Economics Working Papers

2017-2

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Leslie S. Stratton, Nabanita Datta Gupta, David Reimer and Anders Holm

DEPARTMENT OF ECONOMICS AND BUSINESS ECONOMICS
AARHUS UNIVERSITY

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Leslie S. Stratton
Professor
Department of Economics
Virginia Commonwealth University
301 W. Main Street, P.O. Box 844000
Richmond, VA 23284-4000
IZA, Bonn, Germany
804-828-7141
lsstratt@vcu.edu

Nabanita Datta Gupta
Professor
Department of Economics and Business Economics
Aarhus University
Fuglesangs Allé 4, Building 2621, Office B-05
8210 Aarhus V
Denmark
(+45) 8716 5207
ndg@econ.au.dk

David Reimer
Professor with special responsibilities
Danish School of Education
Aarhus University
Niels Juels Gade 84
8200 Aarhus N
Denmark
(+45) 8716 3935
dare@edu.au.dk

Anders Holm
Professor
Department of Sociology
The University of Western Ontario
Room 5327, Social Science Center
London, Ontario N6A 5C2
Canada
519-661-2111 x85515
aholm@uwo.ca

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April 2017

Abstract: This study provides evidence of the importance of cognitive and non-cognitive skills to enrollment in and completion of three types of vocational training (VET): education and health, technical, and business. Math and language exam scores constitute the key measures of cognitive skills; teacher-assigned grades the key measure of non-cognitive skills. The data consist of two nine-year panels of youth completing compulsory education in Denmark. Estimation of completion proceeds separately by gender and VET type, controlling for selection and right censoring. The authors find that all skills are inversely related to VET enrollment, results that are robust to family-specific effects. Estimates for completion vary considerably by program type, demonstrating the methodological importance of distinguishing among different VET courses. While math scores are positively related to certification for all VET tracks, language skills are more important for the non-technical track, and non-cognitive skills appear important only for the business track.

Keywords: Vocational education; Enrollment; Completion; Vocational certification; Ability

JEL Codes: I21

1. Introduction

A substantial body of research has examined the impact of cognitive and non-cognitive skills on the decisions to enroll in and to drop out of high school and college. Here we examine enrollment in and dropout from an important alternative educational route that has received far less attention – vocational education and training (VET). We use language and math exam scores to control for cognitive ability and teacher-assigned grades (that arguably take into account effort/conscientiousness) to capture non-cognitive ability. Given the higher returns generally available from academic study, we posit that on average less able individuals will enroll in VET. However, both cognitive and non-cognitive ability may still matter for completion. Furthermore, we recognize the heterogeneous nature of vocational programs and distinguish among three types of VET - education and health, technical, and business programs. Different skills may matter for these different types of VET. We hypothesize that math skills will have a more significant association with technical VET, while language skills may play a role in less technical VET tracks. As completion may be correlated in the unobservables with the decision to enroll and VET programs often attract older students, selection and censoring must also be addressed. The analysis of VET completion that follows proceeds with Danish register data on two cohorts of compulsory school graduates who are observed for a span of nine years, recognizes the heterogeneous nature of VET programs and skills, and makes clear methodological improvements compared to the existing literature.

In Europe, VET programs enroll a significant population and are typically heavily subsidized. About 33% of persons age 25-64 in the OECD report their highest completed education to be vocational, and 44% of those enrolled in upper secondary education are enrolled in vocational programs (OECD 2014). In Denmark the figures are 42% and 46% respectively.

The costs associated with these programs are substantial both in time (most programs take between three and a half and four years to complete) and money. On average the per student cost of vocational education is higher than the per student cost of academic upper secondary programs (OECD 2014). The Danish government provides substantial subsidies. The Danish Ministry of Finance reported spending 5.9 billion DKK (USD 1 billion) or about 17,500 USD per VET pupil in 2008.

Vocational training is substantially less popular and less centrally organized in the US, but interest in such programs is rising as CEOs/firms have expressed concerns regarding the lack of qualified job applicants for positions requiring VET (Schulze 2016, Rugaber 2017). While the US labor force is projected to grow about 0.5% annually through 2024, employment in the construction and health care sectors, that are typically served by apprenticeship programs (Torpey 2013), is expected to grow twice as fast making enrollment in and completion of VET programs particularly important.[1] As in Europe, most formal apprenticeship programs take about four years to complete (Torpey 2013), though in the US less time is spent in the classroom, and firms and trainees bear more of the costs (Bilginsoy 2003).

Investments in VET do provide a return. Simple comparisons indicate that persons with a vocational education in Denmark have lifetime earnings that are 15% higher as compared to those with only a compulsory education (Danish Employers' Association 2009). Jepsen et al. (2014) find recipients of community college based vocational education in the US experience a significant boost in earnings and employment in the years immediately following receipt. Carneiro et al. (2010) and Eichhorst et al. (2015) also report higher employment probabilities for those completing VET as compared to those completing a more academically focused upper

[1] See employment projections reported by the Bureau of Labor Statistics (BLS) at https://www.bls.gov/news.release/ecopro.toc.htm (accessed January 9, 2017).

secondary degree. There is, however, also evidence (Hanushek et al. 2017) that the employment probabilities of those with more general education catch up to those with only vocational education over time, and that lifetime earnings are higher for academically educated persons. Thus, in general, students pursuing education beyond that which they are legally required to obtain have an incentive, ceteris paribus, to pursue an academic degree.

We posit that the decision to pursue a vocational as opposed to an academic degree is likely related to the expected probability of completing each degree. Enrollment does not guarantee completion in either the academic or the vocational track. On-time graduation rates are actually lower for vocational as compared to academic upper secondary programs in the OECD (64% versus 76%). Estimates for the US (Zeidenberg et al. 2015) suggest a similar pattern. While there is a wealth of evidence linking ability to success in academic education, of interest here is the relation between ability – both cognitive and non-cognitive – and vocational education. Hanushek et al. (2017) present some evidence using literacy scores from the International Adult Literacy Survey. They find that ability (measured as the average of test scores in prose, document, and quantitative literacy) is on average lower for those having vocational as compared to academic education, but this analysis looks only at those who have completed such education. Hanushek et al. do not address the impact of ability on enrollment versus completion of vocational education. The high dropout rate for VET training could be the result of the selection of less able students into such programs when ability matters. We are also the first to employ a specification that allows language and math skills as well as teacher-assigned grades to have distinct effects. We argue that the former, being nationally normed test scores, are likely to be more representative of cognitive skills, while the latter are more representative of non-cognitive skills.

Not only do we examine the impact of skills on both enrollment and completion, we also distinguish between different VET programs. In Denmark there are 11 main types of VET programs. Rather than treating these all as one, we recognize three broad groups: EDHR, education and health-related; TECH or technical; and BUSI or business (see appendix A). EDHR provides training for medical assistants, welfare workers, and teaching assistants; TECH for construction, transportation, and manufacturing workers; BUSI for wholesale and retail purchasing assistants, financial assistants, and general office assistants.[2]

In sum, this research advances the literature on VET in several ways. First, we recognize the heterogeneous nature of VET and distinguish among three different types of programs. Second, we distinguish among several different skills, while also including a full complement of control variables. Third, we control for selection into VET. If the unobservables driving enrollment are correlated with those driving completion, estimates that ignore selection will be biased. We follow previous literature and use measures of the distance to alternative educational institutions and peer behavior to identify the enrollment equation. Fourth, we control for right censoring. Such censoring is important given the high fraction of those still enrolled – between 8 and 16% for our sample depending on the type of VET.

2. Literature review

According to human capital theory, individuals act to maximize their lifetime utility, attending and continuing in higher education if the expected future marginal benefits exceed the expected future marginal costs. Key variables used to model enrollment and persistence (see Bound and Turner 2011 and Stratton 2014 for reviews) include prior academic achievement,

[2] Formal apprenticeship programs in the US emphasize construction and manufacturing (both in the TECH category) and healthcare (EDHR) (Torpey 2013).

parental education, and household income. Generally speaking more academically prepared students find the cost of pursuing an academic degree to be lower, students with more educated parents have more support for and understanding of the educational system, and higher household income reduces the cost burden of higher education.[3]

Two concerns not always addressed in the literature on academic achievement are selection and censoring. Research has demonstrated that taking into account prior educational decisions can be important in modeling subsequent outcomes (see, for example, Cameron and Heckman 1998; Colding 2006a; Colding et al. 2009; and Holm and Jæger 2011). Controls for ability also matter in addressing selection. Holm and Jæger (2009) find that failing to control for ability when jointly modeling enrollment and completion results in substantially higher estimates of the cross-equation correlation in the unobservables and hence potentially biases all the covariate effects. Many studies of academic achievement follow individuals for a fixed period of time and assume students have completed their studies within that time period. Stratton and Wetzel (2013) and Garibaldi et al. (2012) have shown such is not the case with academic programs - that a substantial fraction of those who enter tertiary education are still enrolled well after their expected graduation date. It is unclear to what extent findings from the literature on academic programs will apply to the VET sector, however, censoring in particular is likely to be an issue. On-time VET graduation rates in Denmark are 35%, with 18% more being certified within another two years and even then 20% still enrolled. Bilginsoy (2003) reports similar issues using US data on construction industry apprenticeship programs. Moreover, VET programs often attract adult learners seeking to update their skills, hence students may enter VET training many years after completing compulsory education. Given our analysis sample, these

[3] In this analysis, household income is likely to play a much smaller role as higher education is fully subsidized in Denmark.

late starters may not yet have had time to complete. We address both selection and censoring in the analysis that follows.

The economics literature on VET is limited. Colding (2006a, 2006b) and Colding et al. (2009) examine enrollment in and dropout from VET programs in Denmark, but have no controls for prior academic performance. Bilginsoy (2003) examines dropout and completion from construction-type apprenticeships in the US, but also has no information on ability. One might suppose that performance in VET programs is not particularly dependent on academic performance, but Dickerson and McIntosh (2013) find such controls to be critically important in their analysis of the choice of post-compulsory education (vocational or academic) in England. Furthermore, while recognizing that there exist many different types of VET training, works at best control for such either by distinguishing between programs of different lengths (Lopez-Mayan 2010) or by including dummy variables to control for field (Colding 2006b and Colding et al. 2009). The latter studies mimic work in the higher education field in which researchers control for major using dummy variables (for example, Bradley and Lenton 2007). However, as is the case in the higher education field (Arcidiacono 2004), it seems logical to suppose that both the decision to enter different types of VET programs and the likelihood of completion may differ for individuals with different abilities and characteristics. We address this here by estimating separate models for three types of VET: EDHR, TECH, and BUSI.

A strength of the current study is the availability of several excellent measures of ability. The use of test scores (SAT, ACT, AFQT) to model student academic outcomes is well established (for example, Rivkin 1995, Cameron and Heckman 2001, Belley and Lochner 2007, Bound and Turner 2011). A growing literature now focuses on the role of personality traits or non-cognitive skills as well (Heckman and Rubinstein 2001; Jacob 2002; Heckman et al. 2006;

Archibald et al. 2015). Data on such are, however, typically not available in the data sets used by economists to analyze schooling outcomes.[4] A common alternative approach has been to use exam scores to control for cognitive skills and teacher-assigned grades to control for non-cognitive skills (Jacob 2002; Goldin et al. 2006; Archibald et al. 2015).

This distinction is, of course, imperfect; each measure incorporates elements of both cognitive and non-cognitive ability (see Almlund et al. 2011 for a more in depth discussion). Test scores are viewed as more objective than grades as they are based on a student's command of the subject material. Being nationally normed and standardized, test scores are also readily compared across individuals and over time.[5] On the other hand, test scores reflect performance at only a single point in time, and that limited observation window could introduce noise. A student could be ill or temporarily distracted or could have an irrational fear of tests that affects his/her exam performance. Grades reflect performance over a longer time period and many different types of assignments, mitigating this source of error. However, grades are not normed or standardized – different teachers give different assignments and assign grades differently, different students take different classes, and grading scales differ across schools and over time. More importantly, grades likely reflect not just performance but also student behavior and organizational skills: are assignments turned in on time, does the student disrupt the class, is the student putting forth effort … .[6] Such components are more readily related to non-cognitive than

4 An exception is information on locus of control and self-esteem (Heckman et al. 2006; Archibald et al. 2015).

5 Danish exams are graded in part by the student's teacher and in part by an external reviewer, with the external reviewer's assessment given priority.

6 Rangvid (2015) reports that by law grades in Denmark should, like exams, reflect student knowledge not effort. This would suggest that both reflect only cognitive skills. However, she also acknowledges that grades are more subjective than exam scores and finds significant differences between the two.

to cognitive ability. While exam performance has also been found to be associated with non-cognitive ability, relatively speaking grades have a stronger association (Almlund et al. 2011).

Our rich data include nationally administered, standardized exam scores in mathematics and Danish obtained at the end of ninth grade or compulsory school, and teacher-assigned grades for the ninth grade. Though many studies combine math and verbal skills to form a single measure, these subjects are quite distinct and reflect different skills. The correlation between math and language test scores in Denmark is only 0.54. Were grades simply an alternative measure of cognitive ability, they should be perfectly correlated with exam scores. We find a correlation of 0.69 between math exam scores and math-specific grades and a correlation of 0.73 between Danish exam scores and Danish grades. The teacher grades used in this analysis encompass performance in all subjects, not just math and Danish, and as such include information on ability along other dimensions like science and foreign languages, but are similarly correlated with math and Danish exam scores (0.68 and 0.72 respectively).

Of particular interest here is whether the skills necessary for success differ by type of VET program. Turner and Bowen (1999) find that math and verbal SAT scores have significantly different effects on college major choice. Higher math scores increase the probability of majoring in engineering, math, the physical sciences and, to a lesser extent, economics and the life sciences. Higher verbal scores increase the probability of majoring in the humanities. Furthermore, these effects differ by gender. VET programs are no less varied than college majors. TECH VET encompasses such fields as carpentry, plumbing, and manufacturing that require some math skills, hence our ex-ante expectation is that math scores will be positively related to completion of TECH VET.[7] Verbal skills are not necessarily unimportant - tradespeople wishing to run their own business, for example, need good communication skills to serve customers – but may be less important for TECH. In support of this hypothesis, the 2016 Occupational Requirements Survey in the US indicates that literacy is not required for 11% of workers in construction and extraction occupations as compared with 3% of all workers. An apprentice in BUSI likely needs both math and verbal skills in order to keep appropriate records and provide service to the community. An apprentice in EDHR is likely training for a position as a home health aide or a teaching assistant and as such may require limited skills in general.[8]

3. Data

The data consist of a population sample of individuals born in Denmark between 1983 and 1989 inclusive, who complete compulsory education in Denmark in either the 2002 or the 2003 academic year when they are between the ages of 14 and 18, and who are living in Denmark at age 15. These cohorts were selected because elementary-level exam scores were first recorded in 2002 and many individuals pursue VET later in life, making a long panel

[7] The US Department of Labor (nd) provides some evidence to this effect. "Workers may need some skills—such as basic math and computer aptitude—before starting in manufacturing." (2014/article/manufacturing.htm), "I would say math is number one, and not only for measuring and calculations: You need the critical thinking that you use in math to work through processes, especially for remodels and planning." (2016/interview/plumber.htm), and "I use math, such as geometry and trigonometry" (2016/interview/woodworker.htm). Information from Washington State Department of Labor and Industries (nd) regarding apprenticeship programs indicates that plumbers, steamfitters, pipefitters, and refrigeration workers "Must have completed one year of algebra and one year of plane geometry", that electrical workers must have had algebra, and that many other tradesmen need trade or applied math.

[8] Requirements for an apprenticeship in 'Early Care & Education' focus primarily on the physical nature of the job. There is no mention of math skills and only language skills sufficient to complete the application are required (Washington State Department of Labor and Industries, nd).

important. After excluding about five percent of the total population who pursue no degree after ninth grade, report peculiar enrollment patterns (such as entering tertiary education without any secondary education), or are missing information on maternal age, the final sample includes 101,367 individuals. The data are truncated in September 2011 for those graduating from ninth grade in 2002 and in September 2012 for those graduating in 2003 so that the observation period does not differ by graduation date. Enrollment behavior is observed for a minimum of 100 months, with the majority of individuals observed for 111 months.

Grades 1 through 9 constitute compulsory education in Denmark. Tenth grade is a popular option, particularly for students who have struggled academically[9] or are unsure of which career path to follow. Students subsequently choose among three tracks: they can leave school, enter vocational education (VET), or enter academic upper secondary (high school) education. Having successfully completed academic upper secondary education provides eligibility for higher or tertiary education (college).[10] Figure 1 illustrates the month-by-month pattern of enrollment by general program type for the population. The fraction of the population that is not enrolled is illustrated first, followed by those in tenth grade, vocational, academic upper secondary, and tertiary programs.

The illustration shows that youth generally enroll in tenth grade immediately after ninth grade, and that 56% of these cohorts chose this experience.[11] Academic upper secondary

[9] We find a negative correlation between attending tenth grade and both grades (-0.24) and exam scores (-0.20 for both math and Danish).

[10] It is possible but very rare for VET students to continue on to higher education without acquiring an upper secondary degree.

[11] Enrollment in tenth grade may be an indicator of skill, much like exam scores and grades, but how such enrollment should be construed is not clear. Tenth grade may enable less prepared students to catch up. If so, this indicator may, controlling for prior performance, be a positive indicator of skill. If, however, these students do not catch up or are enrolled for some other reason (for example, because they are uncertain what path to pursue), then this indicator may be

education is typically initiated soon thereafter. This is comparable to high school in the US, Gymnasium in Germany, and A-levels in the UK. There are two main routes in academic upper secondary education or high school: the traditional track (gymnasium) and two more vocationally-oriented tracks (a business and a technical track). Each normally take three years to complete. Only about four percent are enrolled in high school more than four years after completing compulsory education. Not surprisingly enrollment in tertiary education picks up only after students have had the opportunity to complete high school.

Of particular interest here is enrollment in vocational education or VET. VET enrollment is substantially more diffused as compared to any other type of enrollment. The fraction enrolled in VET peaks at 26% in month 14, but does not fall below 20% until five years and is still 7% nine years after completing compulsory education. This illustration demonstrates the importance of addressing censored observations.

Figure 2 breaks down enrollment by type of VET. Enrollment in EDHR training is illustrated in Panel A. These programs have the smallest and most stable average enrollment. However, about a quarter of students who complete one EDHR program reenroll and complete a second more advanced program. As our analysis focuses on the first completion, we recalculated enrollment spells (see the dotted line) to exclude enrollment following the first completion to see how much of the extended EDHR enrollment is attributable to subsequent spells. Enrollment in EDHR remains quite stable following this adjustment. The fraction enrolled hovers between 1.5 and 1.7% for the period 26 to 54 months after compulsory schooling, and remains around 1% through year nine.

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unrelated or even negatively related to completion of VET. In light of this uncertainty, we choose not to focus on this measure. However, while attending tenth grade is a choice, it is a choice that precedes the decision to pursue VET or academic high school, so we do include a control variable identifying those who enrolled in tenth grade in our analyses.

Reenrollment in technical and business VET is much less common, making any adjustment unnecessary. Enrollment in TECH is illustrated in Panel B. These programs have much higher enrollments than EDHR, with more than 10% of the population enrolled in TECH within two years following completion of primary school. Enrollment peaks only slightly higher at 12.8% in year four, falls below 10% at the five-year mark, and continues to fall, ending around 2.6%. Enrollment in BUSI is even more delayed (see Panel C), likely because about one-quarter of those enrolling in BUSI completed business high school first. Less than 1% are enrolled in a BUSI program in the first three years following completion of compulsory schooling. Enrollment peaks at 5.7% of the population five years after compulsory schooling is completed and remains above 1.5% for the duration.

While Figure 2 illustrates enrollment by type of vocational education, it provides an incomplete picture of such programs as a substantial fraction of those enrolling subsequently drop out. Per our calculations, the fraction of those beginning high school who complete their degree within our nine year time frame is approximately 85%. Completion or certification rates for VET (see the top of Table 1) range from 64% for EDHR to 43-45% for BUSI and TECH. Even these numbers are misleading, however, given the substantial fraction still enrolled when last observed: 16% for EDHR and 9% for BUSI and TECH. If those still enrolled nine years later are unlikely to complete VET, then treating them as failures is appropriate; however, if they are late starters who are progressing towards certification, then treating them as failures will bias the results. The final two columns of Table 1 suggest that they are late starters. Those still enrolled on average first entered VET training six to seven years after completing ninth grade, two and a half to four years later than the average completer, and, while they have been enrolled five to ten months less than those who have completed, they have been enrolled for a year or more longer than those who are no longer enrolled. Thus, we favor a specification that controls for censoring as well as VET type and selection, but will examine the sensitivity of our results to these treatments.

Our goal here is to model jointly enrollment in and completion of these three types of vocational education, in order to take into account selection on unobservables. As students often bounce between these programs and between academic high school and VET, we are unable to estimate a single, simple model of enrollment choice.[12] Instead, we examine each type of VET training separately.[13] The data include a rich set of covariates. Sample statistics for these variables are reported in Table 2 for the full sample and for the subsamples who attempt each of the three types of VET programs we model.

Of particular interest are our measures of ability. Both grades and exam scores are entered using a set of six dummy variables identifying: those in the top decile, those in the bottom decile, those in a broad band of mid-level scores (encompassing half of all exam scores and 40% of all grades), those in additional categories linking the extremes and the middle scores (for example, those in the 11th to 30th percentiles of the distribution for math and Danish exam scores), and those missing values. This measurement scheme is preferred to use of the

[12] Of those ever attempting VET, at least seven percent attempt multiple types of VET and 35% attempt academic high school. Less than 12% of those attempting EDHR or TECH VET complete academic high school, however, as noted above, about 25% of those attempting BUSI VET first complete academic business high school.

[13] In the case of EDHR, for example, the selection effect is estimated by comparing those ever enrolling in EDHR with all others ever enrolling in another type of education (high school, TECH, or BUSI) but not EDHR. To the extent that selection is between high school and VET more broadly, this approach will bias our results against finding a selection effect. Estimates of the selection equations estimated by excluding those who only enroll in a different type of VET from the comparison group are available upon request. These results indicate that the importance of exam scores and grades for selection into VET is indeed underestimated, particularly for those performing below average, but results regarding completion are almost identical.

underlying continuous measures as it better accommodates nonlinear effects. Results in Table 2 indicate that those pursuing VET perform less well on both math and language exams than the full cohort; they also receive lower grades. Those attempting EDHR are least well prepared academically; those attempting BUSI are the best prepared academically. These figures suggest, as expected, that those with the highest ability go on to high school.

Rather standard information on nationality, family background, and parental characteristics (age, income, and education) is available. Information on peer enrollment and distance to high schools is also obtained. Using the sample of students (excluding the respondent him/herself) in the respondent's ninth grade class and the two previous graduating classes at the same institution, we identify the first type of education each student's peers enroll in within five years of completing primary school. Variables identifying the fraction of peers pursuing EDHR, BUSI, and TECH training as well as the fraction pursuing a more academic line of study at regular gymnasiums, technical gymnasiums, and business gymnasiums are created.[14] Peer enrollment is intended to capture peer pressure and neighborhood partiality for particular educational paths. The distance to each of the three different types of academic high schools is also measured in order to capture one element of the cost associated with academic education. The distance to different types of vocational schools is not available in our sample. Dickerson and McIntosh (2013), however, found that distance to the nearest academic high school was a more significant factor than distance to the nearest vocational school in a study of vocational training using English data.

[14] Enrollment in tenth grade is ignored. Controls for peer behavior are not constructed for individuals who appear to have been home schooled or enrolled in primary schools with fewer than ten students per graduating class. A dummy variable is used to identify these students.

Other variables sometimes included in models of educational enrollment and/or attainment are those related to local labor market conditions (Farber 1967, Bilginsoy 2003). Such variables capture the opportunity cost of enrollment. Denmark, though, is a relatively small country geographically and the sample consists of only two cohorts, limiting this source of variation. Nevertheless, dummy variables identifying cohort year and four geographic regions are incorporated to control for such market factors.

4. Methods

Since individuals may self-select into educational tracks on the basis of traits unobservable to the researcher, studying completion by limiting the analysis to only those observed enrolling may result in sample selection bias. For instance, students choosing one VET track may possess more or less of a trait that correlates with completion of that track, such as diligence or ambition. If this trait is correlated with any observed covariate, failure to take it into account, will seriously bias all the estimates (Heckman 1979, Holm and Jæger 2009).

To control for such sample selection bias, we estimate a Heckman selection model. Both the decision to enroll in a VET program and the decision to complete or drop-out are binary variables. Thus, the resulting empirical model is a bivariate probit selection model. This model jointly estimates how factors affect initial enrollment and dropout. Individuals enroll in a program if: $y_1^* = x_1\beta_1 + \varepsilon_1 > 0$, where y_1^* is the latent propensity to enter a VET program, x_1 is a vector of covariates affecting the propensity to enter a VET program, and β_1 is a vector of regression coefficients. Finally ε_1 is an error term capturing the effect of unobserved factors on the propensity to enter a VET program. We do not observe y_1^*, only a binary variable $y_1 = 1$ if $y_1^* > 0$ and 0 otherwise. Given that they enroll, individuals complete if $y_2^* = x_2\beta_2 + \varepsilon_2 > 0$, where

y_2^*, x_2, β_2 and ε_2 are defined as above. Again, we do not observe y_2^*, just the binary variable $y_2 = 1$ if $y_2^* > 0$ and 0 otherwise. Completion status is observed if and only if individuals enroll in the program, i.e. y_2 is observed iff $y_1 = 1$. Individuals who are still enrolled (i=1 to N_1) when last observed are treated as censored observations, used to estimate parameters in the enrollment but not the completion equation.

The log-likelihood function for this model is:

$$lnL = \sum_{i=1}^{N}(1 - y_{i1})ln[\Phi(-x_{i1}\beta_1)] + \sum_{i=1}^{N_1} y_{i1}ln[\Phi(x_{i1}\beta_1)]$$

$$+ \sum_{i=N_1+1}^{N}\{y_{i1}y_{i2}ln[\Phi_2(x_{i1}\beta_1, x_{i2}\beta_2, \rho)] + y_{i1}(1 - y_{i2})ln[\Phi_2(x_{i1}\beta_1, -x_{i2}\beta_2, -\rho)]\}$$

where the first element captures those not enrolling in VET, the second element captures those still enrolled/censored, and the final element captures those who enrolled and are not censored (i.e. completed or not). Identification is achieved without relying solely on the assumption of normality as long as there is a variable in the selection equation (x_1) that does not appear in the outcome equation (x_2). We treat select measures of compulsory school peer behavior and distance to high schools as factors that affect enrollment but not completion given that one enrolls. Theoretically these factors should become unimportant once the decision to enroll in VET is made. The assumption that the behavior of compulsory school peers is not pertinent to completion may be violated if peers' enrollment behavior is correlated with peers' completion behavior. Evidence from Anelli and Peri (2016) suggests that while high school peers can influence the college major to which students apply, subsequent performance is primarily a function of ability, providing external support for our use of peer behavior as an identification strategy. Similarly, the assumption that the distance to the nearest high schools is not pertinent to completion may be violated if it is not unusual to enroll in high school after VET. However, most students do not enter the same VET[15], the fraction of peers entering the same VET is incorporated in both the enrollment and completion equations[16], and few students attempt high school after enrolling in VET[17]. In addition to these theoretical arguments regarding instrument validity, our imposed restrictions hold when tested using specifications that are identified only off the assumption of normality. The estimate of ρ will tell us whether the error terms ε_1 and ε_2 are correlated and controlling for selection is necessary.

5. Results

Results are presented separately for the three types of VET identified in this analysis. Our focus is upon the relation between cognitive and non-cognitive skills and completion, and how this relation varies by type of VET program. As is indicated in Table 2, men and women are attracted to different types of VET. Approximately 90% of those attempting EDHR training are women as compared with only 20% of those attempting TECH. Analysis indicates that there are significant differences by gender[18], hence estimation proceeds separately by gender, except in the case of EDHR for which the sample of men is too small. In this case, we pool men and women and include a dummy variable to identify gender.

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[15] As reported in Table 2, on average the fraction of peers pursuing the same type of VET is 2% for those attempting EDHR and 10% for those attempting BUSI. The fraction for those attempting TECH is almost 29%, but there are many different types of TECH VET programs so the fraction entering the identical program is substantially lower.

[16] Similarly, the fraction of peers attending technical (business) high school is also included in both the enrollment and completion equations for TECH (BUSI).

[17] Tabulations indicate that fewer than two percent of those who attempt (or complete) a VET certification subsequently complete a high school degree.

[18] P-values for these tests are 0.0000 for each type of program. Gender differences are commonly observed in higher education (Stratton 2014) and likely to arise here in part because men and women pursue different types of VET even within these separate tracks.

5.1 Enrollment

Parameter estimates for the ability measures from the enrollment equations are presented in Table 3 for men (the combined sample for EDHR) and in Table 4 for women. Further results are available upon request (see Appendix B). The association between our ability measures and enrollment is highly significant. Only 4 of the 72 relevant parameter estimates are not individually significant and all are jointly significant by type of measure (language exam, math exam, grade) at the 0.5% level. The coefficients to the math exam scores uniformly indicate that students with higher skills are less likely to enroll in any VET program. Those with better than median language exam scores and better than median grades are also uniformly less likely to enroll. The associations between enrollment and lower than median language scores and grades are less clear. Enrollment in BUSI and EDHR appears somewhat less sensitive to lower grades, and men with the lowest language scores are, in fact, significantly <u>less</u> likely to enroll in BUSI. Generally, however, our hypothesis that enrollment in VET is negatively associated with skill holds true.[19]

Although we control for a broad array of individual and family characteristics, the association we observe between ability and enrollment may not be causal. There may be some unobserved factor correlated with ability that drives enrollment. To investigate the possibility that some family-specific trait that is correlated with ability is driving enrollment, we use a sample of siblings and pool all types of VET to estimate a linear probability model of enrollment with family-fixed effects. As the effects of exam scores and grades are strong and consistent across all types of VET, these fixed effect estimates are likely to be informative, though possibly noisy. Even controlling for unobservable family-specific effects, we find a strong negative

[19] Results are substantially the same when second generation immigrants are excluded and are even stronger when the control population includes only those attempting high school.

relation between both exam scores and grades and VET enrollment (see Appendix D). Siblings with higher ability scores are less likely to enroll in VET. These results suggest that the relation between ability and VET enrollment is likely to be causal. Failure to take this negative selection into VET into account might bias conclusions regarding the relationship between ability and VET completion.

5.2 Completion

Parameter estimates for the ability measures from the completion equations as well as the cross-equation correlation terms are presented in Table 5 for men (the combined sample for EDHR) and in Table 6 for women. Further results are available upon request (see Appendix C). As described above, to identify the enrollment equation, we exclude select distance and compulsory school peer behavior measures when modeling completion. In the case of EDHR, only information on the fractions of peers attempting EDHR or any high school are included in the completion equation. Information on all the distance measures and on the fraction of peers attending other types of VET is excluded. In the case of TECH, the variables excluded from the completion equation are the fraction of peers attending EDHR and the distance to the nearest academic high school. In the case of BUSI, the variables included in both equations are the fraction of peers attending academic high school, the fraction attending business high school, the fraction attending business VET, and the distance to the nearest business high school. Basically, the distance and peer measures we include in the equation modeling completion are those most closely associated with the type of VET in which the individual enrolled.

An analysis of the correlation terms from the six models indicates that the cross-equation errors are statistically significant and negatively correlated in five of six cases. The negative correlation indicates that individuals who for unobservable reasons are more likely to enroll will be less likely to complete. Thus, individuals who have the highest unobserved preference for VET are those least likely to complete.

Exam scores and grades are generally less significant determinants of completion than of enrollment. Math exam scores are still highly significant. They are jointly statistically significant in every specification and are consistently positively related to completion in all but one case. The exception is that men with above median math exam scores are no more likely to complete business training than men with median math exam scores (the base case). Grades are also jointly statistically significant in every specification. Higher grades increase the probability of completing VET training of all types, though very high grades have little association with men's completion of any VET program. Language skills have a distinctly heterogeneous association with completion. There is no significant association between language skills and completion of EDHR training; the association is positive though weak for BUSI; the association appears to be negative for men pursuing TECH training. We anticipated language skills would be less important for TECH VET as compared to EDHR or BUSI, but did not expect this differential to be drive by a negative relation to completion of TECH. Unfortunately the number of families with multiple siblings enrolling in and having differential success in VET is too small to permit estimation of a within-family model of completion, not to mention that the associations are rather heterogeneous to support pooling.[20]

As these are nonlinear models, interpretation of the magnitude of the coefficients is difficult. We calculate marginal effects on enrollment and on completion, in order to more effectively assess our results. In the case of completion, we present estimates of the probability

[20] Results are substantially the same excluding second generation immigrants. The sole difference is that testing in the lowest decile for language skills becomes significantly negatively related to completion of TECH for women.

of completion conditional on enrolling (the conditional probability - Greene 1996) as this is how estimates not controlling for selection are typically interpreted. Coming from a bivariate model, this conditional marginal effect has both a direct component measuring the impact each variable has via its association with completion and an indirect component measuring its association with enrollment. A brief discussion of the joint effects follows. We present analytic marginal effects, but numerical marginal effects are similar. These marginal effects are calculated for an individual who attended tenth grade; has parents with a vocational education; has sample mean parental age and income, distance to high school, and peer behavior; and otherwise sample modal characteristics. The probability with which such an individual enrolls is illustrated by gender and type of VET in Figure 3, Panel A. This probability ranges from around 10% for EDHR to about 50% for men in TECH. The probability with which the baseline individual completes VET conditional upon having enrolled is illustrated in Panel B. These probabilities mostly range between 70 and 85%, but only 38% of women complete TECH given that they enroll. We normalize the marginal effects reported below as a fraction of these probabilities in order to ease comparisons across program types and populations.

Figure 4 illustrates the marginal effects exam scores and grades have upon enrollment: Panel A for language, B for math, and C for teacher-assigned grades. To be noted first is the <u>substantial</u> magnitude of these effects. The probability of enrolling is over 50% lower for those in the top decile in ten of eighteen cases (2 genders x 3 types of VET x 3 ability measures) and rises by more than 50% for those in the lowest decile in four. These constitute large differences. Math skills are consistently negatively associated with enrollment in all types of VET. Grades are negatively associated with enrollment in all types of VET, with some attenuation for EDHR and BUSI in the lowest decile. That attenuation is even greater in the case of language skills.

Men with the lowest language skills are, indeed, actually 29% less likely to enroll in BUSI than men with modal language skills, and women with the lowest language skills are about equally likely to enroll in BUSI as women with modal language skills. Language skills may be important enough for business occupations that the least skilled individuals choose not to attempt or are steered away from such training.

Figure 5 is organized like Figure 4 but illustrates the marginal effects of our cognitive and non-cognitive skill measures on the conditional probability of completing, again scaled by the baseline probability. These marginal effects are only about half as large in magnitude as those for enrollment and are more heterogeneous. However, in every case showing a positive association between skills and completion, the direct effect of skills on completion had to have been sufficient to overcome the negative indirect effect of skills on enrollment.

Language skills generally do not have a positive association with completion. They have practically no association with completion in the case of BUSI and a fairly strong negative association for TECH, especially for women. Meanwhile, low language scores have little apparent association with completion of EDHR, but higher than modal language skills are associated with a lower (4-15%) conditional probability of completing.

By contrast, the positive direct effect of math skills on completion does generally outweigh the strong negative association between math skills and enrollment, but the effect is neither symmetric nor identical across program type. Low level math skills have little impact on the conditional probability of completing EDHR (-2 to -3%), but are associated with substantially lower conditional probabilities of completing BUSI (-14 to -17%) and TECH (-18 to -34%). On the other hand, those with the highest math skills do not have a substantially higher conditional probability of completing TECH (3 to 6%), but do have a substantially higher conditional probability of completing EDHR (22 to 25%). The association differs by gender for BUSI as better math skills are associated with higher completion for women, but not men.

Likewise, the association between grades and the conditional probability of completing VET varies tremendously. For men, grades matter relatively little when it comes to EDHR or TECH programs, but are highly positively related to the conditional probability of completing BUSI. Similarly, grades matter a lot for women pursuing BUSI. The spread is on the order of 30 to 40%. Low grades are also associated with a substantially lower conditional probability of completing TECH for women (26% lower). High grades have no particular association.

The strong negative association between ability and enrollment causes the joint probability of enrolling and completing to remain negative for all types of VET and all ability measures. The magnitude of that association, however, varies significantly. In the case of TECH VET, men receiving math scores in the lowest decile have only a 4% higher probability of enrolling and completing as compared to those scoring at the median level, whereas for men with language skills (grades) in the lowest decile the joint probability is 27% (26%) higher. For women pursuing TECH training the gradient differentials are smaller as the comparable figures are 3%, 13%, and 10%. High grades and language skills are also associated with much lower joint probabilities of enrolling and completing in TECH (-17% and -25% respectively) as compared to BUSI (-8% and -9%) or EDHR (-8% and -11%) for men, while the differential for women is much less pronounced.

5.3 Summary

Overall these results provide strong evidence that cognitive and non-cognitive skills as captured by exam scores and grades are significantly and substantially negatively related to enrollment in VET programs. Such is particularly true for math skills. Sibling analysis indicates that this result is not attributable to unobserved family-specific factors.

The relation between our skill measures and VET certification conditional on enrollment is substantially more variable. Cognitive skills have a heterogeneous association with completion that differs by skill type (language skills generally matter less than math skills) and by type of VET. These results strongly support distinguishing among different types of VET programs and different types of cognitive skills when analyzing vocational education. Non-cognitive skills (as captured here by teacher-assigned grades) appear to matter more for those pursuing a business career where interpersonal skills are likely more important than for those entering other trades.

5.4 Impact of innovations

Historically, researchers have examined VET programs together as a whole, without accounting for censoring and often without controlling for selection. To demonstrate the impact our innovations have, we estimated (1) an uncensored model of VET completion that does not distinguish among types of VET and does not control for selection; (2) an uncensored model of completion that distinguishes among the three types of VET but does not control for selection; and (3) an uncensored, selection-controlled model of completion that distinguishes among the types of VET (coefficient estimates available upon request). Marginal effects scaled by the baseline probability are constructed for each of these models. An individual with baseline characteristics is predicted to have a 64% probability of completing some type of VET in specification (1). The baseline probabilities for models (2) and (3) have a similar pattern to those reported for our preferred model in Figure 4 though they are smaller, reflecting the classification of those still enrolled as non-completers. Specifically, the baseline probabilities are ten percentage points lower for EDHR, five points lower for BUSI, six points lower for men pursuing TECH, and four points lower for women pursuing TECH, as compared to the baseline probabilities that control for censoring. All else equal, one would expect the censored results to yield smaller marginal effects relative to the baseline because the censored baseline probability is larger.

Figure 6 illustrates the estimated marginal effects of our ability measures on the conditional probability of completing for model (1). The magnitude of the differentials is small relative to our preferred specification, never exceeding ±20%. Language skills are estimated to be negatively related to completion, as is the case for TECH but not BUSI VET. Math skills are estimated to be positively related to completion, as they are in our preferred specification. Grades are estimated to have an inverted U relation to completion, such that those with modal grades have the highest probability of completing VET. This result clearly does not capture the strong positive relation observed for BUSI. Treating all VET programs the same masks the heterogeneous nature of VET programs and seriously biases inferences.

Figure 7 illustrates the conditional marginal effects for model (2), Figure 8 for model (3), relative to baseline. Differences by type of VET are observable even without controls for selection or censoring. The overall pattern associated with language exam scores is the same for all models. Selection increases the magnitude of the marginal effect for low language ability TECH students and decreases the magnitude for high language ability TECH students, but has little effect for EDHR or BUSI. As expected, censoring in general reduces the magnitude of the marginal effects relative to baseline, but censoring does increase the marginal effect noticeably for high scoring EDHR students. The pattern is similar for math exam scores. Controlling for selection modestly increases the impact of high math ability on the conditional marginal probability of completing for most samples. Censoring generally reduces the conditional marginal effect of math scores, particularly for EDHR. The results differ more dramatically in the case of our non-cognitive measure – teacher-assigned grades. Models (2) and (3) generate estimated conditional marginal effects that have a distinctly inverted U-shape rather than the flat shape observed in our preferred specification for those pursuing EDHR and, particularly for model (2), also for those pursuing TECH. Censoring reduces the effect for those with higher than modal grades who perhaps when they enroll, enroll later in life and so appear to be failures in the uncensored models because they are still enrolled. Overall, failure to control for type of VET has the greatest impact on the estimates, while censoring is of some importance for identifying the effect of grades.

6. Discussion and Conclusion

The aim of this paper is to shed light on the relation between skills and vocational training (VET), recognizing the heterogeneous nature of both. To this end, we use nine years of register data on two cohorts of graduates from compulsory school in Denmark to track enrollment in and graduation from VET. We distinguish among three types of VET programs: business (BUSI), technical (TECH), and education/health related (EDHR), providing some discussion ex-ante that these professions rely differentially on language and math skills. Following common practice in the literature, we use nationally administered and normed math and language exam scores as measures of cognitive skills and teacher-assigned grades as measures of non-cognitive skills. Our results indicate that recognizing the heterogeneity of both VET programs and skills is important. We allow for further heterogeneity by modeling completion separately by gender by program. The fact that estimates differ significantly by gender suggests there may be further differentiation not captured by the three programs we recognize.

A majority (55%) of these individuals do at some time enroll in a VET program, however, not all who enroll graduate and many are still enrolled when last observed, as many enroll in VET at a later age. Thirty-six to fifty-five percent have not completed the qualification nine years after completing compulsory schooling; 16 to 44% percent of these are still enrolled. Treating those who are still enrolled as failures biases the results, making grades in particular appear more important for completion than they are. Likewise, failure to jointly model enrollment and completion yields biased results because those more likely to enroll for unobservable reasons are also less likely to complete. Our estimation technique controls for both these sources of bias.

We hypothesized that cognitive skills would be negatively correlated with enrollment in VET because academic programs offer higher returns, but that their correlation with completion would differ by program type. Ex-ante we reported evidence that math skills were more important for completing TECH and hypothesized that both language and math skills would be important for BUSI. Evidence that either are important for EDHR is limited. Non-cognitive skills such as conscientiousness would seem to be positively related to completion of any program, but prior evidence in this regard is limited.

Our findings support the hypotheses regarding enrollment: more able individuals are less likely to enroll in VET. These results hold up to family-specific fixed effects, though we also find some evidence that those with the lowest language skills are less likely to enroll in BUSI, perhaps because of the importance of these skills to this type of certification. Our findings with respect to completion conditional upon enrollment indicate a positive association with math scores for all types of VET, but one that is strongest for those seeking a technical certification, results modestly supporting our ex-ante hypothesis. Language scores, on the other hand, are strongly negatively associated with the conditional probability of completing TECH and have a limited association with either EDHR or BUSI. Our results indicate that grades (our best available measure of non-cognitive skills) are strongly positively associated with the conditional probability of completing BUSI, but have an inverse U-shaped association with completion of TECH and EDHR. Those with the highest non-cognitive skills likely pursue an academic degree for its higher rewards, but non-cognitive skills are still important for completing vocational training. Such skills may be most important for BUSI because many acquiring a business certification have attended a business high school and grades have been shown to be strongly associated with success in academic programs of study. BUSI majors are also more likely to engage in interpersonal interactions where non-cognitive (sometimes called 'soft') skills are more important.

In conclusion, this paper makes substantial contributions to the study of vocational education and training. The implications are threefold. First, cognitive and non-cognitive skills are important not just for those pursuing academic education, but also for those pursuing VET. Math skills in particularly are highly correlated with the probability of becoming VET certified conditional upon attempting. Second, failing to control for enrollment or for censoring biases estimates of the association between skills and VET completion. Third and most importantly, VET programs are heterogeneous. We provide strong evidence that different programs require different skills and employing a one-size-fits-all approach to an analysis of student persistence in VET is inappropriate. Future research should take these results into account in order to model VET better and to aid decision making by students, parents, educators, and policy makers.

Acknowledgements

Thanks to Anders Trolle and Jim Stratton for research assistance and thanks to seminar participants at the 2015 Society of Labor Economists annual meeting, the 2014 EALE Conference in Ljubljana (especially Anders Stenberg), and the College of William & Mary. The authors gratefully acknowledge funding from the Danish Strategic Research Council (grant no. 2139-08-0020).

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Figure 1: Enrollment Time-O-Gram

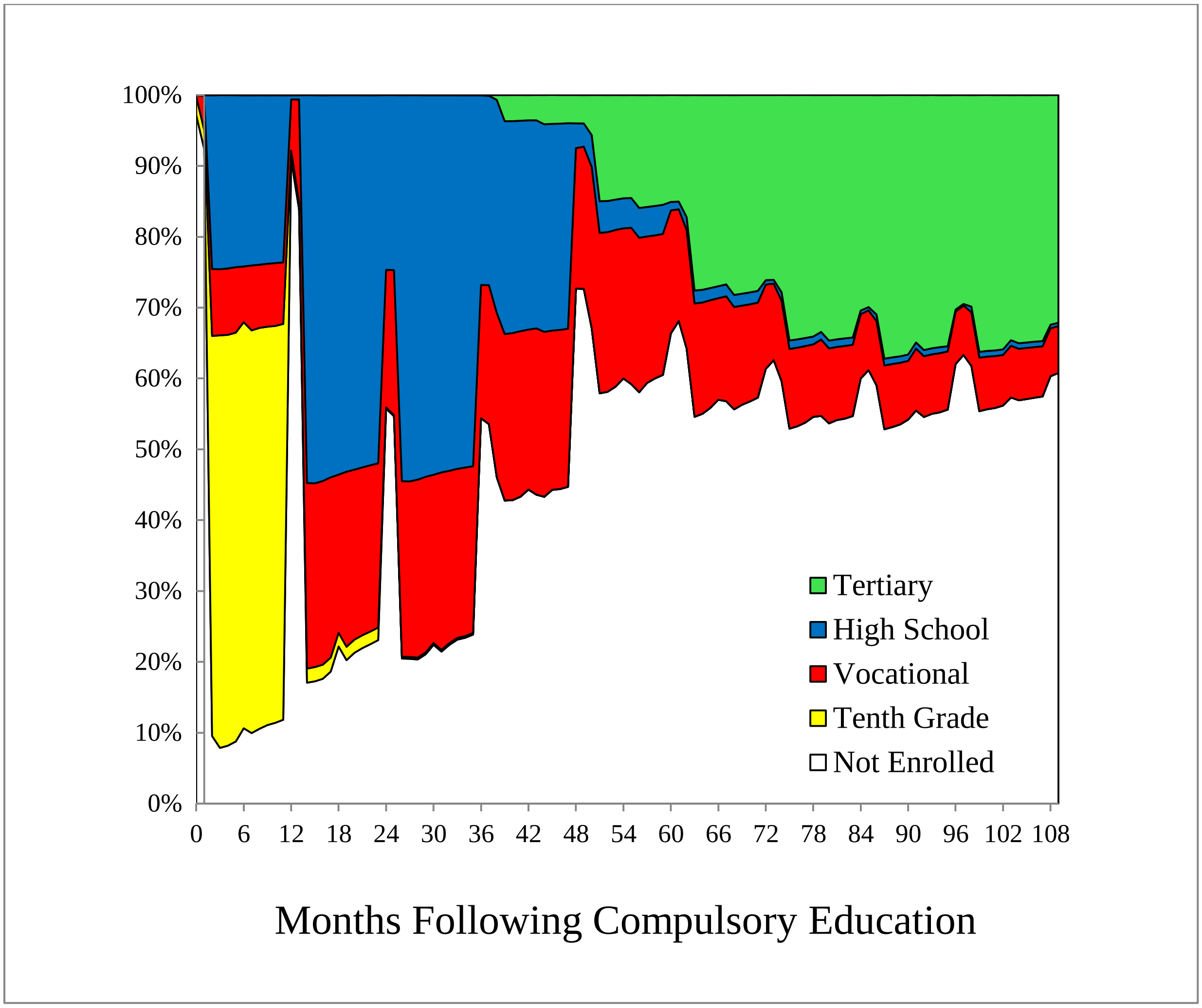


Figure 2
Fraction Enrolled

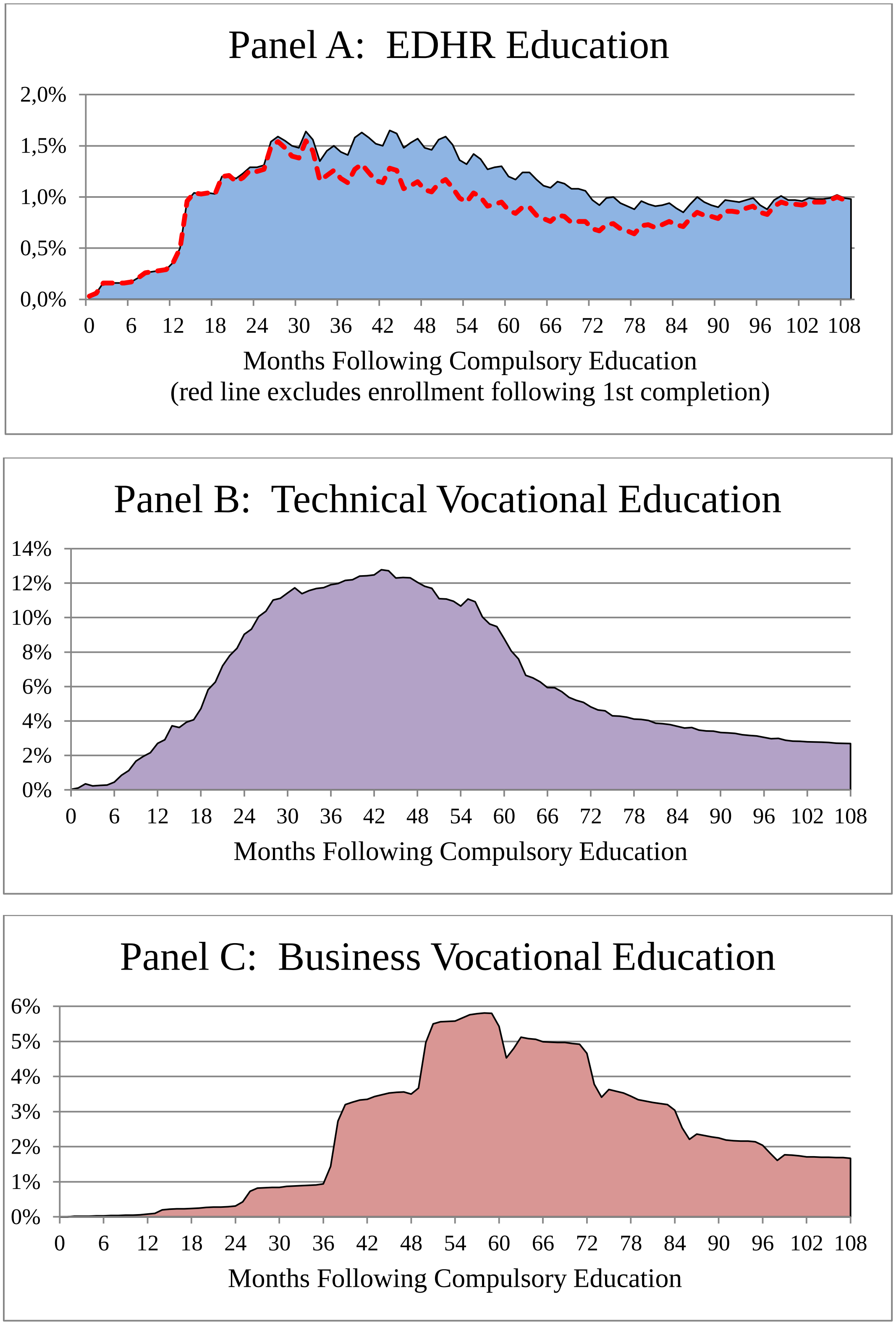
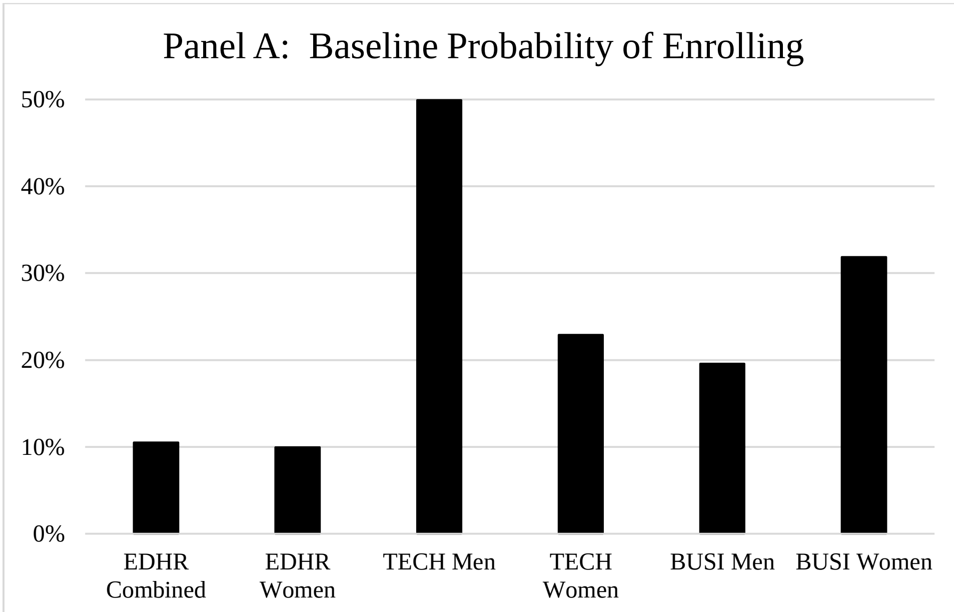


Figure 3


Panel A: Baseline Probability of Enrolling
50%
40%
30%
20%
10%
0%
EDHR Combined
EDHR Women
TECH Men
TECH Women
BUSI Men
BUSI Women

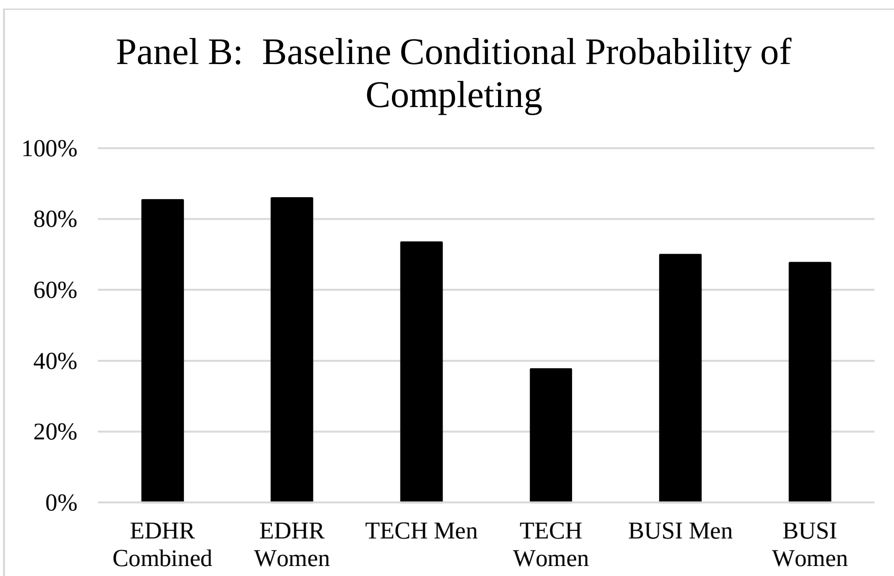
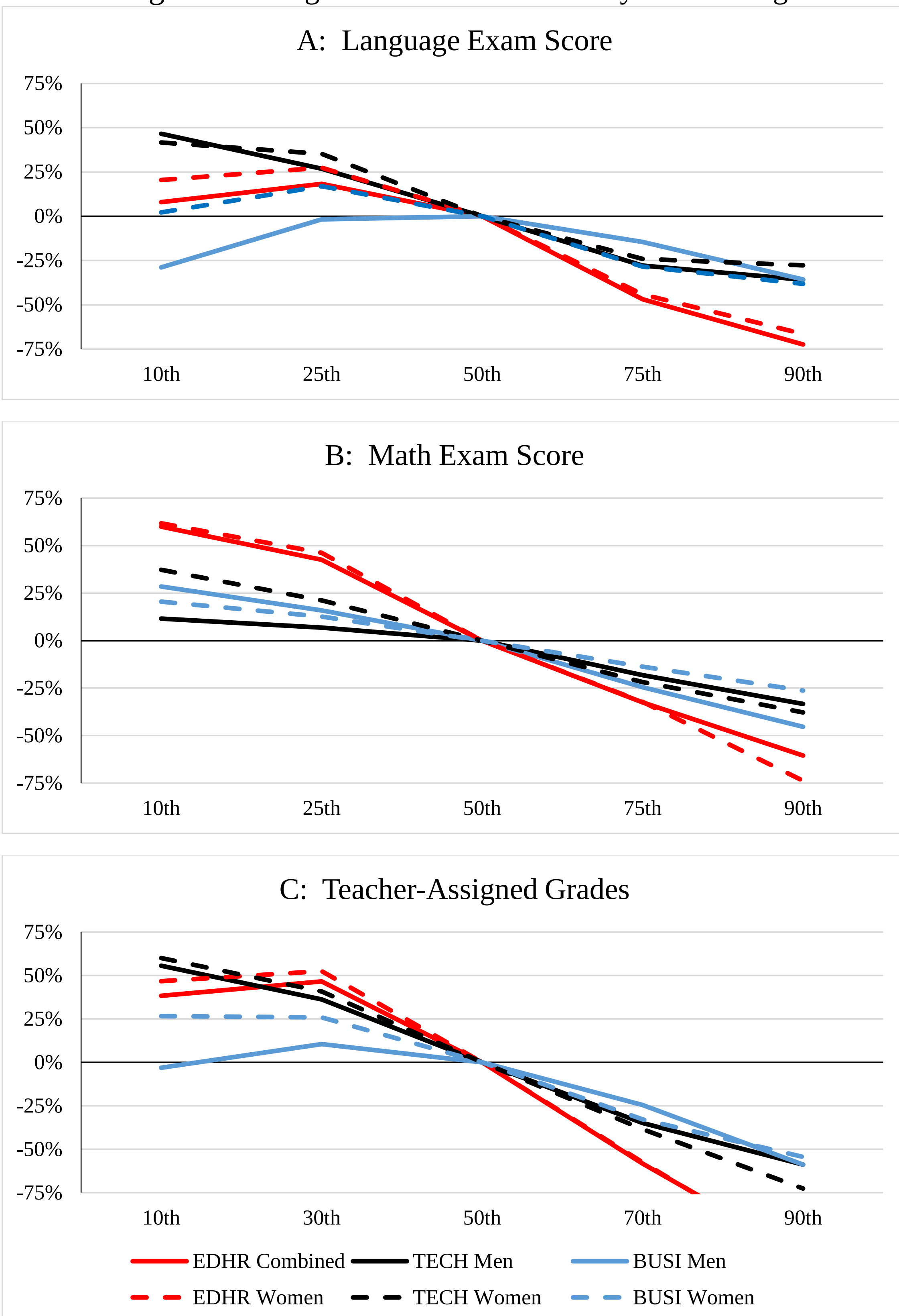
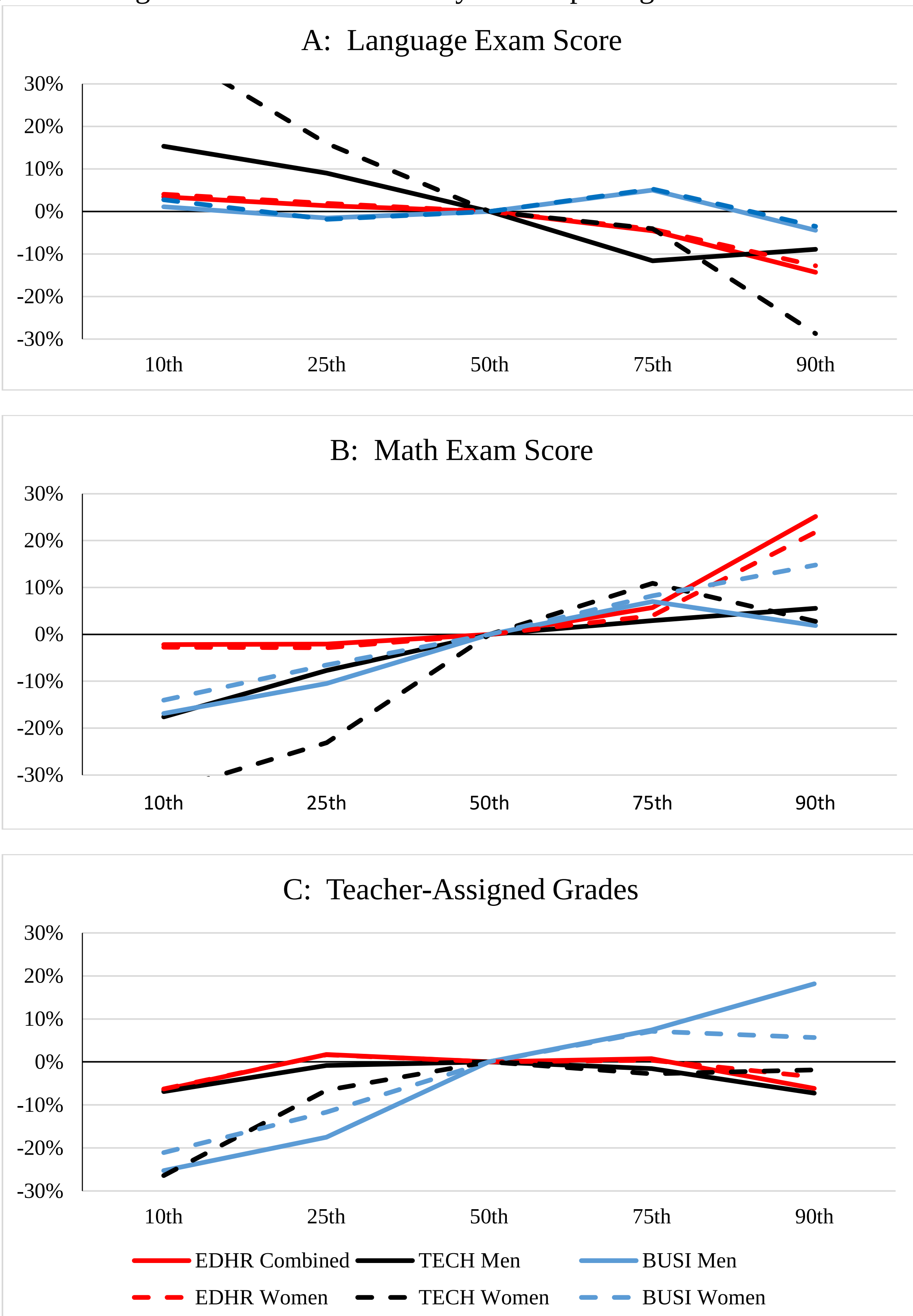

Panel B: Baseline Conditional Probability of Completing
100%
80%
60%
40%
20%
0%
EDHR Combined
EDHR Women
TECH Men
TECH Women
BUSI Men
BUSI Women

Figure 4: Marginal Effects on Probability of Enrolling



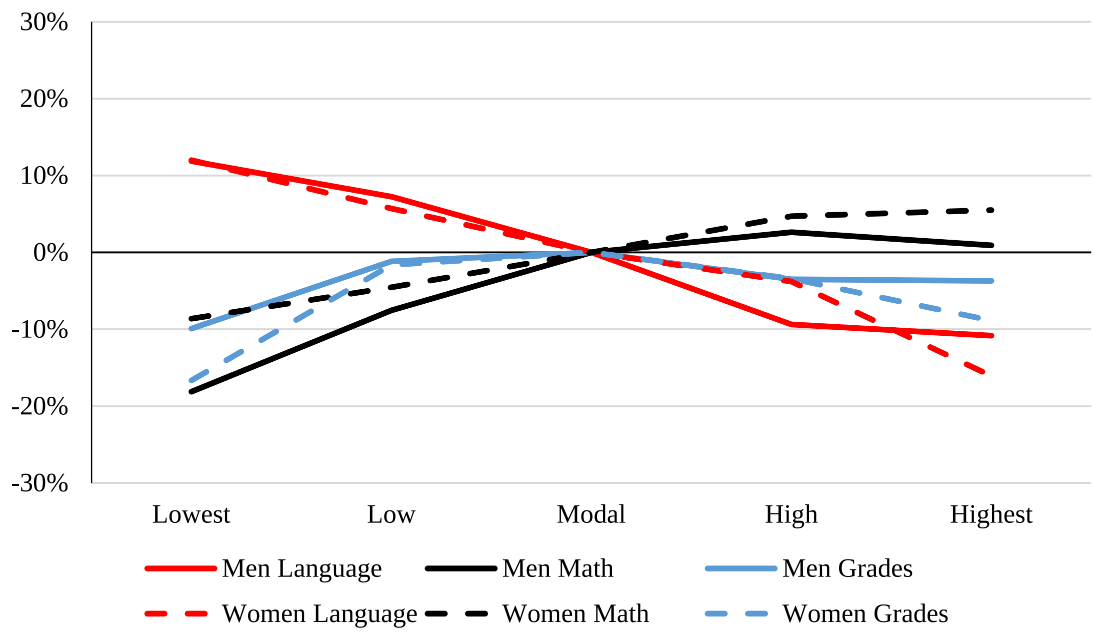
Note: Marginal effects are scaled relative to the baseline probability.

Figure 5: Marginal Effects on Probability of Completing Conditional on Enrolling



Note: Marginal effects are scaled relative to the baseline probability.

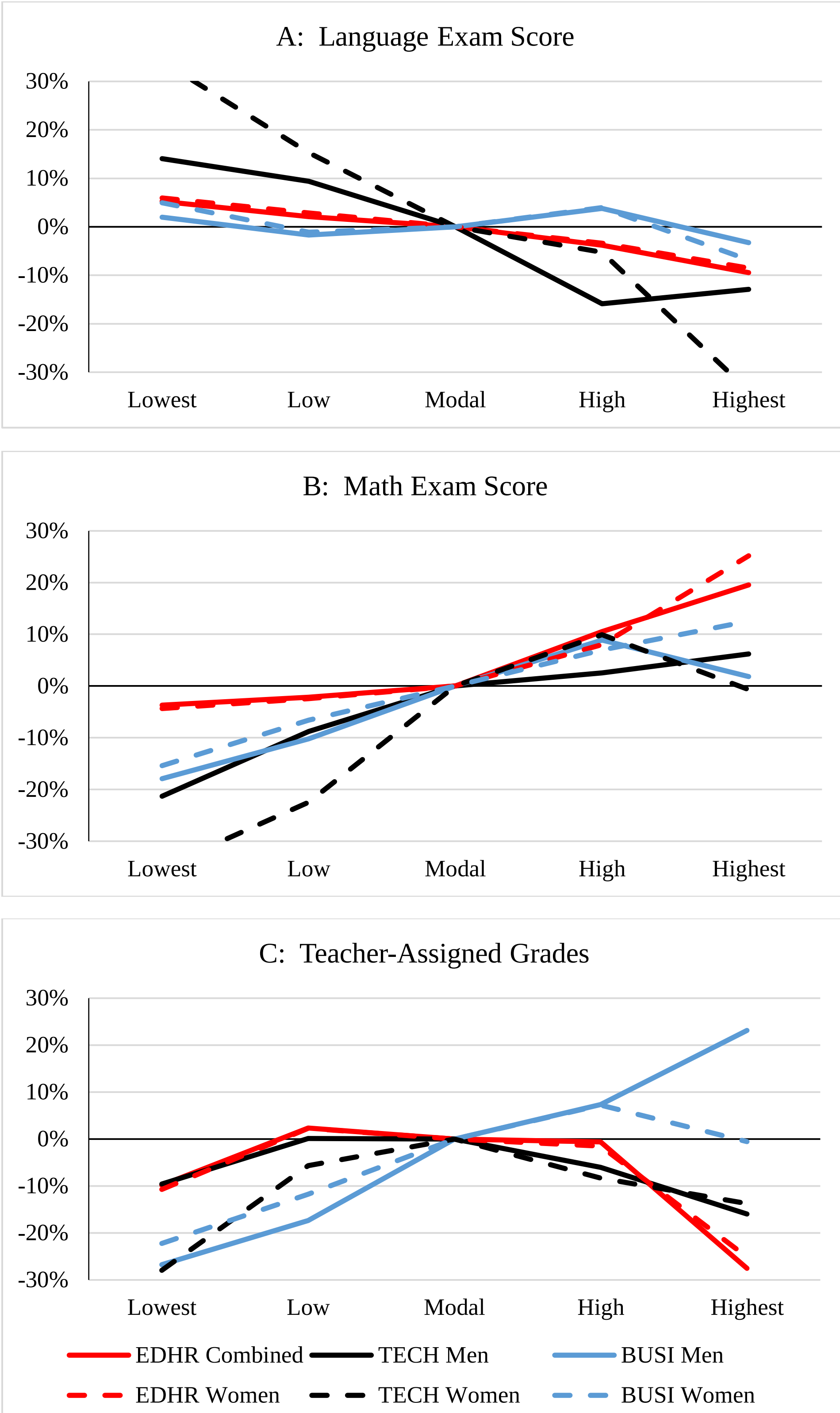
Figure 6: Marginal Effects on Completion
Pooling all VET together
Uncensored & Uncorrected for Enrollment



Note: Marginal effects are scaled relative to the baseline probability.

Figure 7: Marginal Effects on Probability of Completing Conditional on Enrolling

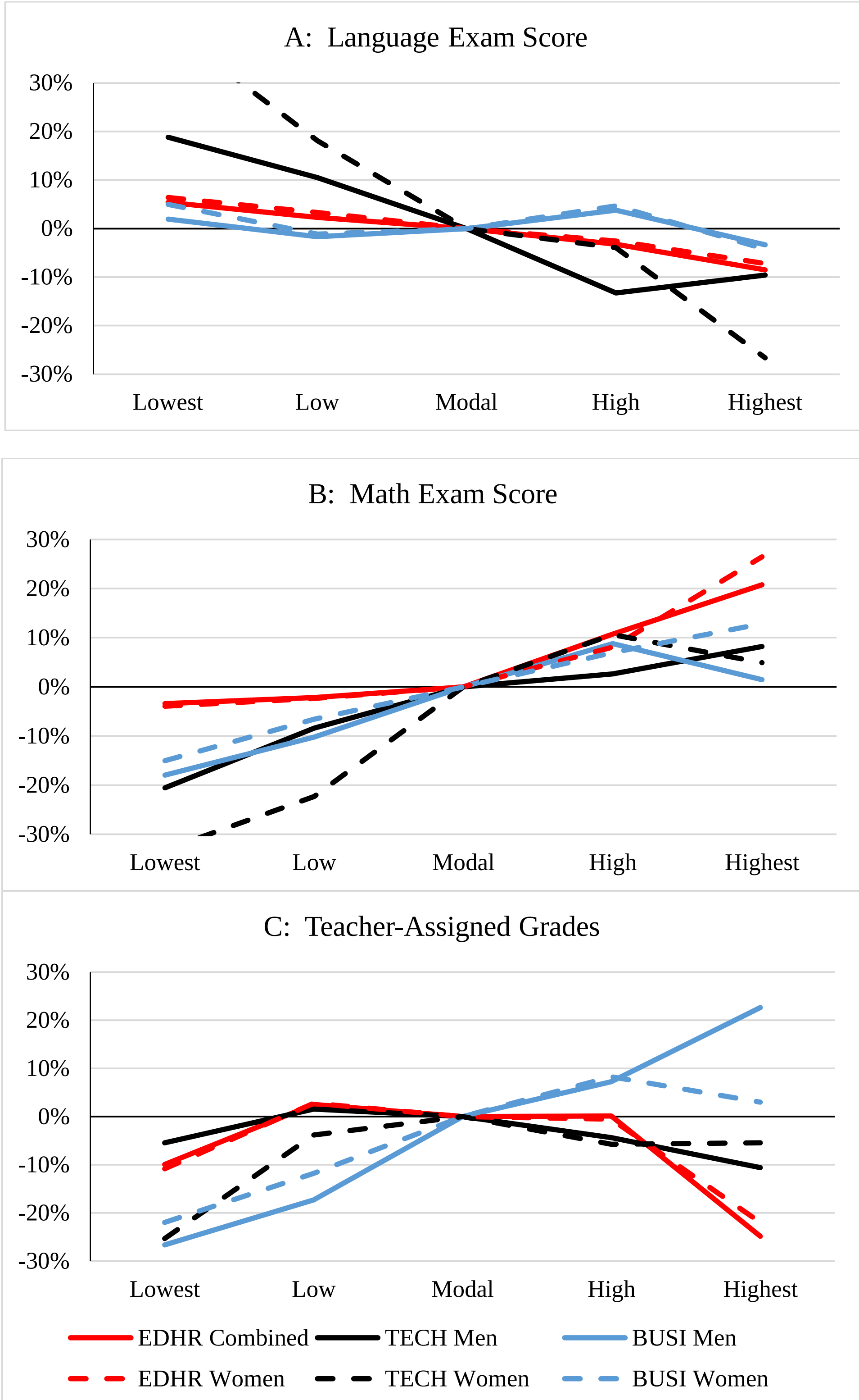
Uncensored & Uncorrected for Enrollment



Note: Marginal effects are scaled relative to the baseline probability.

Figure 8: Marginal Effects on Probability of Completing Conditional on Enrolling

Uncensored but Corrected for Enrollment



Note: Marginal effects are scaled relative to the baseline probability.

Table 1: Educational Outcomes

	%	% of Ever Enrolled	Months prior to Attempt	Months in Training
EDHR Training				
Ever Enrolled	5.38%			
Completed	3.44%	63.81%	36.6	24.0
Still Enrolled	0.87%	16.07%	88.6	19.5
No Longer Enrolled	1.08%	20.12%	49.4	7.8
TECH Training				
Ever Enrolled	38.59%			
Completed	17.54%	45.46%	28.1	44.3
Still Enrolled	3.40%	8.80%	73.3	34.1
No Longer Enrolled	17.65%	45.74%	28.9	12.1
BUSI Training				
Ever Enrolled	22.06%			
Completed	9.61%	43.57%	51.0	34.7
Still Enrolled	1.97%	8.94%	85.0	26.5
No Longer Enrolled	10.48%	47.49%	31.2	14.6
Population Size	101,367			

Table 2: Population Means

	Full Sample	EDHR	TECH	BUSI
Skill Measures				
Language Exam Scores				
Lowest 10%	0.089	0.147	0.180	0.105
11-25%	0.167	0.267	0.265	0.234
26-74%	0.454	0.430	0.362	0.480
75-89%	0.137	0.038	0.043	0.073
Highest 10%	0.070	0.006	0.011	0.020
Missing	0.082	0.112	0.138	0.087
Math Exam Scores				
Lowest 10%	0.081	0.214	0.148	0.133
11-25%	0.156	0.284	0.228	0.221
26-74%	0.393	0.303	0.364	0.401
75-89%	0.220	0.060	0.105	0.131
Highest 10%	0.063	0.003	0.012	0.017
Missing	0.086	0.136	0.143	0.097
Grades				
Lowest 10%	0.082	0.148	0.174	0.110
11-30%	0.199	0.372	0.323	0.289
31-69%	0.359	0.319	0.303	0.386
70-89%	0.187	0.054	0.070	0.108
Highest 10%	0.096	0.006	0.012	0.026
Missing	0.077	0.102	0.118	0.082
Individual Characteristics				
Female	0.492	0.901	0.312	0.605
Age - 16	0.070	0.140	0.137	0.086
Attended Tenth Grade	0.578	0.702	0.610	0.647
Second Gen. Immigrant	0.036	0.051	0.032	0.052
From Non-Nuclear Family	0.317	0.412	0.384	0.354
Parental Characteristics				
Mother's Age	28.016	26.593	27.083	27.242
Father's Age	30.958	2.986	30.216	30.282
Father's Age Missing	0.013	0.015	0.014	0.013
Mother's Real Income	297.762	259.099	269.662	271.562
Mother's Income Missing	0.018	0.018	0.019	0.020
Father's Real Income	448.584	366.545	393.829	407.659
Father's Income Missing	0.104	0.138	0.121	0.113

Education of Most Educated Parent				
Primary	0.062	0.081	0.070	0.081
Vocational	0.409	0.562	0.521	0.525
Academic Gymnasium	0.072	0.043	0.059	0.070
Short	0.277	0.168	0.206	0.197
Long	0.111	0.019	0.036	0.033
Missing	0.069	0.126	0.108	0.096
Information Regarding Primary School Peers				
% Not Enrolled	4.395	5.149	5.027	4.620
% in EDHR VET	1.688	2.014	1.813	1.771
% in Technical VET	25.806	28.724	28.680	27.429
% in Business VET	8.931	9.858	9.418	9.843
% in Academic High School	34.723	30.030	30.007	31.403
% in Technical High School	9.779	9.493	9.398	9.804
% in Business High School	11.649	10.775	10.960	12.058
Peer Info - Missing	0.030	0.040	0.047	0.031
Distance to Nearest … :				
Academic High School	6.391	5.876	6.514	6.605
Technical High School	9.744	8.926	9.675	9.927
Business High School	8.847	8.037	8.789	0.903
Missing	0.139	0.195	0.187	0.146
Region				
Capital Region	0.251	0.252	0.228	0.207
Zealand Region	0.156	0.168	0.172	0.164
Southern Denmark	0.239	0.249	0.245	0.243
Mid Jutland	0.237	0.230	0.226	0.247
Northern Jutland	0.118	0.102	0.129	0.139
2003 Cohort	0.503	0.490	0.496	0.495
Number of Observations	101,367	5,457	39,117	22,364

Table 3: Ability and Enrollment in VET
Men

Variables	EDHR(a)		Technical		Business	
Language Exam Scores:						
Lowest 10%	0.0461		0.5825	***	-0.2040	***
	(0.0290)		(0.0254)		(0.0252)	
11-25%	0.1060	***	0.3356	***	-0.0118	
	(0.0222)		(0.0180)		(0.0194)	
75-89%	-0.2706	***	-0.3477	***	-0.1028	***
	(0.0338)		(0.0257)		(0.0282)	
Highest 10%	-0.4181	***	-0.4485	***	-0.2522	***
	(0.0686)		(0.0463)		(0.0530)	
Math Exam Scores:						
Lowest 10%	0.3461	***	0.1452	***	0.2019	***
	(0.0247)		(0.0255)		(0.0240)	
11-25%	0.2456	***	0.0849	***	0.1131	***
	(0.0230)		(0.0211)		(0.0214)	
75-89%	-0.1877	***	-0.2269	***	-0.1741	***
	(0.0287)		(0.0182)		(0.0208)	
Highest 10%	-0.3492	***	-0.4169	***	-0.3215	***
	(0.0940)		(0.0378)		(0.0428)	
Grades:						
Lowest 10%	0.2212	***	0.6960	***	-0.0219	
	(0.0318)		(0.0295)		(0.0281)	
11-30%	0.2690	***	0.4526	***	0.0745	***
	(0.0222)		(0.0184)		(0.0197)	
70-89%	-0.3368	***	-0.4373	***	-0.1739	***
	(0.0313)		(0.0219)		(0.0250)	
Highest 10%	-0.6408	***	-0.7370	***	-0.4170	***
	(0.0800)		(0.0490)		(0.0548)	
F-Tests:						
Language Exam	131.61	***	1041.33	***	112.23	***
Math Exam	322.79	***	309.29	***	221.53	***
GPA	344.78	***	1582.55	***	115.14	***

Standard errors are reported in parenthesis.
*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.
(a) EDHR results are for the combined sample of men and women.
Also included in the specification are a constant term and all the variables listed in Table 2.

Table 4: Ability and Enrollment in VET

Women

Variables	EDHR		Technical		Business	
Language Exam Scores:						
Lowest 10%	0.1167	***	0.3150	***	0.0189	
	(0.0339)		(0.0303)		(0.0303)	
11-25%	0.1558	***	0.2659	***	0.1522	***
	(0.0247)		(0.0209)		(0.0206)	
75-89%	-0.2508	***	-0.1823	***	-0.2535	***
	(0.0350)		(0.0227)		(0.0211)	
Highest 10%	-0.3780	***	-0.2088	***	-0.3410	***
	(0.0705)		(0.0363)		(0.0337)	
Math Exam Scores:						
Lowest 10%	0.3514	***	0.2819	***	0.1834	***
	(0.0283)		(0.0242)		(0.0240)	
11-25%	0.2626	***	0.1604	***	0.1131	***
	(0.0258)		(0.0215)		(0.0209)	
75-89%	-0.1834	***	-0.1649	***	-0.1222	***
	(0.0309)		(0.0208)		(0.0191)	
Highest 10%	-0.4199	***	-0.2853	***	-0.2342	***
	(0.1008)		(0.0479)		(0.0423)	
Grades:						
Lowest 10%	0.2658	***	0.4537	***	0.2373	***
	(0.0368)		(0.0325)		(0.0323)	
11-30%	0.2985	***	0.3087	***	0.2314	***
	(0.0245)		(0.0204)		(0.0201)	
70-89%	-0.3274	***	-0.2907	***	-0.2931	***
	(0.0323)		(0.0215)		(0.0199)	
Highest 10%	-0.6427	***	-0.5492	***	-0.4864	***
	(0.0817)		(0.0408)		(0.0365)	
F-Tests:						
Language Exam	126.13	***	319.58	***	281.73	***
Math Exam	273.81	***	288.21	***	150.5	***
GPA	335.84	***	666.53	***	500.08	***

Standard errors are reported in parenthesis.

*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.

Also included in the specification are a constant term and all the variables listed in Table 2.

Table 5: Ability and Completion of VET
Men

Variables	EDHR(a)		Technical		Business	
Language Exam Scores:						
Lowest 10%	0.0643		0.1011	***	-0.0407	
	(0.0629)		(0.0323)		(0.0642)	
11-25%	-0.0290		0.0620	*	-0.0326	
	(0.0497)		(0.0268)		(0.0373)	
75-89%	0.0433		-0.1097	*	0.0640	
	(0.1254)		(0.0538)		(0.0708)	
Highest 10%	-0.1293		-0.0197		-0.1587	
	(0.2679)		(0.1030)		(0.1414)	
Math Exam Scores:						
Lowest 10%	-0.2713	***	-0.4030	***	-0.2587	***
	(0.0593)		(0.0257)		(0.0771)	
11-25%	-0.2060	***	-0.1840	***	-0.1636	***
	(0.0517)		(0.0242)		(0.0556)	
75-89%	0.2687	***	0.1384	***	0.0803	
	(0.0725)		(0.0293)		(0.0657)	
Highest 10%	0.8915	*	0.2580	***	-0.0608	
	(0.4311)		(0.0776)		(0.1330)	
Grades:						
Lowest 10%	-0.3101	***	-0.3829	***	-0.4839	***
	(0.0586)		(0.0335)		(0.0641)	
11-30%	-0.1183		-0.1753	***	-0.3081	***
	(0.0648)		(0.0264)		(0.0558)	
70-89%	0.2259	*	0.1235	**	0.0885	
	(0.1052)		(0.0445)		(0.0751)	
Highest 10%	0.2255		0.1142		0.2181	
	(0.3152)		(0.1183)		(0.1959)	
Correlation	-0.7940	***	-0.5911	***	0.3748	
	(0.2382)		(0.0674)		(0.2471)	
F-Tests:						
Language Exam	5.74		25.67	***	6.16	
Math Exam	64.72	***	368.76	***	17.72	***
GPA	37.90	***	137.29	***	61.15	***

Standard errors are reported in parenthesis.

*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.

(a) EDHR results are for the combined sample of men and women.

Also included in these specifications is a constant term and most of the variables listed in Table 1. Excluded from the EDHR specification are all the distance measures, the peer behavior measures related to business and technical VET, and the missing peer behavior dummy. Excluded from the Technical specification are the measures of peer enrollment in EDHR and distance to academic gymnasium. Excluded from the Business specification are the measures of peer enrollment in technical high school, in EDHR, and in technical VET, as well as the distance measures related to academic and technical high schools and both the peer behavior and distance missing dummies.

Table 6: Ability and Completion of VET
Women

Variables	EDHR		Technical		Business	
Language Exam Scores:						
Lowest 10%	0.0356		-0.0386		0.0257	
	(0.0702)		(0.0562)		(0.0373)	
11-25%	-0.0469		-0.1197	***	-0.1142	***
	(0.0544)		(0.0355)		(0.0268)	
75-89%	0.0453		0.1182	***	0.2206	***
	(0.1257)		(0.0357)		(0.0346)	
Highest 10%	-0.1077		0.0098		0.1544	*
	(0.2586)		(0.0738)		(0.0612)	
Math Exam Scores:						
Lowest 10%	-0.2959	***	-0.3905	***	-0.2963	***
	(0.0583)		(0.0328)		(0.0313)	
11-25%	-0.2427	***	-0.2431	***	-0.1544	***
	(0.0533)		(0.0287)		(0.0279)	
75-89%	0.2230	***	0.1827	***	0.1820	***
	(0.0742)		(0.0295)		(0.0300)	
Highest 10%	0.8541	*	0.2324	***	0.3364	***
	(0.4282)		(0.0809)		(0.0770)	
Grades:						
Lowest 10%	-0.3370	***	-0.4843	***	-0.4229	***
	(0.0618)		(0.0376)		(0.0428)	
11-30%	-0.1439	*	-0.2700	***	-0.2928	***
	(0.0647)		(0.0268)		(0.0258)	
70-89%	0.2162	*	0.2076	***	0.2683	***
	(0.1070)		(0.0365)		(0.0325)	
Highest 10%	0.3107		0.4099	***	0.3632	***
	(0.3005)		(0.0780)		(0.0682)	
Correlation	-0.8206	***	-0.9240	***	-0.8493	***
	(0.2304)		(0.0486)		(0.0649)	
F-Tests:						
Language Exam	4.21		31.18	***	74.88	***
Math Exam	64.26	***	245.91	***	158.29	***
GPA	36.98	***	225.83	***	286.12	***

Standard errors are reported in parenthesis.
*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.
Control variables are the same as noted on Table 5.

Appendix A

Aggregation of VET Main Program clusters

Basic courses[a]	Aggregation
1. Business	BUSI
2. Building and construction	TECH
3. Iron and Metal	TECH
4. Graphics	TECH
5. Other technics and industry	TECH
6. Food and housekeeping	TECH
7. Agriculture and fishing	TECH
8. Transport	TECH
9. Safety	TECH
10. Pedagogical	EDHR
11. Health	EDHR

[a] Source: The Danish Ministry of Children and Education.

Appendix B1: Enrollment in VET

Men

Variables	EDHR(a)		TECH		BUSI	
Female	1.2392	***				
	(0.0217)					
Second Gen. Immigrant	-0.2344	***	-0.7734	***	0.3519	***
	(0.0440)		(0.0398)		(0.0373)	
Age - 16	0.1983	***	0.0819	***	0.0131	
	(0.0195)		(0.0172)		(0.0169)	
Attended Tenth Grade	0.0770	***	-0.1928	***	0.0997	***
	(0.0167)		(0.0137)		(0.0143)	
Non-Nuclear Home	0.0086		0.0846	***	0.0372	*
	(0.0173)		(0.0151)		(0.0155)	
Parental Characteristics:						
Father's age	-0.0005		-0.0042	**	-0.0029	
	(0.0018)		(0.0016)		(0.0016)	
Father's age missing	-0.0615		-0.0793		0.0123	
	(0.0678)		(0.0617)		(0.0607)	
Mother's age	-0.0106	***	-0.0144	***	-0.0007	
	(0.0023)		(0.0019)		(0.0020)	
Father's real income	-0.0004	***	-0.0003	***	0.0001	*
	(0.0001)		(0.0000)		(0.0000)	
Father's income missing	0.0331		-0.0352		0.0232	
	(0.0254)		(0.0236)		(0.0239)	
Mother's real income	-0.0002	*	-0.0004	***	-0.0001	*
	(0.0001)		(0.0001)		(0.0001)	
Mother's income missing	-0.0391		0.0069		0.0628	
	(0.0578)		(0.0488)		(0.0491)	
Education of Most Educated Parent						
Primary	-0.0148		-0.0026		-0.0012	
	(0.0367)		(0.0330)		(0.0329)	
Academic Gymnasium	-0.1770	***	-0.2487	***	-0.0002	
	(0.0354)		(0.0249)		(0.0268)	
Short	-0.1721	***	-0.3069	***	-0.1766	***
	(0.0212)		(0.0161)		(0.0179)	
Long	-0.4195	***	-0.6212	***	-0.4143	***
	(0.0472)		(0.0271)		(0.0316)	

Missing	-0.0162		0.0597	*	-0.0437	
	(0.0260)		(0.0284)		(0.0265)	
Information Regarding Primary School Peers						
% in Academic High School	-0.0012		-0.0040	***	-0.0051	***
	(0.0016)		(0.0014)		(0.0014)	
% in Technical High School	-0.0018		-0.0011		-0.0017	
	(0.0021)		(0.0019)		(0.0019)	
% in Business High School	-0.0033		-0.0036	*	0.0079	***
	(0.0018)		(0.0016)		(0.0016)	
% in Technical VET	0.0017		0.0116	***	-0.0058	***
	(0.0018)		(0.0016)		(0.0016)	
% in Business VET	0.0061	**	-0.0002		0.0120	***
	(0.0024)		(0.0021)		(0.0021)	
% in EDHR VET	0.0238	***	0.0032		-0.0004	
	(0.0052)		(0.0047)		(0.0049)	
Peer Info - Missing	0.1029		0.4083	***	-0.2004	
	(0.1499)		(0.1377)		(0.1386)	
Distance to Nearest … :						
Academic High School	-0.0023		0.0060	***	-0.0079	***
	(0.0018)		(0.0015)		(0.0016)	
Technical High School	-0.0009		0.0003		-0.0018	
	(0.0012)		(0.0010)		(0.0011)	
Business High School	-0.0017		-0.0004		0.0006	
	(0.0016)		(0.0012)		(0.0013)	
Missing	-0.0295		0.1349	***	-0.1369	***
	(0.0272)		(0.0238)		(0.0250)	
Region						
Zealand Region	-0.0585	*	-0.0232		0.0711	***
	(0.0258)		(0.0224)		(0.0238)	
Southern Denmark	-0.0528	*	-0.0432	*	0.0876	***
	(0.0239)		(0.0206)		(0.0217)	
Mid Jutland	-0.0165		-0.0484	*	0.0743	***
	(0.0248)		(0.0211)		(0.0223)	
Northern Jutland	-0.1433	***	-0.0011		0.1387	***
	(0.0308)		(0.0253)		(0.0263)	
2003 Cohort	-0.0118		-0.0382	***	0.0027	
	(0.0153)		(0.0129)		(0.0135)	

Missing Language Score	-0.1361	*	0.5548	***	-0.2566	***
	(0.0670)		(0.0633)		(0.0596)	
Missing Math Score	0.3259	***	-0.0041		0.2262	***
	(0.0558)		(0.0641)		(0.0589)	
Missing Grade	0.0964		0.0600		-0.0096	
	(0.0528)		(0.0453)		(0.0457)	
Constant	-1.9868	***	0.8067	***	-0.6044	***
	(0.1617)		(0.1446)		(0.1460)	

Standard errors are reported in parenthesis.

*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.

(a) EDHR results are for the combined sample of men and women.

Appendix B2: Enrollment in VET

Women

Variables	EDHR		Technical		Business	
Second Gen. Immigrant	-0.2577	***	-0.6021	***	-0.1690	***
	(0.0487)		(0.0433)		(0.0379)	
Age - 16	0.2042	***	0.0749	***	0.0032	
	(0.0233)		(0.0189)		(0.0183)	
Attended Tenth Grade	0.0429	*	-0.1193	***	-0.0842	***
	(0.0189)		(0.0147)		(0.0141)	
Non-Nuclear Home	0.0021		0.1248	***	0.0173	
	(0.0194)		(0.0152)		(0.0148)	
Parental Characteristics:						
Father's age	-0.0002		0.0001		-0.0035	*
	(0.0020)		(0.0016)		(0.0016)	
Father's age missing	-0.1333		-0.1658	**	-0.1643	**
	(0.0762)		(0.0617)		(0.0609)	
Mother's age	-0.0138	***	-0.0108	***	-0.0052	**
	(0.0026)		(0.0020)		(0.0019)	
Father's real income	-0.0004	***	-0.0002	***	-0.0001	
	(0.0001)		(0.0000)		(0.0000)	
Father's income missing	0.0361		0.0055		-0.0379	
	(0.0284)		(0.0228)		(0.0225)	
Mother's real income	-0.0004	***	-0.0006	***	-0.0003	***
	(0.0001)		(0.0001)		(0.0001)	
Mother's income missing	-0.0031		0.0113		0.1024	*
	(0.0646)		(0.0515)		(0.0476)	
Education of Most Educated Parent						
Primary	-0.0047		0.0566		0.0211	
	(0.0412)		(0.0335)		(0.0312)	
Academic Gymnasium	-0.2218	***	-0.1266	***	-0.1165	***
	(0.0394)		(0.0282)		(0.0259)	
Short	-0.2233	***	-0.1636	***	-0.3530	***
	(0.0233)		(0.0175)		(0.0168)	
Long	-0.4823	***	-0.2411	***	-0.7306	***
	(0.0518)		(0.0311)		(0.0325)	
Missing	-0.0060		0.0713	**	-0.0206	
	(0.0297)		(0.0254)		(0.0248)	

Information Regarding Primary School Peers						
% in Academic High School	-0.0003		-0.0094	***	-0.0014	
	(0.0019)		(0.0015)		(0.0015)	
% in Technical High School	-0.0006		-0.0148	***	0.0048	**
	(0.0024)		(0.0019)		(0.0018)	
% in Business High School	-0.0010		-0.0138	***	0.0084	***
	(0.0021)		(0.0017)		(0.0016)	
% in Technical VET	0.0033		-0.0015		0.0051	***
	(0.0021)		(0.0017)		(0.0016)	
% in Business VET	0.0053		-0.0108	***	0.0164	***
	(0.0029)		(0.0022)		(0.0021)	
% in EDHR VET	0.0256	***	-0.0104	*	-0.0034	
	(0.0059)		(0.0041)		(0.0043)	
Peer Info - Missing	0.2409		-0.5434	***	0.3476	*
	(0.1807)		(0.1462)		(0.1422)	
Distance to Nearest … :						
Academic High School	-0.0021		0.0025		0.0005	
	(0.0019)		(0.0013)		(0.0014)	
Technical High School	0.0005		0.0007		0.0007	
	(0.0014)		(0.0011)		(0.0009)	
Business High School	-0.0028		-0.0024		0.0004	
	(0.0016)		(0.0013)		(0.0012)	
Missing	-0.0129		0.0452		-0.0358	
	(0.0287)		(0.0232)		(0.0207)	
Region						
Zealand Region	-0.0880	***	-0.0109		0.0629	**
	(0.0291)		(0.0229)		(0.0224)	
Southern Denmark	-0.0375		-0.0823	***	0.0149	
	(0.0271)		(0.0215)		(0.0209)	
Mid Jutland	-0.0094		-0.0866	***	0.0807	***
	(0.0280)		(0.0223)		(0.0214)	
Northern Jutland	-0.1445	***	-0.0017		0.1482	***
	(0.0349)		(0.0260)		(0.0253)	
2003 Cohort	-0.0366	*	-0.0352	**	-0.0405	***
	(0.0172)		(0.0135)		(0.0129)	

Missing Language Score	0.0089		0.1608	*	-0.1426	*
	(0.0759)		(0.0633)		(0.0641)	
Missing Math Score	0.2288	***	0.3366	***	0.0667	
	(0.0612)		(0.0533)		(0.0535)	
Missing Grade	0.0836		-0.0664		0.1262	**
	(0.0597)		(0.0474)		(0.0475)	
Constant	-0.7421	***	0.7568	***	-0.4157	***
	(0.1892)		(0.1528)		(0.1473)	

Standard errors are reported in parenthesis.
*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.

Appendix C1: Completion of VET

Men

Variables	EDHR(a)		Technical		Business	
Female	-0.5580					
	(0.3283)					
Second Gen. Immigrant	0.2384	**	-0.1571	*	-0.3842	***
	(0.0892)		(0.0629)		(0.1312)	
Attended Tenth Grade	0.0386		0.0063		0.1287	***
	(0.0514)		(0.0178)		(0.0315)	
Age - 16	-0.1729	***	-0.0803	***	-0.0549	
	(0.0413)		(0.0190)		(0.0370)	
Non-Nuclear Home	-0.1271	***	-0.3016	***	-0.2474	***
	(0.0423)		(0.0182)		(0.0418)	
Parental Characteristics:						
Father's age	0.0095	*	0.0038	*	0.0023	
	(0.0047)		(0.0019)		(0.0035)	
Father's age missing	-0.1622		-0.0240		0.0674	
	(0.1419)		(0.0699)		(0.1246)	
Mother's age	0.0042		0.0062	**	-0.0072	
	(0.0055)		(0.0024)		(0.0042)	
Father's real income	0.0005	***	0.0005	***	0.0002	***
	(0.0001)		(0.0001)		(0.0001)	
Father's income missing	0.0143		-0.1365	***	-0.1513	***
	(0.0533)		(0.0278)		(0.0527)	
Mother's real income	0.0003		0.0006	***	0.0003	*
	(0.0002)		(0.0001)		(0.0002)	
Mother's income missing	-0.0251		-0.0077		-0.0839	
	(0.1249)		(0.0586)		(0.1066)	
Education of Most Educated Parent						
Primary	-0.0867		-0.1638	***	-0.0536	
	(0.0836)		(0.0392)		(0.0676)	
Academic Gymnasium	0.0254		-0.0527		-0.0690	
	(0.0977)		(0.0348)		(0.0544)	
Short	-0.0133		0.0112		-0.2515	***
	(0.0813)		(0.0236)		(0.0405)	
Long	0.0233		-0.2149	***	-0.4044	***
	(0.1866)		(0.0608)		(0.0945)	
Missing	0.0120		-0.1716	***	-0.2087	***
	(0.0508)		(0.0275)		(0.0549)	

Information Regarding Primary School Peers						
% in Academic High School	0.0022		0.0075	***	0.0006	
	(0.0012)		(0.0015)		(0.0011)	
% in Technical High School	0.0028		0.0105	***		
	(0.0034)		(0.0022)			
% in Business High School	0.0054		0.0155	***	0.0159	***
	(0.0028)		(0.0019)		(0.0026)	
% in Technical VET			0.0090	***		
			(0.0019)			
% in Business VET			0.0073	***	-0.0054	
			(0.0024)		(0.0043)	
% in EDHR VET	-0.0195					
	(0.0100)					
Peer Info - Missing			0.5932	***		
			(0.1475)			
Distance to Nearest … :						
Technical High School			0.0063	***		
			(0.0013)			
Business High School			0.0039	**	0.0019	
			(0.0014)		(0.0018)	
Missing			0.1005	***		
			(0.0273)			
Region						
Zealand Region	0.0613		-0.0209		0.0132	
	(0.0523)		(0.0270)		(0.0493)	
Southern Denmark	0.0030		0.0736	***	0.0746	
	(0.0518)		(0.0251)		(0.0452)	
Mid Jutland	0.0362		0.0904	***	0.0203	
	(0.0499)		(0.0262)		(0.0473)	
Northern Jutland	-0.0167		0.0253		-0.0429	
	(0.0804)		(0.0301)		(0.0593)	
2003 Cohort	-0.0101		-0.0642	***	-0.0723	*
	(0.0329)		(0.0161)		(0.0287)	
Missing Language Score	0.1729		0.2921	***	0.1830	
	(0.1239)		(0.0625)		(0.1566)	
Missing Math Score	-0.4200	***	-0.5931	***	-0.3907	*
	(0.1005)		(0.0597)		(0.1559)	
Missing Grade	-0.1084		-0.1527	***	-0.2097	*
	(0.1089)		(0.0497)		(0.1024)	

Constant	1.7656	***	-0.6345	***	-0.4198	
	(0.5427)		(0.1617)		(0.4004)	

Standard errors are reported in parenthesis.
*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.
(a) EDHR results are for the combined sample of men and women.

Appendix C2: Completion of VET

Women

Variables	EDHR		Technical		Business	
Second Gen. Immigrant	0.2752	***	0.0958		-0.1542	*
	(0.0936)		(0.1230)		(0.0666)	
Age - 16	-0.1537	***	-0.0134		-0.0502	
	(0.0408)		(0.0239)		(0.0265)	
Attended Tenth Grade	0.0602		0.1279	***	0.1189	***
	(0.0476)		(0.0186)		(0.0198)	
Non-Nuclear Home	-0.1121	**	-0.1945	***	-0.1746	***
	(0.0419)		(0.0223)		(0.0256)	
Parental Characteristics:						
Father's age	0.0099	*	-0.0012		-0.0044	
	(0.0050)		(0.0020)		(0.0023)	
Father's age missing	-0.1556		0.2222	***	0.1258	
	(0.1515)		(0.0789)		(0.0873)	
Mother's age	0.0050		0.0113	***	0.0125	***
	(0.0061)		(0.0026)		(0.0028)	
Father's real income	0.0005	***	0.0003	***	0.0003	***
	(0.0001)		(0.0001)		(0.0001)	
Father's income missing	0.0134		-0.0575		-0.0429	
	(0.0559)		(0.0300)		(0.0319)	
Mother's real income	0.0006	**	0.0006	***	0.0006	***
	(0.0002)		(0.0001)		(0.0001)	
Mother's income missing	-0.1146		0.0129		-0.1396	*
	(0.1283)		(0.0625)		(0.0648)	
Education of Most Educated Parent						
Primary	-0.0933		-0.0533		-0.0271	
	(0.0861)		(0.0422)		(0.0434)	
Academic Gymnasium	0.0154		0.0916	*	0.0074	
	(0.1072)		(0.0389)		(0.0390)	
Short	0.0137		0.0844	***	0.0841	*
	(0.0902)		(0.0267)		(0.0412)	
Long	0.0337		0.0350		0.2026	*
	(0.2023)		(0.0650)		(0.0944)	
Missing	0.0036		-0.1243	***	-0.0775	*
	(0.0521)		(0.0311)		(0.0334)	

Information Regarding Primary School Peers						
% in Academic High School	0.0030	*	0.0091	***	0.0036	***
	(0.0013)		(0.0018)		(0.0008)	
% in Technical High School	0.0018		0.0140	***		
	(0.0035)		(0.0024)			
% in Business High School	0.0038		0.0173	***	0.0048	*
	(0.0029)		(0.0022)		(0.0019)	
% in Technical VET			0.0055	*		
			(0.0022)			
% in Business VET			0.0107	***	-0.0120	***
			(0.0027)		(0.0020)	
% in EDHR VET	-0.0141					
	(0.0100)					
Peer Info - Missing			0.6626	***		
			(0.1730)			
Distance to Nearest … :						
Technical High School			-0.0032	*		
			(0.0015)			
Business High School			0.0053	***	0.0006	
			(0.0017)		(0.0011)	
Missing			-0.0027			
			(0.0295)			
Region						
Zealand Region	0.0855		0.0623	*	-0.0742	*
	(0.0548)		(0.0302)		(0.0309)	
Southern Denmark	-0.0059		0.1112	***	-0.0731	*
	(0.0529)		(0.0279)		(0.0296)	
Mid Jutland	0.0562		0.1014	***	-0.1212	***
	(0.0529)		(0.0289)		(0.0300)	
Northern Jutland	0.0249		0.0255		-0.1455	***
	(0.0800)		(0.0333)		(0.0338)	
2003 Cohort	0.0000		0.0062		0.0222	
	(0.0358)		(0.0175)		(0.0182)	

Missing Language Score	0.1266		-0.0391		0.1996	*
	(0.1404)		(0.0752)		(0.0865)	
Missing Math Score	-0.4174	***	-0.3926	***	-0.3505	***
	(0.1160)		(0.0592)		(0.0771)	
Missing Grade	-0.1080		-0.0298		-0.1071	
	(0.1147)		(0.0614)		(0.0677)	
Constant	1.0968	***	-0.6543	***	0.5378	***
	(0.2271)		(0.1999)		(0.0981)	

Standard errors are reported in parenthesis.
*Statistically significant at the .05 level; ** at the .01 level; *** at the .005 level.

Appendix C: Family Fixed Effects

To investigate whether the association we observe between skill and enrollment is attributable to unobserved family-specific factors, we estimate a linear probability model of enrollment that includes family fixed effects. In this analysis, all VET programs are considered as one and boys and girls are pooled in order to yield a sufficiently large sample. In total there are 4814 children from 2394 families in the sibling sample used for this analysis. The sibling sample is comprised of more second generation immigrants and fewer children from non-nuclear households. The sibling sample is also located a bit further away from academic high schools. Else the characteristics of the sibling sample generally match those of the population. (See table D1.)

The analysis proceeds including covariates only for the skill measures, a dummy for gender, and a dummy for those who attended tenth grade. There is literally no variation in many of the control variables (for example, parental education and income) and too little in the others to estimate parameters reliably. The estimated effect of exam scores/grades on enrollment for this sample rests primarily on those families in which one child chooses to enroll in VET and another chooses not to enroll in VET <u>and</u> those children have different reported (not missing) ability measures. Such is the case for less than 20% of these families. Furthermore, to the extent that different exam scores are caused by a temporary illness or otherwise unusual conditions on test day for one sibling, observed sibling differences may reflect noise rather than actual ability differences. Thus, the effect of exam scores on enrollment may be biased towards zero in the family fixed effects model. Such is less likely to be the case for grades.

The results of this analysis are reported in Table D2. All of the exam score/grade coefficients are of the expected sign and ten of twelve are statistically significant at the 5% level.

The other two (reflecting higher than modal language scores) are significant at the 10% level using a one-sided test. Grades are in this case observed to have a more significant and substantial effect on enrollment than exam scores, perhaps because the exam score measures are likely to be noisier measures than the grades. These results indicate that our findings regarding the relation between ability and enrollment are not driven by unobserved family-specific effects.

Table D1. Comparing Sibling Means

	Full Sample	Sibling Sample
Enrolled in some type of VET	0.554	0.559
Enrolled in EDHR	0.054	0.057
Enrolled in TECH	0.234	0.238
Enrolled in BUSI	0.131	0.114
Female	0.492	0.499
Second Gen. Immigrant	0.070	0.092
Age - 16	0.036	0.076
Completed Tenth Grade	0.578	0.574
From Non-Nuclear Family	0.317	0.290
2003 Cohort	0.503	0.501
Region		
Capital Region	0.251	0.250
Zealand Region	0.156	0.162
Southern Denmark	0.239	0.239
Mid Jutland	0.237	0.234
Northern Jutland	0.118	0.116
Danish Exam Scores		
Lowest 10%	0.101	0.112
11-25%	0.155	0.161
26-74%	0.454	0.437
75-89%	0.137	0.131
Highest 10%	0.070	0.070
Missing	0.082	0.088
Math Exam Scores		
Lowest 10%	0.119	0.118
11-25%	0.118	0.112
26-74%	0.393	0.400
75-89%	0.220	0.215
Highest 10%	0.063	0.061
Missing	0.086	0.093
Grades		
Lowest 10%	0.093	0.099
11-30%	0.188	0.182
31-69%	0.367	0.373
70-89%	0.196	0.181
Highest 10%	0.078	0.079
Missing	0.077	0.086

Information Regarding Primary School Peers		
% Not Enrolled	4.395	4.411
% in EDHR VET	1.688	1.675
% in Technical VET	25.806	26.228
% in Business VET	8.931	8.999
% in Academic High School	34.723	33.919
% in Technical High School	9.779	9.722
% in Business High School	11.649	11.411
Peer Info - Missing	0.030	0.036
Distance to Nearest … :		
Academic High School	6.391	6.788
Technical High School	9.744	10.047
Business High School	8.847	9.016
Missing	0.139	0.140
Number of Observations	101,367	4814

Table D2.
Ability and Enrollment in VET with Family Fixed Effects

Variables	Coefficients	
Female Dummy	-0.0865	***
	(0.0170)	
Language Exam Scores:		
Lowest 10%	0.0813	***
	(0.0283)	
11-25%	0.1224	***
	(0.0223)	
75-89%	-0.0546	*
	(0.0280)	
Highest 10%	-0.0527	
	(0.0373)	
Math Exam Scores:		
Lowest 10%	0.0873	***
	(0.0275)	
11-25%	0.0996	***
	(0.0262)	
75-89%	-0.0495	**
	(0.0246)	
Highest 10%	-0.0829	**
	(0.0364)	
Grades:		
Lowest 10%	0.1826	***
	(0.0337)	
11-30%	0.1417	***
	(0.0250)	
70-89%	-0.1283	***
	(0.0266)	
Highest 10%	-0.1145	***
	(0.0419)	
Attended Tenth Grade	-0.0002	
	(0.0208)	
Number of Observations	4814	
Number of Fixed Effects	2394	

Standard errors are reported in parenthesis.
*Statistically significant at the .10 level; ** at the .05 level; *** at the .01 level.

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