Complementarities in High School and College Investments

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Preliminary

Abstract: This paper studies the complementarities between multi-dimensional abilities, high school investments, and college investments in wages. Using a novel administrative data set from Sweden, the analysis accounts for a rich set of observables; latent cognitive, grit, and interpersonal abilities; high school specialization in vocational, academic, and STEM tracks; and college major choices. First, we provide non-parametric evidence of the strong complementarities between abilities, high school investments and college investments. Second, we estimate a generalized Roy model that accounts for additional unobserved heterogeneity using within-school-across-cohort variation in specialization choices. We find that investing in more challenging tracks in high school increases college enrollment and graduation, but not necessarily wages. For students who do not pursue medicine or engineering in college, specializing in STEM in high school leads to slightly lower wages compared to a more balanced academic track.

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1 Introduction

"Skills beget skills" is a ubiquitous feature in models of life-cycle skill formation.[1] While there is abundant empirical work on dynamic complementarities early in the life-cycle, less in known about the complementarities between skills and investments later in the education process. Dynamic complementarity is a feature of the technology of skill formation, where higher investments today will increase the returns to future investments. What if investments are specialized or heterogeneous? Later in the education process students begin to specialize. For example, high school students choose different tracks or courses, and college students choose a major of study. In this case, the existence of dynamic complementarities may mean that specialized investments in high school could lead to higher *or* lower returns to investments in college.

In this paper, we study the complementarities between three components of skill formation: multi-dimensional abilities at the end of compulsory schooling, high school track choices, and college major choices. We use a novel Swedish dataset that has rich information on family background, student abilities, high school choices, college choices, and labor market outcomes. Methodologically, there are two parts to the paper. In the first part, we provide descriptive evidence for dynamic complementarities in the education process. We show that abilities play an important role in how students choose their high school track, how students choose their college major, and whether they graduate from college. Next we perform non-parametric variance decompositions of earnings to show that the three components in isolation explain a substantial fraction of the variation in earnings.[2] The explanatory power of each component, though, is highly dependent on the others. If we first condition on any other component, the explained variation decreases by at least half. Finally, we explicitly show that there are strong complementarities between college major and multi-dimensional abilities. While it is well known that some college

[1] See *e.g.* Cunha and Heckman (2007); Cunha et al. (2006, 2010) and Heckman and Mosso (2014) for a review of the literature on life-cycle skill formation.

[2] There is ample empirical evidence on the importance of cognitive and non-cognitive abilities; see e.g. Heckman and Rubinstein (2001); Heckman et al. (2006); Lindqvist and Vestman (2011); Heckman et al. (2014); Weinberger (2014); Borghans et al. (2016); Deming (2017); Prada and Urzúa (2017), but the process by which multidimensional abilities lead to specialization and produce better economic outcomes is still not well understood.

majors on average earn more than others,[3] we show that the complementarities between college investments and student skills are strong enough that the ranking of majors by earnings is highly dependent on student pre-college skills.

The descriptive findings motivate the second part of the paper where we develop and estimate a generalized Roy model of education choices and labor market outcomes. The strong dynamic complementarities between our three components mean that we cannot evaluate the returns to an investment without characterizing who is receiving the investment and how it might interact with later investments. To study this, we focus on the effect of high school track. Our sequential model of education choices accounts for a rich set of observables, three dimensions of latent ability, and an additional dimension of unobserved heterogeneity that is identified using exogenous sources of variation at each margin. On average, moving students to more challenging tracks in high school increases college enrollment, college graduation, and earnings. Yet the average treatment effects belie heterogeneity in the treatment effects. Complementarities between abilities and high school investments lead low-ability individuals to sometimes receive only half the benefit of high-ability individuals. The differences become larger for later outcomes (*e.g.* graduation and earnings) as abilities and high school investments are also complements in college decisions. We find that moving students from academic tracks to STEM tracks has a small and negative effect. While the STEM track treatment moves more students into engineering and medicine, the majority of the affected students end up working in labor markets where the academic track has higher returns than the STEM track. In other words, investment in STEM track leads to *lower* returns for most non-technical majors. Finally, we consider policies that drop the vocational track in partial equilibrium and find that it results in a substantial increase in college enrollment, but only a small increase in average log wages. Most of the gains are for students who, forced to leave the vocational high school track, go on to obtain a different level of final education.

[3] The college major premium is well-documented (Berger, 1988; Altonji, 1993; Grogger and Eide, 1995; Paglin and Rufolo, 1990; Arcidiacono, 2004; Christiansen et al., 2007; Gemici and Wiswall, 2014; Altonji et al., 2014; Kirkebøen et al., 2016; Hastings et al., 2013; Altmejd, 2018), but it is still not well understood what it embodies. Altonji et al. (2016) provide a recent and comprehensive literature review. Altonji et al. (2012) strongly advocate the importance of analyzing high school and college choices jointly.

This study is done in the Swedish context for three reasons: First, the centralized education system allows for a convenient and nationwide mapping of high school curriculum into vocational, academic, and STEM tracks. Second, it is possible to link high-quality multidimensional measures of ability that are independent of the education system. Third, administrative school records allow us to construct within-school-across-cohort variation to help identify additional unobserved heterogeneity in the model.

Our analysis uses a comprehensive administrative dataset of more than 96,000 Swedish men. We observe detailed measures of abilities at age 18 from the Military Enlistment archives and adjoin grades from courses in ninth and tenth grades. The data includes advanced course choices in ninth grade, high school track choices and grades, detailed education codes for all college enrollment spells, accumulated course credits, and acquired degrees. We focus on the cohorts born in 1974-76 and merge the measures of abilities and education choices to their yearly earnings which we observe until 2013 – when they are in their late 30s. We are also able to link children to their parents and observe a rich set of background variables.

A combination of measures from military enlistment data and ninth and tenth year course grades are used to identify three latent abilities. The military enlistment data includes test scores from an achievement test and the evaluation of a personal interview with a professional psychologist. The Swedish military enlistment data is novel in its availability of socio-emotional measures that are not self-reported. The three latent abilities are estimated using a measurement system that corrects for measurement error, biases in the measures, and education decisions taken before the test. We extend the analysis in Hansen et al. (2004) to show identification of the effect of schooling at the time of the test when measures are not dedicated. Another aspect of our analysis that is novel is the use of independent survey data from primary school to validate the measurement system and determine labels for our latent abilities: cognitive, interpersonal, and grit.

In the first part of the analysis, we use the measurement system to estimate some simple models to understand ability sorting in education decisions and the complementarity between ability and college decisions. The goal of the first part is to provide evidence using the measurement system but to use as little additional structure as possible. We show how to estimate conditional means of latent factors without a discrete choice model and use this to characterize ability sorting in high school and college choices. The sorting for high school track is absolute in that students in the more challenging track are higher in every ability compared to students in less challenging tracks. Students sort strongly into high school tracks on cognitive and grit abilities, and less strongly on interpersonal ability. There is both absolute sorting and differential sorting into college majors. The mean ability of Medicine majors are highest in all three dimensions. The patterns vary widely across the majors, but not in unexpected ways. Engineering majors are well above average in cognitive and grit abilities, but only just above average in interpersonal ability. Science and math majors are above average in cognitive ability, just above average in grit and below average in interpersonal ability. Business students are above average in interpersonal ability, but about average otherwise. In almost all majors, students who graduate have, on average, substantially higher levels of cognitive and grit abilities.

We then use the measurement system to estimate 15 log-earnings equations for each final schooling outcome. We find strong complementarities between abilities and college major for both wages and present value of disposable income. Unsurprisingly, the within-major wage returns to all three abilities are highest for business and lowest for education. Perhaps more surprising is that the within-major wage returns to interpersonal ability is much larger than the others for engineering, science and math, and law. At the same time, within-major wage returns to cognitive and grit abilities are more important for humanities, social science, and medicine majors. The returns to ability patterns for present value (PV) disposable income are similar, except that for most majors the return to interpersonal abilities becomes larger, while the returns to cognitive and grit abilities decline. We finish by showing that the complementarities between abilities and majors means that there is no absolute ranking of majors in terms of earnings. The heterogeneity from a single ability can lead a major to change four spots in the rankings of majors. Once we account for the heterogeneity in abilities and background observables, we find that there are more than six majors (out of twelve) that would be ranked first in expected earnings by a significant portion of our sample.

Motivated by the evidence of strong complementarities between abilities and education, we estimate a multistage sequential choice model of education choices where we approximate decisions at each stage. This model highlights how individuals start investing in more specialized skills before the end of compulsory schooling and how prior abilities and skills affect subsequent education choices and labor market outcomes. Individuals are initially heterogeneous in their abilities (grit, interpersonal, and cognitive) and socioeconomic background characteristics. In the first stage, individuals choose whether to take advanced ninth grade courses in English and math. In the second stage, after completing compulsory schooling, individuals choose high school track: vocational, academic, or academic STEM. In the third stage, high school graduates choose whether to enroll in college or not. If they enroll in college, they choose which level and field to enroll in: four fields in short degrees and eight fields in four-year or longer degrees. In the fourth stage, they choose whether to switch level and/or field, or to continue in the initially chosen level and field. In the fifth stage, they either dropout or graduate with a degree in the field and level chosen in the fourth stage. In the final stage, they work in the labor market, where their earnings are determined by their initial abilities, their advanced ninth grade course choices, their high school track, and their college (level and major) choices. The model allows us to characterize the population at each decision node and who will be affected by a potential policy. This enables us to answer questions such as: What are causal returns at each decision node and how do they depend on abilities? Do individuals choose high school track and majors where they have highest gains to abilities? What is the effect of policies that encourage STEM enrollment at the high school and college level?

We use exogenous variation commonly used in the peer-effects literature to identify an additional source of unobserved heterogeneity (*i.e.* a random effect).[4] This instrument uses random variation in education choices across cohorts within schools. The idea is that

[4]See *e.g.*, Hoxby, 2000; Hanushek et al., 2003; Ammermueller and Pischke, 2009; Lavy and Schlosser, 2011; Lavy et al., 2012; Bifulco et al., 2011; Burke and Sass, 2013; Card and Giuliano, 2015; Carrell et al., 2016; Olivetti et al., 2016; Patacchini and Zenou, 2016.

random variation in a cohort's choices can affect the choices of an individual student. One of the benefits of using the Swedish data is that we can construct instruments at each margin in the model. We construct within-school-across-cohort instruments for the ninth grade cohort choosing advanced courses in ninth grade. The ninth grade cohort is also used to construct a within-school-across-cohort instrument for high school track choice. The high school cohort is used to construct within-school-across-cohort instruments for college enrollment and major choice. We find that these instruments easily pass standard first-stage tests. One concern is that the instrument is capturing variation in cohort ability which could then affect the ability of the student in question. We show that adding controls for cohort ability either has no effect or strengthens the instrument in the first-stage.

In general, the treatment effects of high school track are a fraction of the observed differences due to the strong sorting into high school track. The treatment effect of moving a student into a different track, though, depends on the outcome, the margin, and the population being considered. We consider three margins: vocational to STEM, academic to STEM, and vocational to academic. In general, we find that moving students into more challenging tracks increases college enrollment by 10-30% and increases college graduation by 5-15%. The treatment effects strongly depend on ability. For example, the effect on college graduation of moving a low-ability student out of a vocational track into any academic track is only about half of what high-ability students receive. The complementarity between ability and high school track in graduation rates is due to the importance of cognitive and grit abilities in attaining a degree once enrolled. Results show that moving a marginal student into the STEM track creates interesting substitution patterns, where more students enroll in college and enrollment in STEM majors increase. While more individuals earn a college degree, the rates of dropping out of college also increase. The treatment effects for wages are larger when moving students out of the vocational track. The marginal student sees his wages change by 6%, 6.5%, and -2.8%, for the vocational-STEM margin, vocational-academic margin, and academic-STEM margin, respectively. The negative effects for the academic-STEM margin are driven by the fact that the academic track has higher wage returns in most of the non-technical majors (including high school graduates), indicating important complementarities between what is learned in high school and college.

To our knowledge, this is the first paper analyzing how students sort into different high school tracks based on multidimensional abilities *and* that explicitly takes the sequential nature of education decisions into account. The literature on the impacts of high school curriculum on college and labor market outcomes is largely quasi-experimental, relying on some sources of exogenous variation in curriculum. Altonji (1995) first attempted to draw causal inference on this relationship using the high school average of each course combination as an instrument for the individual choice of this course combination. This is a strong instrument but may not be exogenous as schools in which students choose more advanced math classes may obviously also be the schools with higher ability students and better quality math classes.[5] Most innovations to this literature have either brought better data to the problem (Levine and Zimmerman, 1995; Rose and Betts, 2004) or better instruments (Joensen and Nielsen, 2009; Taylor, 2014; Cortes et al., 2015; Goodman, 2017). Most of the literature finds that studying more (advanced) math has a positive effect on education and labor market outcomes. Joensen and Nielsen (2009) and Joensen and Nielsen (2016) use the introduction of a pilot program in the 80s in Danish high schools that lowered the cost of taking advanced math with other advanced STEM courses. Those who were induced to choose math because they unexpectedly got this option earn almost 30% more in their early careers. The empirical patterns suggest that a large fraction of the strong effect works through the increased probability of completing higher education. Joensen and Nielsen (2016) also find that high ability females who take more advanced math become more likely to graduate with STEM majors and less likely to graduate with humanities and arts majors. Taylor (2014) and Cortes et al. (2015) exploit test-scored based eligibility thresholds to estimate the effects of doubling math instruction. Taylor (2014) finds only very short-term effects on math achievement that decay after a couple of years, while Cortes et al. (2015) finds increases in high school

[5]See e.g. Altonji et al. (2012) for a comprehensive review of this literature.

graduation and college enrollment. Goodman (2017) uses increased state high school graduation requirements as an instrument and finds that Black students increased their math course work and subsequent earnings. All these papers estimate *ex post* total effects, while our model allows us to distinguish direct and indirect effects. We also show that ability sorting and skill complementarities are important and non-trivial. To the best of our knowledge, this is the first paper to empirically quantify ability sorting and complementarities in high school and college investments.

2 Institutional Setting

2.1 Education System in Sweden

In this section, we describe the education environment of the cohorts born in 1974-76 that are the focus of our analysis. Primary through upper-secondary schooling in Sweden is regulated by the Education Act of 1985.[6] Swedish children enroll in 1st grade in the fall of the calendar year in which they turn seven. After nine years of compulsory schooling, most Swedish students enroll in high school. Whereas compulsory schooling is fully comprehensive with very limited choice of optional courses, there are many high school lines to choose from. Students submit their high school applications to the Board of Education in their home municipality. If students want to be considered for multiple high school lines, then they submit a rank-ordered list of up to six lines. The home municipality is responsible to offer high school tracks that – to as large an extent as possible – align with the preferences of all qualified students.[7] If there are more applicants than available seats, then seats are allocated based on 9th grade GPA.[8] High school is generally not very selective, and most students are admitted to (96%) and graduate from (92%) the

[6]See the Education Act `1985:100` for the complete law text and its changes over time, available in Riksdagens law archives). Bjorklund et al. (2005) also provide a thorough description of education in Sweden during this period.

[7]Ninety two percent of high schools are run by the municipality during our sample period. Stockholm county is the main exception in which all but two municipalities run a pooled high school admission process.

[8]See the Secondary School regulation `1987:743` and `1992:394` for the complete details of the application and admission process.

high school track of their preferred choice.[9]

High school lines are broadly classified into vocational and academic high school tracks. To be eligible for the vocational track, the student has to have passing grades in Swedish, English, and mathematics. To be eligible for the academic track, the student has to have passing grades in Swedish, English, Mathematics, and nine additional courses. We further classify the academic high school lines into a non-STEM and a STEM track. The academic non-STEM track consists of the three lines in business, social science, and humanities. The academic STEM track consists of the two lines in science and technical studies. All five 3-year academic high school lines comprise an average of 32 hours of instruction time per week. Table 1 provides a brief summary of the mandated distribution of the core curricula in each of these high school lines. It reveals that there are large difference in the amount of instruction time devoted to math, science, and other technical courses. The students in the technical (science) line on average have 18 (13) hours devoted to math, science, and technical courses per week, while the students in the academic non-STEM track only have 2-4 hours per week on average. Not only do the STEM track students have more time devoted to math, science, and technical courses, they also have more advanced courses on these topics. The choice of high school track thus means a substantial difference in the curriculum and in terms of college readiness for certain majors.

High school graduates comprise the pool of potential college applicants. Meeting the basic requirements for college enrollment requires completing three years of academic high school or two years of vocational high school followed by a year of intensive college preparatory courses. College admission is predominantly conditional on high school grade point average (GPA), but other factors also affect the admission score, including the Swedish Scholastic Aptitude test (SweSAT), high school track and course choices, and labor market experience.[10] For example, only academic STEM track graduates have

[9] We describe high school application and admission in more detail in Appendix A.1.

[10] Öckert (2010) describes the college admission process for the earlier cohorts, while Altmejd (2018) describes it for the later cohorts. The SweSAT has become a more important factor over time, particularly after 1991, and weighed in for 30−40% of our sample. All the details can be found in the Higher Education Act `1992:1434` and the Higher Education Ordinance `1993:100`.

Table 1: Curriculum of Academic High School Tracks

High School Track	**Math, Sci, Tech**	**Social Sci**	**Languages, Arts**
Academic non-STEM			
Business line	0.125	0.156	0.313
Social Science line	0.203	0.297	0.391
Humanities line	0.141	0.297	0.453
Academic STEM			
Technical line	0.563	0.109	0.219
Science line	0.406	0.172	0.313

Notes: This table displays the average fraction of time devoted to each set of courses in the mandated core curricula over the 3-year duration of each academic high school line. Business line students also have an average fraction of 0.266 devoted to occupation-specific studies. Otherwise, the omitted category of courses includes physical education and optional courses that vary within high school line. Note that all academic 3-year high school lines have 32 hours of instruction per week.

the qualifications to enroll in all 4-year STEM college majors without additional supplementary courses, and only students in the science line are directly qualified for *all* 4-year college majors. College admission is largely centrally administered. On top of a high school diploma and transcripts, a college application consists of a rank-ordered list of up to 20 college-program choices.[11] Selectivity varies greatly across college majors: the 4-year programs in Medicine, Law, and Humanities are the most selective. All Medicine and Law college-programs require a GPA above the mean plus one standard deviation, while all Humanities college-programs require a GPA above the mean to be directly admitted. However, Medicine is also the major that admits most students (25%) based on other merits: predominantly personal interviews. The STEM majors are generally the least selective, while the remaining 4-year programs are moderately selective; the bulk of the college-programs require a GPA between the mean and the mean plus one standard deviation, but there are also many college-programs within each of these majors that admit all qualified applicants.[12] Higher education is tuition-free for all students and largely financed by the central government. College students are eligible for universal financial aid of which around one third of the total amount is a grant (or scholarship)

[11]In this respect, the college application in Sweden is similar to Norway (Kirkebøen et al., 2016), Denmark (Humlum et al., 2014), and Chile (Bordon and Fu, 2015; Hastings et al., 2013).

[12]We provide more descriptives and details in Appendix A.2.

and the remaining two thirds are provided as a loan. Student aid is largely independent of parental resources but means-tested on student income and the maximum eligibility period is 240 weeks, i.e. the equivalent of 12 semesters or six enrollment years. Student loans are subsidized, and the loan repayment plan was income-contingent for those in our sample.[13]

3 Data

We merge several administrative registers via a unique individual identifier for the population of Swedes born between 1965 and 1983.

Our measurements of health, abilities, and family background come from the Medical Birth registry that is administered by the National Board of Health and Welfare (*Socialstyrelsen*), the Military Enlistment archives administered by the Swedish Defence Recruitment Agency (*Rekryteringsmyndigheten*) as well as several registers administered by Statistics Sweden (*SCB*).

The Medical Birth registry contains measures of the child's in utero environment and health status at birth; incl. maternal diagnosis and complications during pregnancy and delivery, child birth weight, indicators for whether the child is heavy or light for gestational age, APGAR score at 1, 5, and 10 minutes after birth, and child diagnosis at birth for the cohorts born between 1973 and 1983.

The Military Enlistment archives contain cognitive test scores, psychological assessments, health and physical fitness measures collected during the entrance assessment at the Armed Forces' Enrollment Board. The enlistment was mandatory for all Swedish males at age 18 until 2010, thus for all males in our sample who are Swedish citizens. The entrance assessment spans two days. Each conscript is interviewed by a certified psychologist with the aim to assess the conscript's ability to fulfill the psychological requirements of serving in the Swedish defense, ultimately in armed combat. The set of personal characteristics that give a high score include persistence, social skills, and

[13] The students in our sample are enrolled in college during the pre-2001-reform study aid regime as detailed in Joensen and Mattana (2016).

emotional stability.

To sharpen our interpretation of the latent ability factors, we merge these registers to the Evaluation Through Follow-up (ETF) surveys administered to 3rd, 6th, and 10th grade students by the Department of Education and Special Education at Gothenburg University.[14] This survey was administered to random samples of four cohorts in our population (1967, 72, 77, and 82) and includes extensive measures of aptitude and achievement tests, absenteeism, special education and tuition, and grades in various courses through compulsory schooling, as well as extensive student and parent surveys related to student achievement, confidence, inputs, grit, and interpersonal skills.

We also have detailed data on education choices and outcomes from the Ninth Grade registry (incl. grades in math and English courses, whether advanced math and English courses were selected, and GPA), the High School registry (incl. grades in individual courses, GPA, track and specialization choices), and the Higher Education registry (incl. detailed education codes for all enrollment spells, course credits accumulated during enrollment, and acquired degrees). We classify high school students into three tracks: vocational, academic, and academic STEM. College applicants are screened based on their high school course choices and GPA. Some of them are also admitted based on high performance in the SweSAT on which we have overall test scores and sub-scores on every attempt through the Department of Applied Educational Science at *Umeå Universitet*.

From the Higher Education registry, we observe the level and field of every college enrollment spell and degree. We classify all academic programs into two levels (≤ 3 years; ≥ 4 years) according to the SUN2000Niva code and nine fields (1. Education; 2. Humanities and Art; 3. Social Sciences and Services; 4. Math, Natural, Life and Computer Sciences; 5. Engineering and Technical Sciences; 6. Medicine; 7. Health Sciences, Health and Social Care; 8. Business; 9. Law) according to the SUN2000Inr code. The Swedish education nomenclature (SUN2000) codes build on the International Standard Classification of Education (ISCED97), and we group programs into majors according to the first digit of the SUN2000Inr code. We single out Business and Law

[14] Härnqvist (1998) provides additional details on the construction of the survey.

from the Social Sciences major and Medicine from the Health Sciences major to better compare to previous literature. Some of the 3-year programs have very few students, so we group them together into a STEM (Sci, Math, Eng) and a non-STEM (Hum, Soc Sci) major. Students in the 3- and 4-year Education and Health Sciences majors look similar on observables, so these are grouped together.[15]

The Multigeneration registry allows us to link children to their parents. It also contains information on family size and composition. Additional background variables are obtained from the longitudinal integration database for health insurance and labour market studies (*LISA*) from which we have yearly observations during the period 1990-2013. This allows us to observe individual employment status and earnings when they are 30-48 years old and parental background variables (incl. age, civil status, highest completed education, employment, earnings, and disposable family income). We supplement this with earnings information from the Registerbased Labor Market Statistics (*RAMS*) for the years 1986-89 and from the Income and Tax registry (*IoT*) 1983-85. We also have information on disposable family income from *IoT* for the years 1978-89. This means that we can measure disposable family income of parents (parental earnings) from birth to age 30 for the youngest cohort and from age 13 (18) to 48 for the oldest cohort in our sample.

3.1 Sample Selection

We focus on males, since military enlistment at age 18 was only mandatory for Swedish males and these scores are important measures for our factor model. We select a sample of cohorts born in 1974-76. The reason we focus on these cohorts is twofold: First, the detailed college credit data only exists form 1993 onwards and this is also the year the classification of higher education in Sweden changed considerably. Second, the four subscores for the cognitive test taken at military enlistment are only sparsely observed for those who were born after 1976.

[15] Appendix A.2 provides more details and descriptives by college major.

3.2 Descriptive Statistics

This section describes the background characteristics of students and schools by high school track. Table 2 shows that there is a large difference in average grades at the end of compulsory schooling by high school track. Vocational track students seem negatively selected, while academic STEM high school students seem positively selected on grades in the 9th grade. However, students do not seem to come from schools that are different in terms of average grades. Fifty six percent of our sample attended the vocational track, 20% the academic non-STEM track, and 24% the academic STEM track.

Table 2: Prior Skills by High School Track

		High School Track		
	High School Dropout	**Vocational**	**Academic non-STEM**	**Academic STEM**
Grades, 9th grade				
GPA	-0.97	-0.44	0.55	1.07
Math	-0.63	-0.23	0.11	0.79
English	-0.59	-0.26	0.37	0.60
Swedish	-0.78	-0.41	0.59	0.86
Sports	-0.63	-0.14	0.36	0.34
Courses, 9th grade				
Adv. Math	0.24	0.38	0.87	0.99
Adv. English	0.34	0.46	0.93	0.96
School avg. adv. Math	0.54	0.55	0.59	0.58
School avg. adv. Eng	0.59	0.59	0.64	0.63
N students	**9,291**	**54,498**	**19,198**	**22,926**
Fraction of sample	**0.09**	**0.51**	**0.18**	**0.22**
Fraction of HS Graduates		**0.56**	**0.20**	**0.24**

Notes: This table displays the average ninth grade course grades, GPA, course choices, and ninth grade school average course choices. All averages are displayed by high school track: vocational, academic, and academic STEM. All grades are normalized to have mean 0 and standard deviation 1 in the sample.

Table 3 shows that there are also some differences in the background variables we include as controls in our analysis. Vocational track students are more likely to have mothers that were younger than 24 when they were born, while the academic track students are more likely to have mothers that were older than 30 when they were born.

Academic track students are also more likely to have parents with a college degree. Vocational track students have better average health – both in terms of strength and fitness – at age 18. On average, academic STEM students are as strong as vocational track students, but have lower fitness similar to academic non-STEM students.

Table 3: Control Variables by High School Track

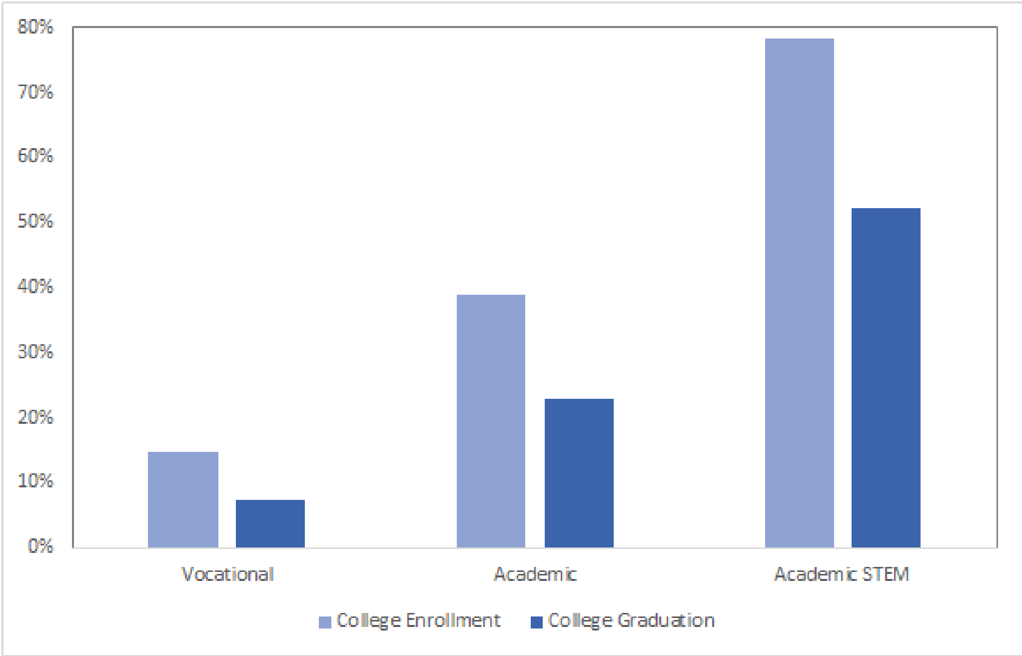
		High School Track		
	High School Dropout	**Vocational**	**Academic non-STEM**	**Academic STEM**
Birth Cohort				
1974	0.51	0.45	0.43	0.45
1975	0.37	0.42	0.41	0.41
Health factors				
Strengh	-0.04	0.08	-0.01	0.10
Fitness	0.32	0.10	-0.19	-0.30
Health missing	0.05	0.05	0.05	0.05
Mother				
Age at child birth	23.88	24.91	25.79	26.17
Age at child birth missing	0.05	0.03	0.04	0.04
Disposable family income	0.51	0.45	0.43	0.45
Education				
$\geq$ College	0.12	0.15	0.37	0.42
$\geq$ High School	0.60	0.67	0.79	0.82
Missing	0.08	0.07	0.07	0.07
Father Education				
$\geq$ College	0.08	0.10	0.31	0.34
$\geq$ High School	0.48	0.55	0.72	0.76
Missing	0.11	0.10	0.09	0.09
N students	**9,291**	**54,498**	**19,198**	**22,926**
Fraction of sample	**0.09**	**0.51**	**0.18**	**0.22**
Fraction of HS Graduates		**0.56**	**0.20**	**0.24**

Notes: This table displays the averages of the additional control variables. All averages are displayed by high school track: vocational, academic, and academic STEM. Health factors are based on health measures of strength and fitness in the military enlistment data and are normalized to have mean 0 and standard deviation 1 in the sample. Disposable family income is measured as the average disposable family income in the mother's household when the child is 5-18 years old, and enters all specifications with a linear and a quadratic term. Parental education is measured when the child is 14-16 years old.

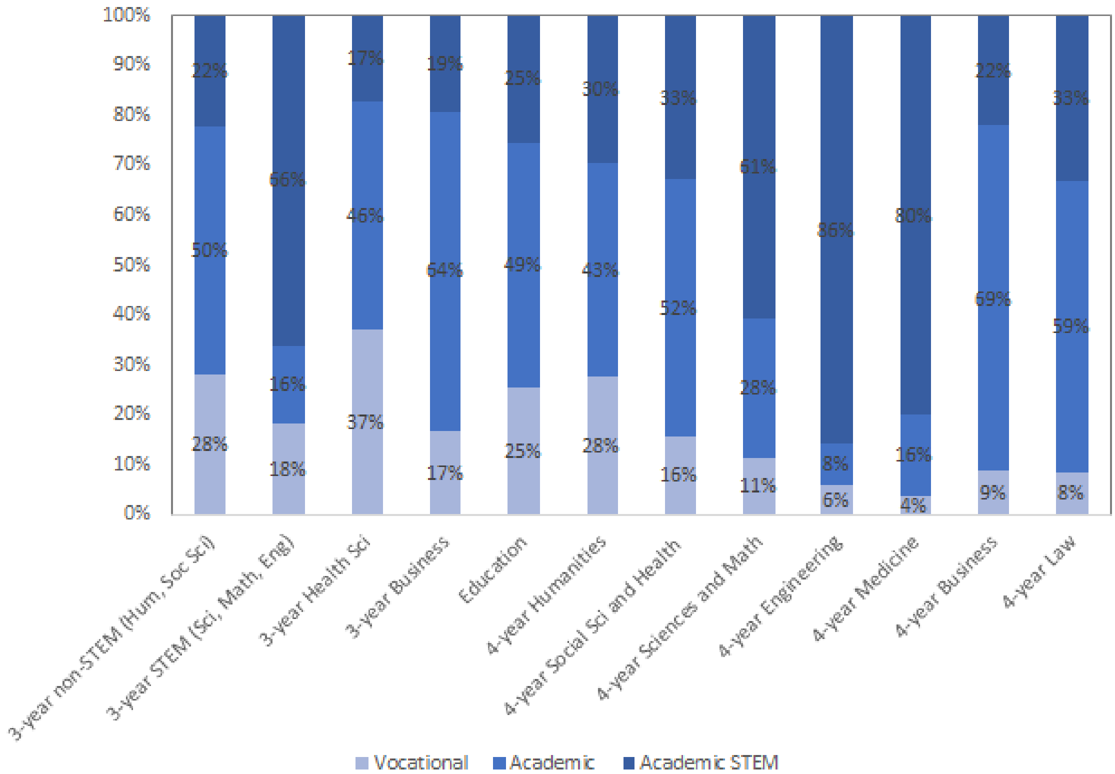
Figure 1 describes the enrollment and graduation rates by high school track and how students from different tracks sort into different college fields. There are strong sorting patterns by high school track and college field. Students who took a STEM track in high school dominate the four STEM college categories. Students who took an academic track in high school represent a large fraction of the students who enroll in Business, Education, Social Sciences, and Health fields. Students who took a vocational track in high school are unlikely to attend a 4-year college.

Figure 1: Graduation Rates and Sorting into College Fields

(A) Enrollment and Graduation Rates



(B) Sorting of High School Tracks into College Fields



Notes: Top figure shows the college enrollment and graduation rates by high school track. Bottom figure shows the high school track composition of each college field.

4 Identification and Estimation of Latent Abilities

One of the main contributions of this paper is to investigate the role of multidimensional abilities in education choices and labor market outcomes. In order to achieve this goal, we estimate a number of models that include latent abilities. In this section, we briefly describe the identification of latent abilities, our estimation strategy for models that include latent abilities, and the empirical specification of our measurement system used to identify latent abilities.

4.1 Identification of Latent Abilities

If abilities were directly observable, we could include them in our models along with other observables on demographics and family background. Instead, abilities need to be identified from proxies like test scores or behavior. In this paper, we will identify latent abilities using evaluations done as part of the compulsory military enlistment and course grades in compulsory and high school. Let $\boldsymbol{M}$ denote a vector of measures or proxies that define the measurement system for latent abilities. Students may be evaluated after they have been exposed to different types or levels of education. For example, students are evaluated by the military at age 18 while most of them are still in different tracks in high school. Let s denote the schooling state of the student and M_{ks} denote the kth measure evaluated at schooling state s. We define $\tilde{M}_{ks}$ as latent variables that map into observed measures M_{ks}:

$$M_{ks} = \begin{cases} \tilde{M}_{ks} & \text{if } M_{ks} \text{ is continuous} \\ \boldsymbol{1}(\tilde{M}_{ks} \geq 0) & \text{if } M_{ks} \text{ is a binary outcome.} \end{cases} \tag{1}$$

The latent variables are assumed to be separable in observables, latent abilities, and an idiosyncratic error term

$$\tilde{M}_{ks} = \alpha_{ks} + \boldsymbol{\beta}_k^M \boldsymbol{X} + \boldsymbol{\lambda}_k^M \boldsymbol{\theta} + u_k,$$

where α_{ks} represents schooling-state specific intercepts for measure k, $\boldsymbol{X}$ is a vector of observables, $\boldsymbol{\theta}$ is a vector of latent abilities, and u_k is the error term. We assume that u_k are mutually independent across each k and are independent of $\boldsymbol{\theta}$ and $\boldsymbol{X}$.

The inclusion of the schooling-state specific intercepts and observables in the measurement system has important implications for the interpretation of the latent abilities. The term α_{ks} captures the effect of schooling state at the time of the test. For example, students who take STEM tracks in high school may perform better on the cognitive evaluations given by the military due to having taken more math and science classes. The inclusion of α_{ks} in the measurement system implies that our latent abilities are measured relative to a reference schooling state. We include observables in the measurement system to account for biases in the evaluations that are due to the student's background.[16] This is not without loss of generality as a student's background (*e.g.* mother's education) is also an important determinant of their ability. Hence, when we report results on latent abilities, we are measuring "residual" latent abilities. That is, the variation in latent abilities that are not explained by (*i.e.* orthogonal to) the observables. Next, we show that the effect of schooling at the time of the test (α_{ks}) and mean ability conditional on each schooling state ($\mu_s = \mathbb{E}[\theta|S = s]$) are jointly identified. This analysis builds on Hansen et al. (2004), where they show identification for a factor model with dedicated measures. In what follows, we keep the dependence on observables, X, implicit for the sake of notational simplicity.

Let there be N factors. Let $\mathcal{S}$ denote the set of possible schooling states at the time the measures are taken, and let $\mathcal{S}_k \subseteq \mathcal{S}$ denote the possible schooling states for measure k. Assume that there are K measures (M_{ks}), where the first K_0 measures are taken before any schooling decision ($\mathcal{S}_k = \{0\}$ for $k \in \{1, ..., K_0\}$). The key identifying assumption is that there are at least as many pre-decision measures as there are factors (*i.e.* $K_0 \geq N$). We also assume that there are enough measures, K, to identify the loadings of an N-factor model.[17]

[16]See *e.g.* Neal and Johnson (1996) and Winship and Korenman (1997).

[17]The number of measures required depends on the number of factors, the normalizations, and over-identifying assumptions used in the measurement system. See Williams (2018) for more details.

Keeping the dependence on X implicit, we model the K measures as

$$M_{ks} = \alpha_{ks} + \boldsymbol{\lambda}_k \boldsymbol{\theta} + u_k, \quad s \in \mathcal{S}_k, \quad k \in \{1, ..., K\},$$

where $\boldsymbol{\lambda}_k$ and $\boldsymbol{\theta}$ are vectors of length N. Note that the set of schooling states differ for different measures.

Since the loadings are independent of schooling state, the identification of the loadings follows the standard identification arguments in the literature (see *e.g.* Williams 2018), where the loadings can be identified by conditioning on one of the schooling states.

The next step is to show the identification of the intercepts α_{ks}. We normalize the mean of each factor distribution to be zero, $\mathbb{E}[\theta] = 0$. Assuming that the measures are not relevant to decisions about the schooling states, the intercepts in the first K_0 models are identified by taking expectations:

$$\alpha_{k0} = \mathbb{E}[M_{k0}] \quad \text{for} \quad k \in \{1, ..., K_0\}.$$

Next, we can identify the conditional mean of each factor by taking conditional expectations of the first N models and solving the resulting system of linear equations:

$$\mathbb{E}[\boldsymbol{M}^N | S = s] = \boldsymbol{\alpha}^N + \boldsymbol{\Lambda}\boldsymbol{\mu}_s \quad \text{for} \quad k \in \{1, ..., N\},$$

where $\boldsymbol{M}^N$ is a vector of length N stacked with the first N measures ($M_{k0},\ k \in \{1, ..., N\}$), $\boldsymbol{\alpha}^N$ is a vector of length N with the already identified intercepts ($\alpha_{k0},\ k \in \{1, ..., N\}$), $\boldsymbol{\Lambda}$ is an $N \times N$ matrix with the already identified loadings, and $\boldsymbol{\mu}_s$ is a vector of length N of the conditional means of the factors for schooling state s. Assuming $\boldsymbol{\Lambda}$ is invertible, then the conditional means of the factors for each schooling state are identified:

$$\boldsymbol{\mu}_s = \boldsymbol{\Lambda}^{-1} \left[\mathbb{E}[\boldsymbol{M}^{\boldsymbol{N}} | S = s] - \boldsymbol{\alpha}^N \right], \quad s \in \mathcal{S}.$$

Finally, the schooling-state specific intercepts in the $k \in \{K_0 + 1, ..., K\}$ models are identified using the conditional means of the factors and of the measures:

$$\alpha_{ks} = \mathbb{E}[M_{ks}|S = s] - \boldsymbol{\lambda}_k \boldsymbol{\mu}_s, \quad s \in \mathcal{S}_k, \quad k \in \{K_0 + 1, ..., K\}.$$

4.2 Estimation Strategy

We estimate the model in two stages using maximum likelihood. The measurement system is estimated in a first stage and is shared for all models estimated in this paper. Economic models W (*e.g.* education choices and earnings) are estimated in the second stage using estimates from the first stage. The distribution of the latent factors is estimated using only measurements. We do not include economic models in the estimation of the measurement system as doing so could produce tautologically strong predictions from the estimated factors.

Assuming independence across individuals (denoted by i), the likelihood is:

$$\begin{aligned}\mathcal{L} &= \prod_i f(\boldsymbol{W}_i, \boldsymbol{M}_i | \boldsymbol{X}_i) \\ &= \prod_i \int f(\boldsymbol{W}_i | \boldsymbol{X}_i, \boldsymbol{\theta}) f(\boldsymbol{M}_i | \boldsymbol{X}_i, \boldsymbol{\theta}) f(\boldsymbol{\theta}) d\boldsymbol{\theta},\end{aligned}$$

where $f(\cdot)$ denotes a probability density function.

For the first stage, the sample likelihood is

$$\begin{aligned}\mathcal{L}^1 &= \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} f(\boldsymbol{M}_i | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}})\, d\overline{\boldsymbol{\theta}} \\ &= \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} \left[\prod_k^K f(M_{i,k} | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \boldsymbol{\gamma}_{M_k}) \right] f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \boldsymbol{\gamma}_\theta)\, d\overline{\boldsymbol{\theta}}\end{aligned}$$

where we numerically integrate over the distributions of the latent factors. The goal of the first stage is to secure estimates of $\boldsymbol{\gamma}_M$ and $\boldsymbol{\gamma}_\theta$, where $\boldsymbol{\gamma}_{M_k}$ and $\boldsymbol{\gamma}_\theta$ are the parameters for the measurement models and the factor distribution, respectively. We assume that the idiosyncratic shocks are mean zero and normally distributed.

We can estimate economic models, where we correct for measurement error and biases in the proxies by integrating over the estimated measurement system of the latent factors. The estimated measurement system, $f(\boldsymbol{M}_i|\boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \hat{\gamma}_M) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \hat{\gamma}_\theta)$, can be thought of as the individual-specific probability distribution function of latent abilities. The likelihood for economic models is then

$$\mathcal{L}^2 = \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} f(\boldsymbol{W}_i|\boldsymbol{X}_i, \boldsymbol{\theta}; \gamma_W) f(\boldsymbol{M}_i|\boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \hat{\gamma}_M) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \hat{\gamma}_\theta)\, d\overline{\boldsymbol{\theta}} \tag{2}$$

where the goal of the second stage is to maximize $\mathcal{L}^2$ and obtain estimates $\hat{\gamma}_W$. Since the economic models ($\boldsymbol{W}$) are independent from the first stage models conditional on $\boldsymbol{X}, \boldsymbol{\theta}$ and we impose no cross-equation restrictions, we obtain consistent estimates of the parameters for economic models.

4.3 Measurement System

Our measurement system consists of measures from the compulsory Swedish military enlistment taken at age 18 and grade data from ninth grade and high school registers. We have to make some normalizations to both identify the model and also make the factors more interpretable.[18] The location and scale of the factors are not identified, so we assume that the factors are mean-zero ($\mathbb{E}[\theta] = 0$) and have unit variance ($\text{Var}[\theta] = 1.0$).

In order to facilitate interpretation of the factors, we specify a triangular measurement system with orthogonal factors.[19] On one hand, the measures from the military data could be treated as dedicated measures, and we would be able to use a different specification that has correlated factors. On the other hand, it would be difficult to argue that the grade measures are dedicated measures of a third factor and do not directly depend on the cognitive ability that is measured in the military enlistment.

We estimate a model with three factors. The first set of measures labelled as "cognitive" by the military psychologists depend exclusively on the first factor.[20] The second

[18]See Williams (2018) for more details on the identification of factor models.

[19]A triangular measurement system is one in which the measures are partitioned into groups based on how they depend on the factors and by design the factors are orthogonal. The first group of measures are dedicated measures for the first factor. The second group of measures depend on the first two factors, the third group of measures depends on the first three factors, and so on.

[20]The military psychologists select about half of the enlistees to be rated on a leadership scale based

set of measures include the variables from the psychological evaluation performed by the military psychologists. They provide two variables that measure "leadership" ability and "emotional stability." The second set of measures depend on both the first and second factors. The last set of measures includes course grades from ninth grade and high school. In particular, the last set of measures includes four course grades (math, English, Swedish, sports) and the residual GPA from ninth grade.[21] The last set also includes math and sports course grades from 10th grade and the residual GPA from high school. The last set of measures depends on all three factors.

The schooling states in the measurement system are (1) taking advanced English in ninth grade, (2) taking advanced math in ninth grade, and (3) taking one of three tracks in high school. The identification of the schooling-state specific intercepts requires three measures that are not affected by schooling states. In our model, those are the ninth grade Swedish grade, sports grade, and residual gpa. Table 4 summarizes the measurement system.

While most studies use the measure descriptions to interpret and label their factors, we instead validate our ability measures using an independent survey. As described in the data section, the Department of Education and Special Education, Gothenburg University, administered surveys to a random sample of 3rd, 6th and 10th grade students. The surveys include extensive measures of school performance and survey questions related to achievement, confidence, input, grit, and interpersonal skills. We estimate an outcome model for each survey item, grade, and test score in the survey dataset, resulting in over 250 items. We then calculate the explained variance from each orthogonal factor and calculate the fraction of total explained variance accounted for by each factor. We make three separate rankings of the proportion of the explained variance accounted for by each factor. Table 5 summarizes the five most informative items from the survey for each dimension of ability. Ten out of the top twenty items were test scores and grades for the first factor. Hence, we label the first factor "Cognitive Ability." The second factor

on their performance on the cognitive test scores. We include this selection as a separate measure of cognitive ability. See Grönqvist and Lindqvist (2016) for more details on this selection.

[21] We include individual course grade measures as covariates in the GPA models to create a "residual GPA" measure.

is relatively most informative about items relating to sports and social interactions. Informal conversations with Swedes who grew up at this time confirmed that "popularity" played a big role in the sports courses. Hence, we label the second factor "Interpersonal Ability." Lastly, the third factor is relatively most informative about the academic persistence of the students and their feelings about their performance in school. Hence, we label the last factor "grit." While these labels for the factors assist in the interpretation of our results, others may interpret them in other ways. For example, the third factor might also be related to "Conscientiousness," "Self-regulation," or "Motivation." In the following sections, we show that these three factors are important for understand sorting in both high school and college, and they are also important for understanding labor market outcomes.

Table 4: Structure of Measurement System

Measures	θ_1	θ_2	θ_3
Military Enlistment Registers			
Cognitive 1: Inductive[b]	x		
Cognitive 2: Verbal[b]	x		
Cognitive 3: Spatial[b]	x		
Cognitive 4: Technical[b]	x		
Leadership Evaluation[a,b]	x		
Leadership Ability[b]	x	x	
Emotional Stability[b]	x	x	
High School Education Registers			
10th Grade Math Grade[b]	x	x	x
10th Grade Sports Grade[b]	x	x	x
High School residual GPA[e]	x	x	x
Ninth Grade Education Registers			
Math Grade[c]	x	x	x
English Grade[c]	x	x	x
Swedish Grade[f]	x	x	x
Sports Grade[f]	x	x	x
Ninth Grade residual GPA[df]	x	x	x

Notes: [a] Binary discrete choice models. [b] Ninth grade advanced course indicators and high school track indicators are included. [c] Advanced course indicators included. [d] Math, English, Swedish and Sports grades are included in the 9th grade residual gpa model.[e] 10th grade math and sports grades are included. [f] These measures do not include any schooling-state specific intercepts.

Table 5: Validation and Interpretation of Factors

θ_1: "Cognitive Ability"
Test Scores: Math, Reading, Spatial, Verbal abilities (10 of top 20)
How often do you spend time doing a hobby (-)
Would you like to ask the teacher for help more often than you do?
How often do you read newspapers and comics?
Do you often think you would like to understand more of what you read?
θ_2: "Interpersonal Ability"
Do you think that you are bad at sports and physical exercise? (-)
How do you feel about talking about things to the whole class?
How often do you do sports?
Has participated in any form of childcare
Do you often spend time on your own during breaks? (-)
θ_3: "Grit Ability"
Do you think that you do well in school?
Do you always do your best even when the tasks are boring?
How often do you do homework or other school work at home?
How do you feel about drawing and painting? (-)
Do you think that you have to learn lots of pointless stuff in school? (-)

Notes: "(-)" indicates that the factor is negatively related to these items.

5 Multidimensional Ability: Sorting and Labor Market Returns

This section investigates possible dynamic complementarities in earnings between pre-college investments and college investments. The goal is to provide evidence for these complementarities with as little structure as possible. There are three parts to the analysis. First, we characterize multidimensional ability sorting into high school track and college majors. Second, we perform nonparametric decompositions of the variance of earnings into background observables, abilities, pre-college education choices, and college major choices. Lastly, we estimate earnings equations and show that earnings within college major graduates are quite heterogeneous,,,, indicating strong dynamic complementarities between ability, background, prior investments, and college major.

5.1 Sorting into High School Track and College Major

In this section, we investigate how students sort by multidimensional ability into high school track and college major. If abilities were observed, we could simply estimate the conditional mean of each ability by high school track or college major. As abilities are not observed, the literature has typically estimated discrete choice models with a measurement system and simulated the models to understand the sorting patterns.[22] While we will use similar discrete choice models when estimating causal effects in section 6, we show here that it is possible to estimate ability sorting without imposing any structure on how individuals make education decisions. The mean latent ability in each education category can be estimated using a set of simple linear models:[23]

$$\boldsymbol{\theta}_{is} = \sum_{s \in \mathcal{S}} \boldsymbol{\beta}_s \mathcal{I}_s + \boldsymbol{\eta}_{is}, \tag{3}$$

where the latent factor ($\boldsymbol{\theta}_{is}$) is on the left-hand side of the equation, $\mathcal{I}_s$ is an indicator for an education choice, and $\boldsymbol{\beta}_s$ are the conditional means of the latent factor for each education choice. In the following, we estimate one such model for each dimension of latent ability via maximum likelihood using the measurement system described in section 4.[24] The figures will be presenting $\hat{\boldsymbol{\beta}}_s$ as estimates of $\mathbb{E}[\boldsymbol{\theta}|S = s]$.

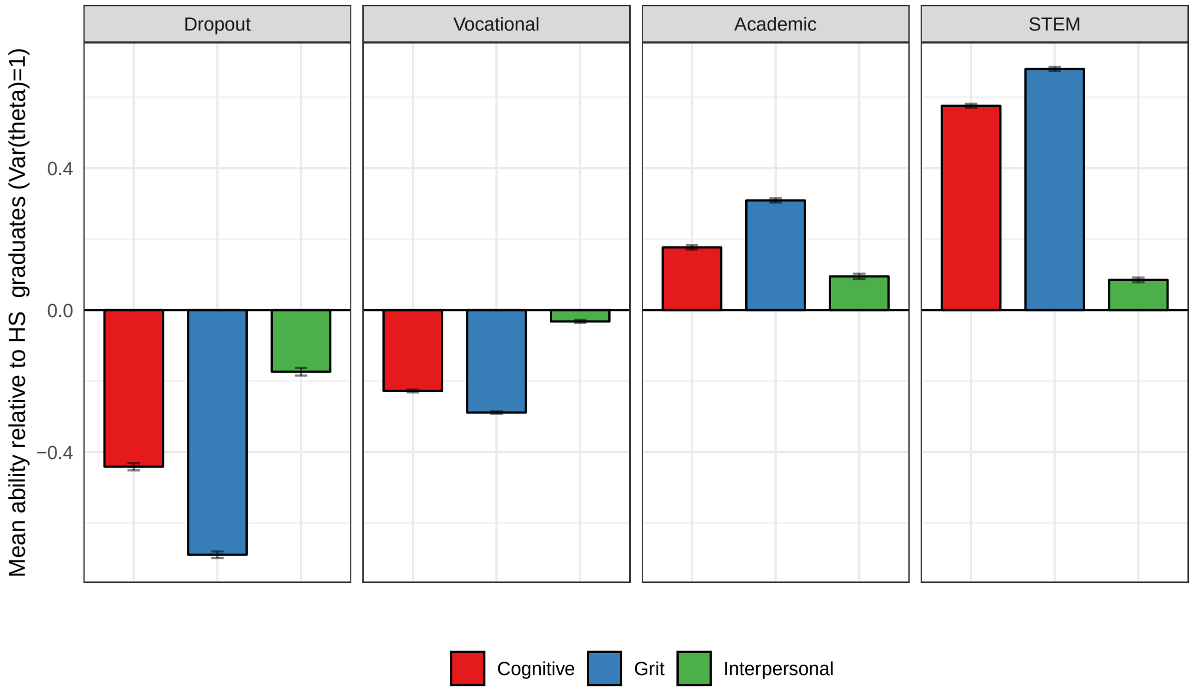
Sorting into High School Track Figure 2 shows how students sort into high school track by ability. The figure shows the average levels of the three abilities based on high school track choice. All three abilities have been normalized to be mean 0 and standard deviation 1 for the population of high school graduates (including individuals who go to college). The figure shows that there is strong sorting on cognitive and grit abilities and weaker sorting on interpersonal abilities. The average cognitive ability of academic (STEM) students are 0.13 (0.47) standard deviations above the mean, while the average cognitive ability of vocational track students is 0.23 standard deviations below the mean.

[22] See *e.g.* Heckman et al. (2018).

[23] These models are estimated via maximum likelihood using the first stage measurement system as described in section 4.

[24] We assume that η_{ij} is normally distributed.

Figure 2: Sorting into High School Track By Ability



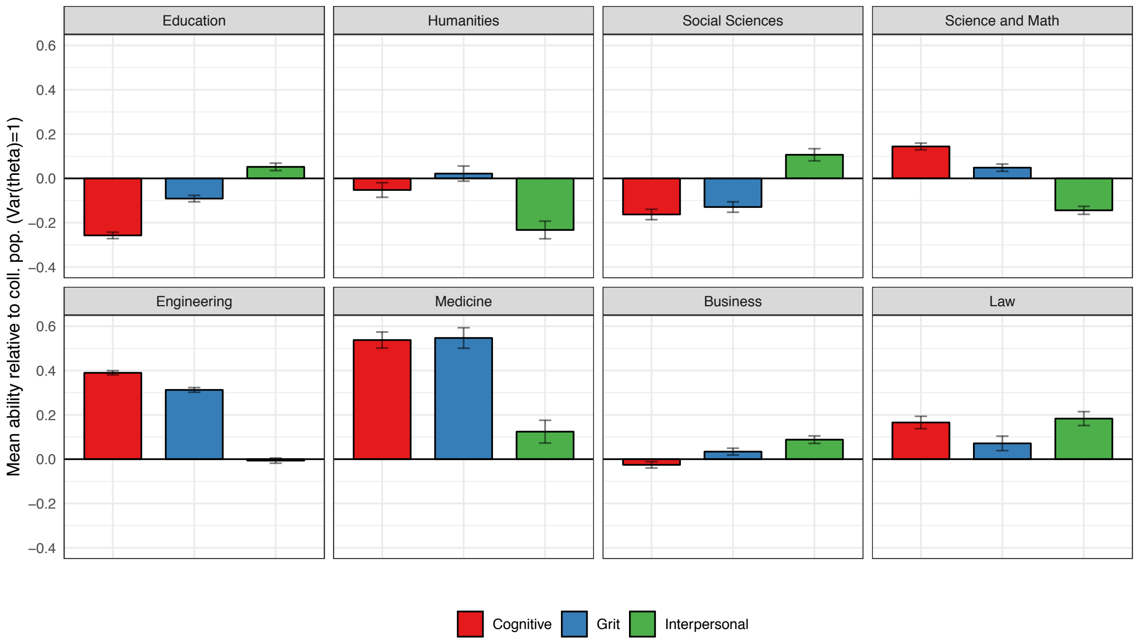
Notes: Table shows the average interpersonal, cognitive, and grit abilities by high school track. All abilities are normalized to be mean 0 and standard deviation one for the population of individuals with at least a high school degree.

Students with lower grit sort into vocational tracks, where the average grit ability is 0.41 standard deviations below the mean. The average grit ability of academic (STEM) track students are 0.27 (0.71) standard deviations above the mean. While the sorting on interpersonal ability is weaker in comparison, the STEM and academic track students are about 0.1 standard deviations above the mean, while vocational students are 0.05 standard deviations below the mean.

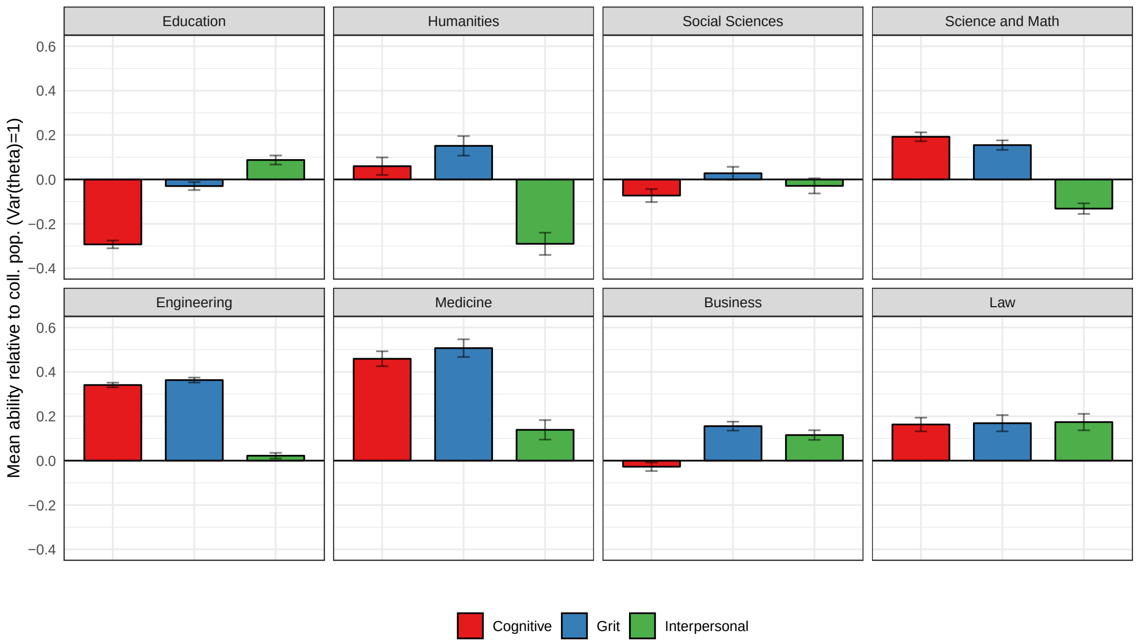
Sorting into College Major Figure 3 shows how students sort into college major enrollment and graduation by ability. The top panel shows the average levels of the three abilities based on initial college enrollment, while the bottom panel shows the average levels of the three abilities for graduates in each major. For both panels all three abilities have been normalized to be mean 0 and standard deviation 1 for the population of people who ever enroll in college. The figure shows that those who enroll in humanities degrees tend to be below average in all three abilities. In contrast, those who enroll in medicine tend to be above average in all three abilities. For other majors there is differential sorting on ability. For example, business majors tend to be high in interpersonal ability but below average in cognitive abilities. Math and science majors tend to be above average in cognitive and grit abilities but below average in interpersonal ability, while Social Science majors are the reverse with above average in interpersonal ability and below average in cognitive and grit abilities. In most cases, graduation selects individuals with higher grit and cognitive ability, significantly increasing the mean grit in all majors while slightly increasing cognitive ability in most.

Figure 3: Sorting into Major Enrollment and Graduation By Skill

Enrollment



Graduation



Notes: Figure shows the average interpersonal, cognitive, and grit abilities by four-year major. All abilities are normalized to be mean 0 and standard deviation one for the population of people who ever enroll in college. The top panel shows average abilities by initial enrollment and the bottom panel shows average abilities for graduates in a major.

5.2 Non-parametric Decomposition of Wages and Present Value of Income

What is the relationship between earlier and later investments when explaining earnings? We start to answer this question by performing a number of non-parametric variance decompositions. In doing so, we provide descriptive evidence while imposing minimal assumptions.[25] Earnings are decomposed into four components: ability, background, pre-college education choices, and college education choices. Each of these components in isolation explain a large portion of the variance of wages (between 12.4% and 23.5%). The goal is to understand how much the variance explained by later investments changes after controlling for earlier investments.

Earnings can be decomposed by repeated application of the law of total variance. One possible decomposition is to start with earlier investments:

$$
\begin{aligned}
\underbrace{Var(w)}_{(0.095)} &= Var\left(\mathbb{E}\left[w|\hat{\boldsymbol{\theta}}\right]\right) + \mathbb{E}\left[Var\left(w|\hat{\boldsymbol{\theta}}\right)\right] \\
&= Var\left(\mathbb{E}\left[w|\hat{\boldsymbol{\theta}}\right]\right) + \mathbb{E}\left[Var\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}},\boldsymbol{X}]|\hat{\boldsymbol{\theta}}\right)\right] + \mathbb{E}\left[Var\left(w|\hat{\boldsymbol{\theta}},\boldsymbol{X}\right)\right] \\
&= \underbrace{Var\left(\mathbb{E}\left[w|\hat{\boldsymbol{\theta}}\right]\right)}_{\text{Ability (0.157)}} + \underbrace{\mathbb{E}\left[Var\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}},\boldsymbol{X}]|\hat{\boldsymbol{\theta}}\right)\right]}_{\text{Observables conditional on ability (0.113)}} \\
&\quad + \underbrace{\mathbb{E}\left[Var\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}},\boldsymbol{X},\boldsymbol{D}_{pre}]|\hat{\boldsymbol{\theta}},X\right)\right]}_{\text{Pre-college choices conditional on ability and background (0.054)}} \\
&\quad + \underbrace{\mathbb{E}\left[Var\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}},\boldsymbol{X},\boldsymbol{D}_{pre},\boldsymbol{D}_{coll}]|\hat{\boldsymbol{\theta}},\boldsymbol{X},\boldsymbol{D}_{pre}\right)\right]}_{\text{College Choices conditional on earlier investments (0.086)}} \\
&\quad + \underbrace{\mathbb{E}\left[Var\left(w|\hat{\boldsymbol{\theta}},\boldsymbol{X},\boldsymbol{D}_{pre},\boldsymbol{D}_{coll}\right)\right]}_{\text{Unexplained (0.590)}}, \qquad (4)
\end{aligned}
$$

where $\hat{\boldsymbol{\theta}}$ represents estimated factor scores for each individual, $\boldsymbol{X}$ represents background observables, $\boldsymbol{D_{pre}}$ represents pre-college education choices, and $\boldsymbol{D_{coll}}$ represents college choices.[26] Underneath the left-hand side term, we show the standard deviation of wages

[25] *e.g.* we do not have to impose assumptions of linearity or separability of error terms.

[26] Factor scores are estimated using the estimated measurement system and finding the vector $\hat{\boldsymbol{\theta}}$ that maximizes the likelihood for *each* individual. $\boldsymbol{D_{pre}}$ includes four indicators, taking advanced math in ninth grade, taking advanced English in ninth grade, graduating high school in an academic track and

in our data. On the right hand side, we show the proportion of the variance explained by each term after performing the non-parametric variance decomposition.[27] The four components in total explain more than 40% of the variance in log wages.

Of course the fraction of the variance explained by each component will depend on the order of the decomposition. Table 6 presents most of the individual terms that would arise from applying the law of total variance in different orders. The first column shows the fraction of the variance explained by each component or combination of components without any conditioning. The second column shows the fraction of the variance explained by each component controlling for all other components. The last six columns show the fraction of variance explained by each component after controlling for each individual component or pair of components.

The various decompositions show strong dependencies between the different components. College choices alone explain about 24% of the variance in wages, but this explained variance declines substantially once pre-college controls are considered. College choices explain only 11.2% when first controlling for ability and family background. Similarly, college choices explain only 10% of the variance of wages when first controlling for pre-college education choices. Recall that pre-college education choices include just four indicators. When first controlling for all pre-college variables, the variance explained by college education choices drops to 8.6% of the variance of wages or 36.6% of the value without controls. The reverse can be studied as well though. Abilities and family background, in isolation, explain about 26% of the variance in wages. When first controlling for both pre-college and college education choices, this drops to just 4.3% of the variance of wages or 16.7% of the value without controls. The drop in variation explained

graduating high school in an STEM-focused academic track. $\boldsymbol{D_{coll}}$ includes 14 indicators: eight major groups for four-year degrees, four major groups for 2-3 years degrees, two for college dropouts from 4-year and 2-3 year programs. The omitted category for $\boldsymbol{D_{coll}}$ is never enrolled in college.

[27] Nonparametric decompositions are performed using conditional inference trees (Hothorn et al., 2006). The algorithm is a recursive partitioning algorithm similar to CART, but it additionally addresses the tendency of recursive partitioning algorithms such as CART to overfit and be biased towards variables with many possible divisions. For models without conditioning variables, the algorithm is run requiring at least 25 observations in each final bin. Models with conditional variables are run in three parts. First the algorithm is run on the conditioning variables with the constraint of final bins having at least 600 observations. Second, the algorithm is run on the other variables bin-by-bin, requiring at least 25 observations in each final bin. Third, a probability weighted sum of variances is taken to get the overall variance of the conditional expectation.

by college choices is evidence of strong selection into college choices, while the drop in variation explained by ability and family background is evidence of complementarities between pre-college investments and college choices.[28] These facts motivate the analyses on ability sorting into education choices and the complementarities between ability and college choices in the next two sections. In section 6, we show that there are strong dynamic complementarities between high school track choices and college major choices as well.

[28]Very strong sorting could also explain the drop in the variation explained by ability and family background. While we see evidence of sorting into education choices, it is not to the degree that could explain this drop.

Table 6: Log Wage Decomposition (proportion of total variance explained)

Panel A: Wages.		Conditioning Variables							
		None	All Others	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{X}$	$(\hat{\boldsymbol{\theta}}, \boldsymbol{X})$	$\boldsymbol{D}_{pre}$	$\boldsymbol{D}_{coll}$	$\boldsymbol{D}_{all}$
Abilities	$\text{Var}(\mathbb{E}[w\|\hat{\boldsymbol{\theta}}])$	0.156	0.032		0.155		0.034	0.033	0.026
Background	$\text{Var}(\mathbb{E}[w\|\boldsymbol{X}])$	0.112	0.029	0.101			0.036	0.032	0.028
Abilities and Background	$\text{Var}(\mathbb{E}[w\|\hat{\boldsymbol{\theta}}, \boldsymbol{X}])$	0.247	0.049	0.101	0.155		0.071	0.062	0.049
Pre-College Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{pre}])$	0.199	0.007	0.083	0.129	0.053		0.014	
College Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{coll}])$	0.264	0.073	0.153	0.194	0.117	0.081		
All Education Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{all}])$	0.280	0.118	0.155	0.201	0.118	0.081	0.014	
Panel B: PV Disposable Income.		Conditioning Variables							
		None	All Others	$\hat{\boldsymbol{\theta}}$	$\boldsymbol{X}$	$(\hat{\boldsymbol{\theta}}, \boldsymbol{X})$	$\boldsymbol{D}_{pre}$	$\boldsymbol{D}_{coll}$	$\boldsymbol{D}_{all}$
Abilities	$\text{Var}(\mathbb{E}[w\|\hat{\boldsymbol{\theta}}])$	0.156	0.031		0.156		0.034	0.033	0.026
Background	$\text{Var}(\mathbb{E}[w\|\boldsymbol{X}])$	0.110	0.028	0.100			0.035	0.031	0.027
Abilities and Background	$\text{Var}(\mathbb{E}[w\|\hat{\boldsymbol{\theta}}, \boldsymbol{X}])$	0.245	0.048	0.100	0.156		0.070	0.060	0.048
Pre-College Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{pre}])$	0.199	0.007	0.083	0.128	0.053		0.014	
College Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{coll}])$	0.265	0.073	0.152	0.195	0.117	0.082		
All Education Choices	$\text{Var}(\mathbb{E}[w\|\boldsymbol{D}_{all}])$	0.280	0.118	0.155	0.200	0.118	0.082	0.014	

Notes: Each element of the table shows a different term from a non-parametric decomposition of wages. The first column shows the amount of variance accounted for by each variable. The second column shows the variance after conditioning on all other variables. For example, the first row, first column is the variance of wages due to ability (*i.e.* $\text{Var}(\mathbb{E}[w|\hat{\boldsymbol{\theta}}])$). The first row, second column is the variance due to ability after conditioning on observables and education choices (*i.e.* $\mathbb{E}\left[\text{Var}\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}}, \boldsymbol{X}, \boldsymbol{D}_{pre}, \boldsymbol{D}_{coll}]|\boldsymbol{X}, \boldsymbol{D}_{pre}, \boldsymbol{D}_{coll}\right)\right]$). The last column for ability ($\boldsymbol{D}_{all}$) is similar, but does not condition on $\boldsymbol{X}$ (*i.e.* $\mathbb{E}\left[\text{Var}\left(\mathbb{E}[w|\hat{\boldsymbol{\theta}}, \boldsymbol{D}_{pre}, \boldsymbol{D}_{coll}]|\boldsymbol{D}_{pre}, \boldsymbol{D}_{coll}\right)\right]$). Nonparametric decompositions are performed using conditional inference trees (Hothorn et al., 2006).

5.3 Labor Market Returns to Multidimensional Ability

We investigate the role of abilities in earnings by estimating separate earnings equations for each final schooling state.[29] Associated with each final schooling state s is a potential model of earnings measure k for each individual. Let Y_{isk} denote the earnings measure k of each individual i in final schooling state s. Earnings are a function of a vector of observables $\boldsymbol{X}_i$, a finite dimensional vector of latent abilities $\boldsymbol{\theta}_i$, and an idiosyncratic error term η_{isk}. We assume a separable model for earnings:

$$Y_{isk} = \boldsymbol{\beta}_{sk}^{Y} \boldsymbol{X}_i + \boldsymbol{\lambda}_{sk}^{Y} \boldsymbol{\theta}_i + \eta_{isk}. \tag{5}$$

By estimating separate models for each final schooling state, we can investigate the complementarities between college major and abilities in the labor market. Figure 5 shows the estimates of $\hat{\boldsymbol{\lambda}}_{sk}^{Y}$ for workers with four-year college degrees.[30] In general, all three abilities have large and positive returns in the labor market, but there is a great deal of heterogeneity. Perhaps unsurprisingly, education majors have smallest returns to ability of four-year degree holders, where increasing any of the three abilities by one standard deviation is associated with a 2% increase in wages. In contrast, business majors have largest returns to all three abilities. What is perhaps surprising is the difference in patterns in returns to the different abilities across majors. For example, the three abilities have roughly the same returns for Social Science Majors, while interpersonal skills have more than twice the return compared to cognitive and grit for Science and Math majors. Indeed, one of the more surprising findings is that wages vary more with interpersonal ability than cognitive ability for science, math, and engineering majors. The pattern is even more striking when we turn to the present value of disposable income. Except for Medicine and Law, PV disposable income is most strongly associated with interpersonal abilities.

[29]The 15 final schooling states are 4-year graduates in eight major groups, 2-3 year college graduates in 4 major groups, college dropouts from 4-year and 2-3 year programs, and high school graduates. See section 3 for more information about schooling categories.

[30]These models are estimated via maximum likelihood using the first stage measurement system as described in section 4.

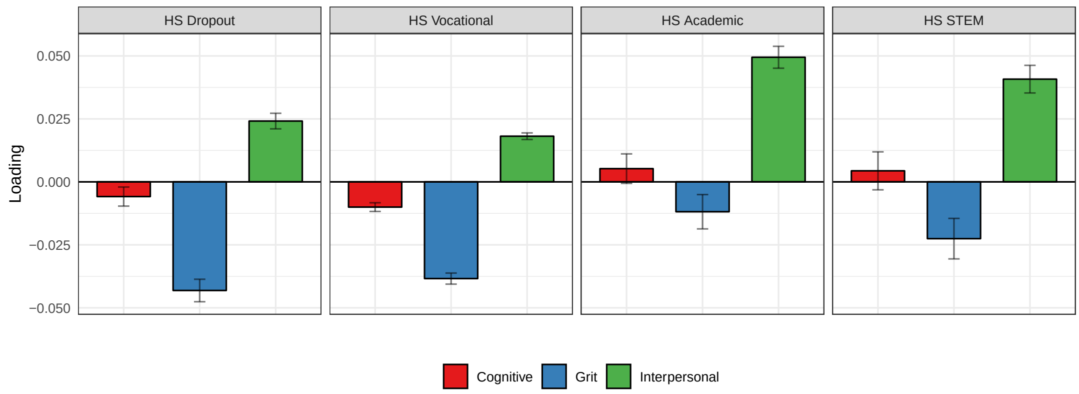
Looking at the associations between ability and earnings does not show how the level of earnings vary by major. The earnings of a particular major may not be strongly related to ability, but high-ability workers may choose a particular major because it offers higher earnings overall. We address this question in two ways in Figure 7 and Table 7. Figure 7 shows how earnings vary by each ability using the mean of the observables to calculate an expected wage for the "average" worker in observables. What is striking is the large amount of variation in earnings when only modifying one ability at a time. What is clear from this figure is that there is no absolute ranking of majors by earnings. Varying only one dimension of ability like grit can move business from being the fourth highest earning major to the highest earning major for an "average" worker.

To get a better idea of the heterogeneity in the rankings of majors by earnings, we create a sample of one million synthetic workers by drawing a vector of observables from our data ($\boldsymbol{X}_i$) and then drawing latent abilities from the factor distribution ($\boldsymbol{\theta} \sim F_{\boldsymbol{\theta}}(\theta; \hat{\gamma}_\theta)$).[31] For each of the synthetic workers, we calculate their expected earnings in the different schooling states ($\mathbb{E}[Y_{sk}] = \boldsymbol{\beta}_{sk}^{Y}\boldsymbol{X} + \boldsymbol{\lambda}_{sk}^{Y}\boldsymbol{\theta}$) and then record which schooling state has the highest expected earnings for that worker ($\arg\max_s\{\mathbb{E}[Y_{sk}]\}$). This accounts for the full heterogeneity in worker background/observables and ability. Table 7 shows the proportion of synthetic workers that would rank each major as the top major in expected earnings. Clearly there is no absolute ranking of majors by earnings. There is not even a major that is ranked highest for more than 0.35 of the population.

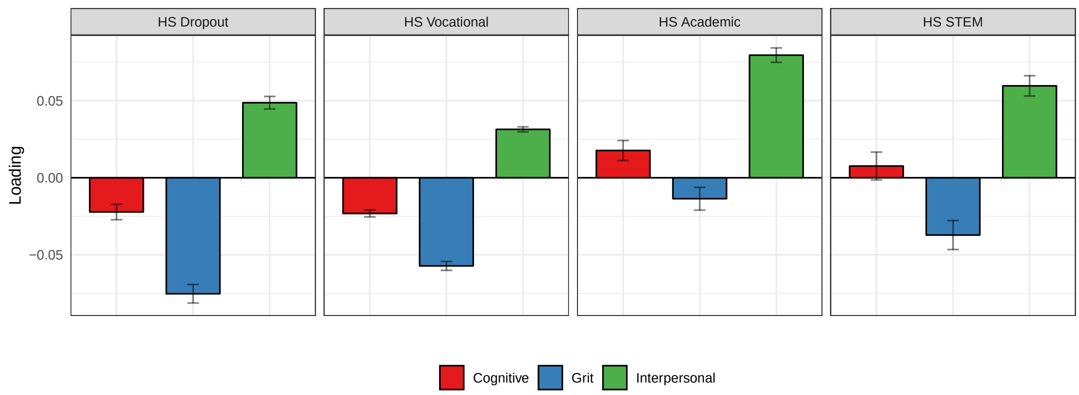
[31] Recall that our latent abilities are residuals. In other words, the factors represent the variation in latent ability after accounting for observables.

Figure 4: Returns to Ability across High School Track ($\hat{\boldsymbol{\lambda}}_{ks}$)

Log Wage Income



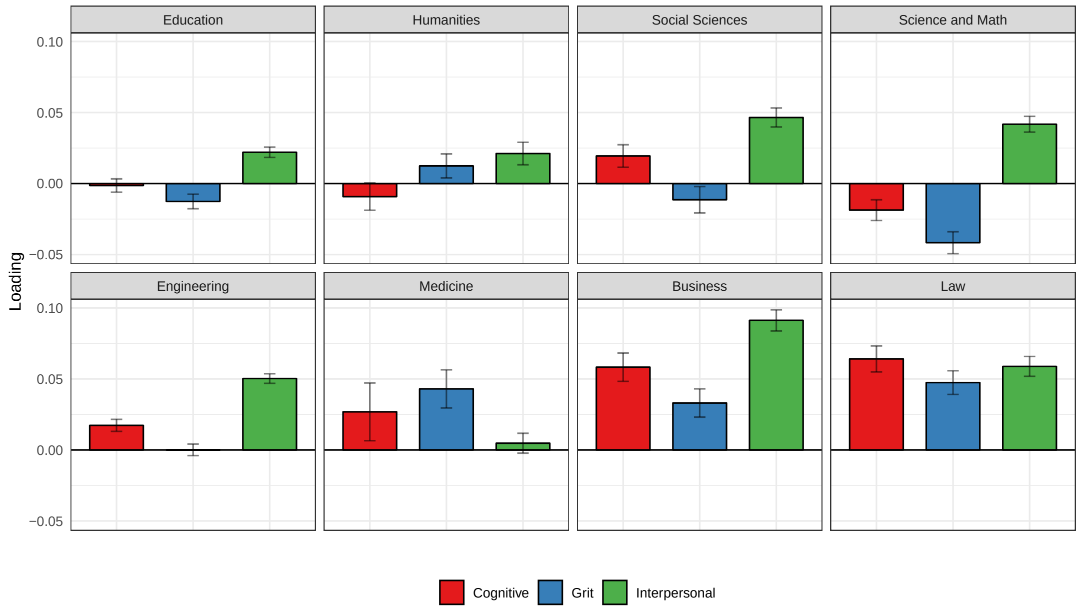
PV Disposable Income



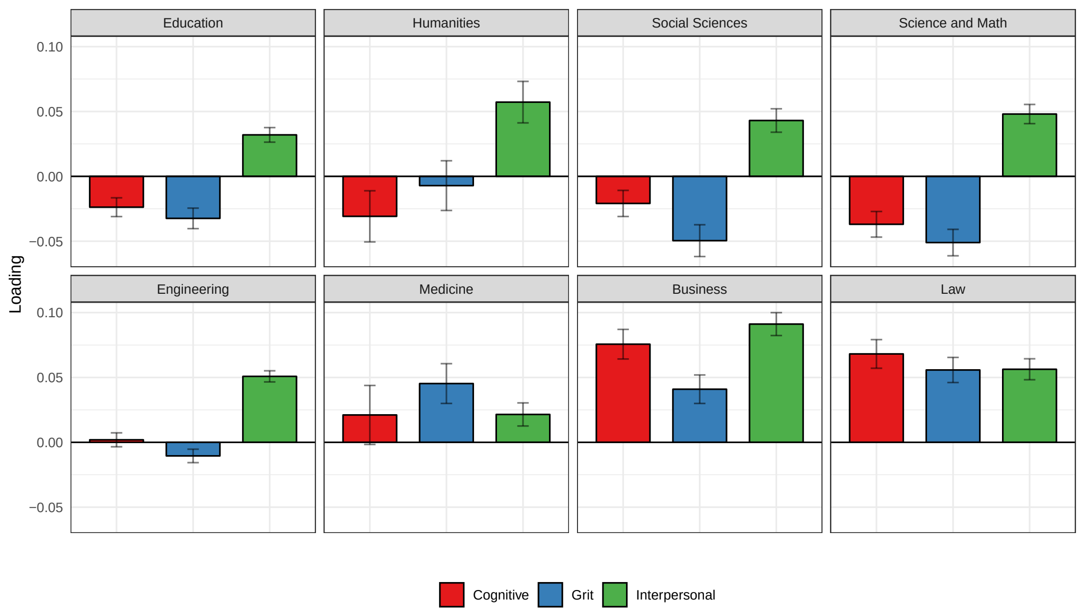
Notes: These figures are comparing the returns to ability ($\hat{\boldsymbol{\lambda}}_{ks}$) for terminal high school graduates.

Figure 5: Returns to Ability across Majors ($\hat{\boldsymbol{\lambda}}_{ks}$)

Log Wage Income

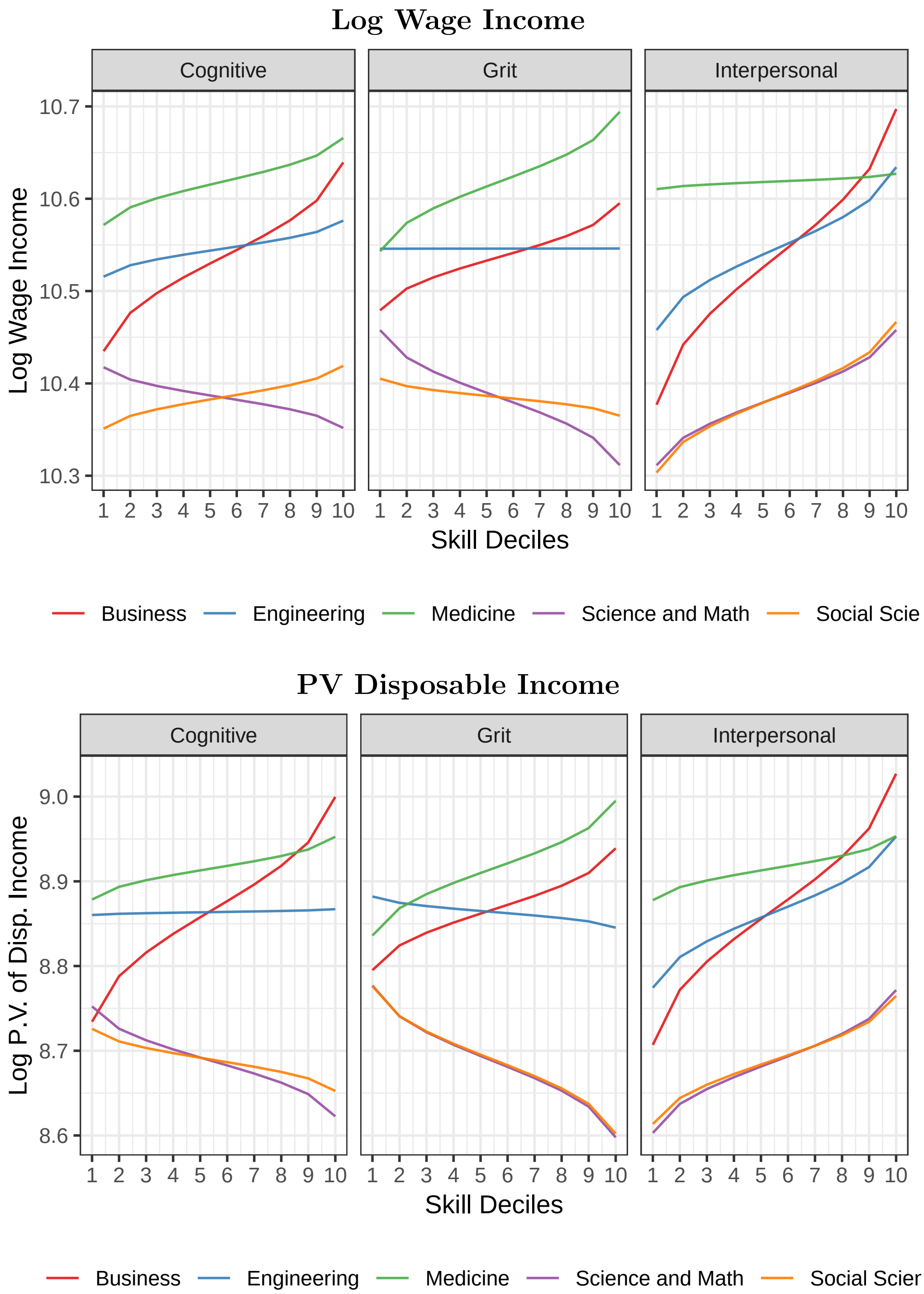


PV Disposable Income



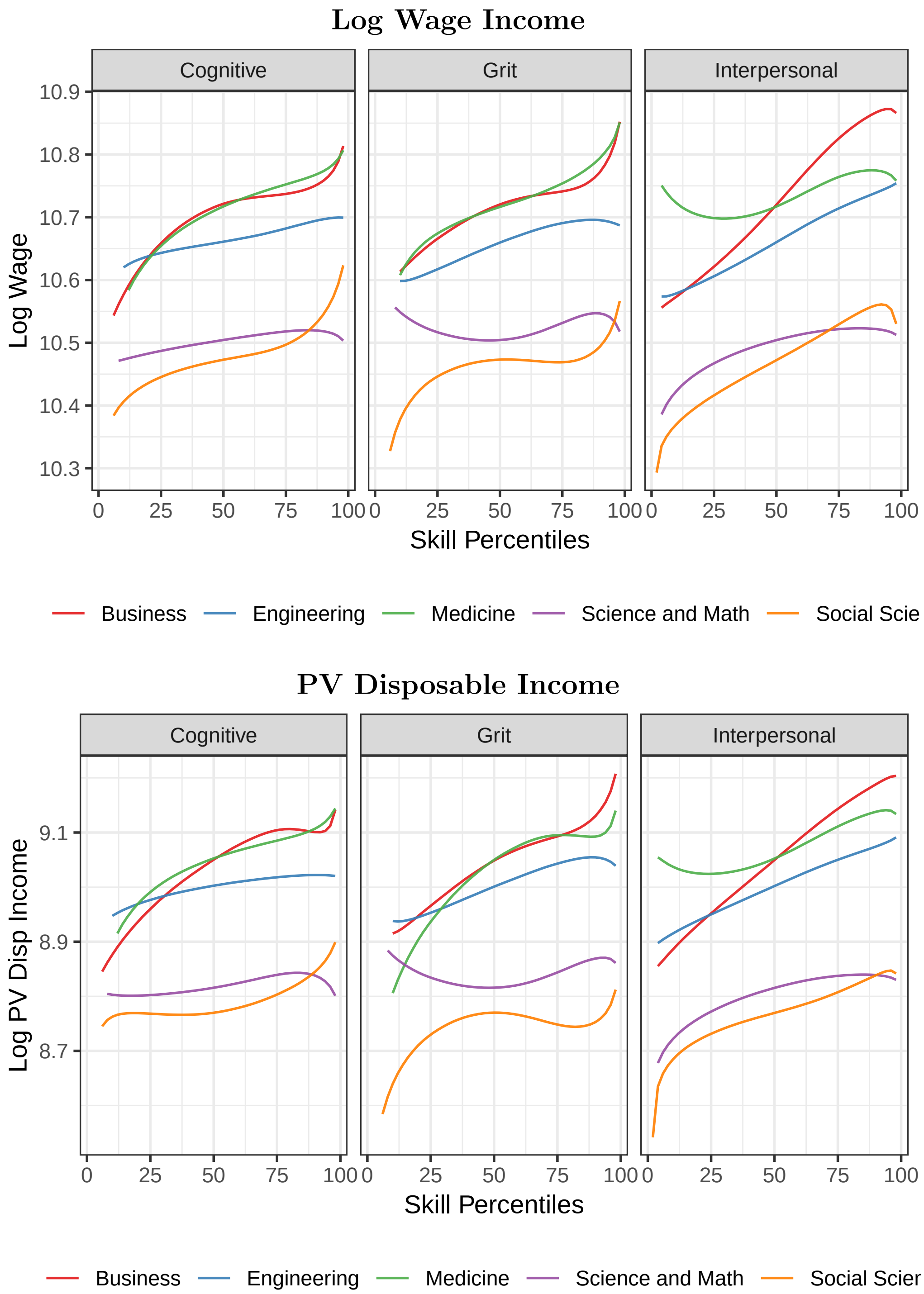
Notes: These figures are comparing the returns to ability ($\hat{\boldsymbol{\lambda}}_{ks}$) for four-year graduates.

Figure 6: Expected Earnings across Majors by Ability



Notes: Figure shows the average log-wage income by decile of cognitive, interpersonal, and grit ability for a select set of four-year college majors. Deciles are calculated based on the population of students who ever enroll in college.

Figure 7: Expected Earnings across Majors by Ability



Notes: Figure shows the average log-wage income by decile of cognitive, interpersonal, and grit ability for a select set of four-year college majors. Deciles are calculated based on the population of students who ever enroll in college.

Table 7: Fraction Ranking each Major First in Expected Earnings

Major	Log Wage	PV Disposable Income
Medicine	0.49	0.40
Business	0.27	0.30
Business (3-year)	0.14	0.13
STEM (3-year)	0.04	0.05
Engineering	0.03	0.06
Law	0.03	0.04

Notes: The table reports the six majors with highest proportion of individuals ranking the major first in terms of expected earnings. A sample of one million synthetic workers are created by drawing a vector of observables from the data and drawing a vector of latent abilities from the estimated factor distribution. The expected log wage and PV disposable income are calculated for each synthetic worker using estimates of equation 5 ($\mathbb{E}[Y_{sk}] = \boldsymbol{\beta}^{Y}_{sk}\boldsymbol{X} + \boldsymbol{\lambda}^{Y}_{sk}\boldsymbol{\theta}$).

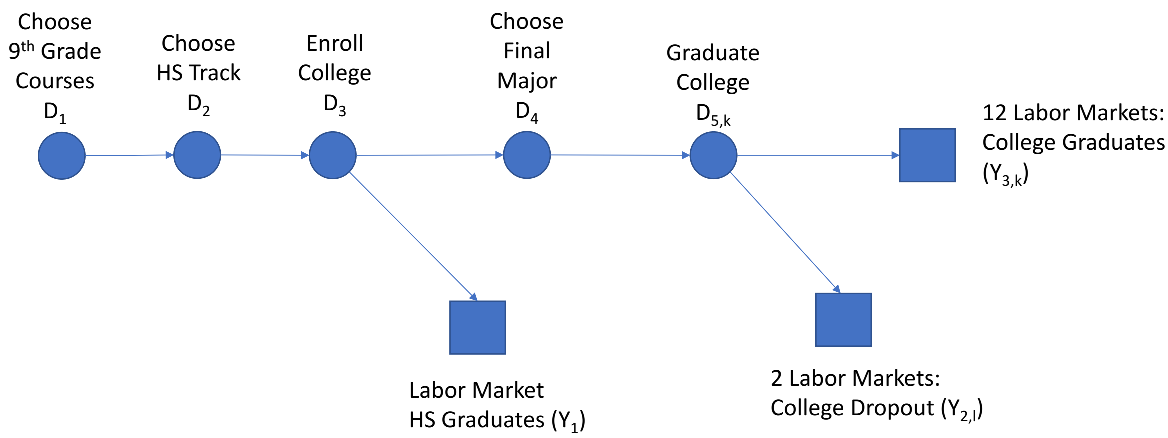
6 Causal estimates of the Effect of High School Track

Building on the analysis of the role of high school choices and abilities in Section 5, this section develops a generalized Roy model of education choice and labor market outcomes and uses this model to study the causal effects of high school tracking decisions on subsequent post-secondary education choices and labor market earnings. In particular, we focus on the heterogeneous impacts of intervening in high school tracking decisions and how the returns to these decisions vary based on students' multi-dimensional abilities.

6.1 Empirical Model of Education and Earnings

This section estimates a sequential model of schooling decisions and labor market outcomes. The decision tree of this model is illustrated in Figure 8. Ninth grade students make two binary decisions whether or not to enroll in the advanced math ($D_{10} = 1$) or advanced English ($D_{11} = 1$) courses at the ninth grade decision nodes (D_{1k_1}). Upon enrolling in high school, students make a multinomial choice of high school track ($D_2(\mathcal{K}_2)$). Let $k_2 \in \mathcal{K}_2 = \{1, 2, 3\}$ denote vocational, academic, and STEM tracks, respectively. High school graduates make a multinomial choice of deciding whether to enroll in college and which field of study they wish to enroll in ($D_3(\mathcal{K}_3)$). Let $k_3 \in \mathcal{K}_3 = \{0, 1, ..., N_{field}\}$ denote the field of study and type of degree, where $k_3 = 0$ denotes no enrollment in college. Once enrolled in college, students make another multinomial choice to switch

Figure 8: Sequential Model of Major Choice and Earnings



field or college, $D_4(\mathcal{K}_4)$. Let $k_4 \in \mathcal{K}_4 = \{1, ..., N_{field}\}$ denote the final field of study and type of degree. Finally, enrolled students make a binary decision whether to graduate or not in their final field of study and type of degree (D_{5k_5}), where $k_5 = k_4 \in \mathcal{K}_4$. Let $j \in \mathcal{J}$ denote the decision node in the education model and $s \in \mathcal{S}$ denote the final schooling level (high school, college dropout or college graduate).

If students do not enroll in college ($D_3(\mathcal{K}_3) = 0$), they enter the high school labor market and earn Y_1. If they enroll in college ($D_3(\mathcal{K}_3) > 0$), but do not graduate ($D_{5k_5} = 0$), they enter the labor market for college drop outs and earn Y_{2k_5}, otherwise they enter the labor market for college graduates and earn Y_{3k_5}, where $k_5 = D_4(\mathcal{K}_4)$.

The choices of high school track, enrolling, degree type, and field of study are characterized by the maximization of a latent variable I_{jk}, where individual i subscripts are suppressed. Let I_{jk} represent the perceived value associated with the choice of high school track ($j = 2$), enrollment degree type and field ($j = 3$), or final degree type and field

($j = 4$):

$$D_j(\mathcal{K}_j) = \arg\max_{k_j \in \mathcal{K}_j} \{I_{jk_j}\} \quad \text{for} \qquad j \in \{2, 3, 4\}$$

where $D_j(\cdot)$ denotes the individual's multinomial choice.

The perceived value for each choice is a function of observable background characteristics ($\boldsymbol{X}_{jk_j}$), choice-specific instruments that do not enter the outcome models ($\boldsymbol{Z}_{jk_j}$), a finite dimensional vector of unobserved abilities $\boldsymbol{\theta}$, and an idiosyncratic error term ε_{jk_j}, which is unobserved by the econometrician:

$$I_{jk_j} = \boldsymbol{\beta}^E_{jk_j} \boldsymbol{X}_{jk_j} + \boldsymbol{\gamma}_{jk_j} \boldsymbol{Z}_{jk_j} + \boldsymbol{\lambda}^E_{jk_j} \boldsymbol{\theta} + \alpha^E_{jk} \upsilon_i + \varepsilon_{jk_j} \quad \text{for} \quad k_j \in \mathcal{K}_j \quad \text{and} \quad j \in \{1, ..., 5\}.$$

We model schooling-specific labor market outcomes which similarly depend on background characteristics, the individual's vector of unobserved abilities, and an additional random effect that affects education decisions and outcomes. Labor market outcome s of individual i with schooling level k is given by:

$$Y_{isk} = \boldsymbol{\beta}^Y_{sk} \boldsymbol{X}_i + \boldsymbol{\lambda}^Y_{sk} \boldsymbol{\theta}_i + \alpha^Y_{sk} \upsilon_i + \varepsilon_{isk}.$$

6.2 Within-School-Across-Cohort Instruments

Following the peer-effects literature, we construct within-school-across-cohort instruments for ninth grade advanced course choice, high school track, and college field enrollment. Since the construction of the instruments is similar for the different margins, we focus on the high school track instrument here. Remember that $k_2 \in \{1, 2, 3\}$ denotes the high school track. Let l denote the ninth-grade school and t denote the year (cohort). First, we calculate the proportion of students in each ninth grade school year that choose each track ($P_{k_2,l,t}$). There are three proportions per school year. Second, we remove track-year fixed effects from these proportions ($\tilde{P}_{k_2,l,t}$). We then calculate the $-t$ school average proportion ($\overline{P}_{k_2,l,-t}$), or, in other words, the average proportion over all years except t for each school. Let this be the "9th grade school average" for year t. Third, for each student i, we calculate the $-i$ proportion of students choosing each track in the school year that student i is enrolled in ninth grade ($P_{k_2,l,t,-i}$). Fourth, we regress $P_{k_2,l,t,-i}$ on $\overline{P}_{k_2,l,-t}$, and the residual of that regression is the IV for student i.

Tables A.12, A.13, and A.14 show the first-stage regressions for the IV associated with the vocational, academic, and STEM tracks, respectively. Focusing on the first specification, we find that the instruments are relevant in all three cases, where the smallest F-statistic is 42.44. The exclusion restriction of this instrument is that it affects the decision to enroll in a high school track and that within-school-cohort-variation in these decisions does not directly affect later outcomes.[32] One potential violation of the exclusion restriction is if a student's cohort affects his or her ability. We test this in two ways. In the second specification we control for the student's ninth-grade GPA and find that instrument does not become less relevant. The coefficient and F-statistic for the vocational and STEM tracks increase. In the third specification, we calculate school average GPA and cohort average GPA as measures of the average ability at the school and of the cohort (GPA in ninth grade is comparable across schools in Sweden). Again, we find that the coefficient on the instrument and the F-statistic of the vocational and STEM tracks become stronger once we control for cohort and school ability. In the case of the academic track, the coefficient does not change in a substantive way. We interpret the results of the second and third specifications as evidence that neither the student's own ability nor potential variation in the ability of the student's peers are violating the exclusion restriction.

6.3 Returns to HS Track

This section lays out a series of results from the estimated model. In the first subsection we document a range of treatment effects of high school track, where the treatment effects are calculated for different margins. The treatment effects are calculated for three

[32]We postulate that what may be driving this variation is that a particularly charismatic and enthusiastic (or a particularly uncharismatic and unenthusiastic) person that the students see as a positive (or negative) role model is coming to a 9th grade school to advertise a particular high school line in any given year.

outcomes: college enrollment, college graduation, log-wages, and the discounted present value of income. In addition, we show how these effects vary by deciles of cognitive ability, interpersonal ability, and grit. In the second sub-section we consider the effect of high school track on the choice of college field for students who are indifferent between choosing the STEM track and one of the other tracks. In the third sub-section we study the impacts of a policy that shuts down the high school vocational track.

6.3.1 Treatment Effects

This section estimates the treatment effects for the three high school track margins. Specifically, we estimate the gains from changing high school track from vocational to STEM, from vocational to academic, and from academic to STEM. The estimates are for the population of individuals with at least a high school degree. We estimate the treatment effects of high school track on college enrollment, college graduation, log-wages, and the log discounted present value of disposable income. For each margin and outcome, we calculate the average treatment effect, the average treatment effect for those with high abilities, the average marginal treatment effect, the average treatment effect for those with low abilities, the treatment on the treated (TT), and the treatment on the untreated (TUT).[33]

Figures 9 and 10 show the full set of treatment effects on college outcomes and log-wages. The top panel of figure 9 shows the treatment effects on college enrollment, and the bottom panel shows the treatment effects on graduation. Figure 9 shows that the average treatment effects for enrolling and graduating from college are in general large and positive. The treatment effects are in general largest for switching students from vocational to STEM tracks, then academic to STEM have the next largest treatment effects, and vocational to academic have the smallest treatment effects. The treatment effects on enrollment and graduation are in general lower for low-ability individuals and highest for those at the margin (AMTE) between the two high school tracks, except for the treatment effect on enrollment for the STEM vs academic margin, where the treatment

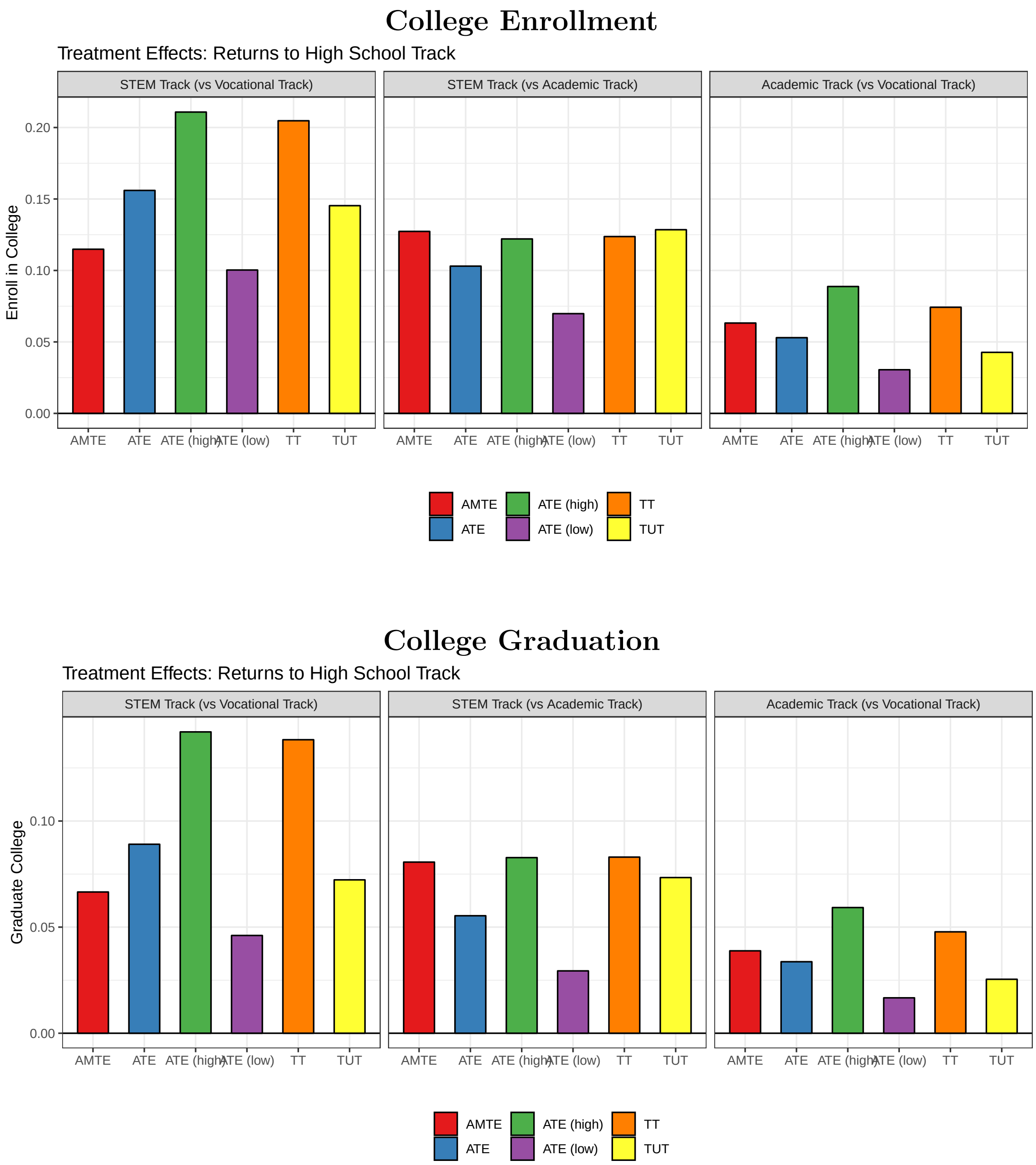
[33]High ability is defined as being in the top 50% of all three abilities, while low ability is defined as being in the bottom 50% of all three abilities.

effects are similar across ability groups. We find that switching students into the STEM track from vocational track increases college enrollment by 25-35% and increases college graduation by 15-20%. Many of those enrolling do not graduate. Smaller effects are seen for the other two margins. Switching a student from the academic track to the STEM track increases enrollment by around 20% and graduation by 6-11%. While only half of the low-ability individuals that enroll end up graduating, most of the high-ability individuals graduate. The vocational-academic margin has the smallest treatment effects, where probability of enrollment increases by 6-15% and the probability of graduating increases only 4-10%.

The treatment effects of high school track on college graduation accounts for the fact that many students who enroll in college do not graduate. Specifically, the graduation treatment effects counterfactually set high school track but then allow agents to make enrollment, switching, and graduation decisions. We find that there is more heterogeneity in graduation decisions than enrollment decisions. For example, the difference between the the treatment effects for high-ability and low-ability individuals is larger for the graduation decision across all three margins. Similarly, the difference between treatment on the treated and treatment on the untreated increases for the STEM vs vocational margin and the academic vs vocational margin.

Figure 10 shows the treatment effects of high school track on log wages and the log discounted present value of disposable income. The effects for log wage are largest when switching students away from the vocational track. Switching students from vocational to academic tracks increases wages by 6-9%, while switching students from the vocational to STEM tracks increases wages by 3-9%. Interestingly, the results suggest that the treatment effects of switching from the academic to STEM track are negative and between -2 to -3%. The negative effects for the STEM vs Academic margin are driven by the fact that the returns to high school track are estimated to be larger for high school graduates and college dropouts. When comparing the STEM and academic tracks to the vocational track, we again see that the effects tend to be largest for high ability individuals and for those who choose those tracts (TT). Results are similar, though somewhat larger, when considering log discounted value of present income.

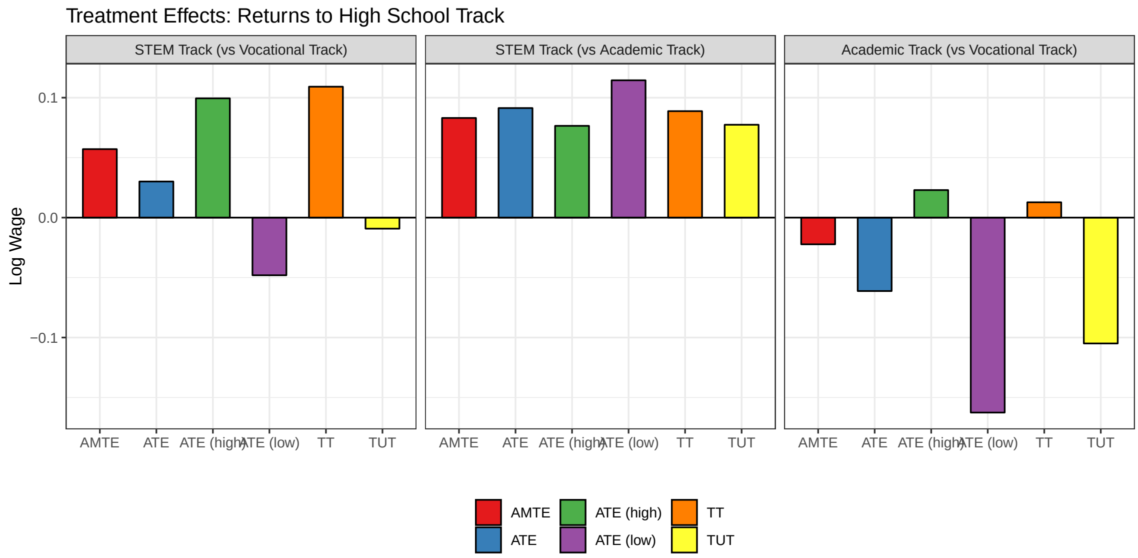
Figure 9: Treatment Effects: College Enrollment and Graduation



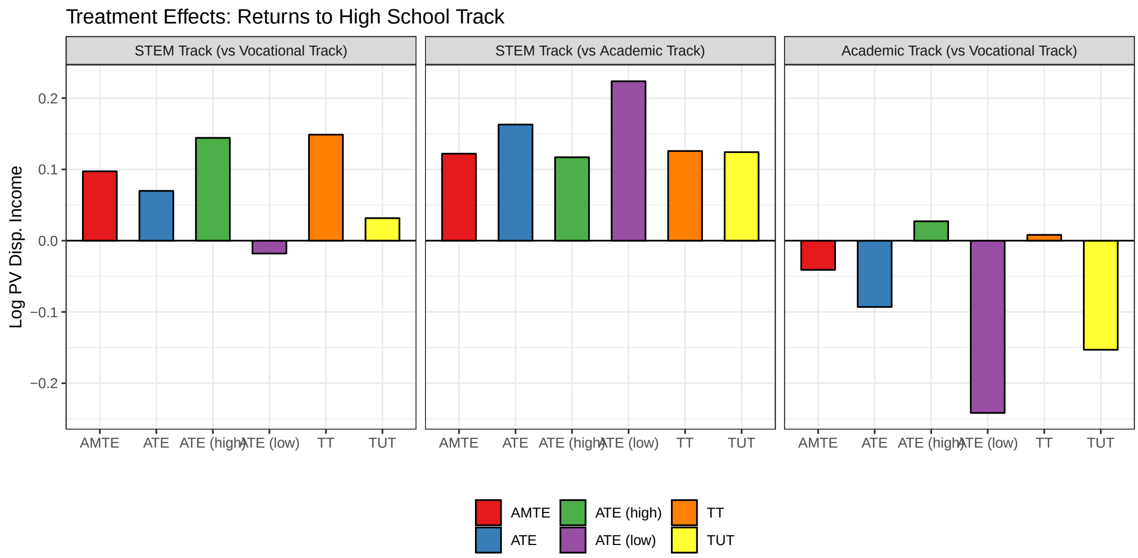
Notes: Figure shows the estimated treatment effects for the three high school track margins on college enrollment (top) and college graduation (bottom). The treatment effects are estimated for everyone who has at least a high school degree. High ability is defined as being in the top half of all three ability distributions, while low ability is defined as being in the bottom half of all three ability distributions.

Figure 10: Treatment Effects: Wages and P.V. Disposable Income

Log Wage



Log P.V. Disposable Income



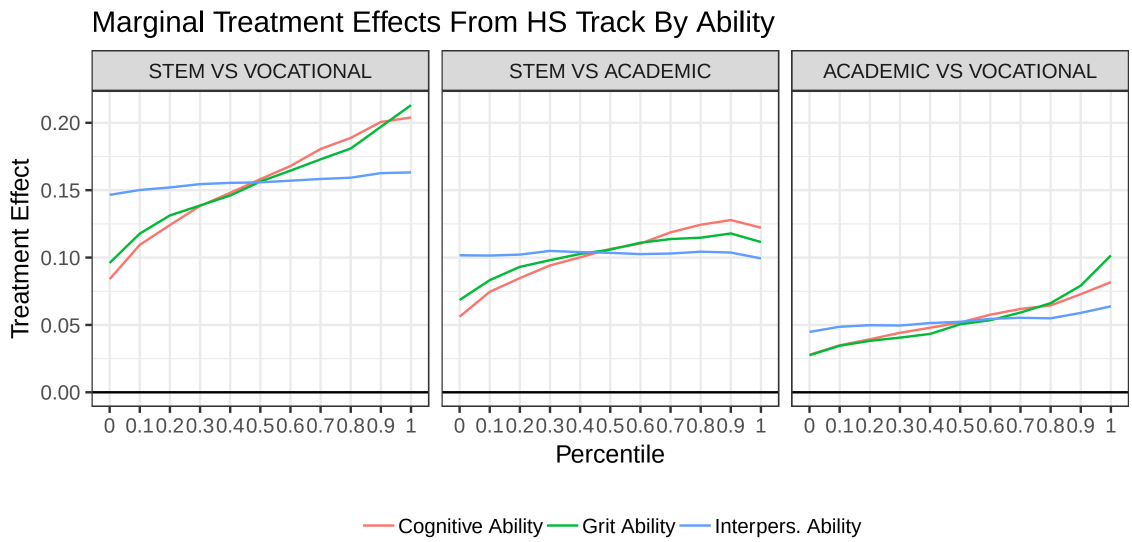
Notes: Figure shows the estimated treatment effects for the three high school track margins on log-wages. The treatment effects are estimated for everyone who has at least a high school degree. High ability is defined as being in the top half of all three ability distributions, while low ability is defined as being in the bottom half of all three ability distributions.

6.3.2 Returns to High School Track by Ability

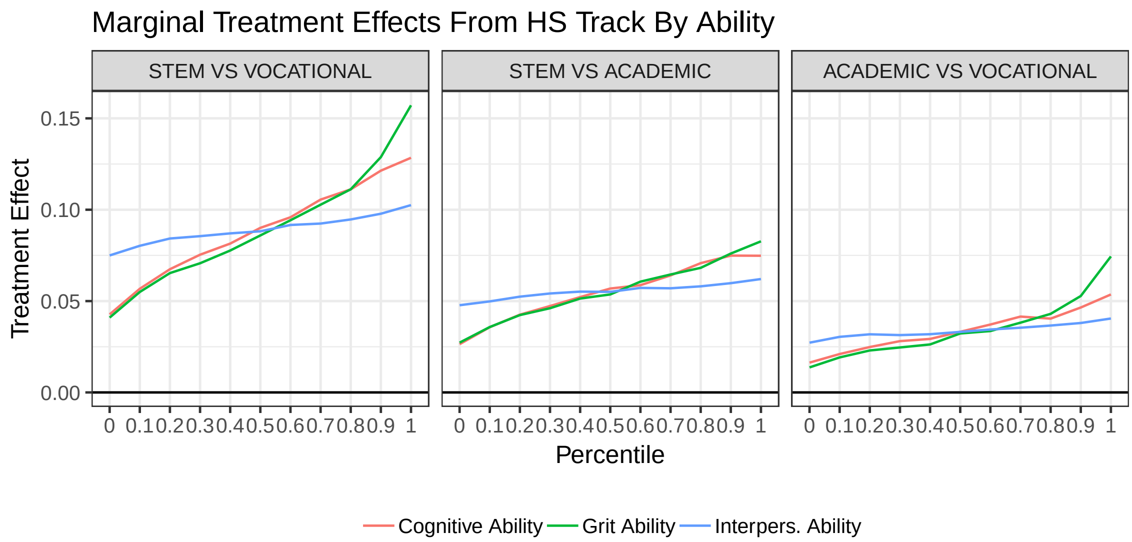
This section reports the average treatment effects to each high school track by decile of the three abilities. Figure 11 shows the treatment effects across each college margin by ability deciles for each of the three abilities. We find that the returns to the STEM track over the vocational track as well as the academic track over the vocational track are increasing in cognitive ability and grit ability for college enrollment, with an increased probability of enrolling by almost 10 percentage points when moving from the bottom to the top decile. In contrast, returns depend little on interpersonal ability. Figure 12 shows similar results for labor market outcomes. We find that the returns to STEM over vocational and academic over vocational are increasing in all three abilities. In contrast, the returns to STEM over academic are negative and relatively flat across the ability deciles, except for the top deciles of cognitive and grit abilities, where the returns to STEM over the academic track are more negative.

Figure 11: Treatment Effects by Ability: post-secondary outcomes

College Enrollment



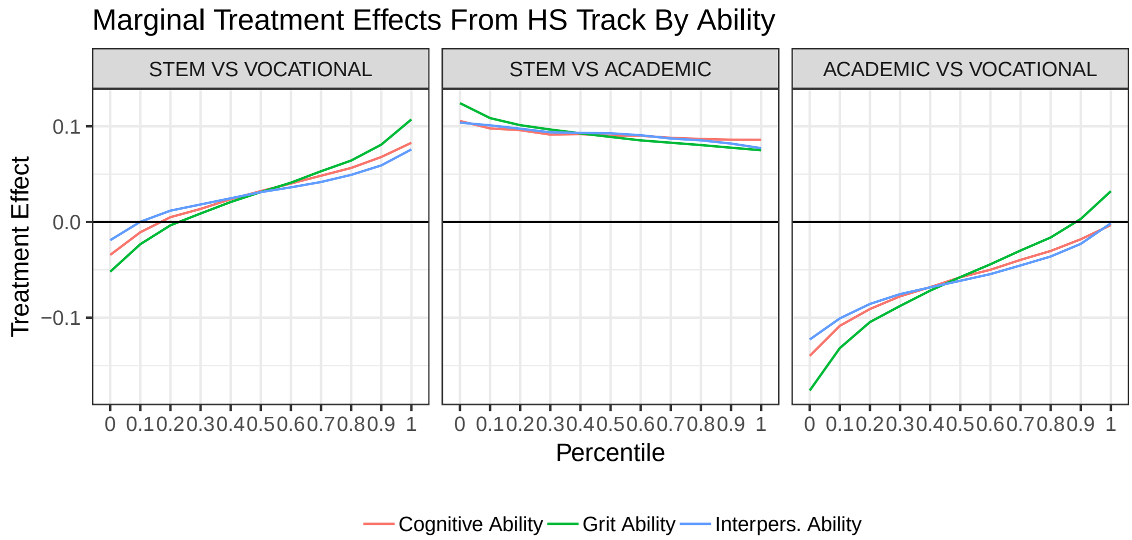
College Graduation



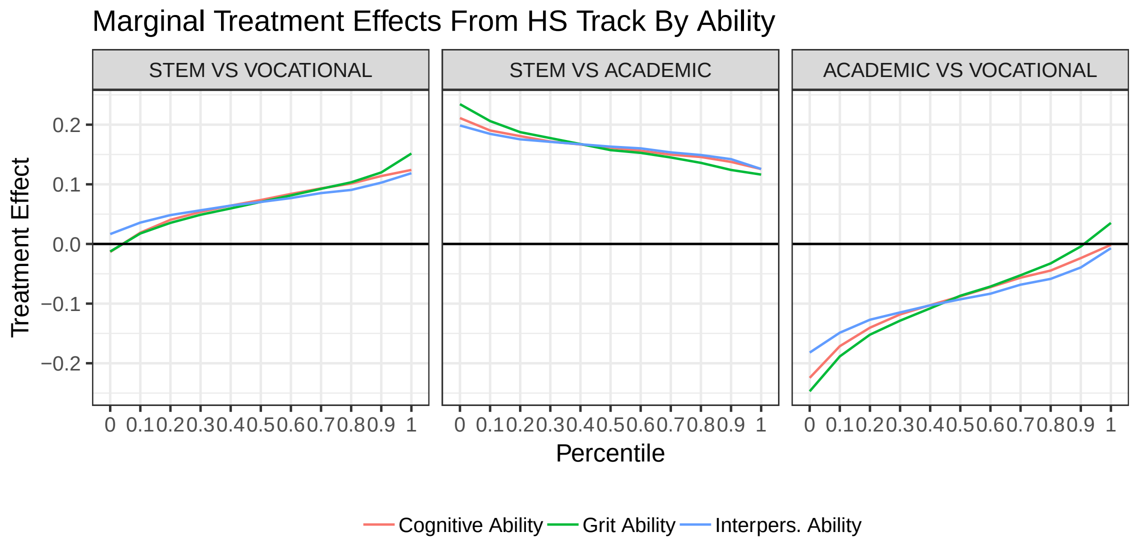
Notes: Figure shows the average treatment effect of changing high school tracks by deciles of cognitive ability, grit ability, and interpersonal ability.

Figure 12: Treatment Effects by Ability: labor market outcomes

Log Wages



Log Discounted Present Value of Disposable Income



Notes: Figure shows the average treatment effect of changing high school tracks by deciles of cognitive ability, grit ability, and interpersonal ability.

6.4 The Effect of High School STEM Track on Major Choice and Earnings

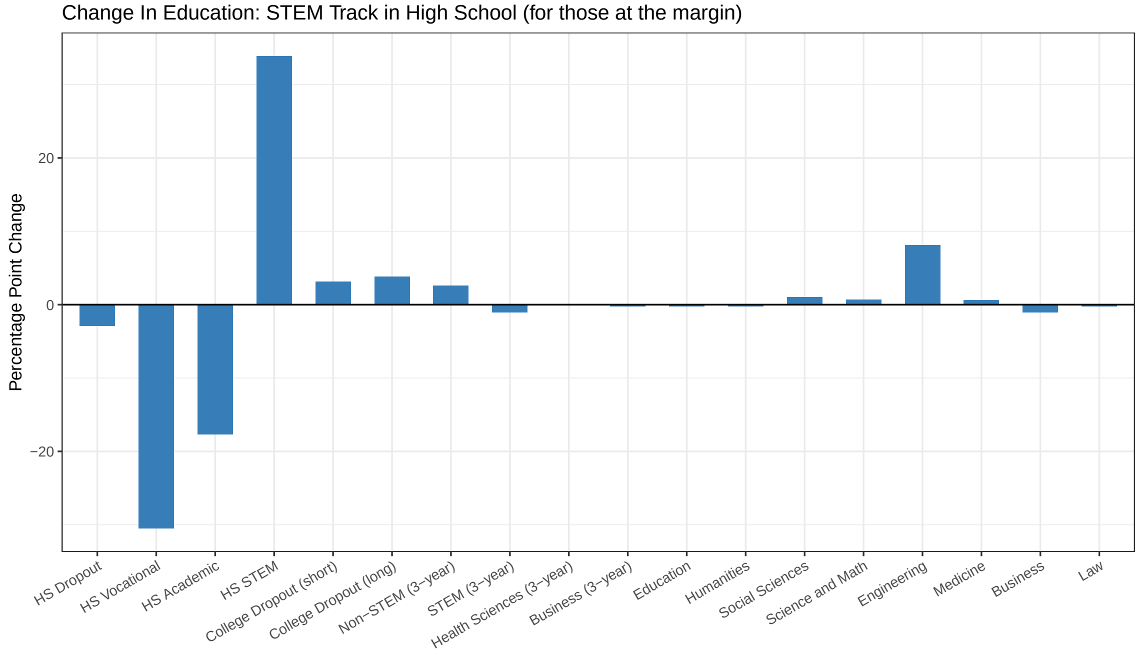
The previous section estimated the treatment effects of switching individuals across different high school track margins on college and wage outcomes. A policy-maker might be interested in how changing high school track reallocates students across majors as well. Figure 13 shows the reallocation patterns for students who did not pursue the STEM track but were close to indifferent between their choice and the STEM track. In particular, each bar shows the percentage point change in final education attainment among marginal students induced into the STEM track. The leftmost bar indicates that there is a 27 percentage point reduction in terminal high school graduates who never enroll in college. This can be compared to the AMTE in the previous section, where the increase in enrollment is a weighted average of the AMTEs across the vocational-STEM and academic-STEM margins. Switching individuals to the STEM track also has important reallocative effects across majors. The marginal students induced into the STEM track are less likely to major in business, law, or education, while more likely to major in engineering, 3-year STEM degrees, as well as non-STEM 3-year degrees. Notably, many of the students who are induced into the STEM track in high school go on to enroll in college, but drop out.

Although pushing students to take the STEM track increases the number of students choosing engineering and science/math majors, taking the STEM track may not lead to an increase in wages. Table 8 reports the average treatment effects for marginal students induced into the STEM track. The rows breakdown the treatment effects for students who do not change their final education attainment and students who change their final education attainment after being induced into the STEM track. The first three columns show the average treatment effect and the average treatment effects conditional on low ability and high ability students. The second three columns show the proportion of marginal students who gain. On average, the treatment effect is small and positive, but these positive effects are driven by those who change their final schooling levels, while being small and slightly negative for those who do not change their final schooling levels.

The effects are somewhat larger for low-ability students. To help better understand the heterogeneous returns of the policy, Figure 17 shows the direct log-wage returns from switching high school track for each final educational educational level. Each panel compares a different high school track margin, while each bar shows the benefits of the high school track change holding final education constant. As the figure shows, changing to the STEM track from the vocational track is associated with increased earnings for social science, business, and law degrees, but is associated with negative returns for many final education levels, such as four-year humanities degrees. Moving people from the academic track to the STEM track is associated with negative direct returns in twelve out of the 15 final educational levels. In contrast, moving students from the vocational track to the academic track raises earnings in 12 of the 15 final eucational levels.

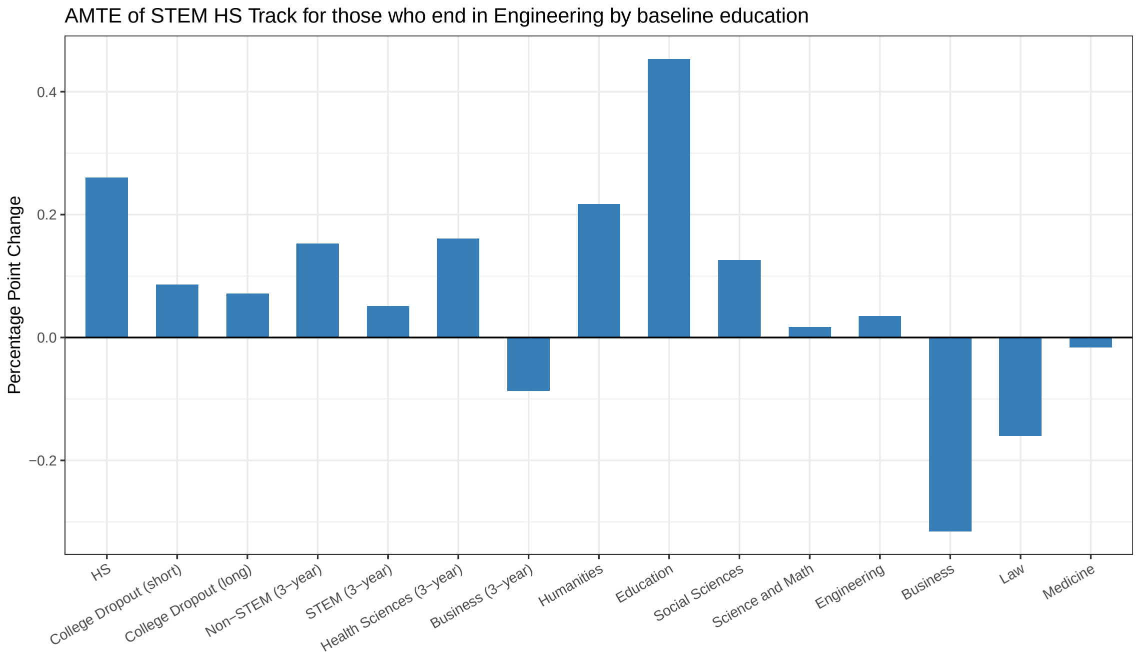
While the treatment effects are largest for those who change final education levels in response to being induced into the STEM track, this population also has a notably smaller share of individuals which gain from the change. While only 36% of all those induced into the STEM track see their wages increase, only 15% of those who do not change their final schooling level benefit, and 60% of those who change their final schooling level benefit. Figure 14 shows the average returns from the STEM-track policy for those who, after the policy, go on to earn an engineering degree. These returns are reported by baseline final education attainment without the policy. While the returns are positive and quite large for most baseline education levels, some individuals end up with lower earnings. In particular, those induced away from business degrees, law degrees and medicine have reduced earnings from the policy.

Figure 13: Marginal Effect of STEM Track on Sorting into College Majors



Notes: Figure shows how switching marginal individuals into the high school STEM track reallocates them across different education outcomes.

Figure 14: AMTE of STEM policy change for those whose final education is engineering by base-line education.



Notes: Figure shows the average treatment effect of the policy shutting down the vocational track in high school for those who then go on to earn a degree in engineering conditional on what their estimated final education would have been if the policy were not implemented.

Table 8: Effects of STEM TRACK (log wages, marginal students)

	ATE			Prop. Gaining		
Group	All	Low Abil	High Abil	All	Low Abil	High Abil
All	0.07	0.07	0.07	0.66	0.66	0.66
No Change in Final Edu	0.04	0.04	0.04	0.75	0.76	0.73
Change in Final Edu	0.08	0.09	0.09	0.62	0.62	0.62

Notes: Table reports the treatment effects from the counterfactual policy of inducing marginal students into the STEM track in high school. Results are reported for all students, students who do not change their final education, and students who change their final education. "Low Abil" ("High Abil") are students in the bottom (top) half of all three abilities. The last three columns reports the proportion of marginal students who have positive wage gains.

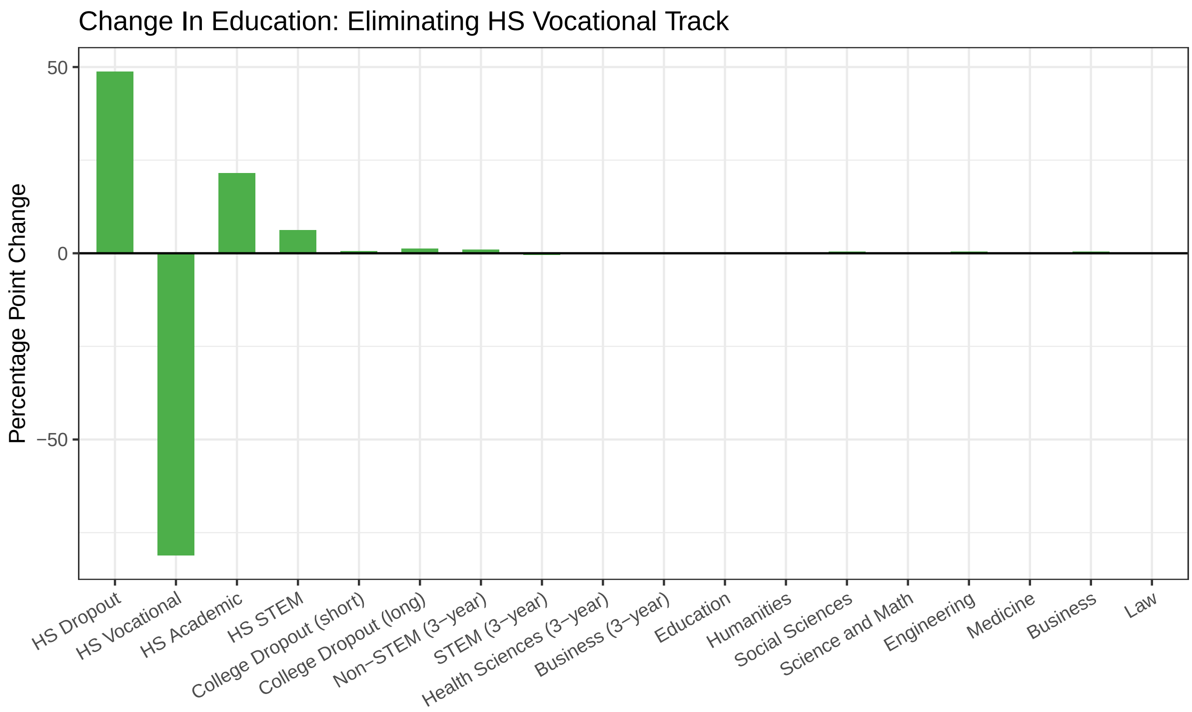
6.5 Shutting Down the High School Vocational Track

Given the low returns associated with the high school vocational track, this section considers a counterfactual policy of eliminating the vocational track from high school. The estimated impacts allow agents to choose their alternative track as well as subsequent education choices conditional on their new choice of high school track. Importantly, the estimates assume skill prices do not change and thus must be thought of as occurring in partial equilibrium, such as a single small school district in Sweden eliminating the high school track.

Figure 15 reports the percentage point change in final education attainment for those forced to leave the high school vocational track. Overall, terminal high school degrees decrease by more than 12%, while 3-year non-STEM degrees increase by more than 3% and a number of other degrees see smaller increases. These effects are not as large as those found for inducing marginal students into the high school STEM track, but targets a much broader and, on average, lower skilled population of students. Similar to when inducing marginal students into the STEM track, many of those induced into trying post-secondary education never earn a degree, resulting in a notable increase in college dropouts.

Table 9 summarizes the effect of the policy on log wages for students by ability level. These effects are further decomposed into those who are induced to change their final

Figure 15: Changes in Final Education from Eliminating Vocational Track

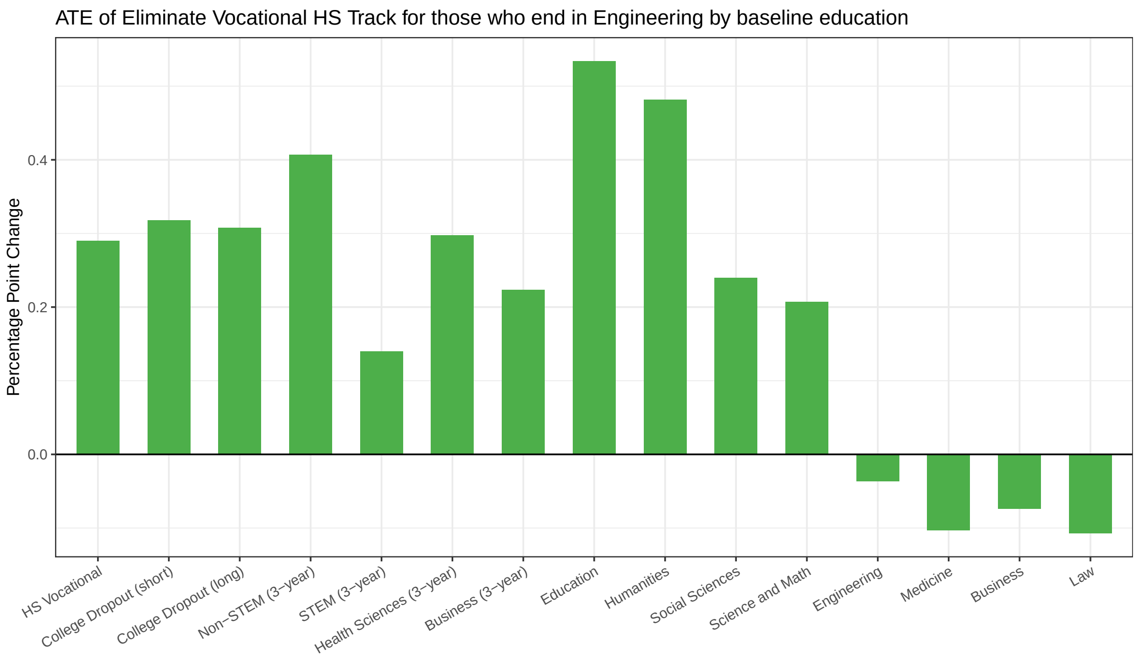


Notes: Figure shows the average treatment effect of the policy shutting down the vocational track in high school for those who then go on to earn a degree in engineering conditional on what their estimated final education would have been if the policy were not implemented.

education attainment and those who are not. Overall, the policy is estimated to increase log wages of those impacted by 6 log points. The treatment effects are notably larger for individuals induced into changing final education levels. The last three columns in the table reports the proportion of the students that gain from the intervention. While the majority of students gain, the proportion is notably larger for low-ability students.

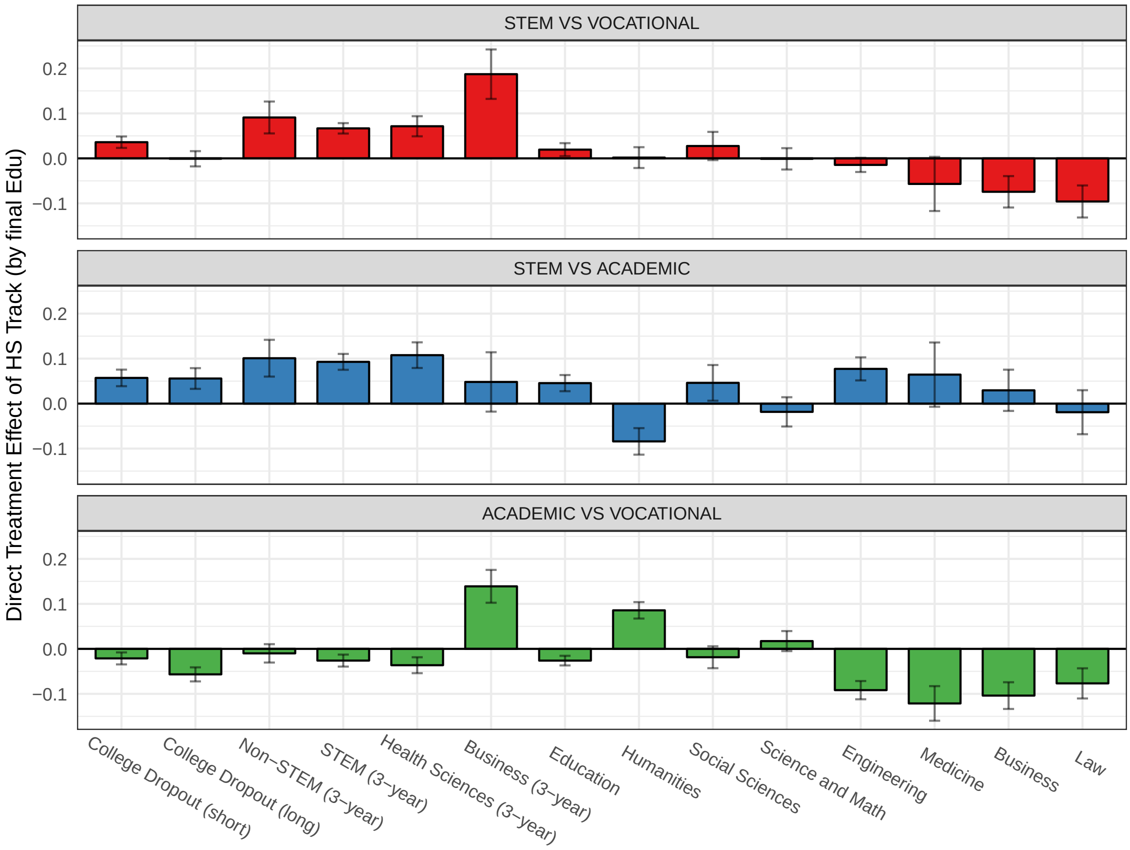
Figure 16 shows the average returns from shutting down the vocational track for those who go on to earn an engineering degree after the policy. These returns are decomposed by baseline final educational attainment in absence of the policy. While the returns positive and quite large for most baseline education levels, some individuals end up with lower earnings. Similar to the STEM policy, those induced away from business degrees and medicine have reduced earnings from the policy.

Figure 16: ATE of shutting down the vocational track for those whose final education is engineering by base-line education.



Notes: Figure shows the impact for those moved out of the vocational track who end up in engineering conditional on what their estimated final educational attainment would have been if they had stayed in the vocational track.

Figure 17: Treatment Effects of HS Track on Log Wages within Final Education Level



Notes: Figure shows the gains from changing high school track conditional on final educational attainment for each of the three high school track margins.

Table 9: Effects of Shutting Down Vocational Track (log wages)

	Avg Treatment Effect			Proportion Gaining		
Group	All	Low Abil	High Abil	All	Low Abil	High Abil
All	-0.03	-0.04	0.01	0.41	0.39	0.47
No Change in Final Edu	-0.01	-0.01	-0.01	0.30	0.30	0.31
Change in Final Edu	-0.03	-0.05	0.02	0.43	0.40	0.51

Notes: Table reports the treatment effects from the counterfactual policy of inducing marginal students into the STEM track in high school. Results are reported for all students, students who do not change their final education, and students who change their final education. "Low Abil" ("High Abil") are students in the bottom (top) half of all three abilities. The last three columns reports the proportion of marginal students who have positive wage gains .

7 Conclusion

In this paper, we have shown the existence of strong complementarities between multidimensional abilities, high school investments, and college investments. Dynamic complementarities continue to be important through the high school and college years. One major difference between our analysis and previous research on human capital formation is the specialization of investments that begin in high school and continue in college. We have shown that specialized investments can lead to higher *or* lower returns to future investments.

The complementarities between abilities and education choices have important implications for policies designed to increase STEM coursework, college enrollment, and college graduation. Policy makers have to be aware of the potentially large heterogeneity in effects and the dynamic complementarities of these policies. The effectiveness of a policy will depend on both the who (*e.g.* family background, abilities, previous investments) and the what (general or specialized investments). For example, a policy that targets specific populations like the one studied by Joensen and Nielsen (2009) and Joensen and Nielsen (2016) is more likely to be successful as the program lowered the costs of taking advanced math courses specifically for STEM interested students.

Our findings also have implications for the broader secondary and post-secondary schooling literature. Recent analyses use application cut-offs in a regression-discontinuity

(RD) design (Kirkebøen et al., 2016; Hastings et al., 2013; Altmejd, 2018). While the RD estimates are certainly credibly causal for the average students near the cut-offs, it is not clear if the estimates can be generalized to the broader population. Even for those at the cut-off, the LATE may mask a significant amount of heterogeneity. There is also a large structural literature investigating college choices, but to the best of our knowledge, the structural literature has not incorporated non-cognitive abilities or high school investments into dynamic models of education choices and labor market outcomes. Combining these approaches would be a fruitful avenue of future research.

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A Data Appendix

In this Appendix, we provide more details on the education data classifications and the high school and college institutions. First, we describe the high school environment. Second, we describe the college environment. Finally, we provide more details on how the present value of income is calculated.

A.1 High School Application to Graduation

In this Appendix, we describe the high school application behavior, admission decisions, and high school graduation outcomes. Applications are submitted by March 15, admission decisions are communicated in July, and retention is measured as enrolled on September 15, 1990; i.e. about a month after initial enrollment. Graduation is measured as highest acquired high school degree in the high school register.

We have data on applicants for high school enrollment 1990-91 academic year from the Swedish Archives (*Riksarkivet*). We focus on males 15-19 years old at the time of application to mimic our estimation sample as closely as possible. We restrict the sample to those with non-missing 9th grade GPA (missing for 636 young males). The sample consists of 68,753 young males of which 41,116 are in our estimation sample.

Table A.1 shows that application behavior, admission decisions, and high school graduation outcomes differ by 9th grade GPA quartile. The overall admission probability is increasing in GPA as 61%/79%/91%/96% in GPA quartile Q1/Q2/Q3/Q4 get admitted.

Most of those admitted, get admitted to one of their top 2 priorities. 35%/51%/78%/94% in GPA quartile Q1/Q2/Q3/Q4 get admitted to their first priority school-line, but these differences are smaller if looking within preferred line (64%/74%/89%/97%) or track (98%/93%/95%/98%). Most of those who get admitted, thus get admitted to their preferred high school track. Graduation rates from the preferred high school track are also high for all GPA quartiles (96%/89%/88%/92%). Although those in the lowest (highest) GPA quartile are much more (less) likely to attend the vocational track and much less (more) likely to attend the academic STEM track. Figure A.1 shows the number of high school-lines listed on the application. On average, 2.3 alternatives are listed. Very few individuals exhaust their list as most list 1-3 priorities, which may indicate that applicants know that they will likely be admitted to one of their top choices.

Table A.2 shows descriptives by 9th grade GPA quartile and preferred high school track. This table also reveals a lot of persistence from application to admission to graduation. Persistence is generally higher for those with high GPA, and that those with higher GPA are also more likely to be admitted to their preferred school-line within all tracks. To the extent there is switching, those with lowest (highest) GPA become even more (less) likely to acquire a vocational high school degree and less (more) likely to acquire an academic STEM high school degree.

The last two figures present additional descriptive evidence that vocational school-lines are more selective than academic school-lines. We categorize all high school-lines by selectivity according to the percentage of applicants who are admitted based on their 1st priority. Figure A.2 shows the fraction of high school-lines in each selectivity category. Panel (a) includes all high school-lines, panel (b) only includes the school-lines in the academic track, while panels (c) and (d) distinguish between the lines in the academic non-STEM and STEM tracks, respectively. Most of the very selective high school-lines are vocational, while the academic STEM school-lines are the least selective. For 97% (99%) of academic (STEM) school-lines at least 50% of those admitted are admitted to their 1st priority: 67% (68%) of academic (STEM) school-lines admit 75-100% of 1st priority applicants and 18% (26%) of academic (STEM) school-lines admit *all* 1st priority applicants. A few – 4% of the vocational and 1% of the academic – school-lines do not admit any applicants. Figure A.3 suggests that this is mainly demand driven as there are too few applicants. It also shows that the more selective school-lines have many more applicants, while the 9th grade GPA of admitted students does not vary significantly by selectivity. This suggests that the high school peer composition is similar by selectivity.

A.1.1 Additional High School Descriptives

Table A.3 describes the characteristics of the high schools that students attend. The average size of the high schools is very similar – around 350 students on average. Students in each track are attending schools that on average have more students in their track. The average vocational track student attends a school where 62% of students are in the vocational track, but 64% (66%) are attending schools that also offer the academic (STEM) track and only 25% of students attend a school that only offers the vocational track. The average academic (STEM) track student attends a school where 51% (43%) of the students are also in the academic (STEM) track. The majority of the schools they attend offer the other tracks too such that only 2% (9%) attend a school that only offers the academic (STEM) track.

Table A.4 shows the most common lines within each high school track. Most vocational track students are in the 2-year lines for Electrical telecommunications (15%), Construction (15%), and Automotive engineering (9%). Most academic non-STEM track students are in the Business (54%) and Social Science (38%) lines, while the academic STEM students are split between the Technical (67%) and Science (31%) lines.

A.2 College Application to Graduation

In this Appendix, we describe the college application, admission, enrollment, and graduation decisions in more detail.

College admission is largely centrally administered. A college applications consist of a list with up to 20 rank-ordered alternatives, and students also submit their high school diploma and transcripts. An alternative consists of a program (e.g. Economics) and a

Table A.1: High School Application, Admission, and Graduation; by 9th grade GPA.

	9th grade GPA quartile			
	Q1	**Q2**	**Q3**	**Q4**
Admitted	0.61	0.79	0.91	0.96
Admitted, 1st priority	0.35	0.51	0.78	0.94
Admitted, 2nd priority	0.16	0.18	0.10	0.02
Admitted, 3rd priority	0.07	0.08	0.03	0.00
Retained, 1st priority	0.39	0.55	0.77	0.89
Retained, 2nd priority	0.15	0.15	0.08	0.02
Retained, 3rd priority	0.07	0.06	0.02	0.01
Line, 1st priority				
Preference (1="listed in all priorities")	0.63	0.60	0.59	0.60
Same as 2nd priority	0.16	0.19	0.16	0.07
Same as 3rd priority	0.12	0.12	0.11	0.05
Admitted	0.64	0.74	0.89	0.97
Graduated	0.61	0.67	0.79	0.87
Track, 1st priority				
Preference (1="listed in all priorities")	0.98	0.91	0.81	0.79
Same as 2nd priority	0.95	0.82	0.67	0.60
Same as 3rd priority	0.94	0.78	0.53	0.32
Admitted	0.98	0.93	0.95	0.98
Graduated	0.96	0.89	0.88	0.92
Vocational	0.96	0.83	0.56	0.20
Academic non-STEM	0.02	0.11	0.25	0.27
Academic STEM	0.01	0.06	0.19	0.53
Admitted, Vocational Track	0.98	0.86	0.55	0.17
Admitted, Academic non-STEM Track	0.01	0.08	0.25	0.27
Admitted, Academic STEM Track	0.01	0.06	0.20	0.56
Graduated, Vocational Track	0.98	0.90	0.62	0.21
Graduated, Academic non-STEM Track	0.01	0.07	0.23	0.29
Graduated, Academic STEM Track	0.01	0.03	0.15	0.50
Graduated	0.64	0.87	0.93	0.96
N	15,736	16,643	17,536	18,838

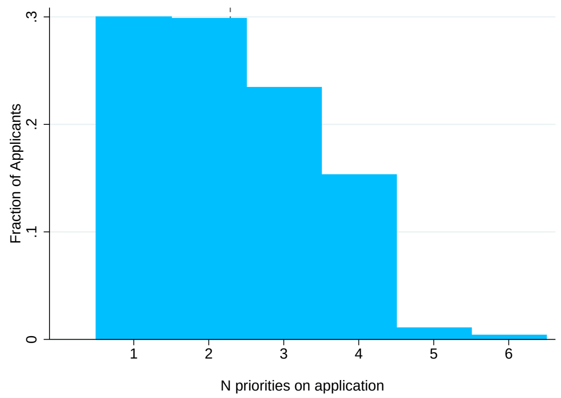
Note: The Table shows descriptive statistics of high school application, admission, and graduation by 9th grade GPA quartile. *Sample*: Applicants for high school enrollment 1990-91 academic year. Males 15-19 years old at the time of application. Applications are submitted by March 15, admission decisions are communicated in July, and retention is measured as enrolled on September 15, 1990; i.e. about a month after initial enrollment. Graduation is measured as highest acquired high school degree. The table displays fractions of applicants within each 9th grade GPA quartile, however, the fraction admitted (graduated) by high school track (vocational, academic non-STEM, and academic STEM) is displayed conditional on admission (graduation).

Table A.2: High School Application, Admission, and Graduation; by 9th grade GPA and 1st Priority High School Track.

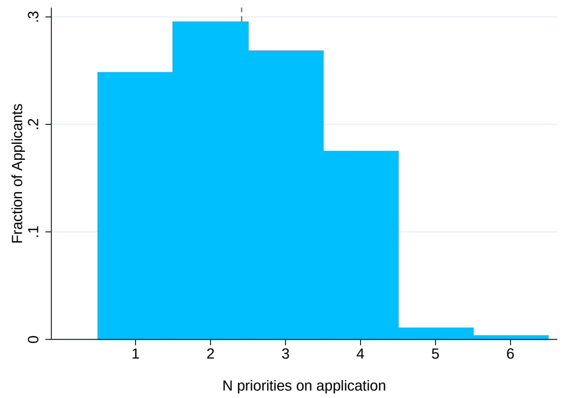
			High School Track						High School-Line			
			Admitted			Graduated			Admitted		Retained	
9th GPA	**HS Track 1st priority**	**% GPA Q**	Vocational	Academic non-STEM	Academic STEM	Vocational	Academic non-STEM	Academic STEM	1st priority	2nd priority	1st priority	2nd priority
GPA, Q1	Vocational	96.30	**99.56**	0.26	0.18	**99.51**	0.36	0.12	35.10	16.04	39.24	15.10
	Academic, non-STEM	2.28	53.03	**42.42**	4.55	70.85	**25.51**	3.64	17.88	11.17	21.51	16.20
	Academic, STEM	1.42	37.24	0.69	**62.07**	70.89	7.59	**21.52**	31.25	7.14	35.71	11.61
GPA, Q2	Vocational	82.68	**98.66**	0.73	0.62	**98.63**	0.98	0.40	53.91	17.91	56.49	14.83
	Academic, non-STEM	11.29	33.11	**60.82**	6.07	48.41	**48.47**	3.13	29.06	20.49	43.11	20.70
	Academic, STEM	6.03	20.17	2.93	**76.89**	48.58	11.24	**40.18**	47.76	12.96	57.53	13.56
GPA, Q3	Vocational	55.63	**97.74**	1.32	0.94	**96.92**	1.97	1.11	76.98	9.88	73.80	7.73
	Academic, non-STEM	24.95	5.97	**92.12**	1.91	17.58	**80.25**	2.17	76.10	10.83	79.98	8.04
	Academic, STEM	19.42	5.34	2.98	**91.67**	18.82	10.60	**70.58**	80.82	9.40	83.17	8.08
GPA, Q4	Vocational	19.92	**96.96**	1.67	1.37	**92.36**	4.10	3.54	82.17	4.74	73.97	4.21
	Academic, non-STEM	27.23	0.49	**98.31**	1.20	4.97	**92.40**	2.64	94.46	1.42	89.47	1.93
	Academic, STEM	52.85	0.40	0.79	**98.80**	3.43	5.23	**91.34**	97.48	1.28	94.93	1.95

Note: The first column of the Table shows the percentage within each 9th grade GPA quartile that states each high school track (vocational, academic non-STEM, and academic STEM) as 1st priority at the time of application. We define an application cell by 9th grade GPA quartile and high school track listed as 1st priority. The subsequent columns display the percent (row %) of applicants in each application cell who make the relevant transition in terms of the percentage admitted and graduating from each high school track, as well as the percentage admitted and retained in the 1st and 2nd application priority. *Sample*: Applicants for high school enrollment 1990-91 academic year. Males 15-19 years old at the time of application. Applications are submitted by March 15, admission decisions are communicated in July, and retention is measured as enrolled on September 15, 1990; i.e. about a month after initial enrollment. Graduation is measured as highest acquired high school degree.

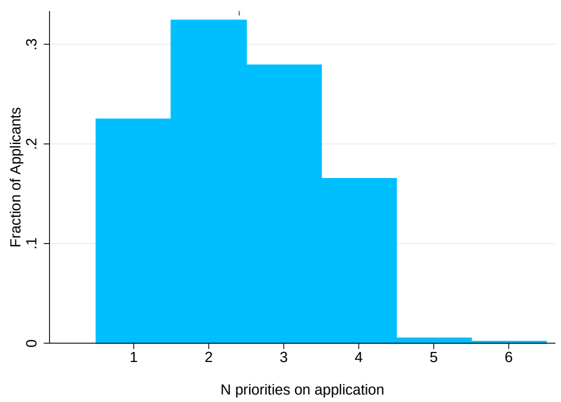
Figure A.1: Distribution of High School-Lines, by 9th grade GPA.



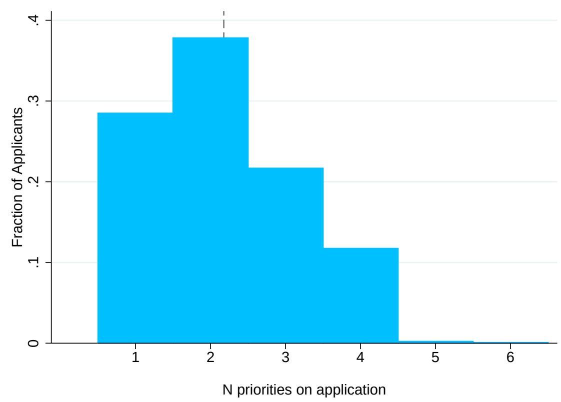
(a) GPA, Q1



(b) GPA, Q2



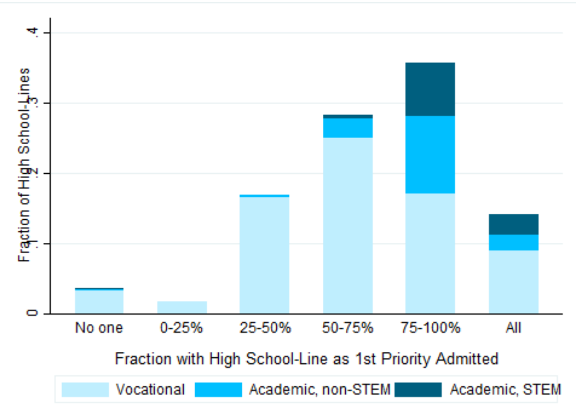
(c) GPA, Q3



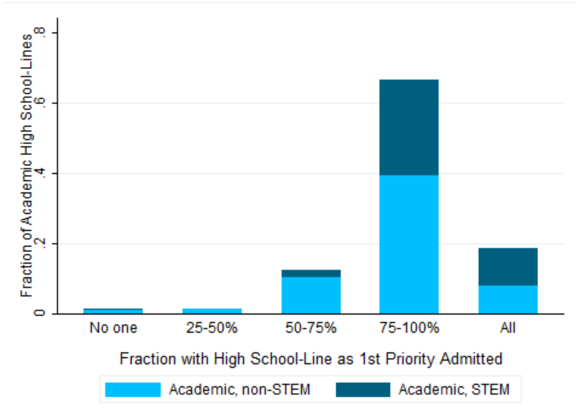
(d) GPA, Q4

Note: The Figure shows the distribution of rank ordered high school-line priorities listed by each 9th grade GPA quartile. High school applicants can list up to six school-line priorities. *Sample*: Applicants for high school enrollment 1990-91 academic year. Males 15-19 years old at the time of application.

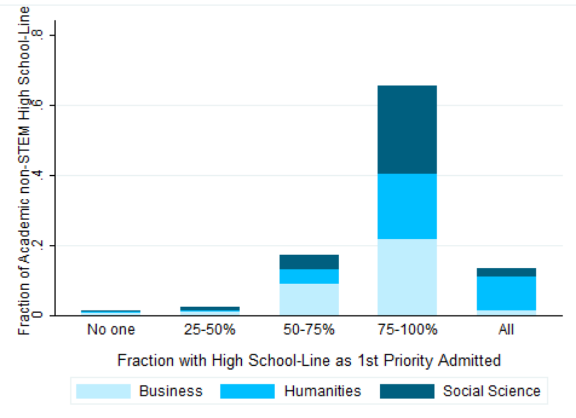
Figure A.2: Distribution of High School-Lines, by Selectivity.



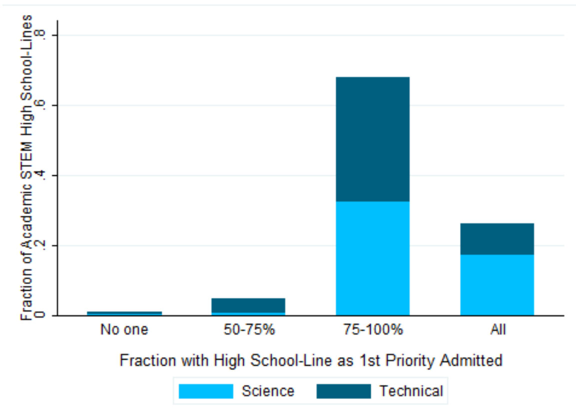
(a) All Lines



(b) Academic Track



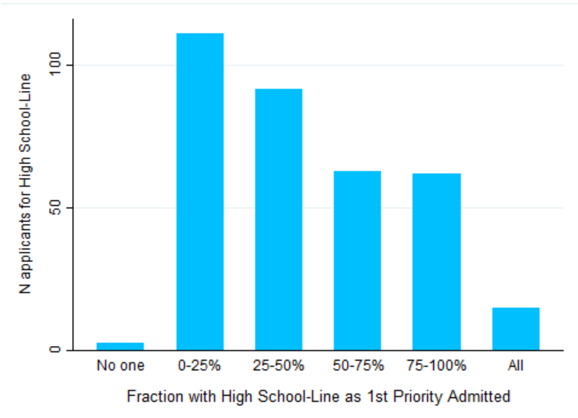
(c) Academic non-STEM Track



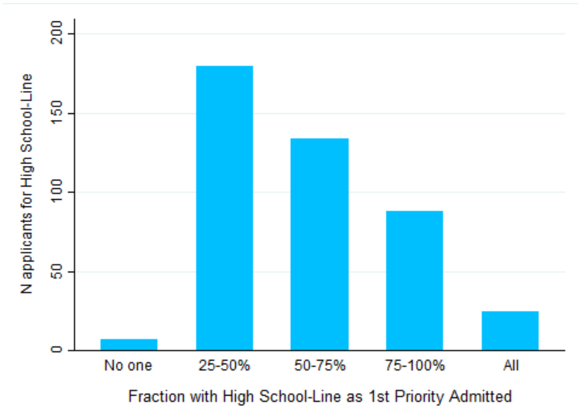
(d) Academic STEM Track

Note: The Figures display the distribution of high school-lines over selectivity categories. The unit of observation is a high school-line. Selectivity is categorized according to the percentage of applicants who are admitted based on their 1st priority. *Sample*: Applicants for high school enrollment 1990-91 academic year.

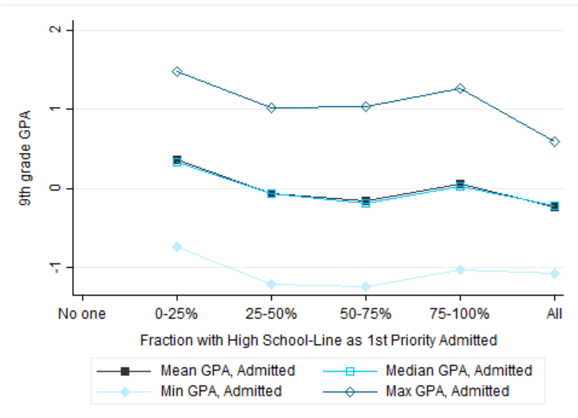
Figure A.3: Applicants and Admitted to High School-Lines, by Selectivity.



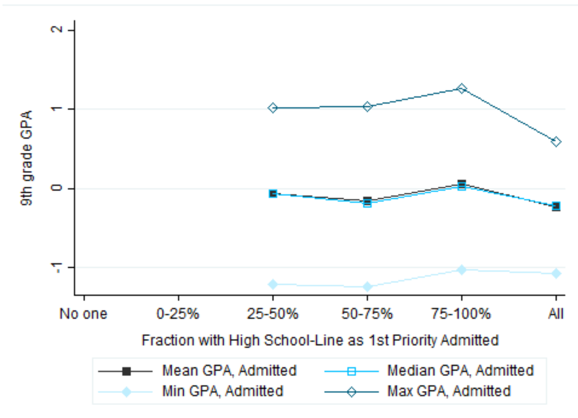
(a) N applicants, All Lines



(b) N applicants, Academic Track



(c) Admitted 9th grade GPA, All Lines



(d) Admitted 9th grade GPA, Academic Track

Note: The Figures display the number of applicants and the mean/median/min/max 9th grade GPA of those admitted by high school-line selectivity. The unit of observation is a high school-line. Selectivity is categorized according to the percentage of applicants who are admitted based on their 1st priority. *Sample*: Applicants for high school enrollment 1990-91 academic year.

Table A.3: High School Characteristics by High School Track

	High School Track		
	Vocational	**Academic non-STEM**	**Academic STEM**
High School Characteristics			
N students in high school	334	332	357
Fraction of students in track			
Vocational	0.62	0.32	0.32
Academic non-STEM	0.22	0.51	0.26
Academic STEM	0.17	0.17	0.43
School has track			
Vocational	1.00	0.89	0.85
Academic non-STEM	0.64	1.00	0.66
Academic STEM	0.66	0.81	1.00
School *only* has track			
Vocational	0.25	0.00	0.00
Academic non-STEM	0.00	0.01	0.00
Academic STEM	0.00	0.00	0.09
N students	**54,498**	**19,198**	**22,926**
Fraction of HS Graduates	**0.56**	**0.20**	**0.24**

Table A.4: Specialization of Students in each High School Track

High School Track	Fraction of track	Line Code
Vocational		
Electrical telecommunications line (2-years)	0.15	14
Construction line (2-years)	0.15	04
Automotive engineering line (2-years)	0.09	20
Social line	0.08	46
Production engineering line	0.07	60
Business and office line	0.06	24
Industrial-technical line	0.05	28
Food technology line	0.04	34
Automotive engineering line (3-years)	0.04	22
Operation and maintenance line	0.03	10
Electrical telecommunications line (3-years)	0.03	16
Wood technology line	0.02	58
Natural resources line	0.02	38
Construction line (3-years)	0.02	06
Health care line	0.01	62
Business line	0.01	26
Academic non-STEM		
Business line (3-years)	0.54	72
Social Science line (3-years)	0.38	78
Humanities line (3-years)	0.04	74
Social Science program (3-years)	0.03	53
Academic STEM		
Technical line (3-years)	0.67	80
Science line (3-years)	0.31	76
Science program (3-years)	0.02	49

Notes: This table displays the fraction of students attending each of the most common lines (rank ordered) within each high school track. All line codes refer to those in place for the graduating cohorts in 1990-96. Programs 53 and 49 were early pilot programs in Social Science and Science, respectively, that replaced the corresponding lines (78 and 76) in 1997. All vocational lines are 2-years apart from 22, 16, and 06 that are the three 3-year versions of the three most popular lines which enroll 39% of the vocational track male students.

college (e.g. Stockholm University). Universities/colleges are responsible for specifying competence requirements and selection within the regulation of the Higher Education Act, while the Swedish National Agency for Higher Education (now UHR) is a supervisory authority that checks that colleges comply with the regulatory framework. If there are more seats than applicants, then all qualified applicants are admitted. Qualifications are determined by high school courses, and may vary by programs and colleges. The basic requirement is a high school degree, and each college-program has additional requirements related to prerequisite high school courses and grades. When there are more applicants for a college-program than there are seats, the selection is based on the following three main admission groups are screening students on: (i) high school GPA, (ii) SweSAT test score, and (iii) SweSAT test score with additional admission points for relevant labor market experience. Each college-program has a fixed number of seats available in each admission group: at least one third has to be admitted through group (i), at least one third has to be admitted through groups (ii) and (iii), and at most a third through alternative admission rules; predominantly personal interviews. GPA and SweSAT cut-offs in each admission group are determined are determined by a serial dictator mechanism. Each student is admitted to the highest priority they are above the cut-off for in one of the admission groups. After admission decisions are communicated in the first round, students who are evaluated to be qualified based on their high school transcripts but are not admitted to their preferred alternative can be wait-listed and admitted in a 2nd round in August as seats can become available if someone does not accept their initial allocation.

Aggregate college admission data is available from the website of the Swedish Council of Higher Education (UHR). We compiled these statistics for 1998-2010 to show differences in selectivity and admission practices.[34] Figure A.4 shows the GPA and SweSAT cut-offs for each college major. It reveals that some majors (e.g. Medicine and Law) are very selective. Panel (c) reveals, however, that Medicine is also the one exception, where a significant fraction of individuals (25%) that are below the cut-off are admitted based on personal interviews. Figure A.5 and Figure **??** show the full distribution of college-

[34]We are in the process of scanning the data for earlier years as these are only available in book form. We are also in the process of cleaning the individual application data from 1993 onward.

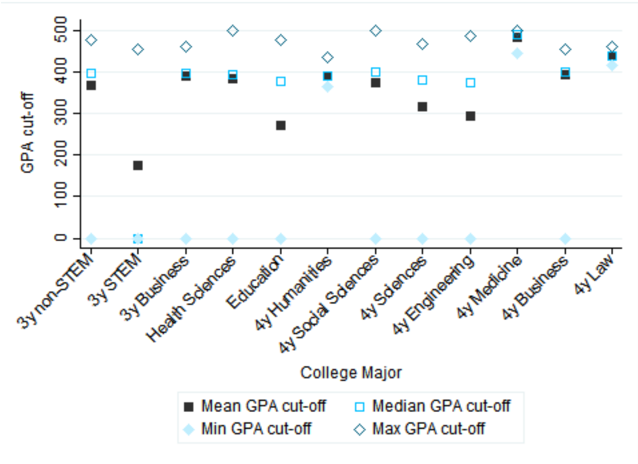
programs by selectivity group and major. Selectivity is categorized according to where the GPA cut-off falls in the GPA distribution of high school graduates. 24% of college-programs admit all students, 15% require a GPA below the mean, 40% require a GPA between the mean and one standard deviation above the mean, 17% require a GPA between one and two standard deviations above the mean, while 4% of college-programs require an even higher GPA. These fractions vary a lot within college major. For example, all Medicine college-programs are in the two most selective categories (almost 80% of them in the most selective group), all Law college-programs are in the second most selective group, all Humanities college-programs require a GPA above the mean to be directly admitted (80% between the mean and the mean+1SD and 10% in each of the two most selective categories). On the other hand, most 3-year STEM programs are in three least selective categories. The STEM majors are generally the least selective, while the remaining 4-year programs are moderately selective – the bulk of the college-programs require a GPA between the mean and the mean+1SD, but there are also many college-programs within each of these majors that admit all qualified applicants.

A.2.1 Additional College Descriptives

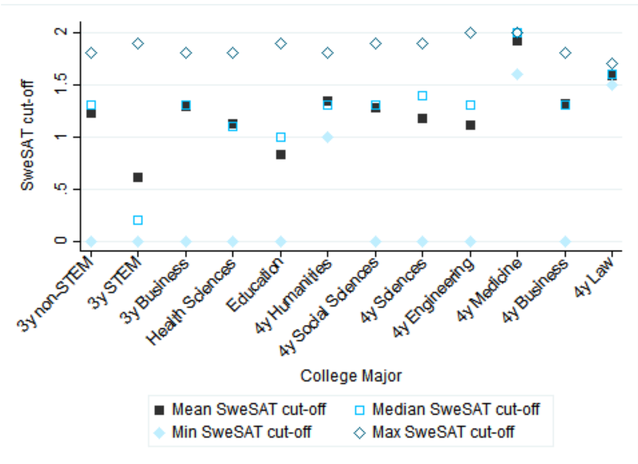
In this subsection, we provide additional descriptive statistics on those who initially enroll in and acquire a degree in each college major. Table A.5 and Table A.6 show the background characteristics that we use as controls, Table A.7 and Table A.8 show the high school grades, high school track choices, and SweSAT test scores,[35] while Table A.9 shows the age at education decision nodes, switching, and graduation behavior. Finally, Table A.10 and Table A.11 show the five most common programs within each college major. This table also shows the SUN2000Inr codes that correspond to each of the fields.

[35]Note that in Figure A.4 GPA is measured on a 0-500 scale, while SweSAT is measured on a 0-2 scale as we use the original standardized scales. In these tables we have standardized grades and test scores to have mean zero and standard deviation one.

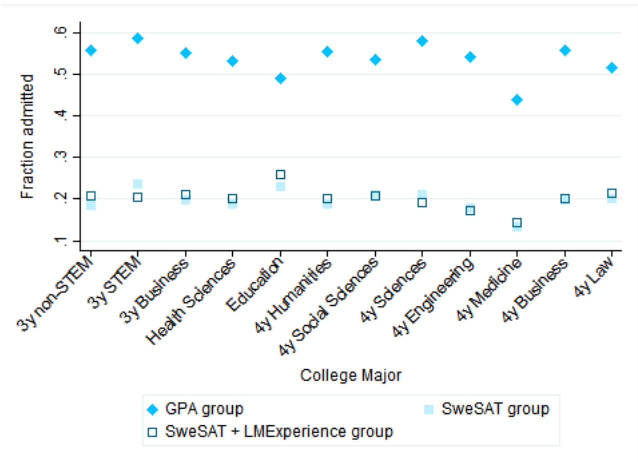
Figure A.4: Selectivity and Admission, by College Major.



(a) GPA cut-off



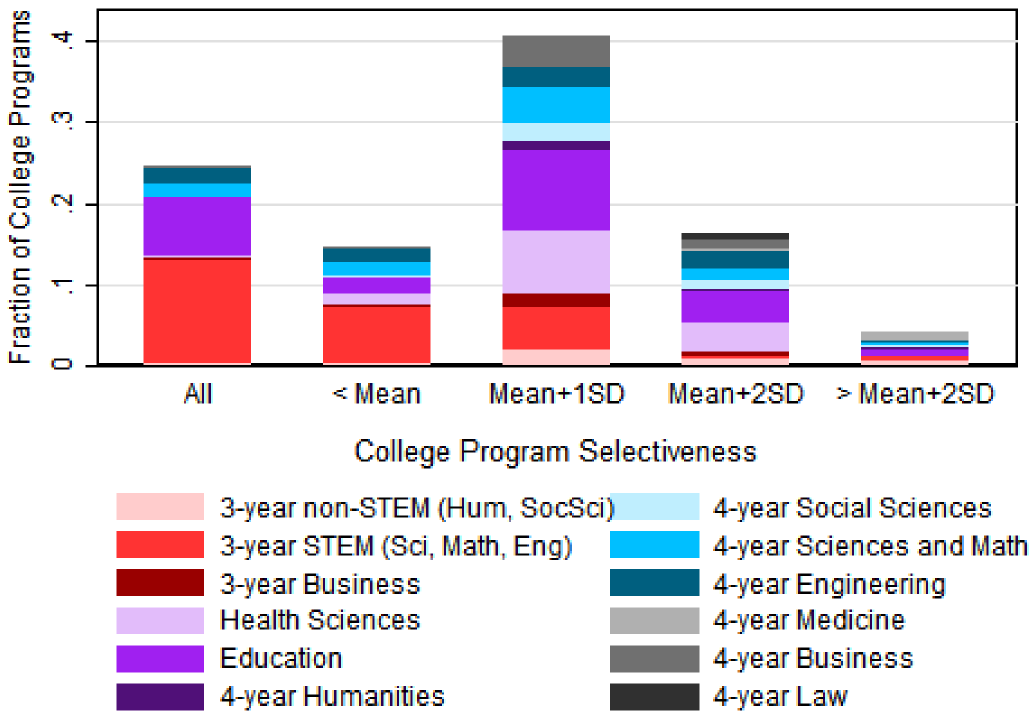
(b) SweSAT cut-off



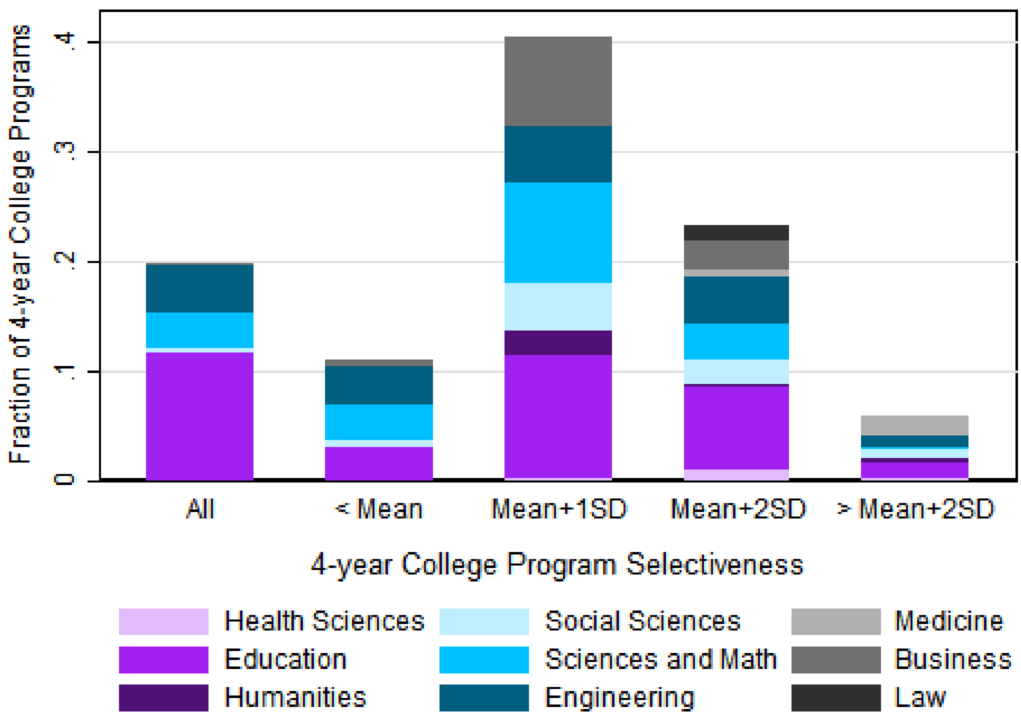
(c) Fraction admitted, by admission group

Note: The Figures display admission statistics for each college major. Panel (a) displays the mean/median/min/max of the GPA cut-off for all college-programs within each college major. Panel (b) displays the mean/median/min/max of the SweSAT cut-off for all college-programs within each college major. Panel (c) displays the fraction admitted in each of the three main admission groups: GPA, SweSAT, and SweSAT plus relevant labor market experience. GPA is measured on a 0-500 scale, while SweSAT is measured on a 0-2 scale. A cut-off of 0 simply means that all were admitted in the relevant admission group. *Sample*: Aggregate admission statistics for 1998-2000 compiled from UHR.

Figure A.5: Distribution of College Programs, by Selectivity.



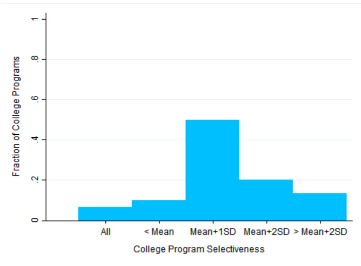
(a) All Programs



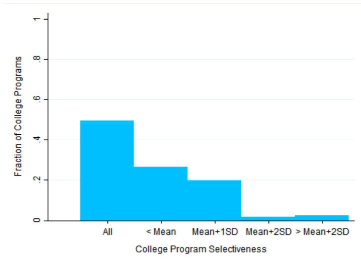
(b) 4-year Programs

Note: The Figures display the fraction of college programs in each selectivity group. Selectivity is categorized according to where the GPA cut-off falls in the overall GPA distribution of high school graduates. The unit of observation is a college-program. *Sample*: Aggregate admission statistics for 1998-2000 compiled from UHR.

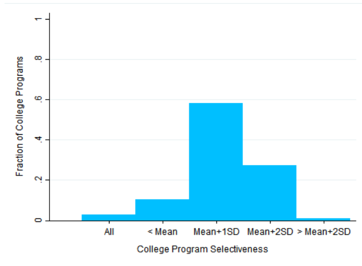
Figure A.6: Distribution of College Programs, by Selectivity and Major.



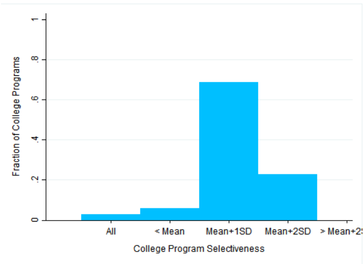
(a) 3-year non-STEM



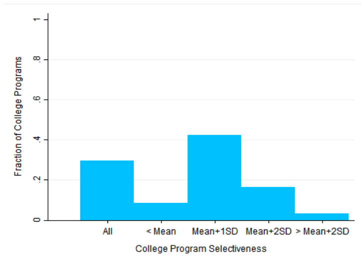
(b) 3-year STEM



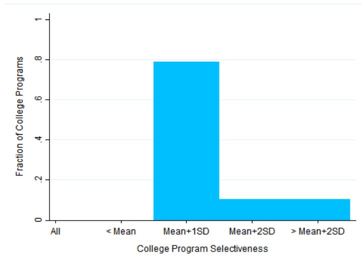
(c) 3-year Business



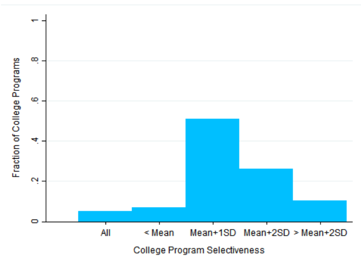
(d) Health Sciences



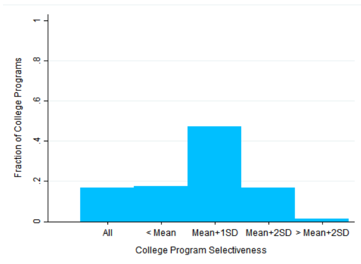
(e) Education



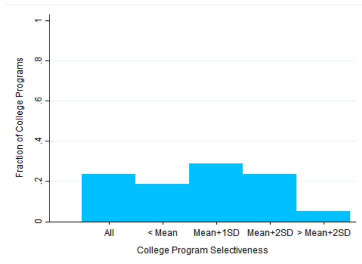
(f) 4-year Humanities



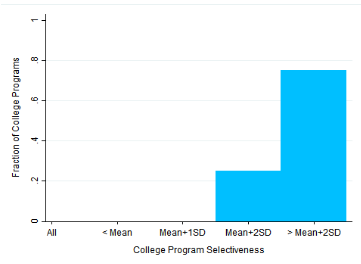
(g) 4-year Social Sciences



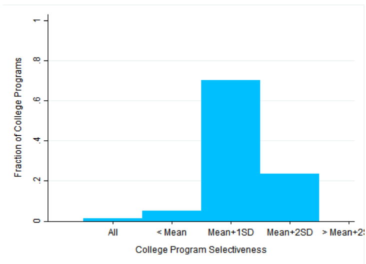
(h) 4-year Sciences



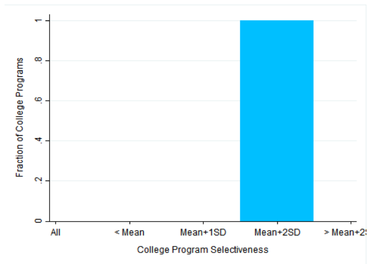
(i) 4-year Engineering



(j) 4-year Medicine



(k) 4-year Business



(l) 4-year Law

Note: The Figures display histograms with the fraction of college programs in each selectivity group within each major. Selectivity is categorized according to where the GPA cut-off falls in the overall GPA distribution of high school graduates. The unit of observation is a college-program. *Sample*: Aggregate admission statistics for 1998-2000 compiled from UHR.

Table A.5: Control Variables by College Major of Initial Enrollment

		College Major											
		3-year					4-year						
	No enroll (HS grad)	**non-STEM**	**STEM**	**Business**	**HealthSci**	**Educ**	**Humanities**	**SocSci**	**Sciences**	**Engineer**	**Medicine**	**Business**	**Law**
Birth Cohort													
1974	0.44	0.43	0.46	0.44	0.46	0.46	0.45	0.44	0.42	0.42	0.48	0.44	0.45
1975	0.41	0.43	0.40	0.42	0.39	0.41	0.41	0.41	0.43	0.42	0.39	0.41	0.41
Health factors													
Strenght	0.08	-0.20	0.08	-0.03	0.06	-0.04	-0.27	-0.06	-0.01	0.06	0.16	0.02	0.06
Fitness	0.02	-0.14	-0.33	-0.28	-0.30	-0.27	-0.11	-0.34	-0.37	-0.46	-0.64	-0.41	-0.34
Health missing	0.05	0.05	0.04	0.03	0.05	0.04	0.07	0.05	0.05	0.04	0.04	0.05	0.05
Mother													
Age, child birth	24.92	26.02	25.81	26.08	25.65	25.83	26.33	26.50	26.20	26.63	26.38	26.04	26.57
Age, child birth missing	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.03	0.05	0.04	0.04
Disp.fam.inc. child 5-18y	0.40	0.44	0.43	0.44	0.42	0.42	0.44	0.46	0.45	0.49	0.52	0.49	0.51
Education													
$\geq$ College	0.16	0.39	0.30	0.32	0.34	0.33	0.46	0.43	0.41	0.47	0.62	0.39	0.48
$\geq$ High School	0.64	0.76	0.75	0.74	0.75	0.74	0.81	0.77	0.79	0.82	0.82	0.77	0.81
Missing	0.13	0.14	0.12	0.11	0.11	0.12	0.10	0.14	0.12	0.11	0.13	0.11	0.11
Father Education													
$\geq$ College	0.10	0.30	0.20	0.22	0.26	0.25	0.34	0.36	0.35	0.38	0.58	0.32	0.44
$\geq$ High School	0.51	0.65	0.64	0.60	0.63	0.63	0.67	0.69	0.69	0.73	0.78	0.69	0.71
Missing	0.20	0.20	0.17	0.20	0.18	0.19	0.19	0.17	0.18	0.17	0.17	0.18	0.19
N students	**59,393**	**1,955**	**11,151**	**1,051**	**1,737**	**3,753**	**687**	**1,431**	**3,258**	**7,584**	**561**	**3,403**	**985**
Fraction of sample	**0.61**	**0.02**	**0.12**	**0.01**	**0.02**	**0.04**	**0.01**	**0.01**	**0.03**	**0.08**	**0.01**	**0.04**	**0.01**
Fraction of college enrollment		**0.05**	**0.30**	**0.03**	**0.05**	**0.10**	**0.02**	**0.04**	**0.09**	**0.20**	**0.01**	**0.09**	**0.03**

Table A.6: Control Variables by College Major of Final Degree

	College Major											
	3-year					4-year						
	non-STEM	STEM	Business	HealthSci	Education	Humanities	SocSci	Sciences	Engineer	Medicine	Business	Law
Birth Cohort												
1974	0.43	0.46	0.46	0.47	0.47	0.46	0.44	0.43	0.43	0.46	0.45	0.46
1975	0.42	0.41	0.41	0.39	0.41	0.41	0.42	0.42	0.42	0.38	0.41	0.41
Health factors												
Strenght	-0.13	0.09	-0.02	0.08	-0.01	-0.25	-0.11	-0.02	0.08	0.20	0.01	0.03
Fitness	-0.23	-0.40	-0.42	-0.34	-0.39	-0.08	-0.40	-0.40	-0.54	-0.68	-0.49	-0.39
Health missing	0.06	0.04	0.03	0.04	0.04	0.06	0.06	0.05	0.04	0.05	0.06	0.05
Mother												
Age, child birth	26.09	26.17	26.31	25.89	26.09	26.86	26.61	26.65	26.80	26.90	26.40	26.69
Age, child birth missing	0.04	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.04	0.03	0.04
Disp.fam.inc. child 5-18y	0.44	0.44	0.45	0.43	0.42	0.44	0.47	0.45	0.49	0.53	0.50	0.52
Education												
$\geq$ College	0.38	0.30	0.35	0.38	0.32	0.42	0.47	0.44	0.48	0.64	0.42	0.51
$\geq$ High School	0.77	0.75	0.78	0.77	0.75	0.79	0.79	0.80	0.82	0.82	0.79	0.82
Missing	0.13	0.11	0.11	0.11	0.12	0.12	0.12	0.12	0.11	0.12	0.11	0.11
Father Education												
$\geq$ College	0.33	0.21	0.22	0.27	0.25	0.34	0.39	0.36	0.39	0.58	0.34	0.46
$\geq$ High School	0.66	0.64	0.62	0.66	0.64	0.68	0.73	0.70	0.74	0.79	0.71	0.72
Missing	0.19	0.16	0.20	0.17	0.17	0.19	0.17	0.17	0.16	0.16	0.17	0.20
N students	**1,600**	**5,455**	**357**	**1,544**	**1,847**	**826**	**1,118**	**1,980**	**6,065**	**592**	**1,858**	**768**
Fraction of sample	**0.02**	**0.06**	**0.00**	**0.02**	**0.02**	**0.01**	**0.01**	**0.02**	**0.06**	**0.01**	**0.02**	**0.01**
Fraction of college enrollment	**0.04**	**0.15**	**0.01**	**0.04**	**0.05**	**0.02**	**0.03**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college graduates	**0.07**	**0.23**	**0.01**	**0.06**	**0.08**	**0.03**	**0.05**	**0.08**	**0.25**	**0.02**	**0.08**	**0.03**

Table A.7: High School and SweSAT by College Major of Initial Enrollment

		College Major											
		3-year					4-year						
	No enroll (HS grad)	**non-STEM**	**STEM**	**Business**	**HealthSci**	**Educ**	**Humanities**	**SocSci**	**Sciences**	**Engineer**	**Medicine**	**Business**	**Law**
Grades, High School													
GPA	-0.33	0.32	0.13	0.28	0.18	0.24	0.45	0.48	0.62	1.13	1.58	0.69	1.06
Math	-0.22	-0.02	0.15	0.15	-0.06	0.02	-0.01	0.10	0.49	0.94	0.95	0.45	0.49
English	-0.19	0.37	-0.07	0.12	0.17	0.15	0.43	0.40	0.47	0.65	1.23	0.42	0.91
Swedish	-0.29	0.50	0.07	0.28	0.23	0.34	0.68	0.59	0.55	0.87	1.49	0.62	1.14
Sports	-0.13	0.01	0.10	0.24	0.23	0.29	-0.06	0.23	0.18	0.29	0.54	0.38	0.30
High School Track													
Vocational	0.78	0.34	0.28	0.23	0.53	0.34	0.26	0.23	0.17	0.09	0.07	0.12	0.11
Academic non-STEM	0.15	0.47	0.11	0.60	0.29	0.43	0.49	0.54	0.26	0.07	0.14	0.68	0.57
Academic STEM	0.07	0.19	0.61	0.17	0.18	0.22	0.25	0.23	0.58	0.85	0.78	0.20	0.31
SweSAT													
Test-taker	0.22	0.78	0.72	0.85	0.86	0.77	0.73	0.88	0.88	0.84	0.93	0.91	0.90
SweSAT score of test-takers													
Total	-0.42	0.21	-0.18	-0.16	-0.23	-0.11	0.25	0.26	0.41	0.64	1.07	0.19	0.72
Vocabulary	-0.13	0.34	-0.25	-0.15	0.14	0.04	0.34	0.25	0.20	0.17	0.67	0.03	0.55
Swedish Read.Comprehens.	-0.41	0.20	-0.13	-0.08	-0.24	-0.05	0.30	0.26	0.33	0.56	0.91	0.23	0.66
English	-0.40	0.24	-0.18	-0.09	-0.30	-0.06	0.37	0.29	0.38	0.57	0.94	0.30	0.73
General Information	-0.35	0.23	-0.25	-0.17	-0.04	-0.03	0.28	0.29	0.25	0.37	0.80	0.08	0.51
Data Sufficiency	-0.47	-0.14	0.16	-0.12	-0.42	-0.22	-0.13	-0.02	0.39	0.71	0.71	0.14	0.32
Interpret Diag/Tabls/Maps	-0.47	-0.08	0.07	-0.02	-0.46	-0.16	-0.03	0.08	0.34	0.68	0.71	0.25	0.39
N students	**59,393**	**1,955**	**11,151**	**1,051**	**1,737**	**3,753**	**687**	**1,431**	**3,258**	**7,584**	**561**	**3,403**	**985**
Fraction of sample	**0.61**	**0.02**	**0.12**	**0.01**	**0.02**	**0.04**	**0.01**	**0.01**	**0.03**	**0.08**	**0.01**	**0.04**	**0.01**
Fraction of college enrollment		**0.05**	**0.30**	**0.03**	**0.05**	**0.10**	**0.02**	**0.04**	**0.09**	**0.20**	**0.01**	**0.09**	**0.03**

Table A.8: High School and SweSAT by College Major of Final Degree

	College Major											
	3-year					4-year						
	non-STEM	**STEM**	**Business**	**HealthSci**	**Education**	**Humanities**	**SocSci**	**Sciences**	**Engineer**	**Medicine**	**Business**	**Law**
Grades, High School												
GPA	0.44	0.29	0.44	0.27	0.30	0.59	0.67	0.76	1.14	1.65	0.86	1.18
Math	0.11	0.26	0.31	0.00	0.07	0.17	0.24	0.57	0.96	1.02	0.58	0.59
English	0.36	-0.03	0.16	0.22	0.09	0.45	0.50	0.46	0.54	1.24	0.50	0.92
Swedish	0.55	0.18	0.34	0.30	0.38	0.74	0.76	0.65	0.85	1.55	0.76	1.23
Sports	0.10	0.18	0.38	0.32	0.40	0.03	0.26	0.22	0.36	0.57	0.46	0.38
High School Track												
Vocational	0.28	0.27	0.17	0.46	0.32	0.29	0.16	0.13	0.06	0.05	0.08	0.09
Academic non-STEM	0.48	0.15	0.65	0.31	0.45	0.47	0.54	0.21	0.05	0.13	0.66	0.56
Academic STEM	0.24	0.58	0.18	0.23	0.23	0.24	0.30	0.66	0.88	0.82	0.26	0.35
SweSAT												
Test-taker	0.81	0.72	0.87	0.86	0.80	0.70	0.91	0.88	0.82	0.93	0.90	0.90
SweSAT score of test-takers												
Total	0.13	-0.15	-0.16	-0.21	-0.23	0.33	0.30	0.41	0.52	1.12	0.20	0.67
Vocabulary	0.20	-0.25	-0.21	0.06	-0.11	0.40	0.23	0.15	0.03	0.65	-0.01	0.43
Swedish Read.Comprehension	0.18	-0.09	-0.04	-0.18	-0.10	0.33	0.33	0.37	0.49	0.94	0.27	0.68
English	0.17	-0.16	-0.02	-0.21	-0.14	0.34	0.39	0.39	0.47	1.01	0.30	0.72
General Information	0.21	-0.22	-0.28	-0.03	-0.11	0.32	0.27	0.28	0.27	0.83	0.10	0.48
Data Sufficiency	-0.11	0.18	-0.07	-0.36	-0.24	-0.02	0.04	0.44	0.70	0.78	0.18	0.34
Interpret Diag/Tables/Maps	-0.02	0.12	0.09	-0.36	-0.15	0.04	0.14	0.38	0.67	0.74	0.31	0.44
N students	**1,600**	**5,455**	**357**	**1,544**	**1,847**	**826**	**1,118**	**1,980**	**6,065**	**592**	**1,858**	**768**
Fraction of sample	**0.02**	**0.06**	**0.00**	**0.02**	**0.02**	**0.01**	**0.01**	**0.02**	**0.06**	**0.01**	**0.02**	**0.01**
Fraction of college enrollment	**0.04**	**0.15**	**0.01**	**0.04**	**0.05**	**0.02**	**0.03**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college graduates	**0.07**	**0.23**	**0.01**	**0.06**	**0.08**	**0.03**	**0.05**	**0.08**	**0.25**	**0.02**	**0.08**	**0.03**

Table A.9: Age, Choices, and Outcomes by College Major

		College Major											
		3-year					4-year						
	No enroll (HS grad)	**non-STEM**	**STEM**	**Business**	**HealthSci**	**Education**	**Humanities**	**SocSci**	**Sciences**	**Engineer**	**Medicine**	**Business**	**Law**
Age at													
9th grade graduation	16.03	16.00	16.01	16.01	16.00	16.01	16.00	16.01	16.00	15.99	15.98	16.00	15.99
High school graduation	18.66	18.92	18.92	18.86	18.98	18.90	18.96	19.03	19.00	19.04	19.11	19.07	19.10
First college enrollment		24.06	21.68	25.22	23.71	23.85	22.52	22.88	21.62	20.62	22.40	21.89	22.11
College Outcomes													
Stayed enrolled, 1st major		0.78	0.80	0.90	0.69	0.70	0.65	0.63	0.69	0.83	0.85	0.78	0.82
Graduated, 1st major		0.38	0.41	0.70	0.30	0.43	0.39	0.36	0.39	0.63	0.79	0.46	0.62
College graduate		0.54	0.55	0.76	0.53	0.69	0.68	0.65	0.62	0.74	0.92	0.62	0.75
N students	**59,393**	**1,955**	**11,151**	**1,051**	**1,737**	**3,753**	**687**	**1,431**	**3,258**	**7,584**	**561**	**3,403**	**985**
Fraction of sample	**0.61**	**0.02**	**0.12**	**0.01**	**0.02**	**0.04**	**0.01**	**0.01**	**0.03**	**0.08**	**0.01**	**0.04**	**0.01**
Fraction of college enroll.		**0.05**	**0.30**	**0.03**	**0.05**	**0.10**	**0.02**	**0.04**	**0.09**	**0.20**	**0.01**	**0.09**	**0.03**
Age at													
9th grade graduation		16.00	16.01	16.01	15.99	16.00	16.00	16.00	16.00	15.99	15.98	16.00	15.98
High school graduation		18.94	18.91	18.88	18.97	18.89	18.89	19.05	19.01	19.04	19.10	19.08	19.10
First college enrollment		22.95	21.61	24.10	22.83	23.16	22.89	22.36	21.20	20.36	21.66	21.47	21.56
Last college degree		28.66	26.31	29.32	31.42	27.33	29.06	28.84	27.61	26.71	27.64	27.68	27.78
College Outcomes													
Stayed enrolled, 1st major		0.46	0.84	0.78	0.88	0.88	0.32	0.46	0.63	0.79	0.74	0.84	0.80
N students		**1,600**	**5,455**	**357**	**1,544**	**1,847**	**826**	**1,118**	**1,980**	**6,065**	**592**	**1,858**	**768**
Fraction of sample		**0.02**	**0.06**	**0.00**	**0.02**	**0.02**	**0.01**	**0.01**	**0.02**	**0.06**	**0.01**	**0.02**	**0.01**
Fraction of college enroll.		**0.04**	**0.15**	**0.01**	**0.04**	**0.05**	**0.02**	**0.03**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college grad.		**0.07**	**0.23**	**0.01**	**0.06**	**0.08**	**0.03**	**0.05**	**0.08**	**0.25**	**0.02**	**0.08**	**0.03**

Table A.10: College Programs within Major, First Enrollment

College Major, 1st enrollment	**Fraction of major**	**SUN2000Inr Code**
3-year non-STEM (Hum, Soc Sci)		
Journalism and Media Science	0.15	321
History and Archeology	0.13	225
Media production	0.10	213
Transportation	0.06	840
Sociology, Ethnology, and Cultural Geography	0.06	312
3-year STEM (Sci, Math, Eng)		
Energy- and Electrical Engineering	0.25	522
Mechanical Engineering	0.21	521
Electronics, Computer Engineering and Automation	0.17	523
Building- and Construction Engineering	0.10	582
Computer Science and Systems Science	0.06	481
3-year Business		
Business Administration, Trade and Administration (general)	0.64	340
Management and Administration	0.14	345
Purchasing, Sales, and Distribution	0.08	341
Business Administration, Trade and Administration (other)	0.08	349
Marketing	0.05	342
Health Sciences		
Nursing	0.47	723
Social work and Guidance	0.24	762
Therapy, Rehabilitation, and Dietary treatment	0.15	726
Technically oriented health education	0.05	725
Pharmacy	0.04	727
Education		
Specialist Teacher	0.41	145
Pedagogy and Teacher education (other)	0.21	149
Teacher, primary school	0.14	144
Teacher, preschool and leisure activities	0.14	143
Teacher, vocational and practical/aesthetic subjects	0.09	146
4-year Humanities		
Religion	0.19	221
History and Archeology	0.18	225
Music, Dance, and Drama	0.16	212
Foreign Language	0.15	222
Media production	0.08	213
4-year Social Sciences		
Social and Behavioral Science (general)	0.48	310
Psychology	0.11	311
Sociology, Ethnology, and Cultural Geography	0.06	312
Transportation	0.06	840
Political Science	0.06	313
4-year Sciences and Math		
Computer Science and Systems Science	0.38	481
Mathematics and Science (other)	0.25	469
Biology and Biochemistry	0.07	421
Physics	0.06	441
Chemistry	0.04	442
4-year Engineering		
Mechanical Engineering	0.17	521
Electronics, Computer Engineering and Automation	0.17	523
Technology and Industry Engineering (general)	0.16	520
Energy- and Electrical Engineering	0.14	522
Industrial Economics and Organization	0.08	526
4-year Medicine		
Medicine	1.00	721
4-year Business		
Business Administration, Trade and Administration (general)	0.87	340
Marketing	0.10	345
Management and Administration	0.02	342
Business Administration, Trade and Administration (other)	0.01	349
4-year Law		
Law	1.00	380

Table A.11: College Programs within Major, Final Graduation

College Major, final graduation	Fraction of major	SUN2000Inr Code
3-year non-STEM (Hum, Soc Sci)		
Political Science	0.11	313
Transportation	0.11	840
Journalism and Media Science	0.10	321
Economics and Economic History	0.10	314
Sociology, Ethnology, and Cultural Geography	0.09	312
3-year STEM (Sci, Math, Eng)		
Energy- and Electrical Engineering	0.22	522
Mechanical Engineering	0.20	521
Electronics, Computer Engineering and Automation	0.16	523
Building- and Construction Engineering	0.11	582
Computer Science and Systems Science	0.10	481
3-year Business		
Business Administration, Trade and Administration (general)	0.50	340
Business Administration, Trade and Administration (other)	0.22	349
Banking, Insurance, and Finance	0.15	343
Management and Administration	0.13	345
Health Sciences		
Nursing	0.50	723
Therapy, Rehabilitation, and Dietary treatment	0.17	726
Social work and Guidance	0.16	762
Dental care	0.06	724
Pharmacy	0.05	727
Education		
Specialist Teacher	0.43	145
Teacher, primary school	0.28	144
Teacher, preschool and leisure activities	0.18	143
Pedagogy	0.08	142
Pedagogy and Teacher education (other)	0.02	149
4-year Humanities		
Music, Dance, and Drama	0.20	212
History and Archeology	0.20	225
Foreign Language	0.16	222
Religion	0.16	221
Form and Visual Arts	0.09	211
4-year Social Sciences		
Economics and Economic History	0.28	314
Political Science	0.25	313
Psychology	0.21	311
Sociology, Ethnology, and Cultural Geography	0.13	312
Library and Documentation	0.07	322
4-year Sciences and Math		
Computer Science and Systems Science	0.39	481
Biology and Biochemistry	0.18	421
Chemistry	0.12	442
Physics	0.08	441
Agriculture	0.05	443
4-year Engineering		
Mechanical Engineering	0.23	521
Energy- and Electrical Engineering	0.16	522
Technology and Industry Engineering (general)	0.15	520
Electronics, Computer Engineering and Automation	0.14	523
Industrial Economics and Organization	0.11	526
4-year Medicine		
Medicine	1.00	721
4-year Business		
Management and Administration	0.47	343
Banking, Insurance, and Finance	0.28	345
Business Administration, Trade and Administration (general)	0.24	340
Business Administration, Trade and Administration (other)	0.00	349
4-year Law		
Law	1.00	380

A.3 Calculating Present Value of Income

In this Appendix, we provide more details on the calculation of the present value of income.

The 1974-1976 birth cohorts were 37-39 years old at the end of the sample period. Thus, we must impute income until age 65 in order to estimate how major choices affect the discounted present value of income. To impute income, we estimate the regressions:

$$ln(Y_t) - ln(Y_{t-1}) = \beta_0 + T_t^{'}\beta_T + A_t^{'}\beta_A + \beta_C D_C + +D_C T_t^{'}\beta_{TC} + D_C A_t^{'}\beta_{AC} + \epsilon_t$$

which relate income growth to year dummies, T_t, age dummies, A_t, an indicator for being a college graduate, D_C, and this indicator interacted with year and age dummies. The regression is estimated using earnings data from 1990 to 2013 and is estimated on those born between 1965 and 1980 and their fathers who were born between 1945 and 1952. Since income can be zero or negative, all non-positive values of income are set to one before taking logs.

Using the model above, we predict earnings for everyone in our sample from the last age they are observed to age 65. Specifically, we use the income average over the last three years of the sample and the estimated growth rate above to simulate out each individual's income to age 65, assuming that market conditions remain the same as in 2013.

Given predicted income up to age 65, we then calculate the present discounted value of wage income and the present discounted value of disposable income from ages 20 to 65 assuming the yearly discount rate $\beta = 0.95$.

Figure A.7 shows the earnings profiles for seven different groups of birth cohorts. Each profile shows their average earnings between 1990 and 2013 in SEK 2010. The top panel shows total disposable income while the bottom panel shows wage income.[36] From 1990 to 2013, Sweden also experience substantial real earnings growth, which explains the vertical distance between young and old cohorts visible in the figures.

[36]Note that Sweden had a large recession in the early 1990s which is visible in both plots as a period of flat or decreasing earnings.

Figure A.7: Earnings by Age and Cohort (disposable income and wage income)

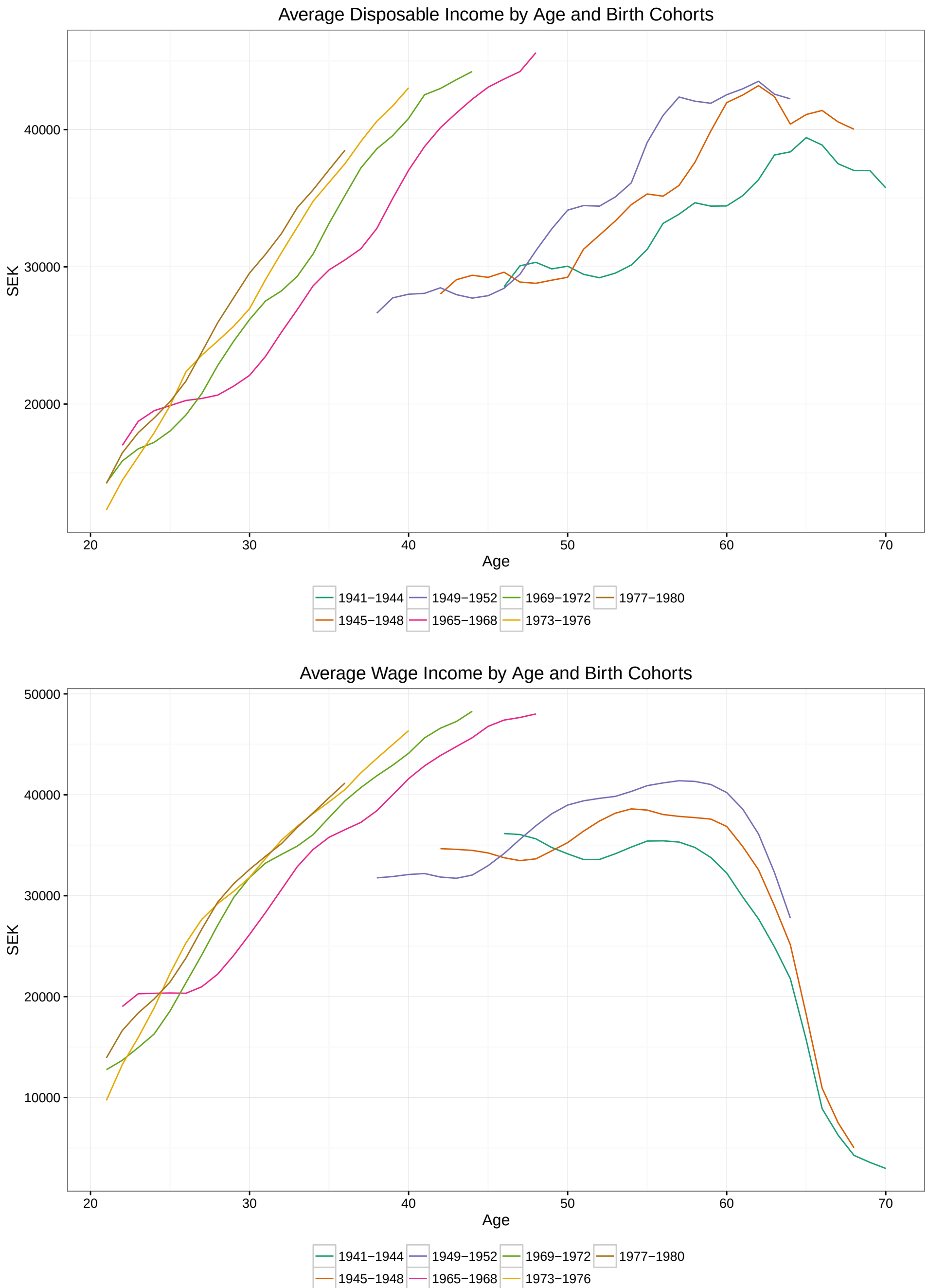
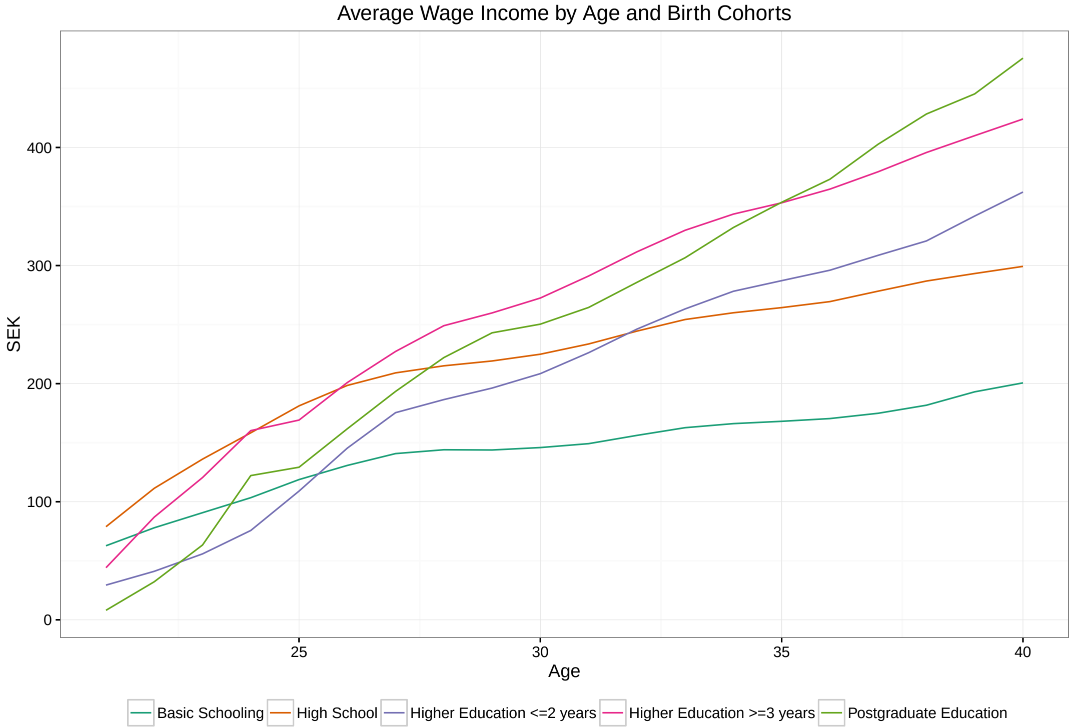


Figure A.8: Earnings Profiles by Age and Education (wage income)



B Within-School-Across-Cohort Instruments

Table A.12: First Stage Vocational Trk Instrument table

	(1) Vocational Trk	(2) Vocational Trk	(3) Vocational Trk
Vocational Trk Instrument	0.315***	0.333***	0.348***
	(0.0157)	(0.0150)	(0.0154)
9th grade Schl Ave Vocational Trk	0.719***	0.673***	0.716***
	(0.0143)	(0.0139)	(0.0150)
Own 9th grade GPA		-0.179***	-0.181***
		(0.00194)	(0.00194)
Cohort Ave 9th grade GPA			0.0440*
			(0.0196)
School Ave 9th grade GPA			0.131***
			(0.0153)
Constant	0.337***	0.208***	-0.180***
	(0.0196)	(0.0191)	(0.0492)
1st Stage F-stat	402.9	490.0	506.8
R^2	0.391	0.449	0.449
$E[y]$	0.412	0.412	0.412
Sample Size	80606	80606	80606

Notes: Standard errors in parentheses. High School peer instruments and ability controls are with respect to peers in 9th grade. All specifications include the following controls: mother's education, father's education, family Income, parents married, healthy at birth, mother's age at birth, cohort dummies. Also included are 9th grade school average rates of advanced english and math. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.13: First Stage Academic Trk Instrument table

	(1) Academic Trk	(2) Academic Trk	(3) Academic Trk
Academic Trk Instrument	0.414***	0.411***	0.409***
	(0.0194)	(0.0194)	(0.0195)
9th grade Schl Ave Academic Trk	0.882***	0.895***	0.894***
	(0.0201)	(0.0199)	(0.0206)
Own 9th grade GPA		-0.0470***	-0.0471***
		(0.00227)	(0.00228)
Cohort Ave 9th grade GPA			0.0147
			(0.0230)
School Ave 9th grade GPA			0.00490
			(0.0184)
Constant	-0.0161	-0.0624***	-0.0747
	(0.0142)	(0.0144)	(0.0505)
1st Stage F-stat	454.5	449.9	439.4
R^2	0.106	0.110	0.110
$E[y]$	0.311	0.311	0.311
Sample Size	80606	80606	80606

Notes: Standard errors in parentheses. High School peer instruments and ability controls are with respect to peers in 9th grade. All specifications include the following controls: mother's education, father's education, family Income, parents married, healthy at birth, mother's age at birth, cohort dummies. Also included are 9th grade school average rates of advanced english and math. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.14: First Stage STEM Trk Instrument table

	(1) STEM Trk	(2) STEM Trk	(3) STEM Trk
STEM Trk Instrument	0.193***	0.213***	0.263***
	(0.0296)	(0.0273)	(0.0281)
9th grade Schl Ave STEM Trk	0.435***	0.343***	0.473***
	(0.0405)	(0.0375)	(0.0393)
Own 9th grade GPA		0.226***	0.228***
		(0.00179)	(0.00180)
Cohort Ave 9th grade GPA			-0.0614**
			(0.0193)
School Ave 9th grade GPA			-0.156***
			(0.0156)
Constant	-0.0518***	0.165***	0.581***
	(0.0129)	(0.0121)	(0.0439)
1st Stage F-stat	42.44	61.28	87.62
R^2	0.242	0.352	0.353
$E[y]$	0.276	0.276	0.276
Sample Size	80606	80606	80606

Notes: Standard errors in parentheses. High School peer instruments and ability controls are with respect to peers in 9th grade. All specifications include the following controls: mother's education, father's education, family Income, parents married, healthy at birth, mother's age at birth, cohort dummies. Also included are 9th grade school average rates of advanced english and math. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Additional Counterfactual Results

Table A.15: AMTE of inducing marginal students into the STEM track by pre- and post- intervention final education

	HS	College Dropout (short)	College Dropout (long)	Non-STEM (3-year)	STEM (3-year)	Health Sciences (3-year)	Business (3-year)	Humanities	Education	Social Sciences	Science and Math	Engineering	Business	Law	Medicine
HS	-0.01	0.15	0.07	0.10	0.23	0.05	0.22	-0.09	-0.21	0.22	0.18	0.31	0.41	0.33	0.43
College Dropout (short)	-0.19	-0.00	-0.14		0.06	-0.09				0.03	-0.02	0.11	0.16	0.11	0.27
College Dropout (long)	-0.16	0.06	-0.03	-0.07	0.10	-0.10		-0.20	-0.43	0.08	0.01	0.11	0.34	0.22	0.20
Non-STEM (3-year)	-0.15	0.09	-0.02	-0.02	0.12	-0.09				0.11	0.05	0.16	0.36	0.22	0.28
STEM (3-year)	-0.23	-0.09	-0.18		-0.00						-0.09	0.06			
Health Sciences (3-year)		0.07	-0.03		0.15	-0.01					0.07	0.20	0.34		0.34
Business (3-year)	-0.26	-0.10	-0.23		-0.09		0.00				-0.19	-0.07			
Humanities	-0.07	0.10	-0.01	0.05	0.18	0.01		-0.07	-0.19	0.14	0.08	0.21			0.36
Education	0.22	0.30	0.20	0.28	0.37	0.18			-0.03	0.36	0.31	0.45	0.60		0.56
Social Sciences	-0.17	0.05	-0.09		0.10	-0.06				0.01	-0.01	0.12			0.19
Science and Math		-0.07	-0.15		-0.00						-0.02	0.06			0.22
Engineering		-0.02			-0.08							0.01			
Business	-0.49	-0.27	-0.44	-0.51	-0.25	-0.40		-0.57	-0.84	-0.35	-0.39	-0.28	-0.03	-0.21	-0.21
Law	-0.41	-0.19	-0.31		-0.13	-0.37					-0.24	-0.16		-0.00	-0.07
Medicine		-0.16	-0.23		-0.06							-0.02			0.02

Notes: Table shows the average marginal treatment effect of the high school STEM track by pre- and post-intervention final education levels. The rows are baseline final education choices prior to the intervention and the column are counterfactual final education attainment after eliminating the vocational track. Omitted cells are for transitions with probabilities of less than 0.000025 based on the simulations.

Table A.16: ATE of eliminating vocational track by pre- and post- intervention final education

	HS	College Dropout (short)	College Dropout (long)	Non-STEM (3-year)	STEM (3-year)	Health Sciences (3-year)	Business (3-year)	Humanities	Education	Social Sciences	Science and Math	Engineering	Business	Law	Medicine
HS	0.03	0.17	0.13	0.17	0.26	0.06	0.22	0.05	-0.14	0.26	0.23	0.32	0.48	0.39	0.46
College Dropout (short)	-0.10	0.01	-0.05	0.04	0.13	-0.08	0.06	-0.01	-0.23	0.14	0.07	0.14	0.28	0.21	
College Dropout (long)	-0.07	0.12	0.01	0.07	0.14	0.02	0.08	0.03	-0.16	0.13	0.09	0.20	0.37	0.34	
Non-STEM (3-year)	0.05	0.17	0.08	0.03	0.23		0.19		-0.20	0.18	0.18	0.27	0.42	0.36	
STEM (3-year)	-0.20	-0.07	-0.11	-0.09	0.00	-0.18	0.01	-0.14	-0.33	-0.00	-0.02	0.07	0.19	0.18	
Health Sciences (3-year)		0.07	0.03	0.10	0.13	-0.00	0.13		-0.14	0.16	0.10	0.19	0.34		
Business (3-year)		-0.15					0.00								
Humanities		0.17	0.07	0.12	0.23			0.02	-0.13	0.21	0.18	0.32	0.45		
Education		0.28	0.25		0.40				0.01	0.36	0.34	0.47	0.71		
Social Sciences		0.20	0.05		0.26					0.03		0.30			
Science and Math	-0.18	0.00	-0.07						-0.31		0.00	0.06	0.23		
Engineering	-0.23	-0.06	-0.11	-0.12	-0.07	-0.20			-0.39	-0.14	-0.01	0.00	0.23	0.22	
Business		-0.16	-0.37		-0.14							-0.09	0.01		
Law		0.06	-0.14		0.08							0.04		0.02	
Medicine			-0.17									-0.04			0.00

Notes: Table shows the average treatment effect of eliminating the vocational track (for those in the vocational track) by pre- and post-intervention final education levels. The rows are baseline final education choices prior to the intervention and the column are counterfactual final education attainment after eliminating the vocational track. Omitted cells are for transitions with probabilities of less than 0.000025 based on the simulations.