Complementarities in High School and College Investments

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Abstract. How do pre-college investments affect college enrollment, graduation, and labor market outcomes? Using Swedish registry data, we document how students sort on multidimensional abilities into high school tracks, and sort on both abilities and high school track into college majors. These sorting patterns highlight the presence of dynamic selection on both the level and type of education, and suggest that there may be dynamic complementarities between secondary and post-secondary investments. With the goal of estimating dynamic complementarities, we develop a dynamic Roy model to account for selection and differential returns to abilities, prior investments, and other persistent unobservables. We identify the model using noisy measures of abilities combined with quasi-experimental variation at the high school and college application stages. We find heterogeneous returns to abilities by final education, and economically important dynamic complementarities between high school and college investments. Consequently, we find larger returns to counterfactual policies promoting investments in STEM skills in high school compared to in college.

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JEL: C32, C38, I21, J24, J31.

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1 Introduction

Many policies aim to increase overall college attainment or attainment in certain majors, to improve opportunities for disadvantaged students and to increase the supply of skilled workers. With these goals in mind, a policy maker must choose when in a student's education trajectory to invest and what type of investment to make. This choice depends on whether earlier investments increase the return to later investments, i.e. if there are dynamic complementarities. While dynamic complementarities are extensively studied in early childhood (Heckman and Mosso, 2014; Almond et al., 2018), little is known about the complementarities between secondary and post-secondary investments. We estimate the dynamic complementarities between high school and college investments, showing that tracking decisions made in high school not only influence post-secondary choices, but also their returns.

In this paper, we study the education trajectories of students from when they start specializing in ninth grade through the end of college. We explore how initial endowments and high school choices complement post-secondary education choices, and how these complementarities affect labor market outcomes. First, we document sorting on multidimensional abilities into high school tracks, and rich sorting on both abilities and high school tracks into college majors. These patterns suggest that students may sort based on heterogeneous returns that depend on their abilities. Second, motivated by the descriptive evidence, we develop a dynamic Roy model to account for selection driven by abilities, prior investments, and other persistent unobservables. We identify this model using noisy measures of abilities combined with quasi-experimental variation at the high school tracking and college application stages. Third, we use the model to estimate the dynamic complementarity between high school and college investments, and to show how the returns to these investments depend on the abilities of the student. We find heterogeneous returns to abilities by final education, and important dynamic complementarities between high school and college investments. Consequently, we find larger returns to counterfactual policies promoting investments in Science, Technology, Engineering, and Mathematics (STEM) skills in high school compared to in college.

We use Swedish registry data on the population of men born between 1974 and 1976. We link measures of multidimensional abilities, detailed family background, high school course choices and performance, college applications, college enrollment histories, college graduation, and labor market outcomes until age 37-39. Four aspects of the institutional setting enable our analysis. First, we observe students choosing high school tracks at the end of ninth grade, which affects what courses they take during high school. This tracking mirrors more implicit tracking or variation in courses taken that is common in the United

States and other countries (Betts, 2011; Woessmann, 2016). Second, men in our cohorts completed a two-day long enlistment screening for mandatory military service including cognitive exams, personal interviews with psychologists, and measures of physical health. Combined with performance measures from ninth and tenth grade, these measures allow us to use a factor model to estimate the cognitive, interpersonal, and grit abilities of students. Third, Sweden uses a centralized college application process, where we observe students' applications, whether they were above the admission threshold for a particular program, and where they enrolled. Finally, we have panel data on college enrollment where we see if they switch programs, if they graduate, and what degree they complete. The institutional setting and data also provide us with plausibly exogenous variation in high school track and college admission.

To begin, we present descriptive evidence documenting rich dynamic sorting that depends on multiple dimensions of ability. First, we show that high school tracks alone explain 20% of the variation in wages, while our ability measures alone explain more than 25%. When combined, high school tracks and abilities explain only about 26%. These patterns of interdependence repeat for other combinations of abilities, high school tracks, and college decisions. Second, we show that students sort strongly on abilities into high school track, going to college, and college major. Students sort into high school tracks on cognitive ability and grit, but there is weaker sorting on interpersonal ability. Similar patterns emerge for going to college, but with differential sorting among majors. Majors such as engineering have high cognitive and grit abilities, while law is relatively balanced across the three abilities, and education is lower in cognitive ability but higher in interpersonal abilities. Both sets of results suggest complementarities between abilities, high school track, and post-secondary education outcomes.

Based on the descriptive evidence, we build a dynamic generalized Roy model to jointly model education decisions (starting in ninth grade through the end of college) and labor market outcomes. We show how our model can be thought of as flexibly estimating choice probabilities and state transition functions conditional on a period's current state variables and choices. Hence, our model can be thought of as an approximation to a full dynamic model, but without the need to make assumptions on the utility function. To capture endogenous sorting on unobservables known by the student but not the econometrician, we include a detailed measurement system for estimating a multidimensional vector of abilities. In addition, we estimate eight latent types which capture correlations between education decisions and outcomes. The types are identified using exogenous variation in high school tracking and college applications. Students in the model account for admission probabilities when applying, and we directly model the application process. The model enables us to estimate how a detailed sequence of specialization choices depend on latent abilities and prior choices, and how these all together affect outcomes.

We use the estimated model to directly study the complementarities between abilities, high school track, and post-secondary education decisions. First, we show that the returns to ability differ by final education using the model estimates that account for rich multidimensional selection. For example, the returns to grit are nearly three times as large for business than for engineering, and the returns to cognitive ability are more than twice as large in the social sciences than in education. In addition, we find that expected earnings across degrees are quite heterogeneous. Indeed, seven different majors are ranked as having the highest expected earnings depending on a student's ability, background, and previous high school investments. Second, we calculate treatment effects of the different high school tracks. These treatment effects include the direct effect of a high school track on earnings, but also the impact of high school track on college application, enrollment, and graduation decisions. We find that the returns to the STEM track are high relative to the academic or vocational track. We additionally find evidence that students sort, at least partially, on gains, with larger treatment on the treated estimates (TT) than treatment on the untreated (TUT). For example, consider the treatment of switching a student from vocational track to academic STEM track. We find that those who endogenously choose the STEM track gain twice as much as those who choose the vocational track.

Lastly, we use the model to simulate two counterfactual policies designed to promote STEM education. The first policy encourages those at the margin for the high school STEM track to pursue the STEM track. The second counterfactual policy incentivizes those already applying to college to apply to STEM programs. Both counterfactual policies leave all other choices unconstrained. We find that both policies create additional college STEM enrollees and graduates, but that the policy moving marginal students to the STEM track in high school leads to larger wage gains and a larger proportion of those affected benefiting. These results highlight the importance of understanding (1) how students sort through the education process, (2) how the returns to education investments can vary by ability, and (3) the dynamic complementarities between earlier and later investments.

We bridge and extend several strands of literature. First, there is ample empirical evidence on the importance of cognitive and non-cognitive abilities for education and labor market success; see *e.g.* Heckman and Rubinstein (2001); Machin et al. (2001); Heckman et al. (2006); Borghans et al. (2008); Lindqvist and Vestman (2011); Heckman et al. (2014); Weinberger (2014); Borghans et al. (2016); Prada and Urzúa (2017); Heckman et al. (2018a,b); Deming (2017); Deming and Noray (2020).[1] But the process by which

[1] Several papers stress the importance of other dimensions of non-cognitive abilities for high school

multidimensional abilities lead to specialization and produce better economic outcomes is still not well understood.

Second, there is a growing literature on the importance of early specialization for labor market outcomes. Identification of causal effects is challenging because of the endogenous sorting into alternatives. When analyzing multiple unordered alternatives, we also need to take into account that individuals have different next-best alternatives (Kirkebøen et al., 2016). To overcome these challenges, most of the literature has focused on binary choices. One strand of the literature focuses on STEM versus non-STEM specialization in high school (Altonji, 1995; Levine and Zimmerman, 1995; Rose and Betts, 2004; Joensen and Nielsen, 2009; Taylor, 2014; Cortes et al., 2015; Goodman, 2019).[2] Another strand of the literature focuses on the importance of the choice of vocational versus general training at the upper-secondary level (Oosterbeek and Webbink, 2007; Malamud and Pop-Eleches, 2011; Hall, 2012, 2016; Hanushek et al., 2017; Golsteyn and Stenberg, 2017; Zilic, 2018; Bertrand et al., 2019). In this paper, we directly model students' decision processes, allowing students to have different next-best alternatives.[3] We find that many students sort on comparative advantage in high school. This is consistent with Dahl et al. (2023), who use quasi-random variation around cut-offs in ninth grade GPA in admissions into high school lines in Sweden to estimate the causal effect of the vocational track and each academic line (technical, natural science, social science, business, humanities) relative to the next-best alternative. Though they focus on older cohorts, their estimates broadly align with our estimates of the high school treatment effects for marginal students. Our paper complements theirs by estimating a generalized Roy model to identify who the marginal students are, how their returns depend on abilities and background, and how they compare to average returns. These are all key parameters for policymakers deciding when to invest and which skills to invest in.

Third, the college major premium is well-documented,[4] but it is still not well un-

and college major choices. Dimensions determining high school specialization in mathematics and science include competitiveness (Buser et al., 2014, 2017), locus of control, self-esteem, and work ethics (Mendolia and Walker, 2014), preferences and beliefs (Fiala et al., 2022), awareness (Giustinelli and Pavoni, 2017), peers and school quality (Bianchi, 2020), and teacher implicit bias (Carlana, 2019). In Sweden, Golsteyn and Stenberg (2017) also relate the measures of leadership skills and psychological stability to the choice of vocational versus academic secondary education and later-life earnings.

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

[3]Specialization is also discussed in terms of occupation-specific experience or human capital, such as Heckman and Sedlacek (1985) and Neal (1998). Several papers document a strong association between college major and occupation (Black et al., 2003; Altonji et al., 2012, 2016; Kinsler and Pavan, 2015; Altonji et al., 2016; Ransom and Phipps, 2017; Arcidiacono et al., 2020; Sloane et al., 2021). While also an important form of specialization, we do not consider occupational sorting in this paper, instead focusing on sorting and specialization in school.

[4]See, for example, Berger (1988); Paglin and Rufolo (1990); Altonji (1993); Grogger and Eide (1995); Arcidiacono (2004); Christiansen et al. (2007); Beffy et al. (2012); Altonji et al. (2014); Kinsler and Pavan (2015); Kirkebøen et al. (2016); Hastings et al. (2013); Altmejd (2018); Aucejo and James (2021).

derstood what it embodies. Altonji et al. (2012) advocate the importance of analyzing high school and college choices jointly to get at the importance of timing of specific investments. A few papers jointly analyze the importance of high school investments for college outcomes (Joensen and Nielsen, 2016; Card and Payne, 2017; Belzil and Poinas, 2018; De Groote et al., 2018; Fiala et al., 2022), math and verbal skills for the transition from high school to college (Aucejo and James, 2021; Delaney and Devereux, 2020), mechanical ability for college enrollment (Prada and Urzúa, 2017), and finally, Saltiel (2023) shows the important role of non-cognitive ability and math self-efficacy for gender differences in college major enrollment, graduation, and returns.[5] We contribute to this literature by quantifying how ability affects high school sorting, and how ability and high school sorting then affect college choices and labor market outcomes. Methodologically, we bridge the quasi-experimental literature pioneered by Kirkebøen et al. (2016) using discontinuities in college admission and the more structural literature by directly modeling the constraints in college admission process. We additionally estimate the size of the dynamic complementarities between high school and college investments, which is key for understanding the sources of inequality and the effectiveness of human capital policy (Heckman et al., 2005).

2 Institutional Setting

In this section, we describe the education environment and other institutional details of Sweden for 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 first 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.[7] 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

Altonji et al. (2016) and Patnaik et al. (2021) provide reviews.

[5]Other complementary papers that use a generalized Roy model to estimate heterogeneous treatment effects of college major choice include Rodríguez et al. (2016) and Mourifie et al. (2020).

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

[7]Meghir and Palme (2005) and Meghir et al. (2018) provide more background and evaluate the impacts of the Swedish compulsory schooling reform that mandated nine years.

students.[8] If there are more applicants than available seats, then seats are allocated based on ninth grade GPA.[9] In this period, high school lines were generally not selective, and most students are admitted to (96%) and graduate from (92%) the high school track of their preferred choice.

High school lines are broadly classified into vocational and academic high school tracks. 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 B.3 provides a brief summary of the mandated distribution of the core curricula in each of these high school lines. There are large differences in the amount of instruction time devoted to math, science, and other technical courses. For example, the students in the technical line have 18 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. 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 readiness for certain college 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 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 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. A college application includes a rank-ordered list of up to 12 college-program choices.[11] Selectivity varies greatly across

[8] 92% 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.

[9] We describe high school application and admission in more detail in Appendix B.1. See the Secondary School regulation `1987:743` and `1992:394` for the complete details of the process.

[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 it was the key factor for admission for more than a third of our sample. All the details can be found in the Higher Education Act `1992:1434` and the Higher Education Ordinance `1993:100`.

[11] In this respect, the college application in Sweden is similar to, for example, Norway (Kirkebøen et al., 2016), Denmark (Humlum et al., 2014; Heinesen et al., 2022), Chile (Hastings et al., 2013; Bordon and Fu, 2015). (Altmejd et al., 2021) directly compare college application in Sweden to Croatia, Chile,

college majors: the 4-year programs in Medicine, Law, and Humanities are the most selective. All Medicine and Law college-programs require a GPA one standard deviation above the mean, 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 through 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) 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 (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 in 1974-76. Our measurements of health, abilities, and family background come from the Military Enlistment archives administered by the Swedish Defence Recruitment Agency (*Rekryteringsmyndigheten*), the Swedish National Archives (*Riksarkivet*), and several registers administered by Statistics Sweden (*SCB*).

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 emotional stability (Lindqvist and Vestman, 2011).

and the United States.

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

[13]The students in our sample are enrolled in college during the pre-2001-reform study aid regime as detailed in Joensen and Mattana (2020).

To validate our interpretation of the latent ability factors, we merge these registers to the Evaluation Through Follow-up (ETF) surveys administered to third, sixth, and tenth grade students by the Department of Education and Special Education at Gothenburg University.[14] We use the survey of a random sample the 1972 cohort which 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 (non-STEM), and academic STEM. As discussed in the prior section, 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*. We have access to the complete histories of college applications and admissions from 1993 onwards through the Swedish National Archives. These include the complete set of admission scores in each admission group as we basically observe the complete data from the college admission process.

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 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 few students, so we group them into STEM (Science, Math, Engineering) and non-STEM (Humanities, Social Science) majors. Students in the 3- and 4-year Education and Health Sciences majors (excluding medicine) look similar on observables and labor market outcomes, so these are

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

grouped together.[15]

The Multigeneration registry allows us to link children to their parents and background variables 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 until they are 37-39 years old, as well as parental background variables (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 age 2-4 (7-9) for our sample.

3.1 Sample Selection

We focus on males born in 1974-1976. We restrict to males since military enlistment at age 18 was only mandatory for Swedish males and these scores are important measures of latent ability. We choose the 1974-1976 birth cohorts for two reasons. 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 sub-scores for the cognitive test taken at military enlistment are only sparsely observed for those who were born after 1976.

3.2 Descriptive Statistics

This section describes the background characteristics of students and schools by high school track. Appendix Table A.1 shows that there is a large difference in average grades at the end of compulsory schooling by high school track. Vocational track students are negatively selected on ninth grade GPA, while academic STEM high school students are positively selected. Fifty-six percent of our sample attended the vocational track, 20% the academic non-STEM track, and 24% the academic STEM track.

Appendix Table A.1 also 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 parents with less education. The parents of those in academic non-STEM tracks also have somewhat less education than the parents of those in Academic STEM tracks. Vocational track students have better average health – both in terms of strength and

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

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.

3.3 Measuring Multidimensional Abilities

Since most proxies of ability are measured with error, we use a factor model to recover latent abilities. In Section 3.3.1, we briefly describe the identification of latent abilities when some measures are taken after schooling investments have been made. In Section 3.3.2, we describe our estimation strategy for models that include latent abilities.

3.3.1 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 such as test scores or behavior. In this paper, we identify latent abilities using evaluations done as part of the compulsory military enlistment and course grades in compulsory and high school. Let the measurement system, $\boldsymbol{M}$, denote a vector of measures or proxies of 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 when most are still enrolled 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},

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

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 $\boldsymbol{\theta}$, $\boldsymbol{X}$, and the error terms in schooling decisions and labor market outcomes.

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 direct effect of schooling 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 ($s = 0$). In Appendix Section D, we show that the schooling-state specific intercepts are separately identified from differences in how students sort across schooling states. The key assumption is that we have as many pre-specialization measures as factors. Since pre-specialization measures have not been affected by future investments, the conditional means of the pre-specialization measures are informative of how students sort into different schooling paths. Any additional difference in later measures by, for example, STEM vs. vocational schooling, must be due to the different types of skills learned in those programs beyond the abilities of the students in ninth grade.

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 deciles of latent abilities, we are measuring "residual" latent abilities. That is, the variation in latent abilities that is orthogonal to the observables. We include the observables whenever we estimate a model with latent abilities and, hence, still capture differences across students due to both observables and latent abilities.[17]

3.3.2 Estimation Strategy

Our measurement system consists of measures from the compulsory Swedish military enlistment taken at age 18 and course 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 our population.

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

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

[17] One can think of the residual latent factors as projections of the latent factors onto the orthogonal component of the student characteristics and then the Frisch-Waugh-Lovell theorem should apply (approximately).

[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.

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 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 grades from ninth grade and high school: math and sports grades from both ninth and tenth grades, Swedish and English from ninth grade, and residual GPA from both ninth and tenth grades.[21] This 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 1 summarizes the measurement system.

Rather than using the measure descriptions to interpret and label the 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 third, sixth, and tenth 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. Appendix Table A.2 summarizes the five items from the survey that were most informed by one dimension of ability. In the case of the first factor, ten out of the top twenty items were test scores and grades. Hence, we label the first factor “Cognitive Ability.” The second factor is relatively most informative about items relating to sports and social interactions. Informal conversations with Swedes of similar cohorts confirmed

[20]The military psychologists select about half of the enlistees to be rated on a leadership scale based 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 the “residual GPA” measures.

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 associated with "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 are also important for understanding labor market outcomes.

Table 1: Structure of Measurement System

Measures	θ_1	θ_2	θ_3
Military Enlistment Registers			
Four Cognitive measures:[b]	x		
Inductive, Verbal, Spatial, and Technical			
Leadership Evaluation[a,b]	x		
Leadership Ability[b]	x	x	
Emotional Stability[b]	x	x	
Ninth Grade Education Registers			
Ninth Grade Math & English Grades[c]	x	x	x
Ninth Grade Swedish & Sports Grades[f]	x	x	x
Ninth Grade residual GPA[df]	x	x	x
High School Education Registers			
Tenth Grade Math & Sports Grades[b]	x	x	x
High School residual GPA[e]	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 Ninth grade residual gpa model.[e] Tenth grade math and sports grades are included. [f] These measures do not include any schooling-state specific intercepts.

4 Descriptive Evidence

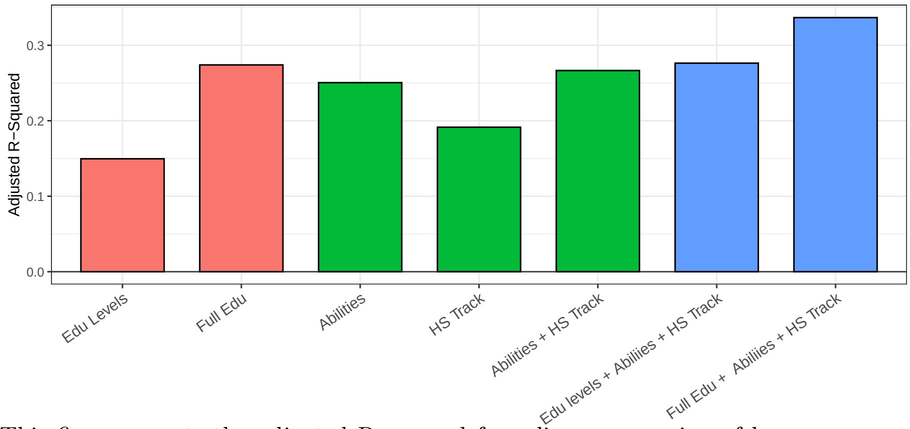
This section starts by providing descriptive evidence of dynamic complementarities between the abilities students arrive in high school with, high school investments, and college investments. It then documents how students sort into different specializations in both high school and in college.

4.1 Evidence of the Complementarities in Education Investments

Figure 1 reports the adjusted R-squared from a series of linear regressions of log wages on various sets of covariates: proxies for cognitive and non-cognitive abilities measured before high school graduation (4 variables), high school track indicators (4 indicators), indicators for educational level (5 indicators), and a full set of final education indicators which include high school track and college major (18 indicators). Figure 1 shows the regressions for all individuals, while the Figure F.1 restricts to college enrollees. Starting with Figure 1, the first red bar shows the R-squared when including indicators for final education level, and finds an adjusted R-squared of 0.15. The second red bar uses a richer specification that includes specific high school track and major, and explains almost twice as much of the variation in log wages, with an adjusted R-squared of 0.27. This is consistent with, for example, Altonji et al. (2012), who point out that there is substantial variation in earnings across majors within college graduates, commonly comparable to the average difference between high school and college graduates. The green bars (columns 3-5) run similar regressions but using proxies for cognitive and non-cognitive abilities measured before high school graduation, high school track indicators, or both. We see that ability proxies and high school track also explain a substantial amount of variation with adjusted R-squareds of 0.25 and 0.19, while combining them gives an R-squared of 0.27. This shows that a substantial portion of the variation in log wages can be explained using only measures from high-school aged students. The final three bars (in blue) show the combination of education levels with high school tracks and ability. When combining high school track, abilities, and detailed final education indicators, the adjusted R-squared is 0.34. This highlights that abilities and high school tracks have predictive power even after including detailed final education indicators, increasing the R-squared from 0.27 to 0.34.

Figure F.1 repeats the exercise for only those who enroll in college, and drops the no-longer relevant indicator variables. For this more homogeneous sample the R-squared values are smaller, but again high school tracks and ability proxies are predictive, explaining over 0.17 of the variation in log wages, compared to 0.23 when using the full set of education indicators. Finally, adding high school track and ability proxies to the regression with final education indicators increases the R-squared from 0.23 to 0.31. Overall, this shows that abilities and tracking choices measured in high school are quite predictive of later earnings, even among college enrollees and after controlling for 14 detailed final education indicators.

Figure 1: The Predictive Power of Abilities and Education



Notes: This figure reports the adjusted R-squared from linear regression of log wages on combinations of abilities and education indicators. "Abilities" include the general cognitive ability, emotional stability, and leadership scores from the conscription exam and the residual from ninth grade GPA regressed on general cognitive ability. "Edu levels" include indicators for high school dropout, terminal high school graduate, some college, 3-year degree, and 4-year degree. "HS Track" includes indicators for dropout, vocational track, academic track, and STEM track. "All Edu" is a series of indicators that include high school dropout, three high school tracks, an indicator for 3-year college dropout, an indicator for 4-year college dropout, and twelve indicators for various college majors. All ability measures enter linearly and all education measures enter as indicator variables. This figure reports the regressions for all individuals, while Figure F.1 reports the regressions for only those who enroll in college.

4.2 Sorting into High School Track and College Major

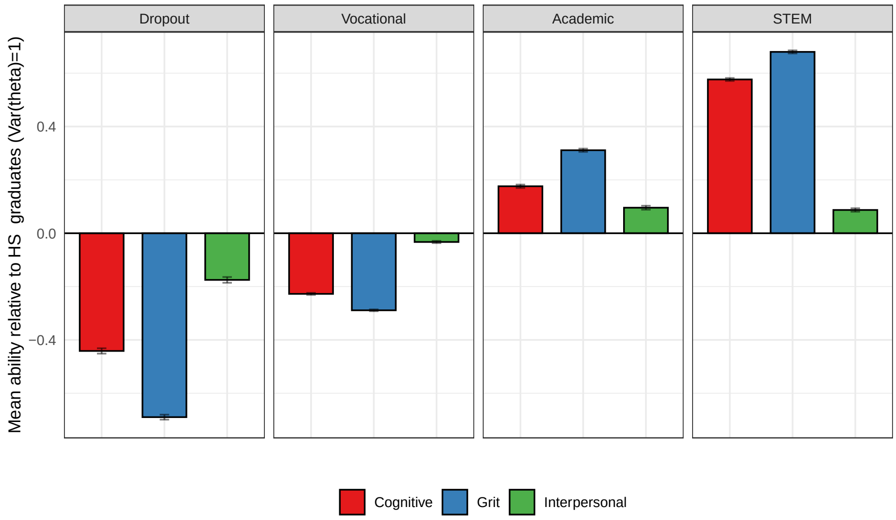
In this section, we investigate how students sort by multidimensional ability into high school track and college major. If abilities were observed, we could simply estimate the conditional mean of each ability by high school track or college major. As abilities are not observed, the literature has typically estimated discrete choice models with a measurement system and simulated the models to understand the sorting patterns (Heckman et al., 2018b). While we will use similar discrete choice models when estimating causal effects in section 6.2, we estimate the mean ability for different subgroups 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:

$$\boldsymbol{\theta}_{is} = \sum_{s \in \mathcal{S}} \boldsymbol{\beta}_s \mathcal{I}_s + \boldsymbol{\eta}_{is}, \tag{2}$$

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 state. We estimate one such model for each dimension of latent ability and set of mutually exclusive educational states.[22]

[22]These models are estimated via maximum likelihood using the first stage measurement system as described in section 3.3.2, where we assume that η_{is} is normally distributed. See Appendix Section E.1

Figure 2: Sorting into High School Track by Ability



Notes: Figure 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 full population.

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 full population. The figure shows that there is strong sorting on grit and cognitive abilities and weaker sorting on interpersonal abilities. The average cognitive ability of academic (STEM) students are 0.18 (0.58) standard deviations above the mean, while the average cognitive ability of vocational track students is 0.23 standard deviations below the mean. Sorting on grit has a similar pattern but is more extreme, while there is substantially less sorting on interpersonal ability.

Sorting into College Figure 3 show how students sort into post-secondary decisions by abilities (left panel) and high school track (right panel). The left panel shows the average cognitive, grit, and interpersonal abilities of those who apply, enroll, and graduate from college. Abilities are normalized to be mean 0 and standard deviation 1 in the population. Those who apply to college are around 0.35 standard deviations higher in cognitive ability and 0.4 standard deviations higher in grit. Moving from applications to enrollment sees a large jump in cognitive ability, likely related to admissions, while moving from enrollment to graduation sees a large jump in grit. Students also sort on interpersonal ability, but substantially less.

The right panel shows the means of high school track indicators for those who ap-

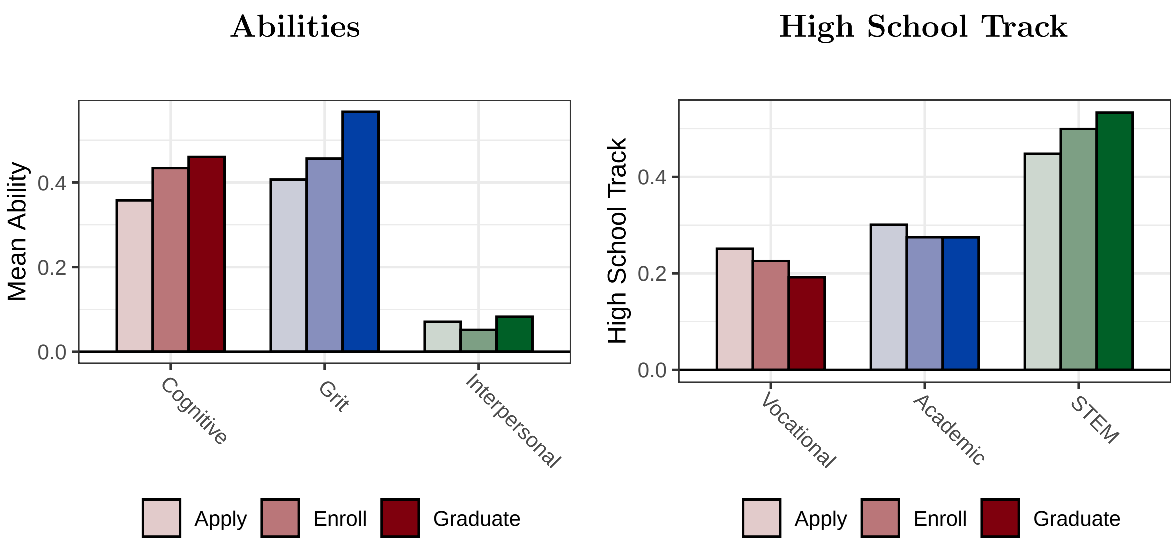
for a description of the likelihood estimation.

ply, enroll, and graduate from college by high school track. Those from the vocational track makes up around 25 percent of applicants, but only 20 percent of graduates. In contrast, those in the STEM track make up 45 percent of applicants and over 50 percent of graduates.

Figure 4 builds on the prior figure by showing how students sort into applying to, enrolling in, and graduating from specific majors. An "applying" student is assigned to the first major they list on their application. The top panel shows sorting patterns on ability where each sub-panel is a specific 4-year major. The ability measures have been normalized to have a mean of 0 and standard deviation of 1 among those who apply to college (including to 3-year majors). There are important sorting patterns on abilities across majors. For example, those who apply, enroll, and graduate in engineering tend to be high in cognitive ability and grit, but slightly below average in interpersonal skills. In contrast, for education majors, cognitive ability is below average, while grit is around average, and interpersonal skills are slightly above average. Finally, for business, graduates are over 0.2 standard deviations higher in grit, but only 0.1 higher in interpersonal ability, and 0.05 higher in cognitive ability.

The bottom panel of Figure 4 shows the proportion of applicants, enrollees, and graduates that come from each high school track for each 4-year major. Some programs, such as education, are somewhat balanced, with less than half coming from any of the three tracks, while other programs are skewed, such as engineering and medicine, where over 75 percent of graduates come from STEM tracks, or business and law where 55 to 60 percent of graduates come from non-STEM academic tracks.

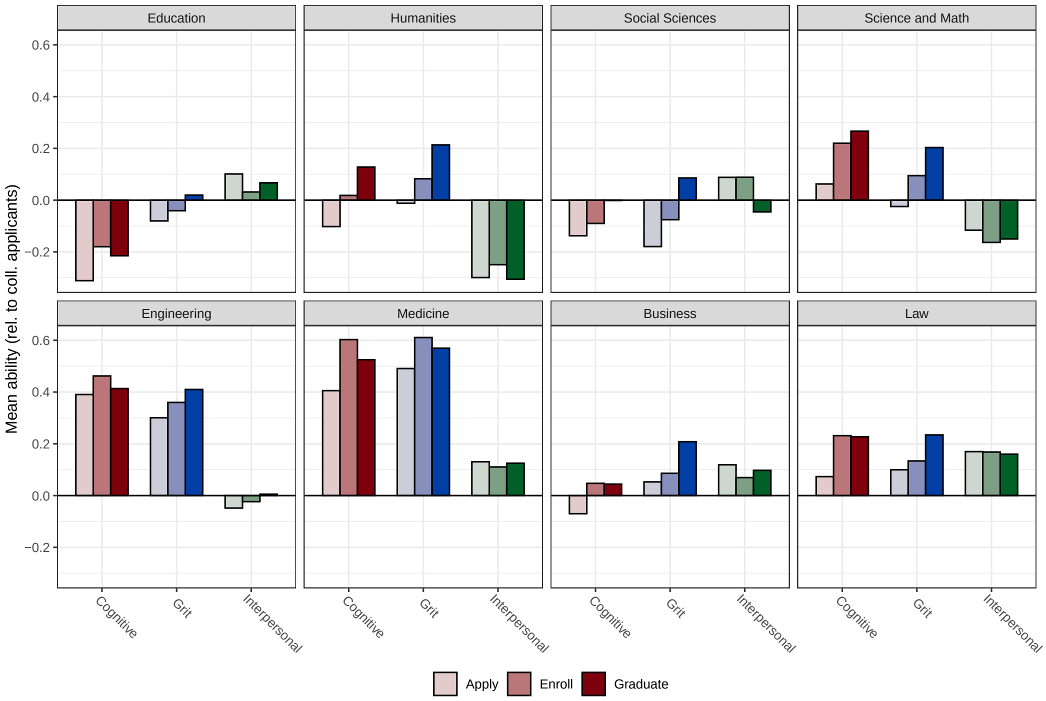
Figure 3: Sorting into College: Applications, Enrollment, and Graduation



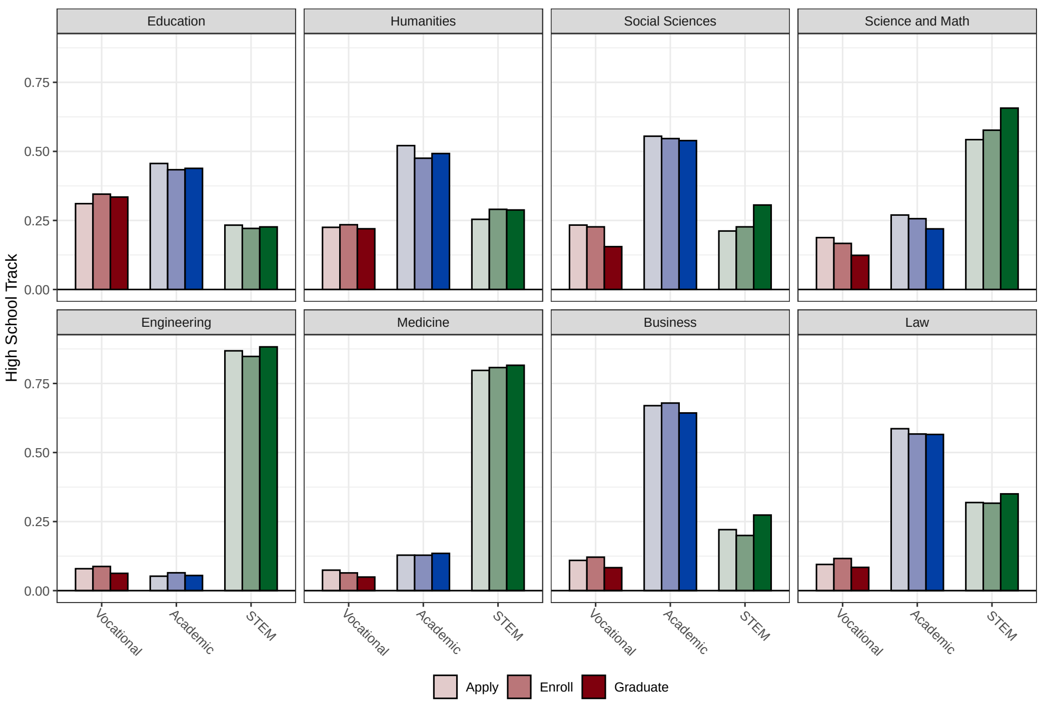
Notes: The left panel plots the average cognitive (red), grit (blue), and interpersonal (green) abilities of those who apply, enroll, and graduate from college. Each skill is normalized in the population to have a mean of zero and standard deviation of one. The right panel shows the average of high school track indicators for vocational track, academic track, and STEM track among those whose apply, enroll, and graduate.

Figure 4: Sorting into Majors: Application, Enrollment, and Graduation

Abilities



High School Track



Notes: The top panel 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 three bars shades of each color show the average for those that apply, those that enroll, and those that graduate in the major. A applying student is assigned to the first major they list on their application. The bottom panel shows the proportion of applicants/enrollees/graduates that come from each high school track (*e.g.* $E[\text{Track} = \text{STEM}|\text{Applied} = 1]$).

5 Empirical Model and Estimation Strategy

5.1 Our Modeling Approach

The education choice model in this paper corresponds to an underlying dynamic discrete choice problem of students. Following the overview in Aguirregabiria and Mira (2010), consider the model from period $t = 0$ to $t = T$, where each period students have a set of observed state variables $\boldsymbol{s}_t$, and make a decision $d_t \in \{1, ..., D_t\}$. In period t students observe state variable $\boldsymbol{s}_t$ and make decisions to maximize expected utility:

$$\mathbb{E}\left[\sum_{k=0}^{T-k} \beta^k U(d_{t+k}, \boldsymbol{s}_{t+k} \mid d_t, \boldsymbol{s}_t)\right]$$

where U is the student's utility function and β is the discount factor. The student's dynamic programming problem can then be written as:

$$V(\boldsymbol{s}_t) = \max_{d_t \in D_t}\left(U(d_t, \boldsymbol{s}_t) + \beta \int V(\boldsymbol{s}_{t+1}) dF(\boldsymbol{s}_{t+1} \mid d_t, \boldsymbol{s}_t)\right).$$

The choice-specific value function is given by

$$v(d_t, \boldsymbol{s}_t) = U(d_t, \boldsymbol{s}_t) + \beta \int V(\boldsymbol{s}_{t+1}) dF(\boldsymbol{s}_{t+1} \mid d_t, \boldsymbol{s}_t).$$

We assume that the state variable $\boldsymbol{s}_t = \{\boldsymbol{x}_t, \boldsymbol{\theta}, \boldsymbol{\epsilon}_t\}$, where $\boldsymbol{x}_t$ are state variables observed by the econometrician, $\boldsymbol{\theta}$ is a set of persistent, potentially vector valued, state variables known by the student but unobserved by the econometrician, and $\boldsymbol{\epsilon}_t$ are transient shocks observed by the student at time t, but not observed by the researcher.[23] Finally, students may also have some observable outcomes each period that directly enter the utility function or be of interest to policy makers, such as earnings, given by $y_t = Y(d_t, \boldsymbol{s}_t)$.

We make a number of assumptions that are common in the dynamic discrete choice literature, particularly in the literature which uses conditional choice probability (CCP) methods such as Hotz and Miller (1993) and Arcidiacono and Miller (2011). First, we assume that the unobservable shocks are iid over time and across students with distribution G_ϵ. Second, we assume that the transition of state variables depend on decisions and the state variables from the previous period, but not the shocks from the previous period. *i.e.* $F_x(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, \boldsymbol{\theta}, \boldsymbol{\epsilon}) = F_x(\boldsymbol{x}_{t+1}|\boldsymbol{x}_t, \boldsymbol{\theta})$. These two assumptions together give us

[23] For simplicity, here we use $\boldsymbol{\theta}$ for all persistent latent state variables unobserved by the econometrician, while later we break this into latent abilities $\boldsymbol{\theta}$ and latent types $\boldsymbol{\upsilon}$.

Rust's conditional independence assumptions as discussed in Rust (1994) and reviewed in Aguirregabiria and Mira (2010). Given these assumptions, $F(\boldsymbol{x}_{t+1}, \boldsymbol{\epsilon}_{t+1}|d_t, \boldsymbol{x}_t, \boldsymbol{\epsilon}_t, \boldsymbol{\theta}) = F_x(\boldsymbol{x}_{t+1}|d_t, \boldsymbol{x}_t, \boldsymbol{\theta})G_\epsilon(\boldsymbol{\epsilon}_{t+1})$.

Under the assumptions above, the choice specific value function can be written as

$$\begin{aligned} v(d_t, \boldsymbol{s}_t) &= U(d_t, \boldsymbol{s}_t) + \beta \int \int V(\boldsymbol{s}_{t+1}) dG_\epsilon(\boldsymbol{\epsilon}_{t+1}) dF_x(\boldsymbol{x}_{t+1}|d_t, \boldsymbol{x}_t, \boldsymbol{\theta}) \\ &= U(d_t, \boldsymbol{s}_t) + \beta \int \bar{V}(\boldsymbol{s}_{t+1}) dF_x(\boldsymbol{x}_{t+1}|d_t, \boldsymbol{x}_t, \boldsymbol{\theta}), \end{aligned}$$

where $\bar{V}(\boldsymbol{s}_{t+1}) \equiv \int V(\boldsymbol{s}_{t+1}) dG_\epsilon(\boldsymbol{\epsilon}_{t+1})$ is the integrated value function. Given this setup, we can write the probability than an individual chooses action $d_{t,j}$ in period t as

$$\Pr(d_{j,t}|\boldsymbol{x}_t, \boldsymbol{\theta}) = \int \mathbf{I}\left\{\arg\max_{d_t}[v_t(d_t, \boldsymbol{x}_t, \boldsymbol{\theta}) + \epsilon_t(d_t)] = d_{j,t}\right\} dG_\epsilon(\boldsymbol{\epsilon}_t).$$

As noted in Benkard et al. (2018), many economically relevant counterfactuals can be estimated through simulation without explicitly solving the dynamic program or taking a stand on the functional form of the utility function. In particular, the joint probability of a given set of states and set of actions can be written as:

$$\begin{aligned} &\Pr\left(d_0, (d_1, \boldsymbol{s}_1), ..., (d_T, \boldsymbol{s}_T) \mid \boldsymbol{s}_0\right) = \\ &\quad \Pr(d_T \mid \boldsymbol{s}_T) F_{\boldsymbol{s}}(\boldsymbol{s}_T|d_{T-1}, \boldsymbol{s}_{T-1}) ... \Pr(\boldsymbol{d}_1 \mid d_0, \boldsymbol{s}_0) F_{\boldsymbol{s}}(\boldsymbol{s}_1|d_0, \boldsymbol{s}_0) \Pr(d_0|\boldsymbol{s}_0). \end{aligned} \tag{3}$$

Under the assumptions of the model, each of these components can be estimated non-parametrically from the data, giving estimates of $\Pr(d_t|\boldsymbol{s}_t)$ and $F_{\boldsymbol{s}}(s_t \mid d_{t-1}, \boldsymbol{s}_{t-1})$ for all combinations of choices and state variables. Using these estimated choice probabilities, it is then possible to estimate how fixing a particular choice at a given value at time t affects decisions at time $t+k$. For example, consider a student with $\boldsymbol{s}_t$ at time t, then

$$\begin{aligned} &\Pr(d_T \mid \boldsymbol{s}_T) F_{\boldsymbol{s}}(\boldsymbol{s}_T|d_{T-1}, \boldsymbol{s}_{T-1}) ... \Pr(\boldsymbol{d}_{t+1} \mid d_t, \boldsymbol{s}_t) F_{\boldsymbol{s}}(\boldsymbol{s}_{t+1} \mid \text{fix } d_t = 1, \boldsymbol{s}_t) \\ - &\Pr(d_T \mid \boldsymbol{s}_T) F_{\boldsymbol{s}}(\boldsymbol{s}_T|d_{T-1}, \boldsymbol{s}_{T-1}) ... \Pr(\boldsymbol{d}_{t+1} \mid d_t, \boldsymbol{s}_t) F_{\boldsymbol{s}}(\boldsymbol{s}_{t+1} \mid \text{fix } d_t = 0, \boldsymbol{s}_t) \end{aligned}$$

gives the change in the joint probability of observing the realization $\{(d_{t+1}, \boldsymbol{s}_{t+1}), ..., (d_T, \boldsymbol{s}_T)\}$ counterfactually fixing choice d_t from 0 to 1.

Furthermore, assume that in each period there is an observed outcome Y_t, such as earnings, that is given by:

$$Y_t = y_t\left(d_t, \boldsymbol{x}_t, \boldsymbol{\theta}\right) + \eta_{d_t} \tag{4}$$

and

$$\mathbb{E}[Y_t] = \int\int\int y_t(d_t, \boldsymbol{x}_t, \boldsymbol{\theta}) dF_{\boldsymbol{\epsilon}}(\boldsymbol{\epsilon_t}) dF_{\boldsymbol{x}_t}(\boldsymbol{x}_t|\boldsymbol{\theta}) dF_{\boldsymbol{\theta}}(\boldsymbol{\theta}), \tag{5}$$

where $y_t(d_t, \boldsymbol{x}_t, \boldsymbol{\theta})$ is the hedonic portion of earnings and η_{d_t} is a mean-zoro idiosyncratic shock for those who choose d_t. The observable state variables $\boldsymbol{x}_t$ may include prior decisions or functions of prior decisions, such as experience. For simplicity, we assume that the idiosyncratic shock η_{d_t} is independent of prior and future shocks, though it is possible to allow for serial correlation in this setup. Researchers or policy makers may then wish to understand how expected earnings for an individual would change if we had fixed a given decision in time period $t-k$. In other words,

$$\mathbb{E}[Y_t(d_{t-k} = 1)] - \mathbb{E}[Y_t(d_{t-k} = 0)]$$

where

$$\mathbb{E}[Y_t(d_{t-k} = 1)] = \int\int\int y_t(d_t, \boldsymbol{x}_t, \boldsymbol{\theta}) dF_{\boldsymbol{\epsilon}}(\boldsymbol{\epsilon_t}) dF_{\boldsymbol{x}_t}(\boldsymbol{x}_t|\boldsymbol{\theta}, \text{fix } d_{t-k} = 1) dF_{\boldsymbol{\theta}}(\boldsymbol{\theta})$$

and

$$\mathbb{E}[Y_t(d_{t-k} = 0)] = \int\int\int y_t(d_t, \boldsymbol{x}_t, \boldsymbol{\theta}) dF_{\boldsymbol{\epsilon}}(\boldsymbol{\epsilon_t}) dF_{\boldsymbol{x}_t}(\boldsymbol{x}_t|\boldsymbol{\theta}, \text{fix } d_{t-k} = 0) dF_{\boldsymbol{\theta}}(\boldsymbol{\theta}).$$

Above, "fix d_{t-k}" represents exogenously setting the decision in period $t-k$, but allowing students to then make endogeneous decisions moving forward, where the distribution of state variables x_t will differ depending on if d_{t-k} is fixed to 1 or 0.

Using this setup, it is possible to simulate how fixing a choice at a particular time period will affect expected future choices and outcomes. Similarly, we can construct these expectations conditional on observable choices, covariates, or latent skills, such as $\mathbb{E}[Y_t(d_{t-k} = 0)|\boldsymbol{\theta} = \tilde{\boldsymbol{\theta}}]$. Given this setup, it is possible to calculate many dynamic treatment effects of choices at time t on future choices and outcomes while imposing a subset of the assumptions necessary for conditional choice probability estimation of fully-specified dynamic discrete choice models. In particular, it requires we correctly estimate the probabilities given in Equation 3, the conditional expected value of the outcomes of interest, the distribution of persistent latent state variables ($F(\boldsymbol{\theta})$), and place some restrictions on the dependence between error terms in the choice equation and outcomes, but does not require us to specify student's utility function or the functional form of $G(\epsilon_t)$

to estimate dynamic treatment effects of interest. Moreover, estimating the dynamic treatment effects does not require us to solve the dynamic model. A cost of this approach is that we are not able to calculate welfare nor consider policies that do not directly modify the observed state vector $\boldsymbol{x}_t$. For example, we can consider policies that modify schooling decisions, but not policies that offer a large scholarship for studying a STEM major.

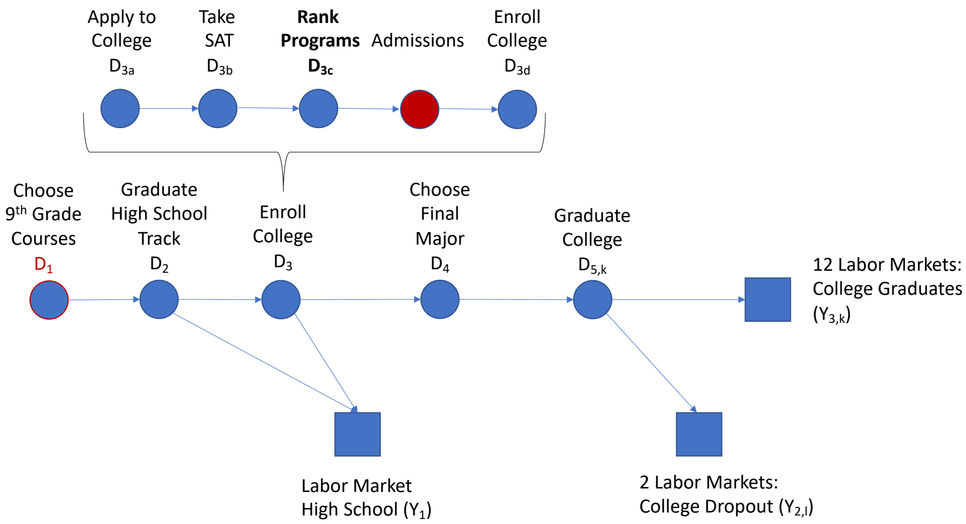
5.2 Empirical Model of Education and Earnings

This section discusses how we map the conceptual model described in the previous section to our institutional setting. Figure 5 describes the sequence of educational decisions we include in our sequential Roy model. 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 $k_2 \in \mathcal{K}_2 = \{1, 2, 3, 4\}$ denote high school dropout, vocational track graduate, academic track graduate, and STEM track graduate, respectively. High school graduates make two sequential binary choices: to apply to college (D_{3a}) and then whether to take the Swedish SAT (D_{3b}), which was optional for college applications. Next, students make a series of 12 multinomial choices of which major-college programs they want to list on their application (D_{3c}). The college application is modelled using the exploded-nested-logit model described in the next section. The central admissions system determines the first program that is above the threshold and the student is admitted to that program. Finally, the student makes one additional binary choice on if to enroll in the first program to which they were admitted (D_{3d}). 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. Let $D_3(\mathcal{K}_3)$ summarize the initial enrollment after the application process.

Once enrolled in college, students make another multinomial choice to switch field or college, $D_4(\mathcal{K}_4)$.This is important as many students switch major after the initial enrollment. 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

Figure 5: Sequential Model of Major Choice and Earnings



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 and final enrollment 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 ($j = 2$), or final degree type and field ($j = 4$):

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

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 $\boldsymbol{\theta}$, a finite dimensional vector of unobserved types $\boldsymbol{\upsilon}$, and an idiosyncratic error term ε_{jk_j}, which is unobserved by the econometrician:

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

5.2.1 College Application Model

In this section, we introduce a model of ordinal rankings of major-college choices. Swedish students submit ranked lists of up to twelve major-college choice pairs, where there are more than 2,000 potential alternatives in each year. The student with the highest admissions score is admitted to their first choice, and the student with the next highest score is admitted to their first choice if there is still space, otherwise they are admitted to their next ranked choice. For our cohorts, admissions scores are determined primarily by each student's high school grade point average (GPA). Let I_{il} be student i's perceived value of major-college pair l. Students choose their ranked ordered list by solving the maximization problems[24]

$$D_i^1(\mathcal{L}_i) = \arg\max_{l \in \mathcal{L}_i^1}\{I_{il}\},$$
$$D_i^2(\mathcal{L}_i) = \arg\max_{l \in \mathcal{L}_i^2}\{I_{il}\}, ...,$$

where $D_i^j(\mathcal{L}_i)$ denotes individual i's jth ranked choice given their choice set $\mathcal{L}_i^j$ (*i.e.* $\mathcal{L}_i^1 \equiv \mathcal{L}_i$, $\mathcal{L}_i^2 \equiv \mathcal{L}_i \setminus D_i^1(\mathcal{L}_i)$, *etc*). We allow the choice set to vary by individual as some competitive choices may have an *ex ante* zero probability of admission given a student's admission score.[25]

We describe the student's problem as an exploded mixed nested logit, where we group major-college pairs into major groups, $\mathcal{K}_3$. The major groups form the nests with multiple major-college alternatives in each nest. Following Train (2009), we can write the latent utility of major-college alternative l for student i using the the nested logit model formulation:

$$I_{il} \quad = \quad f_k(\boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\theta}_i, \boldsymbol{\upsilon}_i) + \delta_{il} + \varepsilon_{il},$$

where $f_k(\boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\theta}_i, \boldsymbol{\upsilon}_i)$ depends only on variables that describe nest k_3. These variables differ over nests but not over alternatives within each nest. The within-nest utility of major-college pair l for a student is δ_{il}, which captures differences in college and major characteristics (expected income, utility of major/college, etc) within a nest. The alternative-specific utility δ_{il} may also represent location-dependent and student-specific preferences. Let B_{ik} denote the set of major-college pairs in nest $k \in \mathcal{K}_3$ considered by student i. The choice probability of ranking major-college pair l highest can then be decomposed into marginal and conditional probabilities.

$$P\left[D_i^1 = l\right] = P\left[D_i^1 = l | D_i^1 \in B_{ik}\right] P\left[D_i^1 \in B_{ik}\right], \tag{6}$$

[24]In this section, we keep the "$3c$" subscript implicit when describing the college application model here in order simplify the notation when deriving the results.

[25]Artemov et al. (2020) show that students do not rank certain alternatives even if they strictly dominate other choices, because they do not expect to be admitted. Fack et al. (2019) discuss how to estimate preferences when students may "skip the impossible" where truth-telling is only a weakly dominant strategy.

where $P\left[D_i^1 = l | D_i^1 \in B_{ik}\right]$ is the conditional probability of ranking major-college pair l first conditional on choosing a major-college pair in nest B_{ik} and $P\left[D_i^1 \in B_{ik}\right]$ is the probability of ranking first a major-college pair in nest B_{ik}. These choice probabilities are

$$P\left[D_i^1 \in B_{ik}\right] = \frac{e^{f_k(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{v})+\lambda_k H_{ik}}}{\sum_{j=1}^{K} e^{f_j(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{v})+\lambda_j H_{ij}}} \tag{7}$$

$$P\left[D_i^1 = l | D_i^1 \in B_{ik}\right] = \begin{cases} \frac{e^{\delta_{il}/\lambda_k}}{\sum_{j\in B_{ik}} e^{\delta_{ij}/\lambda_k}} & \text{if} \quad l \in \mathcal{L}_i \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where $H_{ik} = \ln \sum_{j\in B_{ik}} e^{\delta_{ij}/\lambda_k}$ is the scaled expected utility of nest k and $\lambda_k \in (0,1]$ is a parameter that describes the amount of correlation between ε_{il} within nest k. If $\lambda_k = 1$, then the errors are uncorrelated, and if $\lambda_k = 0$ the errors are perfectly correlated.

In order to make the model tractable, we assume that individuals in a geographic $\times$ GPA$\times$ high school track bin (g_i) have the same preferences over alternatives within a nest. In other words, we specify $\delta_{il} \equiv \delta_l(g_i)$ the utility of a major-choice pair within a nest. Furthermore, an individual's GPA_i may be below the admissions threshold of certain programs in the consideration set. We denote the restricted consideration set of an individual as $B_{ik} \equiv B_k(GPA_i)$.

The restricted expected utility for nest k, $H_k(g_i, GPA_i)$, for a student in geographic-gpa-track bin g_i with GPA_i can be expressed in terms of the unrestricted expected utility. The expected utility for an individual with GPA_i in geographic-GPA bin g_i is

$$\begin{aligned} H_k(g_i, GPA_i) &= \ln \sum_{j\in B_k(GPA_i)} e^{\delta_j(g_i)/\lambda_k} \\ &= \ln \left[\left(\sum_{j\in B_k} e^{\delta_j(g_i)/\lambda_k} \right) \frac{\sum_{j\in B_k(GPA_i)} e^{\delta_j(g_i)/\lambda_k}}{\sum_{j\in B_k} e^{\delta_j(g_i)/\lambda_k}} \right] \\ &= \ln \left[\left(\sum_{j\in B_k} e^{\delta_j(g_i)/\lambda_k} \right) \left(P\left[D_i^1 \in B_k(GPA_i) | D_i^1 \in B_k, g_i\right] \right) \right] \\ &= H_k(g_i) + \ln \left(P\left[D_i^1 \in B_k(GPA_i) | D_i^1 \in B_k, g_i\right] \right). \end{aligned}$$

In order to estimate $P\left[D_i^j \in B_{ik}\right]$ for $j > 1$, we need to remove the previously chosen major-college alternative from the choice set for lower rankings. In other words, H_{ik} will depending on the ranked choice considered. In an exploded logit model, the choice probability for rank r is the choice probability removing the higher ranked choices. Consider the choice probability of the second-ranked choice, where the first-ranked choice is l' in nest k'. First, we adjust $H_k(g_i, GPA_i)$ to remove the first ranked choice. Define

$H_k^2(g_i, GPA_i)$ for the second choice as

$$H_k^2(g_i, GPA_i) = \begin{cases} H_k(g_i, GPA_i) & \text{if} \quad k \neq k' \\ H_k(g_i, GPA_i) + \ln\left(1 - P\left[D_i^1 = l' | D_i^1 \in B_{k'}(GPA_i), g_i\right]\right) & \text{if} \quad k = k' \end{cases} \tag{9}$$

The probability of choosing nest k as a second choice is then

$$P\left[D_i^2 \in B_k | g_i, GPA_i, D_i^1 = l'\right] = \frac{e^{f_k(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\upsilon}) + \lambda_k H_k^2(g_i, GPA_i)}}{\sum_{j=1}^{K} e^{f_j(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\upsilon}) + \lambda_j H_j^2(g_i, GPA_i)}}. \tag{10}$$

In other words, the latent utility of each nest needs to be adjusted by

$$\lambda_k \ln\left(1 - P\left[D_i^1 = l' | D_i^1 \in B_k(GPA_i), g_i\right]\right) \tag{11}$$

as major-college pair l' has already been chosen. Given our assumptions, the share of program l' in nest B_k ($P\left[D^1 = l' | D^1 \in B_k(GPA), g\right]$) can be non-parametrically estimated directly from the data for each bin g and with knowledge of the GPA threshold for program l'.

5.2.2 Labor Market Outcomes

We model schooling-specific labor market outcomes which similarly depend on background characteristics, the individual's vector of unobserved abilities, and a vector of latent types that affects education decisions and outcomes. Labor market outcome m of individual i with schooling level s is given by:[26]

$$Y_{ism} = \boldsymbol{\beta}_{sm}^{Y} \boldsymbol{X}_i + \boldsymbol{\lambda}_{sm}^{Y} \boldsymbol{\theta}_i + \boldsymbol{\alpha}_{sm}^{Y} \boldsymbol{\upsilon}_i + \varepsilon_{ism}. \tag{12}$$

5.3 Estimation Strategy

5.3.1 Exclusion Restrictions

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 describe the high school track instrument here. Remember that $k_2 \in \{2, 3, 4\}$ denotes the high school track. Let n denote the ninth-grade school and t denote the year (cohort). First, we calculate the proportion

[26] 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.

of students in each ninth grade school year that choose each track ($P_{k_2,n,t}$). There are three proportions per school year. Second, we remove track-year fixed effects from these proportions ($\tilde{P}_{k_2,n,t}$). We then calculate the $-t$ school average proportion ($\overline{P}_{k_2,n,-t}$), or, in other words, the average proportion over all years except t for each school. Let this be the "ninth 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 ($P_{k_2,n,t,-i}$). Fourth, we regress $P_{k_2,n,t,-i}$ on $\overline{P}_{k_2,n,-t}$, and the residual of that regression is the IV for student i.

Appendix Tables C.1-C.3 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 86.45. 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. 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 reported in the first-stage tables 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. Appendix Section C.1.2 reports balance tables for all of the within-school-across-cohort instruments.

Discontinuities in Probability of Admission In the college applications data, we see if students score above the admissions thresholds based on high school GPA or the Swedish SAT. These discontinuities result in regression discontinuities similar to those used in Kirkebøen et al. (2016). The first panel of Appendix Figure C.2 shows that at the GPA threshold for a particular program there is a jump of over 60 percentage points in being admitted. If instead of admissions we consider enrolling in the same major, we see that there is a twelve percentage point jump at the GPA cutoff. This evidence shows that those barely missing the GPA cutoff for admission are much less likely to be admitted to a program, and that this causes students to be less likely to enroll in that major.

While the RD above considers individual programs, our model only estimates the outer nest of the nested logit on which major to apply to (see Section 5.2.1). We map the admissions threshold into the model in the following way. First, we construct bins based on high school track, five bins of high school GPA and 15 geographic clusters.[27]

Second, within each of these bins, we then calculate the share of students applying to each specific program within a given major. These shares vary by geographic location, GPA bin, and high school track.[28] Third, for every student we predict the probability they would be admitted to a given program if they applied using the GPA and Swedish SAT admissions thresholds, a cubic in GPA, a cubic in Swedish SAT, and high school track indicators. This logistic regression is reported in Appendix Table C.21.

Fourth, we calculated a major-specific weighted average of the probability of being admitted using the prior two pieces: (1) the probabilities from the prior step and (2) the share of students from the same track-GPA-region bin who apply to each program when applying to that major. This produces a weighted average for the probability of being admitted. Taking logs, this provides the log admit share in Equation 11, which is included directly as a control in the application choice model. Finally, note that the log admit share can discontinuously jump for students when a small change in GPA or Swedish SAT score results in the loss of a program which makes up a large share of the programs which applicants in their track-GPA-region bin apply to. This provides exogenous variation in choices between otherwise very similar students.

5.3.2 Estimation and Model Fit

The model is estimated via maximum likelihood, as described in Appendix E.1. Appendix G presents the estimated parameters of the model and Appendix E.2 documents that the model accurately predicts the patterns in the data. Treatment effects and counterfactuals are then estimated through simulation. Standard errors and confidence intervals are constructed via bootstrap, where the model is re-estimated and simulated for

[27] We use the size-constrained clustering (Sävje et al., 2019; Higgins et al., 2016) to construct the geographic clusters. For each municipality, we calculate the fraction of applications that apply to each university regardless of program. We then run the size-constrained algorithm where we vary the minimum size (number of applications) required for every cluster. We chose the minimum cluster size that corresponds to 15 clusters, balancing the noise in calculating program shares with too few applications and loss of geographic variation from merging too many municipalities together.

[28] We include geographic clusters to capture the fact that students tend to apply to programs closer to where they live. For example, Appendix Figure C.1 shows which 4-year engineering programs students apply for two of our geographic clusters. One is in the far north of Sweden while one is in the far south. While both groups apply to programs around Stockholm, each group is much more likely to apply to programs in or close to their region. Geographical variation creates additional variation in the admission thresholds that students face when applying to a major as the the admission thresholds for the programs that are nearer to them have greater importance.

each bootstrap sample.

We estimate the model with eight types.[29] Appendix E.3 shows how the types strongly sort into high school tracks and college majors. Figure E.2 shows how each type sorts into only a few majors, playing an important role in explaining the persistence of programs within a college application. Types 5, 6, and 8 sort mostly into the STEM majors, while Types 1, 3, and 7 are students studying social science, business, and law. Combining Figure E.2 with the model estimates in Tables G.17 and G.18, we find important sorting on gains by type, capturing an important source of unobserved heterogeneity. For example, Type 5 has a large comparative advantage (about 0.2 log points) in wages as an engineer or science graduate compared to other types. Likewise, Type 2 earns more as a doctor and Type 4 has an advantage as a teacher. We interpret the types as partially representing occupational preferences of students, but likely they also capture motivation and other unobserved skills and abilities.

6 Results

This section uses the estimated model to directly study the complementarities between abilities, high school track, post-secondary education decisions. First, we show that the returns to ability differ by final education level using the model estimates that account for rich multidimensional selection. Second, we calculate treatment effects to high school tracks. Finally, we use the model to simulate out two counterfactual policies designed to promote STEM education at different points in the educational trajectory.

6.1 Labor Market Returns to Multidimensional Ability

We investigate the role of abilities in earnings by estimating separate earnings equations for each final schooling state as described in Section 5.2.2. By estimating separate models for each final schooling state, we can investigate the complementarities between college major and abilities in the labor market. Figure 6 shows the estimates of $\hat{\boldsymbol{\lambda}}^{Y}_{sm}$ for workers with four-year college degrees. In general, all three abilities have large and positive returns in the labor market, but there is a great deal of heterogeneity. For example, education majors have smallest returns to ability of four-year degree holders, where increasing any of the three abilities by one standard deviation increases wages by around two percent. 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

[29]Adding a ninth type to the model did not significantly improve the fit or change the results, but substantially increased the computational burden.

majors. For example, the three abilities have similar 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 considering the present value of disposable income.[30]

The prior figures suggest that the returns to specific educational choices may depend heavily on the abilities of the students. This may be further compounded by differences in the loadings on the latent types and covariates. To better characterize the full heterogeneity in returns, we use the model to calculate the proportion of individuals who have their highest expected earnings in each major. To do this 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 ($\boldsymbol{\theta} \sim F_{\boldsymbol{\theta}}(\boldsymbol{\theta}; \hat{\gamma}_\theta)$) and finally drawing a latent type from the probability distribution of latent types conditional on the latent abilities ($\boldsymbol{\upsilon} \sim F_{\boldsymbol{\upsilon}}(\boldsymbol{\upsilon}|\boldsymbol{\theta}; \hat{\boldsymbol{\gamma}}_\upsilon)$).[31] For each of the synthetic workers, we calculate their expected earnings in the different schooling states ($\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}] = \boldsymbol{\beta}^Y_{sm}\boldsymbol{X} + \boldsymbol{\lambda}^Y_{sm}\boldsymbol{\theta} + \boldsymbol{\alpha}^Y_{sm}\boldsymbol{\upsilon}$) and then record which schooling state has the highest and second highest expected earnings for that worker ($s^*_m(\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}) = \arg\max_s\{\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}]\}$). This accounts for the full heterogeneity in worker background/observables, ability, and latent types. Table 2 shows the proportion of synthetic workers that would rank each major first and second in expected log wages and Table F.1 shows the same for expected present discounted value of disposable income. Clearly there is no absolute ranking of majors by expected earnings. The model suggests a large portion of the sample (0.31) would expect to earn the most though studying business, but six other majors also represent the expected log-wage maximizing choice for at least one percent of students. The table also shows second choices, which further show that there is substantial heterogeneity in the returns to majors.

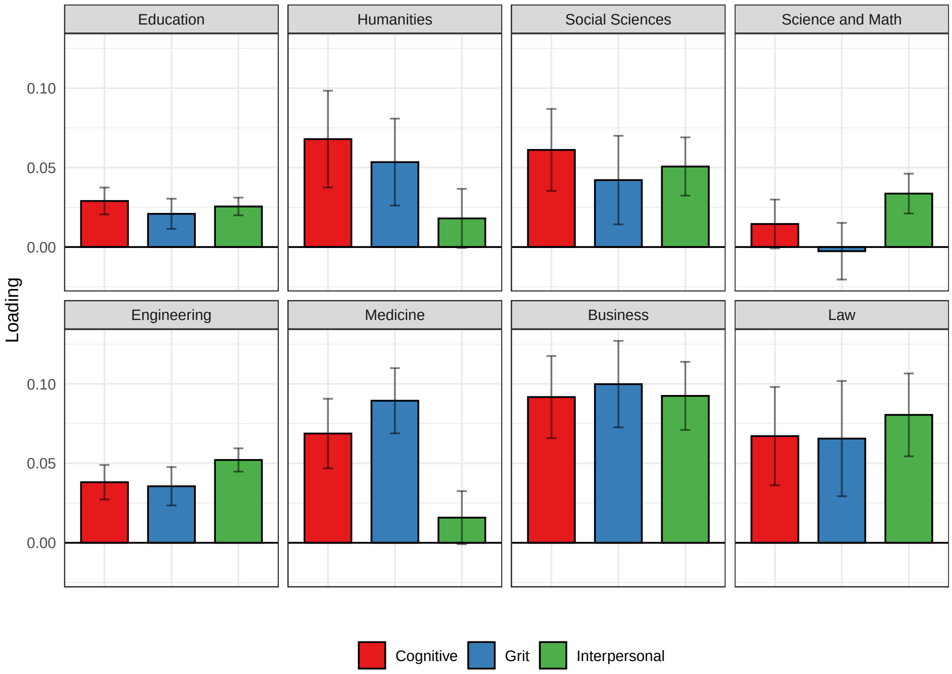
6.2 Causal Effects of High School Track

Building on the analysis of the role of high school choices and abilities in Section 4.2, this section uses the Roy model estimated in Section 5 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

[30]Tables B.13 and B.14 show that the returns to abilities by final major are robust to controlling for college and college program fixed effects.

[31]Recall that our latent abilities are residuals and the probability of each type depends on these latent abilities. In other words, the factors represent the variation in latent ability after accounting for observables.

Figure 6: Returns to Ability across Majors ($\hat{\boldsymbol{\lambda}}_{sm}$) for Log Wages



Notes: These figures compare the returns to ability ($\hat{\boldsymbol{\lambda}}_{sm}$) for four-year graduates from Equation 12. The first (red) bar shows the loading on cognitive ability, the second (blue) bar shows the loading on grit ability, and the third (green) bar shows the loading on interpersonal ability. This figure shows estimates for log wages, while Figure F.2 shows estimates for log present discounted value of disposable income. Each sub-panel shows the estimates for different four-year majors. Error bars show bootstrapped 95% confidence intervals.

high school tracking decisions and how the returns to these decisions vary based on students' multidimensional abilities. Specifically, we estimate the gains from changing high school track from vocational to STEM, from vocational to academic, and from academic to STEM. 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 use the model to calculate the average treatment effect (ATE), the average treatment effect for those with low abilities, the average treatment effect for those with high abilities, the treatment on the untreated (TUT), the treatment on the treated (TT), and the average marginal treatment effect (AMTE).[32]

Each treatment effect is calculated via simulation through integrating over the relevant population's individual-specific treatment effects as discussed in Section 5. These treatment effects do not restrict the future decisions of the individuals. Fixing a high school track can then influence future decisions through the change in the state variables

[32]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. The AMTE is calculated via simulation. A simulant is marginal if the difference in the expected payout is less than 0.05 standard deviations of the difference in idiosyncratic shocks (in absolute value), and the top choice is one of the two choices being considered.

Table 2: Fraction Ranking each Major First and Second in Expected Log Wages

	Ranking	
	1st	2nd
Business	0.31	0.21
Engineering	0.28	0.21
Medicine	0.18	0.18
Law	0.12	0.15
STEM (3-year)	0.05	0.09
Business (3-year)	0.03	0.10
Social Sciences	0.03	0.04
Science and Math	0.00	0.01

Notes: The table reports the proportion of individuals ranking a major first or second in terms of expected log wage, while Table F.1 reports the same for expected log present discounted value of disposable income. All majors which have a value of 0.01 or higher in any column are reported. A sample of one million synthetic workers are created by drawing a vector of observables from the data, drawing a vector of latent abilities from the estimated factor distribution, and drawing a latent type from the type probability distribution. The expected log wage is calculated for each synthetic worker using estimates of Equation 12 ($\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}] = \boldsymbol{\beta}^{Y}_{sm}\boldsymbol{X} + \boldsymbol{\lambda}^{Y}_{sm}\boldsymbol{\theta} + \boldsymbol{\alpha}^{Y}_{sm}\boldsymbol{\upsilon}$).

as shown in Section 5.1.

Figures 7 shows the estimated treatment effect of high school track on college outcomes. The top panel of shows the treatment effects on college enrollment, and the bottom panel shows the treatment effects on college graduation. Each sub-panel reports the treatment effects for one specific comparison: STEM vs vocational track, STEM vs academic track, and academic vs vocational track.

We find that the average treatment effects for enrolling and graduating from college are large for STEM vs vocational. We estimate that students that are marginal between the STEM and vocational track are much more likely to enroll in college if they take the STEM track, with an AMTE of 37 percentage points. The treatment effects of STEM vs academic track, and academic vs vocational tracks are smaller, with AMTEs of around 14 percent on enrollment and 7 to 8 percent on graduation. Finally, we see that for STEM vs vocational and academic vs vocational, the impacts are larger for high ability students, and the treatment on the treated is larger than the treatment on the untreated.

The treatment effects of high school track on college graduation (bottom panel) 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 students to make enrollment, switching, and graduation decisions. We find that there is more heterogeneity in graduation decisions than enrollment decisions, and that the treatment effects noticeably attenuate. For example the AMTE of STEM vs vocational is just under 20 percentage points. In addition, the gap between the ATE for low and high ability students grows, as does the does the gap between the treatment on the treated and the treatment on the untreated.

Figure 8 shows similar results for log wages and Figure F.3 shows treatment effects for log present value of disposable income. These treatment effects include the direct effects of high school track, as well as the indirect effects of high school track on the post-secondary education choices and their returns. We estimate an AMTE of 0.11 on log wages for STEM vs vocational track, and approximately 0.06 for STEM vs academic track and academic vs vocational tracks.[33] Similar to college graduation, we see selection on gains at all three margins, with the TT being 0.02 to 0.09 larger than the TUT. For STEM vs vocational and academic vs vocational returns are larger for students with high ability. For STEM vs academic track, the estimates are larger for low ability students, though the confidence intervals are large. The patterns are similar when considering the log discounted present value of disposable income, though the effects are somewhat larger.

The prior estimates are of the full treatment effects of switching high school tracks, inclusive of how those early decisions then influence later application, enrollment, switching, and graduation decisions in college. We also consider the direct effect of high school track on earnings conditional on the final education outcome. Figure 9 plots the estimated dynamic complementarities of switching high school tracks within each final education outcome. For example, the figure shows that counterfactually switching high school tracks from vocational to STEM would increase log wages for engineers by 0.06, while switching from academic to STEM track would increase log wages of engineers by 0.12. Across most final education levels, the STEM track has higher returns than the vocational track. Switching from vocational to academic would raise log wages for many final education levels, such as science and math, socials studies, business, and law. Yet, it would also lower wages in engineering and the health sciences, demonstrating important dynamic complementarities.

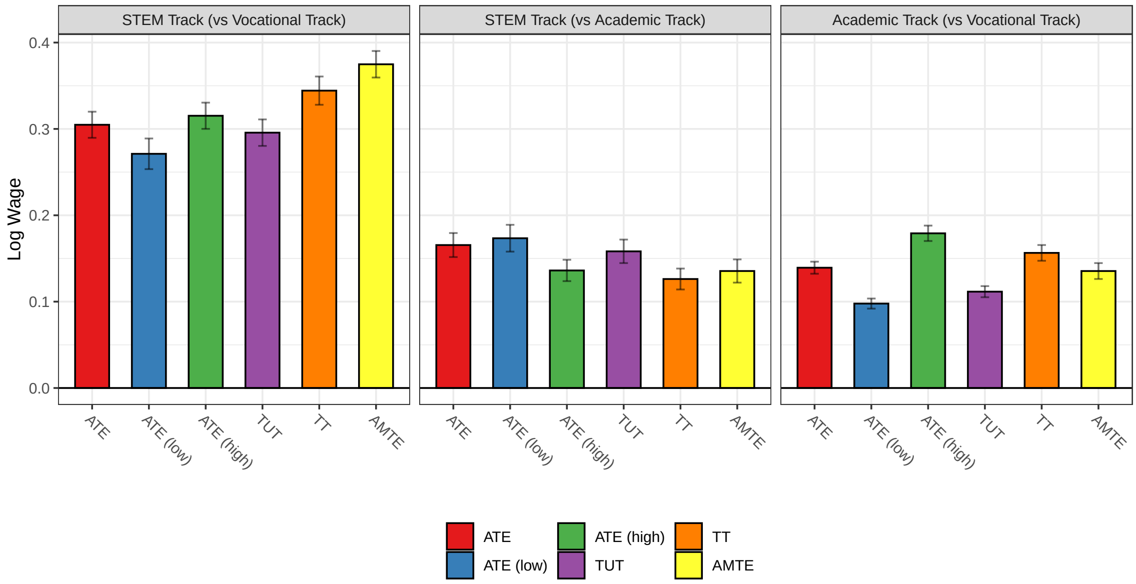
6.3 Counterfactual Policies Targeting STEM Skills

In this section we use the model to estimate and interpret the impacts of two counterfactual policies designed to promote STEM skills. The first policy targets students who did not pursue the STEM track, but only marginally preferred their high school choice over the STEM track. We then look at how inducing these marginal students into the STEM track impacts future education decisions and earnings. The second policy targets

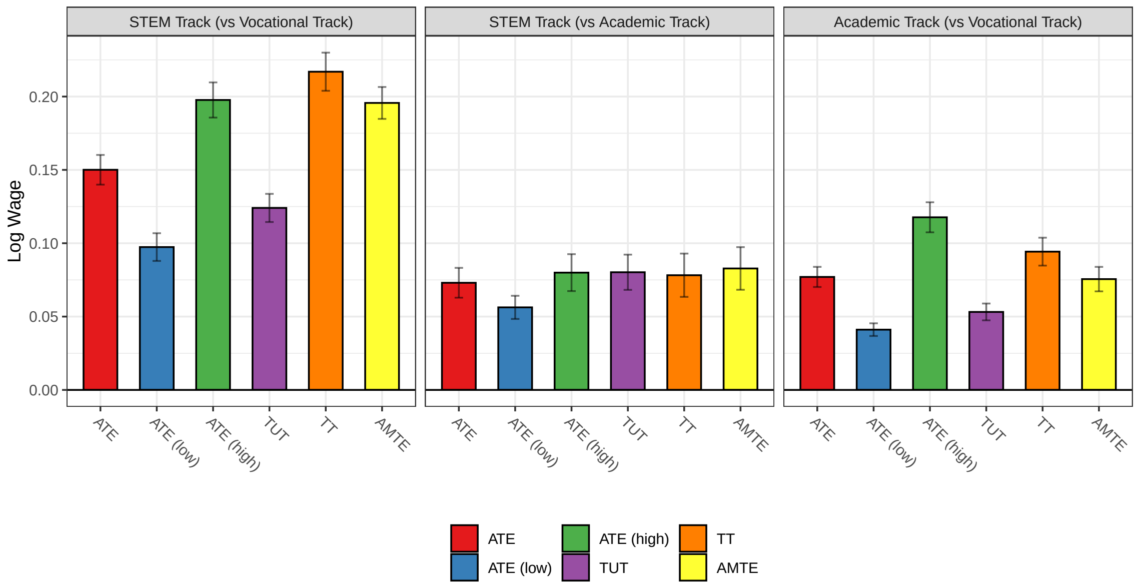
[33]Our finding that many students sort on comparative advantage in high school tracks is broadly consistent with Dahl et al. (2023). Like us, they find that returns to the two STEM lines are generally highest, ranging from 7% to only 0.7% depending on the next best alternative.

Figure 7: Treatment Effects: College Enrollment and Graduation

College Enrollment

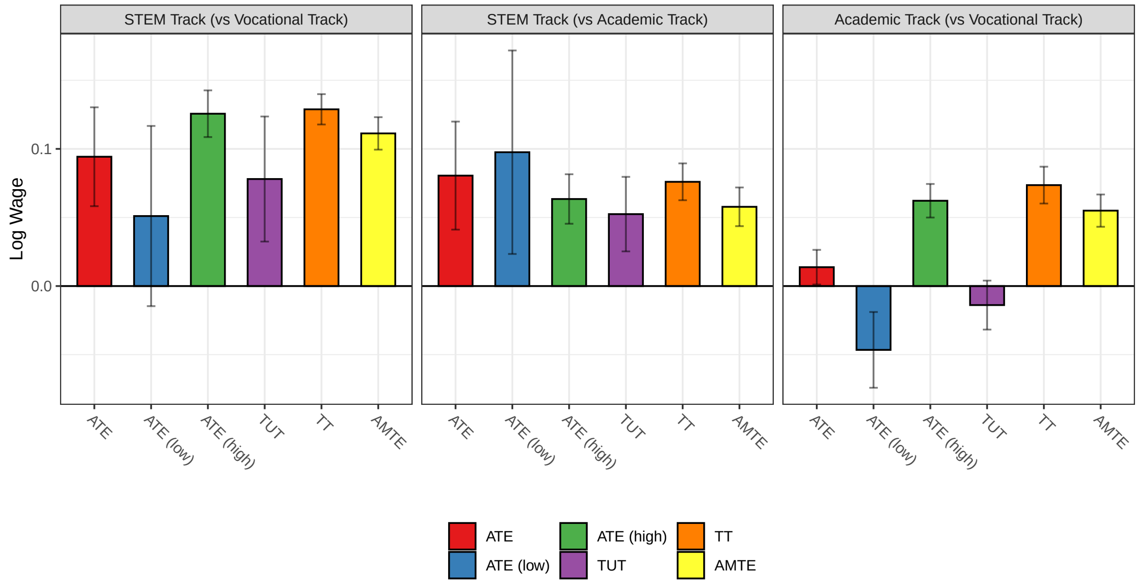


College Graduation



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. Error bars show bootstrapped 95% confidence intervals.

Figure 8: Treatment Effects: Log Wage



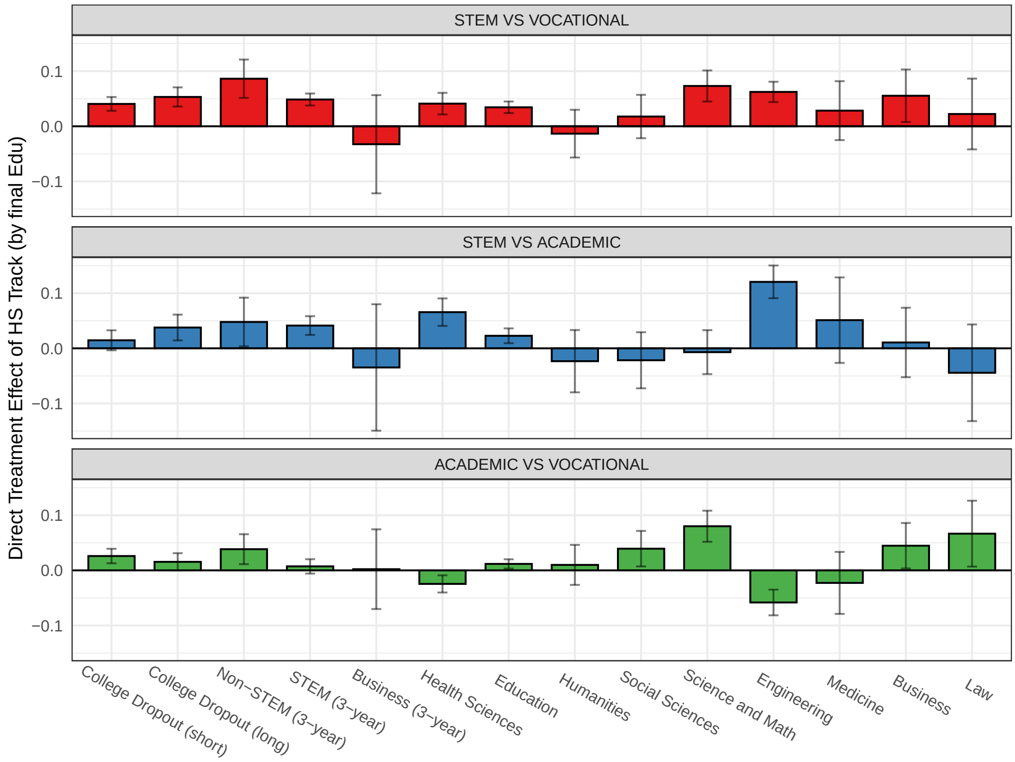
Notes: This figure shows the estimated treatment effects for the three high school track margins on log wages, while Figure F.3 shows the treatment effects for log present value of disposable income. The treatment effects are estimated for everyone who has at least a high school degree. High ability 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. Error bars show bootstrapped 95% confidence intervals.

students who have chosen to apply to college, and provides small incentives to apply to STEM programs (science and math, engineering, medicine, and 3-year STEM programs). We then look at how these incentives change the post-secondary outcomes of the marginal students, and the treatment effects for the marginal students whose post-secondary education outcomes change due to the incentives.

6.3.1 Encouraging the STEM Track in High School

Figure 10 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. Each bar shows the percentage point change in that level of final education attainment among marginal students induced into the STEM track. As may be expected, we see a reshuffling of terminal high school graduates across tracks with a large drop in terminal vocational high school degrees, a drop in those with terminal academic high school degrees, and a small drop in high school dropouts. We similarly see a large increase in terminal STEM-track high school graduates. We also see a general increase in post-secondary enrollment. The largest increase is a seven percentage point increase in the share of students with engineering degrees. The next largest is a five percentage point increase in those with a

Figure 9: Treatment Effects of HS Track on Log Wages within Final Education Level

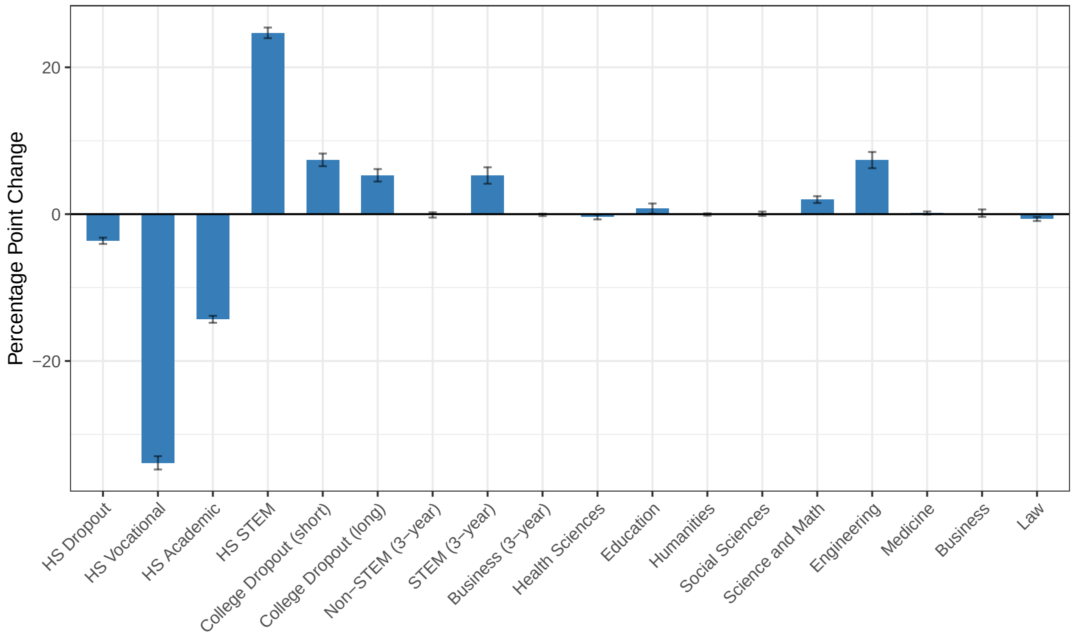


Notes: Figure shows the gains from changing high school track conditional on final educational attainment for each of the three high school track margins. Error bars show bootstrapped 95% confidence intervals.

3-year STEM degree, and we see a small increase in those with a Science or Math degree. We also see a notable increase in college dropouts, both from 4-year and 3-year programs.

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 3 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 AMTE and the AMTE 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 on log wage is 0.09 and does not notably differ by low or high ability. The wage gains are driven by those who change final schooling level, who have gains of 0.11 compared to 0.04 for those who do not. We also estimate that the gains are largely positive across the distribution. We estimate that 71% of the effected marginal students have higher expected wages, though this proportion is larger for those who do not change education. Putting the pieces together, the policy has a direct benefit and an indirect

Figure 10: 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. Error bars show bootstrapped 95% confidence intervals.

benefit of inducing students to then pursue more lucrative post-secondary options, but there are some whose wages are reduced by the policy, especially among those who switch final education levels.

Finally, we study the impacts on one particular group of individuals. Specifically, we estimate the impact of the policy on marginal students who went on to earn an engineering degree. Figure 11 plots the AMTE for engineering for those induced into engineering, conditional on what their final education would have been in absence of the policy. We find positive gains for most of those who switch tracks due to the policy and then graduate with an engineering degree. The estimates are largest for those induced out of terminal high school degrees, education, or health science. Yet, we do not find positive AMTEs for everyone. Those who the policy moved from 3-year or 4-year business degrees have negative AMTEs, though they are not statistically significant.

6.3.2 Encouraging Applications to STEM Programs in College

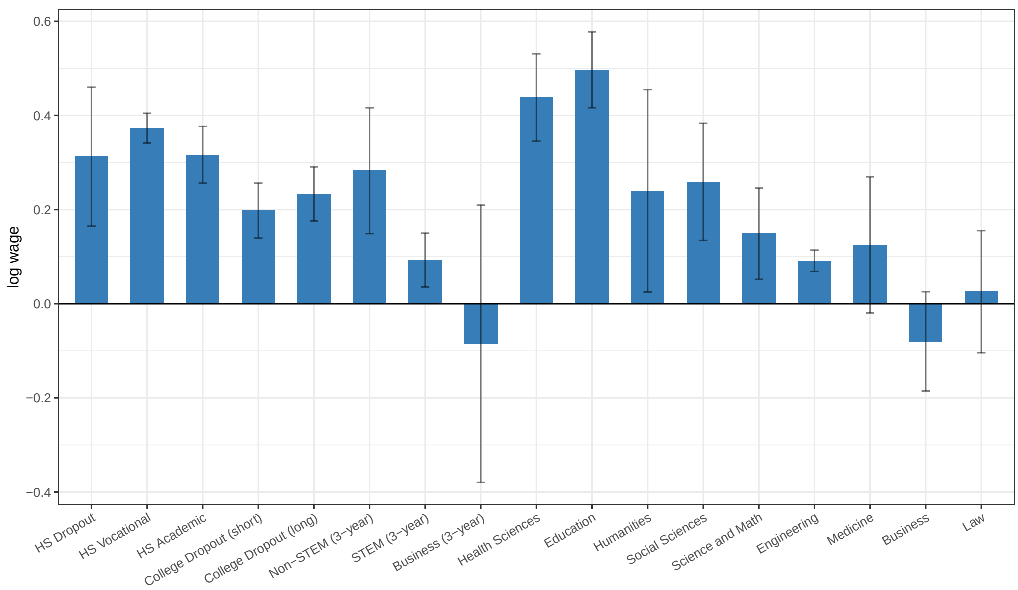
The second policy targets students who have chosen to apply to college, and provides small incentives to apply to STEM programs (science and math, engineering, medicine, and 3-year STEM programs). This induces marginal students to list more STEM programs on their application. Figure 12 shows how the policy affects final education, with

Table 3: Effects of STEM TRACK (log wages, marginal students)

	AMTE			Prop. Gaining		
Group	All	Low Abil	High Abil	All	Low Abil	High Abil
All	0.086	0.095	0.076	0.709	0.716	0.703
	(0.006)	(0.011)	(0.007)	(0.014)	(0.018)	(0.020)
No Change in Final Edu	0.040	0.045	0.036	0.911	0.952	0.873
	(0.005)	(0.005)	(0.006)	(0.041)	(0.033)	(0.055)
Change in Final Edu	0.108	0.114	0.100	0.613	0.625	0.602
	(0.008)	(0.015)	(0.010)	(0.010)	(0.021)	(0.011)

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. Bootstrapped standard errors are reported in parentheses.

Figure 11: AMTE of STEM Track for those whose Final Education is **Engineering** by Baseline Education.



Notes: Figure shows the average treatment effect of inducing marginal students into the STEM high school track 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. Appendix Table F.2 provides similar estimates conditional on other final education levels. Error bars show bootstrapped 95% confidence intervals.

each bar reporting the percentage point change in that final education category. Encouraging STEM applications results in a large increase in graduation from 3-year STEM programs, moderate increases in graduation from Engineering and Science and Math programs, and a small increase in graduation from medicine programs.[34] We also see an increase in students enrolling in 3-year college programs, but dropping out. Those now enrolling in STEM degrees draw broadly from the other programs, with the largest reduction coming from education and business.[35]

Table 4 shows that the policy, on average, small to moderate gains for those induced to change final education levels, with an average gain in log wages of 0.039. The effects are slightly larger for those with high school STEM degrees. The last three columns of the table report the proportion gaining from the policy, and we find that only a bit over half of those induced to change education choices by the policy benefited.

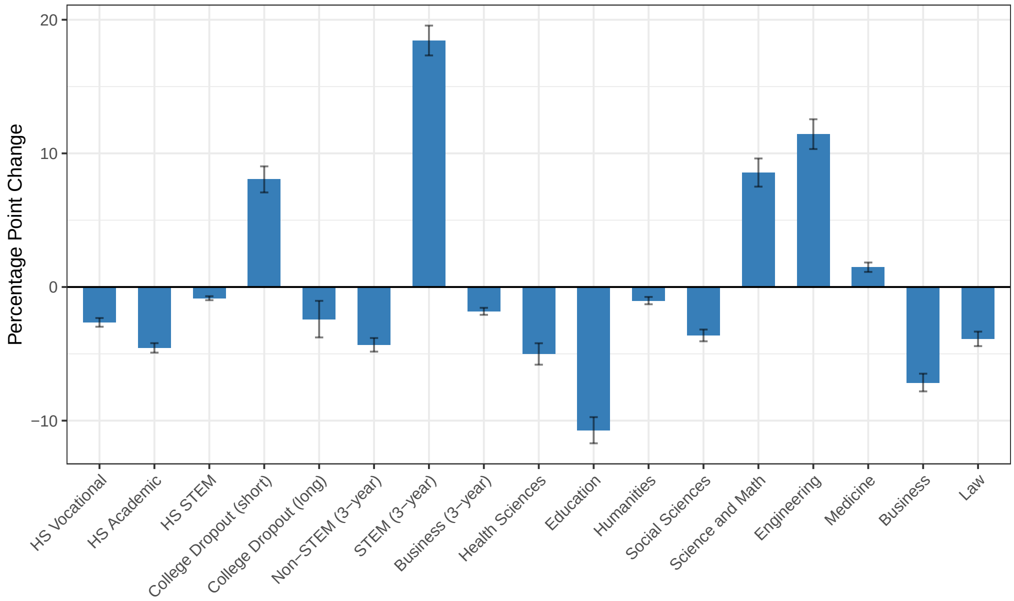
Figure 13 shows the AMTE of the program for those who were induced to switch into engineering, broken down by the level of education they would have otherwise obtained. We see that their returns are positive for most bins, but negative for those induced out of four-year business programs.

Overall, the two counterfactual policies suggest that targeting marginal STEM track students in high school has higher returns than than encouraging applications to STEM programs during the college application process. Moreover, we see that the impact of the college policy are larger for those who took the STEM track in high school. Both suggest that targeting students in high school may be more effective.

[34]Note that in all simulations we assume the admissions thresholds remain fixed.

[35]In the model applicants must be admitted to a program and then decide to enroll, which drives small changes in the number of terminal high school graduates.

Figure 12: Marginal Effect of Encouraging STEM Applications on Sorting into College Majors



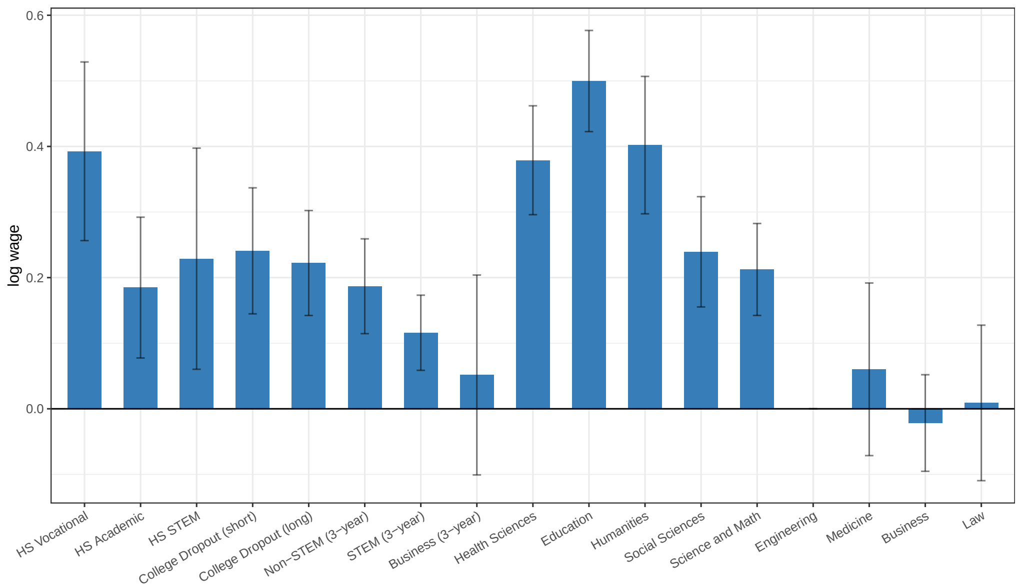
Notes: Figure shows how switching marginal individuals into the high school STEM track reallocates them across different education outcomes. Error bars show bootstrapped 95% confidence intervals.

Table 4: Effects of Encouraging STEM College Applications (log wages, switchers)

	AMTE			**Prop. Gaining**		
Group	All	Low Abil	High Abil	All	Low Abil	High Abil
All	0.039	0.032	0.039	0.545	0.538	0.552
	(0.005)	(0.008)	(0.010)	(0.005)	(0.008)	(0.011)
STEM HS Track	0.056	0.049	0.021	0.555	0.547	0.543
	(0.009)	(0.012)	(0.023)	(0.008)	(0.012)	(0.023)
Not STEM HS Track	0.030	0.0014	0.041	0.540	0.527	0.553
	(0.006)	(0.009)	(0.011)	(0.007)	(0.010)	(0.012)

Notes: Table reports the treatment effects for those induced to switch final education levels from the counterfactual policy of encouraging STEM college major applications among those who apply to college. Results are reported for all students, students who took the STEM track in college, and students who did not take the STEM track in college. "Low Abil" ("High Abil") are students in the bottom (top) half of all three abilities. The last three columns reports the proportion of students who switched final education levels who have positive wage gains. Bootstrapped standard errors are reported in parentheses.

Figure 13: AMTE of Encouraging STEM Applications for those whose Final Education is **Engineering** by Baseline Education.



Notes: Figure shows the average treatment effect of the policy encouraging students to apply to STEM college programs 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. Appendix Table F.3 provides similar estimates conditional on other final education levels. Error bars show bootstrapped 95% confidence intervals.

7 Conclusion

In this paper, we document 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. Using Swedish data, we have documented that the abilities which students start high school with and their high school choices are important determinants of their later labor market outcomes. In addition, we show that students sort into high school track based on abilities, and into college majors based on abilities and high school track. To account for these rich sorting patterns, we develop a dynamic generalized Roy model of high school choices, college choices, and labor market outcomes. This model uses exogenous variation in high school and college, combined with a large measurement system to identify the latent distribution of abilities and additional latent types which drive selection. Using the model, we document heterogeneous returns to abilities and high school investments across final schooling levels. We additionally show that the returns to the STEM track in high school tend to be large compared to the vocational track, and that there are more modest gains to STEM vs academic tracks and academic vs vocational tracks. These results are also heterogeneous, and we find evidence of selection on gains into high school track.

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Online Appendix for:
Complementarities in High School and College Investments

A Additional Tables

Table A.1: Prior Skills, Health, and Family Background by High School Track

	High School Dropout	High School Track: Vocational	High School Track: Academic non-STEM	High School Track: Academic STEM
Standardized Grades, Ninth grade				
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
GPA	-0.97	-0.44	0.55	1.07
Health measures				
Strenght	-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				
Disposable family income child	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
Fraction 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
Fraction 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.

Table A.2: 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.

B 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.

B.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 ninth 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 B.1 shows that application behavior, admission decisions, and high school graduation outcomes differ by ninth 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. On average, students list 2.3 alternatives on their application. 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 B.2 shows descriptives by ninth 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 first priority. Figure B.1 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 first priority: 67% (68%) of academic (STEM) school-lines admit 75-100% of first priority applicants and 18% (26%) of academic (STEM) school-lines admit *all* first priority applicants. A few – 4% of the vocational and 1% of the academic – school-lines do not admit any applicants. Figure B.2 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 ninth grade GPA of admitted students does not vary significantly by selectivity. This suggests that the high school peer composition is similar by selectivity.

B.1.1 Additional High School Descriptives

Table B.4 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 B.5 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.

Table B.1: High School Application, Admission, and Graduation; by ninth grade GPA.

	Ninth grade GPA quartile			
	Q1	**Q2**	**Q3**	**Q4**
Admitted	0.61	0.79	0.91	0.96
Admitted, first priority	0.35	0.51	0.78	0.94
Admitted, second priority	0.16	0.18	0.10	0.02
Admitted, third priority	0.07	0.08	0.03	0.00
Retained, first priority	0.39	0.55	0.77	0.89
Retained, second priority	0.15	0.15	0.08	0.02
Retained, third priority	0.07	0.06	0.02	0.01
Line, first priority				
Preference (1="listed in all priorities")	0.63	0.60	0.59	0.60
Same as second priority	0.16	0.19	0.16	0.07
Same as third 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, first priority				
Preference (1="listed in all priorities")	0.98	0.91	0.81	0.79
Same as second priority	0.95	0.82	0.67	0.60
Same as third 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

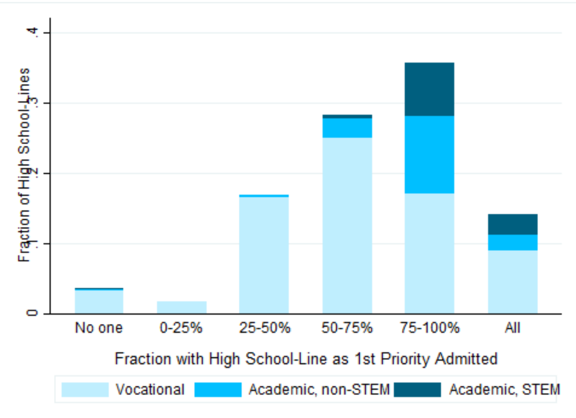
Note: The Table shows descriptive statistics of high school application, admission, and graduation by ninth grade GPA quartile. *Sample*: Applicants for high school enrollment 1990-91 academic year. Males 15-19 years old at the time of application. Applications are submitted by March 15, admission decisions 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 ninth 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 B.2: High School Application, Admission, and Graduation; by ninth grade GPA and first Priority High School Track.

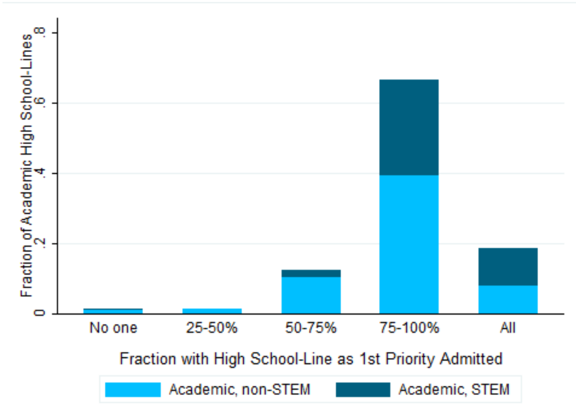
			High School Track						High School-Line				
			Admitted			Graduated			Admitted		Retained		Graduated
Ninth GPA	**HS Track 1st priority**	**% GPA Q**	Vocational	Academic non-STEM	Academic STEM	Vocational	Academic non-STEM	Academic STEM	1st priority	Second priority	1st priority	Second priority	1st priority
	Vocational	96.30	**99.56**	0.26	0.18	**99.51**	0.36	0.12	35.10	16.04	39.24	15.10	62.74
GPA, Q1	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	21.05
	Academic, STEM	1.42	37.24	0.69	**62.07**	70.89	7.59	**21.52**	31.25	7.14	35.71	11.61	18.35
	Vocational	82.68	**98.66**	0.73	0.62	**98.63**	0.98	0.40	53.91	17.91	56.49	14.83	72.98
GPA, Q2	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	42.57
	Academic, STEM	6.03	20.17	2.93	**76.89**	48.58	11.24	**40.18**	47.76	12.96	57.53	13.56	35.75
	Vocational	55.63	**97.74**	1.32	0.94	**96.92**	1.97	1.11	76.98	9.88	73.80	7.73	84.64
GPA, Q3	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	74.87
	Academic, STEM	19.42	5.34	2.98	**91.67**	18.82	10.60	**70.58**	80.82	9.40	83.17	8.08	66.15
	Vocational	19.92	**96.96**	1.67	1.37	**92.36**	4.10	3.54	82.17	4.74	73.97	4.21	84.76
GPA, Q4	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	88.35
	Academic, STEM	52.85	0.40	0.79	**98.80**	3.43	5.23	**91.34**	97.48	1.28	94.93	1.95	87.00

Note: The first column of the Table shows the percentage within each ninth grade GPA quartile that states each high school track (vocational, academic non-STEM, and academic STEM) as first priority at the time of application. We define an application cell by ninth grade GPA quartile and high school track listed as first 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 first and second 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.

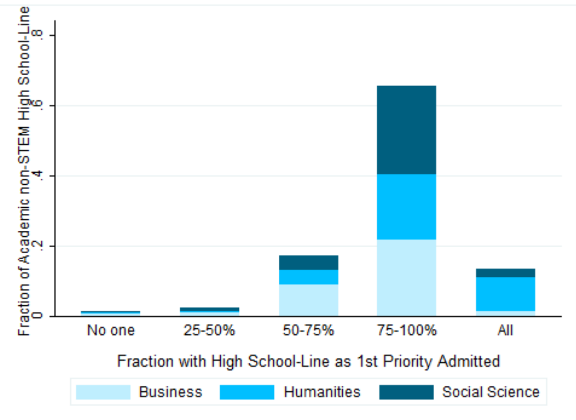
Figure B.1: Distribution of High School-Lines, by Selectivity.



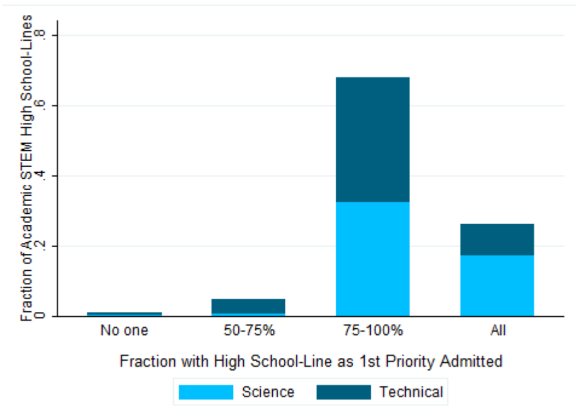
(a) All Lines



(b) Academic Track



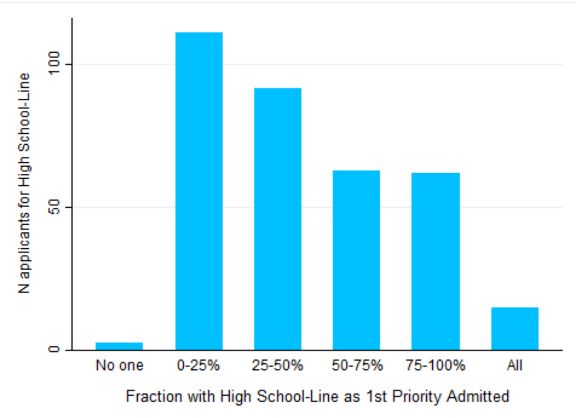
(c) Academic non-STEM Track



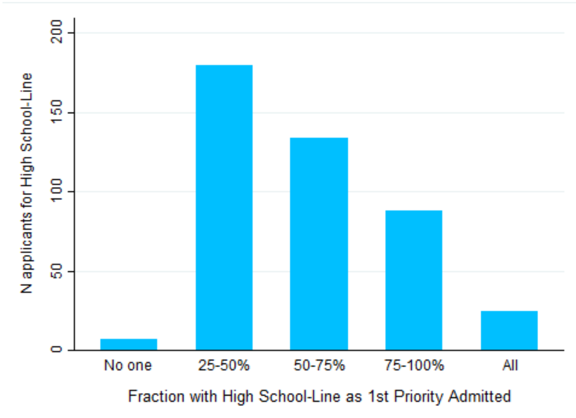
(d) Academic STEM Track

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 first priority. *Sample*: Applicants for high school enrollment 1990-91 academic year.

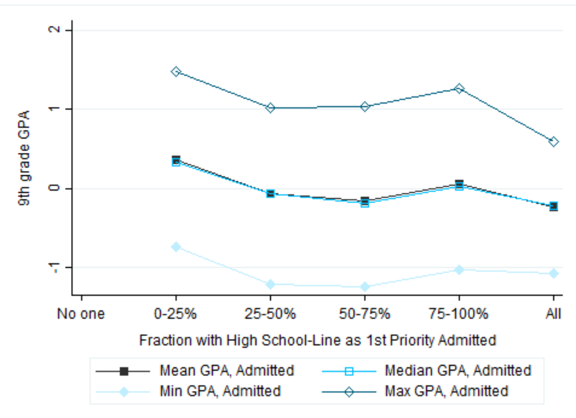
Figure B.2: Applicants and Admitted to High School-Lines, by Selectivity.



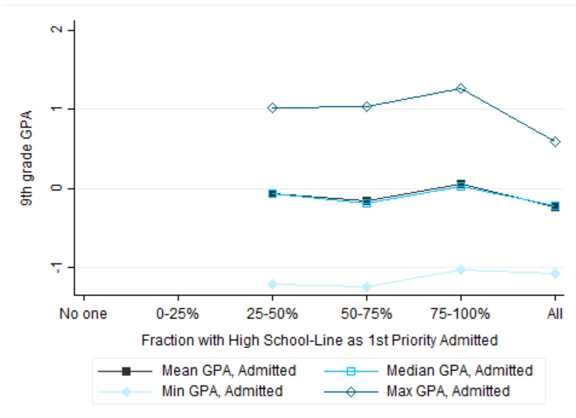
(a) N applicants, All Lines



(b) N applicants, Academic Track



(c) Admitted ninth grade GPA, All Lines



(d) Admitted ninth grade GPA, Academic Track

Note: The Figures display the number of applicants and the mean/median/min/max ninth 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 first priority. *Sample*: Applicants for high school enrollment 1990-91 academic year.

Table B.3: 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.

Table B.4: 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 B.5: 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.

B.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 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 second 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.[36] Figure B.3 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. Finally, the micro data on college applications and admissions from the Swedish National Archives (*Riksarkivet*) enables us to directly assess to which extent

[36] 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.

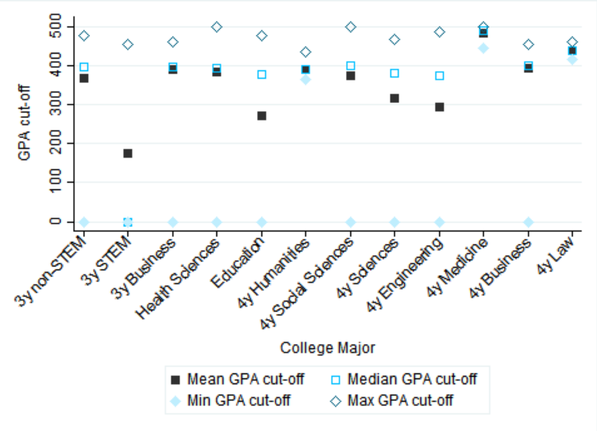
admission probabilities are taken into account when applying. Figure B.4 reveals that students with high high school GPA have highes admission probabilities, apply to more selective programs, and are more likely to be admitted to their more preferred programs. We also find that applicatins differ substantially by geographic cluster. Figure B.2.1 singles out the location of the leading colleges and universities by one international and one national ranking, the Shanghai Jiao Tong Academic Ranking of World Universities (ARWU) and the commonly used Swedish Fokus ranking. We see substantial geographic variation. Students are particularly likely to prefer the college that is closest to home when there is a highly ranked college within the cluster.

B.2.1 Additional College Descriptives

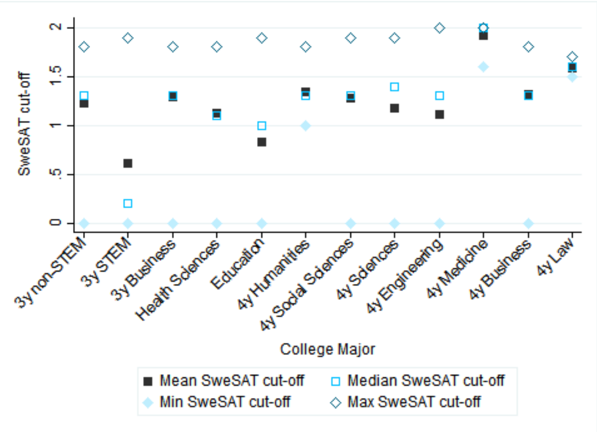
In this subsection, we provide additional descriptive statistics on those who initially enroll in and acquire a degree in each college major. Table B.6 and Table B.7 show the background characteristics that we use as controls, Table B.8 and Table B.9 show the high school grades, high school track choices, and SweSAT test scores,[37] while Table B.10 shows the age at education decision nodes, switching, and graduation behavior. Finally, Table B.11 and Table B.12 show the five most common programs within each college major. This table also shows the SUN2000Inr codes that correspond to each of the fields.

[37] Note that in Figure B.3 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.

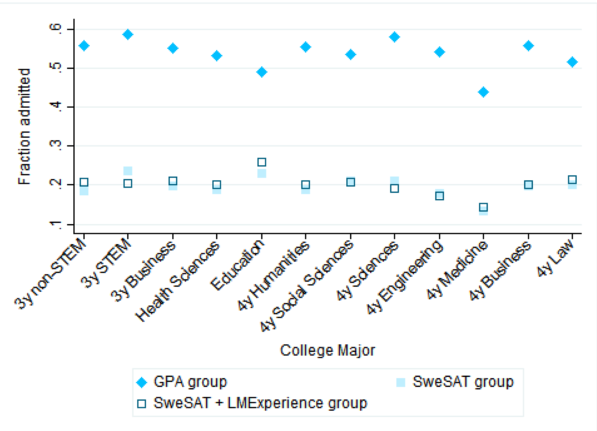
Figure B.3: Selectivity and Admission, by College Major.



(a) GPA cut-off



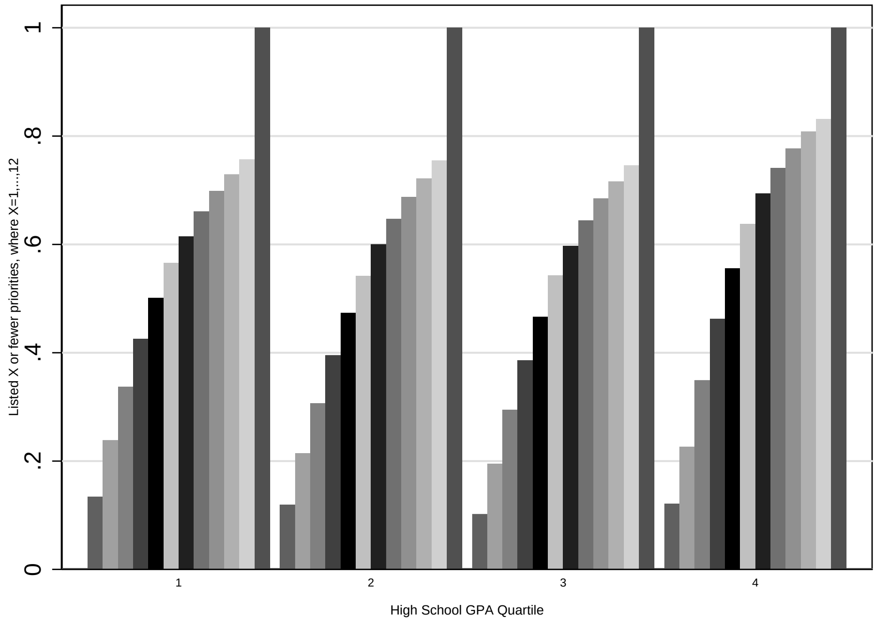
(b) SweSAT cut-off



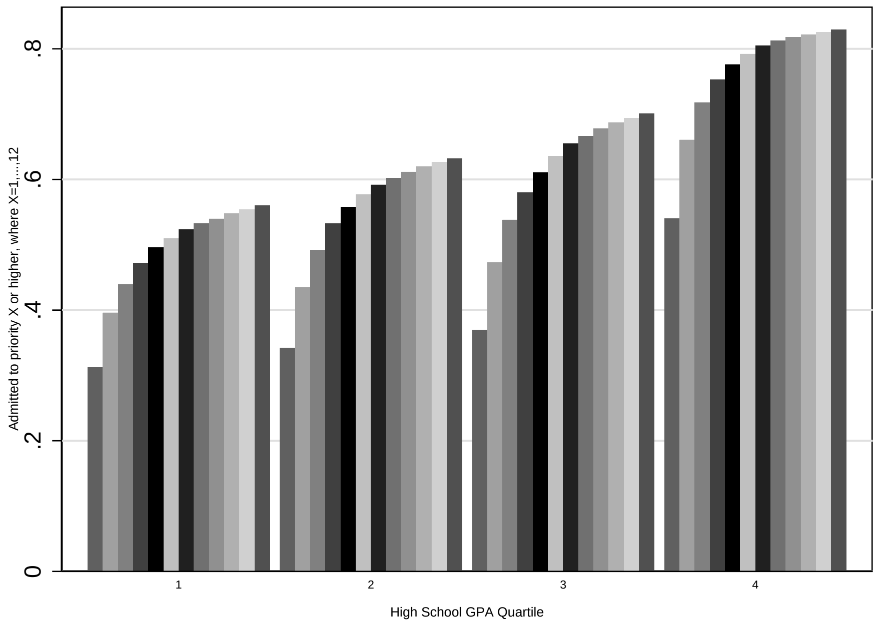
(c) Fraction admitted, by admission group

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 B.4: College Application and Admission.



(a) Fraction listed at least X priorities



(b) Fraction Admitted to Priority X or higher

Note: This Figure describes how many priorities are listed on college applications and which priority individuals were admitted to, by hich school GPA quartile. Panel (a) shows the fraction of applicants within each GPA quartile listing at least X priorities, where $X \in \{1, ..., 12\}$. Panel (b) shows the fraction of applicants within each GPA quartile that is admitted to priority X or a higher/preferred priority, where $X \in \{1, ..., 12\}$.

Table B.6: Control Variables by College Major of Initial Enrollment

		College Major											
		3-year					4-year						
	No enrollment (HS graduate)	non-STEM	STEM	Business	Health Sci	Education	Humanities	SocSci	Sciences	Engineer	Medicine	Business	Law
Courses, 9th grade													
Adv. Math	0.46	0.76	0.89	0.84	0.67	0.76	0.82	0.84	0.92	0.97	0.98	0.91	0.91
Adv. English	0.53	0.89	0.84	0.88	0.80	0.86	0.93	0.92	0.93	0.95	0.99	0.94	0.96
Health factors													
Strenght	0.08	-0.19	0.10	-0.02	0.08	-0.03	-0.26	-0.03	0.01	0.08	0.18	0.04	0.08
Fitness	0.07	-0.08	-0.23	-0.17	-0.19	-0.15	-0.09	-0.23	-0.28	-0.34	-0.47	-0.28	-0.21
Health missing	0.05	0.05	0.04	0.03	0.04	0.04	0.07	0.05	0.05	0.04	0.05	0.05	0.05
Mother													
Disposable family income child age 5-18	2.84	3.12	3.08	3.18	3.02	3.04	3.19	3.23	3.21	3.44	3.65	3.45	3.56
Education													
$\geq$ College	0.17	0.41	0.31	0.33	0.37	0.34	0.49	0.45	0.43	0.50	0.65	0.41	0.51
$\geq$ High School	0.68	0.82	0.78	0.78	0.79	0.78	0.85	0.82	0.82	0.85	0.87	0.81	0.85
Missing	0.07	0.07	0.07	0.06	0.07	0.07	0.07	0.07	0.08	0.07	0.09	0.07	0.07
Father Education													
$\geq$ College	0.12	0.33	0.22	0.25	0.28	0.28	0.42	0.37	0.38	0.41	0.62	0.35	0.48
$\geq$ High School	0.57	0.73	0.70	0.69	0.70	0.70	0.76	0.76	0.75	0.80	0.84	0.76	0.78
Missing	0.10	0.10	0.09	0.08	0.08	0.09	0.09	0.09	0.10	0.09	0.09	0.09	0.10
N students	**59,173**	**1,966**	**11,125**	**1,033**	**1,778**	**3,699**	**789**	**1,433**	**3,277**	**7,521**	**499**	**3,375**	**954**
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**	**0.03**	**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 B.7: 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
Courses, 9th grade												
Adv. Math	0.81	0.90	0.87	0.70	0.79	0.84	0.87	0.94	0.98	0.99	0.95	0.93
Adv. English	0.90	0.85	0.90	0.82	0.86	0.94	0.93	0.94	0.96	0.99	0.96	0.97
Health factors												
Strenght	-0.14	0.11	0.11	0.10	0.00	-0.30	-0.13	-0.02	0.11	0.24	0.03	0.05
Fitness	-0.15	-0.29	-0.28	-0.20	-0.21	0.02	-0.26	-0.30	-0.41	-0.52	-0.36	-0.26
Health missing	0.06	0.04	0.05	0.04	0.04	0.07	0.05	0.05	0.04	0.05	0.05	0.05
Mother												
Disposable family income child age 5-18	3.17	3.10	3.23	3.08	3.05	3.15	3.32	3.23	3.48	3.68	3.55	3.62
Education												
$\geq$ College	0.40	0.31	0.35	0.40	0.35	0.49	0.50	0.46	0.50	0.65	0.45	0.53
$\geq$ High School	0.81	0.78	0.77	0.81	0.80	0.84	0.85	0.84	0.85	0.86	0.84	0.84
Missing	0.08	0.07	0.08	0.07	0.07	0.07	0.06	0.08	0.07	0.08	0.06	0.08
Father Education												
$\geq$ College	0.36	0.23	0.25	0.29	0.28	0.41	0.43	0.40	0.42	0.61	0.37	0.50
$\geq$ High School	0.73	0.70	0.69	0.71	0.71	0.76	0.81	0.77	0.80	0.83	0.78	0.80
Missing	0.10	0.08	0.11	0.08	0.08	0.10	0.08	0.09	0.08	0.10	0.08	0.11
N students	**1,565**	**5,465**	**477**	**1,518**	**2,396**	**514**	**922**	**1,754**	**6,055**	**630**	**1,959**	**748**
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**	**0.06**	**0.01**	**0.02**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college graduates	**0.07**	**0.23**	**0.02**	**0.06**	**0.10**	**0.02**	**0.04**	**0.07**	**0.25**	**0.03**	**0.08**	**0.03**

Table B.8: 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	-0.32	0.32	0.12	0.28	0.18	0.24	0.55	0.47	0.59	1.09	1.64	0.66	1.02
Math	-0.22	-0.02	0.15	0.16	-0.06	0.02	0.07	0.10	0.48	0.93	1.02	0.45	0.49
English	-0.19	0.37	-0.07	0.12	0.17	0.15	0.49	0.39	0.47	0.65	1.33	0.43	0.90
Swedish	-0.29	0.50	0.07	0.28	0.23	0.34	0.76	0.58	0.54	0.87	1.59	0.62	1.14
Sports	-0.13	0.02	0.10	0.23	0.24	0.29	-0.03	0.24	0.17	0.29	0.54	0.37	0.30
High School Track													
Vocational	0.78	0.34	0.28	0.24	0.52	0.35	0.23	0.23	0.17	0.09	0.06	0.12	0.12
Academic non-STEM	0.15	0.47	0.11	0.60	0.29	0.43	0.48	0.55	0.26	0.06	0.13	0.68	0.57
Academic STEM	0.07	0.20	0.61	0.17	0.19	0.22	0.29	0.23	0.58	0.85	0.81	0.20	0.32
SweSAT													
Test-taker	0.10	0.78	0.72	0.85	0.86	0.77	0.75	0.88	0.88	0.83	0.92	0.91	0.89
SweSAT score of test-takers													
Total	-0.50	0.13	-0.27	-0.24	-0.32	-0.20	0.25	0.17	0.32	0.56	1.14	0.11	0.64
Vocabulary	-0.14	0.33	-0.25	-0.14	0.12	0.04	0.35	0.24	0.19	0.16	0.74	0.02	0.54
Swedish Reading Comprehension	-0.39	0.22	-0.12	-0.06	-0.23	-0.04	0.38	0.27	0.34	0.57	1.03	0.24	0.66
English	-0.39	0.26	-0.17	-0.08	-0.28	-0.05	0.44	0.29	0.39	0.58	1.06	0.31	0.74
General Information	-0.35	0.23	-0.24	-0.16	-0.06	-0.03	0.34	0.28	0.25	0.37	0.89	0.08	0.51
Data Sufficiency	-0.46	-0.12	0.17	-0.11	-0.40	-0.20	-0.03	-0.01	0.40	0.72	0.80	0.15	0.34
Interpret Diagrams, Tables, and Maps	-0.45	-0.05	0.09	0.00	-0.45	-0.14	0.08	0.09	0.35	0.69	0.81	0.27	0.40
N students	**59,173**	**1,966**	**11,125**	**1,033**	**1,778**	**3,699**	**789**	**1,433**	**3,277**	**7,521**	**499**	**3,375**	**954**
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**	**0.03**	**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 B.9: 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	0.42	0.28	0.40	0.27	0.29	0.71	0.66	0.75	1.10	1.58	0.83	1.14
Math	0.11	0.26	0.30	0.00	0.07	0.25	0.23	0.58	0.97	1.02	0.58	0.58
English	0.36	-0.03	0.15	0.22	0.11	0.55	0.54	0.49	0.54	1.21	0.50	0.92
Swedish	0.54	0.19	0.35	0.31	0.37	0.90	0.81	0.68	0.85	1.53	0.76	1.23
Sports	0.10	0.18	0.41	0.32	0.36	-0.03	0.21	0.21	0.36	0.57	0.44	0.38
High School Track												
Vocational	0.28	0.27	0.18	0.47	0.33	0.22	0.16	0.12	0.06	0.05	0.08	0.08
Academic non-STEM	0.49	0.15	0.61	0.30	0.44	0.49	0.54	0.22	0.05	0.13	0.64	0.57
Academic STEM	0.23	0.59	0.21	0.23	0.23	0.29	0.31	0.66	0.88	0.82	0.27	0.35
SweSAT												
Test-taker	0.81	0.72	0.87	0.86	0.78	0.72	0.91	0.88	0.82	0.93	0.90	0.90
SweSAT score of test-takers												
Total	0.06	-0.24	-0.15	-0.30	-0.27	0.36	0.28	0.37	0.44	1.03	0.10	0.60
Vocabulary	0.20	-0.26	-0.12	0.06	-0.06	0.44	0.26	0.17	0.02	0.63	-0.04	0.43
Swedish Read. Comprehension	0.19	-0.08	0.00	-0.17	-0.07	0.47	0.41	0.42	0.50	0.93	0.26	0.69
English	0.19	-0.15	0.03	-0.21	-0.10	0.46	0.47	0.44	0.48	1.00	0.30	0.73
General Information	0.23	-0.21	-0.14	-0.03	-0.08	0.43	0.33	0.29	0.27	0.80	0.08	0.48
Data Sufficiency	-0.10	0.19	0.03	-0.34	-0.21	0.06	0.09	0.46	0.71	0.78	0.18	0.35
Interpret Diag/Tables/ Maps	0.00	0.14	0.09	-0.35	-0.14	0.14	0.19	0.41	0.68	0.75	0.32	0.44
N students	**1,565**	**5,465**	**477**	**1,518**	**2,396**	**514**	**922**	**1,754**	**6,055**	**630**	**1,959**	**748**
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**	**0.06**	**0.01**	**0.02**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college graduates	**0.07**	**0.23**	**0.02**	**0.06**	**0.10**	**0.02**	**0.04**	**0.07**	**0.25**	**0.03**	**0.08**	**0.03**

Table B.10: Age, Choices, and Outcomes by College Major

		College Major											
		3-year					4-year						
	No enroll (HS grad)	**non-STEM**	**STEM**	**Business**	**Health Sci**	**Education**	**Humanities**	**SocSci**	**Sciences**	**Engineer**	**Medicine**	**Business**	**Law**
Age at													
9th grade graduation	16.03	16.00	16.01	16.01	16.01	16.01	15.99	16.00	16.00	15.99	15.98	16.00	15.99
High school graduation	18.66	18.92	18.92	18.98	18.87	18.90	18.98	19.03	19.01	19.04	19.10	19.06	19.10
First academic college enrollment		24.03	21.68	23.66	25.18	23.84	22.40	22.85	21.63	20.62	22.24	21.90	22.14
College Outcomes													
Stayed enrolled, initial college major		0.76	0.81	0.57	0.91	0.82	0.55	0.60	0.68	0.84	0.91	0.74	0.80
Graduated, initial college major		0.37	0.41	0.17	0.70	0.56	0.32	0.31	0.37	0.63	0.85	0.41	0.61
College graduate		0.55	0.55	0.53	0.77	0.69	0.70	0.65	0.62	0.74	0.92	0.62	0.75
N students	**59,173**	**1,966**	**11,125**	**1,033**	**1,778**	**3,699**	**789**	**1,433**	**3,277**	**7,521**	**499**	**3,375**	**954**
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**	**0.03**	**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**
Age at													
9th grade graduation		16.00	16.01	15.99	16.01	16.01	16.00	16.00	16.00	15.99	15.98	16.00	15.99
High school graduation		18.93	18.91	18.97	18.88	18.89	18.94	19.05	19.00	19.03	19.10	19.08	19.11
First academic college enrollment		23.00	21.59	22.78	24.17	23.18	22.71	22.27	21.12	20.36	21.53	21.43	21.54
Last academic college degree		28.66	26.29	31.22	29.32	27.31	29.06	28.85	27.61	26.73	27.89	27.72	27.77
College Outcomes													
Stayed enrolled, initial college major		0.47	0.83	0.36	0.82	0.86	0.50	0.48	0.68	0.79	0.67	0.70	0.78
N students		**1,565**	**5,465**	**477**	**1,518**	**2,396**	**514**	**922**	**1,754**	**6,055**	**630**	**1,959**	**748**
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**	**0.06**	**0.01**	**0.02**	**0.05**	**0.16**	**0.02**	**0.05**	**0.02**
Fraction of college graduates		**0.07**	**0.23**	**0.02**	**0.06**	**0.10**	**0.02**	**0.04**	**0.07**	**0.25**	**0.03**	**0.08**	**0.03**

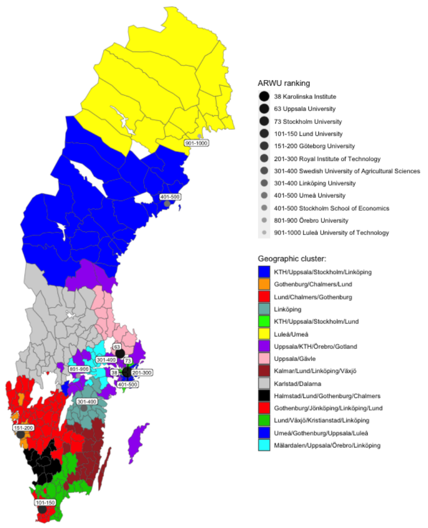
Table B.11: College Programs within Major, First Enrollment

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

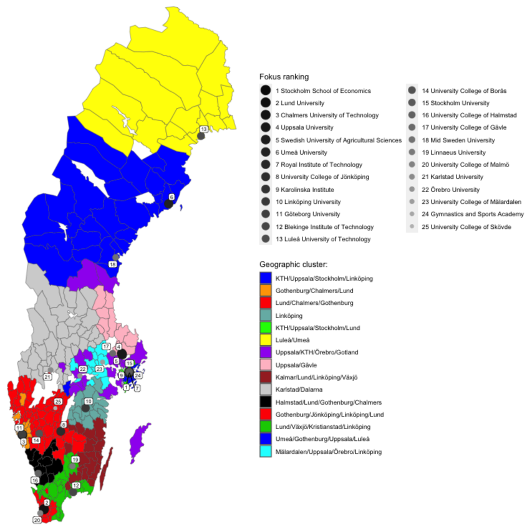
Table B.12: College Programs within Major, Final Graduation

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

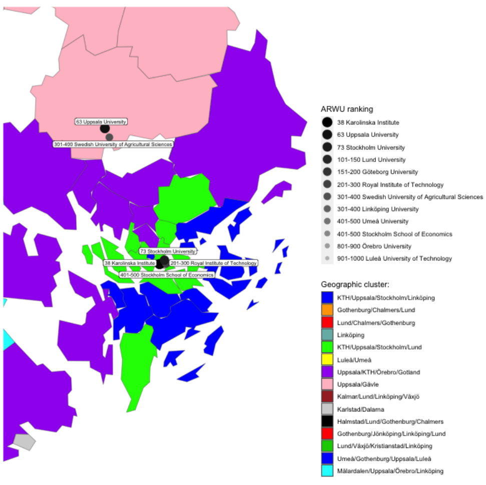
Figure B.5: Maps of College Applications in Sweden and Stockholm (15 clusters)



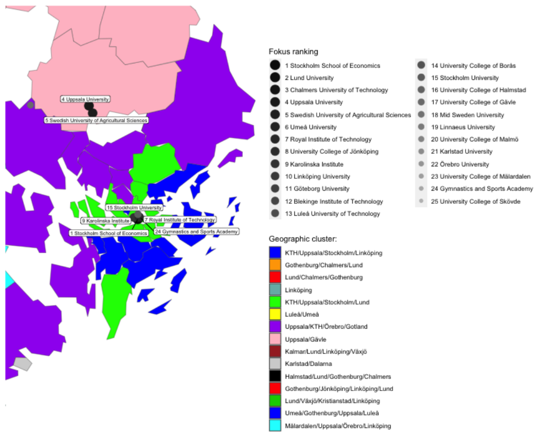
(a) Sweden (ARWU ranking)



(b) Sweden (Fokus ranking)

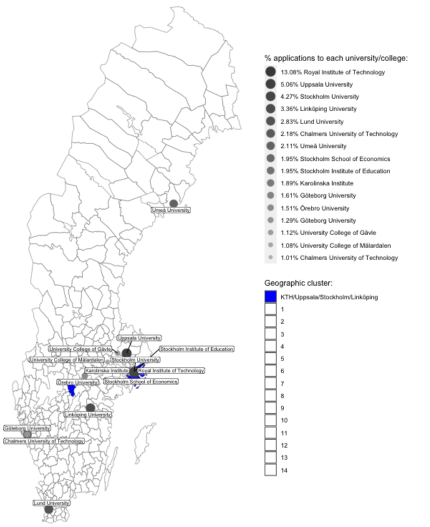


(c) Stockholm (ARWU ranking)

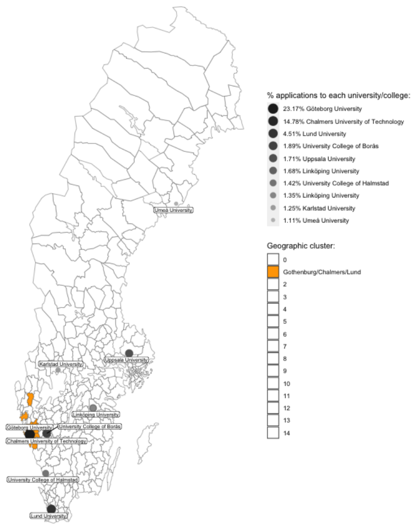


(d) Stockholm (Fokus ranking)

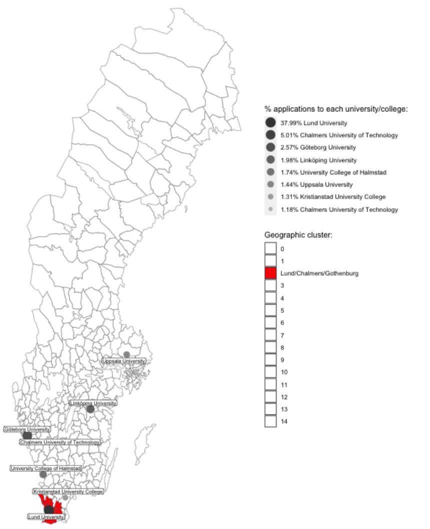
Figure B.6: % Applications to Each University/College by Geographic Cluster



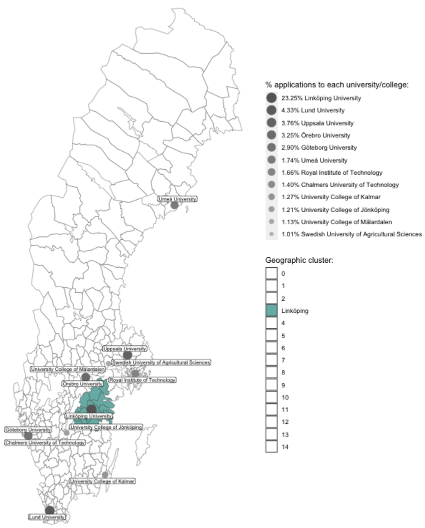
(a) KTH/Uppsala/Stockholm/Linköping



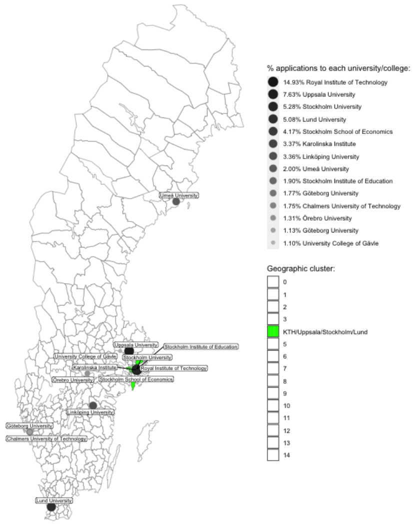
(b) Gothenburg/Chalmers/Lund



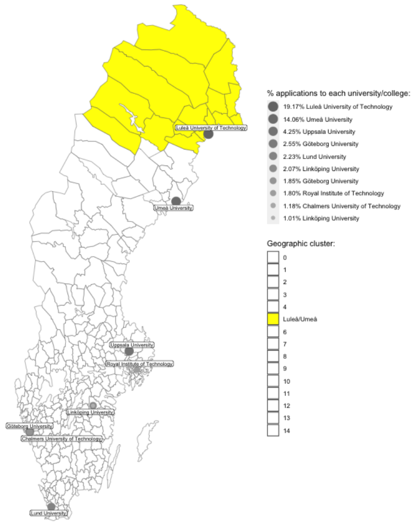
(c) Lund/Chalmers/Gothenburg



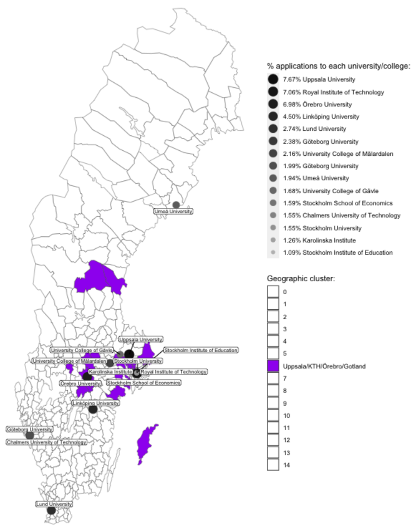
(d) Linköping



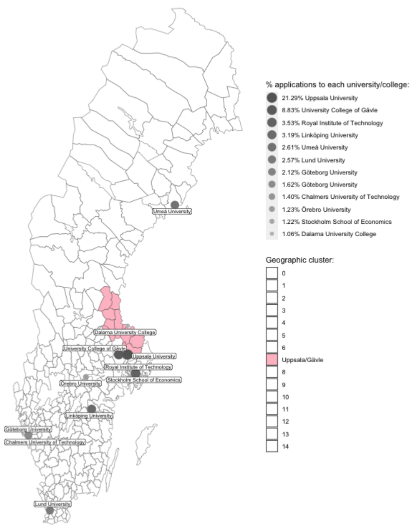
(e) KTH/Uppsala/Stockholm/Lund



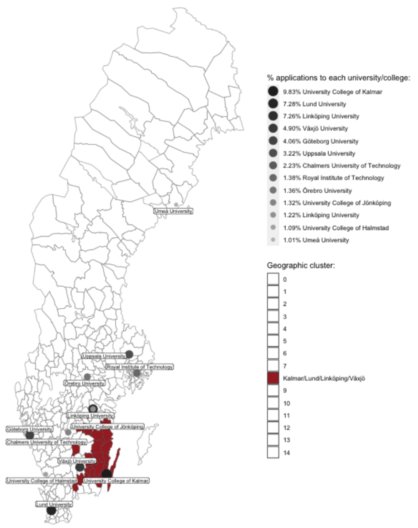
(f) Luleå/Umeå



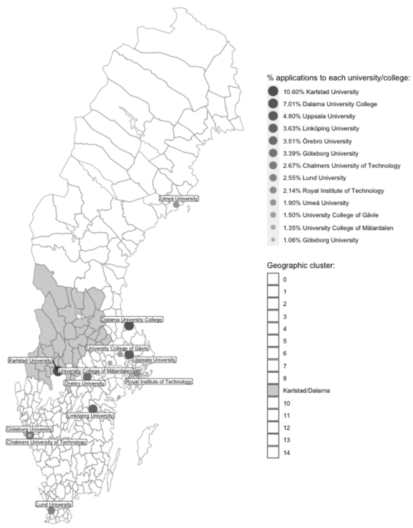
(g) Uppsala/KTH/Örebro/Gotland



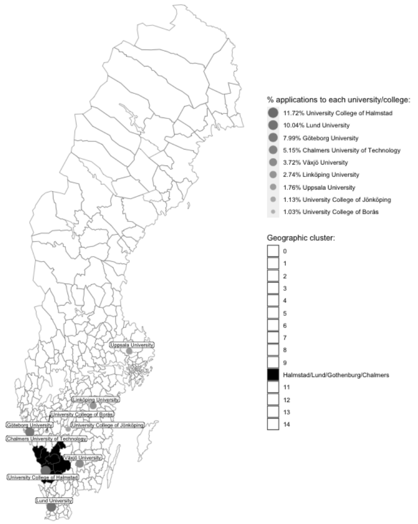
(h) Uppsala/Gävle



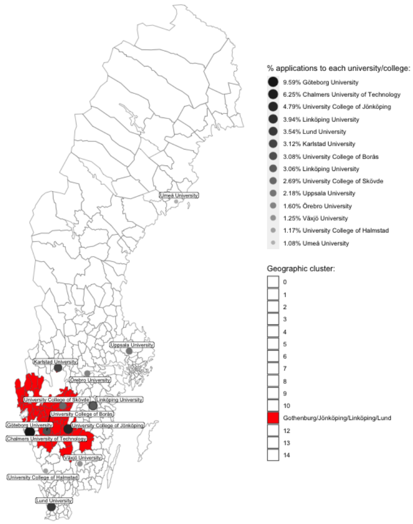
(i) Kalmar/Lund/Linköping/Växjö



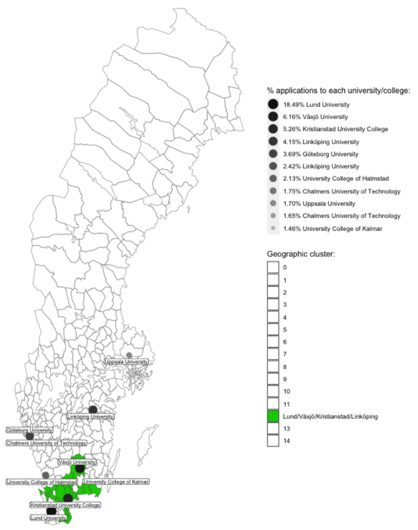
(j) Karlstad/Dalarna



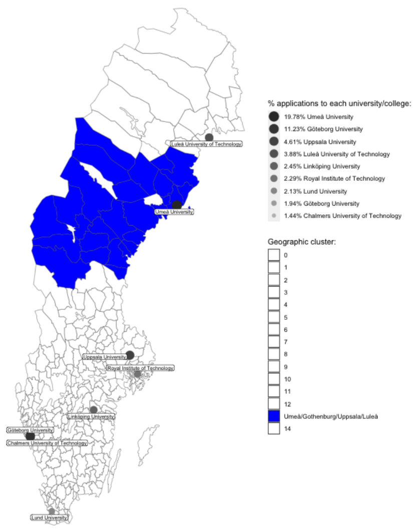
(k) Halmstad/Lund/Gbg/Chalmers



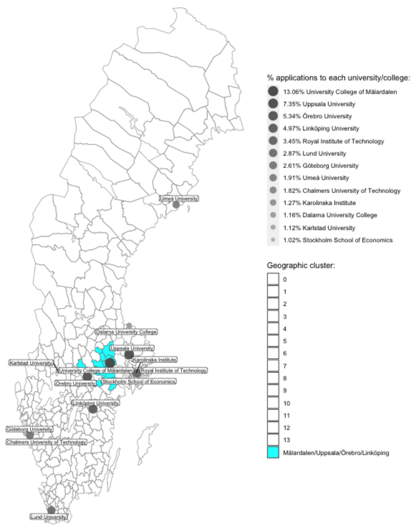
(l) Gbg/Jönköping/Linköping/Lund



(m) Lund/Växjö/Kristianstad/Linköping



(n) Umeå/Gothenburg/Uppsala/Luleå



(o) Mälardalen/Uppsala/Örebro/Linköping

Table B.13: Sensitivity of the Association Between Abilities and Wages within Final College Major

	College Major											
	3-year					4-year						
	non-STEM (Hum, Soc Sci)	STEM (Sci, Math, Eng)	Business	Health Sci	Education	Humanities	Social Sci	Sciences	Engineering	Medicine	Business	Law
Ability												
Cognitive	0.029	0.016	0.100	0.027	0.027	0.064	0.071	0.011	0.025	0.056	0.069	0.042
Interpersonal	0.049	0.037	0.069	0.026	0.022	0.020	0.052	0.033	0.043	0.016	0.081	0.069
Grit	0.027	0.018	0.094	0.036	0.019	0.054	0.057	0.001	0.028	0.071	0.081	0.057
Controls	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.129	0.082	0.116	0.113	0.076	0.105	0.123	0.060	0.096	0.135	0.140	0.139
Ability												
Cognitive	0.022	0.016	0.081	0.024	0.028	0.065	0.060	0.011	0.017	0.056	0.043	0.040
Interpersonal	0.048	0.036	0.070	0.023	0.022	0.021	0.040	0.035	0.039	0.014	0.078	0.067
Grit	0.027	0.019	0.082	0.033	0.019	0.059	0.047	0.002	0.024	0.074	0.053	0.057
Controls	+	+	+	+	+	+	+	+	+	+	+	+
College FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.160	0.103	0.177	0.136	0.109	0.118	0.186	0.090	0.128	0.144	0.180	0.152
Ability												
Cognitive	0.022	0.017	0.082	0.019	0.024	0.069	0.060	0.011	0.014	0.056	0.044	0.040
Interpersonal	0.040	0.035	0.072	0.022	0.022	0.026	0.027	0.035	0.037	0.014	0.077	0.067
Grit	0.024	0.020	0.083	0.027	0.018	0.068	0.034	0.008	0.019	0.074	0.056	0.057
Controls	+	+	+	+	+	+	+	+	+	+	+	+
College FEs	+	+	+	+	+	+	+	+	+	+	+	+
Program FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.258	0.132	0.172	0.217	0.188	0.170	0.305	0.228	0.168	0.144	0.211	0.152
Ability												
Cognitive	0.028	0.019	0.100	0.022	0.023	0.070	0.061	0.014	0.023	0.056	0.054	0.042
Interpersonal	0.042	0.035	0.069	0.024	0.022	0.029	0.028	0.035	0.040	0.016	0.078	0.069
Grit	0.027	0.020	0.093	0.030	0.018	0.070	0.035	0.011	0.025	0.071	0.065	0.057
Controls	+	+	+	+	+	+	+	+	+	+	+	+
Program FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.236	0.118	0.106	0.199	0.149	0.169	0.300	0.222	0.144	0.135	0.194	0.139
N students	1565	5465	477	1518	2396	514	922	1754	6055	630	1959	748
N with Wage>0	917	3578	286	1181	1932	293	607	1151	3959	554	1187	492
N with Wage>0 and all FEs	917	3578	286	1181	1932	293	607	1151	3959	554	1187	492

Table B.14: Sensitivity of the Association Between Abilities and the Present Value of Disposable Income within Final College Major

	College Major											
	3-year					**4-year**						
	non-STEM (Hum, Soc Sci)	**STEM (Sci, Math, Eng)**	**Business**	**Health Sci**	**Education**	**Humanities**	**Social Sci**	**Sciences**	**Engineering**	**Medicine**	**Business**	**Law**
Ability												
Cognitive	0.006	0.031	0.085	0.026	0.021	0.036	0.019	-0.010	0.010	0.043	0.096	0.077
Interpersonal	0.082	0.053	0.086	0.047	0.042	0.059	0.064	0.044	0.052	0.029	0.091	0.075
Grit	0.014	0.035	0.109	0.034	0.024	0.049	0.029	0.007	0.029	0.068	0.110	0.083
Controls	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.081	0.060	0.100	0.047	0.047	0.045	0.082	0.040	0.059	0.089	0.114	0.125
Ability												
Cognitive	0.007	0.035	0.071	0.022	0.024	0.028	0.005	-0.004	0.009	0.046	0.064	0.074
Interpersonal	0.079	0.053	0.085	0.041	0.042	0.043	0.050	0.046	0.051	0.027	0.087	0.072
Grit	0.016	0.039	0.088	0.030	0.026	0.027	0.015	0.013	0.029	0.072	0.077	0.086
Controls	+	+	+	+	+	+	+	+	+	+	+	+
College FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.084	0.082	0.144	0.067	0.061	0.141	0.124	0.057	0.067	0.095	0.140	0.139
Ability												
Cognitive	0.013	0.036	0.072	0.022	0.022	0.029	0.012	-0.001	0.013	0.046	0.065	0.074
Interpersonal	0.064	0.051	0.086	0.040	0.042	0.039	0.035	0.048	0.047	0.027	0.085	0.072
Grit	0.018	0.039	0.088	0.030	0.025	0.030	0.007	0.020	0.031	0.072	0.077	0.086
Controls	+	+	+	+	+	+	+	+	+	+	+	+
College FEs	+	+	+	+	+	+	+	+	+	+	+	+
Program FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.144	0.115	0.142	0.145	0.067	0.217	0.181	0.140	0.094	0.095	0.149	0.139
Ability												
Cognitive	0.016	0.036	0.086	0.026	0.020	0.034	0.014	-0.004	0.014	0.043	0.079	0.077
Interpersonal	0.063	0.053	0.088	0.044	0.042	0.048	0.037	0.048	0.048	0.029	0.085	0.075
Grit	0.018	0.039	0.109	0.035	0.023	0.046	0.010	0.019	0.031	0.068	0.092	0.083
Controls	+	+	+	+	+	+	+	+	+	+	+	+
Program FEs	+	+	+	+	+	+	+	+	+	+	+	+
Adjusted R^2	0.150	0.110	0.095	0.134	0.053	0.180	0.188	0.143	0.092	0.089	0.142	0.125
N students	1565	5465	477	1518	2396	514	922	1754	6055	630	1959	748
N with PVincome>0	1426	5192	440	1456	2343	467	831	1632	5542	602	1739	708
N with PVincome>0 and all FEs	1426	5192	440	1456	2343	467	831	1632	5542	602	1739	708

B.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 indicators, T_t, age indicators, A_t, an indicator for being a college graduate, D_C, and this indicator interacted with year and age indicators. 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.

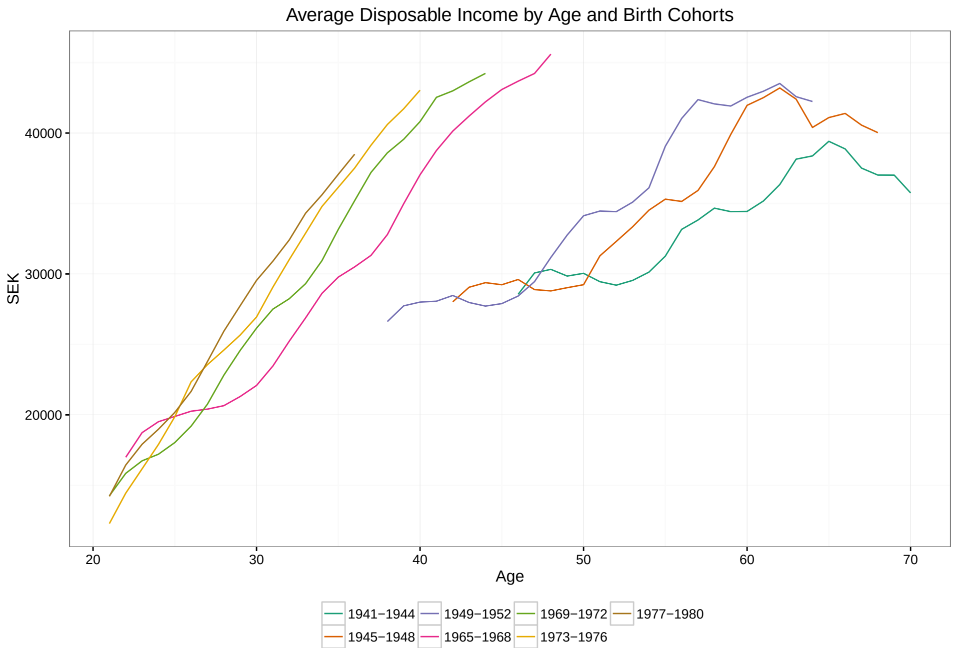
Using the model above, we predict earnings for everyone in our sample from the last age they are observed to age 65. Specifically, we use the income average over the last three years of the sample and the estimated growth rate above to simulate out each individual's income to age 65, assuming that market 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 B.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.[38] 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.

[38]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 B.7: Earnings by Age and Cohort (disposable income and wage income)



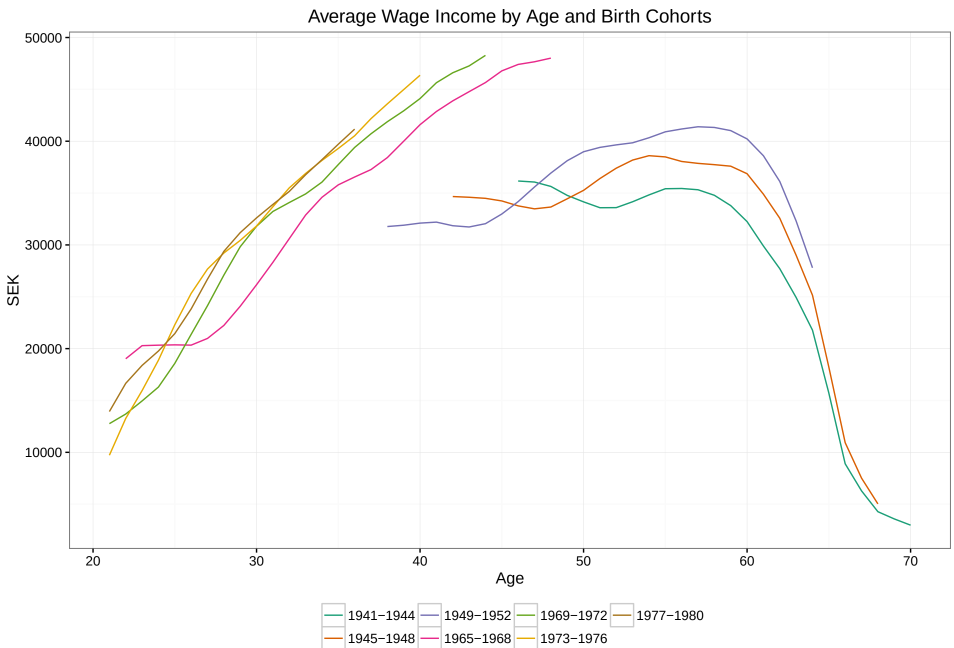
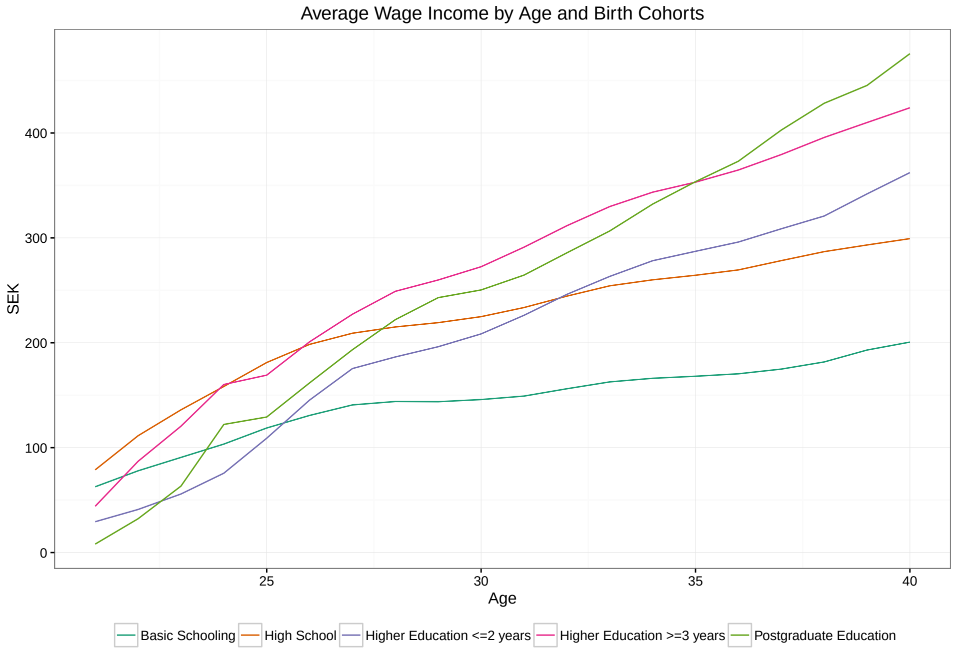


Figure B.8: Earnings Profiles by Age and Education (wage income)



C Instruments for High School and College Choices

C.1 Within-School-Across-Cohort Instruments

C.1.1 First Stage Regression Tables

Table C.1: First Stage Vocational Trk Instrument table

	(1) Vocational Trk	(2) Vocational Trk	(3) Vocational Trk
Vocational Trk IV	0.0146***	0.0143***	0.0171***
	(0.00172)	(0.00163)	(0.00169)
9th grade Schl Ave Vocational Trk	0.669***	0.628***	0.682***
	(0.0205)	(0.0201)	(0.0204)
School Ave 9th grade Adv Math	0.198***	0.127***	0.100***
	(0.0272)	(0.0232)	(0.0223)
School Ave 9th grade Adv English	0.0720**	0.0611**	0.0335
	(0.0224)	(0.0197)	(0.0179)
Own 9th grade GPA		-0.133***	-0.135***
		(0.00239)	(0.00240)
Cohort Ave 9th grade GPA			0.0712***
			(0.0131)
School Ave 9th grade GPA			0.105***
			(0.0142)
Constant	0.456***	0.324***	0.00494
	(0.0256)	(0.0245)	(0.0504)
1st Stage F-stat	71.49	77.19	103.5
R^2	0.266	0.302	0.303
$E[y]$	0.515	0.515	0.515
Sample Size	105913	105913	105913

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 C.2: First Stage Academic Trk Instrument table

	(1) Academic Trk	(2) Academic Trk	(3) Academic Trk
Academic Trk IV	0.0162***	0.0160***	0.0165***
	(0.00163)	(0.00161)	(0.00166)
9th grade Schl Ave Academic Trk	0.803***	0.791***	0.811***
	(0.0248)	(0.0240)	(0.0255)
School Ave 9th grade Adv Math	-0.0858***	-0.0734***	-0.0698***
	(0.0161)	(0.0154)	(0.0154)
School Ave 9th grade Adv English	-0.0585***	-0.0564***	-0.0530**
	(0.0171)	(0.0162)	(0.0167)
Own 9th grade GPA		0.0233***	0.0235***
		(0.00204)	(0.00207)
Cohort Ave 9th grade GPA			-0.0116
			(0.00997)
School Ave 9th grade GPA			-0.0181
			(0.0125)
Constant	-0.0718***	-0.0432**	0.00504
	(0.0128)	(0.0132)	(0.0361)
1st Stage F-stat	98.50	98.91	98.56
R^2	0.126	0.128	0.128
$E[y]$	0.181	0.181	0.181
Sample Size	105913	105913	105913

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 C.3: First Stage STEM Trk Instrument table

	(1) STEM Trk	(2) STEM Trk	(3) STEM Trk
STEM Trk IV	0.00660***	0.00693***	0.0135***
	(0.00149)	(0.00136)	(0.00145)
9th grade Schl Ave STEM Trk	0.403***	0.335***	0.634***
	(0.0363)	(0.0372)	(0.0325)
School Ave 9th grade Adv Math	-0.168***	-0.0709**	-0.0395*
	(0.0258)	(0.0232)	(0.0180)
School Ave 9th grade Adv English	-0.0284	-0.0196	0.0206
	(0.0208)	(0.0222)	(0.0158)
Own 9th grade GPA		0.185***	0.189***
		(0.00182)	(0.00183)
Cohort Ave 9th grade GPA			-0.0984***
			(0.0108)
School Ave 9th grade GPA			-0.221***
			(0.0131)
Constant	-0.221***	0.0115	0.590***
	(0.0127)	(0.0120)	(0.0362)
1st Stage F-stat	19.66	26.06	86.45
R^2	0.225	0.330	0.332
$E[y]$	0.216	0.216	0.216
Sample Size	105913	105913	105913

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 C.4: First Stage Major Do not Enroll Instrument table

	(1) Do not Enroll	(2) Do not Enroll	(3) Do not Enroll
Do not Enroll IV	0.0192***	0.0167***	0.0160***
	(0.00168)	(0.00165)	(0.00179)
HS Ave Do not Enroll	0.781***	0.716***	0.828***
	(0.0208)	(0.0206)	(0.0239)
Own Cog Abil		-0.0963***	-0.0982***
		(0.00174)	(0.00176)
Own Interpers Abil		-0.00731***	-0.00798***
		(0.00147)	(0.00148)
HS cohort Ave Cog Abil			-0.00174
			(0.00543)
HS cohort Ave Interpers Abil			-0.00573
			(0.00499)
HS Ave Cog Abil			0.0600***
			(0.00665)
HS Ave Interpers Abil			0.00730
			(0.00535)
Constant	0.380***	0.354***	-0.0253
	(0.0230)	(0.0230)	(0.0473)
1st Stage F-stat	131.5	102.7	79.82
R^2	0.363	0.385	0.386
$E[y]$	0.607	0.607	0.607
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.5: First Stage Major 3yr non-STEM Instrument table

	(1) 3yr non-STEM	(2) 3yr non-STEM	(3) 3yr non-STEM
3yr non-STEM IV	0.00138	0.00131	0.00122
	(0.000778)	(0.000775)	(0.000776)
HS Ave 3yr non-STEM	0.411***	0.399***	0.387***
	(0.0505)	(0.0502)	(0.0489)
Own Cog Abil		0.00639***	0.00632***
		(0.000631)	(0.000632)
Own Interpers Abil		-0.00337***	-0.00332***
		(0.000614)	(0.000616)
HS cohort Ave Cog Abil			0.00278
			(0.00197)
HS cohort Ave Interpers Abil			-0.000363
			(0.00188)
HS Ave Cog Abil			0.00192
			(0.00252)
HS Ave Interpers Abil			-0.00154
			(0.00224)
Constant	-0.0117*	-0.00902	-0.00931
	(0.00492)	(0.00496)	(0.0117)
1st Stage F-stat	3.135	2.842	2.456
R^2	0.0144	0.0158	0.0158
$E[y]$	0.0202	0.0202	0.0202
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.6: First Stage Major 3yr STEM Instrument table

	(1) 3yr STEM	(2) 3yr STEM	(3) 3yr STEM
3yr STEM IV	0.0194***	0.0194***	0.0194***
	(0.00142)	(0.00142)	(0.00143)
HS Ave 3yr STEM	0.992***	0.994***	0.988***
	(0.0229)	(0.0230)	(0.0230)
Own Cog Abil		0.00948***	0.00998***
		(0.00140)	(0.00142)
Own Interpers Abil		-0.00168	-0.00185
		(0.00112)	(0.00113)
HS cohort Ave Cog Abil			-0.00693
			(0.00362)
HS cohort Ave Interpers Abil			-0.000783
			(0.00317)
HS Ave Cog Abil			-0.0127**
			(0.00404)
HS Ave Interpers Abil			0.00725*
			(0.00367)
Constant	-0.0343**	-0.0280**	-0.00995
	(0.0105)	(0.0107)	(0.0202)
1st Stage F-stat	187.1	186.7	183.6
R^2	0.133	0.133	0.133
$E[y]$	0.117	0.117	0.117
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.7: First Stage Major 3yr Health Instrument table

	(1) 3yr Health	(2) 3yr Health	(3) 3yr Health
3yr Health IV	0.00561***	0.00559***	0.00548***
	(0.00126)	(0.00126)	(0.00126)
HS Ave 3yr Health	0.753***	0.751***	0.751***
	(0.0483)	(0.0483)	(0.0481)
Own Cog Abil		-0.000193	-0.000274
		(0.000556)	(0.000560)
Own Interpers Abil		0.00257***	0.00254***
		(0.000527)	(0.000534)
HS cohort Ave Cog Abil			0.00121
			(0.00206)
HS cohort Ave Interpers Abil			0.00409
			(0.00224)
HS Ave Cog Abil			0.00122
			(0.00210)
HS Ave Interpers Abil			-0.000317
			(0.00192)
Constant	-0.00821	-0.00643	-0.00939
	(0.00437)	(0.00439)	(0.00987)
1st Stage F-stat	19.69	19.61	19.03
R^2	0.0185	0.0187	0.0188
$E[y]$	0.0186	0.0186	0.0186
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.8: First Stage Major 3yr Business Instrument table

	(1) 3yr Business	(2) 3yr Business	(3) 3yr Business
3yr Business IV	0.00418***	0.00418***	0.00411***
	(0.000771)	(0.000771)	(0.000770)
HS Ave 3yr Business	0.748***	0.749***	0.746***
	(0.0602)	(0.0602)	(0.0602)
Own Cog Abil		0.000265	0.000290
		(0.000417)	(0.000424)
Own Interpers Abil		0.000754*	0.000826*
		(0.000377)	(0.000378)
HS cohort Ave Cog Abil			0.00128
			(0.00136)
HS cohort Ave Interpers Abil			0.000957
			(0.00127)
HS Ave Cog Abil			-0.000386
			(0.00135)
HS Ave Interpers Abil			-0.00201
			(0.00129)
Constant	-0.00386	-0.00308	0.00824
	(0.00362)	(0.00366)	(0.00737)
1st Stage F-stat	29.35	29.37	28.57
R^2	0.0179	0.0180	0.0181
$E[y]$	0.0109	0.0109	0.0109
Sample Size	91608	91608	91608

Standard errors in parentheses
College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.
All specifications include the following controls: Mother's education, Father's education,
Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.
Also included are high school track and 9th grade school average rates of advanced english and math.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.9: First Stage Major Education Instrument table

	(1) Education	(2) Education	(3) Education
Education IV	0.00724***	0.00722***	0.00709***
	(0.00113)	(0.00113)	(0.00114)
HS Ave Education	0.857***	0.857***	0.851***
	(0.0404)	(0.0405)	(0.0416)
Own Cog Abil		0.00154	0.00148
		(0.000806)	(0.000811)
Own Interpers Abil		0.00247***	0.00267***
		(0.000716)	(0.000725)
HS cohort Ave Cog Abil			0.000837
			(0.00271)
HS cohort Ave Interpers Abil			0.00190
			(0.00250)
HS Ave Cog Abil			0.00290
			(0.00295)
HS Ave Interpers Abil			-0.00607*
			(0.00268)
Constant	-0.00833	-0.00524	0.0117
	(0.00663)	(0.00668)	(0.0134)
1st Stage F-stat	40.88	40.63	38.89
R^2	0.0282	0.0284	0.0285
$E[y]$	0.0385	0.0385	0.0385
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.10: First Stage Major Humanities Instrument table

	(1) Humanities	(2) Humanities	(3) Humanities
Humanities IV	0.00313***	0.00308***	0.00290***
	(0.000624)	(0.000622)	(0.000621)
HS Ave Humanities	0.566***	0.551***	0.489***
	(0.0667)	(0.0666)	(0.0669)
Own Cog Abil		0.00307***	0.00289***
		(0.000412)	(0.000411)
Own Interpers Abil		-0.00208***	-0.00201***
		(0.000370)	(0.000370)
HS cohort Ave Cog Abil			0.000916
			(0.00133)
HS cohort Ave Interpers Abil			-0.000718
			(0.00132)
HS Ave Cog Abil			0.00581***
			(0.00151)
HS Ave Interpers Abil			-0.00300*
			(0.00140)
Constant	-0.00446	-0.00351	-0.0135
	(0.00313)	(0.00315)	(0.00690)
1st Stage F-stat	25.14	24.50	21.83
R^2	0.0109	0.0118	0.0120
$E[y]$	0.00797	0.00797	0.00797
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.11: First Stage Major Social Sciences Instrument table

	(1) Social Sciences	(2) Social Sciences	(3) Social Sciences
Social Sciences IV	0.00319***	0.00317***	0.00315***
	(0.000806)	(0.000806)	(0.000807)
HS Ave Social Sciences	0.545***	0.539***	0.540***
	(0.0576)	(0.0577)	(0.0599)
Own Cog Abil		0.00248***	0.00248***
		(0.000499)	(0.000504)
Own Interpers Abil		0.00187***	0.00193***
		(0.000469)	(0.000477)
HS cohort Ave Cog Abil			0.000982
			(0.00166)
HS cohort Ave Interpers Abil			-0.000975
			(0.00166)
HS Ave Cog Abil			0.000372
			(0.00181)
HS Ave Interpers Abil			-0.00133
			(0.00160)
Constant	-0.0120**	-0.00859*	-0.00384
	(0.00420)	(0.00428)	(0.00837)
1st Stage F-stat	15.63	15.46	15.19
R^2	0.0172	0.0177	0.0177
$E[y]$	0.0150	0.0150	0.0150
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.12: First Stage Major Science/Math Instrument table

	(1) Science/Math	(2) Science/Math	(3) Science/Math
Science/Math IV	0.0112***	0.0110***	0.0110***
	(0.00111)	(0.00111)	(0.00111)
HS Ave Science/Math	0.816***	0.795***	0.799***
	(0.0511)	(0.0512)	(0.0523)
Own Cog Abil		0.0152***	0.0152***
		(0.000808)	(0.000811)
Own Interpers Abil		-0.00464***	-0.00460***
		(0.000678)	(0.000685)
HS cohort Ave Cog Abil			0.00205
			(0.00249)
HS cohort Ave Interpers Abil			0.000108
			(0.00233)
HS Ave Cog Abil			-0.000809
			(0.00277)
HS Ave Interpers Abil			-0.000911
			(0.00236)
Constant	-0.000735	0.00831	0.0162
	(0.00636)	(0.00640)	(0.0142)
1st Stage F-stat	102.3	99.50	98.29
R^2	0.0388	0.0427	0.0427
$E[y]$	0.0343	0.0343	0.0343
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.13: First Stage Major Engineering Instrument table

	(1) Engineering	(2) Engineering	(3) Engineering
Engineering IV	0.0124***	0.0118***	0.0120***
	(0.00178)	(0.00177)	(0.00181)
HS Ave Engineering	0.773***	0.732***	0.794***
	(0.0388)	(0.0387)	(0.0395)
Own Cog Abil		0.0419***	0.0429***
		(0.00116)	(0.00116)
Own Interpers Abil		0.00335***	0.00351***
		(0.000890)	(0.000897)
HS cohort Ave Cog Abil			-0.00471
			(0.00296)
HS cohort Ave Interpers Abil			0.00403
			(0.00279)
HS Ave Cog Abil			-0.0266***
			(0.00330)
HS Ave Interpers Abil			-0.000279
			(0.00306)
Constant	-0.0533***	-0.0175*	0.0943***
	(0.00868)	(0.00873)	(0.0164)
1st Stage F-stat	48.78	44.18	43.82
R^2	0.197	0.211	0.211
$E[y]$	0.0796	0.0796	0.0796
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.14: First Stage Major Medicine Instrument table

	(1) Medicine	(2) Medicine	(3) Medicine
Medicine IV	0.00272***	0.00270***	0.00272***
	(0.000747)	(0.000744)	(0.000750)
HS Ave Medicine	0.924***	0.914***	0.918***
	(0.107)	(0.106)	(0.109)
Own Cog Abil		0.00340***	0.00344***
		(0.000325)	(0.000328)
Own Interpers Abil		0.00122***	0.00130***
		(0.000298)	(0.000301)
HS cohort Ave Cog Abil			-0.000256
			(0.000973)
HS cohort Ave Interpers Abil			-0.00182
			(0.00103)
HS Ave Cog Abil			-0.000163
			(0.00112)
HS Ave Interpers Abil			-0.00156
			(0.000935)
Constant	-0.00458*	-0.000942	0.00682
	(0.00221)	(0.00222)	(0.00561)
1st Stage F-stat	13.25	13.13	13.10
R^2	0.0273	0.0290	0.0291
$E[y]$	0.00522	0.00522	0.00522
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.15: First Stage Major Business Instrument table

	(1) Business	(2) Business	(3) Business
Business IV	0.00592***	0.00578***	0.00568***
	(0.00126)	(0.00125)	(0.00126)
HS Ave Business	0.574***	0.563***	0.581***
	(0.0588)	(0.0587)	(0.0608)
Own Cog Abil		0.00887***	0.00899***
		(0.000765)	(0.000773)
Own Interpers Abil		0.00418***	0.00432***
		(0.000674)	(0.000688)
HS cohort Ave Cog Abil			0.00272
			(0.00244)
HS cohort Ave Interpers Abil			0.000738
			(0.00213)
HS Ave Cog Abil			-0.00253
			(0.00240)
HS Ave Interpers Abil			-0.00340
			(0.00247)
Constant	-0.0221***	-0.0118	0.0151
	(0.00668)	(0.00675)	(0.0137)
1st Stage F-stat	22.11	21.22	20.23
R^2	0.0626	0.0645	0.0646
$E[y]$	0.0353	0.0353	0.0353
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.16: First Stage Major Law Instrument table

	(1) Law	(2) Law	(3) Law
Law IV	0.00294***	0.00285***	0.00275***
	(0.000632)	(0.000631)	(0.000637)
HS Ave Law	0.709***	0.689***	0.676***
	(0.0906)	(0.0903)	(0.0941)
Own Cog Abil		0.00459***	0.00450***
		(0.000493)	(0.000492)
Own Interpers Abil		0.00260***	0.00273***
		(0.000393)	(0.000401)
HS cohort Ave Cog Abil			0.00238
			(0.00139)
HS cohort Ave Interpers Abil			-0.00361**
			(0.00129)
HS Ave Cog Abil			0.00337*
			(0.00149)
HS Ave Interpers Abil			-0.00312*
			(0.00148)
Constant	-0.0119**	-0.00638	-0.00582
	(0.00414)	(0.00410)	(0.00809)
1st Stage F-stat	21.54	20.33	18.58
R^2	0.0198	0.0218	0.0220
$E[y]$	0.0101	0.0101	0.0101
Sample Size	91608	91608	91608

Standard errors in parentheses

College Enrollment peer instruments and ability controls are with respect to peers in high school graduating class.

All specifications include the following controls: Mother's education, Father's education,

Family Income, Parent's Married, healthy at birth, mother's age at birth, cohort dummies.

Also included are high school track and 9th grade school average rates of advanced english and math.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.1.2 Balance Regression Tables

Table C.17: Balance Tests for 9th Grade Course Instruments

	(1) 9th Adv Math IV	(2) 9th Adv English IV
Mother College	-0.00366	0.000998
	(0.00629)	(0.00613)
Mother High School	-0.0126*	-0.00444
	(0.00578)	(0.00563)
Father College	-0.00622	-0.00176
	(0.00704)	(0.00687)
Father High School	-0.0109*	0.000839
	(0.00542)	(0.00528)
Std. Family Income (1973)	0.00269	0.000203
	(0.00266)	(0.00259)
Mother's Age at Birth	0.000764	-0.000152
	(0.000509)	(0.000497)
Missing Mother's Age	0.00893	0.00534
	(0.0184)	(0.0180)
F-stat	3.160	0.199
Prob > F	0.00242	0.986
Within R^2	0.000211	0.0000133
Sample Size	105887	105887

Standard errors in parentheses

9th Grade peer instruments and ability controls are with respect to peers in 9th grade.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.18: Balance Tests for HS Track Instruments

	(1) Vocational Trk IV	(2) Academic Trk IV	(3) STEM Trk IV
Mother College	-0.00419	-0.00501	-0.000106
	(0.00681)	(0.00615)	(0.00678)
Mother High School	0.00308	-0.0103	-0.00345
	(0.00624)	(0.00564)	(0.00621)
Father College	0.00814	0.00344	-0.00490
	(0.00761)	(0.00688)	(0.00757)
Father High School	0.00445	-0.00264	-0.00448
	(0.00586)	(0.00530)	(0.00583)
Std. Family Income (1973)	-0.00291	0.00462	0.00294
	(0.00288)	(0.00260)	(0.00287)
Mother's Age at Birth	-0.000729	-0.000253	0.000239
	(0.000550)	(0.000497)	(0.000548)
Missing Mother's Age	-0.0107	0.00373	-0.00498
	(0.0199)	(0.0180)	(0.0198)
F-stat	0.836	1.273	0.527
Prob > F	0.557	0.259	0.815
Within R^2	0.0000574	0.0000873	0.0000362
Sample Size	105810	105810	105810

Standard errors in parentheses

High School peer instruments and ability controls are with respect to peers in 9th grade.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.19: Balance Tests for College Major Instruments

	(1) 3yr non-STEM IV	(2) 3yr STEM IV	(3) 3yr Health IV	(4) 3yr Business IV	(5) Education IV	(6) Humanities IV
Mother College	-0.00170	-0.00431	0.000132	-0.00207	0.00974	-0.00128
	(0.00629)	(0.00659)	(0.00722)	(0.00627)	(0.00688)	(0.00733)
Mother High School	0.0104	-0.00277	0.00796	-0.000323	0.00240	0.00586
	(0.00590)	(0.00617)	(0.00677)	(0.00588)	(0.00645)	(0.00687)
Father College	-0.00725	0.00252	-0.00373	0.00299	-0.00356	-0.00109
	(0.00702)	(0.00735)	(0.00805)	(0.00699)	(0.00767)	(0.00817)
Father High School	0.00269	0.0111	-0.00134	-0.00158	-0.00441	-0.00383
	(0.00552)	(0.00577)	(0.00633)	(0.00550)	(0.00603)	(0.00642)
Std. Family Income (1973)	-0.00134	0.00133	-0.00141	0.00192	0.00135	0.00677*
	(0.00267)	(0.00279)	(0.00306)	(0.00266)	(0.00292)	(0.00311)
Mother's Age at Birth	-0.0000821	0.000234	0.000597	0.00000814	0.000788	0.000354
	(0.000518)	(0.000543)	(0.000595)	(0.000517)	(0.000567)	(0.000604)
Missing Mother's Age	0.0195	0.00331	-0.000253	0.0116	0.0284	0.00296
	(0.0188)	(0.0197)	(0.0216)	(0.0187)	(0.0205)	(0.0219)
Own 9th grade GPA	0.00294	0.00612	0.00230	0.00355	0.0109**	0.00940*
	(0.00356)	(0.00372)	(0.00408)	(0.00355)	(0.00389)	(0.00414)
F-stat	1.042	1.078	0.515	0.343	1.876	1.647
Prob > F	0.401	0.375	0.846	0.950	0.0590	0.106
Within R^2	0.0000872	0.0000902	0.0000431	0.0000286	0.000157	0.000138
Sample Size	96588	96588	96588	96588	96588	96588

Standard errors in parentheses

High School peer instruments and ability controls are with respect to peers in 9th grade.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.20: Balance Tests for College Major Instruments

	(1) Social Sciences IV	(2) Science/Math IV	(3) Engineering IV	(4) Medicine IV	(5) Business IV	(6) Law IV
Mother College	0.00726	-0.000938	-0.00254	0.0139*	-0.0158*	-0.00903
	(0.00659)	(0.00687)	(0.00634)	(0.00658)	(0.00679)	(0.00694)
Mother High School	0.000726	0.00277	0.000588	-0.00378	0.00148	0.000838
	(0.00617)	(0.00644)	(0.00594)	(0.00617)	(0.00636)	(0.00650)
Father College	-0.00491	0.00297	0.00372	-0.0102	0.00648	-0.00680
	(0.00734)	(0.00766)	(0.00707)	(0.00734)	(0.00757)	(0.00774)
Father High School	0.00835	-0.00325	0.00277	0.00198	-0.00992	0.00302
	(0.00577)	(0.00602)	(0.00556)	(0.00577)	(0.00595)	(0.00608)
Std. Family Income (1973)	0.000800	0.00882**	-0.000563	-0.00530	-0.000153	-0.00221
	(0.00279)	(0.00291)	(0.00269)	(0.00279)	(0.00288)	(0.00294)
Mother's Age at Birth	-0.000953	0.000401	0.000316	-0.00104	-0.000402	-0.000105
	(0.000543)	(0.000566)	(0.000522)	(0.000542)	(0.000559)	(0.000571)
Missing Mother's Age	-0.0189	-0.00131	0.0146	-0.0357	-0.00379	0.00217
	(0.0197)	(0.0205)	(0.0189)	(0.0196)	(0.0203)	(0.0207)
Own 9th grade GPA	0.00886*	0.0130***	0.0152***	-0.00332	0.00523	-0.00483
	(0.00372)	(0.00388)	(0.00358)	(0.00372)	(0.00384)	(0.00392)
F-stat	1.766	3.362	2.508	1.880	1.468	0.931
Prob > F	0.0785	0.000738	0.0101	0.0585	0.163	0.489
Within R^2	0.000148	0.000281	0.000210	0.000157	0.000123	0.0000778
Sample Size	96588	96588	96588	96588	96588	96588

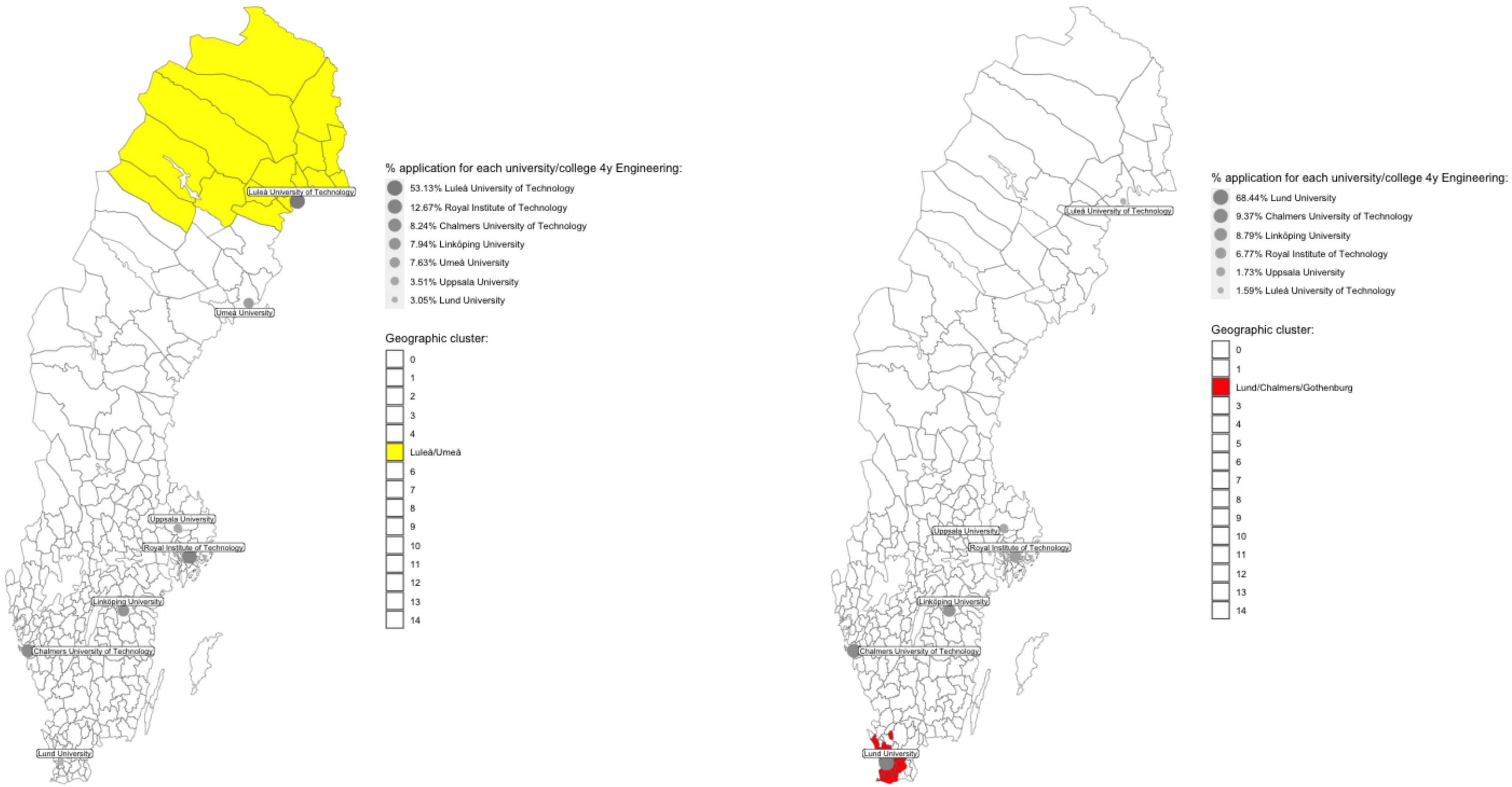
Standard errors in parentheses

College major instruments and ability controls are with respect to peers in high school.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

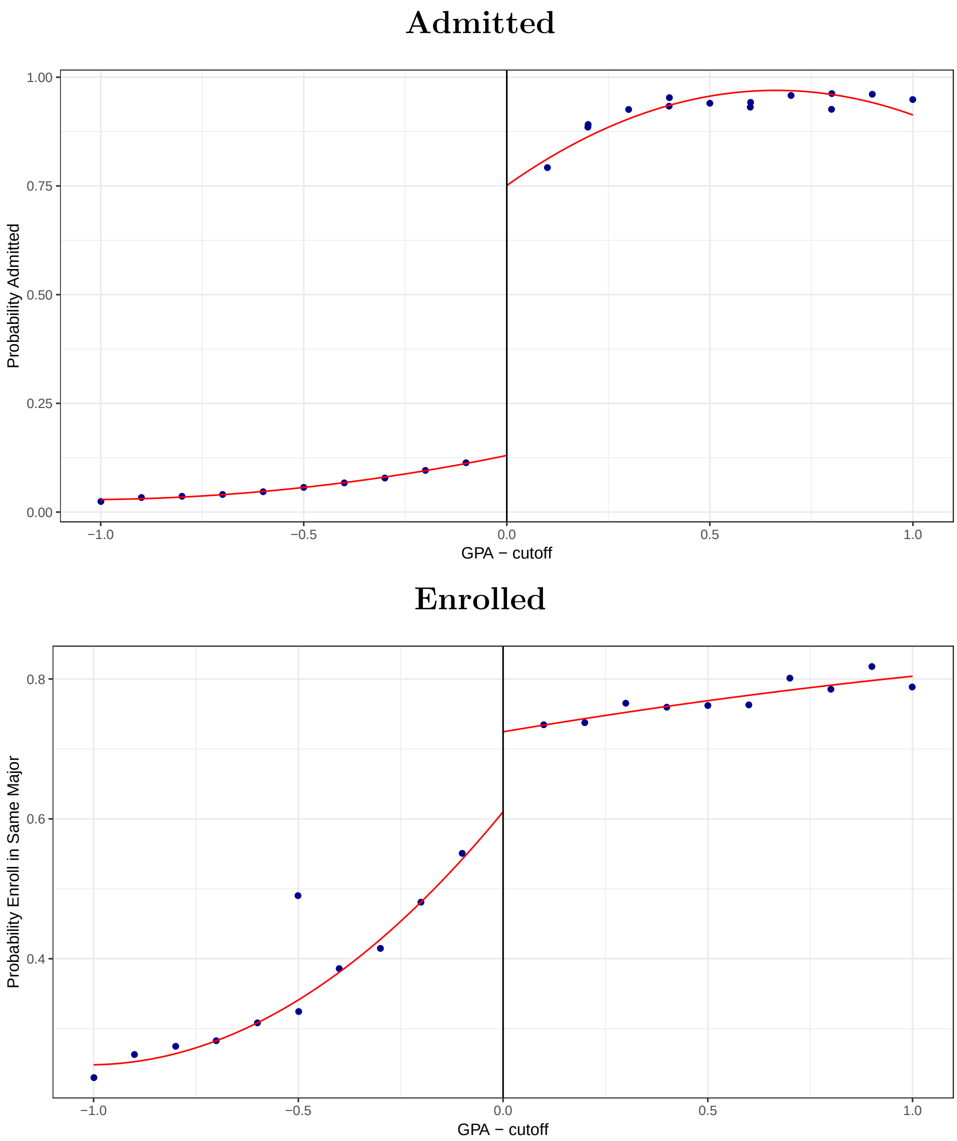
C.2 Admissions Cutoff Instruments

Figure C.1: Share of 4-year engineering applications by geographic area (North and South)



Notes: This figure shows the proportion of applications sent to each specific school for two specific geographic clusters (cluster 5 and 2) corresponding to the North and South of Sweden.

Figure C.2: Regression discontinuity plots for admission and enrollment based on GPA cutoff



Notes: These RD plot follow Kirkebøen et al. (2016) and plots the first stage RD impact on admission and enrollment using the GPA admissions threshold discontinuity.

Table C.21: RD regression for admission probability

	Admitted
GPA > threshold	0.757***
	(0.006)
Swe SAT > threshold	0.705***
	(0.009)
GPA & Swe SAT > threshold	−0.635***
	(0.010)
poly(GPA, 3)1	−1.716**
	(0.678)
poly(GPA, 3)2	7.075***
	(0.574)
poly(GPA, 3)3	−4.365***
	(0.629)
poly(Swe Sat, 3)1	3.813**
	(1.941)
poly(Swe Sat, 3)2	3.373***
	(1.163)
poly(Swe Sat, 3)3	−0.844
	(0.794)
No Swe Sat Score	0.050***
	(0.017)
HS Academic Track	0.017**
	(0.007)
HS STEM Track	−0.021***
	(0.007)
HS Track missing	0.027**
	(0.011)
Constant	0.132***
	(0.009)
Observations	19,993
R^2	0.635
Adjusted R^2	0.635

Notes: This table shows the logistic regression of admission on the indicator for being above the GPA cutoff for the program, being above the test scores (Swe SAT) cutoff for the program, and being above both cutoffs. The regression additionally controls for a cubic in GPA, a cubic in Swe SAT, an indicator for having a Swe SAT score (since it is not required), and high school track indicators. Polynomials use orthogonal polynomials. This is a stacked regression for all applicants and applications which were considered by the Swedish admissions system. The threshold indicators correspond to the specific program (school-by-field of study pair) for which the student applied. Table reports the coefficients from the logistic regression.

D Identification of Factor Model

In this section, 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.[39]

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

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

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 with respect to each schooling state $S = s$ 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 ($M_{k0},\ k \in \{1, ..., N\}$),

[39] 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.

$\boldsymbol{\alpha}^N$ 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:

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

E Estimation Strategy and Model Fit

E.1 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 $\boldsymbol{D}$ and $\boldsymbol{Y}$ (*i.e.* educational 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:

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

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

$$\mathcal{L}^2 = \prod_i \int_{\overline{\boldsymbol{\theta}} \in \boldsymbol{\Theta}} \sum_{\boldsymbol{\upsilon}} f(\boldsymbol{Y}_i, \boldsymbol{D}_i | \boldsymbol{X}_i, \boldsymbol{\upsilon}, \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \gamma_Y, \gamma_D) f_{\boldsymbol{\upsilon}}(\boldsymbol{\upsilon} | \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \gamma_\upsilon) \tag{E.1}$$
$$\times\, f(\boldsymbol{M}_i | \boldsymbol{X}_i, \boldsymbol{\theta} = \overline{\boldsymbol{\theta}}; \hat{\gamma}_M) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}}; \hat{\gamma}_\theta)\, d\overline{\boldsymbol{\theta}},$$

where the goal of the second stage is to maximize $\mathcal{L}^2$ and obtain estimates $\hat{\boldsymbol{\gamma}}_\upsilon$, $\hat{\boldsymbol{\gamma}}_Y$ and $\hat{\boldsymbol{\gamma}}_D$. Since the economic models $(\boldsymbol{Y}, \boldsymbol{D})$ 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.

E.2 Model fit

This section provides tables comparing the fit of the model to the data for the various educational decisions.

Table E.1: Probability of taking advanced english in 9th grade

9th Grade Adv Eng	Sim	Data
No	0.3524	0.3578
Yes	0.6476	0.6422

Table E.2: Probability of taking advanced math in 9th grade

9th Grade Adv Math	Sim	Data
No	0.4093	0.4145
Yes	0.5907	0.5855

Table E.3: Probability of HS Tracks

HS Track	Sim	Data
Dropout	0.0877	0.0877
Vocational	0.5177	0.5146
Academic	0.1842	0.1813
STEM	0.2104	0.2165

Table E.4: Probability of Applying to college

Apply to College	Sim	Data
No	0.5270	0.5294
Yes	0.4730	0.4706

Table E.5: Prob of applying to college conditional on HS track

HS Track	Sim	Data
HS: Vocational	0.2180	0.2086
HS: Academic	0.7089	0.7101
HS: STEM	0.8938	0.8929

Table E.6: Prob of enrollment cond. on first application

Majors	Sim	Data
Non-STEM (3-year)	0.3921	0.6186
STEM (3-year)	0.9041	0.9278
Business (3-year)	0.3618	0.5969
Health Sciences	0.4431	0.7965
Education	0.8593	0.8438
Humanities	0.3418	0.6818
Social Sciences	0.3692	0.5770
Science and Math	0.5861	0.7082
Engineering	0.8271	0.7517
Medicine	0.1143	0.5258
Business	0.5259	0.6906
Law	0.1231	0.5759

Table E.7: Prob of graduating in major conditional on enrolling (data vs simulation)

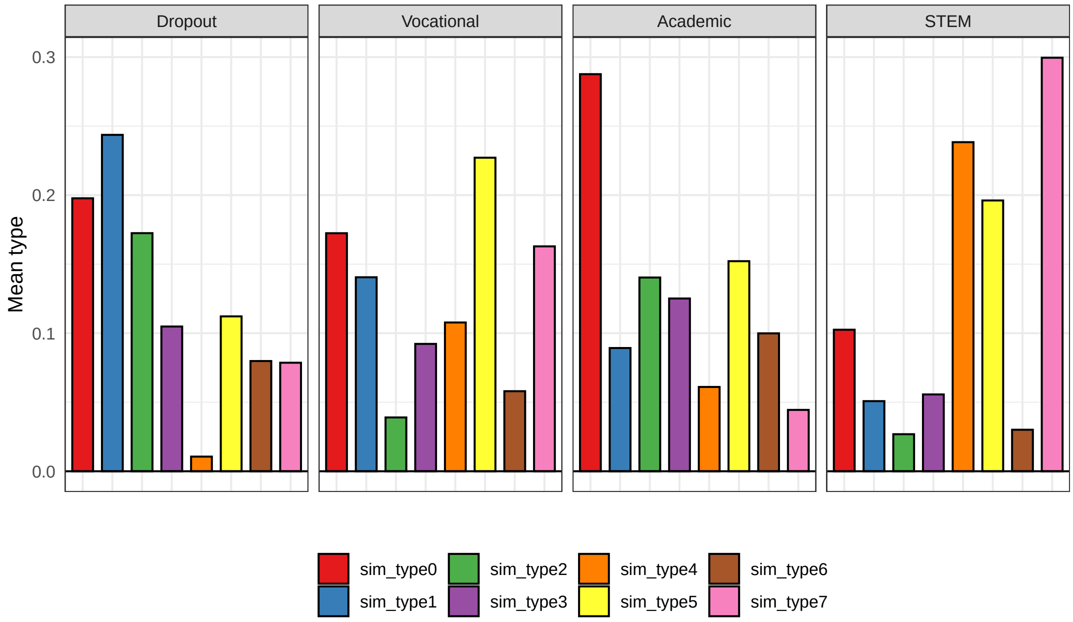
EnrollMajor	Simulation	Data
Business	0.4334	0.4077
Business (3-year)	0.2715	0.1684
Education	0.5564	0.5556
Engineering	0.6019	0.6342
Health Sciences	0.7358	0.7025
Humanities	0.2770	0.3245
Law	0.6692	0.6111
Medicine	0.7915	0.8497
Non-STEM (3-year)	0.3897	0.3749
STEM (3-year)	0.4209	0.4093
Science and Math	0.3789	0.3662
Social Sciences	0.3789	0.3119

Table E.8: Probability of final education (data vs simulation)

edu	Sim	Data	Difference	Prop. Difference
Business	0.0177	0.0185	-0.0008	-0.0432
Business (3-year)	0.0038	0.0045	-0.0007	-0.1500
CollDO_high	0.0731	0.0629	0.0102	0.1625
CollDO_low	0.0606	0.0641	-0.0035	-0.0554
Education	0.0293	0.0226	0.0067	0.2948
Engineering	0.0605	0.0572	0.0034	0.0590
HS Academic	0.0842	0.0841	0.0001	0.0014
HS Dropout	0.0877	0.0877	-0.0000	-0.0003
HS STEM	0.0344	0.0399	-0.0055	-0.1377
HS Vocational	0.4301	0.4348	-0.0047	-0.0108
Health Sciences	0.0124	0.0143	-0.0019	-0.1321
Humanities	0.0027	0.0049	-0.0022	-0.4535
Law	0.0082	0.0071	0.0011	0.1624
Medicine	0.0049	0.0059	-0.0010	-0.1754
Non-STEM (3-year)	0.0119	0.0148	-0.0029	-0.1978
STEM (3-year)	0.0515	0.0516	-0.0001	-0.0012
Science and Math	0.0187	0.0166	0.0021	0.1277
Social Sciences	0.0084	0.0087	-0.0003	-0.0323

E.3 Role of Types in the Model

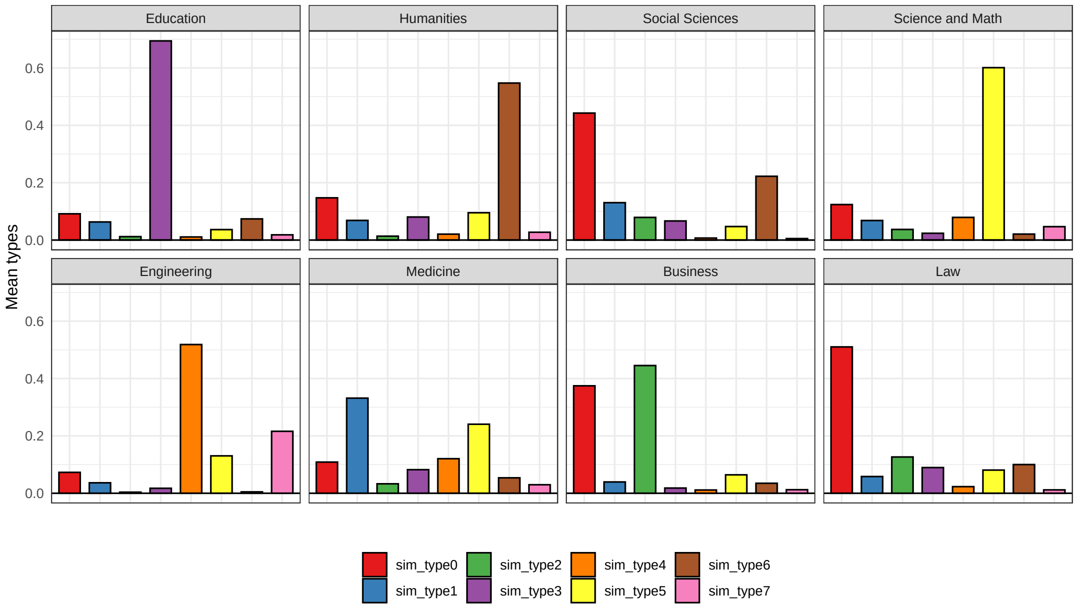
Figure E.1: Sorting of Types into High School Tracks



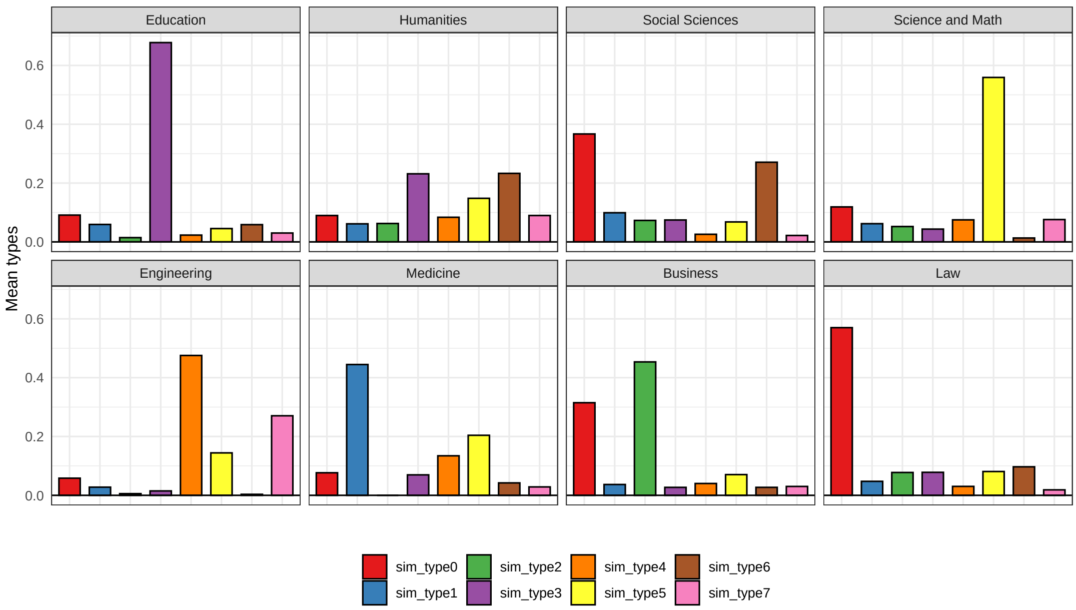
Notes: This figure shows the fraction of high school students that are of each type.

Figure E.2: Sorting of Types into College Majors

Enrollment



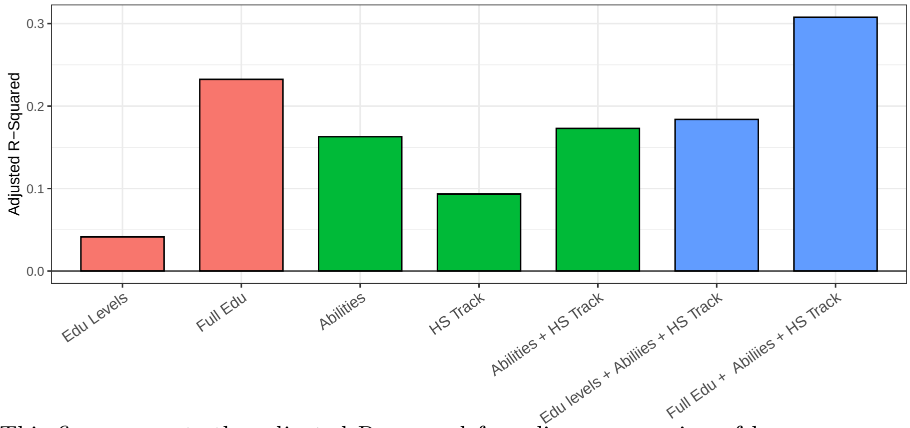
Graduation



Notes: These figures show the fraction of enrollees (top) and graduates (bottom) that are of each type.

F Additional Results

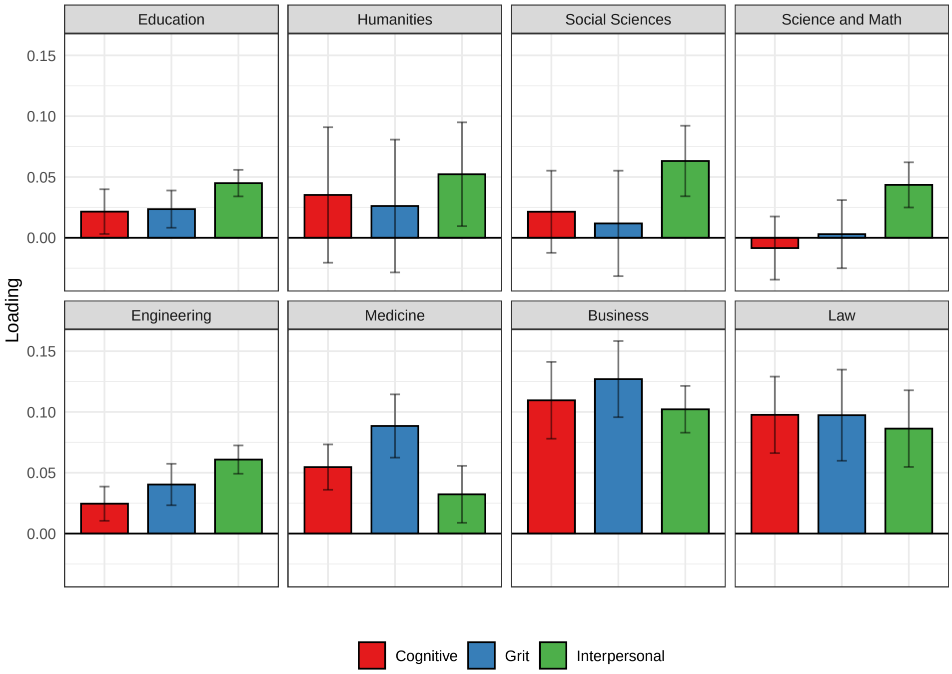
Figure F.1: The Predictive Power of Abilities and Education for College Enrollees



Notes: This figure reports the adjusted R-squared from linear regression of log wages on combinations of abilities and education indicators. "Abilities" include the general cognitive ability, emotional stability, and leadership scores from the conscription exam and the residual from ninth grade GPA regressed on general cognitive ability. "Edu levels" include indicators for high school dropout, terminal high school graduate, some college, 3-year degree, and 4-year degree. "HS Track" includes indicators for dropout, vocational track, academic track, and STEM track. "All Edu" is a series of indicators that include high school dropout, three high school tracks, an indicator for 3-year college dropout, an indicator for 4-year college dropout, and twelve indicators for various college majors. All ability measures enter linearly and all education measures enter as indicator variables. This figure reports the regressions for only those who enroll in college (and drops the education indicators that are no longer relevant), while Figure 1 reports the regressions for all individuals.

F.1 Results on Present Value of Income

Figure F.2: Returns to Ability across Majors ($\hat{\boldsymbol{\lambda}}_{sm}$) for Present Value of Disposable Income



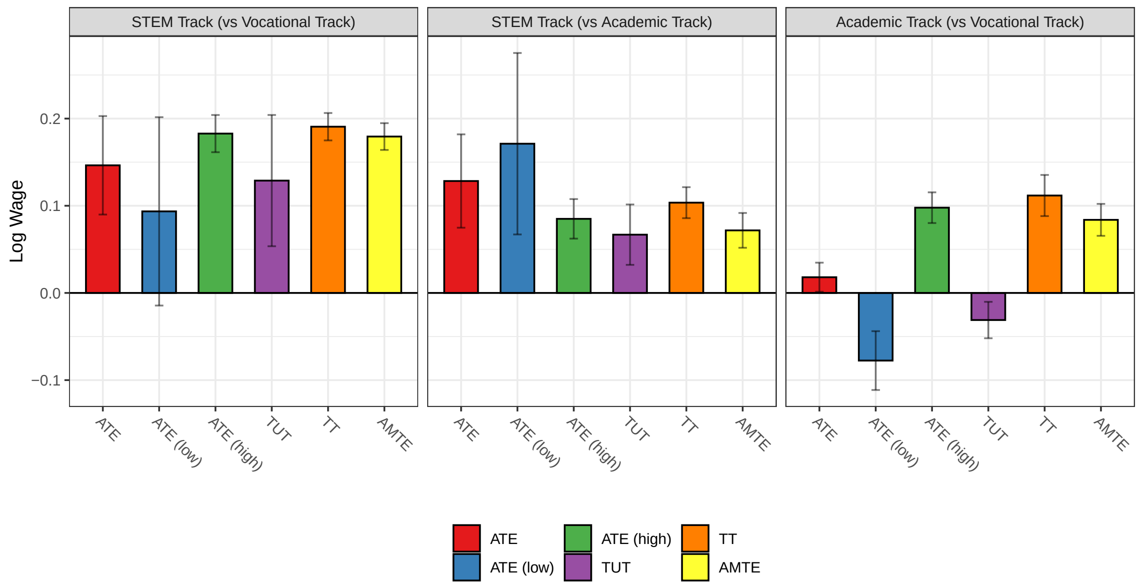
Notes: These figures are comparing the returns to ability ($\hat{\boldsymbol{\lambda}}_{sm}$) for four-year graduates from Equation 12. The first (red) bar shows the loading on cognitive ability, the second (blue) bar shows the loading on grit ability, and the third (green) bar shows the loading on interpersonal ability. This figure shows estimates for log present discounted value of disposable income while Figure 6 shows estimates for log wages. Each sub-panel shows the estimates for different four-year majors. Error bars show bootstrapped 95% confidence intervals.

Table F.1: Fraction Ranking each Major First and Second in Expected Earnings

	PV Disposable Income	
	1st	2nd
Engineering	0.30	0.20
Business	0.27	0.15
Law	0.16	0.22
Medicine	0.13	0.15
STEM (3-year)	0.10	0.15
Business (3-year)	0.03	0.04
Social Sciences	0.01	0.07
Science and Math	0.00	0.02
Education	0.00	0.01

Notes: The table reports the proportion of individuals ranking a major first or second in terms of expected log present discounted value of disposable income. All majors which have a value of 0.01 or higher in any column are reported. A sample of one million synthetic workers are created by drawing a vector of observables from the data, drawing a vector of latent abilities from the estimated factor distribution, and drawing a latent type from the type probability distribution. The expected log PV disposable income are calculated for each synthetic worker using estimates of Equation 12 ($\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}] = \boldsymbol{\beta}_{sm}^{Y}\boldsymbol{X} + \boldsymbol{\lambda}_{sm}^{Y}\boldsymbol{\theta} + \boldsymbol{\alpha}_{sm}^{Y}\boldsymbol{\upsilon}$).

Figure F.3: Treatment Effects: Log Present Value Disposable Income



Notes: This figure shows the estimated treatment effects for the three high school track margins on log present value of disposable income, while Figure 8 shows the treatment effects for 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. Error bars show bootstrapped 95% confidence intervals.

F.2 Detailed results on AMTE of policies

Table F.2: AMTE of inducing marginal students into the STEM track by pre- and post- intervention final education

edu	HS STEM	College Dropout (short)	College Dropout (long)	Non-STEM (3-year)	STEM (3-year)	Business (3-year)	Health Sciences	Education	Humanities	Social Sciences	Science and Math	Engineering	Medicine	Business	Law
HS Dropout	0.24	0.16	0.13		0.29		0.10	0.11			0.28	0.31		0.10	
HS Vocational	0.08	0.08	0.17	0.10	0.18	0.13	0.13	0.01		0.18	0.19	0.37	0.38	0.35	0.31
HS Academic	0.06	0.05	0.08	0.11	0.19		0.00	-0.10		0.06	0.04	0.32		0.14	0.07
College Dropout (short)		0.03	-0.01		0.13			0.01			0.07	0.20			
College Dropout (long)	0.28	0.04	0.04		0.13			-0.14		-0.09	0.04	0.23		0.13	
Non-STEM (3-year)		0.04	0.07	0.06	0.20						0.07	0.28			
STEM (3-year)		-0.05	-0.07		0.05						0.07	0.09			
Business (3-year)						-0.03									
Health Sciences		-0.02	0.04		0.15		0.06	-0.08			0.16	0.44	0.46		
Education		0.14	0.11		0.15			0.03			0.27	0.50			
Humanities			0.16						-0.02						
Social Sciences		0.01	-0.01					-0.16		-0.02		0.26			
Science and Math		-0.04	0.07		0.03						0.02	0.15			
Engineering		-0.13			-0.03							0.09			
Medicine			-0.21									0.13	0.05		
Business		-0.27	-0.13		-0.08						-0.15	-0.08		0.02	
Law			-0.20									0.03		0.07	-0.04

Notes: Table shows the average marginal treatment effect of the high school STEM track for those near the margin of choosing STEM 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 F.3: AMTE of encouraging STEM applications for college by pre- and post- intervention final education

edu	HS Vocational	HS Academic	HS STEM	College Dropout (short)	College Dropout (long)	Non-STEM (3-year)	STEM (3-year)	Business (3-year)	Health Sciences	Education	Humanities	Social Sciences	Science and Math	Engineering	Medicine	Business	Law
HS Vocational				-0.01	0.07	0.09	0.15		0.09	-0.04			0.18	0.39			
HS Academic				-0.01	0.01	-0.02	0.01		-0.01	-0.16		0.14	0.08	0.18		0.10	0.16
HS STEM				-0.05	0.02		0.04						-0.06	0.23			
College Dropout (short)	-0.06	0.00			-0.01	-0.14	0.12		0.06	-0.06		0.01	0.09	0.24	0.39	0.17	
College Dropout (long)	-0.04	-0.05		0.02		0.06	0.08	-0.02	0.02	-0.13	0.03	0.02	0.07	0.22	0.25	0.20	0.13
Non-STEM (3-year)	-0.23	-0.03		0.03	-0.07		0.13		-0.12	-0.18		-0.02	0.01	0.19	0.22	0.34	
STEM (3-year)				-0.12	-0.13	-0.06			-0.07	-0.26		-0.13	-0.01	0.12	0.34	0.07	
Business (3-year)		0.08		-0.15	-0.10		-0.04						-0.06	0.05		-0.08	
Health Sciences	-0.13	-0.01		-0.02	-0.02	0.17	0.07			-0.10		0.13	0.15	0.38	0.38	0.32	0.32
Education	-0.04	0.17		0.06	0.12	0.18	0.14	0.15	0.12			0.14	0.27	0.50	0.52	0.45	0.34
Humanities				0.03	0.09		0.20						0.13	0.40			
Social Sciences		0.03		-0.03	0.02	-0.18	0.07		-0.05	-0.14			0.02	0.24	0.19	0.08	
Science and Math				-0.10	-0.08	0.09	0.02		-0.11	-0.29		-0.11		0.21		0.20	
Engineering				-0.20	-0.20	-0.26	-0.09		-0.40	-0.52		-0.29	-0.18		0.07	0.08	
Medicine					-0.35		-0.30						-0.35	0.06			
Business		-0.03		-0.17	-0.15	-0.17	-0.14	0.06	-0.44	-0.56		-0.16	-0.15	-0.02	-0.12		-0.03
Law				-0.15	-0.22	-0.29	-0.14		-0.31	-0.45		-0.16	-0.21	0.01	-0.05	-0.01	

Notes: Table shows the average marginal treatment effects of encouraging applications to STEM majors for those induced to change their final education level, 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 encouraging STEM applications. Omitted cells are for transitions with probabilities of less than 0.000025 based on the simulations.

G Model Parameter Estimates

Table G.1: Estimates for Type Probability Model

Variable	Type 2		Type 3		Type 4		Type 5		Type 6		Type 7		Type 8	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Intercept	-0.467	0.051	-1.010	0.037	-0.688	0.040	-0.477	0.026	0.089	0.039	-1.088	0.033	-0.116	0.033
Cognitive	-0.209	0.021	0.193	0.020	-0.096	0.020	0.320	0.017	0.113	0.021	-0.051	0.020	0.225	0.018
Interpersonal	0.011	0.022	0.054	0.021	-0.005	0.020	-0.113	0.016	-0.146	0.019	-0.229	0.020	-0.058	0.017
Grit	-0.193	0.024	0.179	0.023	0.034	0.022	0.283	0.018	0.017	0.022	0.024	0.023	0.139	0.020
N	105913		105913		105913		105913		105913		105913		105913	

Notes: Table reports estimates for the type probability model.

Table G.2: Estimates for Primary Grades Models

Variable	Ninth Grade English Grade		Ninth Grade Math Grade		Ninth Grade Sports Grade		Ninth Grade Swedish Grade		Ninth Grade GPA	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.217	0.008	0.270	0.009	0.056	0.008	0.276	0.008	0.238	0.006
Mother High School	0.123	0.008	0.142	0.008	0.041	0.008	0.165	0.007	0.104	0.006
Mother Educ missing	0.148	0.018	0.256	0.019	0.070	0.017	0.274	0.017	0.193	0.014
Father College	0.309	0.009	0.315	0.010	0.062	0.009	0.326	0.009	0.271	0.007
Father High School	0.138	0.008	0.147	0.008	0.054	0.007	0.145	0.007	0.121	0.006
Father Educ missing	0.180	0.016	0.107	0.016	0.035	0.015	0.099	0.014	0.104	0.011
Family Income (1973)	0.097	0.004	0.148	0.004	0.130	0.004	0.121	0.004	0.131	0.003
Health Endurance	-0.002	0.003	0.019	0.003	0.208	0.003	-0.008	0.003	0.025	0.002
Health Strength	-0.066	0.002	-0.096	0.003	-0.191	0.002	-0.088	0.002	-0.093	0.002
Health missing	-0.047	0.014	-0.074	0.015	-0.052	0.013	-0.037	0.013	-0.035	0.011
School-Ave Fam Income	0.201	0.011	0.106	0.012	0.022	0.010	0.091	0.010	0.025	0.008
Intercept	-0.827	0.032	-0.567	0.034	-0.548	0.030	-0.978	0.029	-0.729	0.024
Took 9th Adv. English	-0.547	0.006								
Took 9th Adv. Math			-0.880	0.006						
9th Math Grade									0.007	0.002
9th English Grade									0.020	0.002
9th Gymn Grade									0.065	0.002
9th Gym Grade miss									-0.192	0.024
9th Swedish Grade									0.165	0.003
9th Swedish Grade miss									-0.053	0.030
Cognitive	0.482	0.003	0.586	0.004	0.012	0.003	0.430	0.003	0.376	0.003
Interpersonal	0.029	0.003	0.063	0.003	0.287	0.003	0.096	0.003	0.112	0.003
Grit	0.498	0.004	0.607	0.003	0.397	0.003	0.518	0.003	0.552	0.003
1/Precision	0.720	0.002	0.615	0.002	0.772	0.002	0.610	0.002	0.285	0.001
N	105913		105913		105612		105725		105913	

Notes: Table reports estimates for the primary grades models.

Table G.3: Estimates for Secondary Grade Models

Variable	Tenth Sports Grade		Tenth Math Grade		HS GPA (Vocational)		HS GPA (Academic)	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.063	0.008	0.257	0.009	10.081	0.554	16.399	0.509
Mother High School	0.039	0.008	0.118	0.010	4.577	0.463	6.157	0.621
Mother Educ missing	0.056	0.018	0.240	0.021	8.463	1.086	12.617	1.301
Father College	0.089	0.009	0.311	0.010	12.273	0.664	20.563	0.555
Father High School	0.056	0.007	0.113	0.009	4.739	0.433	7.922	0.562
Father Educ missing	0.053	0.016	0.073	0.018	3.765	0.937	8.645	1.133
Family Income (1973)	0.131	0.004	0.131	0.004	4.721	0.275	7.223	0.244
Health Endurance	0.203	0.003	0.004	0.003	0.624	0.184	-0.404	0.203
Health Strength	-0.213	0.002	-0.094	0.003	-3.170	0.150	-4.557	0.189
Health missing	-0.112	0.014	-0.112	0.016	-2.904	0.864	-2.867	0.940
School-Ave Fam Income	0.117	0.011	0.161	0.012	9.245	0.779	15.405	0.675
Intercept	-0.871	0.031	-1.197	0.035	262.544	2.237	206.876	2.201
HS Academic Track	0.070	0.009	-0.990	0.009				
HS STEM Track	-0.170	0.009	-1.079	0.010			-8.857	0.370
Took 9th Adv. Math			0.605	0.008	5.572	0.405	-6.692	0.722
Took 9th Adv. English					13.528	0.366	11.921	0.750
10th Sports Grade					19.078	0.207	5.763	0.228
10th Sports Grade miss					-36.180	1.217	4.082	2.524
10th Math Grade					21.916	0.264	29.817	0.242
10th Math Grade miss					0.860	0.330	-25.822	2.292
Cognitive	0.014	0.004	0.536	0.004	23.119	0.234	23.600	0.292
Interpersonal	0.335	0.003	0.035	0.003	3.432	0.211	5.847	0.222
Grit	0.329	0.004	0.458	0.004	20.753	0.276	29.874	0.291
1/Precision	0.804	0.002	0.711	0.002	36.504	0.119	31.739	0.130
N	95424		72853		54498		42124	

Notes: Table reports estimates for the secondary grades models.

Table G.4: Estimates for Military Enlistment Cognitive Measure Models

Variable	Cognitive measure 1		Cognitive measure 2		Cognitive measure 3		Cognitive measure 4	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.129	0.006	0.194	0.007	0.152	0.008	0.169	0.008
Mother High School	0.107	0.006	0.118	0.006	0.109	0.007	0.144	0.007
Mother Educ missing	0.141	0.014	0.165	0.014	0.089	0.016	0.183	0.017
Father College	0.131	0.007	0.205	0.007	0.121	0.008	0.119	0.009
Father High School	0.061	0.006	0.087	0.006	0.093	0.007	0.088	0.007
Father Educ missing	0.037	0.012	0.068	0.013	0.119	0.014	0.034	0.014
Family Income (1973)	0.038	0.003	0.001	0.003	0.023	0.004	0.031	0.004
Health Endurance	0.014	0.002	0.006	0.002	0.045	0.003	0.098	0.003
Health Strength	-0.036	0.002	-0.016	0.002	-0.045	0.002	-0.051	0.002
Health missing	-0.132	0.012	-0.074	0.012	-0.066	0.014	-0.053	0.014
School-Ave Fam Income	0.069	0.009	0.120	0.009	0.171	0.010	0.101	0.010
Intercept	-1.009	0.025	-1.135	0.027	-1.121	0.030	-0.879	0.031
Took 9th Adv. English	0.345	0.006	0.505	0.006	0.039	0.007	0.082	0.007
Took 9th Adv. Math	0.397	0.006	0.164	0.006	0.367	0.007	0.273	0.007
HS Vocational Track	0.079	0.008	0.058	0.008	0.065	0.009	0.083	0.010
HS Academic Track	0.123	0.010	0.292	0.011	-0.139	0.012	-0.183	0.012
HS STEM Track	0.348	0.010	0.304	0.011	0.298	0.012	0.438	0.012
Cognitive	0.536	0.002	0.474	0.003	0.517	0.003	0.547	0.003
Interpersonal	0.000		0.000		0.000		0.000	
Grit	0.000		0.000		0.000		0.000	
1/Precision	0.516	0.002	0.610	0.002	0.707	0.002	0.657	0.002
N	100254		100564		100564		90592	

Notes: Table reports estimates for the military enlistment cognitive models.

Table G.5: Estimates for Military Enlistment Socio-emotional Measure Models

Variable	Lead missing		Emotional Stability		Leadership	
	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.221	0.017	0.067	0.008	0.161	0.014
Mother High School	-0.249	0.016	0.103	0.007	0.194	0.014
Mother Educ missing	-0.289	0.036	0.185	0.017	0.330	0.031
Father College	-0.177	0.018	0.075	0.009	0.179	0.015
Father High School	-0.165	0.015	0.043	0.007	0.108	0.013
Father Educ missing	-0.078	0.032	-0.051	0.014	-0.025	0.027
Family Income (1973)	-0.060	0.008	0.131	0.004	0.243	0.007
Health Endurance	-0.091	0.006	0.268	0.003	0.399	0.005
Health Strength	0.100	0.005	-0.155	0.002	-0.225	0.004
Health missing	0.827	0.028	-0.234	0.014	-0.431	0.027
School-Ave Fam Income	-0.256	0.022	0.176	0.010	0.362	0.019
Intercept	1.894	0.067	-1.418	0.030	1.954	0.056
Took 9th Adv. English	-0.477	0.014	0.044	0.007	0.155	0.013
Took 9th Adv. Math	-0.643	0.015	0.089	0.007	0.189	0.013
HS Vocational Track	-0.145	0.022	0.282	0.009	0.467	0.020
HS Academic Track	0.009	0.027	0.349	0.012	0.620	0.023
HS STEM Track	0.037	0.028	0.351	0.013	0.615	0.024
Cognitive	-1.092	0.010	0.266	0.003	0.580	0.006
Interpersonal	0.000		0.759	0.002	1.237	0.004
Grit	0.000		0.000		0.000	
1/Precision			0.347	0.002	0.540	0.003
N	105913		100975		58465	

Notes: Table reports estimates for the military enlistment socio-emotional measures models.

Table G.7: Estimates for Apply to College Model

Variable	Apply College	
	β	StdEr.
Mother College	0.315	0.014
Mother High School	0.176	0.014
Mother Educ missing	0.222	0.032
Father College	0.345	0.016
Father High School	0.181	0.013
Father Educ missing	0.191	0.028
Family Income (1973)	0.091	0.007
Health Endurance	-0.056	0.005
Health Strength	-0.067	0.005
Health missing	-0.175	0.024
School-Ave Fam Income	0.003	0.019
Intercept	-2.094	0.065
Took 9th Adv. English	0.194	0.016
Took 9th Adv. Math	0.186	0.016
HS Academic Track	0.829	0.018
HS STEM Track	1.408	0.021
HS GPA Bin2	0.365	0.014
HS GPA Bin3	0.537	0.017
HS GPA Bin4	0.690	0.023
Cognitive	0.231	0.008
Interpersonal	0.036	0.005
Grit	0.181	0.009
Type 2	0.288	0.062
Type 3	0.827	0.044
Type 4	0.989	0.064
Type 5	0.394	0.040
Type 6	0.017	0.046
Type 7	0.552	0.047
Type 8	0.186	0.040
N	96622	

Notes: Table reports estimates for the apply-to-college decision.

Table G.8: Estimates for SweSAT and Enroll Models

Variable	Take SweSAT		Total SweSAT Score		Enroll after Admission	
	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.101	0.018	0.126	0.004	0.147	0.023
Mother High School	0.063	0.022	0.070	0.005	0.096	0.030
Mother Educ missing	0.068	0.046	0.087	0.011	0.162	0.060
Father College	0.143	0.019	0.137	0.004	0.183	0.025
Father High School	-0.026	0.020	0.056	0.005	0.074	0.027
Father Educ missing	0.062	0.041	0.075	0.009	0.042	0.053
Family Income (1973)	0.040	0.009	0.006	0.002	0.038	0.011
Health Endurance	0.004	0.007	-0.014	0.002	-0.016	0.009
Health Strength	-0.013	0.007	-0.004	0.002	-0.044	0.009
Health missing	-0.013	0.034	0.028	0.008	-0.037	0.046
School-Ave Fam Income	0.144	0.026	0.084	0.005	0.048	0.032
Intercept	-0.333	0.084	0.100	0.018	0.180	0.103
Took 9th Adv. English	0.275	0.023	0.207	0.006	0.021	0.033
Took 9th Adv. Math	0.089	0.023	0.075	0.006	0.037	0.032
HS Academic Track	0.659	0.025	-0.069	0.005	-0.078	0.030
HS STEM Track	0.635	0.027	-0.025	0.006	0.187	0.034
HS GPA Bin2	-0.021	0.021				
HS GPA Bin3	-0.153	0.024				
HS GPA Bin4	-0.531	0.030				
Cognitive	0.141	0.010	0.271	0.002	0.210	0.011
Interpersonal	0.021	0.007	-0.022	0.001	-0.015	0.009
Grit	-0.043	0.011	0.106	0.002	0.140	0.012
Type 2	0.247	0.050	0.036	0.010	0.267	0.049
Type 3	0.119	0.049	-0.041	0.010	0.029	0.046
Type 4	-0.080	0.040	-0.004	0.009	0.218	0.041
Type 5	-0.119	0.044	-0.057	0.009	0.996	0.056
Type 6	-0.046	0.045	-0.014	0.009	0.236	0.044
Type 7	-0.072	0.054	0.023	0.012	-0.042	0.053
Type 8	-0.449	0.042	-0.075	0.009	0.483	0.042
1/Precision			0.303	0.001		
N	45471		36333		35283	

Notes: Table reports estimates for the SweSAT and enrollment models

Table G.9: Estimates for Major-College Application Model

Variable	3yr non-STEM		3yr STEM		3yr Business		Health Sci		Educ		Humanities		Soc Sci		Sciences		Engineer		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.184	0.039	-0.088	0.032	-0.049	0.041	0.048	0.045	0.123	0.039	0.186	0.065	0.196	0.034	0.022	0.032	0.145	0.033	0.587	0.067	0.025	0.030	0.036	0.041
Mother High School	0.054	0.049	-0.054	0.039	-0.076	0.049	-0.073	0.054	0.031	0.046	-0.028	0.084	0.051	0.044	-0.040	0.040	0.114	0.043	0.106	0.100	0.010	0.038	-0.015	0.055
Mother Educ missing	-0.087	0.096	-0.074	0.079	-0.146	0.101	0.032	0.106	0.192	0.095	0.077	0.156	0.099	0.085	-0.003	0.078	0.058	0.083	0.560	0.162	-0.013	0.075	-0.093	0.104
Father College	-0.085	0.043	-0.203	0.035	-0.194	0.044	0.092	0.048	0.077	0.043	-0.060	0.070	0.129	0.037	0.101	0.034	0.231	0.036	0.446	0.070	0.006	0.032	0.178	0.044
Father High School	0.120	0.044	0.018	0.035	-0.093	0.044	-0.091	0.047	-0.059	0.041	0.147	0.075	0.041	0.039	0.000	0.036	0.118	0.038	-0.083	0.084	0.058	0.035	0.116	0.051
Father Educ missing	0.189	0.084	-0.154	0.071	-0.107	0.089	-0.053	0.094	-0.387	0.085	0.082	0.139	0.087	0.075	0.090	0.070	0.215	0.074	0.145	0.143	0.120	0.066	0.293	0.092
Family Income (1973)	-0.116	0.020	-0.112	0.016	0.101	0.019	-0.094	0.024	-0.110	0.020	-0.273	0.034	-0.038	0.017	-0.123	0.015	0.008	0.016	0.022	0.033	0.155	0.014	0.089	0.018
Health Endurance	-0.129	0.015	0.027	0.012	-0.005	0.016	0.037	0.016	0.002	0.015	-0.164	0.025	-0.028	0.013	-0.015	0.012	0.071	0.013	0.193	0.025	-0.004	0.012	0.032	0.016
Health Strength	0.034	0.014	-0.004	0.012	-0.020	0.016	0.007	0.016	0.021	0.014	0.127	0.023	-0.006	0.013	0.003	0.012	-0.050	0.013	-0.028	0.027	-0.030	0.012	0.042	0.016
Health missing	0.005	0.075	0.084	0.065	-0.632	0.091	-0.151	0.093	-0.011	0.075	0.099	0.120	0.110	0.063	0.167	0.063	-0.059	0.069	-0.108	0.180	-0.116	0.057	-0.092	0.078
School-Ave Fam Inc	-0.280	0.056	-0.334	0.047	-0.136	0.055	-0.405	0.066	-0.696	0.060	-0.405	0.097	-0.161	0.048	-0.023	0.043	0.143	0.046	0.125	0.081	0.128	0.039	0.012	0.054
Intercept	0.312	0.201	-0.516	0.181	-0.330	0.199	0.595	0.234	1.013	0.217	-1.282	0.348	0.971	0.168	-1.294	0.169	-2.952	0.172	-2.097	0.382	-0.479	0.144	0.068	0.202
Took 9th Adv. Eng	0.374	0.055	-0.156	0.042	-0.159	0.057	0.224	0.054	0.084	0.049	0.396	0.094	-0.127	0.049	0.341	0.044	-0.291	0.048	0.682	0.132	-0.343	0.047	-0.117	0.074
Took 9th Adv. Math	-0.361	0.047	0.524	0.043	0.101	0.054	-0.107	0.051	-0.144	0.045	-0.311	0.077	-0.414	0.043	0.517	0.044	0.453	0.051	0.337	0.116	0.017	0.043	-0.791	0.060
HS Academic Track	-0.287	0.059	-0.346	0.045	0.397	0.056	-0.762	0.068	-0.232	0.060	-0.069	0.090	-0.284	0.053	-0.258	0.045	-0.362	0.050	-0.720	0.109	0.486	0.052	0.597	0.067
HS STEM Track	-0.355	0.068	0.542	0.063	-0.153	0.073	-1.028	0.078	0.006	0.071	0.070	0.109	-0.470	0.060	0.056	0.056	1.248	0.070	0.555	0.123	0.434	0.054	0.564	0.077
HS GPA Bin 1	0.133	0.060	0.282	0.045	0.022	0.055	-0.067	0.069	0.086	0.064	0.074	0.099	-0.165	0.048	-0.027	0.042	0.257	0.037	-0.551	0.081	0.077	0.037	-0.082	0.064
HS GPA Bin 2	-0.005	0.059	0.420	0.047	-0.004	0.055	-0.047	0.070	0.064	0.065	0.206	0.093	-0.177	0.046	-0.055	0.047	0.522	0.043	-0.037	0.095	0.160	0.041	0.075	0.060
HS GPA Bin 3	-0.096	0.065	0.249	0.051	-0.109	0.061	-0.272	0.075	0.067	0.073	0.163	0.101	-0.267	0.053	-0.083	0.053	1.112	0.051	0.647	0.122	0.190	0.048	0.562	0.072
HS GPA Bin 4	-0.300	0.077	-0.089	0.057	-0.395	0.075	-0.348	0.088	-0.069	0.081	0.075	0.121	-0.196	0.063	0.183	0.062	1.773	0.062	0.886	0.155	0.509	0.057	0.915	0.085
SweSAT Score	0.275	0.058	-0.186	0.047	-0.092	0.059	-0.112	0.069	0.061	0.056	0.378	0.096	0.437	0.049	0.241	0.047	0.232	0.048	-0.416	0.097	0.143	0.044	0.489	0.061
SweSAT miss	-0.052	0.061	-0.183	0.051	-0.408	0.062	-0.191	0.061	-0.024	0.057	-0.193	0.110	-0.136	0.054	-0.156	0.053	-0.036	0.057	-1.787	0.148	-0.312	0.049	-0.325	0.077
Within-Sch-Across-Cohort IV	0.015	0.012	0.038	0.008	-0.023	0.014	0.025	0.011	0.064	0.012	0.043	0.012	0.063	0.009	0.087	0.007	0.014	0.007	0.004	0.012	0.046	0.007	0.018	0.010
School Ave Enroll	3.874	0.824	2.457	0.155	-1.655	0.710	5.281	1.048	5.413	0.467	12.182	1.945	11.742	0.732	6.250	0.361	1.553	0.185	7.762	1.325	3.415	0.310	3.922	0.995
Log Admit Share	0.039	0.025	-0.418	0.087	-0.080	0.020	-0.007	0.019	-0.020	0.042	0.118	0.039	0.153	0.018	0.034	0.029	0.364	0.058	0.724	0.035	0.041	0.015	0.191	0.013
Min Log Distance	0.009	0.012	0.094	0.010	-0.052	0.012	0.054	0.013	0.068	0.012	0.045	0.019	0.025	0.010	0.052	0.009	0.035	0.010	-0.049	0.018	-0.012	0.009	-0.056	0.012
Cognitive	0.058	0.026	0.012	0.021	-0.048	0.027	-0.107	0.030	0.052	0.027	-0.088	0.043	0.006	0.023	0.063	0.021	0.238	0.023	0.336	0.049	0.041	0.020	0.031	0.028
Interpersonal	-0.035	0.015	-0.083	0.013	0.052	0.016	0.070	0.017	0.040	0.015	-0.179	0.024	0.112	0.013	-0.090	0.012	0.021	0.013	0.115	0.025	0.071	0.012	0.127	0.016
Grit	0.027	0.029	-0.177	0.023	0.041	0.029	-0.022	0.034	0.091	0.031	-0.106	0.046	0.071	0.024	-0.094	0.022	-0.038	0.024	0.268	0.054	0.133	0.021	0.129	0.029
Type 2	-1.051	0.088	-0.825	0.102	-2.076	0.125	2.805	0.065	-0.131	0.085	-0.624	0.176	-1.180	0.063	-0.313	0.081	-0.728	0.093	3.356	0.151	-2.222	0.065	-2.137	0.085
Type 3	-0.861	0.086	-0.287	0.118	1.226	0.057	-1.785	0.180	-1.579	0.134	-2.095	0.288	-1.362	0.071	-0.585	0.106	-2.322	0.153	-1.280	0.354	0.704	0.036	-1.731	0.077
Type 4	-0.343	0.072	-0.274	0.087	-1.755	0.104	0.540	0.076	3.113	0.064	0.441	0.123	-1.040	0.057	-0.615	0.081	-0.611	0.088	0.215	0.210	-2.256	0.063	-1.870	0.076
Type 5	-2.582	0.152	1.879	0.071	-2.810	0.179	-1.664	0.149	-1.215	0.115	-1.217	0.202	-3.182	0.136	0.541	0.065	2.846	0.059	1.283	0.175	-2.398	0.073	-2.611	0.114
Type 6	-0.663	0.079	1.745	0.070	-0.888	0.085	-0.571	0.103	-0.367	0.098	0.244	0.127	-1.767	0.069	2.217	0.055	0.824	0.069	1.322	0.175	-1.364	0.055	-2.365	0.087
Type 7	1.814	0.056	0.032	0.118	-0.233	0.090	0.520	0.099	0.768	0.102	2.264	0.100	0.224	0.066	-0.671	0.104	-1.934	0.171	0.252	0.274	-1.488	0.065	-1.252	0.084
Type 8	-0.610	0.099	3.738	0.077	-0.791	0.113	-1.199	0.181	0.214	0.098	0.030	0.181	-2.568	0.148	0.526	0.082	2.150	0.073	-0.759	0.358	-1.815	0.085	-3.478	0.255
N	37012		37012		37012		37012		37012		37012		37012		37012		37012		37012		37012		37012	

Notes: Table reports model estimates for the college application model.

Table G.10: Estimates for Switch Major Model

Variable	3yr STEM		3yr Bus		Hlth Sci		Educ		Humanit.		Soc Sci		Sci		Eng		Med		Bus		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.164	0.083	-0.090	0.121	0.197	0.128	0.118	0.097	0.313	0.130	0.177	0.100	-0.005	0.094	0.030	0.088	0.329	0.183	0.074	0.092	0.187	0.152
Mother High School	0.149	0.108	0.058	0.147	0.277	0.168	0.170	0.123	0.126	0.181	0.043	0.136	0.191	0.126	0.274	0.119	-0.066	0.287	0.282	0.124	-0.343	0.213
Mother Educ missing	0.110	0.213	-0.412	0.295	0.139	0.332	-0.175	0.242	-0.207	0.341	-0.371	0.261	0.221	0.244	0.313	0.230	0.068	0.495	-0.074	0.239	-0.521	0.378
Father College	-0.353	0.089	-0.381	0.132	-0.176	0.137	-0.165	0.103	-0.072	0.137	0.016	0.105	-0.222	0.100	-0.079	0.093	0.171	0.186	-0.156	0.098	-0.040	0.162
Father High School	-0.008	0.097	-0.034	0.133	-0.202	0.145	0.103	0.110	0.133	0.157	0.216	0.123	0.063	0.112	0.220	0.106	0.072	0.258	-0.023	0.110	0.228	0.202
Father Educ missing	-0.264	0.190	0.311	0.253	-0.093	0.292	0.136	0.214	0.297	0.293	0.225	0.231	-0.208	0.218	0.056	0.205	0.323	0.443	0.072	0.211	0.609	0.338
Family Income (1973)	0.031	0.041	0.076	0.057	0.055	0.064	-0.023	0.050	-0.027	0.064	0.029	0.047	-0.020	0.046	0.107	0.042	0.138	0.076	0.211	0.042	0.111	0.064
Health Endurance	0.174	0.033	0.201	0.047	0.099	0.050	0.098	0.038	-0.031	0.052	-0.007	0.040	0.080	0.037	0.229	0.035	0.370	0.069	0.115	0.037	0.092	0.060
Health Strength	-0.019	0.031	-0.044	0.045	0.074	0.047	0.016	0.036	0.050	0.048	-0.083	0.040	0.020	0.036	-0.096	0.034	-0.144	0.074	-0.114	0.037	-0.065	0.062
Health missing	-0.010	0.159	0.218	0.225	-0.048	0.244	0.074	0.183	0.068	0.226	-0.110	0.185	0.024	0.176	-0.088	0.167	0.227	0.311	-0.027	0.173	-0.164	0.288
School-Ave Fam Inc.	-0.318	0.115	0.069	0.161	-0.520	0.187	-0.359	0.140	-0.101	0.176	-0.004	0.130	-0.113	0.126	-0.076	0.115	0.050	0.207	0.438	0.115	0.065	0.171
Intercept	-0.597	0.443	-2.656	0.535	-1.124	0.661	-0.307	0.550	-4.266	0.696	-1.234	0.507	-4.274	0.471	-4.385	0.416	-8.234	0.898	-3.242	0.424	-1.770	0.610
Took 9th Adv. Eng.	-0.154	0.121	-0.302	0.173	-0.002	0.177	-0.006	0.137	0.164	0.208	-0.249	0.159	0.004	0.147	-0.225	0.137	0.130	0.451	-0.362	0.151	-0.173	0.294
Took 9th Adv. Math	0.512	0.113	0.093	0.156	0.010	0.157	0.154	0.119	0.199	0.169	-0.315	0.133	0.570	0.139	0.639	0.143	0.803	0.416	0.376	0.137	-0.757	0.230
HS Academic Track	-0.143	0.111	0.091	0.157	-0.133	0.165	-0.029	0.122	0.278	0.166	0.229	0.134	0.025	0.130	0.220	0.132	0.169	0.331	0.340	0.128	0.682	0.230
HS STEM Track	0.173	0.127	0.134	0.201	0.014	0.200	-0.137	0.152	0.056	0.208	0.352	0.169	0.571	0.148	1.199	0.139	1.339	0.342	0.371	0.157	0.920	0.277
HS GPA Bin 1	-0.043	0.100	-0.030	0.173	0.120	0.230	0.009	0.152	-0.138	0.233	-0.215	0.171	0.079	0.130	0.216	0.091	0.563	0.266	-0.132	0.122	-0.022	0.260
HS GPA Bin 2	0.042	0.107	-0.388	0.167	0.134	0.233	-0.035	0.147	0.091	0.204	0.001	0.151	0.206	0.139	0.553	0.104	0.503	0.293	-0.176	0.130	0.012	0.236
HS GPA Bin 3	-0.016	0.114	-0.483	0.180	0.059	0.236	-0.187	0.160	0.001	0.211	-0.115	0.164	0.296	0.145	0.756	0.119	1.283	0.333	-0.153	0.144	0.346	0.273
HS GPA Bin 4	-0.135	0.125	-0.511	0.205	0.109	0.261	-0.252	0.173	0.187	0.236	0.069	0.186	0.503	0.163	1.194	0.140	1.565	0.401	0.017	0.163	0.678	0.309
SweSAT Score	-0.676	0.110	-0.285	0.159	-0.227	0.165	-0.441	0.128	-0.152	0.172	0.146	0.130	-0.300	0.125	-0.889	0.116	0.759	0.244	-0.572	0.122	0.078	0.196
SweSAT miss	-0.225	0.131	-0.410	0.190	-0.675	0.202	-0.133	0.149	0.391	0.213	-0.403	0.173	-0.256	0.158	-0.772	0.145	-0.204	0.421	-0.836	0.159	-0.866	0.296
Denroll2	-0.937	0.244	0.000	0.000	-1.913	0.263	-1.792	0.310	-0.307	0.262	-1.725	0.290	0.000	0.000	0.000	0.000	0.000	0.000	-2.077	0.243	-2.333	0.298
Denroll3	5.140	0.236	1.722	0.199	1.081	0.252	0.819	0.314	0.231	0.356	-0.052	0.325	4.032	0.216	4.276	0.156	0.000	0.000	1.084	0.215	0.000	0.000
Denroll4	1.626	0.270	4.885	0.157	0.000	0.000	0.138	0.371	0.000	0.000	-0.151	0.368	2.134	0.338	0.000	0.000	0.000	0.000	2.211	0.212	0.000	0.000
Denroll5	0.880	0.322	0.000	0.000	5.023	0.235	0.685	0.362	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	2.447	0.282	0.000	0.000	0.000	0.000
Denroll6	0.993	0.262	0.000	0.000	0.617	0.261	3.980	0.292	2.216	0.275	0.244	0.310	3.263	0.233	1.746	0.230	0.000	0.000	0.000	0.000	0.000	0.000
Denroll7	0.000	0.000	0.000	0.000	0.000	0.000	0.647	0.337	4.329	0.260	1.516	0.297	2.978	0.277	2.104	0.253	0.000	0.000	0.705	0.266	0.000	0.000
Denroll8	-0.521	0.294	0.000	0.000	-0.691	0.299	-0.557	0.328	0.542	0.303	2.338	0.271	1.632	0.266	0.000	0.000	0.000	0.000	0.285	0.209	-0.258	0.241
Denroll9	3.498	0.270	1.969	0.287	2.158	0.280	2.038	0.335	1.603	0.363	1.420	0.327	6.914	0.238	3.806	0.208	2.886	0.259	1.890	0.250	1.239	0.301
Denroll10	2.975	0.252	0.000	0.000	0.927	0.289	1.053	0.329	0.898	0.350	0.006	0.338	3.679	0.235	5.869	0.168	2.083	0.232	1.500	0.226	0.649	0.276
Denroll11	0.000	0.000	0.000	0.000	0.735	0.497	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	5.166	0.266	0.000	0.000	0.000	0.000
Denroll12	1.111	0.265	3.213	0.158	0.554	0.281	0.693	0.322	0.000	0.000	1.069	0.292	3.254	0.235	2.005	0.218	0.000	0.000	3.886	0.192	0.571	0.235
Denroll13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.455	0.344	2.363	0.342	0.000	0.000	0.000	0.000	1.127	0.252	4.432	0.198
Cognitive	0.103	0.049	0.056	0.075	-0.052	0.079	0.022	0.058	0.153	0.076	0.079	0.062	0.107	0.058	0.219	0.054	0.138	0.121	0.199	0.058	0.031	0.095
Interpersonal	0.017	0.031	0.106	0.045	0.110	0.047	0.084	0.035	-0.049	0.047	0.039	0.037	-0.021	0.035	0.046	0.032	0.183	0.065	0.166	0.035	0.162	0.058
Grit	-0.116	0.050	0.038	0.078	-0.048	0.082	-0.026	0.061	0.097	0.079	0.092	0.063	-0.092	0.058	-0.018	0.054	0.068	0.118	0.174	0.058	0.045	0.097
Type 2	0.278	0.248	-0.744	0.472	1.847	0.271	0.422	0.271	0.719	0.557	-0.221	0.250	0.400	0.259	0.203	0.257	2.935	0.387	-0.416	0.256	-1.470	0.377
Type 3	-0.019	0.228	0.543	0.211	0.376	0.351	-0.312	0.294	0.937	0.510	-0.652	0.215	0.249	0.238	-0.258	0.279	-24.897	2.27e5	0.532	0.172	-1.819	0.323
Type 4	-0.151	0.189	0.035	0.274	1.068	0.277	0.791	0.187	0.930	0.368	-0.397	0.206	-0.035	0.213	-0.430	0.232	0.799	0.472	-0.488	0.207	-1.547	0.330
Type 5	0.711	0.207	0.999	0.308	1.089	0.324	0.714	0.271	1.940	0.492	0.138	0.301	0.741	0.231	1.661	0.209	1.696	0.421	0.482	0.233	-0.822	0.422
Type 6	0.567	0.183	0.345	0.260	0.645	0.292	0.227	0.240	1.351	0.426	-0.470	0.226	1.049	0.190	0.605	0.192	0.840	0.410	-0.317	0.201	-1.392	0.332
Type 7	-0.052	0.223	-0.469	0.268	0.995	0.312	0.445	0.237	1.412	0.350	0.177	0.185	-1.189	0.345	-1.450	0.369	-0.301	0.598	-0.970	0.231	-0.897	0.293
Type 8	1.106	0.196	0.205	0.325	1.120	0.314	0.832	0.261	2.014	0.467	-0.199	0.328	0.448	0.230	1.136	0.205	0.247	0.561	0.006	0.245	-1.147	0.484
N	37449		37449		37449		37449		37449		37449		37449		37449		37449		37449		37449	

Notes: Table reports estimates for the switching majors model.

Table G.11: Estimates for Graduate College Models I

Variable	3yr non-STEM		3yr STEM		3yr Business		Health Sci		Education		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.119	0.065	0.119	0.032	0.240	0.104	0.223	0.080	0.046	0.056	0.039	0.135
Mother High School	0.268	0.087	0.022	0.038	0.067	0.121	0.043	0.100	0.133	0.070	0.012	0.191
Mother Educ missing	0.221	0.168	0.077	0.086	0.392	0.246	0.164	0.205	0.335	0.138	0.053	0.358
Father College	0.203	0.069	0.206	0.036	0.091	0.118	0.053	0.086	0.065	0.059	0.473	0.141
Father High School	-0.118	0.078	0.045	0.034	0.160	0.110	0.152	0.085	0.035	0.062	0.182	0.162
Father Educ missing	-0.028	0.149	0.045	0.077	0.242	0.204	0.071	0.180	-0.285	0.120	0.332	0.299
Family Income (1973)	0.065	0.033	0.126	0.018	0.139	0.047	0.124	0.045	0.065	0.031	0.144	0.067
Health Endurance	0.036	0.027	0.004	0.013	0.072	0.041	0.072	0.031	0.035	0.022	0.008	0.055
Health Strength	-0.062	0.024	-0.107	0.012	-0.099	0.040	-0.079	0.029	-0.116	0.020	0.067	0.052
Health missing	0.175	0.129	-0.070	0.064	0.398	0.206	-0.094	0.158	-0.199	0.106	-0.005	0.234
School-Ave Fam Income	0.012	0.087	0.075	0.051	0.024	0.136	-0.090	0.129	-0.060	0.092	-0.141	0.188
Intercept	0.020	0.265	-0.544	0.177	-1.125	0.430	0.263	0.393	0.242	0.279	0.338	0.593
Took 9th Adv. English	-0.130	0.095	-0.123	0.040	-0.056	0.141	0.031	0.090	-0.129	0.071	0.059	0.214
Took 9th Adv. Math	0.108	0.077	-0.000	0.048	-0.003	0.131	-0.013	0.084	0.065	0.062	-0.295	0.165
HS Academic Track	0.127	0.072	-0.003	0.048	0.141	0.126	-0.122	0.089	-0.042	0.060	0.159	0.156
HS STEM Track	0.012	0.092	-0.188	0.039	-0.088	0.157	-0.085	0.114	-0.288	0.077	-0.277	0.186
Cognitive	-0.002	0.029	0.169	0.016	0.155	0.050	0.191	0.039	0.093	0.026	0.331	0.061
Interpersonal	0.117	0.023	0.093	0.012	0.123	0.040	0.162	0.029	0.074	0.020	0.122	0.047
Grit	0.131	0.032	0.343	0.018	0.263	0.055	0.237	0.043	0.288	0.030	0.371	0.067
Type 2	0.000		0.427	0.190	0.000		0.174	0.079	0.000		0.000	
Type 3	0.000		0.196	0.171	0.223	0.080	0.000		0.000		0.000	
Type 4	0.000		-0.383	0.117	0.000		0.000		0.039	0.135	0.000	
Type 5	0.000		-0.156	0.094	0.000		0.000		0.000		0.000	
Type 6	0.000		-0.123	0.099	0.000		0.000		0.000		0.000	
Type 7	0.045	0.034	0.056	0.173	0.000		0.000		0.473	0.141	0.244	0.111
Type 8	0.000		-0.142	0.087	0.000		0.000		0.000		0.000	
N	2508		10234		998		1974		3593		735	

Notes: Table reports estimates for the college graduation models.

Table G.12: Estimates for Graduate College Models II

Variable	Soc Sci		Sciences		Engineer		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.149	0.085	0.217	0.057	0.233	0.039	0.264	0.187	0.150	0.055	0.253	0.115
Mother High School	0.118	0.120	0.196	0.082	0.061	0.061	-0.643	0.415	0.146	0.077	0.112	0.171
Mother Educ missing	-0.017	0.243	0.510	0.164	0.257	0.113	-0.947	0.614	0.152	0.156	0.151	0.301
Father College	0.151	0.089	0.200	0.060	0.191	0.040	0.227	0.193	0.085	0.057	0.144	0.122
Father High School	0.244	0.111	0.044	0.072	-0.059	0.053	-0.272	0.307	0.116	0.069	0.198	0.160
Father Educ missing	0.427	0.214	-0.174	0.146	-0.104	0.102	0.557	0.538	0.155	0.137	0.250	0.262
Family Income (1973)	0.070	0.041	0.061	0.029	0.145	0.018	0.197	0.082	0.063	0.022	0.135	0.048
Health Endurance	-0.051	0.036	0.004	0.024	-0.000	0.016	0.131	0.072	-0.025	0.023	-0.050	0.047
Health Strength	-0.041	0.035	-0.089	0.023	-0.144	0.015	-0.180	0.074	-0.121	0.024	-0.129	0.048
Health missing	-0.172	0.166	-0.052	0.107	-0.058	0.079	-0.227	0.317	0.129	0.106	-0.062	0.232
School-Ave Fam Income	0.239	0.121	-0.116	0.080	0.028	0.051	0.548	0.280	0.104	0.062	0.199	0.124
Intercept	-1.159	0.379	-0.058	0.270	-0.510	0.189	-1.769	1.047	-1.172	0.218	-0.920	0.441
Took 9th Adv. English	-0.081	0.136	-0.140	0.100	-0.083	0.078	-0.133	0.612	0.039	0.104	-0.136	0.243
Took 9th Adv. Math	-0.123	0.118	-0.088	0.103	-0.021	0.104	0.691	0.501	0.159	0.094	0.060	0.171
HS Academic Track	0.103	0.112	0.001	0.085	-0.110	0.082	0.298	0.393	0.048	0.085	0.059	0.170
HS STEM Track	0.157	0.136	0.241	0.086	0.022	0.067	-0.330	0.344	0.134	0.099	-0.214	0.194
Cognitive	0.126	0.039	0.129	0.028	0.147	0.019	0.136	0.086	0.102	0.027	0.179	0.053
Interpersonal	-0.011	0.033	0.059	0.021	0.115	0.015	0.064	0.065	0.018	0.021	0.054	0.045
Grit	0.250	0.045	0.231	0.030	0.301	0.020	0.380	0.077	0.232	0.028	0.354	0.052
Type 2	0.000		0.000		0.000		0.825	0.170	0.000		0.000	
Type 3	0.329	0.133	-0.270	0.121	0.000		0.000		-0.057	0.196	-0.346	0.242
Type 4	0.000		0.000		0.000		0.000		0.000		0.000	
Type 5	0.000		0.233	0.039	0.264	0.187	0.000		0.000		0.000	
Type 6	0.000		0.061	0.061	-0.643	0.415	0.000		0.000		0.000	
Type 7	0.200	0.060	0.000		0.000		0.000		0.144	0.122	0.014	0.012
Type 8	0.000		0.000		0.227	0.193	0.000		0.000		0.000	
N	1428		3026		7960		703		3321		969	

Notes: Table reports estimates for the college graduation models

Table G.13: Estimates for Log PV Disposable Income Models I

Variable	HSDO		HS-Voc		HS-Aca		HS-STEM		CollDO-low		CollDO-high	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.019	0.011	0.009	0.004	0.032	0.012	0.059	0.019	-0.004	0.014	0.014	0.016
Mother High School	0.008	0.007	0.015	0.003	0.032	0.014	-0.023	0.022	0.045	0.017	0.013	0.021
Mother Educ missing	0.037	0.016	0.022	0.007	0.074	0.029	0.070	0.046	0.046	0.037	0.012	0.043
Father College	0.014	0.012	0.006	0.005	0.038	0.012	0.008	0.020	0.001	0.016	0.050	0.017
Father High School	-0.012	0.007	0.012	0.003	0.016	0.013	0.049	0.020	0.019	0.015	0.015	0.019
Father Educ missing	-0.012	0.014	0.005	0.006	0.019	0.026	0.033	0.041	-0.030	0.032	0.025	0.037
Family Income (1973)	0.052	0.004	0.057	0.002	0.083	0.005	0.077	0.009	0.092	0.008	0.079	0.007
Health Endurance	0.027	0.003	0.027	0.001	0.043	0.005	0.035	0.007	0.030	0.006	0.042	0.006
Health Strength	-0.010	0.002	-0.018	0.001	-0.035	0.004	-0.019	0.006	-0.030	0.005	-0.032	0.006
Health missing	-0.007	0.014	-0.028	0.006	-0.013	0.021	0.026	0.033	-0.075	0.029	-0.091	0.030
School-Ave Fam Income	0.063	0.013	0.072	0.005	0.148	0.014	0.140	0.025	0.032	0.022	0.052	0.021
Intercept	7.968	0.037	7.998	0.016	7.585	0.050	7.765	0.099	8.314	0.073	8.129	0.070
Took 9th Adv. English	-0.000	0.011	-0.007	0.004	0.047	0.018	0.028	0.030	-0.030	0.017	-0.041	0.025
Took 9th Adv. Math	0.032	0.011	0.004	0.005	0.038	0.014	-0.021	0.047	-0.025	0.019	0.031	0.023
HS Academic Track									0.084	0.019	0.047	0.021
HS STEM Track									0.057	0.018	0.057	0.023
Cognitive	0.034	0.004	0.035	0.002	0.074	0.006	0.058	0.009	0.054	0.007	0.061	0.007
Interpersonal	0.031	0.003	0.037	0.001	0.089	0.004	0.076	0.007	0.087	0.005	0.089	0.006
Grit	0.013	0.005	0.041	0.002	0.066	0.007	0.049	0.009	0.073	0.008	0.077	0.008
Type 2	0.099	0.017	-0.090	0.009	-0.108	0.030	-0.136	0.086	-0.467	0.046	-0.272	0.063
Type 3	0.303	0.014	0.566	0.009	0.499	0.022	0.647	0.071	-0.177	0.052	0.292	0.038
Type 4	-0.429	0.030	-0.040	0.010	-0.064	0.023	-0.007	0.058	-0.714	0.048	-0.248	0.032
Type 5	0.790	0.027	-0.532	0.010	-0.969	0.028	-0.016	0.067	-0.120	0.041	-0.020	0.031
Type 6	-0.110	0.035	0.059	0.009	0.081	0.024	-0.019	0.058	-0.228	0.041	-0.078	0.032
Type 7	-1.061	0.017	-1.020	0.008	-0.055	0.028	-0.252	0.082	-0.363	0.045	-0.385	0.051
Type 8	-0.726	0.033	0.220	0.006	0.039	0.048	0.075	0.044	-0.095	0.035	-0.095	0.040
1/Precision	0.161	0.003	0.174	0.001	0.370	0.004	0.441	0.006	0.429	0.005	0.496	0.005
N	8369		43958		8129		3890		6336		6198	

Notes: Table reports estimates for the log PV disposable income models

Table G.14: Estimates for Log PV Disposable Income Models II

Variable	3yr non-STEM		3yr STEM		3yr Business		Health Sci		Educ		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.022	0.032	-0.010	0.011	0.067	0.054	0.029	0.021	-0.014	0.014	0.062	0.057
Mother High School	0.082	0.044	0.004	0.013	-0.004	0.067	0.002	0.026	0.043	0.017	-0.057	0.082
Mother Educ missing	0.124	0.081	0.023	0.030	-0.061	0.133	0.064	0.054	0.056	0.035	0.174	0.151
Father College	0.000	0.034	0.016	0.012	-0.020	0.060	0.017	0.022	0.001	0.015	-0.064	0.058
Father High School	-0.020	0.038	0.022	0.011	0.077	0.059	0.013	0.023	-0.004	0.015	0.094	0.071
Father Educ missing	-0.088	0.072	0.009	0.028	0.071	0.112	-0.056	0.049	-0.011	0.032	-0.105	0.127
Family Income (1973)	0.073	0.015	0.051	0.006	0.078	0.024	0.030	0.011	0.031	0.008	0.034	0.027
Health Endurance	0.049	0.013	0.023	0.004	0.077	0.021	0.027	0.008	0.022	0.005	0.031	0.022
Health Strength	-0.040	0.012	-0.008	0.004	-0.047	0.023	-0.007	0.008	0.004	0.005	0.037	0.020
Health missing	-0.109	0.058	-0.009	0.022	-0.099	0.094	-0.021	0.042	-0.046	0.028	0.048	0.091
School-Ave Fam Income	0.031	0.042	0.034	0.017	0.097	0.068	0.041	0.034	-0.027	0.023	-0.150	0.072
Intercept	8.263	0.129	8.759	0.057	8.132	0.225	8.451	0.103	8.464	0.071	8.360	0.244
Took 9th Adv. English	-0.065	0.048	-0.040	0.014	-0.004	0.081	-0.052	0.025	-0.008	0.018	0.261	0.100
Took 9th Adv. Math	-0.007	0.040	-0.015	0.017	0.023	0.075	0.041	0.022	0.009	0.016	0.065	0.071
HS Academic Track	0.107	0.036	0.010	0.016	0.021	0.071	-0.047	0.023	-0.003	0.015	0.021	0.064
HS STEM Track	0.149	0.045	0.041	0.013	-0.103	0.087	-0.017	0.028	0.026	0.019	-0.001	0.079
Cognitive	0.016	0.014	0.035	0.006	0.104	0.026	0.033	0.010	0.022	0.007	0.035	0.024
Interpersonal	0.098	0.011	0.056	0.004	0.111	0.021	0.061	0.008	0.045	0.005	0.052	0.019
Grit	0.022	0.016	0.041	0.006	0.123	0.029	0.041	0.011	0.024	0.007	0.026	0.026
Type 2	0.000		-0.306	0.047	0.000		-0.002	0.020	0.000		0.000	
Type 3	0.000		-0.186	0.042	0.439	0.015	0.000		0.000		0.000	
Type 4	0.000		-1.218	0.047	0.000		0.000		0.259	0.004	0.000	
Type 5	0.000		-0.156	0.027	0.000		0.000		0.000		0.000	
Type 6	0.000		-0.207	0.028	0.000		0.000		0.000		0.000	
Type 7	0.016	0.012	-0.260	0.044	0.000		0.000		0.174	0.151	0.006	0.036
Type 8	0.000		-0.120	0.024	0.000		0.000		0.000		0.000	
1/Precision	0.486	0.009	0.288	0.004	0.439	0.015	0.313	0.006	0.259	0.004	0.467	0.016
N	1426		5192		440		1456		2343		467	

Notes: Table reports estimates for the log PV disposable income models

Table G.15: Estimates for Log PV Disposable Income Models III

Variable	Soc Sci		Sciences		Engineer		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	-0.020	0.035	-0.026	0.024	-0.009	0.012	0.034	0.034	0.006	0.028	0.051	0.039
Mother High School	0.063	0.054	-0.049	0.038	-0.003	0.021	-0.097	0.058	0.041	0.042	0.136	0.065
Mother Educ missing	0.025	0.099	0.013	0.071	0.028	0.039	-0.043	0.090	-0.133	0.085	0.134	0.101
Father College	0.006	0.036	0.016	0.025	-0.010	0.013	0.064	0.034	0.080	0.030	0.013	0.042
Father High School	0.020	0.050	-0.016	0.032	0.015	0.017	-0.010	0.052	0.056	0.037	0.113	0.058
Father Educ missing	-0.038	0.086	-0.085	0.065	-0.007	0.035	0.007	0.082	0.276	0.075	0.141	0.086
Family Income (1973)	0.072	0.016	0.041	0.012	0.056	0.006	0.038	0.012	0.096	0.012	0.082	0.015
Health Endurance	0.054	0.015	0.040	0.010	0.034	0.005	0.011	0.012	0.023	0.012	0.043	0.016
Health Strength	0.004	0.015	0.007	0.010	-0.019	0.005	-0.013	0.014	-0.016	0.014	-0.034	0.016
Health missing	0.133	0.071	0.014	0.046	-0.034	0.025	-0.035	0.058	0.004	0.051	0.045	0.076
School-Ave Fam Income	0.099	0.047	-0.016	0.035	0.040	0.016	0.043	0.037	0.100	0.032	0.106	0.039
Intercept	8.026	0.152	8.620	0.121	8.626	0.066	8.589	0.186	8.132	0.120	7.974	0.158
Took 9th Adv. English	-0.022	0.060	0.046	0.044	0.050	0.028	-0.012	0.136	-0.013	0.060	0.038	0.107
Took 9th Adv. Math	0.024	0.051	0.130	0.048	0.037	0.040	0.082	0.121	-0.019	0.055	-0.007	0.067
HS Academic Track	0.082	0.049	0.047	0.039	-0.058	0.031	-0.058	0.071	0.025	0.048	0.020	0.070
HS STEM Track	0.095	0.058	-0.003	0.039	0.057	0.025	0.020	0.068	0.013	0.055	-0.031	0.076
Cognitive	0.021	0.016	-0.008	0.012	0.025	0.006	0.055	0.015	0.110	0.013	0.098	0.017
Interpersonal	0.063	0.013	0.044	0.009	0.061	0.005	0.032	0.010	0.102	0.011	0.086	0.014
Grit	0.012	0.018	0.003	0.013	0.040	0.006	0.088	0.013	0.127	0.014	0.097	0.017
Type 2	0.000		0.000		0.000		0.130	0.030	0.000		0.000	
Type 3	-0.059	0.049	-0.088	0.074	0.000		0.000		-0.716	0.147	0.143	0.093
Type 4	0.000		0.000		0.000		0.000		0.000		0.000	
Type 5	0.000		0.398	0.007	0.370	0.004	0.000		0.000		0.000	
Type 6	0.000		-0.009	0.012	0.034	0.034	0.000		0.000		0.000	
Type 7	0.013	0.071	0.000		0.000		0.000		0.134	0.101	0.020	0.016
Type 8	0.000		0.000		-0.043	0.090	0.000		0.000		0.000	
1/Precision	0.396	0.010	0.398	0.007	0.370	0.004	0.290	0.009	0.470	0.010	0.401	0.012
N	831		1632		5542		602		1739		708	

Notes: Table reports estimates for the log PV disposable income models

Table G.16: Estimates for Log Wage Models I

Variable	HSDO		HS-Voc		HS-Aca		HS-STEM		CollDO-low		CollDO-high	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.015	0.010	0.024	0.004	0.053	0.011	0.027	0.015	0.012	0.010	0.063	0.012
Mother High School	0.013	0.007	0.015	0.003	0.023	0.013	0.017	0.018	0.042	0.012	-0.011	0.016
Mother Educ missing	0.020	0.016	0.016	0.007	0.083	0.028	0.009	0.036	0.017	0.026	0.033	0.033
Father College	0.026	0.013	0.008	0.005	0.019	0.012	0.056	0.016	0.009	0.011	0.057	0.012
Father High School	-0.002	0.007	0.015	0.003	0.030	0.012	0.036	0.016	0.041	0.011	0.029	0.014
Father Educ missing	0.010	0.014	0.011	0.006	0.008	0.025	0.074	0.033	0.024	0.023	0.033	0.029
Family Income (1973)	0.020	0.005	0.031	0.002	0.062	0.005	0.053	0.008	0.045	0.006	0.047	0.006
Health Endurance	0.020	0.003	0.020	0.001	0.023	0.004	0.016	0.006	0.019	0.004	0.024	0.005
Health Strength	-0.007	0.002	-0.015	0.001	-0.020	0.004	-0.012	0.005	-0.019	0.003	-0.023	0.004
Health missing	-0.004	0.015	0.003	0.006	-0.001	0.021	0.019	0.028	0.005	0.021	-0.007	0.024
School-Ave Fam Income	0.045	0.014	0.080	0.005	0.167	0.014	0.151	0.020	0.080	0.016	0.125	0.016
Intercept	9.935	0.040	9.870	0.016	9.489	0.049	9.660	0.078	10.104	0.055	9.819	0.054
Took 9th Adv. English	0.016	0.010	-0.000	0.004	0.045	0.017	0.021	0.024	-0.026	0.012	-0.005	0.018
Took 9th Adv. Math	0.041	0.010	0.005	0.004	0.027	0.014	0.034	0.036	-0.007	0.013	0.020	0.017
HS Academic Track									0.026	0.013	0.015	0.016
HS STEM Track									0.041	0.013	0.053	0.017
Cognitive	0.022	0.003	0.029	0.002	0.054	0.005	0.044	0.007	0.040	0.005	0.050	0.006
Interpersonal	0.018	0.003	0.026	0.001	0.056	0.004	0.048	0.006	0.044	0.004	0.054	0.004
Grit	0.000	0.005	0.030	0.002	0.054	0.006	0.049	0.008	0.051	0.006	0.056	0.006
Type 2	0.077	0.015	-0.084	0.009	-0.069	0.025	-0.094	0.050	-0.351	0.033	-0.187	0.036
Type 3	0.313	0.014	0.618	0.009	0.512	0.020	0.579	0.059	-0.146	0.042	0.311	0.031
Type 4	-0.154	0.017	-0.034	0.009	-0.038	0.021	-0.021	0.044	-0.380	0.032	-0.214	0.023
Type 5	0.862	0.033	-0.176	0.008	-0.349	0.044	-0.017	0.045	-0.096	0.034	0.003	0.023
Type 6	-0.053	0.022	0.059	0.009	0.091	0.023	-0.013	0.042	-0.209	0.032	-0.044	0.024
Type 7	-0.182	0.025	-0.223	0.018	0.028	0.025	-0.134	0.049	-0.275	0.033	-0.225	0.032
Type 8	-0.024	0.044	0.252	0.006	0.053	0.047	0.049	0.033	-0.116	0.028	-0.081	0.028
1/Precision	0.128	0.003	0.127	0.001	0.258	0.004	0.256	0.005	0.235	0.003	0.279	0.004
N	3183		20271		4112		2094		3745		3666	

Notes: Table reports estimates for the log wage models.

Table G.17: Estimates for Log Wage Models II

Variable	3yr non-STEM		3yr STEM		3yr Business		Health Sci		Educ		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.036	0.024	0.021	0.009	0.112	0.055	0.018	0.014	0.014	0.008	0.054	0.031
Mother High School	0.008	0.033	-0.007	0.010	-0.052	0.069	0.019	0.018	0.015	0.010	0.012	0.043
Mother Educ missing	0.021	0.062	-0.018	0.026	-0.042	0.130	0.059	0.038	0.016	0.019	0.039	0.083
Father College	0.041	0.025	0.013	0.010	0.044	0.060	0.057	0.015	0.021	0.008	-0.004	0.031
Father High School	0.035	0.029	0.018	0.009	0.111	0.058	0.027	0.015	0.009	0.008	0.047	0.038
Father Educ missing	0.051	0.056	0.044	0.024	0.148	0.109	-0.003	0.034	0.007	0.017	0.006	0.073
Family Income (1973)	0.066	0.012	0.028	0.005	0.040	0.022	0.019	0.008	0.005	0.005	0.004	0.016
Health Endurance	0.029	0.010	0.013	0.003	0.069	0.021	0.019	0.006	0.010	0.003	0.012	0.012
Health Strength	-0.038	0.009	-0.017	0.003	-0.037	0.021	-0.008	0.005	-0.004	0.003	0.001	0.011
Health missing	-0.018	0.044	0.042	0.017	-0.060	0.113	0.044	0.030	0.015	0.016	0.067	0.046
School-Ave Fam Income	0.053	0.032	0.064	0.014	0.255	0.074	0.050	0.024	0.017	0.013	-0.011	0.041
Intercept	9.951	0.097	10.381	0.049	9.480	0.232	10.047	0.072	10.098	0.041	10.081	0.143
Took 9th Adv. English	-0.024	0.038	-0.014	0.011	-0.040	0.082	-0.033	0.017	-0.010	0.010	0.085	0.061
Took 9th Adv. Math	0.012	0.029	-0.011	0.014	0.002	0.073	0.021	0.015	-0.005	0.009	-0.005	0.042
HS Academic Track	0.038	0.027	0.007	0.013	0.002	0.072	-0.025	0.016	0.012	0.008	0.010	0.036
HS STEM Track	0.086	0.035	0.049	0.011	-0.033	0.089	0.041	0.020	0.034	0.011	-0.013	0.043
Cognitive	0.043	0.011	0.028	0.005	0.125	0.026	0.035	0.007	0.029	0.004	0.068	0.013
Interpersonal	0.061	0.009	0.044	0.003	0.092	0.021	0.034	0.005	0.026	0.003	0.018	0.010
Grit	0.040	0.012	0.028	0.005	0.109	0.028	0.046	0.007	0.021	0.004	0.053	0.014
Type 2	0.000		-0.317	0.040	0.000		-0.002	0.014	0.000		0.000	
Type 3	0.000		-0.212	0.036	0.348	0.015	0.000		0.000		0.000	
Type 4	0.000		-0.498	0.041	0.000		0.000		0.128	0.002	0.000	
Type 5	0.000		-0.167	0.024	0.000		0.000		0.000		0.000	
Type 6	0.000		-0.214	0.025	0.000		0.000		0.000		0.000	
Type 7	0.013	0.010	-0.283	0.038	0.000		0.000		0.039	0.083	0.046	0.024
Type 8	0.000		-0.153	0.022	0.000		0.000		0.000		0.000	
1/Precision	0.292	0.007	0.200	0.003	0.348	0.015	0.191	0.004	0.128	0.002	0.197	0.009
N	917		3578		286		1181		1932		293	

Notes: Table reports estimates for the log wage models.

Table G.18: Estimates for Log Wage Models III

Variable	Soc Sci		Sciences		Engineer		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Mother College	0.029	0.023	-0.013	0.018	0.014	0.009	0.046	0.027	0.047	0.025	0.030	0.033
Mother High School	0.015	0.036	-0.033	0.027	0.012	0.016	-0.050	0.047	-0.018	0.036	0.087	0.051
Mother Educ missing	0.145	0.073	0.065	0.055	0.003	0.029	-0.011	0.074	-0.112	0.079	0.020	0.082
Father College	0.046	0.024	0.009	0.018	0.011	0.010	0.064	0.028	0.090	0.026	-0.012	0.035
Father High School	0.007	0.034	0.023	0.023	0.035	0.013	-0.023	0.043	0.045	0.032	0.053	0.048
Father Educ missing	-0.073	0.066	-0.093	0.049	0.042	0.026	0.001	0.068	0.170	0.069	0.068	0.074
Family Income (1973)	0.045	0.011	0.036	0.010	0.040	0.005	0.023	0.010	0.061	0.011	0.058	0.013
Health Endurance	0.031	0.010	0.018	0.007	0.018	0.004	0.014	0.009	0.043	0.011	0.029	0.013
Health Strength	-0.011	0.010	0.000	0.007	-0.018	0.004	-0.018	0.011	-0.025	0.012	-0.037	0.014
Health missing	0.107	0.052	0.068	0.033	0.005	0.020	0.009	0.046	-0.002	0.043	0.182	0.067
School-Ave Fam Income	0.086	0.036	-0.023	0.025	0.063	0.013	-0.001	0.029	0.125	0.029	0.039	0.035
Intercept	9.916	0.119	10.347	0.088	10.317	0.054	10.436	0.145	9.873	0.110	9.969	0.133
Took 9th Adv. English	-0.027	0.038	-0.007	0.032	0.012	0.021	-0.025	0.105	-0.000	0.054	0.066	0.090
Took 9th Adv. Math	0.016	0.032	0.079	0.036	-0.004	0.030	0.075	0.093	0.012	0.051	0.032	0.057
HS Academic Track	0.039	0.032	0.080	0.028	-0.058	0.023	-0.023	0.056	0.045	0.041	0.067	0.060
HS STEM Track	0.018	0.039	0.073	0.028	0.062	0.018	0.028	0.053	0.055	0.048	0.022	0.064
Cognitive	0.061	0.011	0.015	0.009	0.038	0.005	0.069	0.012	0.092	0.012	0.067	0.015
Interpersonal	0.051	0.008	0.034	0.007	0.052	0.004	0.016	0.008	0.092	0.009	0.080	0.012
Grit	0.042	0.012	-0.003	0.009	0.036	0.005	0.089	0.011	0.100	0.012	0.066	0.015
Type 2	0.000		0.000		0.000		0.119	0.026	0.000		0.000	
Type 3	-0.011	0.030	-0.062	0.046	0.000		0.000		-0.339	0.077	0.129	0.079
Type 4	0.000		0.000		0.000		0.000		0.000		0.000	
Type 5	0.000		0.241	0.005	0.239	0.003	0.000		0.000		0.000	
Type 6	0.000		0.014	0.009	0.046	0.027	0.000		0.000		0.000	
Type 7	0.065	0.055	0.000		0.000		0.000		0.020	0.082	0.000	0.000
Type 8	0.000		0.000		-0.011	0.074	0.000		0.000		0.000	
1/Precision	0.217	0.007	0.241	0.005	0.239	0.003	0.223	0.007	0.346	0.007	0.272	0.010
N	607		1151		3959		554		1187		492	

Notes: Table reports estimates for the log wage models.