal effect of vocational studies on school-to-work transitions, but at the cost of long-term outcomes, this should be observed for marginal students.

Using data from all applications to upper secondary schooling in Sweden from 1971 to 1991, our findings are consistent with the most common theoretical predictions. Participation in vocational schooling improves short-term earnings but earnings later tend to converge. Specifically, men are shown to have significantly higher earnings of around 2 % until the age of 27, whereas women with vocational schooling have an earnings advantage until the age of 23. Importantly, these effects do not seem to be mediated by differential participation in higher education.

References

Aakvik, A., K. G. Salvanes, K. Vaage. 2010. Measuring heterogeneity in the returns to education using an education reform. *European Economic Review* 54(4) 483–500.

Abdulkadiroğlu, A., J. Angrist, P. Pathak. 2014. The elite illusion: Achievement effects at boston and new york exam schools. *Econometrica* 82(1) 137–196.

Angrist, J. D., A. B. Krueger. 1991. Does compulsory school attendance affect schooling and earnings? *The Quarterly Journal of Economics* 106(4) 979–1014.

Brunello, G. 2001. On the Complementarity between Education and Training in Europe. IZA Discussion Papers 309, Institute for the Study of Labor (IZA).

Clark, D. 2010. Selective schools and academic achievement. *The B.E. Journal of Economic Analysis & Policy* 10(1) 1–40.

Duflo, E., P. Dupas, M. Kremer. 2011. Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in kenya. *American Economic Review* 101(5) 1739–74.

Dustmann, C., P. Puhani, U. Schönberg. 2016. The Long-Term Effects of Early Track Choice. *Economic Journal* forthcoming.

Hall, C. 2012. The effects of reducing tracking in upper secondary school: Evidence from a large-scale pilot scheme. *Journal of Human Resources* 47(1) 237–269.

Hanushek, E. A., G. Schwerdt, L. Woessmann, L. Zhang. 2016. General education, vocational education, and labor-market outcomes over the life-cycle. *Journal of Human Resources* forthcoming.

Harmon, C., I. Walker. 1995. Estimates of the economic return to schooling for the united kingdom. *The American Economic Review* 85(5) 1278–1286.

Imbens, G. W., T. Lemieux. 2008. Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142(2) 615 – 635.

Jackson, C. K. 2010. Do Students Benefit from Attending Better Schools? Evidence from Rule-based Student Assignments in Trinidad and Tobago. *Economic Journal* 120(549) 1399–1429.

Kaufmann, K., M. Messner, A. Solis. 2015. Returns to elite higher education in the marriage market: Evidence from Chile.

Kirkebøen, L., E. Leuven, M. Mogstad. 2016. Field of study, earnings, and self-selection. *Quarterly Journal of Economics* .

Korpi, T., P. De Graaf, J. Hendrickx, R. Layte. 2003. Vocational training and career employment precariousness in great britain, the netherlands and sweden. *Acta Sociologica* 46(1) 17–30.

Krueger, D., K. B. Kumar. 2004a. Skill-specific rather than general education: A reason for us-europe growth differences? *Journal of Economic Growth* 9(2) 167–207.

Krueger, D., K. B. Kumar. 2004b. US-Europe differences in technology-driven growth: quantifying the role of education. *Journal of Monetary Economics* 51(1) 161–190.

Malamud, O., C. Pop-Eleches. 2010. General education versus vocational training: Evidence from an economy in transition. *The Review of Economics and Statistics* 92(1) 43–60.

McCrary, J. 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics* 142(2) 698–714.

Meghir, C., M. r. Palme. 2005. Educational Reform, Ability, and Family Background. *American Economic Review* 95(1) 414–424.

Oosterbeek, H., D. Webbink. 2007. Wage effects of an extra year of basic vocational education. *Economics of Education Review* 26(4) 408–419.

Pischke, J.-S., T. von Wachter. 2008. Zero returns to compulsory schooling in germany: Evidence and interpretation. *The Review of Economics and Statistics* 90(3) 592–598.

Pop-Eleches, C., M. Urquiola. 2013. Going to a better school: Effects and behavioral responses. *American Economic Review* 103(4) 1289–1324.

Rosenbaum, J. E. 2001. *Beyond College for All: Career Paths for the Forgotten Half*. Russell Sage Foundation, New York.

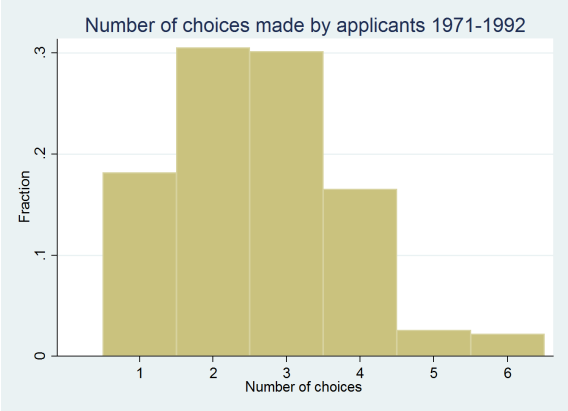
Shavit, Y., W. Müller. 1998. *From School to Work*. Oxford University Press.

Solis, A. 2015. Does higher education cause political participation? Evidence from a regression discontinuity design. Unpublished manuscript.

Wolter, S., P. Ryan. 2011. Apprenticeship. Eric A. Hanushek, Stephen Machin, Ludger Woessmann, eds., *Handbook of the Economics of Education*, vol. 3, chap. 11. Elsevier, Amsterdam, North Holland, 521–576.

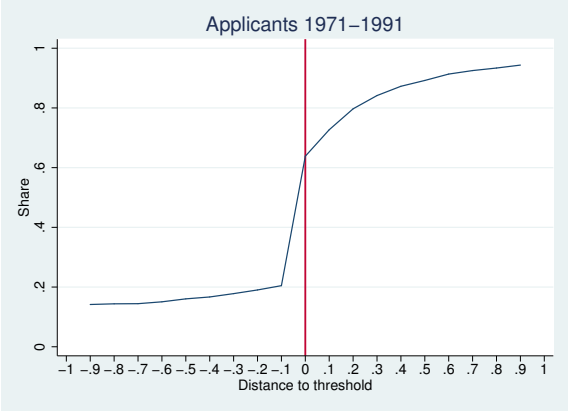
Figures

Figure 1: Distribution of individuals' choices



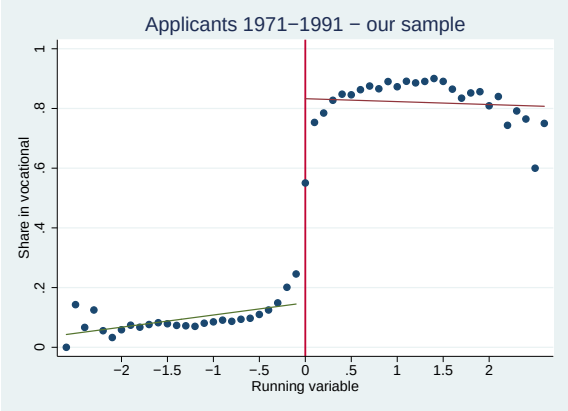
Note: The figure shows the distribution of the total number of choices across all students in our sample.

Figure 2: Probability of acceptance to applied choice around threshold



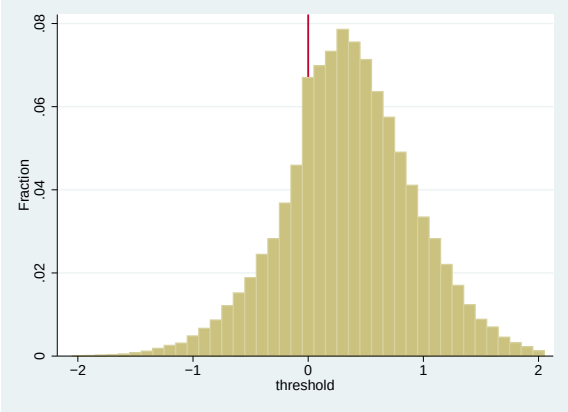
Note: The figure shows the distribution of individuals around threshold acceptance to applied choice around threshold.

Figure 3: Probability of acceptance to vocational program



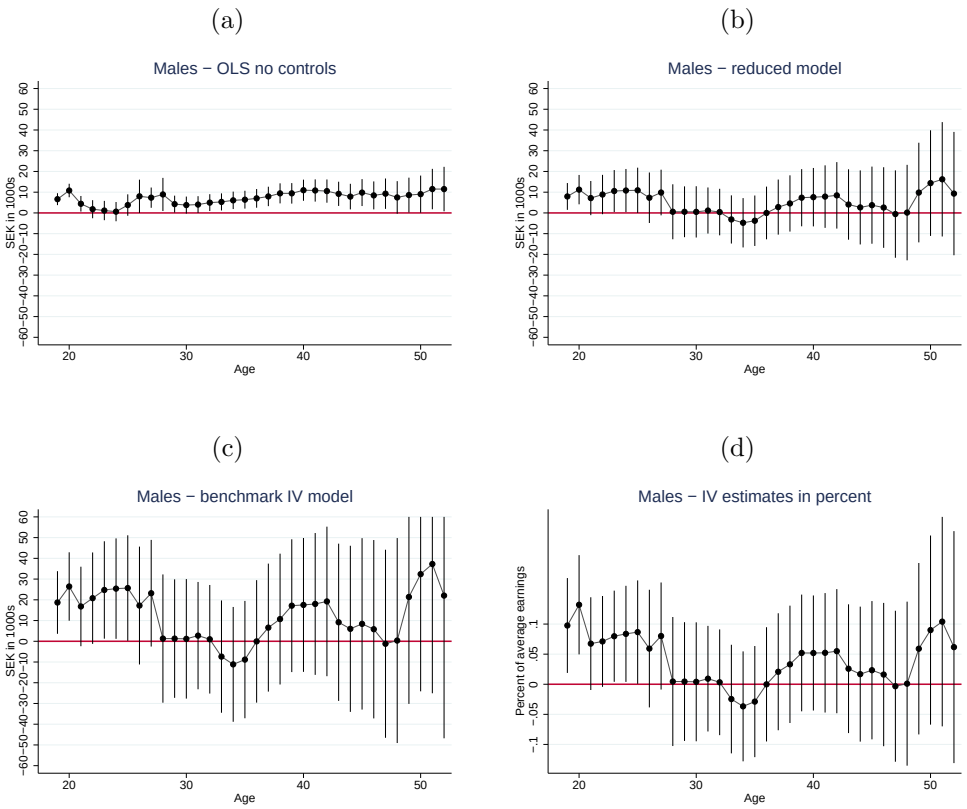
Note: The figure shows the distribution of individuals around threshold acceptance to applied choice around threshold.

Figure 4: GPA distribution around threshold



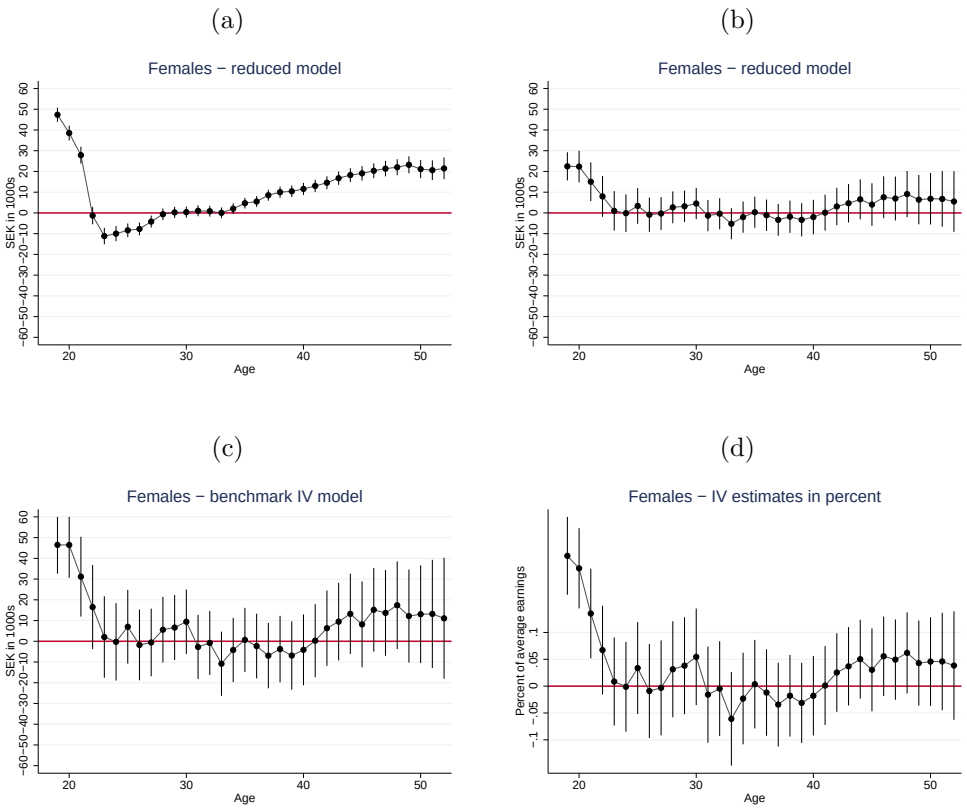
Note: The figure shows the distribution of individuals around threshold, defined as zero.

Figure 5: Absolute earnings advantage of vocational versus general tracks (males)



Note: The figures show the relative earnings advantage of vocational schooling tracks over general schooling tracks for male individuals. Each point represents one estimate. Panel (a) is based on regressions without any controls; Panel (b) is based on regressions which include all observable attributes; Panel (c) is based on the full model; Panel (d) displays the full model estimates translated in percentage terms of absolute earnings.

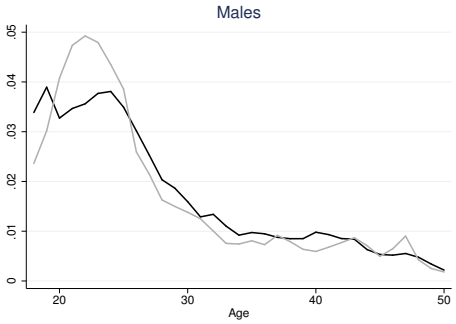
Figure 6: Absolute earnings advantage of vocational versus general tracks (females)



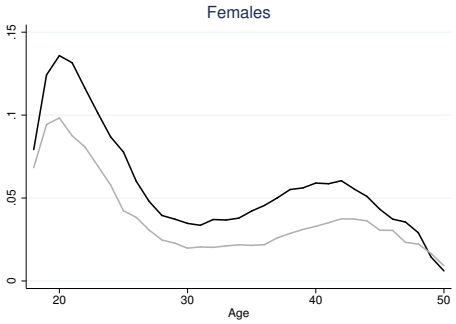
Note: The figures show the relative earnings advantage of vocational schooling tracks over general schooling tracks for male individuals. Each point represents one estimate. Panel (a) is based on regressions without any controls; Panel (b) is based on regressions which include all observable attributes; Panel (c) is based on the full model; Panel (d) displays the full model estimates translated in percentage terms of absolute earnings.

Figure 7: Further education

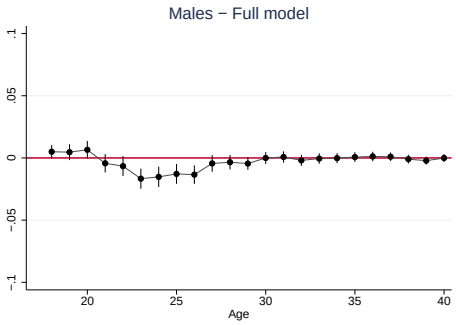
(a) College registrations (male)



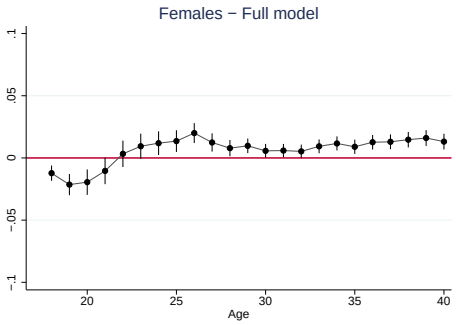
(b) College registrations (female)



(c) Accumulated college exams (male)



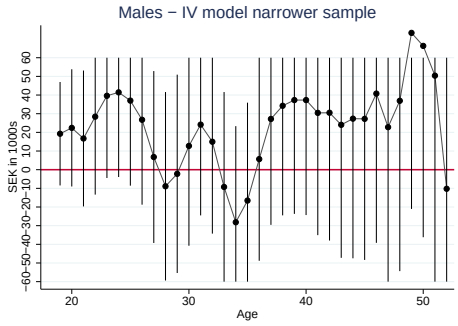
(d) Accumulated college exams (female)



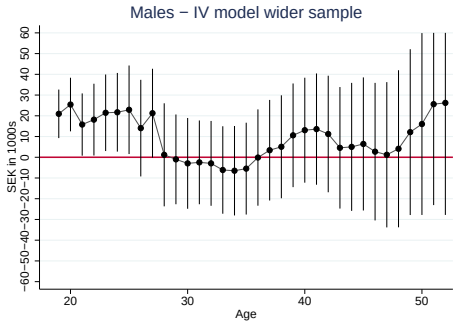
Note: Panels (a) and (b) show the share of individuals with college registrations. Panels (c) and (d) shows the estimated causal effect of vocational schooling on accumulated college exams.

Figure 8: Absolute earnings advantage of vocational versus general tracks with varying triangular weights around threshold (males)

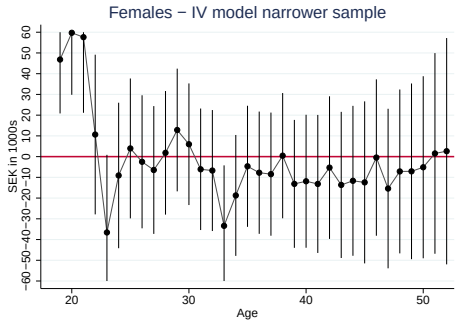
(a) Bandwidth .40 grade points



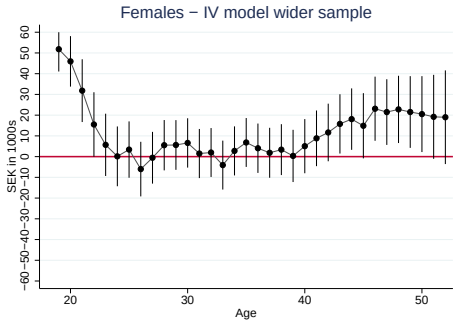
(b) Bandwidth .30 grade points



(c) Bandwidth .20 grade points



(d) Bandwidth .10 grade points



Note: The figures show the relative earnings advantage of vocational schooling tracks over general schooling tracks for male individuals. Each point represents one estimate. Panels (a) and (c) are based on more narrow samples with GPA less than .50 around the threshold; Panel (b) and (d) show the corresponding estimates with GPA less than 1.50 around the threshold.

Tables

Table 1: Number of hours per week; curricula of the 2-year upper secondary programs of main interest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	General tracks			Vocational tracks						
Type of subject	Social	Busi	Tech	Consum.	Nurs	Office	Vehic	Mech	Elec.	Constr.
Non-vocational 1:										
Swedish	3.5	4	2	3.5	3.5	3.5	2	2	2	2
English	3	4	1.5							
Mathematics	3	1.5	4							
Social science	3	3	1							
History/Religion	3.5	1	1							
Natural science	6		5.25							
Business Administration		8.5	0.5			5				
Sum non-vocational 1	22	22	15.25	3.5	3.5	8.5	2	2	2	2
Non-vocational 2:										
Optional	3	4.5		3	3	3	3	3	3	3
Technical subjects[1]			15.25							
Sum non-vocational 1& 2	25	26.5	30.5	6.5	6.5	11.5	5	5	5	5
Non-vocational 3:										
Worklife knowledge				1	1	1	1	1	1	1
Social studies	2.5			0.33						
Ergonomics			1							
Psychology				0.58	1.65					
Typing/Stenography	2	4.5				3.67				
Consumers[2]				7.2						
Social medicine[3]					2.8					
Sum non-vocational 1, 2 & 3	29.5	31	31.5	15.6	12	16.2	6	6	6	6
Vocational subjects:										
Professional practice				18.38	13.73	9	31	31	31	31
Nursing				0.83	6.38					
Childcare				1.17	4.33					
Office						10.5				
Sum vocational subjects	0	0	0	20.4	24.4	19.5	31	31	31	31
Other subjects[4]	5.5	4.5	4	2.5	2.8	2.5	2.5	2.5	2.5	2.5
Total weekly hours	35	35.5	35.5	38.5	39.2	38.2	39.5	39.5	39.5	39.5
Non-voc 1	63 %	62 %	43 %	9 %	9 %	22 %	5 %	5 %	5 %	5 %
Non-voc 1 & 2	71 %	75 %	86 %	17 %	17 %	30 %	13 %	13 %	13 %	13 %
Non-voc 1 & 2 & 3	84 %	87 %	89 %	41 %	31 %	42 %	15 %	15 %	15 %	15 %
Voc	0 %	0 %	0 %	53 %	62 %	51 %	78 %	78 %	78 %	78 %

Note: The curricula described concern the most popular 2-year upper secondary programs. Classroom subjects are divided into "non-vocational", "vocational" and "other" (physical education, music and drawing). The "non-vocational" subjects are in turn been divided into three categories: 1, 2 and 3, where the first group provides the most general knowledge and "non-vocational 3" includes subjects related to a track's intended professional activity (e.g., typing in business programs, social policy in social sciences programs).

[1] In total 24 subjects divided across four different educational paths, electro-technical, chemical-technical, machine-technical and construction.

[2] Consumer studies include Household economy, hygiene, family science, consumer studies, living environments, design.

[3] Nursing includes household economy, hygiene social medicine, anatomy.

[4] Music, drawing, P.E.

Table 2: Students' choice combinations

	(1) All	(2) Estimation sample
Voc 1st & Voc 2nd	0.218	0.000
Voc 1st & Gen 2nd	0.045	0.614
Voc 1st & Office 2nd	0.018	0.000
Gen 1st & Voc 2nd	0.035	0.386
Gen 1st & Gen 2nd	0.067	0.000
Gen 1st & Office 2nd	0.021	0.000
Gen3 1st & Voc 2nd	0.023	0.000
Gen3 1st & Gen 2nd	0.296	0.000
Gen3 1st & Office 2nd	0.007	0.000
No comb defined	0.270	0.000
Observations	1,749,290	49,209

Note: The office program is treated neither as a general nor as a vocational program. The number of general subjects in the office program is twice as high as other vocational programs, and about half of those in general programs (see Table 1).

Table 3: Descriptive mean statistics by gender and education type

	(1) Vocational	(2) General	(3) Vocational	(4) General
	Male		Female	
2-year course	1.000	1.000	1.000	1.000
GPA	3.131	2.985	3.537	3.181
Threshold	0.131	0.098	0.175	0.081
First time applicant	1.000	1.000	1.000	1.000
Aged 16 when accepted	0.920	0.909	0.935	0.933
Parents are immigrants	0.167	0.156	0.161	0.149
Born abroad	0.037	0.032	0.032	0.032
Adopted	0.021	0.023	0.024	0.025
Mother college degree	0.085	0.070	0.086	0.059
Father college degree	0.081	0.063	0.095	0.061
Annual earnings (father)	234.962	243.313	233.155	224.890
Annual earnings (mother	127.580	126.941	121.669	121.874
Observations	13,931	7,706	13,336	13,830

Note: Figures show the mean of observable variables for the estimation sample, stratified by gender and program type. Mothers' and fathers' education and annual earnings are measured at the age of 16.

Table 4: Descriptive mean statistics by gender and education type. Total sample and restricted samples.

	(1)	(2)	(3)	(4)	(5)	(6)
	Males			Females		
	Full	2-year	Rest. sample	Full	2 years	Rest. sample
2-year course	0.589	1.000	1.000	0.550	1.000	1.000
GPA	3.181	2.853	3.079	3.474	3.169	3.356
threshold	0.323	0.209	0.119	0.441	0.276	0.127
First time applicant	0.964	0.959	1.000	0.966	0.957	1.000
Aged 16 when accepted	0.872	0.842	0.916	0.877	0.838	0.934
Parents are immigrants	0.172	0.173	0.163	0.172	0.170	0.155
Born abroad	0.038	0.039	0.035	0.040	0.039	0.032
Adopted	0.018	0.020	0.022	0.022	0.024	0.025
Mother college degree	0.107	0.048	0.080	0.109	0.049	0.073
Father college degree	0.124	0.049	0.074	0.127	0.055	0.078
Wage (father)	250.860	215.514	237.933	249.885	216.984	228.960
Wage (mother)	132.537	119.724	127.352	133.072	117.890	121.773
Observations	1,056,229	622,016	21,637	956,722	526,233	27,166

Note: Columns (1) and (4) show the mean of observable variables for the full sample, Columns (2) and (5) for all 2-year programs, and Columns (3) and (6) for a restricted sample with running variable below .50 in absolute value. Mothers' and fathers' education and annual earnings are measured at the age of 16.