# COMPLEMENTARITIES IN HIGH SCHOOL AND COLLEGE INVESTMENTS

By

John Eric Humphries, Juanna Schrøter Joensen,

Gregory F. Veramendi

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YALE UNIVERSITY
Box 208281
New Haven, Connecticut 06520-8281

http://cowles.yale.edu/

# Complementarities in High School and College Investments

John Eric Humphries   Juanna Schrøter Joensen   Gregory F. Veramendi *

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**Abstract.**

This paper examines how high school specialization shapes college investment decisions and their subsequent returns through dynamic complementarities. Using Swedish administrative data, we estimate a dynamic Roy model that accounts for selection on multidimensional skills, family background, prior investments, and unobserved heterogeneity. We identify the model using rich skill measures and quasi-experimental variation in program popularity. For marginal students, STEM specialization in high school increases wages by 9%, with more than half this return attributed to dynamic complementarities that enhance the productivity of subsequent college investments. Consequently, we find that counterfactual policies encouraging high school STEM specialization generate twice the returns of equivalent college-level interventions. These findings demonstrate how the timing of specialized human capital investments matters during adolescence, with important implications for education policies that encourage or restrict specialization.

Keywords: Dynamic complementarities, High School Curriculum, College Major Choice, Cognitive and Non-cognitive Skills, Education Investment.
JEL: C32, C38, I21, J24, J31.

*Humphries: Yale University and NBER; johneric.humphries@yale.edu. Joensen: University of Chicago, Stockholm School of Economics, TrygFonden's Centre for Child Research–Aarhus University, and IZA; jjoensen@uchicago.edu. Veramendi: Royal Holloway, University of London and CESifo; gregory.veramendi@rhul.ac.uk. We thank Joe Altonji, Jim Heckman, Fabian Lange, and numerous seminar and conference participants for insightful comments and Paola Riveros Castro, Nina Jalava, Lukas Jonsson, Xinyue Liang, Joel Wållgren, and SISRM summer RAs for excellent research assistance. We gratefully acknowledge financial support from the Swedish Foundation for Humanities and Social Sciences (Riksbankens Jubileumsfond) grant P12-0968 enabling the data collection for this project. We are also grateful to the Stockholm School of Economics for hosting our research project. This project has been evaluated for ethical compliance by the Swedish Central Ethical Review Board (EPN) approval 2013/428-31 and privacy compliance by Statistics Sweden (SCB) disclaimer 231046/878029-8. The usual disclaimers apply.

# 1 Introduction

Students typically begin choosing specialized programs or advanced courses during adolescence. These early decisions may significantly shape subsequent education choices, career trajectories, and econonomic outcomes. On one hand, high school specialization may yield direct labor market benefits, steer students toward higher-return college majors, or enhance the returns to specific college majors through dynamic complementarities—where earlier investments increase the productivity of later investments. On the other hand, dynamic complementarities could reduce returns if high school preparation and college investments are poorly aligned. This potential trade-off suggests that policies influencing high school specialization, whether encouraging or restricting it, may have large impacts on college choices and their labor market returns.[1] While existing research has studied how high school graduation opens up access to college (e.g., Cameron and Heckman, 2001; Altonji et al., 2012; Heckman et al., 2018b), considerably less is known about how specialization *within* high school shapes subsequent college investments and returns.

In this paper, we study how initial endowments and high school specialization complement post-secondary education choices, and how these complementarities then affect labor market outcomes. To quantify the importance of these complementarities, we develop and estimate a dynamic Roy model that accounts for selection on multi-dimensional skills, family background, prior investments, and persistent unobservables. We identify the model using noisy measures of skills combined with quasi-experimental variation at the high school specialization and college application stages. Using Swedish data, we find that dynamic complementarities play a large role in the returns to high school specialization. For example, students who chose to specialize in STEM in high school received a 7.6% increase in wages on average. We estimate that 58% of this effect is due to dynamic complementarities, while changes in post-secondary choices account for 22%, and direct returns in the labor market account for 20%. We then show that counterfactual policies targeting marginal STEM enrollees in high school have larger returns than similar policies targeting college applicants.

Four aspects of the Swedish institutional setting enable our analysis. First, we ob-

[1] Such policies are hotly debated. For example, in 2014 the San Francisco school district made the controversial decision to delay math specialization until tenth grade (Huffaker et al., 2024), restricting specialization occurring in high school. Similar limits are recommended in the 2023 California Math Framework. Conversely, districts like Wake County, North Carolina have pursued the opposite approach, implementing universal access to eighth-grade algebra and expanding pathways to advanced mathematics (Dougherty et al., 2017). These contrasting approaches reflect broader debates about whether early specialization enhances or constrains student outcomes, with federal reports (e.g., U.S. President's Council of Advisors on Science and Technology, 2012) calling for education reforms to increase the number of college graduates in Science, Technology, Engineering, and Mathematics (STEM) fields.

serve students choosing high school programs at the end of ninth grade, which determines what courses they take during high school. This specialization mirrors high school course choices that are common in the United States and other countries (e.g., Betts, 2011; Woessmann, 2016; Nomi et al., 2021). Moreover, high school programs can be compared across schools as they are regulated at the national level. Second, men in our cohorts completed an enlistment screening for mandatory military service, including cognitive exams, personal interviews with psychologists, and measures of physical health. Combined with measures of performance from ninth and tenth grade courses, these measures allow us to identify the latent cognitive, interpersonal, and grit skills of students using a factor model. Third, we observe detailed information about the academic history of individuals, including which schools they attend, their college applications, and admissions outcomes. Within-school-across-cohort variation in specialization choices and variation around college admission thresholds allow us to identify persistent unobserved heterogeneity. Fourth, we have panel data on college enrollment where we see if they switch programs and what, if any, degree they complete. We use Swedish registry data on the population of men born between 1974 and 1976, where we can link comparable measures of skills, family background, ninth-grade performance, high school choices and performance, college choice and graduation, and labor market outcomes.

Our paper makes three main contributions. First, 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. The model includes both specialization decisions and attainment in high school and college. To capture endogenous sorting on unobservables, we include a detailed measurement system for estimating a multidimensional vector of latent skills. In addition, we include eight latent types that capture residual correlations between education decisions and outcomes. We also directly model the college application process, where student applications will depend on both preferences (for program and institution) and constraints in terms of their admission probabilities; i.e., whether they are above or below expected college program thresholds. The model enables us to estimate how a detailed sequence of specialization choices depends on prior choices, latent skills and types, and how these jointly affect outcomes. We show how our model approximates a full dynamic model by flexibly estimating choice probabilities and state transitions conditional on a period's current state variables and choices, trading off structural specificity for greater flexibility and a rich set of observed and unobserved heterogeneity. While this means that we cannot calculate welfare or evaluate certain counterfactuals, it avoids fully specifying structural elements like the utility function.[2]

[2]For example, while we cannot explicitly simulate the dynamic impacts of relaxing borrowing constraints (e.g., Caucutt and Lochner, 2020), study aid (e.g., Joensen and Mattana, 2021), or information

Using the estimated model, we verify the basic elements of the generalized Roy model: self-selection and differential returns to skills. We document rich sorting on multidimensional skills into high school programs, followed by sorting on both skills and high school track into college majors. These patterns suggest that students may sort based on heterogeneous returns that depend on their skills or other unobserved characteristics. We then show that the returns to skills and high school track differ by final education. For example, the returns to grit are over twice as large as the returns to interpersonal skills for those studying Medicine, while the opposite is true for Social Sciences majors. Similarly, for those who major in Engineering, the returns to an academic STEM specialization in high school are high relative to non-STEM, while the opposite is true for those who major in Law. These heterogeneous returns imply that expected relative earnings across degrees will differ depending on the student. Indeed, when we rank majors by expected earnings for each student based on their skills, background, and high school investments, we find that seven different majors are ranked highest across the students in our population.

Second, we calculate treatment effects for the different high school specializations and find that, on average, the returns to the academic STEM track are high relative to the academic non-STEM or vocational tracks. However, these average results mask substantial heterogeneity. For example, the treatment effects on the treated (TT) is notably higher than the treatment effect on the untreated (TUT) for each pairwise comparison: academic STEM vs non-STEM, academic STEM vs vocational, and academic non-STEM vs vocational. In fact, for academic non-STEM vs vocational, the TT is large and positive, while the TUT is negative, meaning that students sort on gains.

High school specialization can impact later labor market outcomes through several channels. It may yield direct labor market benefits, steer students toward higher-return college majors, or enhance the returns to specific college majors through dynamic complementarities. We decompose the treatment effects of high school specialization into these three components. When considering academic STEM vs non-STEM specializations, we find that over half of the overall treatment effect comes from dynamic complementarities (e.g., reaping the higher returns to engineering), with the rest approximately equally split between direct effects and changes in future education choices. For academic STEM vs vocational, the treatment effects are larger, largely driven by larger impacts from changes in later education choices (e.g., becoming an electrical engineer rather than an electrician). Finally, the relative importance of these three components varies by skill endowments. When decomposing the treatment effect of academic STEM vs non-STEM,

interventions (e.g., Arcidiacono et al., 2025), we still capture rich heterogeneity in such impacts and our estimates do not depend on assumptions about individual beliefs about the returns to investments, knowledge of their graduation probabilities, or the extent to which they face financial or non-financial constraints.

direct effects are much more important for those with low levels of cognitive skills or grit, while dynamic complementarities are more important for those with high levels of skills. Overall, these results highlight the important role of dynamic complementarities in explaining the impacts of specialization in high school.

Third, we use the model to evaluate two counterfactual policies designed to promote STEM education at different stages. The first policy encourages those at the margin for the high school STEM track to pursue it. The second policy incentivizes students already applying to college to choose STEM programs. Both policies leave all other choices unconstrained. We find that each policy increases the number of college STEM enrollees and graduates, but the high school policy creates larger wage gains and benefits a greater share of those affected. For example, we estimate that those induced into the academic STEM specialization in high school have 8.6% higher wages and that 71% of them benefit from higher wages. In contrast, we estimate that the policy encouraging applying to STEM majors in college increases wages by 2.5% for those who change their final education due to the policy, and only 54% benefit from higher wages. The high school policy has larger returns in part because those induced into the STEM track become more likely to enroll in college and pursue STEM degrees. In addition, the returns to college STEM degrees are larger for those who took the STEM track in high school. 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 skills, and (3) the dynamic complementarities between earlier and later investments.

Overall, our findings reveal four key insights for education policy. First, we document substantial dynamic complementarities between high school and college investments, with complementarities explaining up to half of the total return to high school STEM specialization. Second, the magnitude of these complementarities varies systematically with student skills, being strongest for students with high cognitive skills and grit. Third, the timing of specialization matters: early STEM investments yield larger returns than encouraging STEM at the college application stage for marginal students, primarily because high school specialization develops the prerequisites needed to succeed in college STEM majors. Finally, we show that interventions targeting specialization have heterogeneous effects across the skills distribution, with important implications for both the efficiency and equity of education policy.

**Related literature.** Our paper bridges and extends several strands of literature. First, we build on research examining dynamic complementarities in human capital formation, which has primarily focused on early childhood but rarely on the adolescent period when education specialization typically begins. Second, we extend methodological approaches to education choice by developing a framework with multiple unordered specialization options at both high school and college levels. Third, we contribute to the literature on high school specialization by modeling how these early choices create constraints and opportunities for later investments. Fourth, we advance the understanding of what the returns to college major embody. Throughout these contributions, we highlight the importance of understanding both the timing and type of specialized investments for developing effective human capital policy.

Identifying dynamic complementarities is challenging, with most of the literature focused on young children. The literature has taken three approaches to identification. The first approach uses panel data on inputs and outcomes to structurally estimate the technology of skill formation in which inputs are allowed to interact with one another (e.g., Cunha et al., 2010; Agostinelli and Wiswall, 2016; Attanasio et al., 2020; Aucejo and James, 2021; Joensen et al., 2022). The second approach leverages quasi-experimental variation in policies affecting human capital investments at two points early in the life-cycle (e.g., Malamud et al., 2016; Rossin-Slater and Wüst, 2020), requiring what Almond and Mazumder (2013) describe as being akin to asking for "lightning to strike twice." The third approach uses field experiments with randomization at multiple education stages in early childhood, preschool, or elementary school (Carneiro et al., 2022; Meghir et al., 2023; List and Uchida, 2024).

Methodologically, we build on Heckman et al. (2018a,b) who develop a framework to analyze sequential education choices and their returns.[3] This approach enables flexible estimation of a variety of ex post returns to sequences of education investments and how they depend on both observed and unobserved heterogeneity. We expand their framework in three key ways. First, while they focus on binary choices at each stage, our model incorporates multiple unordered choices at both high school and college levels, capturing the complex specialization options students face. Second, we explicitly model the constraints imposed by competitive college admissions, which creates identification challenges similar to those in the (dynamic) treatment effect literature. Third, we use multiple sources of exogenous variation to identify unobserved heterogeneity in the unordered choice models. Together, these extensions allow us to estimate the dynamic complementarities between high school and college investments on labor market outcomes.

Empirically, we extend the literature on dynamic complementarities into the critical high school to college transition and explicitly model how earlier investments change future opportunities and constraints. While dynamic complementarities have been extensively studied during early childhood, we know little about them during adolescence—a

[3] Also see Cameron and Heckman (2001) for an earlier example and Eisenhauer et al. (2015) for related methodological discussions.

sensitive period for advanced cognitive skill development (Hoxby, 2021) when students begin making specialized choices with significant labor market consequences (Altonji et al., 2012). This period is particularly consequential as adolescence represents a critical juncture where specialization decisions begin to lock in career trajectories.

Prior work has studied specialization in high school and college separately. At the high school level, most literature estimating causal effects has focused on binary choices—analyzing either academic STEM versus non-STEM specialization (Altonji, 1995; Joensen and Nielsen, 2009; Cortes et al., 2015; Goodman, 2019) or vocational versus general training (Oosterbeek and Webbink, 2007; Malamud and Pop-Eleches, 2011; Hall, 2012, 2016; Hanushek et al., 2017; Dustmann et al., 2017; Golsteyn and Stenberg, 2017; Zilic, 2018; Bertrand et al., 2021).[4] Among the papers estimating labor market effects of high school specialization, Dahl et al. (2023) provides the most closely related evidence. They estimate the causal effects of different academic high school lines and the vocational track in Swedish high schools. They focus on the subset of oversubscribed programs and use a regression discontinuity design to estimate local average treatment effects for students near admission thresholds. Their estimates align closely with our estimates of average treatment effects for marginal students, providing external validation to our approach.

At the college level, many papers study the returns to college major. See, for example, Kirkebøen et al. (2016), or Altonji et al. (2016) and Patnaik et al. (2021) for reviews of this literature.[5] However, little is known about how the returns to college majors are shaped by previous education investments. Altonji et al. (2012) advocate the importance of analyzing high school and college choices jointly to get at the importance of the timing of specific investments. A few papers analyze the importance of high school investments for college outcomes (Joensen and Nielsen, 2016; Card and Payne, 2021; Belzil and Poinas, 2018; De Groote and Declercq, 2021; Fiala et al., 2022). Related papers study the role of math and verbal skills for the transition from high school to college (Aucejo and James, 2021; Delaney and Devereux, 2020), mechanical skills for college enrollment (Prada and Urzúa, 2017), and finally, Saltiel (2023) shows the important role of non-cognitive skills and math self-efficacy for gender differences in college major enrollment, graduation, and returns. Our paper brings together skills, high school investments, and college investments into a single framework, helping us better understand dynamic complementarities and the broader returns to high school investments.

Finally, we also contribute to the large literature on the importance of cognitive and

[4]See Altonji et al. (2012) for a review of this literature. Golsteyn and Stenberg (2017) also relate the Swedish military enlistment measures of leadership skills and psychological stability to the choice of vocational versus academic secondary education and later life earnings.

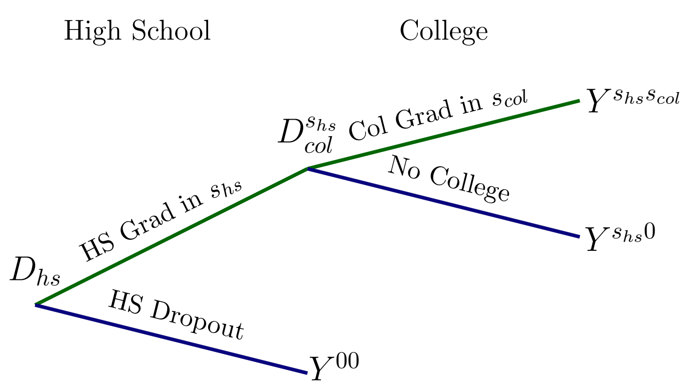
[5]In complementary work Rodríguez et al. (2016) and Mourifie et al. (2020) use generalized Roy models to study the heterogeneous treatment effects of college majors.

non-cognitive skills. See, for example, Lindqvist and Vestman (2011) and Edin et al. (2022) for the Swedish context and Heckman et al. (2021) for a recent review. We contribute to this literature by estimating how students sort on multidimensional skills into high school tracks and college majors, and how these skills interact with education investments to generate labor market returns.

## 2 Simple Dynamic Model of Specialized Investments

While high school graduation and college graduation are often treated as binary variables, both involve additional specialization choices. To fix ideas, we begin by characterizing the treatment effect of specializing in high school, showing that it can be decomposed into the direct impact of specialization, the impact of specialization on college choices, and the dynamic complementarities between high school and college choices. Consider the model visualized in Figure 1 with two sequential multinomial decisions. Students first choose to graduate from high school with specialization $D_{hs} \in \{1, .., S_{hs}\}$ or not ($D_{hs} = 0$), and then they choose to go to college with specialization $D_{col} \in \{1, ..., S_{col}\}$ or not ($D_{col} = 0$).

Figure 1: Stylized Two-Period Choice Model




We define a student's potential outcome when fixing $D_{hs} = s_{hs}$ and $D_{col} = s_{col}$ as $Y^{s_{hs}s_{col}}$. Likewise, we define the potential outcome for $D_{col}$, where $D_{col}^{s_{hs}}$ is the potential college choice when fixing high school specialization $D_{hs} = s_{hs}$. The college choice may be influenced by what they study in high school either because they develop specialized human capital, learn about themselves, learn about college specializations, or their preferences change. Finally, we define a more compact notation using the indicator $H_s^{s_{hs}} = \mathbf{1}(D_{col}^{s_{hs}} = s)$ if a student's final college state is $s$ when their high school specialization is fixed to $s_{hs}$.

Consider the simplified setting where specialization in high school is between STEM ($D_{hs} = 2$) or not STEM ($D_{hs} = 1$). We can write the individual treatment effect of specializing in high school STEM ($D_{hs} = 2$) on outcome $Y$ as

$$
\begin{aligned}
\Delta_{D_1}(Y) &= \sum_{s=0}^{S_{col}} Y^{2s} H_s^2 - Y^{1s} H_s^1 \\
&= (Y^{20} - Y^{10}) H_0^2 + \sum_{s=0}^{S_{col}} Y^{1s}[H_s^2 - H_s^1] + \sum_{s=1}^{S_{col}} (Y^{2s} - Y^{1s}) H_s^2 \\
&= \underbrace{(Y^{20} - Y^{10}) H_0^2}_{\text{Direct Effect}} + \underbrace{\sum_{s=1}^{S_{col}} (Y^{1s} - Y^{10})[H_s^2 - H_s^1]}_{\text{Changes to College Choice}} + \underbrace{\sum_{s=1}^{S_{col}} (Y^{2s} - Y^{1s})\ H_s^2}_{\text{Dyn. Complementarity}}, \qquad (1)
\end{aligned}
$$

where we use the identity $H_0^j = 1 - \sum_{s=1}^{S_{col}} H_s^j$ in the last step.

The first term is the direct effect (i.e., how much high school STEM changes the potential outcome without a college degree), the second term is the effect from changes in college choices only (i.e., the change in the non-STEM return to college from switching college choices), and the third term is the dynamic complementarity (i.e., how much high school STEM changes the college return). Imagine a policy maker who wishes to restrict students from specializing in STEM. Even if college choices could be fixed, the costs of losing the direct effect and the dynamic complementarity with college investments would remain. An important goal of this paper is to understand the relative importance of these three components and how they depend on student background and skills.

Estimating dynamic complementarities using standard causal methods is challenging. Even with (quasi-)random variation at both margins, it is not possible to know if the compliers at one stage (e.g., high school) are the same as the compliers at later stages (e.g., college), except under perfect compliance. It is difficult, however, to find a setting where specialization in high school and college could be assigned with perfect compliance.

Our solution is to use a generalized Roy Model to jointly estimate (i) the conditional choice probabilities (CCP) for different specializations and (ii) the causal effects of these specializations. To do this, we impose additional structure in order to estimate (i) and (ii) for different populations characterized by rich heterogeneity on multidimensional skills, persistent latent unobservables, and other background characteristics. As we discuss in Section 4, we use a sequence of education choices combined with multiple sources quasi-experimental variation to identify latent distributions of skills and other persistent unobservables. We then invoke conditional independence assumptions, but conditioning on both a rich set of observable and persistent unobservables.

# 3 Institutional Setting and Data

In this section, we describe the education environment and other institutional details of Sweden for the cohorts born in 1974-76, which 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 for offering high school lines that – to as large an extent as possible – align with the preferences of all qualified students.[8] If there are more applicants than available seats, then seats are allocated based on ninth-grade grade point average (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 programs. We classify or group the academic high school lines into non-STEM and a STEM "tracks." This classification allows for both vertical sorting between academic and vocational tracks, as well as horizontal sorting between STEM and non-STEM within the academic track. The academic non-STEM track consists of the three lines in business, social science, and humanities. The academic STEM track consists of 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. Appendix Table A.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

[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 provides 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.

[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 A.2. See the Secondary School regulation `1987:743` and `1992:394` for the complete details of the process.

advanced courses on these topics. The choice of high school line 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 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 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]

[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., 2017; 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, and the United States.

[12]We provide more descriptives and details in Appendix A.3.

[13]The students in our sample are enrolled in college during the pre-2001-reform study aid regime as detailed in Joensen and Mattana (2021).

## 3.1 Data

We merge several administrative registers via a unique individual identifier for the population of Swedes born in 1974-76. Our measurements of health, skills, 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, and 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 of assessing 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).

To validate our interpretation of the latent skill 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 of 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 University. We have access to the complete histories of college applications and admissions from 1993 onwards through the Swedish National

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

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 ($\leq$ 3 years; $\geq$ 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 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 labor market studies (*LISA*) from which we have yearly observations during the period 1990-2013. This allows us to observe individual income until they are 37-39 years old, as well as parental background variables (including highest completed education and disposable family income). We supplement this with information on disposable family income from $IoT$ for the years 1978-89 so that we can control for average disposable family income in the mother's household at ages 5-18.

### 3.1.1 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 skills. We choose the 1974-1976 birth cohorts for two reasons. Our sample begins with the 1974 birth-year cohort because the detailed college credit data only exists from 1993 onwards and this is also the year the classification of higher education in Sweden changed considerably. Our sample ends with the 1976 birth-year cohort because the cognitive scores from the military enlistment were significantly changed in July 1994.

[15]Appendix A.3 provides more details and descriptives by college major.

### 3.2 Measuring Multidimensional Skills

We identify latent skills using evaluations done as part of the compulsory military enlistment and course grades in compulsory and the first year of high school. Let the measurement system, $\boldsymbol{M}$, denote a vector of measures or proxies of skills. Students may be evaluated after they have been exposed to different types and levels of education. Let $M_{ms}$ denote the $m$th measure evaluated at schooling state $s$. We define $\tilde{M}_{ms}$ as latent variables that map into observed measures $M_{ms}$:

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

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

$$\tilde{M}_{ms} = \alpha_{ms} + \boldsymbol{\beta}_m^M \boldsymbol{X} + \boldsymbol{\lambda}_m^M \boldsymbol{\theta} + u_m,$$

where $\alpha_{ms}$ represents schooling-state specific intercepts for measure $m$, $\boldsymbol{X}$ is a vector of observables, $\boldsymbol{\theta}$ is a vector of latent skills, and $u_m$ is the error term. We assume that $u_m$ are mutually independent across each $m$ and are independent of $\boldsymbol{\theta}$, $\boldsymbol{X}$, and the error terms in schooling decisions and labor market outcomes.

Our specification accounts for two potential biases in the measures. First, we include observables ($\boldsymbol{X}$) in the measurement system to account for biases in the evaluations that are due to the student's background.[16] Hence, when we report deciles of latent skills, we are measuring "residual" latent skills.[17] Second, some of the measures are determined after students have partially completed some specializations (Hansen et al., 2004). For example, students are evaluated by the military at age 18 when their performance might be affected by their high school specialization. The inclusion of $\alpha_{ms}$ in the measurement system implies that our latent skills are measured relative to the skills of students in ninth grade ($s = 0$). In Appendix Section B.1, we show that the effect of schooling at the time of the test ($\alpha_{ms}$) is separately identified from differences in how students sort across schooling states. The key assumption is that we have as many pre-specialization

[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).

measures as factors.[18]

The relationship between the individual measures and the three factors is summarized in the left panel of Table 1. In order to facilitate interpretation of the factors, we specify a triangular measurement system with orthogonal factors.[19] Appendix Section B provides more details about the measures and estimation. The estimates of the measurement system are described in Appendix Section F.

To interpret and label the three skill factors, we validate them using an independent survey administered to a random subset of students in third and sixth grade. We estimate the relationship between the three factors and over 250 survey questions and instruments, ranking each item by the fraction of variance explained by each factor. The right panel of Table 1 shows the top five survey items for each factor. The first factor loads most heavily on test scores and grades (ten of the top twenty items), which we label "Cognitive Skill". The second factor predicts items related to sports, public speaking comfort, and social interactions, which we label "Interpersonal Skill". The third factor best predicts academic persistence and students' feelings about school performance, which we label "Grit Skills". While these labels facilitate interpretation, the factors could reasonably be labeled differently. For example, the third factor might represent perseverance, conscientiousness, self-regulation, or motivation.[20]

[18]Since pre-specialization measures are not 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 education, must be due to the different types of skills learned in those programs beyond the skills of the students in ninth grade.

[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.

[20]Heckman et al. (2021) synthesize recent research on skill measurement and provide more context on these concepts.

Table 1: Structure of Measurement System and Interpretation of Factors

| Panel A: Measures | $\theta_1$ | $\theta_2$ | $\theta_3$ | Panel B: UGU Survey Items |
|---|---|---|---|---|
| **Enlistment Registers** | | | | **$\theta_1$: "Cognitive Skills"** |
| 4 Cognitive Test Scores:[b] | x | | | Test Scores (10 of top 20) |
| Leadership Evaluation[a,b] | x | | | Spend time doing a hobby (-) |
| Leadership Skills[b] | x | x | | Ask the teacher for help more often? |
| Emotional Stability[b] | x | x | | How often read newspapers and comics? |
| | | | | Like to understand more of what you read? |
| **9th Grade Registers** | | | | **$\theta_2$: "Interpersonal Skills"** |
| Math Grades[c] | x | x | x | Bad at sports and physical exercise? (-) |
| English Grades[c] | x | x | x | How you feel about talking to the whole class? |
| Swedish Grades[f] | x | x | x | How often do you do sports? |
| Sports Grades[f] | x | x | x | Participated in any form of childcare |
| Residual GPA[df] | x | x | x | Often spend time on own during breaks? (-) |
| **10th Grade Registers** | | | | **$\theta_3$: "Grit Skills"** |
| Math Grades[b] | x | x | x | Think that you do well in school? |
| Sports Grades[b] | x | x | x | Do your best even when tasks are boring? |
| Residual GPA[e] | x | x | x | How often do school work at home? |
| | | | | How do you feel about drawing and painting? (-) |
| | | | | Have to learn lots of pointless stuff in school? (-) |

*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. (-) indicates that the factor is negatively related to these items.

# 4 Empirical Model and Estimation Strategy

This section lays out our empirical model. To begin, we show how our model approximates a full dynamic model by flexibly estimating choice probabilities and state transitions conditional on a period's current state variables and choices, trading off structural specificity for greater flexibility and a rich set of observed and unobserved heterogeneity. Next, we describe our empirical model of the Swedish education setting. In particular, we explain how we take into account the college application process. Finally, we discuss our estimation strategy and model fit.

## 4.1 Our Modeling Approach

We start with the general education choice model that corresponds to the underlying dynamic discrete choice problem of students. Consider the model, where each period from $t = 0$ to $t = T$ students have a set of observed state variables $\boldsymbol{A}_t$, and make a decision $D_t \in \mathcal{K}_t = \{1, ..., N_t\}$. In period $t$ students observe state variables $\boldsymbol{A}_t$ and make decisions to maximize expected utility, where $U$ is the student's utility function and $\beta$ is the discount factor. The student's dynamic programming problem can then be written as:

$$V(\boldsymbol{A}_t) = \max_{D_t \in \mathcal{K}_t} \left( U(D_t, \boldsymbol{A}_t) + \beta \int V(\boldsymbol{A}_{t+1}) dF \left[ \boldsymbol{A}_{t+1} \mid D_t, \boldsymbol{A}_t \right] \right).$$

We assume that the state variable $\boldsymbol{A}_t = \{\boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\epsilon}_t\}$, where $\boldsymbol{X}_t$ are state variables observed by the econometrician including the history past choices, $\boldsymbol{\xi}$ is a set of persistent 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.[21] Finally, students may also have some observable outcomes each period that directly enter the utility function or may be of interest to policy makers, such as earnings, given by $Y_t = Y_t(\boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\eta}_t)$.

We make two main 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 i.i.d. over time and across students with distribution $G_\epsilon$. 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., $F_x \left[ \boldsymbol{X}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\epsilon}_t \right] = F_x \left[ \boldsymbol{X}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\xi} \right]$). These two assumptions together give us Rust's conditional independence assumptions as discussed in Rust (1994) and reviewed in Aguirregabiria and Mira (2010). Given these assumptions, $F \left[ \boldsymbol{X}_{t+1}, \boldsymbol{\epsilon}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\epsilon}_t, \boldsymbol{\xi} \right] = F_x \left[ \boldsymbol{X}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\xi} \right] G_\epsilon(\boldsymbol{\epsilon}_{t+1})$.

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

$$\begin{aligned} v(D_t, \boldsymbol{A}_t) &= U(D_t, \boldsymbol{A}_t) + \beta \int \int V(\boldsymbol{A}_{t+1}) dG_\epsilon(\boldsymbol{\epsilon}_{t+1}) dF_x \left[ \boldsymbol{X}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\xi} \right] \\ &= U(D_t, \boldsymbol{A}_t) + \beta \int \bar{V}(\boldsymbol{A}_{t+1}) dF_x \left[ \boldsymbol{X}_{t+1} \mid D_t, \boldsymbol{X}_t, \boldsymbol{\xi} \right], \end{aligned}$$

where $\bar{V}(\boldsymbol{A}_{t+1}) \equiv \int V(\boldsymbol{A}_{t+1}) dG_\epsilon(\boldsymbol{\epsilon}_{t+1})$ is the integrated value function. We can now write the probability than an individual chooses action $D_t = k$ in period $t$ as

$$\mathrm{P}(D_t = k | \boldsymbol{X}_t, \boldsymbol{\xi}) = \int \mathbf{1} \left\{ \arg \max_{D_t \in \mathcal{K}_t} [v_t(D_t, \boldsymbol{X}_t, \boldsymbol{\xi}) + \epsilon_t(D_t)] = k \right\} dG_\epsilon(\boldsymbol{\epsilon}_t).$$

As noted in Benkard et al. (2018), many economically relevant counterfactuals can be estimated through simulation without explicitly solving the dynamic program or taking

[21] For simplicity, here we use $\boldsymbol{\xi}$ for all persistent latent state variables unobserved by the econometrician, while later we break this into latent skills $\boldsymbol{\theta}$ and latent types $\boldsymbol{\upsilon}$ (i.e. $\xi = \{\boldsymbol{\theta}, \boldsymbol{\upsilon}\}$).

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:

$$\begin{aligned}&\mathrm{P}\left(D_0,(D_1,\boldsymbol{X}_1),...,(D_T,\boldsymbol{X}_T)\mid \boldsymbol{X}_0,\boldsymbol{\xi}\right)= \\ &\mathrm{P}(D_T\mid \boldsymbol{\xi},\boldsymbol{X}_T)F_{\boldsymbol{X}}\left[\boldsymbol{X}_T\mid D_{T-1},\boldsymbol{\xi},\boldsymbol{X}_{T-1}\right]...\mathrm{P}(D_1\mid \boldsymbol{\xi},\boldsymbol{X}_1)F_{\boldsymbol{X}}\left[\boldsymbol{X}_1\mid D_0,\boldsymbol{\xi},\boldsymbol{X}_0\right]\mathrm{P}(D_0\mid \boldsymbol{\xi},\boldsymbol{X}_0).\end{aligned} \tag{2}$$

Under the assumptions of the model, each of these components can be estimated non-parametrically from the data, giving estimates of $\mathrm{P}(D_t|\boldsymbol{\xi},\boldsymbol{X}_t)$ and $F_{\boldsymbol{X}}\left[\boldsymbol{X}_t\mid D_{t-1},\boldsymbol{\xi},\boldsymbol{X}_{t-1}\right]$ 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 time $t$ affects decisions at time $t+\tau$.[22] For example, consider a student with $\boldsymbol{X}_t$ at time $t$, then

$$\begin{aligned}&\mathrm{P}(D_T\mid \boldsymbol{\xi},\boldsymbol{X}_T)F_{\boldsymbol{X}}\left[\boldsymbol{X}_T|D_{T-1},\boldsymbol{\xi},\boldsymbol{X}_{T-1}\right]...\mathrm{P}(D_{t+1}\mid \boldsymbol{\xi},\boldsymbol{X}_{t+1})F_{\boldsymbol{X}}\left[\boldsymbol{X}_{t+1}(D_t=1)\mid \boldsymbol{\xi},\boldsymbol{X}_t\right]\\ -&\mathrm{P}(D_T\mid \boldsymbol{\xi},\boldsymbol{X}_T)F_{\boldsymbol{X}}\left[\boldsymbol{X}_T|D_{T-1},\boldsymbol{\xi},\boldsymbol{X}_{T-1}\right]...\mathrm{P}(D_{t+1}\mid \boldsymbol{\xi},\boldsymbol{X}_{t+1})F_{\boldsymbol{X}}\left[\boldsymbol{X}_{t+1}(D_t=0)\mid \boldsymbol{\xi},\boldsymbol{X}_t\right]\end{aligned}$$

gives the change in the joint probability of observing the realization $\{(D_{t+1},\boldsymbol{X}_{t+1}),...,(D_T,\boldsymbol{X}_T)\}$ counterfactually fixing choice $D_t$ from 0 to 1. In Appendix Section D.1.1, we show how fixing a particular choice at time $t$ affects outcomes $Y_t$.

Using this setup, it is possible to simulate how fixing a choice at a particular time period will affect expected future choices and outcomes for different populations. We can then calculate various 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 conditional choice probabilities given in equation (2), the conditional expected value of the outcomes of interest, the distribution of persistent latent state variables ($F_{\boldsymbol{\xi}}(\boldsymbol{\xi})$), and place some restrictions on the dependence between error terms in the choice equation and outcomes. However, our approach does not require us to specify the student's utility function 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.[23]

[22] We follow Heckman and Pinto (2015) in using parentheses when *fixing* a variable (e.g. $F_{\boldsymbol{X}}\left[\boldsymbol{X}_{t+1}(D_t=1)\mid \boldsymbol{\xi},\boldsymbol{X}_t\right]$) rather than *conditioning* on it (e.g. $F_{\boldsymbol{X}}\left[\boldsymbol{X}_{t+1}|D_t,\boldsymbol{\xi},\boldsymbol{X}_t\right]$). We use superscripts to denote fixing choices in the simpler model of Section 2, as there are only two choices.

[23] Another limitation that applies to our approach, and all CCP approaches, is that the state variables must be sufficiently rich to capture the future changes of interest. For example, future expected wages

### 4.2 Empirical Model of Education and Earnings

This section discusses how we map the conceptual model described in Section 4.1 to our institutional setting. Note that in the empirical model, we replace time subscripts $t$ with the stages of education subscripts $j$. Figure 2 provides an overview of 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 $k_2 \in \mathcal{K}_2 = \{0, 1, 2, 3\}$ denote high school dropout, vocational track graduate, academic non-STEM track graduate, and academic 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 whether to enroll in the first program to which they are 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, $D_4(\mathcal{K}_4)$.[24] 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).

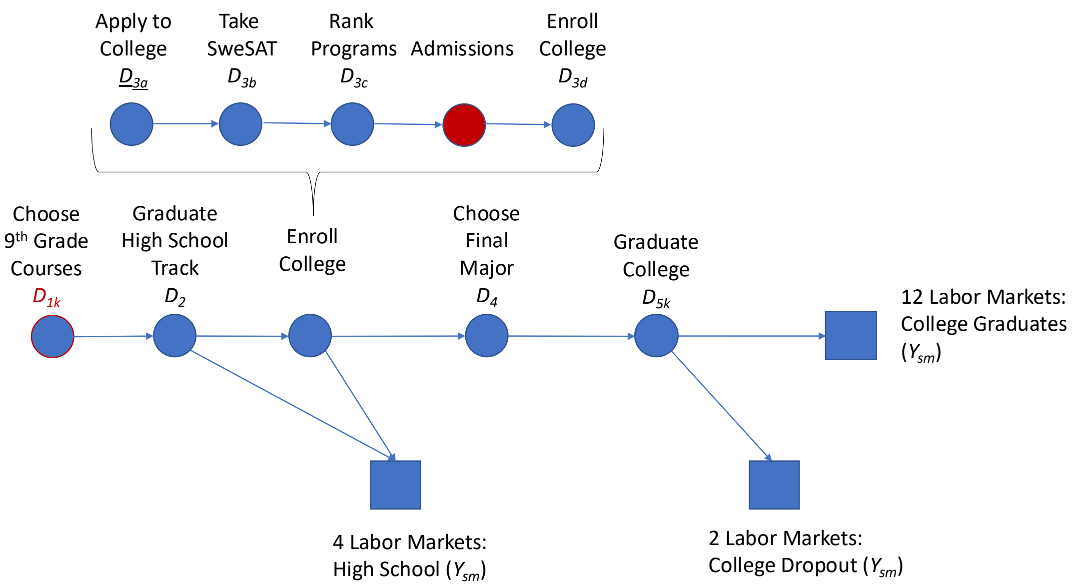
If students do not enroll in college ($D_3(\mathcal{K}_3) = 0$), they enter the high school labor market and earn $Y_{1k_2}$. If they enroll in college ($D_3(\mathcal{K}_3) > 0$), but do not graduate ($D_{5k_5} = 0$), they enter the labor market for college drop outs and earn $Y_{2k_5}$, otherwise they enter the labor market for college graduates and earn $Y_{3k_5}$, where $k_5 = D_4(\mathcal{K}_4)$.

The choices of high school track and final enrollment are characterized by the max-

from a given choice need to depend on the state variables included. Therefore, the model may not be well-suited for some counterfactuals.

[24] Allowing for switching and dropout is key because of the importance of information revelation and learning about skills after initial college enrollment (Altonji, 1993; Arcidiacono, 2004; Stinebrickner and Stinebrickner, 2012, 2013; Wiswall and Zafar, 2015; Arcidiacono et al., 2025).

Figure 2: Sequential Model of Education Specialization Choice and Earnings




(a) Model Diagram

| | $F(\nu)$ | $M_{ms}$ | $D_{1k_1}$ | $D_2$ | GPA & SAT | $D_{3a-3d}$ | $D_4$ | $D_{5k_5}$ | $Y_{ms}$ |
|---|---|---|---|---|---|---|---|---|---|
| Skills ($\boldsymbol{\theta}$) | x | x | x | x | x | x | x | x | x |
| Observables ($\boldsymbol{X}$) | | x | x | x | x | x | x | x | x |
| Types ($\boldsymbol{\nu}$) | | | x | x | x | x | x | x | x |
| Ninth-grade Adv.courses ($D_1$) | | | | x | x | x | x | x | x |
| High School Track ($D_2$) | | | | | x | x | x | x | x |
| Instruments ($\boldsymbol{Z}$) | | | | x | | x | | | |
| High School GPA & SweSAT | | | | | | x | x | | |
| Initial Enrollment ($D_3$) | | | | | | | x | | |

(b) Structure of Models

*Notes*: Panel (a) shows a diagram of the sequential choice model used in this paper and panel (b) shows how each model depends on various elements of the state space, including previous choices. Observables include indicators for high school or college degree of each parent, average disposable family income child age 5-18, strength measure, fitness measure, and average family income of students at the grade school they attended. Within-School-Across-Cohort instruments ($\boldsymbol{Z}$) are included for high school track choices ($D_2$) relative to ninth grade cohort choices and college application choices ($D_{3c}$) relative to the high school track cohort choices.

imization 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 ($j = 4$). The conditional choice probability for choice $k_j$ is then

$$Pr(D_j = k_j) = \int \mathbf{1}\left\{\arg\max_{k_j \in \mathcal{K}_j}\{I_{jk_j}\} = k_j\right\} dG_{\epsilon}(\boldsymbol{\epsilon}_j) \quad \text{for} \qquad j \in \{2, 4\}$$

where $D_j(\cdot)$ denotes the individual's multinomial choice. The perceived value for each choice is a function of observable state variable ($\boldsymbol{X}_{jk_j}$) including previous choices, choice-specific instruments that do not enter the outcome models ($\boldsymbol{Z}_{jk_j}$), a finite dimensional vector of unobserved skills $\boldsymbol{\theta}$, a finite dimensional vector of unobserved types $\boldsymbol{\upsilon}$, and an idiosyncratic error term $\varepsilon_{jk_j}$, which is unobserved by the econometrician:

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

See Figure 2b for details about how previous choices and instruments enter each decision node.

#### 4.2.1 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 hundreds of 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 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:

$$D^1_{3c,i}(\mathcal{L}_i) = \arg\max_{l \in \mathcal{L}^1_i}\{I_{il}\},$$
$$D^2_{3c,i}(\mathcal{L}_i) = \arg\max_{l \in \mathcal{L}^2_i}\{I_{il}\}, ...,$$

where $D^j_{3c,i}(\mathcal{L}_i)$ denotes individual $i$'s $j$th ranked choice given their choice set $\mathcal{L}^j_i$ (i.e. $\mathcal{L}^1_i \equiv \mathcal{L}_i$, $\mathcal{L}^2_i \equiv \mathcal{L}_i \setminus D^1_{3c,i}\mathcal{L}_i)$, 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]

[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

We describe the student's problem as an exploded mixed nested logit model, where we group major-college pairs into major groups or nests, $k_3 \in \mathcal{K}_3$. The latent utility of major-college alternative $l \in \mathcal{L}(k_3)$ for student $i$ is then

$$I_{il} \quad = \quad f_{k_3}(\boldsymbol{X}_{i3}, \boldsymbol{Z}_i, \boldsymbol{\theta}_i, \boldsymbol{v}_i) + \delta_{il} + \varepsilon_{il},$$

where $f_{k_3}(\boldsymbol{X}_{i3}, \boldsymbol{Z}_i, \boldsymbol{\theta}_i, \boldsymbol{v}_i)$ 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 $\delta_{il}$, which captures differences in college and major characteristics (expected income, utility of major/college, etc) within a nest. The alternative-specific utility $\delta_{il}$ may also represent location-dependent and student-specific preferences.

Three main assumptions are needed for an identification strategy that is tractable for estimation:

**A1** : Utility of a major-college pair within a nest depends on geographic region, application scores (i.e. GPA and SweSAT scores), and qualifications (i.e. high school track) used for admissions. Let $g_i$ denote a geographic region $\times$ GPA $\times$ SweSAT score $\times$ high school track bin. The within-nest utility of major-college pair $l$ depends only on the bin $g_i$:[26]

$$\delta_{il} \equiv \delta_l(g_i).$$

**A2** : An individual's consideration set in nest $k_3$, denoted $B_{ik_3}$, only depends on whether the application scores (i.e. GPA and SweSAT scores) are above or below the expected admissions threshold:[27]

$$B_{ik_3} \equiv B_{k_3}(GPA_i, SweSAT_i).$$

**A3** : The error terms, $\varepsilon_{il}$, are distributed type-I generalized extreme value.

**Proposition 1** *Under assumptions A1-A3, $f_{k_3}(\boldsymbol{X}_{i3}, \boldsymbol{Z}_i, \boldsymbol{\theta}_i, \boldsymbol{v}_i)$ is identified by estimating the conditional choice probabilities of the outer nest with correction terms that depend only*

estimate preferences when truth-telling is only a weakly dominant strategy.

[26]Appendix Figure A.2 shows the 15 geographic regions we use along with the locations of the universities. Appendix Figure C.2 shows an example of geographic preferences for engineering programs of students who live in two different regions.

[27]Following the approach of Kirkebøen et al. (2016), Appendix Figure C.2 shows that there is a large increase in admissions when just crossing the GPA admissions threshold for a focal major. Appendix Table C.2 shows large jumps at both the GPA and SweSAT thresholds when modeled jointly.

*on the share of applications going to each program within bin $g_i$:*

$$\ln\left(P\left[D^1_{3c,i} \in B_k(GPA_i, SweSAT_i)|D^1_{3c,i} \in B_k, g_i\right]\right).$$

*See Appendix Section D.1.2 for the proof.*

### 4.2.2 Labor Market Outcomes

We model schooling-specific labor market outcomes which similarly depend on background characteristics, the individual's vector of unobserved skills, and a vector of latent types that affects education decisions and outcomes. Labor market outcome $m$ of individual $i$ with final education $s$ is given by:[28]

$$Y_{ism} = \boldsymbol{\beta}^Y_{sm}\boldsymbol{X}_{is} + \boldsymbol{\lambda}^Y_{sm}\boldsymbol{\theta}_i + \boldsymbol{\alpha}^Y_{sm}\boldsymbol{\upsilon}_i + \eta_{ism}, \tag{3}$$

where $X_{is}$ includes indicators for ninth grade specializations and, if they enrolled in college, high-school specialization choices. See Figure 2 for a description how previous choices enter each model.

## 4.3 Estimation Strategy

We now turn to how we estimate the model of sequential education choices and their relationship with labor market outcomes as specified in the previous section.

### 4.3.1 Exclusion Restrictions

Our identification strategy relies on exclusion restrictions in high school and college application decisions that identify the distribution of unobserved heterogeneity (Section 4.3.2). We exploit variation in program popularity across cohorts within schools, which we attribute to differential recruitment efforts. High school and college recruiters visit schools annually to promote their programs, and particularly charismatic (or uncharismatic) recruiters can make programs more (or less) attractive to entire cohorts.

Following the peer-effects literature, we construct within-school-across-cohort (WSAC) instruments for ninth grade advanced course choice, high school track, and college field applications.[29] Let $P^{k_j}_{-icp}$ represent the proportion of student $i$'s classmates in cohort $c$

[28] The 18 final schooling states are 4-year college graduates in eight major groups, college graduates in 4 short (2-3 year) major groups, college dropouts from 4-year and short programs, high school graduates from the three tracks, and high school dropouts. See Section 3.1 for more details on education categories.

[29] Originally proposed in Hoxby (2000), see Cattan et al. (2023) for a recent example studying the effect of classmates with elite parents.

and school program $p$ who make choice $D_j = k_j$. For example, for each STEM track high school student, we calculate the fraction of their classmates (within school-cohort-track) who list engineering as their first college choice. We estimate the following model for each choice $D_j = k_j$:

$$W_{icp}(k_j) = \beta_1 P^{k_j}_{-icp} + X'_{icp}\beta^{k_j}_2 + \gamma^{k_j}_c + \alpha^{k_j}_p + \delta^{k_j}_p c + \eta^{k_j}_{icp}, \quad (4)$$

where $W_{icp}(k_j)$ indicates whether student $i$ makes choice $k_j$, $\gamma^{k_j}_c$ are cohort fixed effects, $\alpha^{k_j}_p$ are school-program fixed effects, and $\delta^{k_j}_p c$ capture program-specific time trends.[30]

**Validating the Exclusion Restrictions.** Appendix Table C.1 shows our estimates of $\beta_1$ for high school track and college application choices. This may be due to an aggregate shock, like a particularly effective recruiter coming to the school, or because a popular student in the cohort chooses a program. Column (1) of Table C.1 shows that classmates' choices strongly predict individual choices. While we do not need to identify peer effects per se, there are mechanisms that may change the choices of classmates that violate the exclusion restriction. For example, the exclusion restriction could be violated if cohort composition affects student skills or if a new teacher influences both cohort skills *and* choices. We test for such violations in two ways: First, in column (2) we control for individual skills using ninth-grade GPA (for high school choices) or military enlistment scores (for college choices). The instrument's predictive power remains unchanged, suggesting individual skill differences do not drive the results. Second, in column (3) we control for cohort average skill using the same measures. Again, the instrument coefficient remains stable or increases, indicating that cohort-level skill variation does not explain the relevance of the instrument. These robustness checks support our interpretation that WSAC variation captures recruitment-driven popularity shocks rather than skill-related confounds, validating our exclusion restriction.

### 4.3.2 Identification of Unobserved Heterogeneity (Types)

While we account for a rich set of observables, latent skills, and past education choices, there may be unobserved confounders that drive both education choices and outcomes. As discussed above, we model these potential confounders through the inclusion of latent types. The instruments shift similar individuals to different specializations in high school and college, allowing us to identify the role of unobserved types in education choices and adult earnings.

[30] We residualize $P^{k_j}_{-icp}$ to construct instruments $Z^{k_j}_j$ for the perceived value of choice $k_j$ in our decision model (Section 4.2): $P^{k_j}_{-icp} = X'_{icp}\beta^{k_j}_2 + \gamma^{k_j}_c + \alpha^{k_j}_p + \delta^{k_j}_p c + \epsilon^{k_j}_{icp}$. We use $Z^{k_j}_{ij} = \hat{\epsilon}^{k_j}_{icp}$ as instruments.

For example, consider an individual $i$ who takes an academic STEM track in high school, majors in engineering in college, and earns a high income as an adult. A similar individual in the same school $i'$ might find themselves in a ninth grade cohort where the instrument shifts them to an academic non-STEM track. If individual $i'$ goes on to major in engineering and earn a similar income as individual $i$, then we know that the preference for engineering and possibly other unobservables drive the strong correlation between high school track and major choice (i.e. the type will be important) rather than the high school track changing preferences and perceived values. Now imagine a different pair of similar individuals applying to college. Changes in the college major due to instrument variation will be informative about whether the college major has a causal effect on earnings. Furthermore, comparisons can be made between individuals who are shifted from major $k$ to $k'$ and individuals who are shifted from $k'$ to $k$. Differences in the change in earnings identifies comparative advantage due to the unobserved heterogeneity. In this way, identifying unobserved types from the exclusion restrictions is a key element of our identification strategy.

### 4.3.3 Estimation and Model Fit

The model is estimated via maximum likelihood, as described in Appendix D.2. Appendix F presents the estimated parameters of the model and Appendix D.3 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 501 bootstrap samples.

We estimate the model with eight types.[31] Appendix D.4 shows how the types strongly sort into high school tracks and college majors. Figure D.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 D.2 with the model estimates in Tables F.13 and F.14, 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.

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

# 5 Results

In this section, we use the estimated model to study the complementarities between skills, high school track, and post-secondary education decisions. First, we provide evidence on how individuals sort into high school track and final education based on their background, skills, and latent types. Second, we calculate treatment effects of high school tracks, highlighting important heterogeneous effects and quantifying selection on gains. Third, we provide direct evidence of dynamic complementarities by decomposing treatment effects into a direct effect, changes in college choices, and dynamic complementarities between high school and college choices. Lastly, we use the model to simulate two counterfactual policies designed to promote STEM education at different points in the educational trajectory.

## 5.1 Sorting and Heterogeneous Returns

The goal of this section is to highlight the rich heterogeneity in family background and skills that we observe across students and how this heterogeneity is meaningful for high school choices, college choices, and earnings.

**Determinants of High School and College Choices** Table 2 characterizes how individuals sort into high school tracks and final education. Even in "egalitarian" Sweden we find stark differences in background in both educational attainment and sorting into specializations. For high school track, we see that those who drop out have the lowest family income as a child, are the most likely to have a parent who dropped out of high school (55%), and are least likely to have a parent who graduated from college (16%). Those in the vocational track had somewhat higher family income, were less likely to have parents who dropped out of high school, and were more likely to have a parent who graduated from college. This pattern continues as we move from the vocational track to the academic non-STEM track, and from the academic non-STEM track to the academic STEM track. We also find the same sorting pattern on skills. High school dropouts have the lowest levels of skills, with cognitive skills $0.36\sigma$ below average, grit $0.68\sigma$ below average, and interpersonal skills $0.11\sigma$ below average. The average skills monotonically increase as we move between tracks, with those in the academic STEM track having the highest average level of all three skills.

The bottom panel in the data characterizes how individuals sort into final education levels. Here, the sorting patterns are more nuanced. For example, those majoring in business have similar levels of grit and higher interpersonal skills than those majoring in science and computer science, but lower cognitive skills. On average, humanities majors have higher cognitive and grit skills than those education majors, but notably lower interpersonal skills. Those majoring in medicine, the most competitive major, have high levels of all three skills, while those majoring in health sciences have the highest level of interpersonal skills, but relatively low cognitive skills and grit compared to other college graduates. We also see sorting on parental income and education. For example, those majoring in the most competitive majors, medicine and law, also have the highest average family income while growing up, and are the most likely to have parents who graduated from high school. These differences by final education specialization reflect preferences, admissions constraints, enrollment, and selection into graduation. See Appendix Figures B.2 and B.3 to see how skill sorting patterns change at application, enrollment, and graduation stages.

Lastly, the final two columns report the most common latent type in each high school track and level of final education, as well as the share in that category with that type. As discussed in Section 4, these latent types capture residual correlation between choices and outcomes not explained by skills and covariates and are estimated from our model. We also find sorting based on these latent variables. For example, 57% of those majoring in law are estimated to be type 0, which is also the most common type for those in the academic non-STEM track in High School, and for those who major in social sciences and non-STEM 3-year degrees in college. Similarly, 45% of those majoring in 4-year business degrees and 48% of those majoring in 3-year business degrees are estimated to be type 2. 69% of Health Sciences and 45% of those studying medicine are type 1. While these types are difficult to interpret directly, the sorting patterns highlight that they play an important role in sorting and often cluster in logical ways.

**Labor Market Returns to Multidimensional Skills** As described in Section 4.2.2, we estimate separate earnings models for each final level of education, allowing the returns to skills to differ by education and specialization. By estimating separate models for each final schooling state, we can investigate the complementarities between college major and skills in the labor market. Figure 3 shows the estimates of $\hat{\boldsymbol{\lambda}}^{Y}_{sm}$ for workers with four-year college degrees. In general, all three skills have large and positive returns in the labor market, but there is a great deal of heterogeneity. For example, education majors have relatively low returns to skill, where increasing any of the three skills by one standard deviation increases wages by around 2.5 percent. In contrast, business majors have the largest returns to all three skills. What is perhaps surprising is the difference in patterns in returns to the different skills across majors. For example, the three skills have similar returns for social science majors, while interpersonal skills have more than twice the return compared to cognitive skills and grit for science and computer Science majors.

Table 2: Sorting into high school tracks and final education

| | | Covariates | | | Skills and Latent Types | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Share* | *Family Income* | *Any Dropout Par.* | *Any Coll Parent* | *Cognitive* | *Grit* | *Interpersonal* | *Modal Type* | *Modal Type Share* |
| **High School Track:** | | | | | | | | | |
| Dropout | 0.09 | 2.64 | 0.55 | 0.16 | -0.35 | -0.68 | -0.11 | 1 | 0.244 |
| Vocational | 0.51 | 2.77 | 0.48 | 0.21 | -0.20 | -0.26 | -0.03 | 5 | 0.227 |
| Academic Non-STEM | 0.18 | 3.29 | 0.27 | 0.48 | 0.13 | 0.31 | 0.07 | 0 | 0.288 |
| Academic STEM | 0.22 | 3.33 | 0.22 | 0.52 | 0.51 | 0.63 | 0.04 | 7 | 0.300 |
| **Final Education:** | | | | | | | | | |
| HS Dropout | 0.09 | 2.64 | 0.55 | 0.16 | -0.35 | -0.68 | -0.11 | 1 | 0.244 |
| HS Vocational | 0.43 | 2.75 | 0.50 | 0.18 | -0.26 | -0.27 | -0.03 | 5 | 0.243 |
| HS Academic Non-STEM | 0.08 | 3.22 | 0.30 | 0.42 | -0.06 | 0.26 | 0.13 | 0 | 0.356 |
| HS Academic STEM | 0.04 | 3.13 | 0.29 | 0.39 | 0.21 | 0.40 | 0.14 | 7 | 0.305 |
| College Dropout (short) | 0.06 | 3.06 | 0.31 | 0.40 | 0.29 | 0.12 | -0.04 | 7 | 0.362 |
| College Dropout (long) | 0.06 | 3.23 | 0.24 | 0.50 | 0.47 | 0.28 | -0.02 | 4 | 0.204 |
| Non-STEM (short) | 0.01 | 3.20 | 0.24 | 0.52 | 0.20 | 0.36 | -0.05 | 0 | 0.286 |
| Business (short) | 0.00 | 3.27 | 0.29 | 0.43 | 0.20 | 0.44 | 0.13 | 2 | 0.478 |
| STEM (short) | 0.05 | 3.13 | 0.30 | 0.41 | 0.30 | 0.38 | 0.05 | 7 | 0.443 |
| Health Sciences | 0.01 | 3.10 | 0.28 | 0.49 | 0.04 | 0.18 | 0.21 | 1 | 0.688 |
| Education | 0.02 | 3.07 | 0.28 | 0.45 | 0.08 | 0.43 | 0.12 | 3 | 0.678 |
| Humanities | 0.00 | 3.18 | 0.21 | 0.58 | 0.42 | 0.58 | -0.26 | 6 | 0.233 |
| Social Sciences | 0.01 | 3.36 | 0.17 | 0.61 | 0.31 | 0.45 | -0.05 | 0 | 0.367 |
| Business | 0.02 | 3.61 | 0.20 | 0.56 | 0.33 | 0.58 | 0.12 | 2 | 0.454 |
| Law | 0.01 | 3.68 | 0.15 | 0.66 | 0.53 | 0.57 | 0.15 | 0 | 0.570 |
| Science and Comp-Sci | 0.02 | 3.27 | 0.20 | 0.58 | 0.56 | 0.55 | -0.11 | 5 | 0.559 |
| Engineering | 0.06 | 3.53 | 0.16 | 0.61 | 0.70 | 0.72 | 0.03 | 4 | 0.475 |
| Medicine | 0.01 | 3.76 | 0.11 | 0.74 | 0.78 | 0.89 | 0.12 | 1 | 0.445 |

*Notes*: This table characterizes how individuals sort into high school track (top panel) and final education (bottom panel). The first column reports the share of individuals in our data with that final level of education or high school track. The columns under "Covariates" report the means of childhood family income, an indicator for if either of their parents did not graduate from high school, and an indicator for if either of their parents has a college degree. The columns under "Skills and Latent Types" report the average cognitive, grit, and interpersonal skills, the modal latent type, and the share of individuals in that final education (or high school track) with that latent type. The skill measures are the factor scores for the individuals in our data, which have mean zero and are measured in standard deviations of the population. The latent types are from the full model, which has eight potential latent types (numbered 0-7 here).

Indeed, one of the more surprising findings is that wages vary more with interpersonal skill than with cognitive skill for science, math, and engineering majors.[32]

[32] Appendix Figure E.2 shows patterns for the discounted present value of income. Appendix Figures A.3–A.6 estimates a number of linear models between wages and skills or between wages and high school track by college major. Fixed effects for institution, college program, municipality are added to show that the heterogeneity in skill and HS track are not driven by specific programs, institutions, or

The prior figures show that the returns to specific education choices depend heavily on the skills of the students. This may be further compounded by differences in the loadings on the latent types and covariates. To better characterize the heterogeneity in returns, we use the model to calculate the proportion of individuals who would select a given major if they were simply maximizing their expected earnings. 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 skills from the factor distribution ($\boldsymbol{\theta} \sim F_{\boldsymbol{\theta}}(\boldsymbol{\theta}; \hat{\boldsymbol{\gamma}}_\theta)$) and finally drawing a latent type from the probability function of latent types conditional on the latent skills ($\boldsymbol{\upsilon} \sim P_{\boldsymbol{\upsilon}}(\boldsymbol{\upsilon}|\boldsymbol{\theta}; \hat{\gamma}_\upsilon)$).[33] For each of the synthetic workers, we calculate their expected earnings in the different final 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, skills, and latent types. Table 3 shows the proportion of college applicants in the simulation that would rank each major first and second in expected log wages.Clearly, there is no absolute ranking of majors by expected earnings. The model suggests a large portion of the sample would expect to earn the most through studying business (31%) or engineering (28%), but five other majors also represent the expected log-wage maximizing choice for at least one percent of students, ranging from Social Sciences to shorter STEM degrees. The table also shows the proportion ranking each major second in terms of expected log wages, again demonstrating substantial heterogeneity in the returns to majors.

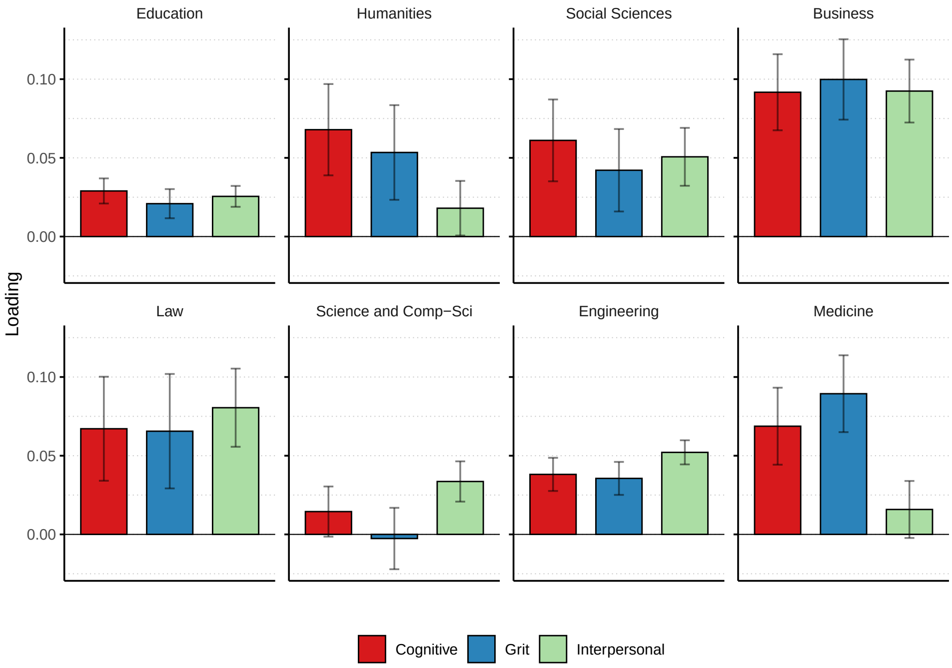
## 5.2 Causal Effects of High School Track

Building on the analysis of the role of high school choices and skills in Section 5.1, this section uses the generalized Roy model estimated in Section 4 to study the causal effects of high school specialization decisions on subsequent post-secondary education choices and labor market earnings. In particular, we focus on the heterogeneous impacts of high school specialization decisions and how the returns to these decisions vary based on students' multidimensional skills. Specifically, we estimate the gains from changing high school track from academic non-STEM to academic STEM, vocational to academic STEM, and from vocational to academic non-STEM. We estimate the treatment effects of high school track on college enrollment, college graduation, and log wages. For each margin and outcome, we use the model to calculate the average treatment effect (ATE), the average

municipalities.

[33]Recall that our latent skills are residuals and the probability of each type depends on these latent skills. In other words, the skill factors represent the variation in latent skill after accounting for observables and the latent types capture remaining residual correlations between choices and outcomes.

Figure 3: Returns to Skills across Majors ($\hat{\boldsymbol{\lambda}}_{sm}$) for Log Wages




*Notes*: This figure shows the returns to skills ($\hat{\boldsymbol{\lambda}}_{sm}$) for four-year graduates from equation (3). Each sub-panel shows the estimates for different four-year majors. The first (red) bar shows the loading on cognitive skills, the second (blue) bar shows the loading on grit skills, and the third (green) bar shows the loading on interpersonal skills. This figure shows estimates for log wages, while Appendix Figure E.2 shows estimates for log present discounted value of disposable income. Error bars show bootstrapped 95% confidence intervals.

treatment effect for those with low skills, the average treatment effect for those with high skills, the treatment on the untreated (TUT), the treatment on the treated (TT), and the average marginal treatment effect (AMTE).[34] The TT is the average treatment effect for those who chose the first choice, while the TUT is the average treatment effect for those who chose the second choice in each pairwise comparison. The AMTE is the average treatment effect for those close to indifferent between the two choices.

Each treatment effect is calculated via simulation by integrating over the relevant population's individual-specific treatment effects as discussed in Section 4. 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 as shown in Section 4.1.

The first two panels of Figure 4 show the estimated treatment effect of high school

[34]High skilled is defined as being in the top 50% of all three skills, while low skilled is defined as being in the bottom 50% of all three skills. The AMTE is calculated via simulation. A simulant is marginal if the difference in the perceived value ($I_{jk_j}$) 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 3: 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 (short) | 0.05 | 0.09 |
| Business (short) | 0.03 | 0.10 |
| Social Sciences | 0.03 | 0.04 |
| Science and Comp-Sci | 0.00 | 0.01 |

*Notes:* The table reports the proportion of individuals who applied to college ranking a major first or second in terms of expected log wage. Appendix Table E.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 skills 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 (3) ($\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}] = \boldsymbol{\beta}_{sm}^{Y}\boldsymbol{X} + \boldsymbol{\lambda}_{sm}^{Y}\boldsymbol{\theta} + \boldsymbol{\alpha}_{sm}^{Y}\boldsymbol{\upsilon}$).

track on college outcomes. The top panel shows the treatment effects on college enrollment, and the middle panel shows the treatment effects on college graduation. Each sub-panel reports the treatment effects for one specific comparison: academic STEM vs non-STEM, academic STEM vs vocational, and academic non-STEM vs vocational track. We find that the treatment effects on enrollment and graduation are positive on all three margins, with larger effects on enrollment than graduation, and evidence of selection on gains for either academic vs vocational specializations.

The average treatment effects for college enrollment are the largest for academic STEM vs vocational. We estimate that students who are marginal between the STEM and vocational track are 37 percentage points more likely to enroll in college. The treatment effects for academic STEM vs non-STEM and academic non-STEM vs vocational are smaller, with AMTEs of around 14 percent. We also find that high-skilled students have larger impacts from choosing academic STEM or non-STEM over vocational tracks. For example, the impacts on enrolling in college from specializing in academic non-STEM vs vocational are nine percentage points larger for high-skilled vs low-skilled students. Finally, we find evidence of sorting on gains, with the TT on enrollment being larger than the TUT for academic STEM vs vocational (34 vs 30%) and academic non-STEM vs vocational (16 vs 11%).

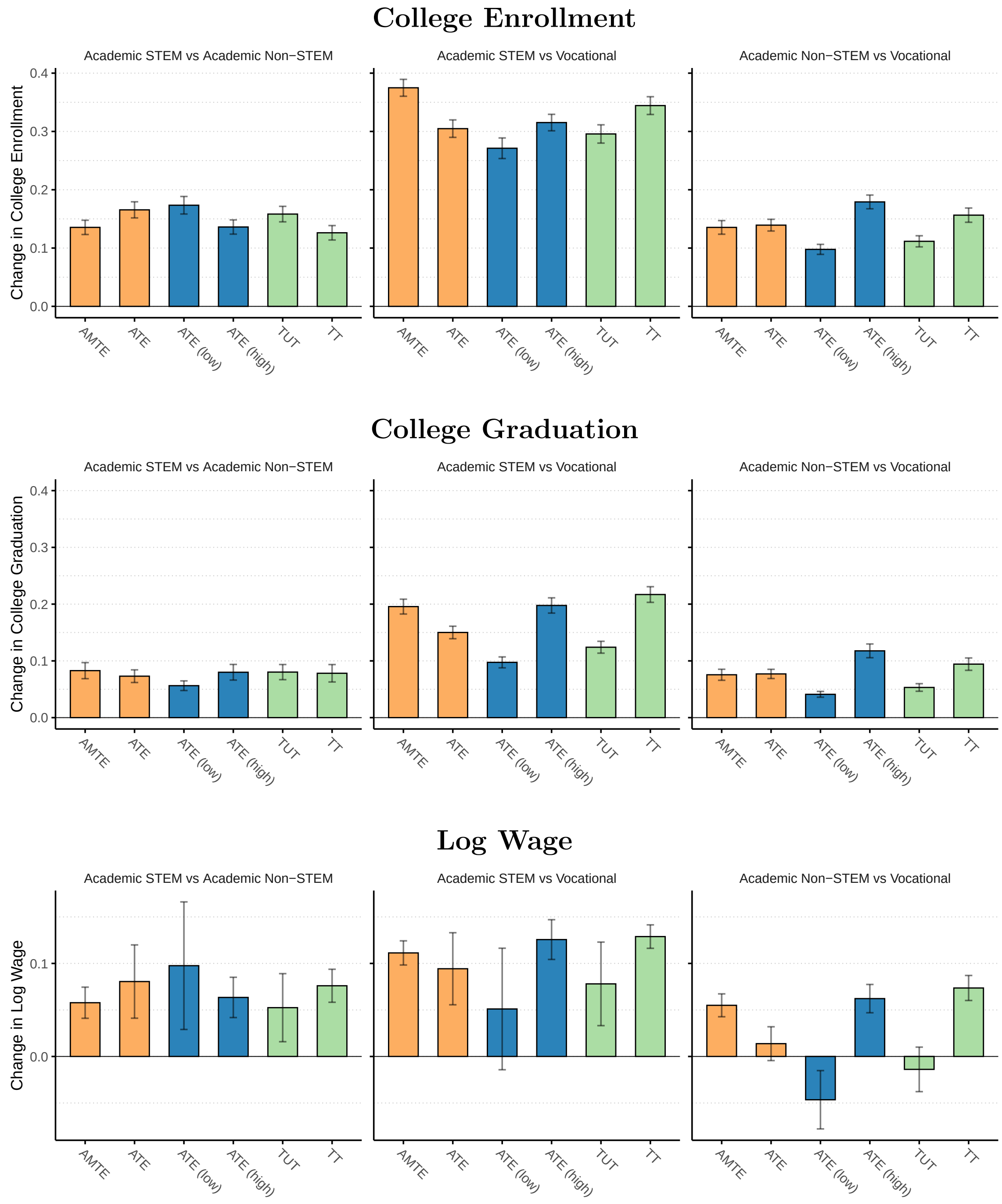
The treatment effects of high school track on college graduation (middle panel) account for the fact that many students who enroll in college do not graduate. Specifically, the graduation treatment effects counterfactually set high school track but then allow students to make enrollment, switching, and 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 academic STEM vs vocational is 19.6 percentage points compared 37.5 on enrollment. In addition, the gap between the ATE for low- and high-skilled students grows, as does the gap between the TT and TUT estimates.

The bottom panel of Figure 4 shows similar results for log wages. These treatment effects include the direct effects of high school track and the indirect effects of high school specialization on post-secondary education choices and their returns. We estimate an AMTE of 0.11 on log wages for academic STEM vs vocational, and approximately 0.06 for academic STEM vs non-STEM and academic non-STEM vs vocational. 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 skills. For STEM vs academic track, the estimates are larger for low skilled students.[35] These differences are statistically significant at the 5% level except for Academic STEM vs non-STEM. The patterns are also similar when considering the log discounted present value of disposable income, though the effects are somewhat larger (see Appendix Figure E.3). Interestingly, for academic non-STEM vs vocational, the TT and ATE for high-skilled students are positive, while the point estimates for TUT and the ATE for low-skilled students are negative.

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. Appendix Figure E.1 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 academic STEM would increase log wages for engineers by 0.06, while switching from academic non-STEM 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 non-STEM would raise log wages for many final education levels, such as science and computer science, social studies, business, and law. Yet, it would also lower wages in engineering and the health sciences, demonstrating important dynamic complementarities.

[35] 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 4: Treatment Effects: College Enrollment, Graduation, and Log Wages




*Notes*: Figure shows the estimated treatment effects for the three high school track margins on college enrollment (top), college graduation (middle), and log wage (bottom). "ATE" is the average treatment effect, estimated for everyone with at least a high school degree. "AMTE" is the average marginal treatment effect, and is estimated for those near indifferent between the two high school tracks. "ATE (low)" and "ATE (high)" report treatment effects for those with low and high baseline skills. High-skilled is defined as being in the top half of all three skill distributions, while low-skilled is defined as being in the bottom half of all three skill distributions. "TT" is the treatment on the treated, while "TUT" is treatment on the untreated. The AMTE, TT, and TUT are all estimated for those chose one of the two high school specializations being considered. Error bars show bootstrapped 95% confidence intervals.

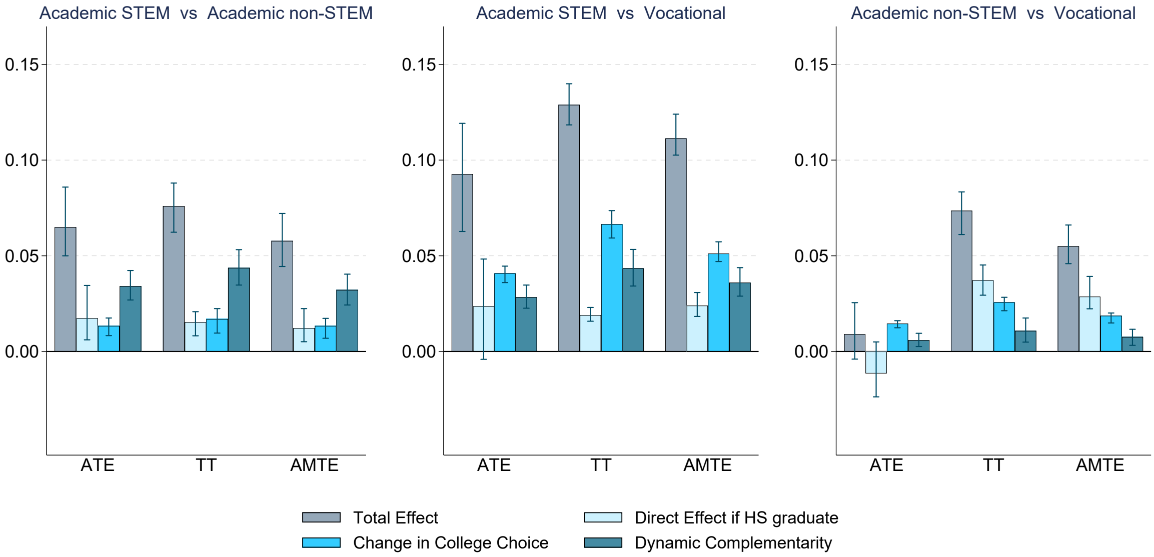
### 5.3 Decomposing the Effect of High School Track

The treatment effects discussed in the prior section are a combination of direct effects, changes in future education choices, and dynamic complementarities between high school and college investments. In this section, we decompose the treatment effect using Equation 1 in Section 2, but allowing for the larger set of final college outcomes from the full model (e.g., college dropouts from different types of programs and college major graduates).

In Figure 5, we use our model to estimate and decompose equation (1) for the average treatment effect of the full population (ATE), the treatment effect for the treated (TT), and the treatment effect for those that are at the margin between the two specializations in high school (AMTE). For the academic STEM vs non-STEM, over half of the treatment effects are due to the dynamic complementarities between studying STEM in high school and the majors the students choose in college, with direct effects and changes in college choices each accounting for around 20%. For academic STEM vs vocational, dynamic complementarities are also large (31-34% of the total effect), but changes in college choices also play a large role, accounting for 44-52% of the total effect. As previously shown in Figure 4, for academic non-STEM vs vocational, the ATE is much smaller than the TT and AMTE. Moreover, the direct effect is the largest component for the TT and AMTE, followed by changes in college choices, and then dynamic complementarities.

Figure 6 studies how the decomposition of the average treatment effect on the treated varies by baseline skills. Each row represents one of the pairwise comparisons: academic STEM vs non-STEM, academic STEM vs vocational, and academic non-STEM vs vocational. Each column represents a different skill: cognitive, grit, and interpersonal. Each figure then shows how the decomposition of the overall treatment effect varies by decile of baseline skill. For academic STEM vs non-STEM, the overall effects modestly decline in the deciles of each skill, which is driven by a decline in the direct effect. For cognitive and grit skills, the decline in direct effects is partially offset by growing dynamic complementarities. For academic STEM vs vocational, the overall treatment effects are increasing in deciles of all three skills, which is driven by a combination of increasing direct effect and, for cognitive and grit skills, dynamic complementarities. Finally, for academic non-STEM vs vocational, dynamic complementarities are small and vary little with skill deciles, while direct effects are increasing in all three skills, and the component from changes in college choices is increasing for cognitive skills and grit.

Figure 5: Decomposition of Treatment Effects

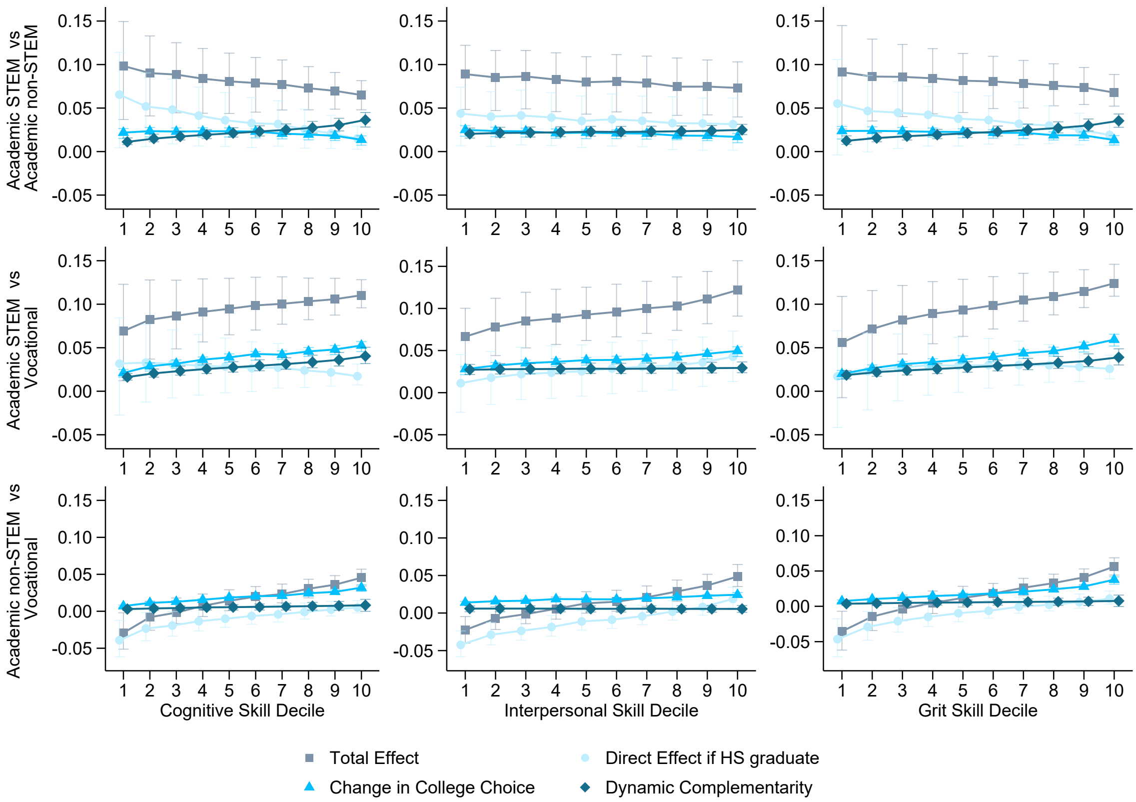



*Notes*: This figure shows the decomposition of the treatment effect of choosing: academic STEM vs. non-STEM, academic STEM vs. vocational, and academic non-STEM vs. vocational high school track in equation (1) for three populations: the Average Treatment Effect for the full population (ATE), the Treatment effect for the Treated (TT), and the Average Marginal Treatment Effect (AMTE) for those that are at the margin between the two high school specialization choices. Error bars show bootstrapped 95% confidence intervals.

## 5.4 Counterfactual Policies Targeting STEM education

This section uses the model to estimate and interpret the impacts of two counterfactual policies designed to promote STEM education. The first policy targets students who did not pursue the academic STEM track in high school, but only marginally preferred their high school choice over the STEM track. We then consider how inducing these marginal students into the STEM track impacts future education decisions and earnings. The second policy targets students who have chosen to apply to college and provides small incentives to apply to STEM programs (science and computer science, engineering, medicine, health sciences, 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. Both policy counterfactuals correspond to a dynamic model where the policy change was not known in advance. For example, in the second policy counterfactual, students' high school choices do not respond to the incentives to apply to STEM programs in their college application. Similarly, these policy counterfactuals are partial equilibrium and do not account for potential changes in returns from changing the supply of certain levels of education to the market.

Figure 6: Decomposition of the Average Treatment on the Treated by Skill Decile




*Notes*: This figure plots the total Treatment Effect on the Treated (TT) and its decomposition in equation (1) conditional on skill deciles. The rows show different comparisons of counterfactual high school tracks: academic STEM vs academic non-STEM, academic STEM vs vocational, and academic non-STEM vs vocational. The columns show comparisons for the three skill dimensions: cognitive, interpersonal, and grit. Error bars show bootstrapped 95% confidence intervals.

### 5.4.1 Encouraging the STEM Track in High School

Figure 7a shows how inducing marginal students into the academic STEM track in high school changes final educational attainment. 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 non-STEM 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 3-year STEM degree, and we see a small increase in those with a science/ computer science degree. We also find reductions in some majors, such as law, though these are empirically small.

Lastly, we see a notable increase in college dropouts from short and long programs.

Although pushing students to take the academic STEM track in high school increases the number of students majoring in engineering and science/computer science in college, taking the STEM track in high school may not increase wages. Table 4 reports the average treatment effects for marginal students induced into the STEM track. The rows break down the results for everyone, students who do not change their final education attainment after being induced into the STEM track, and students who change their final education attainment. The first three columns show the AMTE and the AMTE for low-skilled and high-skilled students. The second three columns show the proportion of marginal students who gain (i.e., have positive treatment effects). On average, the treatment effect on log wage is 0.09 and does not notably differ by skill. 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 affected marginal students have higher expected wages, though this proportion is larger for those who do not change education. Putting the pieces together, the average gains are smaller for those who don't change final education levels, but the proportion who gain is higher. This result highlights that switching tracks causes many students to pursue more lucrative post-secondary options, but changes in post-secondary education from the policy can also lower wages.

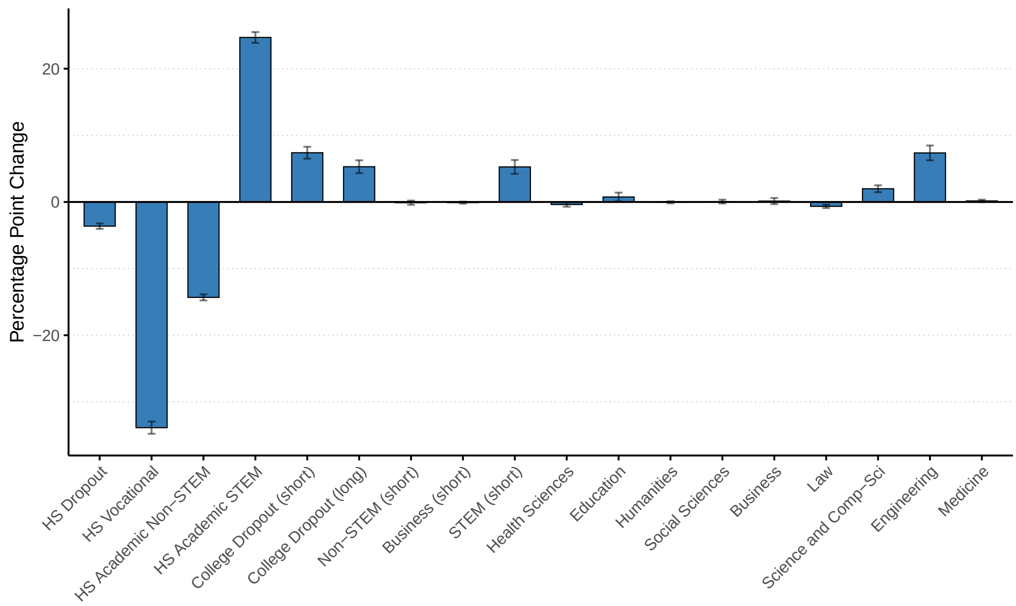
Table 4: Effects of STEM Track (log wages, marginal students)

| | **AMTE** | | | **Prop. Gaining** | | |
|---|---|---|---|---|---|---|
| **Group** | All | Low Skill | High Skill | All | Low Skill | High Skill |
| All | 0.086 | 0.094 | 0.077 | 0.710 | 0.716 | 0.705 |
| | (0.007) | (0.012) | (0.009) | (0.015) | (0.019) | (0.021) |
| No Change in Final Edu | 0.040 | 0.045 | 0.036 | 0.910 | 0.952 | 0.873 |
| | (0.005) | (0.006) | (0.006) | (0.041) | (0.033) | (0.052) |
| Change in Final Edu | 0.108 | 0.114 | 0.102 | 0.613 | 0.623 | 0.604 |
| | (0.010) | (0.016) | (0.012) | (0.011) | (0.021) | (0.012) |

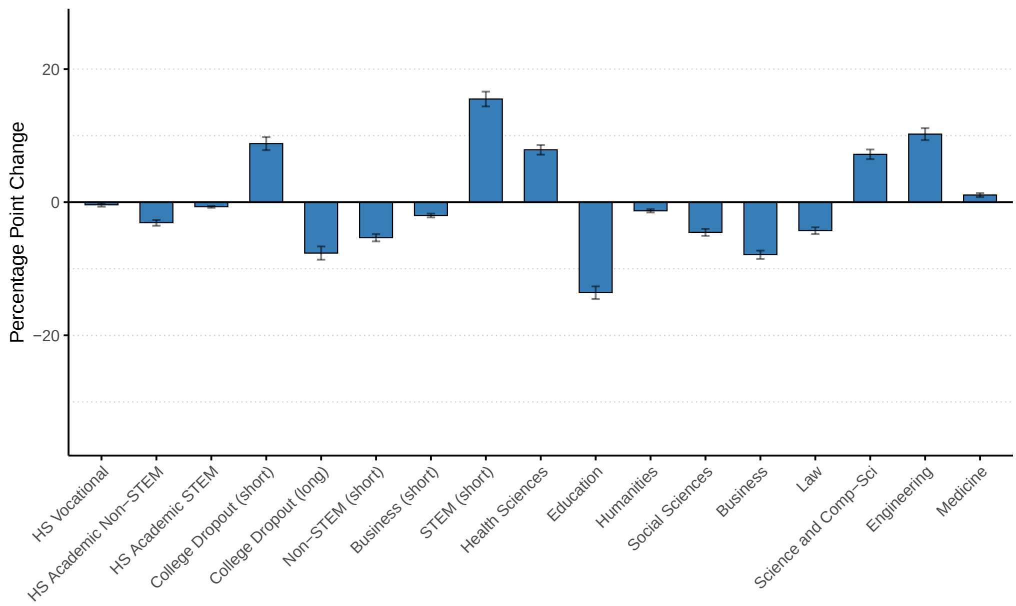
*Notes*: Table reports the treatment effects from the counterfactual policy of inducing marginal students into the STEM track in high school. Results are reported for all students, students who do not change their final education, and students who change their final education. "Low Abil" ("High Abil")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

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. Table E.2 shows the AMTE for those induced into different majors, conditional on what their final education would have been in absence of the policy. For example,

Figure 7: Effects of Policies on Sorting into Final Education




(a) Marginal Effect of Academic STEM Track on Sorting




(b) Marginal Effect of Encouraging STEM Applications on Sorting

*Notes*: Figure (a) shows how switching marginal individuals into the high school STEM track reallocates them across different education outcomes. The analysis is restricted to those who do not take the academic STEM track but are marginal to this choice and the height of the bar is the percentage point change in the number of marginal students in that final education from switching them to the academic STEM track. Figure (b) shows how education choices change for those induced to change their final education through a policy incentivizing enrollment in STEM college majors (STEM (short), Health Sciences, Science and Comp-Sci, and Engineering). The analysis is restricted to those who change education levels due to the policy. The height of the bars is the percentage point change in the number of compliers in that education level. Error bars show bootstrapped 95% confidence intervals.

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.

### 5.4.2 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 computer science, engineering, medicine, and short STEM programs). This induces marginal students to list more STEM programs on their college applications. Figure 7b shows how the policy affects students' final education, with each bar reporting the percentage point change in that final education category. Encouraging STEM applications results in a large increase in graduation from short STEM programs, moderate increases in graduation from engineering and science and computer science programs, and a small increase in graduation from medicine programs.[36] We also see an increase in students enrolling in short 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, followed by short non-STEM degrees and social sciences.[37]

Table 5 reports the AMTE and the proportion of affected students gaining from the policy. The rows report results for all students who were affected by the policy (All), those who took academic STEM track in high school, and those who didn't take the academic STEM track. Similar to Table 4, the columns report the AMTE and the proportion gaining for all, low-skilled, and high-skilled students. On average, the policy has small to moderate wage gains with an AMTE of 0.025, notably smaller than the AMTE for our policy encouraging academic STEM specialization in high school. Similarly, we estimate that only 54 percent of those affected by the policy gain from it. The estimates are broadly similar when split by low- and high-skill students, with high-skill students having slightly larger gains. Interestingly, the AMTE is 0.05 for those who studied academic STEM in high school, compared to 0.013 for those who did not. This difference further shows that dynamic complementarities are important.

Appendix Table E.2 shows the AMTE of the policy for those who were induced to switch into different majors, broken down by the level of education they would have otherwise obtained. For example, we see that the returns for engineering are positive for

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

[37]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.

Table 5: Effects of Encouraging STEM College Applications (log wages, switchers)

| | **AMTE** | | | **Prop. Gaining** | | |
|---|---|---|---|---|---|---|
| **Group** | All | Low Skill | High Skill | All | Low Skill | High Skill |
| All | 0.025 | 0.018 | 0.027 | 0.535 | 0.526 | 0.540 |
| | (0.006) | (0.009) | (0.011) | (0.006) | (0.009) | (0.014) |
| STEM HS Track | 0.050 | 0.041 | 0.026 | 0.555 | 0.545 | 0.562 |
| | (0.010) | (0.013) | (0.032) | (0.008) | (0.012) | (0.038) |
| Not STEM HS Track | 0.013 | -0.005 | 0.027 | 0.525 | 0.507 | 0.538 |
| | (0.006) | (0.01) | (0.011) | (0.006) | (0.010) | (0.014) |

*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 high school, and students who did not take the STEM track in high school. "Low Abil" ("High Abil") are students in the bottom (top) half of all three skills. 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.

most individuals, 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 encouraging applications to STEM programs during the college application process. Moreover, the impact of the college policy is larger for those who took the STEM track in high school. Both suggest that targeting students in high school may be more effective.

# 6 Conclusion

In this paper, we study how initial endowments and high school specialization complement post-secondary education choices, and how these complementarities then affect labor market outcomes. Using Swedish data, we find that dynamic complementarities play a large role in the returns to high school specialization. We document large but heterogeneous returns from specializing in STEM in high school, and show that around half of the return comes from complementarities between high school and college investments.

The paper makes three main contributions. First, we build a dynamic generalized Roy model to jointly model high school and college education decisions and labor market outcomes. The model includes both specialization decisions (i.e., track and major) and attainment in high school and college. Using the model, we document rich sorting on multidimensional skills into high school track, followed by sorting on both skills and high school track into college majors. Second, we use the model to estimate and decompose treatment effects from specializing in specific high school tracks in high school. We find that the returns to the academic STEM track are high on average, but do not benefit everyone. We then decompose the treatment effects into a direct effect, changes in college enrollment and major decisions, and complementarities between high school and college choices. For the academic STEM track, complementarities account for around 60% of the wage gains, with changes in college and direct effects each accounting for around 20%. Third, we use the model to evaluate two counterfactual policies designed to promote marginal STEM enrollment either in high school or when applying to college. We find that both colleges increase the number of STEM enrollees and graduates in college, but that the high school policy creates larger wage gains and benefits a greater share of those affected.

Our findings highlight a fundamental trade-off in education system design: early specialization can enhance returns through dynamic complementarities for students who maintain a consistent specialization path, but may change options and reduce returns for students who switch fields. This suggests that policies encouraging early specialization should be accompanied by flexibility for students to adjust their education paths as they discover their comparative advantages. More broadly, our findings demonstrate that understanding the interplay between skills, the timing of specialized investments, and the constraints in education systems is crucial for developing human capital policies that improve both individual outcomes and economic efficiency.

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# Appendix for:

Complementarities in High School and College Investments

John Eric Humphries Juanna Schrøter Joensen Gregory F. Veramendi

# A Data Appendix

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

## A.1 Description of Data Sources

We combine data from several Swedish administrative registers for the cohorts born in 1974-76 and their parents. We merge the ninth grade, high school, and higher education registers to obtain longitudinal education histories. Finally, we merge the data from the education registries with the Wage Structure data ("*Lönestrukturstatistik*") and the longitudinal integration database for health insurance and labour market studies (*LISA*) to obtain information on earnings, employment, occupation, and additional background variables. The administrative data for the full population is quite detailed from 9th grade through college, and we supplement these data with the Evaluation Through Follow-up survey (ETF72) focusing on 3rd through 9th grade for the cohort in third grade in the 1981/82 academic year.

In the following, we describe the data sources and variable definitions in more detail. Appendix A.1.1 describes the labor market data, Appendix A.1.2 the education registers and survey data, while Appendix A.1.3 describes the Swedish scholastic aptitude test data and Appendix A.1.4 describes the military enlistment archives. We use most of the same data sources as in our companion paper (Humphries et al., 2024) and the following data source description shares a significant overlap.

### A.1.1 Labor Market Data

**Wages:** The Wage Structure ("Lönestrukturstatistik") data is a yearly snapshot that is intended to get an overview of the evolution of the wage structure in the economy.

The data is collected by SCB and employer organizations through a survey of employers during a sample week once a year. The sampling differs by sector. The public sector has the broadest coverage, since data is collected for everyone employed in the state, regions, and municipalities during the sample week. For the private sector, however, only a subset of employers are surveyed about their workers during the sample week. The two key variables we use to construct our primary outcome measure are full-time-equivalent (FTE) wages (measured by *MLON*) and actual work time as a fraction of full-time (measured by *TJOMF*). Our primary outcome is log monthly wages for full-time workers in 2010-2013. We report wages in 1000s SEK and real 2010 prices.

**Disposable Income:** Our secondary outcome variable is log present value of disposable income. We observed the yearly disposable income, which is gross labor income from all employment spells minus all net taxes (based on the variable *DispInk*) in the *LISA* database. We also report earnings in 1000s SEK and real 2010 prices, and Section A.4 details how we calculate the present value.

### A.1.2 Education Data

**9th grade registry:** We use data on course choices to define two binary indicator variables for whether an individual took a more advanced track in math and/or English or not. We also use data on Swedish, English, math, physical education (PE) grades, and grade point average (GPA) as proxies for skills in the measurement system described in more detail in Appendix B.

**High school registry:** Similarly to the 9th grade registry, we focus on specialization choices and performance measured by Swedish, English, math, PE grades, and GPA. We classify high school students into three tracks: vocational and two academic tracks in non-STEM and STEM. A reform implied that the high school graduating cohorts from 1996 and earlier are classified according to the high school lines they attend, while those graduating in 1997 are classified according to the programs they attend. The academic STEM track consists of the science (76) and technical (80,81) lines pre-reform, the science program (49) is also added during the transition years, and the science program (NV) for the post-reform cohorts. The academic non-STEM track comprises the humanities line (74), business (72), and social science lines (78) pre-reform, the arts program (19) and social science program (53) are also added during the transition years, and the arts program (ES) and the social science program (SP) for the post-reform cohorts. Finally, all vocational high school lines and programs are grouped in the vocational high school track.

**Higher education registry:** From the Higher Education registry, we use data on acquired college degrees. We classify all academic programs into two levels ($\leq$ 3 years; $\geq$ 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 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 grouped together.

We merge these registers to the "Evaluation Through Follow-up" surveys (ETF72 and ETF77) administered to 3rd, 6th, and 10th grade students by the Department of Education and Special Education at Gothenburg University.[38] This survey was administered to a random sample of the oldest and youngest cohorts in our population who were sampled when in 3rd grade in the 1981/82 and 1986/87 school-years, respectively. These individuals are mostly born in 1972 (10% sample) and 1977 (5% sample). This data 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.

### A.1.3 Swedish Scholastic Aptitude Test

The Swedish Scholastic Aptitude Test (SweSAT) is a norm-referenced test whose primary aim is to assess the test-takers' general aptitude for studies. The test should, as fairly as possible, rank the applicants with respect to expected success in higher education. The test consists of 160 multiple choice questions and is given twice a year, once in spring for admission the following autumn, and once in autumn for admission the following spring. All sections are taken in one day, lasting between 7.5-8 hours including breaks between each section and a lunch break. Apart from the English language reading comprehension test, all sections are taken in Swedish. The result on the test is normalized to a scale between 0.0 and 2.0, with 0.05 increments. Around a third of those enrolled in

[38] Härnqvist (1998) and Giota (2006) provide additional details on the construction of the survey.

college in the cohorts we study are admitted based on high performance in the SweSAT. We have data on the overall test scores and sub-scores on every attempt through the Department of Applied Educational Science at *Umeå Universitet*. The sub-scores include: Vocabulary; Swedish and English Reading Comprehension; General Information; Data Sufficiency; Interpretation of Diagrams, Tables, and Maps.

### A.1.4 Military Enlistment Archives

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).

## A.2 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 A.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 admitted students are therefore enrolled in 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 A.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.

Table A.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 A.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 |
| **GPA, Q1** | Vocational | 96.30 | **99.56** | 0.26 | 0.18 | **99.51** | 0.36 | 0.12 | 35.10 | 16.04 | 39.24 | 15.10 | 62.74 |
| | 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 |
| **GPA, Q2** | Vocational | 82.68 | **98.66** | 0.73 | 0.62 | **98.63** | 0.98 | 0.40 | 53.91 | 17.91 | 56.49 | 14.83 | 72.98 |
| | 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 |
| **GPA, Q3** | Vocational | 55.63 | **97.74** | 1.32 | 0.94 | **96.92** | 1.97 | 1.11 | 76.98 | 9.88 | 73.80 | 7.73 | 84.64 |
| | 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 |
| **GPA, Q4** | Vocational | 19.92 | **96.96** | 1.67 | 1.37 | **92.36** | 4.10 | 3.54 | 82.17 | 4.74 | 73.97 | 4.21 | 84.76 |
| | 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.

### A.2.1 Additional High School Descriptives

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

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

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

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

## A.3 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 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.

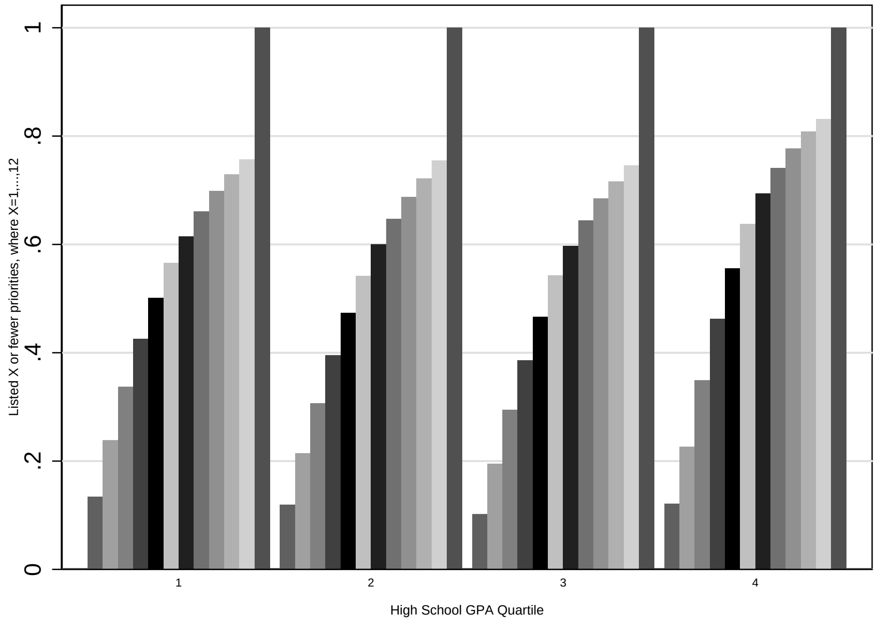
Using microdata on college applications and admissions from the Swedish National Archives (Riksarkivet), we can directly assess to which extent admission probabilities are taken into account when applying. Figure A.1 reveals that students with higher high school GPA have higher admission probabilities, apply to more selective programs, and are more likely to be admitted to their more preferred programs. We also find that applications differ substantially by geographic cluster. Figure A.2 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.

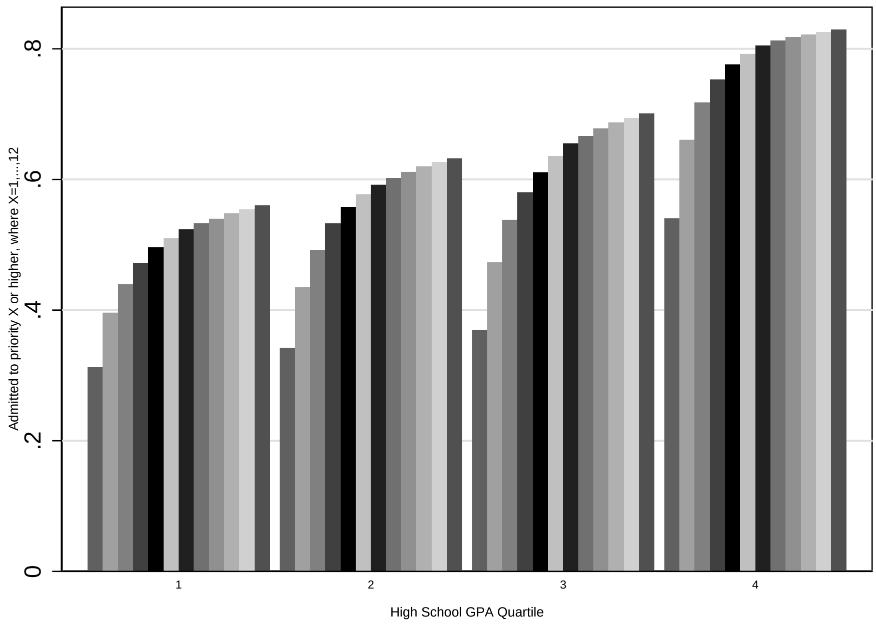
### A.3.1 Additional College Descriptives

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

Figure A.1: 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 A.5: High School and SweSAT by College Major of Initial Enrollment

| | | **College Major** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **3-year or shorter** | | | | | **4-year or longer** | | | | | | |
| | **No Enroll (HS grad)** | **non-STEM** | **Business** | **STEM** | **HealthSci** | **Educ** | **Humanities** | **SocSci** | **Business** | **Law** | **Sciences** | **Engineer** | **Medicine** |
| **Grades, High School** | | | | | | | | | | | | | |
| GPA | -0.32 | 0.32 | 0.28 | 0.12 | 0.18 | 0.24 | 0.55 | 0.47 | 0.66 | 1.02 | 0.59 | 1.09 | 1.64 |
| Math | -0.22 | -0.02 | 0.16 | 0.15 | -0.06 | 0.02 | 0.07 | 0.10 | 0.45 | 0.49 | 0.48 | 0.93 | 1.02 |
| English | -0.19 | 0.37 | 0.12 | -0.07 | 0.17 | 0.15 | 0.49 | 0.39 | 0.43 | 0.90 | 0.47 | 0.65 | 1.33 |
| Swedish | -0.29 | 0.50 | 0.28 | 0.07 | 0.23 | 0.34 | 0.76 | 0.58 | 0.62 | 1.14 | 0.54 | 0.87 | 1.59 |
| Sports | -0.13 | 0.02 | 0.23 | 0.10 | 0.24 | 0.29 | -0.03 | 0.24 | 0.37 | 0.30 | 0.17 | 0.29 | 0.54 |
| **High School Track** | | | | | | | | | | | | | |
| Vocational | 0.78 | 0.34 | 0.24 | 0.28 | 0.52 | 0.35 | 0.23 | 0.23 | 0.12 | 0.12 | 0.17 | 0.09 | 0.06 |
| Academic non-STEM | 0.15 | 0.47 | 0.60 | 0.11 | 0.29 | 0.43 | 0.48 | 0.55 | 0.68 | 0.57 | 0.26 | 0.06 | 0.13 |
| Academic STEM | 0.07 | 0.20 | 0.17 | 0.61 | 0.19 | 0.22 | 0.29 | 0.23 | 0.20 | 0.32 | 0.58 | 0.85 | 0.81 |
| **SweSAT** | | | | | | | | | | | | | |
| Test-taker | 0.10 | 0.78 | 0.85 | 0.72 | 0.86 | 0.77 | 0.75 | 0.88 | 0.91 | 0.89 | 0.88 | 0.83 | 0.92 |
| SweSAT score of test-takers | | | | | | | | | | | | | |
| Total | -0.50 | 0.13 | -0.24 | -0.27 | -0.32 | -0.20 | 0.25 | 0.17 | 0.11 | 0.64 | 0.32 | 0.56 | 1.14 |
| Vocabulary | -0.14 | 0.33 | -0.14 | -0.25 | 0.12 | 0.04 | 0.35 | 0.24 | 0.02 | 0.54 | 0.19 | 0.16 | 0.74 |
| Swedish Reading Comprehension | -0.39 | 0.22 | -0.06 | -0.12 | -0.23 | -0.04 | 0.38 | 0.27 | 0.24 | 0.66 | 0.34 | 0.57 | 1.03 |
| English | -0.39 | 0.26 | -0.08 | -0.17 | -0.28 | -0.05 | 0.44 | 0.29 | 0.31 | 0.74 | 0.39 | 0.58 | 1.06 |
| General Information | -0.35 | 0.23 | -0.16 | -0.24 | -0.06 | -0.03 | 0.34 | 0.28 | 0.08 | 0.51 | 0.25 | 0.37 | 0.89 |
| Data Sufficiency | -0.46 | -0.12 | -0.11 | 0.17 | -0.40 | -0.20 | -0.03 | -0.01 | 0.15 | 0.34 | 0.40 | 0.72 | 0.80 |
| Interpret Diagrams, Tables, and Maps | -0.45 | -0.05 | 0.00 | 0.09 | -0.45 | -0.14 | 0.08 | 0.09 | 0.27 | 0.40 | 0.35 | 0.69 | 0.81 |
| **N students** | **59,173** | **1,966** | **1,033** | **11,125** | **1,778** | **3,699** | **789** | **1,433** | **3,375** | **954** | **3,277** | **7,521** | **499** |
| **Fraction of sample** | **0.61** | **0.02** | **0.01** | **0.12** | **0.02** | **0.04** | **0.01** | **0.01** | **0.03** | **0.01** | **0.03** | **0.08** | **0.01** |
| **Fraction of college enrollment** | | **0.05** | **0.03** | **0.30** | **0.05** | **0.10** | **0.02** | **0.04** | **0.09** | **0.03** | **0.09** | **0.20** | **0.01** |

Table A.6: High School and SweSAT by College Major of Final Degree

| | College Major | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3-year or shorter | | | | | 4-year or longer | | | | | | |
| | **Non-STEM** | **Business** | **STEM** | **HealthSci** | **Education** | **Humanities** | **SocSci** | **Business** | **Law** | **Sciences** | **Engineer** | **Medicine** |
| **Grades, High School** | | | | | | | | | | | | |
| GPA | 0.42 | 0.40 | 0.28 | 0.27 | 0.29 | 0.71 | 0.66 | 0.83 | 1.14 | 0.75 | 1.10 | 1.58 |
| Math | 0.11 | 0.30 | 0.26 | 0.00 | 0.07 | 0.25 | 0.23 | 0.58 | 0.58 | 0.58 | 0.97 | 1.02 |
| English | 0.36 | 0.15 | -0.03 | 0.22 | 0.11 | 0.55 | 0.54 | 0.50 | 0.92 | 0.49 | 0.54 | 1.21 |
| Swedish | 0.54 | 0.35 | 0.19 | 0.31 | 0.37 | 0.90 | 0.81 | 0.76 | 1.23 | 0.68 | 0.85 | 1.53 |
| Sports | 0.10 | 0.41 | 0.18 | 0.32 | 0.36 | -0.03 | 0.21 | 0.44 | 0.38 | 0.21 | 0.36 | 0.57 |
| **High School Track** | | | | | | | | | | | | |
| Vocational | 0.28 | 0.18 | 0.27 | 0.47 | 0.33 | 0.22 | 0.16 | 0.08 | 0.08 | 0.12 | 0.06 | 0.05 |
| Academic non-STEM | 0.49 | 0.61 | 0.15 | 0.30 | 0.44 | 0.49 | 0.54 | 0.64 | 0.57 | 0.22 | 0.05 | 0.13 |
| Academic STEM | 0.23 | 0.21 | 0.59 | 0.23 | 0.23 | 0.29 | 0.31 | 0.27 | 0.35 | 0.66 | 0.88 | 0.82 |
| **SweSAT** | | | | | | | | | | | | |
| Test-taker | 0.81 | 0.87 | 0.72 | 0.86 | 0.78 | 0.72 | 0.91 | 0.90 | 0.90 | 0.88 | 0.82 | 0.93 |
| SweSAT score of test-takers | | | | | | | | | | | | |
| Total | 0.06 | -0.15 | -0.24 | -0.30 | -0.27 | 0.36 | 0.28 | 0.10 | 0.60 | 0.37 | 0.44 | 1.03 |
| Vocabulary | 0.20 | -0.12 | -0.26 | 0.06 | -0.06 | 0.44 | 0.26 | -0.04 | 0.43 | 0.17 | 0.02 | 0.63 |
| Swedish Read. Comprehension | 0.19 | 0.00 | -0.08 | -0.17 | -0.07 | 0.47 | 0.41 | 0.26 | 0.69 | 0.42 | 0.50 | 0.93 |
| English | 0.19 | 0.03 | -0.15 | -0.21 | -0.10 | 0.46 | 0.47 | 0.30 | 0.73 | 0.44 | 0.48 | 1.00 |
| General Information | 0.23 | -0.14 | -0.21 | -0.03 | -0.08 | 0.43 | 0.33 | 0.08 | 0.48 | 0.29 | 0.27 | 0.80 |
| Data Sufficiency | -0.10 | 0.03 | 0.19 | -0.34 | -0.21 | 0.06 | 0.09 | 0.18 | 0.35 | 0.46 | 0.71 | 0.78 |
| Interpret Diag/Tables/ Maps | 0.00 | 0.09 | 0.14 | -0.35 | -0.14 | 0.14 | 0.19 | 0.32 | 0.44 | 0.41 | 0.68 | 0.75 |
| **N students** | **1,565** | **477** | **5,465** | **1,518** | **2,396** | **514** | **922** | **1,959** | **748** | **1,754** | **6,055** | **630** |
| **Fraction of sample** | **0.02** | **0.00** | **0.06** | **0.02** | **0.02** | **0.01** | **0.01** | **0.02** | **0.01** | **0.02** | **0.06** | **0.01** |
| **Fraction of college enrollment** | **0.04** | **0.01** | **0.15** | **0.04** | **0.06** | **0.01** | **0.02** | **0.05** | **0.02** | **0.05** | **0.16** | **0.02** |
| **Fraction of college graduates** | **0.07** | **0.02** | **0.23** | **0.06** | **0.10** | **0.02** | **0.04** | **0.08** | **0.03** | **0.07** | **0.25** | **0.03** |

Table A.7: Age, Choices, and Outcomes by College Major

| | | College Major | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 3-year or shorter | | | | | 4-year or longer | | | | | | |
| | No enroll (HS grad) | Non-STEM | Business | STEM | Health Sci | Education | Humanities | SocSci | Sciences | Business | Law | Engineer | Medicine |
| **Age at** | | | | | | | | | | | | | |
| 9th grade graduation | 16.03 | 16.00 | 16.01 | 16.01 | 16.01 | 16.01 | 15.99 | 16.00 | 16.00 | 16.00 | 15.99 | 15.99 | 15.98 |
| High school graduation | 18.66 | 18.92 | 18.98 | 18.92 | 18.87 | 18.90 | 18.98 | 19.03 | 19.01 | 19.06 | 19.10 | 19.04 | 19.10 |
| First academic college enrollment | | 24.03 | 23.66 | 21.68 | 25.18 | 23.84 | 22.40 | 22.85 | 21.63 | 21.90 | 22.14 | 20.62 | 22.24 |
| **College Outcomes** | | | | | | | | | | | | | |
| Stayed enrolled, initial college major | | 0.76 | 0.57 | 0.81 | 0.91 | 0.82 | 0.55 | 0.60 | 0.68 | 0.74 | 0.80 | 0.84 | 0.91 |
| Graduated, initial college major | | 0.37 | 0.17 | 0.41 | 0.70 | 0.56 | 0.32 | 0.31 | 0.37 | 0.41 | 0.61 | 0.63 | 0.85 |
| College graduate | | 0.55 | 0.53 | 0.55 | 0.77 | 0.69 | 0.70 | 0.65 | 0.62 | 0.62 | 0.75 | 0.74 | 0.92 |
| **Labor Market Outcomes** | | | | | | | | | | | | | |
| Monthly Wages | | 33,909 | 40,380 | 37,962 | 30,756 | 28,568 | 34,035 | 37,581 | 37,568 | 48,022 | 46,885 | 44,689 | 54,110 |
| PV Disposable Income (1000s) | | 4,822 | 6,342 | 6,214 | 5,348 | 4,868 | 4,474 | 5,579 | 5,671 | 7,155 | 7,822 | 6,618 | 8,711 |
| **N students** | **59,173** | **1,966** | **1,033** | **11,125** | **1,778** | **3,699** | **789** | **1,433** | **3,277** | **3,375** | **954** | **7,521** | **499** |
| **Fraction of sample** | **0.61** | **0.02** | **0.01** | **0.12** | **0.02** | **0.04** | **0.01** | **0.01** | **0.03** | **0.03** | **0.01** | **0.08** | **0.01** |
| **Fraction of college enrollment** | | **0.05** | **0.03** | **0.30** | **0.05** | **0.10** | **0.02** | **0.04** | **0.09** | **0.09** | **0.03** | **0.20** | **0.01** |
| **Age at** | | | | | | | | | | | | | |
| 9th grade graduation | | 16.00 | 15.99 | 16.01 | 16.01 | 16.01 | 16.00 | 16.00 | 16.00 | 16.00 | 15.99 | 15.99 | 15.98 |
| High school graduation | | 18.93 | 18.97 | 18.91 | 18.88 | 18.89 | 18.94 | 19.05 | 19.00 | 19.08 | 19.11 | 19.03 | 19.10 |
| First academic college enrollment | | 23.00 | 22.78 | 21.59 | 24.17 | 23.18 | 22.71 | 22.27 | 21.12 | 21.43 | 21.54 | 20.36 | 21.53 |
| Last academic college degree | | 28.66 | 22.75 | 26.29 | 29.32 | 27.31 | 29.06 | 28.85 | 27.61 | 27.72 | 27.77 | 26.73 | 27.89 |
| **College Outcomes** | | | | | | | | | | | | | |
| Stayed enrolled, initial college major | | 0.47 | 0.36 | 0.83 | 0.82 | 0.86 | 0.50 | 0.48 | 0.68 | 0.70 | 0.78 | 0.79 | 0.67 |
| **Labor Market Outcomes** | | | | | | | | | | | | | |
| Monthly Wages | | 35,917 | 45,961 | 38,954 | 31,252 | 28,119 | 31,564 | 38,295 | 37,980 | 51,842 | 48,470 | 46,154 | 52,402 |
| PV Disposable Income (1000s) | | 5,199 | 7,299 | 6,755 | 5,664 | 5,188 | 4,068 | 5,503 | 5,960 | 7,912 | 8,945 | 7,168 | 8,892 |
| **N students** | | **1,565** | **477** | **5,465** | **1,518** | **2,396** | **514** | **922** | **1,754** | **1,959** | **748** | **6,055** | **630** |
| **Fraction of sample** | | **0.02** | **0.00** | **0.06** | **0.02** | **0.02** | **0.01** | **0.01** | **0.02** | **0.06** | **0.01** | **0.02** | **0.01** |
| **Fraction of college enrollment** | | **0.04** | **0.01** | **0.15** | **0.04** | **0.06** | **0.01** | **0.02** | **0.05** | **0.05** | **0.02** | **0.16** | **0.02** |
| **Fraction of college graduates** | | **0.07** | **0.02** | **0.23** | **0.06** | **0.10** | **0.02** | **0.04** | **0.07** | **0.08** | **0.03** | **0.25** | **0.03** |

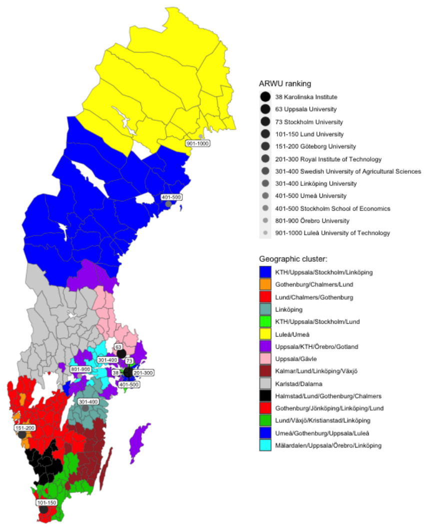
Table A.8: College Programs within Major, First Enrollment

| College Major, 1st enrollment | Fraction of major | SUN2000Inr Code |
|---|---|---|
| **Non-STEM (short)** | | |
| Journalism and Media Science | 0.14 | 321 |
| History and Archeology | 0.13 | 225 |
| Media production | 0.10 | 213 |
| Transportation | 0.05 | 840 |
| Sociology, Ethnology, and Cultural Geography | 0.06 | 312 |
| **Business (short)** | | |
| 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 |
| **STEM (short)** | | |
| 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 |
| **Health Sci** | | |
| Nursing | 0.47 | 723 |
| Social work and Guidance | 0.23 | 762 |
| Therapy, Rehabilitation, and Dietary treatment | 0.15 | 726 |
| Dental care | 0.05 | 724 |
| Technically oriented health education | 0.05 | 725 |
| **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 |
| **Humanities** | | |
| Foreign Language | 0.21 | 222 |
| History and Archeology | 0.18 | 225 |
| Religion | 0.17 | 221 |
| Music, Dance, and Drama | 0.15 | 212 |
| Media production | 0.07 | 213 |
| **Social Sciences** | | |
| Social and Behavioral Science (general) | 0.47 | 310 |
| Psychology | 0.11 | 311 |
| Sociology, Ethnology, and Cultural Geography | 0.07 | 312 |
| Transportation | 0.07 | 840 |
| Political Science | 0.06 | 313 |
| **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 |
| **Law** | | |
| Law | 1.00 | 380 |
| **Sciences and Computer Science** | | |
| Computer Science and Systems Science | 0.37 | 481 |
| Mathematics and Science (other) | 0.25 | 469 |
| Biology and Biochemistry | 0.07 | 421 |
| Physics | 0.06 | 441 |
| Chemistry | 0.04 | 442 |
| **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 |
| **Medicine** | | |
| Medicine | 1.00 | 721 |

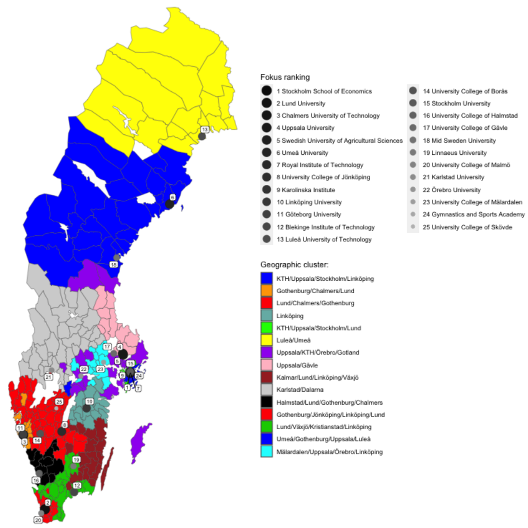
Table A.9: College Programs within Major, Final Graduation

| College Major, final graduation | Fraction of major | SUN2000Inr Code |
|---|---|---|
| **Non-STEM (short)** | | |
| Journalism and Media Science | 0.10 | 321 |
| Political Science | 0.10 | 313 |
| Economics and Economic History | 0.10 | 314 |
| Transportation | 0.10 | 840 |
| Sociology, Ethnology, and Cultural Geography | 0.08 | 312 |
| **Business (short)** | | |
| Business Administration, Trade and Administration (general) | 0.93 | 340 |
| Business Administration, Trade and Administration (other) | 0.03 | 349 |
| Management and Administration | 0.02 | 345 |
| Banking, Insurance, and Finance | 0.02 | 343 |
| Purchasing, Sales, and Distribution | 0.01 | 341 |
| **STEM (short)** | | |
| Energy and Electrical Engineering | 0.21 | 522 |
| Mechanical Engineering | 0.20 | 521 |
| Electronics, Computer Engineering and Automation | 0.15 | 523 |
| Building- and Construction Engineering | 0.12 | 582 |
| Computer Science and Systems Science | 0.10 | 481 |
| **Health Sci** | | |
| Nursing | 0.49 | 723 |
| Social work and Guidance | 0.17 | 762 |
| Therapy, Rehabilitation, and Dietary treatment | 0.17 | 726 |
| Dental care | 0.06 | 724 |
| Technically oriented health education | 0.05 | 725 |
| **Education** | | |
| Specialist Teacher | 0.44 | 145 |
| Teacher, primary school | 0.21 | 144 |
| Teacher, preschool and leisure activities | 0.15 | 143 |
| Teacher, vocational and practical/aesthetic subjects | 0.15 | 146 |
| Pedagogy | 0.04 | 142 |
| **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 |
| **Social Sciences** | | |
| Economics and Economic History | 0.28 | 314 |
| Political Science | 0.25 | 313 |
| Psychology | 0.20 | 311 |
| Sociology, Ethnology, and Cultural Geography | 0.13 | 312 |
| Library and Documentation | 0.07 | 322 |
| **Business** | | |
| Management and Administration | 0.88 | 343 |
| Banking, Insurance, and Finance | 0.07 | 345 |
| Business Administration, Trade and Administration (general) | 0.04 | 340 |
| Business Administration, Trade and Administration (other) | 0.00 | 349 |
| **Law** | | |
| Law | 1.00 | 380 |
| **Sciences and Computer Science** | | |
| Computer Science and Systems Science | 0.38 | 481 |
| Biology and Biochemistry | 0.18 | 421 |
| Chemistry | 0.12 | 442 |
| Physics | 0.07 | 441 |
| Earth Sciences and Geography | 0.05 | 443 |
| **Engineering** | | |
| Mechanical Engineering | 0.22 | 521 |
| Energy and Electrical Engineering | 0.15 | 522 |
| Technology and Industry Engineering (general) | 0.14 | 520 |
| Electronics, Computer Engineering and Automation | 0.14 | 523 |
| Industrial Economics and Organization | 0.10 | 526 |
| **Medicine** | | |
| Medicine | 1.00 | 721 |

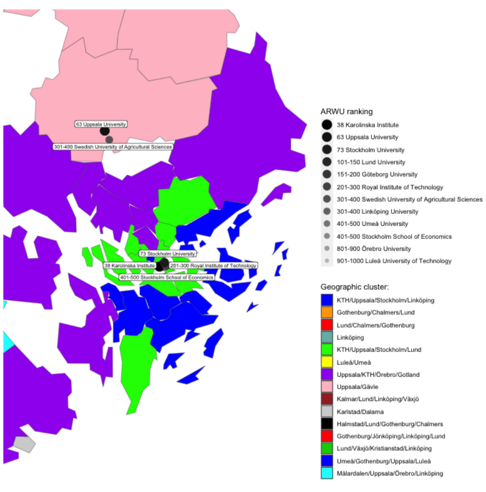
Figure A.2: Maps of College Applications in Sweden and Stockholm (15 clusters)



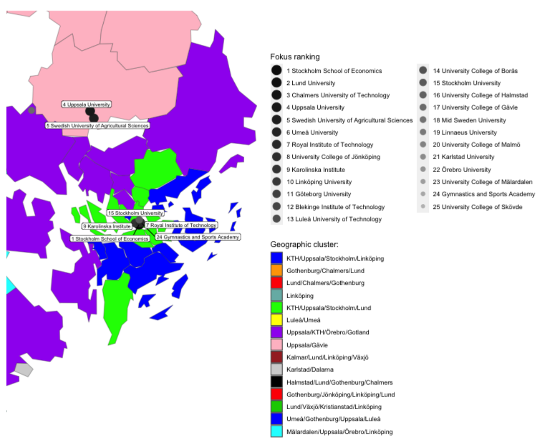

(a) Sweden (ARWU ranking)




(b) Sweden (Fokus ranking)



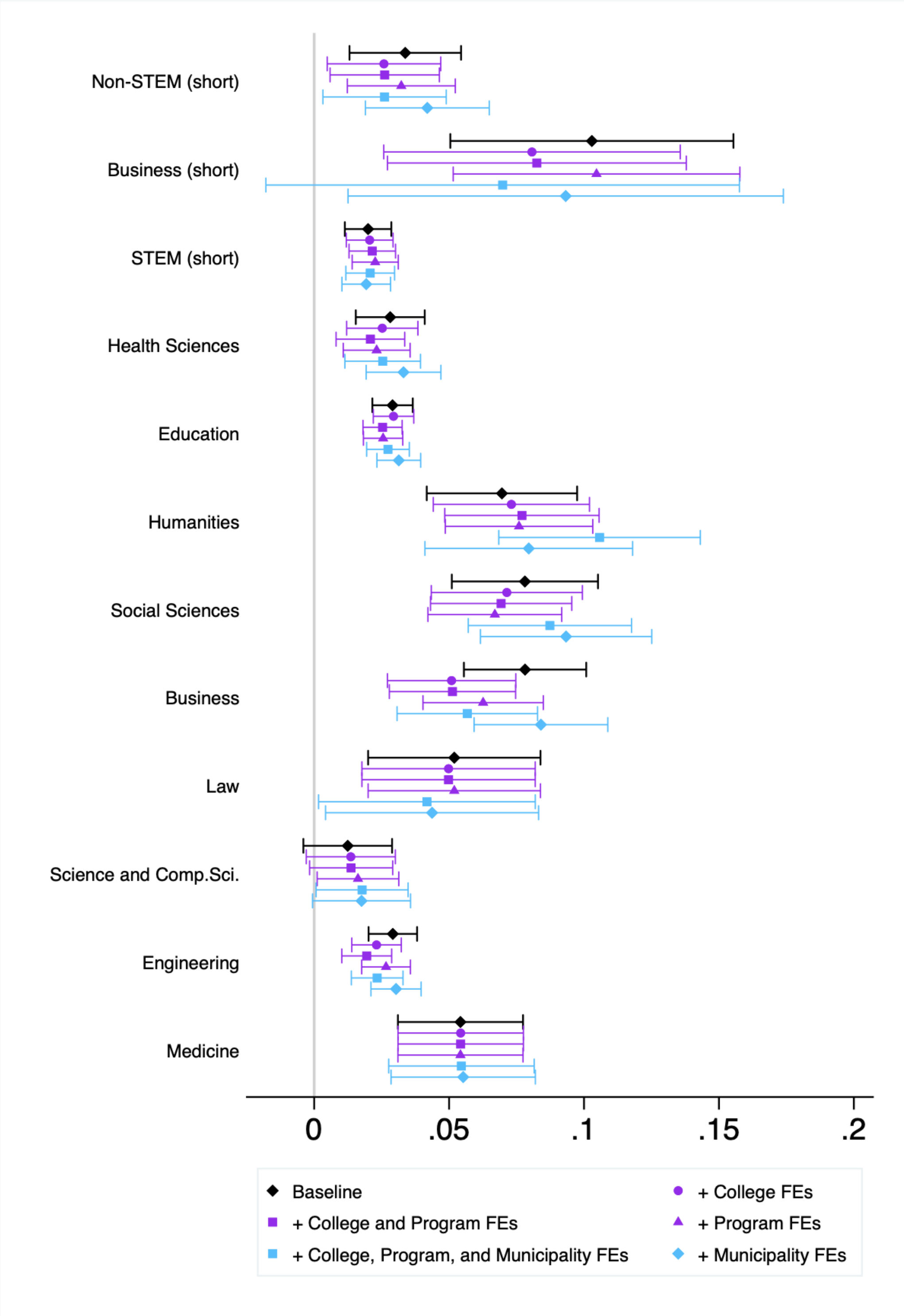

(c) Stockholm (ARWU ranking)




(d) Stockholm (Fokus ranking)

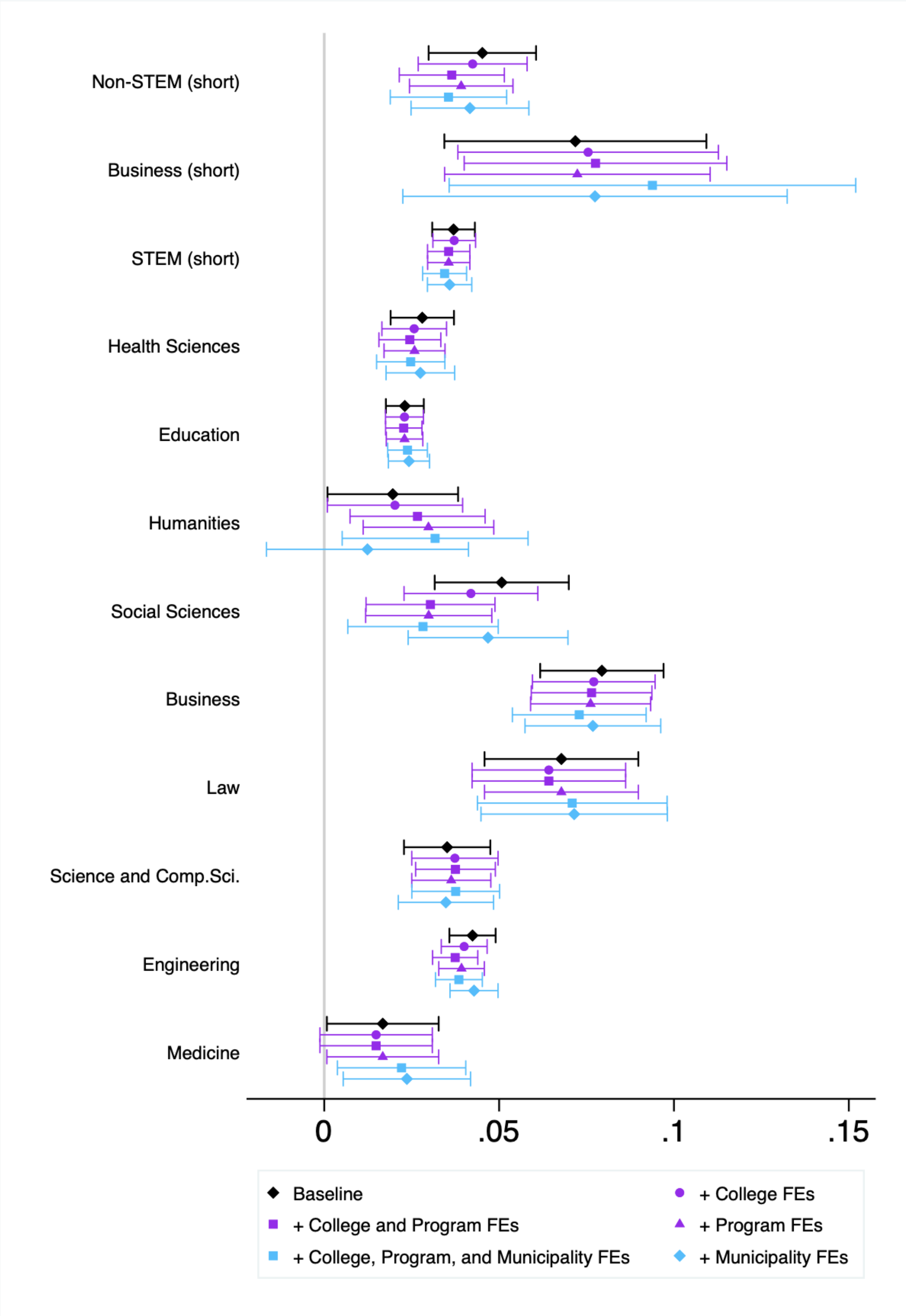
*Note*: This Figure plots the 15 geographic clusters we us when modeling college applications. The figure additionally shows the topped-ranked universities (based on ARWU ranking).

Figure A.3: Sensitivity of the Association Between Cognitive Skills and Wages within Final College Major



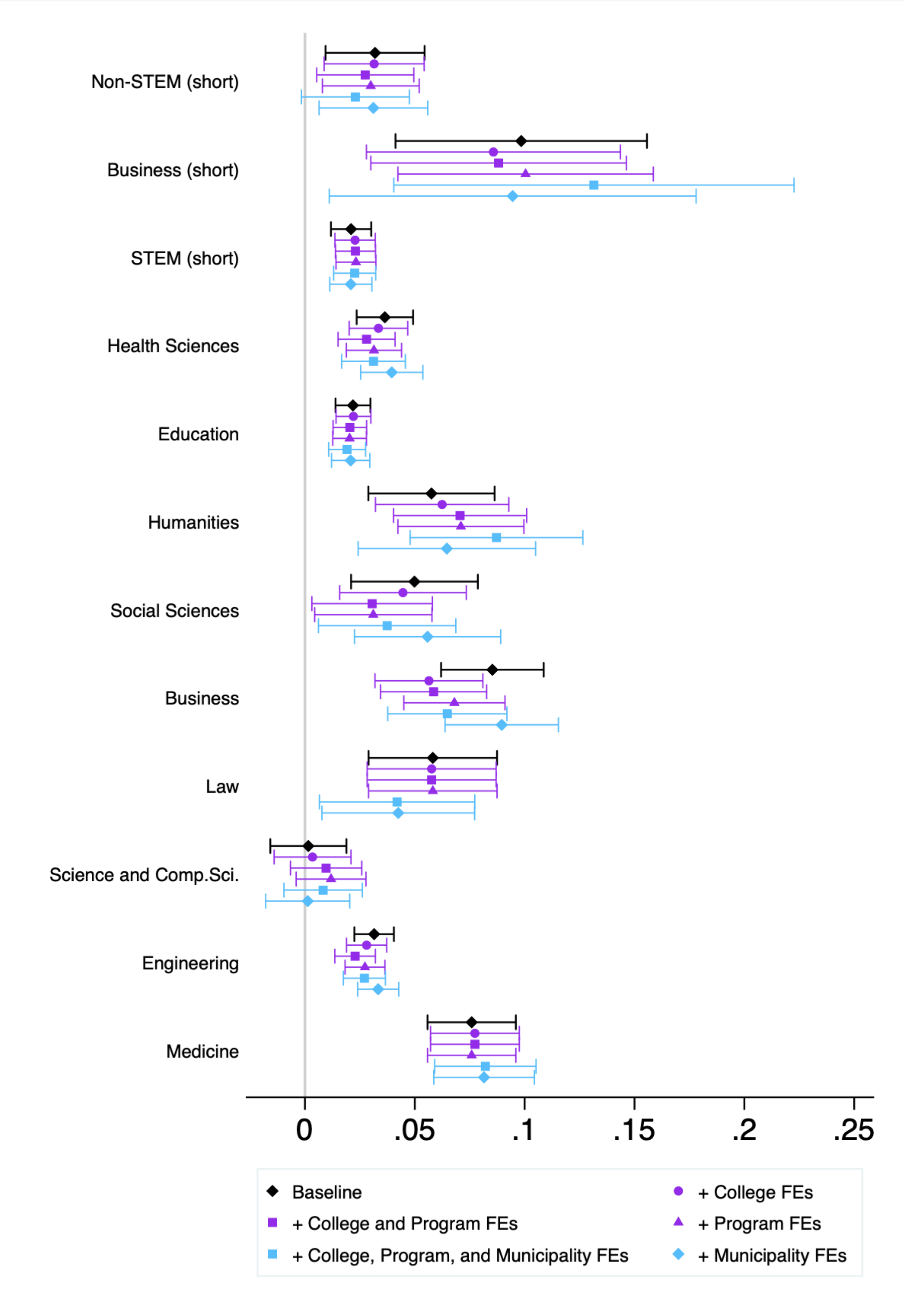

*Note*: This figure displays OLS estimates of $\lambda^{Y}_{s,\theta^{cog}}$ on cognitive skills and 95% confidence interval I-caps from log full-time wage regressions like equation (3) within each of the 12 final college majors $s$ given by: $Y_{is} = \boldsymbol{\beta}^{Y}_{s}\boldsymbol{X}_{i} + \boldsymbol{\beta}^{Y}_{s,D_2}\boldsymbol{D}_{2i} + \boldsymbol{\lambda}^{Y}_{s}\boldsymbol{\theta}_{i} + \varepsilon_{is}$, where we additionally include fixed effects indicating categories of college programs, institutions, and municipalities in $\boldsymbol{X}$. Baseline controls include average disposable family income in mother's household at child age 5-18, mother's and father's education level indicators, strength, fitness, ninth grade advanced course choices, high school track choices, multidimensional skills, college major-specific high school GPA quartiles, and the 15 geo clusters.

Figure A.4: Sensitivity of the Association Between Interpersonal Skills and Wages within Final College Major



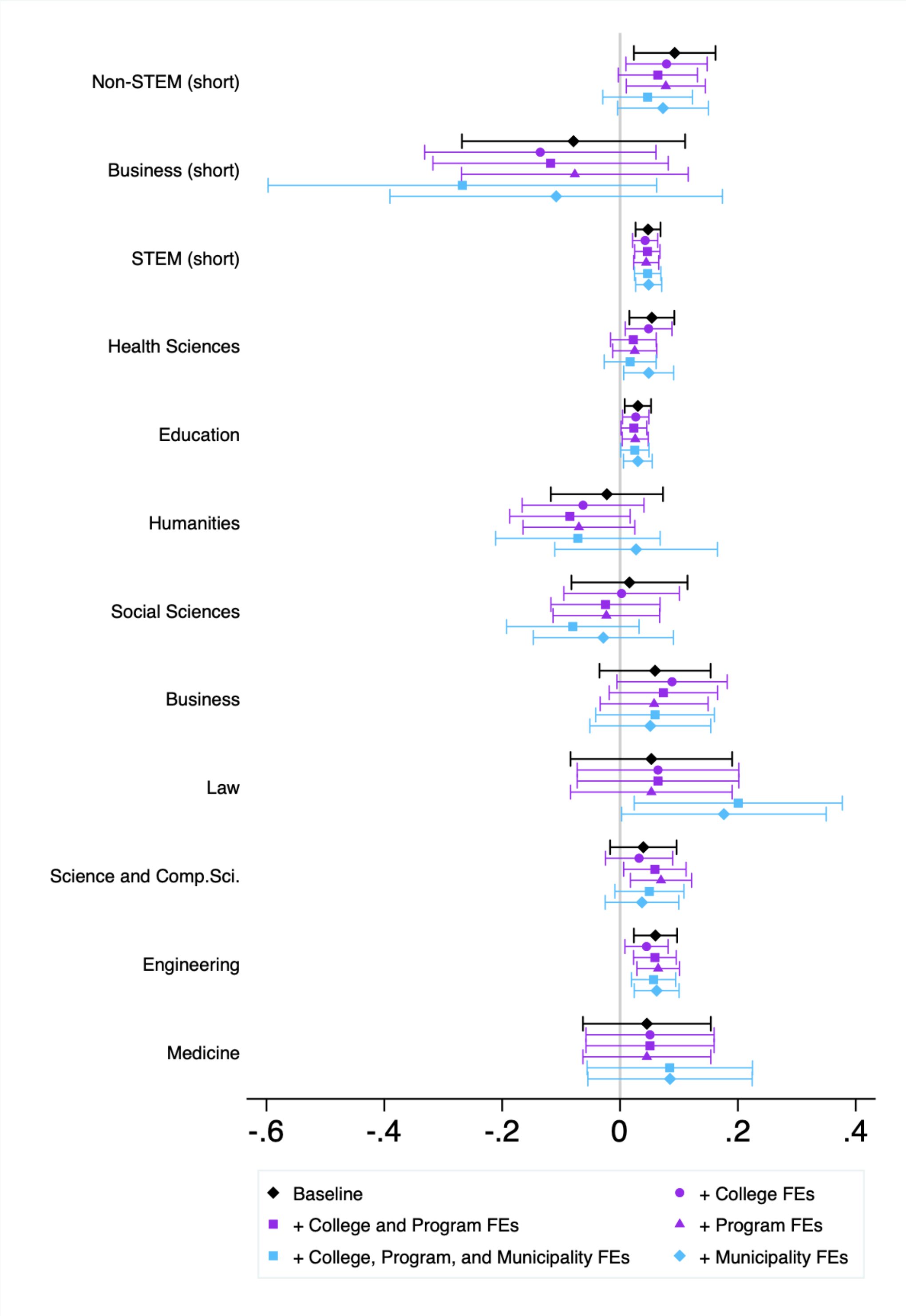

*Note*: This figure displays OLS estimates of $\lambda^{Y}_{s,\theta interp}$ on interpersonal skills and 95% confidence interval I-caps from log full-time wage regressions like equation (3) within each of the 12 final college majors $s$ given by: $Y_{is} = \boldsymbol{\beta}^{Y}_{s}\boldsymbol{X}_i + \boldsymbol{\beta}^{Y}_{s,D_2}\boldsymbol{D}_{2i} + \boldsymbol{\lambda}^{Y}_{s}\boldsymbol{\theta}_i + \varepsilon_{is}$, where we additionally include fixed effects indicating categories of college programs, institutions, and municipalities in $\boldsymbol{X}$. Baseline controls include average disposable family income in mother's household at child age 5-18, mother's and father's education level indicators, strength, fitness, ninth grade advanced course choices, high school track choices, multidimensional skills, college major-specific high school GPA quartiles, and the 15 geo clusters.

Figure A.5: Sensitivity of the Association Between Grit Skills and Wages within Final College Major



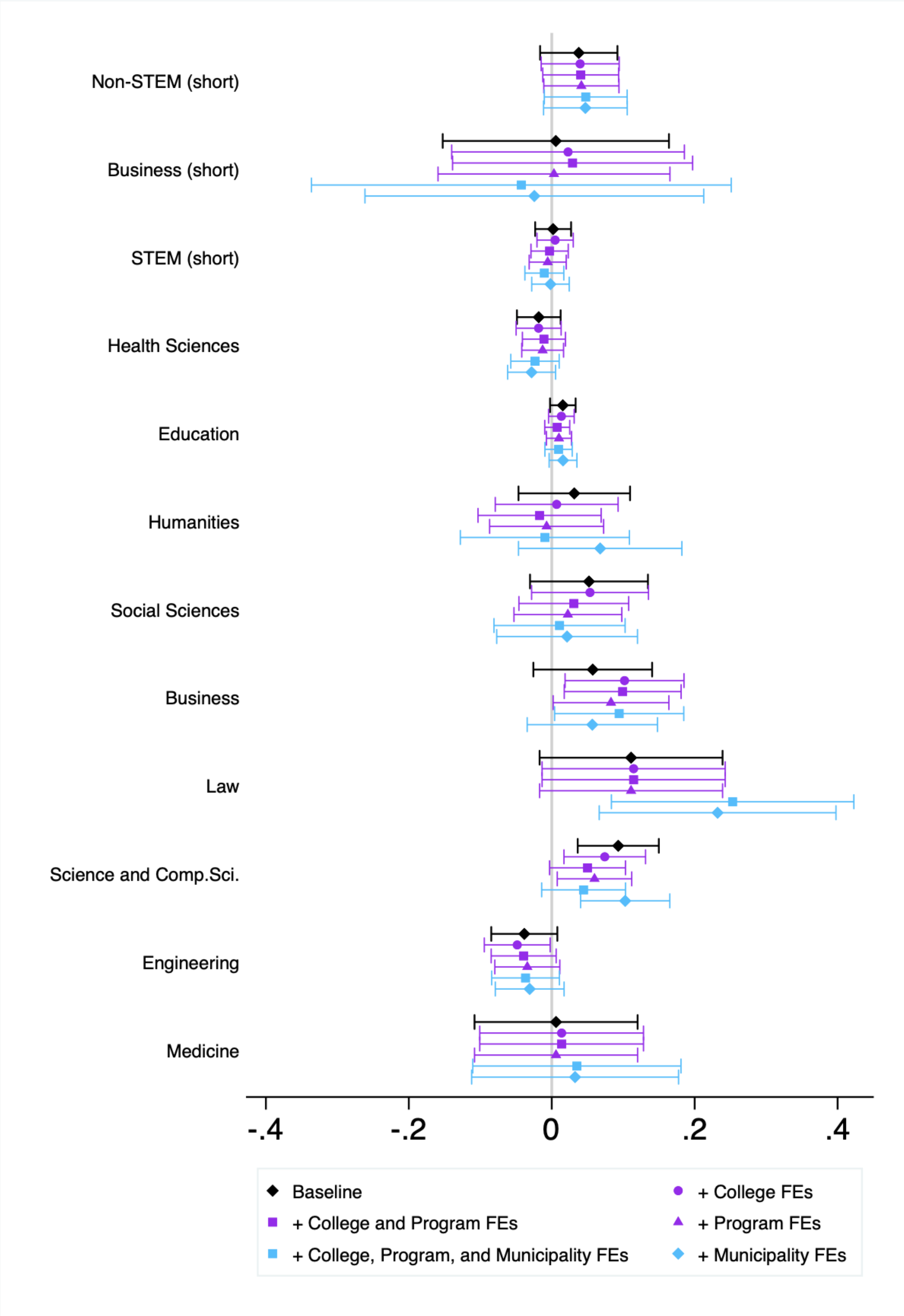

*Note*: This figure displays OLS estimates of $\lambda^{Y}_{s,\theta grit}$ on grit skills and 95% confidence interval I-caps from log full-time wage regressions like equation (3) within each of the 12 final college majors $s$ given by: $Y_{is} = \boldsymbol{\beta}^{Y}_{s}\boldsymbol{X}_i + \boldsymbol{\beta}^{Y}_{s,D_2}\boldsymbol{D}_{2i} + \boldsymbol{\lambda}^{Y}_{s}\boldsymbol{\theta}_i + \varepsilon_{is}$, where we additionally include fixed effects indicating categories of college programs, institutions, and municipalities in $\boldsymbol{X}$. Baseline controls include average disposable family income in mother's household at child age 5-18, mother's and father's education level indicators, strength, fitness, ninth grade advanced course choices, high school track choices, multidimensional skills, college major-specific high school GPA quartiles, and the 15 geo clusters.

Figure A.6: Sensitivity of the Association Between Academic STEM High School and Wages within Final College Major




*Note*: This figure displays OLS estimates of $\beta^{Y}_{s,D_2(\mathcal{K}_2)=4}$ on the academic STEM high school track indicator and 95% confidence interval I-caps from log full-time wage regressions like equation (3) within each of the 12 final college majors $s$ given by: $Y_{is} = \boldsymbol{\beta}^{Y}_{s}\boldsymbol{X}_i + \boldsymbol{\beta}^{Y}_{s,D_2}\boldsymbol{D}_{2i} + \boldsymbol{\lambda}^{Y}_{s}\boldsymbol{\theta}_i + \varepsilon_{is}$, where we additionally include fixed effects indicating categories of college programs, institutions, and municipalities in $\boldsymbol{X}$. Baseline controls include average disposable family income in mother's household at child age 5-18, mother's and father's education level indicators, strength, fitness, ninth grade advanced course choices, high school track choices, multidimensional skills, college major-specific high school GPA quartiles, and the 15 geo clusters.

Figure A.7: Sensitivity of the Association Between Academic Non-STEM High School and Wages within Final College Major




*Note*: This figure displays OLS estimates of $\beta^Y_{s,D_2(\mathcal{K}_2)=3}$ on the academic non-STEM high school track indicator and 95% confidence interval I-caps from log full-time wage regressions like equation (3) within each of the 12 final college majors $s$ given by: $Y_{is} = \boldsymbol{\beta}^Y_s \boldsymbol{X}_i + \boldsymbol{\beta}^Y_{s,D_2} \boldsymbol{D}_{2i} + \boldsymbol{\lambda}^Y_s \boldsymbol{\theta}_i + \varepsilon_{is}$, where we additionally include fixed effects indicating categories of college programs, institutions, and municipalities in $\boldsymbol{X}$. Baseline controls include average disposable family income in mother's household at child age 5-18, mother's and father's education level indicators, strength, fitness, ninth grade advanced course choices, high school track choices, multidimensional skills, college major-specific high school GPA quartiles, and the 15 geo clusters.

## A.4 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 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 $\beta = 0.95$.

# B Identification and Estimation of Latent Skills

Since most proxies of skill are measured with error, we use a factor model to recover latent skills. First, we briefly describe the identification of latent skills when some measures are taken after schooling investments have been made. Second, we describe the specification of the measurement system.

**Identification of Latent Skills** If skills were directly observable, we could include them in our models along with other observables on demographics and family background. Instead, skills need to be identified from proxies such as test scores or behavior. In this paper, we identify latent skills 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 skills. 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 $M_{ms}$ denote the $m$th measure evaluated at schooling state $s$. We define $\tilde{M}_{ms}$ as latent variables that map into observed measures $M_{ms}$,

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

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

$$\tilde{M}_{ms} = \alpha_{ms} + \boldsymbol{\beta}_m^M \boldsymbol{X} + \boldsymbol{\lambda}_m^M \boldsymbol{\theta} + u_m,$$

where $\alpha_{ms}$ represents schooling-state specific intercepts for measure $m$, $\boldsymbol{X}$ is a vector of observables, $\boldsymbol{\theta}$ is a vector of latent skills, and $u_m$ is the error term. We assume that $u_m$ are mutually independent across each $m$ 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 skills. The term $\alpha_{ms}$ 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 $\alpha_{ms}$ in the measurement system implies that our latent skills are measured relative to a reference schooling state ($s = 0$). In Appendix Section B.1, 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 skills 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.[39] This is not without loss of generality as a student's background (e.g. mother's education) is also an important determinant of their skills. Hence, when we report deciles of latent skills, we are measuring "residual" latent skills. That is, the variation in latent skills that is orthogonal to the observables.

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

We include the observables whenever we estimate a model with latent skills and, hence, still capture differences across students due to both observables and latent skills.[40]

**Specification of Measurement System** 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.[41]

In order to facilitate interpretation of the factors, we specify a triangular measurement system with orthogonal factors.[42] On one hand, the measures from the military data could be treated as dedicated measures, and we would be able to use a different specification that has correlated factors. On the other hand, it would be difficult to argue that the grade measures are dedicated measures of a third factor and do not directly depend on the cognitive skills 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.[43] The second set of measures include the variables from the psychological evaluation performed by the military psychologists. They provide two variables that measure "leadership" skills 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.[44] 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.

[40] 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).

[41] See Williams (2020) for more details on the identification of factor models. 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.

[42] 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.

[43] 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 skills. See Grönqvist and Lindqvist (2016) for more details on this selection.

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

## B.1 Identification of Factor Model

In this section, we show that the effect of schooling at the time of the test ($\alpha_{ms}$) and mean skills 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.[45] 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 ($M_{ms}$), 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.[46]

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

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

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 2020), 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 $\alpha_{ms}$. 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:

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

[45] In the Swedish setting, Carlsson et al. (2015) also show that schooling can have an effect on the cognitive military test scores. Particularly the crystallized intelligence test scores (synonyms and technical comprehension) but not to the same extent the fluid intelligence test scores (spatial and logic).

[46] The number of measures required depends on the number of factors, the normalizations, and over-identifying assumptions used in the measurement system. See Williams (2020) for more details.

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

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

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:

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

## B.2 Sorting into High School Track and College Major

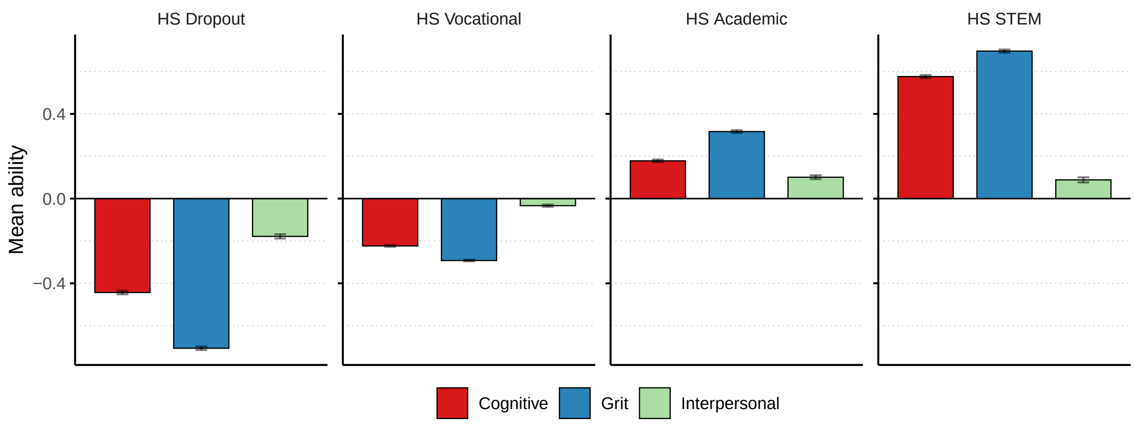
In this section, we investigate how students sort by multidimensional skills into high school track and college major. If skills were observed, we could simply estimate the conditional mean of each skill by high school track or college major. One approach, taken in Table 2, calculates the average of noisy estimates of the skills for different groups of individuals in our data. 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 5.2, we develop an alternative approach that estimates the mean skills for different subgroups without imposing any structure on how individuals make education decisions. The mean latent skill in each education category can be estimated using a set of simple linear models:

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

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 skill and set of mutually exclusive educational states.[47]

[47] These models are estimated via maximum likelihood using the first stage measurement system as described in section D, where we assume that $\eta_{is}$ is normally distributed. See Appendix Section D.2 for a description of the likelihood estimation.

Figure B.1: Sorting into High School Track by Skills



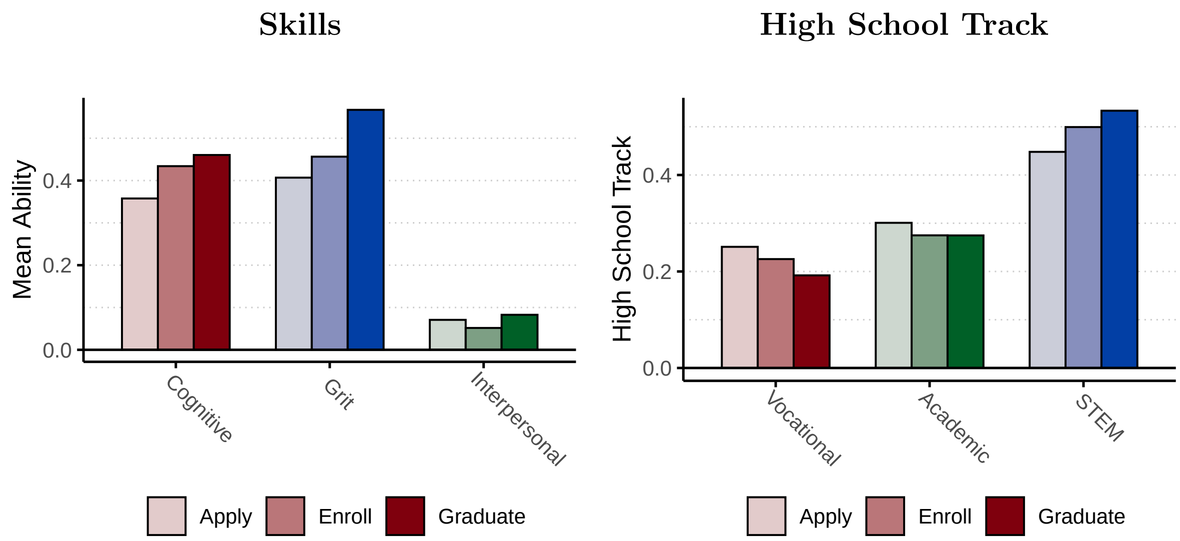

*Notes*: Figure shows the average interpersonal, cognitive, and grit skills by high school track. All skills are normalized to be mean 0 and standard deviation one for the full population.

**Sorting into High School Track** Figure B.1 shows how students sort into high school track by skill. The figure shows the average levels of the three skills based on high school track choice. All three skills 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 skills and weaker sorting on interpersonal skills. The average cognitive skills of academic (STEM) students are 0.18 (0.58) standard deviations above the mean, while the average cognitive skills 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 skills.

**Sorting into College** Figure B.2 show how students sort into post-secondary decisions by skills (left panel) and high school track (right panel). The left panel shows the average cognitive, grit, and interpersonal skills of those who apply, enroll, and graduate from college. skills 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 skills and 0.4 standard deviations higher in grit. Moving from applications to enrollment sees a large jump in cognitive skills, likely related to admissions, while moving from enrollment to graduation sees a large jump in grit. Students also sort on interpersonal skills, but substantially less.

The right panel shows the means of high school track indicators for those who apply, 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

Figure B.2: Sorting into College: Applications, Enrollment, and Graduation




*Notes*: The left panel plots the average cognitive (red), grit (blue), and interpersonal (green) skills 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.

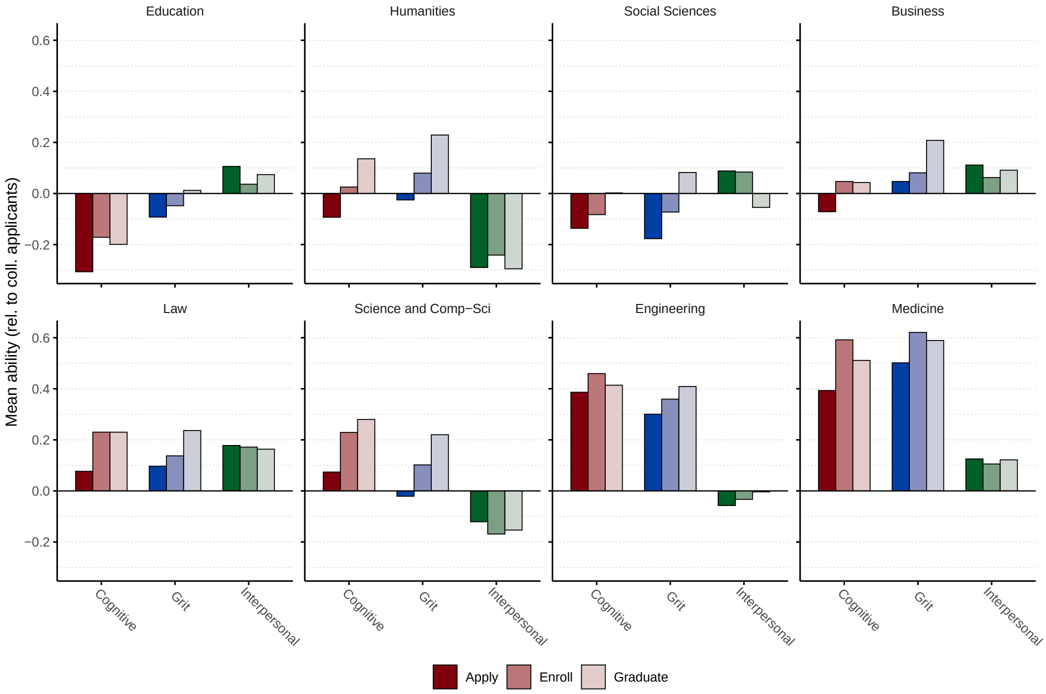
of graduates.

Figure B.3 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 skills where each sub-panel is a specific 4-year major. The skills 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 skills across majors. For example, those who apply, enroll, and graduate in engineering tend to be high in cognitive skills and grit, but slightly below average in interpersonal skills. In contrast, for education majors, cognitive skills 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 skills, and 0.05 higher in cognitive skills.

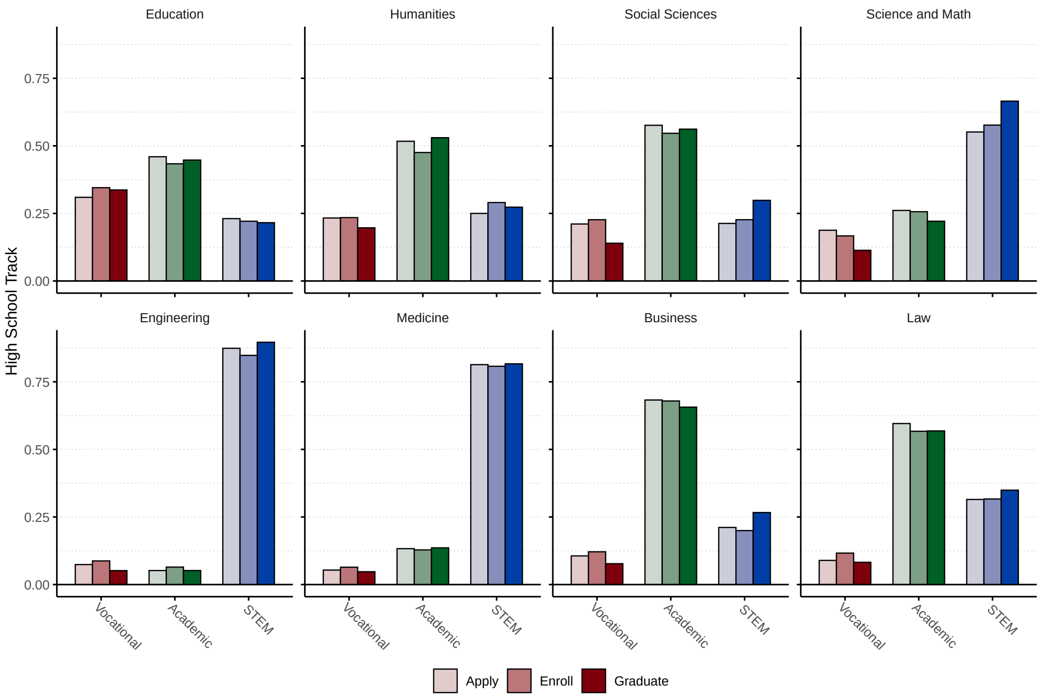
The bottom panel of Figure B.3 shows the proportion of applicants, enrollees, and graduates that come from each high school track for each 4-year major. Some programs, such as education, are somewhat balanced, with less than half coming from any of the three tracks, while other programs are skewed, such 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 B.3: Sorting into Majors: Application, Enrollment, and Graduation

## Skills




## High School Track




*Notes*: The top panel shows the average interpersonal, cognitive, and grit skills by four-year major. All skills 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. $E[\text{Track} = \text{STEM}|\text{Applied} = 1]$).

# C Instruments for High School and College Choices

## C.1 Within-School-Across-Cohort Instruments

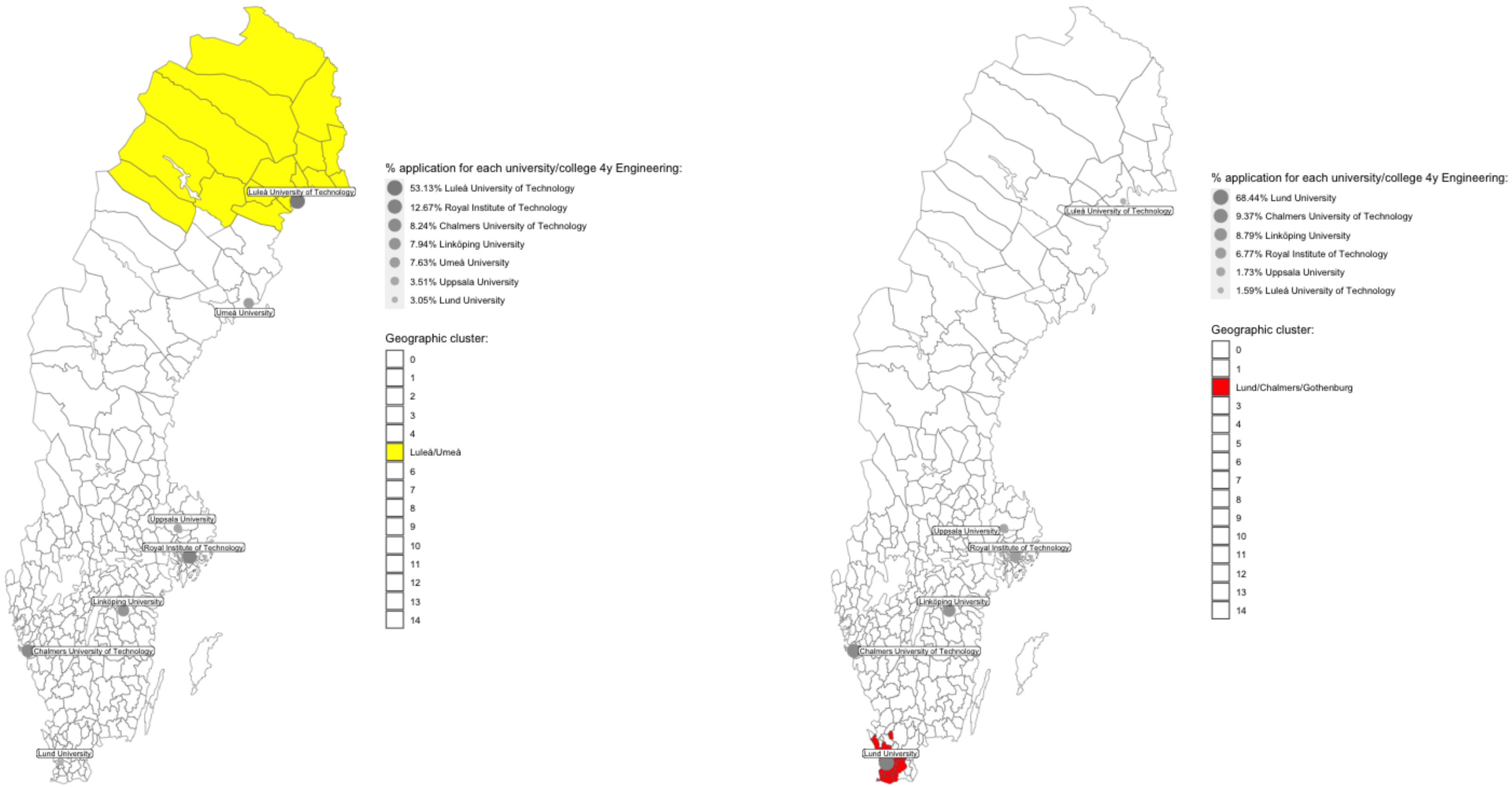
Table C.1: The Effect of Peers' Choices on Own Choices (within-school-across-cohort)

| | (1) | (2) | (3) |
|---|---|---|---|
| **High School Choice:** | | | |
| Vocational | 0.0146*** | 0.0143*** | 0.0171*** |
| | (0.00172) | (0.00163) | (0.00169) |
| Academic non-STEM | 0.0162*** | 0.0160*** | 0.0165*** |
| | (0.00163) | (0.00161) | (0.00166) |
| Academic STEM | 0.00660*** | 0.00693*** | 0.0135*** |
| | (0.00149) | (0.00136) | (0.00145) |
| **College Application Choice:** | | | |
| Business (short) | 0.00418*** | 0.00418*** | 0.00411*** |
| | (0.000771) | (0.000771) | (0.000770) |
| STEM (short) | 0.0194*** | 0.0194*** | 0.0194*** |
| | (0.00142) | (0.00142) | (0.00143) |
| Health Sciences | 0.00561*** | 0.00559*** | 0.00548*** |
| | (0.00126) | (0.00126) | (0.00126) |
| Education | 0.00724*** | 0.00722*** | 0.00709*** |
| | (0.00113) | (0.00113) | (0.00114) |
| Humanities | 0.00313*** | 0.00308*** | 0.00290*** |
| | (0.000624) | (0.000622) | (0.000621) |
| Social Sciences | 0.00319*** | 0.00317*** | 0.00315*** |
| | (0.000806) | (0.000806) | (0.000807) |
| Business | 0.00592*** | 0.00578*** | 0.00568*** |
| | (0.00126) | (0.00125) | (0.00126) |
| Law | 0.00294*** | 0.00285*** | 0.00275*** |
| | (0.000632) | (0.000631) | (0.000637) |
| Science and Comp.Sci | 0.0112*** | 0.0110*** | 0.0110*** |
| | (0.00111) | (0.00111) | (0.00111) |
| Engineering | 0.0124*** | 0.0118*** | 0.0120*** |
| | (0.00178) | (0.00177) | (0.00181) |
| Medicine | 0.00272*** | 0.00270*** | 0.00272*** |
| | (0.000747) | (0.000744) | (0.000750) |
| School and Cohort FE | x | x | x |
| School-Specific Time Trend | x | x | x |
| Own Skills | | x | x |
| Avg. Skills of Classmates | | | x |

*Notes*: Standard errors in parentheses. Each entry in the table represents a separate estimation of a linear probability model for making the choice listed in the first column ($D_{ij} = k_j$) on the fraction of classmates making the same choice ($P^{k_j}_{-icp}$). High School models are with respect to classmates in 9th grade. College choice models are with respect to classmates in the same track in the same high school. Skills in 9th grade is measured using 9th grade GPA. Skills in High School is measured using skills as measured by the military enlistment measures on cognitive and leadership abilities. All specifications additionally include the following controls: mother's education, father's education, family income, parents married, healthy at birth, mother's age at birth, cohort dummies. Also included are 9th grade school average rates of advanced english and math. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

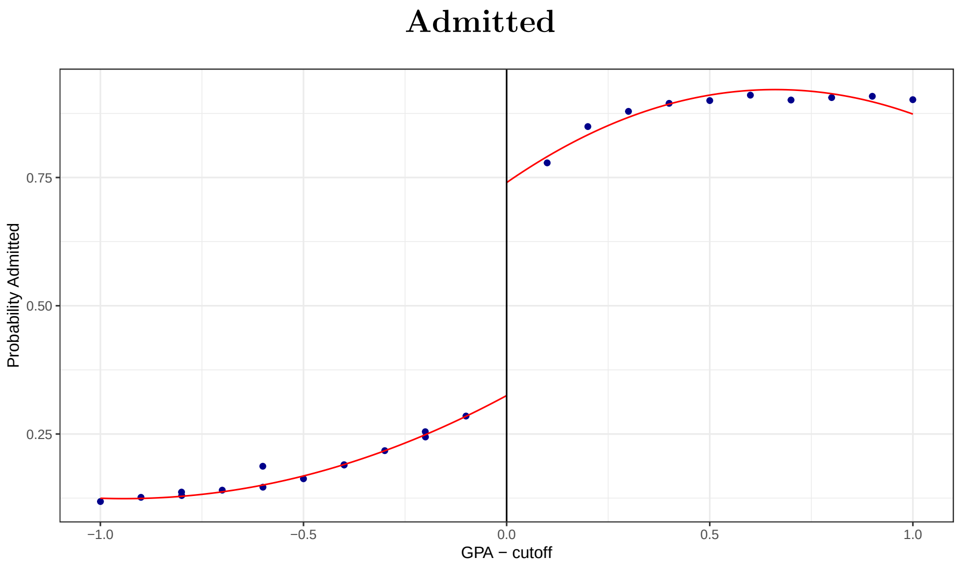
### C.2 College Admissions Cutoffs

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 based on GPA cutoff




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

Table C.2: 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 Non-STEM Track | 0.017** |
| | (0.007) |
| HS Academic 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 Estimation Strategy and Model Fit

## D.1 Model

### D.1.1 Treatment effects in General Model

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

$$\mathbb{E}[Y_t] = \int\int\int Y_t(\boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\eta}_t) dF_{\boldsymbol{\eta}_t}(\boldsymbol{\eta}_t) dF_{\boldsymbol{X}_t}(\boldsymbol{X}_t|\boldsymbol{\xi}) dF_{\boldsymbol{\xi}}(\boldsymbol{\xi}), \tag{D.1}$$

where $Y_t(\boldsymbol{X}_t, \boldsymbol{\xi})$ is the hedonic portion of earnings and $\boldsymbol{\eta}_t$ is a mean-zero idiosyncratic shock. 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 $\boldsymbol{\eta}_t$ 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 $t - \tau$. In other words,

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

where

$$\mathbb{E}[Y_t(D_{t-\tau} = 1)] = \int\int\int Y_t(\boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\eta}_t) dF_{\boldsymbol{\eta}}(\boldsymbol{\eta_t}) dF_{\boldsymbol{X}_t}(\boldsymbol{X}_t(D_{t-\tau} = 1)|\boldsymbol{\xi}) dF_{\boldsymbol{\xi}}(\boldsymbol{\xi})$$

and

$$\mathbb{E}[Y_t(D_{t-\tau} = 0)] = \int\int\int Y_t(\boldsymbol{X}_t, \boldsymbol{\xi}, \boldsymbol{\eta}_t) dF_{\boldsymbol{\eta}}(\boldsymbol{\eta_t}) dF_{\boldsymbol{X}_t}(\boldsymbol{X}_t(D_{t-\tau} = 0)|\boldsymbol{\xi}) dF_{\boldsymbol{\xi}}(\boldsymbol{\xi}).$$

Above, $Y_t(D_{t-\tau} = k)$ represents the potential outcome $Y_t$ if choice $D_{t-\tau}$ is exogenously set to choice $k$, but students are then allowed to make endogenous decisions moving forward. Similarly, $\boldsymbol{X}_t(D_{t-\tau} = k)$ represents the state variables at time $t$ when exogenously fixing choice $D_{t-\tau}$ to $k$.

### D.1.2 Empirical Model of Applications

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 $B_{ik} \equiv B_k(GPA_i)$.

Let $B_{ik_3}$ denote the set of major-college pairs in nest $k_3 \in \mathcal{K}_3$ considered by student $i$. The choice probability of ranking major-college pair $l$ highest can then be decomposed into marginal and conditional probabilities.

$$P\left[D_i^1 = l\right] = P\left[D_i^1 = l | D_i^1 \in B_{ik}\right] P\left[D_i^1 \in B_{ik}\right], \tag{D.2}$$

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

$$P\left[D_i^1 \in B_{ik}\right] = \frac{e^{f_k(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{v})+\lambda_k H_{ik}}}{\sum_{j=1}^{K} e^{f_j(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{v})+\lambda_j H_{ij}}} \tag{D.3}$$

$$P\left[D_i^1 = l | D_i^1 \in B_{ik}\right] = \begin{cases} \frac{e^{\delta_{il}/\lambda_k}}{\sum_{j \in B_{ik}} e^{\delta_{ij}/\lambda_k}} & \text{if} \quad l \in \mathcal{L}_i \\ 0 & \text{otherwise} \end{cases} \tag{D.4}$$

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 $\varepsilon_{il}$ within nest $k$. If $\lambda_k = 1$, then the errors are uncorrelated, and if $\lambda_k = 0$ the errors are perfectly correlated.

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

$$H_k^2(g_i, GPA_i) = \begin{cases} H_k(g_i, GPA_i) & \text{if} \quad k \neq k' \\ H_k(g_i, GPA_i) + \ln\left(1 - P\left[D_i^1 = l' | D_i^1 \in B_{k'}(GPA_i), g_i\right]\right) & \text{if} \quad k = k' \end{cases} \tag{D.5}$$

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

$$P\left[D_i^2 \in B_k | g_i, GPA_i, D_i^1 = l'\right] = \frac{e^{f_k(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\upsilon})+\lambda_k H_k^2(g_i,GPA_i)}}{\sum_{j=1}^{K} e^{f_j(\boldsymbol{X},\boldsymbol{Z},\boldsymbol{\theta},\boldsymbol{\upsilon})+\lambda_j H_j^2(g_i,GPA_i)}}. \tag{D.6}$$

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

$$\lambda_k \ln\left(1 - P\left[D_i^1 = l' | D_i^1 \in B_k(GPA_i), g_i\right]\right) \tag{D.7}$$

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 $l'$.

## D.2 Estimation Strategy

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

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

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

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 skills. The likelihood for economic models is then

$$\begin{aligned}\mathcal{L}^2 = \prod_i \int_{\overline{\boldsymbol{\theta}}\in\boldsymbol{\Theta}} \sum_{\overline{\upsilon}} & p_{\boldsymbol{\upsilon}}(\upsilon=\overline{\upsilon}|\boldsymbol{\theta}=\overline{\boldsymbol{\theta}};\gamma_\upsilon) f(\boldsymbol{Y}_i,\boldsymbol{D}_i|\boldsymbol{X}_i,\boldsymbol{\upsilon},\boldsymbol{\theta}=\overline{\boldsymbol{\theta}};\gamma_Y,\gamma_D) \\ & \times f(\boldsymbol{M}_i|\boldsymbol{X}_i,\boldsymbol{\theta}=\overline{\boldsymbol{\theta}};\hat{\gamma}_M) f_{\boldsymbol{\theta}}(\overline{\boldsymbol{\theta}};\hat{\gamma}_\theta)\, d\overline{\boldsymbol{\theta}},\end{aligned} \tag{D.8}$$

where the goal of the second stage is to maximize $\mathcal{L}^2$ and obtain estimates $\hat{\gamma}_\upsilon$, $\hat{\gamma}_Y$ and $\hat{\gamma}_D$. 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.

## D.3 Model fit

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

Table D.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 |

*Notes:* This table reports the share of students taking advanced english in 9th grade in the simulation and data.

Table D.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 |

*Notes:* This table reports the share of students taking advanced math in 9th grade in the simulation and data.

Table D.3: Probability of HS Tracks

| HS Track | Sim | Data |
|---|---|---|
| High School Dropout | 0.0877 | 0.0877 |
| Vocational | 0.5177 | 0.5146 |
| Academic Non-STEM | 0.1842 | 0.1813 |
| Academic STEM | 0.2104 | 0.2165 |

*Notes:* This table reports the share of students in each high school track in the simulation and the data.

Table D.4: Probability of Applying to college

| Apply Coll | Sim | Data |
|---|---|---|
| No | 0.5270 | 0.5294 |
| Yes | 0.4730 | 0.4706 |

*Notes:* This table reports the share of students applying to college in the simulation and data.

Table D.5: Prob of applying to college conditional on High School track

| High School Track | Sim | Data |
|---|---|---|
| Vocational | 0.2180 | 0.2086 |
| Academic Non-STEM | 0.7089 | 0.7101 |
| Academic STEM | 0.8938 | 0.8929 |

*Notes:* This table reports the share of students applying to college conditional on high school track in the simulation and the data.

Table D.6: Prob of enrollment conditional on major of first application

| Majors | Sim | Data |
|---|---|---|
| Non-STEM (short) | 0.3921 | 0.6186 |
| STEM (short) | 0.9041 | 0.9278 |
| Business (short) | 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 |
| Business | 0.5259 | 0.6906 |
| Law | 0.1231 | 0.5759 |
| Science and Comp-Sci | 0.5861 | 0.7082 |
| Engineering | 0.8271 | 0.7517 |
| Medicine | 0.1143 | 0.5258 |

*Notes:* This table reports the probability of enrolling in a particular major conditional on hte first application being to that major in the simulation and data.

Table D.7: Comparing Prob of graduating in a given major conditional on enrolling in the major (data vs simulation)

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

*Notes:* This table reports the probability of graduating in a given major conditional on enrolling in the simulation and data.

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

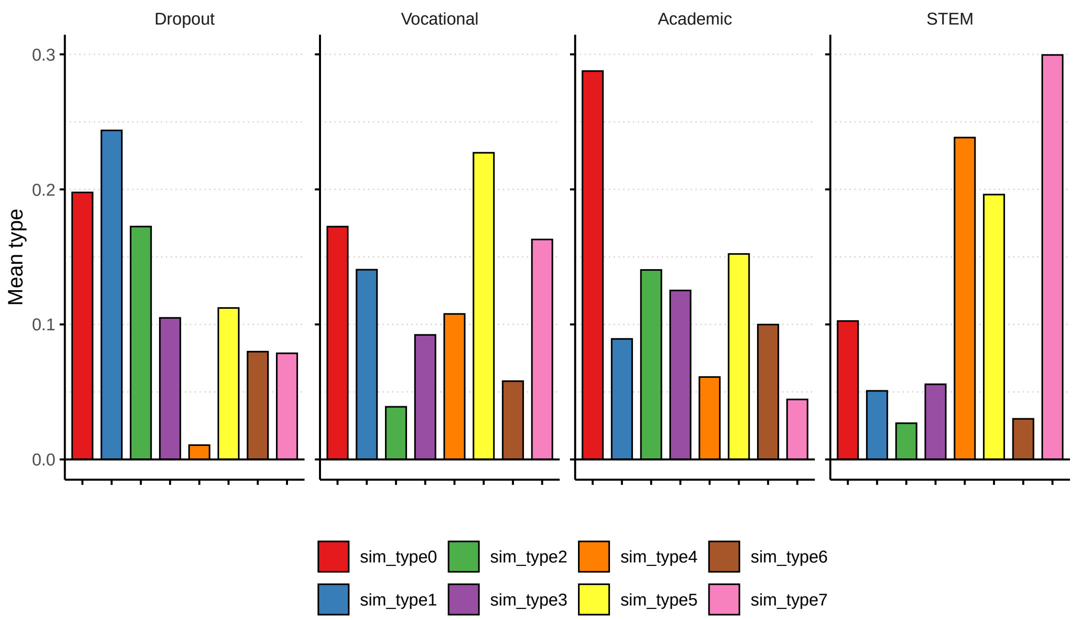
| Final Education Level | Sim | Data | Diff | Prop Diff |
|---|---|---|---|---|
| Business | 0.0177 | 0.0185 | -0.0008 | -0.0432 |
| Business (short) | 0.0038 | 0.0045 | -0.0007 | -0.1500 |
| CollDO_high | 0.0731 | 0.0629 | 0.0102 | 0.1625 |
| CollDO_low | 0.0606 | 0.0641 | -0.0035 | -0.0554 |
| Education | 0.0293 | 0.0226 | 0.0067 | 0.2948 |
| Engineering | 0.0605 | 0.0572 | 0.0034 | 0.0590 |
| HS Academic Non-STEM | 0.0842 | 0.0841 | 0.0001 | 0.0014 |
| HS Dropout | 0.0877 | 0.0877 | -0.0000 | -0.0003 |
| HS Academic 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 (short) | 0.0119 | 0.0148 | -0.0029 | -0.1978 |
| STEM (short) | 0.0515 | 0.0516 | -0.0001 | -0.0012 |
| Science and Comp-Sci | 0.0187 | 0.0166 | 0.0021 | 0.1277 |
| Social Sciences | 0.0084 | 0.0087 | -0.0003 | -0.0323 |

*Notes:* This table reports the share of students in each final education level in the simulation and data. The 'Diff" column reports the difference between the simulation and data while "Prop Diff" reports the proportinal difference.

## D.4 Role of Types in the Model

This section provides details on how students sort based on their latent types. Figure D.1 shows the share of each type in each of our four terminal high school tracks. Figure D.2 shows the fraction of enrollees (top panel) and graduates (bottom panel) that are each type in each of the long majors.

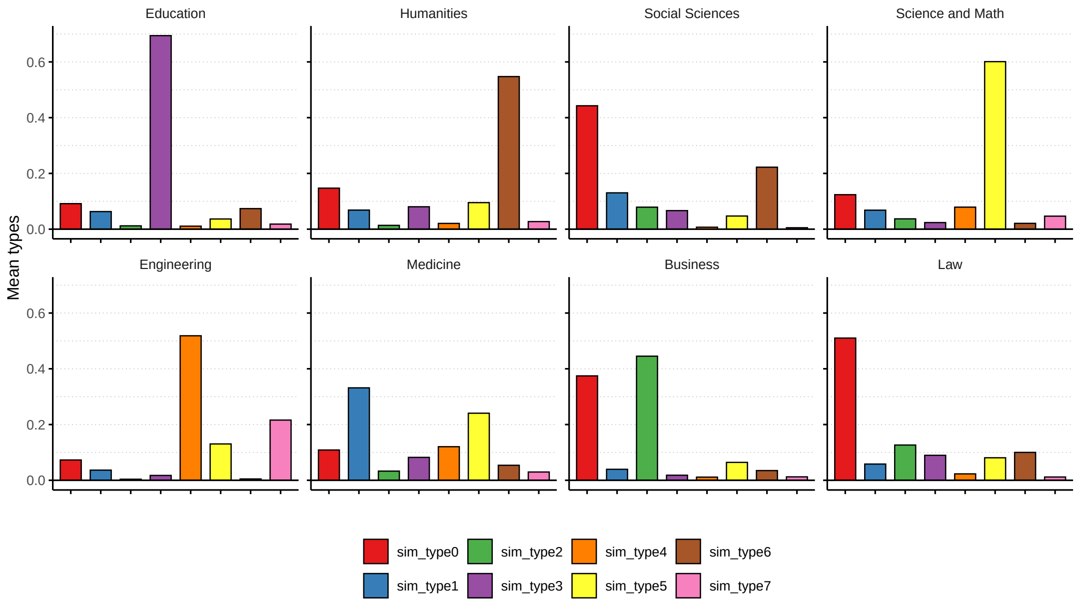
Figure D.1: Sorting of Types into High School Tracks



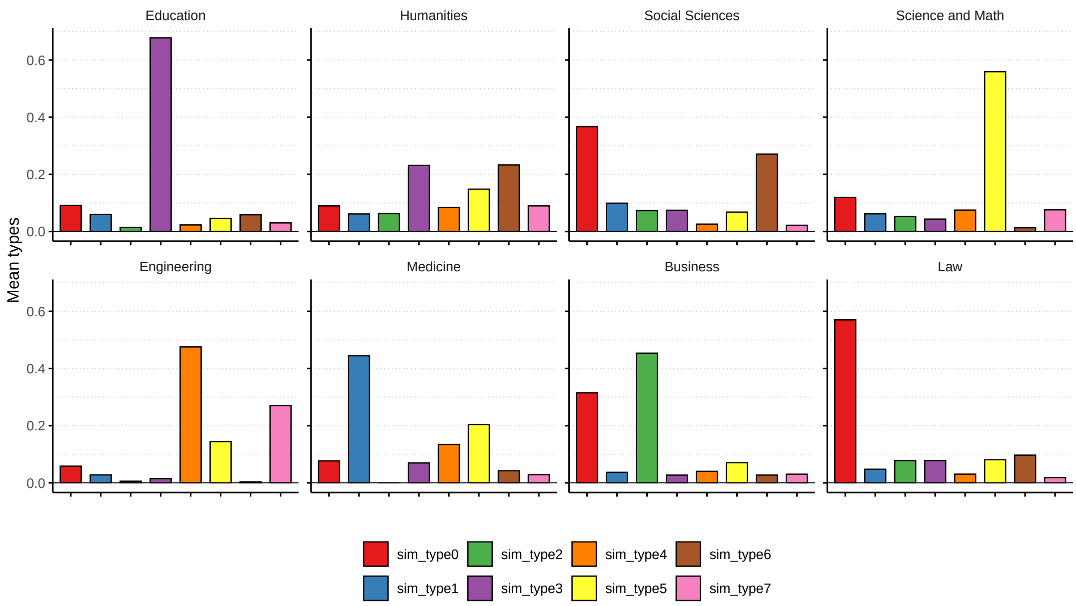

*Notes*: This figure shows the fraction of high school students that are of each type.

Figure D.2: Sorting of Types into College Majors

## Enrollment



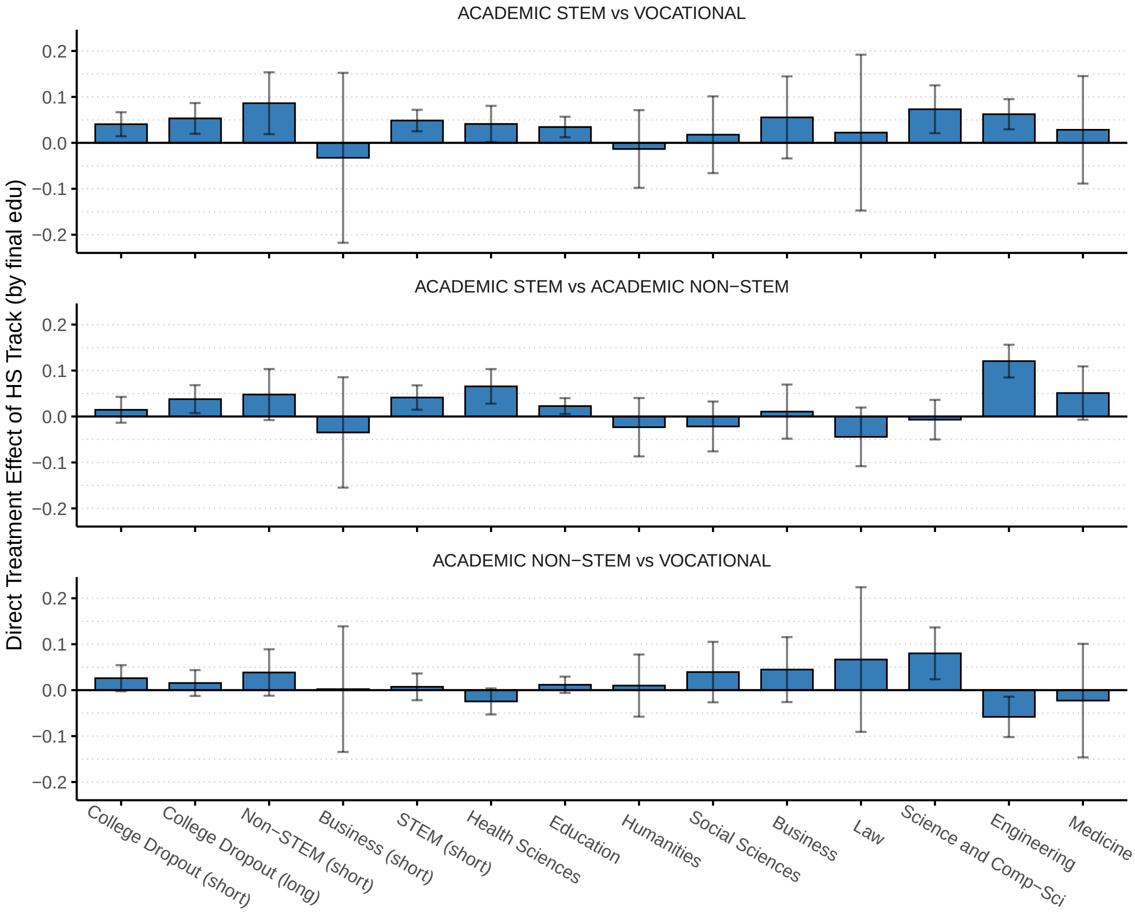

## Graduation




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

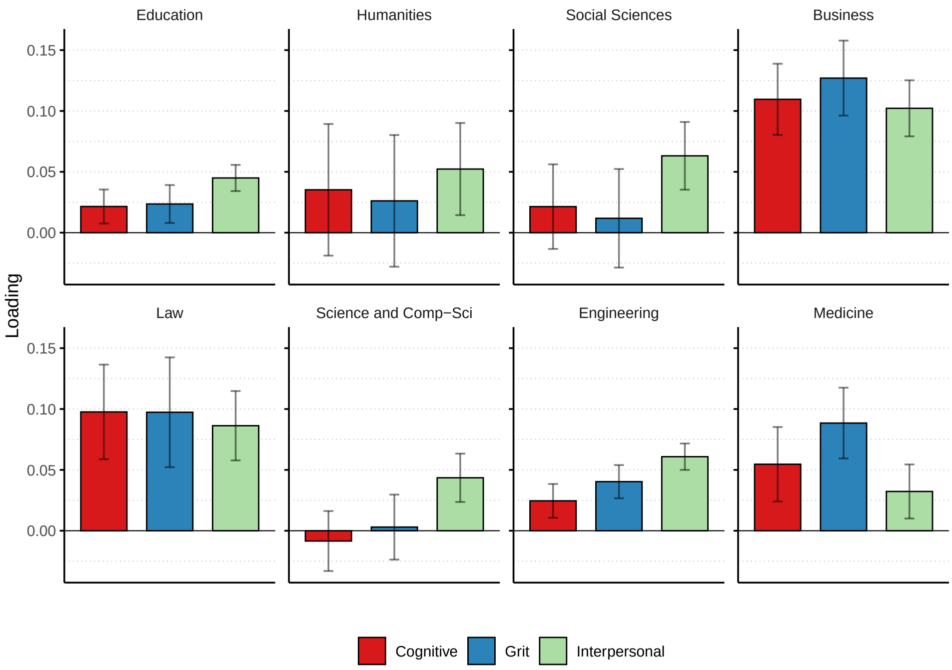
# E Additional Results

Figure E.1: Treatment Effects of HS Track on Log Wages within Final Education Level



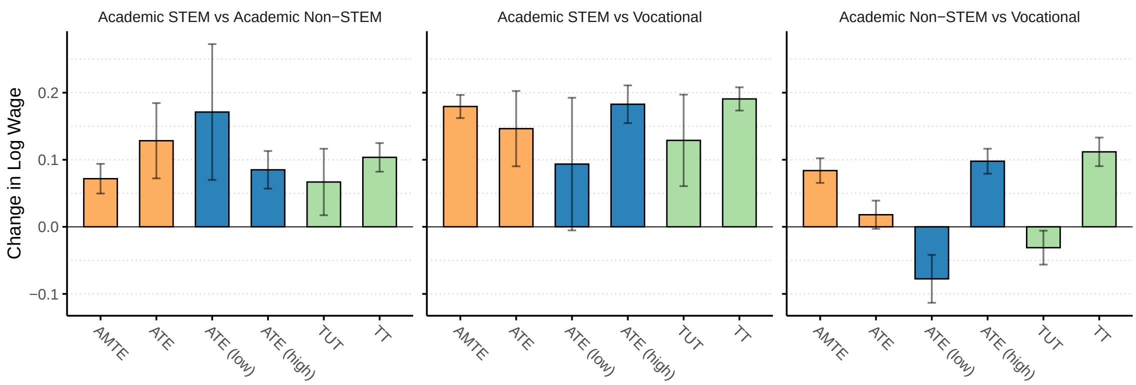

*Notes:* Figure shows the gains from changing high school track conditional on final educational attainment for each of the three high school track margins. Error bars show bootstrapped 95% confidence intervals.

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




*Notes*: These figures are comparing the returns to skill ($\hat{\boldsymbol{\lambda}}_{sm}$) for four-year graduates from equation (3). The first (red) bar shows the loading on cognitive skill, the second (blue) bar shows the loading on grit skill, and the third (green) bar shows the loading on interpersonal skill. This figure shows estimates for log present discounted value of disposable income while Figure 3 shows estimates for log wages. Each sub-panel shows the estimates for different four-year majors. Error bars show bootstrapped 95% confidence intervals.

Figure E.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 4 shows the treatment effects for log wages, college enrollment, and college graduation. The treatment effects are estimated for everyone who has at least a high school degree. High skilled is defined as being in the top half of all three skills distributions, while low skilled is defined as being in the bottom half of all three skills distributions. Error bars show bootstrapped 95% confidence intervals.

Table E.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 (short) | 0.10 | 0.15 |
| Business (short) | 0.03 | 0.04 |
| Social Sciences | 0.01 | 0.07 |
| Science and Comp-Sci | 0.00 | 0.02 |
| Education | 0.00 | 0.01 |

*Notes:* The table reports the proportion of individuals who applied to college 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 skills 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 (3) ($\mathbb{E}[Y_{sm}|\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{\upsilon}] = \boldsymbol{\beta}^{Y}_{sm}\boldsymbol{X} + \boldsymbol{\lambda}^{Y}_{sm}\boldsymbol{\theta} + \boldsymbol{\alpha}^{Y}_{sm}\boldsymbol{\upsilon}$).

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

| edu | HS Academic STEM | College Dropout (short) | College Dropout (long) | Non-STEM (short) | Business (short) | STEM (short) | Health Sciences | Education | Humanities | Social Sciences | Business | Law | Science and Comp-Sci | Engineering | Medicine |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HS Dropout | 0.24 | 0.16 | 0.13 | | | 0.29 | 0.10 | 0.11 | | | 0.10 | | 0.28 | 0.31 | |
| HS Vocational | 0.08 | 0.08 | 0.17 | 0.09 | 0.13 | 0.18 | 0.13 | 0.01 | | 0.18 | 0.35 | 0.31 | 0.19 | 0.37 | 0.37 |
| HS Academic Non-STEM | 0.06 | 0.05 | 0.08 | 0.09 | | 0.19 | -0.00 | -0.09 | | 0.07 | 0.14 | 0.07 | 0.04 | 0.31 | |
| College Dropout (short) | | 0.03 | -0.01 | | | 0.15 | | 0.02 | | | | | 0.07 | 0.20 | |
| College Dropout (long) | 0.27 | 0.05 | 0.04 | | | 0.12 | | -0.14 | | -0.08 | 0.12 | | 0.04 | 0.24 | |
| Non-STEM (short) | | 0.05 | 0.07 | 0.06 | | 0.20 | | | | | | | 0.07 | 0.25 | |
| Business (short) | | | | | -0.03 | | | | | | | | | | |
| STEM (short) | | -0.05 | -0.07 | | | 0.05 | | | | | | | | 0.09 | |
| Health Sciences | | -0.03 | 0.04 | | | 0.15 | 0.06 | -0.06 | | | | | 0.16 | 0.44 | 0.47 |
| Education | | 0.15 | 0.12 | | | 0.17 | | 0.03 | | | | | 0.26 | 0.49 | |
| Humanities | | | 0.14 | | | | | | -0.02 | | | | | | |
| Social Sciences | | 0.01 | -0.01 | | | | | -0.16 | | -0.02 | | | | 0.27 | |
| Business | | -0.27 | -0.12 | | | -0.09 | | | | | 0.02 | | -0.15 | -0.08 | |
| Law | | | -0.20 | | | | | | | | 0.07 | -0.04 | | 0.03 | |
| Science and Comp-Sci | | -0.04 | 0.06 | | | 0.03 | | | | | | | 0.02 | 0.15 | |
| Engineering | | -0.14 | | | | -0.03 | | | | | | | | 0.09 | |
| Medicine | | | -0.21 | | | | | | | | | | | 0.13 | 0.05 |

*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 E.3: AMTE of encouraging STEM applications for college by pre- and post- intervention final education

| edu | HS Vocational | HS Academic Non-STEM | HS Academic STEM | College Dropout (short) | College Dropout (long) | Non-STEM (short) | Business (short) | STEM (short) | Health Sciences | Education | Humanities | Social Sciences | Business | Law | Science and Comp-Sci | Engineering | Medicine |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HS Vocational | | | | -0.01 | 0.03 | | | 0.08 | 0.10 | | | | | | -0.02 | | |
| HS Academic Non-STEM | | | | -0.00 | 0.02 | -0.02 | | -0.01 | -0.10 | -0.23 | | 0.16 | 0.06 | | 0.08 | 0.14 | |
| HS Academic STEM | | | | -0.03 | 0.03 | | | 0.02 | | | | | | | -0.07 | 0.19 | |
| College Dropout (short) | -0.01 | 0.05 | | | -0.01 | -0.16 | | 0.11 | 0.01 | -0.07 | | 0.02 | 0.17 | | 0.07 | 0.20 | 0.43 |
| College Dropout (long) | -0.02 | -0.02 | | 0.01 | | 0.01 | 0.01 | 0.08 | 0.02 | -0.11 | 0.00 | -0.00 | 0.20 | 0.12 | 0.05 | 0.22 | 0.22 |
| Non-STEM (short) | -0.17 | -0.02 | | 0.02 | -0.07 | | | 0.12 | -0.08 | -0.15 | | 0.05 | 0.34 | | 0.01 | 0.20 | |
| Business (short) | | -0.02 | | -0.15 | -0.07 | | | -0.06 | -0.22 | | | | -0.02 | | -0.07 | 0.05 | |
| STEM (short) | -0.27 | -0.17 | | -0.11 | -0.12 | -0.09 | | | -0.13 | -0.27 | | -0.17 | 0.08 | | -0.01 | 0.10 | |
| Health Sciences | -0.15 | -0.03 | | 0.01 | 0.05 | 0.19 | | 0.13 | | -0.07 | | | | | 0.20 | 0.39 | 0.35 |
| Education | -0.02 | 0.09 | | 0.06 | 0.13 | 0.12 | 0.15 | 0.14 | 0.10 | | | 0.15 | 0.48 | 0.36 | 0.27 | 0.49 | 0.50 |
| Humanities | | | | 0.04 | 0.07 | | | 0.17 | -0.01 | | | | | | 0.12 | 0.36 | |
| Social Sciences | -0.11 | -0.08 | | -0.03 | 0.01 | -0.19 | | 0.07 | -0.11 | -0.11 | | | 0.10 | | 0.02 | 0.25 | 0.20 |
| Business | | -0.13 | | -0.18 | -0.15 | -0.15 | 0.05 | -0.13 | -0.37 | -0.54 | | -0.13 | | -0.04 | -0.15 | -0.02 | -0.10 |
| Law | | | | -0.16 | -0.22 | -0.28 | | -0.12 | -0.30 | -0.45 | | -0.15 | -0.01 | | -0.20 | -0.01 | -0.05 |
| Science and Comp-Sci | | | | -0.08 | -0.05 | 0.00 | | 0.05 | -0.19 | -0.19 | | | 0.17 | | | 0.21 | |
| Engineering | | | | -0.16 | -0.19 | -0.15 | | -0.07 | -0.39 | -0.50 | | -0.34 | 0.09 | | -0.16 | | 0.01 |
| Medicine | | | | | -0.31 | | | -0.23 | -0.36 | | | | | | | 0.04 | |

*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.

# F Model Parameter Estimates

Table F.1: Estimates for Type Probability Model

| Variable | Type 2 | | Type 3 | | Type 4 | | Type 5 | | Type 6 | | Type 7 | | Type 8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -0.467 | 0.251 | -1.010 | 0.114 | -0.688 | 0.067 | -0.477 | 0.049 | 0.089 | 0.112 | -1.088 | 0.083 | -0.116 | 0.077 |
| Cognitive | -0.209 | 0.051 | 0.193 | 0.030 | -0.096 | 0.026 | 0.320 | 0.024 | 0.113 | 0.038 | -0.051 | 0.034 | 0.225 | 0.030 |
| Interpersonal | 0.011 | 0.038 | 0.054 | 0.026 | -0.005 | 0.027 | -0.113 | 0.021 | -0.146 | 0.028 | -0.229 | 0.033 | -0.058 | 0.022 |
| Grit | -0.193 | 0.059 | 0.179 | 0.040 | 0.034 | 0.031 | 0.283 | 0.030 | 0.017 | 0.045 | 0.024 | 0.047 | 0.139 | 0.030 |
| N | 105913 | | 105913 | | 105913 | | 105913 | | 105913 | | 105913 | | 105913 | |

*Notes*: Table reports estimates for the type probability model.

Table F.2: Estimates for Primary Grades Models (Measurement System $M_{ms}$)

| Variable | Ninth Grade English Grade | | Ninth Grade Math Grade | | Ninth Grade Sports Grade | | Ninth Grade Swedish Grade | | Ninth Grade GPA | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -0.827 | 0.040 | -0.567 | 0.045 | -0.548 | 0.032 | -0.978 | 0.037 | -0.729 | 0.034 |
| Mother College | 0.217 | 0.010 | 0.270 | 0.012 | 0.056 | 0.009 | 0.276 | 0.010 | 0.238 | 0.009 |
| Mother High School | 0.123 | 0.010 | 0.142 | 0.010 | 0.041 | 0.009 | 0.165 | 0.009 | 0.104 | 0.008 |
| Mother Educ missing | 0.148 | 0.023 | 0.256 | 0.026 | 0.070 | 0.019 | 0.274 | 0.022 | 0.193 | 0.019 |
| Father College | 0.309 | 0.012 | 0.315 | 0.014 | 0.062 | 0.010 | 0.326 | 0.012 | 0.271 | 0.011 |
| Father High School | 0.138 | 0.009 | 0.147 | 0.010 | 0.054 | 0.008 | 0.145 | 0.008 | 0.121 | 0.007 |
| Father Educ missing | 0.180 | 0.019 | 0.107 | 0.021 | 0.035 | 0.017 | 0.099 | 0.019 | 0.104 | 0.016 |
| Family Income | 0.097 | 0.005 | 0.148 | 0.006 | 0.130 | 0.004 | 0.121 | 0.005 | 0.131 | 0.005 |
| School-Ave Fam Income | 0.201 | 0.014 | 0.106 | 0.016 | 0.022 | 0.011 | 0.091 | 0.013 | 0.025 | 0.012 |
| Health Endurance | -0.002 | 0.004 | 0.019 | 0.004 | 0.208 | 0.003 | -0.008 | 0.004 | 0.025 | 0.003 |
| Health Strength | -0.066 | 0.003 | -0.096 | 0.003 | -0.191 | 0.002 | -0.088 | 0.003 | -0.093 | 0.002 |
| Health missing | -0.047 | 0.018 | -0.074 | 0.020 | -0.052 | 0.015 | -0.037 | 0.017 | -0.035 | 0.015 |
| 9th Math Grade | | | | | | | | | 0.007 | 0.003 |
| 9th English Grade | | | | | | | | | 0.020 | 0.002 |
| 9th Sports Grade | | | | | | | | | 0.065 | 0.002 |
| 9th Sports missing | | | | | | | | | -0.192 | 0.029 |
| 9th Swedish Grade | | | | | | | | | 0.165 | 0.003 |
| 9th Swedish Missing | | | | | | | | | -0.053 | 0.033 |
| Took 9th Adv. Math | | | -0.880 | 0.006 | | | | | | |
| Took 9th Adv. English | -0.547 | 0.007 | | | | | | | | |
| Cognitive | 0.482 | 0.005 | 0.586 | 0.005 | 0.012 | 0.004 | 0.430 | 0.005 | 0.376 | 0.004 |
| Interpersonal | 0.029 | 0.004 | 0.063 | 0.005 | 0.287 | 0.004 | 0.096 | 0.004 | 0.112 | 0.004 |
| Grit | 0.498 | 0.005 | 0.607 | 0.005 | 0.397 | 0.004 | 0.518 | 0.004 | 0.552 | 0.003 |
| 1/Precision | 0.720 | 0.002 | 0.615 | 0.003 | 0.772 | 0.002 | 0.610 | 0.003 | 0.285 | 0.001 |
| N | 105913 | | 105913 | | 105612 | | 105725 | | 105913 | |

*Notes*: Table reports estimates for the primary grades models.

Table F.3: Estimates for Secondary Grade Models (Measurement System $M_{ms}$)

| Variable | Tenth Sports Grade | | Tenth Math Grade | | HS GPA (Vocational) | | HS GPA (Academic) | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -0.871 | 0.034 | -1.197 | 0.044 | 262.544 | 2.577 | 206.876 | 2.697 |
| Mother College | 0.063 | 0.009 | 0.257 | 0.011 | 10.081 | 0.635 | 16.399 | 0.599 |
| Mother High School | 0.039 | 0.009 | 0.118 | 0.011 | 4.577 | 0.527 | 6.157 | 0.718 |
| Mother Educ missing | 0.056 | 0.021 | 0.240 | 0.026 | 8.463 | 1.306 | 12.617 | 1.560 |
| Father College | 0.089 | 0.010 | 0.311 | 0.014 | 12.273 | 0.771 | 20.563 | 0.780 |
| Father High School | 0.056 | 0.008 | 0.113 | 0.011 | 4.739 | 0.516 | 7.922 | 0.628 |
| Father Educ missing | 0.053 | 0.019 | 0.073 | 0.021 | 3.765 | 1.058 | 8.645 | 1.315 |
| Family Income | 0.131 | 0.004 | 0.131 | 0.005 | 4.721 | 0.327 | 7.223 | 0.309 |
| School-Ave Fam Income | 0.117 | 0.013 | 0.161 | 0.015 | 9.245 | 0.919 | 15.405 | 0.880 |
| Health Endurance | 0.203 | 0.003 | 0.004 | 0.004 | 0.624 | 0.210 | -0.404 | 0.250 |
| Health Strength | -0.213 | 0.003 | -0.094 | 0.003 | -3.170 | 0.158 | -4.557 | 0.207 |
| Health missing | -0.112 | 0.017 | -0.112 | 0.020 | -2.904 | 1.015 | -2.867 | 1.167 |
| 10th Math Grade | | | | | 21.916 | 0.261 | 29.817 | 0.254 |
| 10th Math Missing | | | | | 0.860 | 0.339 | -25.822 | 3.974 |
| 10th Sports Grade | | | | | 19.078 | 0.229 | 5.763 | 0.235 |
| 10th Sports Missing | | | | | -36.180 | 1.899 | 4.082 | 3.885 |
| Took 9th Adv. Math | | | 0.605 | 0.008 | 5.572 | 0.432 | -6.692 | 0.814 |
| Took 9th Adv. English | | | | | 13.528 | 0.377 | 11.921 | 0.794 |
| HS Academic Track | 0.070 | 0.009 | -0.990 | 0.009 | | | | |
| HS STEM Track | -0.170 | 0.009 | -1.079 | 0.010 | | | -8.857 | 0.375 |
| Cognitive | 0.014 | 0.004 | 0.536 | 0.005 | 23.119 | 0.282 | 23.600 | 0.362 |
| Interpersonal | 0.335 | 0.004 | 0.035 | 0.004 | 3.432 | 0.248 | 5.847 | 0.267 |
| Grit | 0.329 | 0.005 | 0.458 | 0.005 | 20.753 | 0.322 | 29.874 | 0.336 |
| 1/Precision | 0.804 | 0.003 | 0.711 | 0.002 | 36.504 | 0.177 | 31.739 | 0.152 |
| N | 95424 | | 72853 | | 54498 | | 42124 | |

*Notes*: Table reports estimates for the secondary grades models.

Table F.4: Estimates for Military Enlistment Cognitive Measure Models (Measurement System $M_{ms}$)

| Variable | Cognitive measure 1 | | Cognitive measure 2 | | Cognitive measure 3 | | Cognitive measure 4 | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -1.009 | 0.030 | -1.135 | 0.030 | -1.121 | 0.034 | -0.879 | 0.035 |
| Mother College | 0.129 | 0.008 | 0.194 | 0.007 | 0.152 | 0.008 | 0.169 | 0.009 |
| Mother High School | 0.107 | 0.007 | 0.118 | 0.007 | 0.109 | 0.008 | 0.144 | 0.008 |
| Mother Educ missing | 0.141 | 0.016 | 0.165 | 0.016 | 0.089 | 0.018 | 0.183 | 0.019 |
| Father College | 0.131 | 0.009 | 0.205 | 0.009 | 0.121 | 0.010 | 0.119 | 0.010 |
| Father High School | 0.061 | 0.007 | 0.087 | 0.007 | 0.093 | 0.007 | 0.088 | 0.008 |
| Father Educ missing | 0.037 | 0.015 | 0.068 | 0.014 | 0.119 | 0.016 | 0.034 | 0.017 |
| Family Income | 0.038 | 0.004 | 0.001 | 0.004 | 0.023 | 0.004 | 0.031 | 0.004 |
| School-Ave Fam Income | 0.069 | 0.011 | 0.120 | 0.010 | 0.171 | 0.011 | 0.101 | 0.012 |
| Health Endurance | 0.014 | 0.003 | 0.006 | 0.003 | 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 | 0.014 | -0.074 | 0.014 | -0.066 | 0.016 | -0.053 | 0.015 |
| Took 9th Adv. Math | 0.397 | 0.006 | 0.164 | 0.007 | 0.367 | 0.007 | 0.273 | 0.008 |
| Took 9th Adv. English | 0.345 | 0.006 | 0.505 | 0.006 | 0.039 | 0.007 | 0.082 | 0.007 |
| HS Vocational Track | 0.079 | 0.008 | 0.058 | 0.009 | 0.065 | 0.010 | 0.083 | 0.010 |
| HS Academic Track | 0.123 | 0.010 | 0.292 | 0.011 | -0.139 | 0.014 | -0.183 | 0.013 |
| HS STEM Track | 0.348 | 0.012 | 0.304 | 0.012 | 0.298 | 0.014 | 0.438 | 0.013 |
| Cognitive | 0.536 | 0.003 | 0.474 | 0.003 | 0.517 | 0.003 | 0.547 | 0.003 |
| 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 F.5: Estimates for Military Enlistment Socio-emotional Measure Models (Measurement System $M_{ms}$)

| Variable | Lead missing | | Emotional Stability | | Leadership | |
|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 1.894 | 0.072 | -1.418 | 0.045 | 1.954 | 0.078 |
| Mother College | -0.221 | 0.018 | 0.067 | 0.012 | 0.161 | 0.022 |
| Mother High School | -0.249 | 0.016 | 0.103 | 0.010 | 0.194 | 0.019 |
| Mother Educ missing | -0.289 | 0.040 | 0.185 | 0.024 | 0.330 | 0.046 |
| Father College | -0.177 | 0.021 | 0.075 | 0.013 | 0.179 | 0.024 |
| Father High School | -0.165 | 0.016 | 0.043 | 0.010 | 0.108 | 0.018 |
| Father Educ missing | -0.078 | 0.034 | -0.051 | 0.021 | -0.025 | 0.039 |
| Family Income | -0.060 | 0.009 | 0.131 | 0.006 | 0.243 | 0.011 |
| School-Ave Fam Income | -0.256 | 0.024 | 0.176 | 0.016 | 0.362 | 0.028 |
| Health Endurance | -0.091 | 0.007 | 0.268 | 0.004 | 0.399 | 0.007 |
| Health Strength | 0.100 | 0.005 | -0.155 | 0.003 | -0.225 | 0.006 |
| Health missing | 0.827 | 0.032 | -0.234 | 0.023 | -0.431 | 0.041 |
| Took 9th Adv. Math | -0.643 | 0.015 | 0.089 | 0.010 | 0.189 | 0.019 |
| Took 9th Adv. English | -0.477 | 0.015 | 0.044 | 0.009 | 0.155 | 0.017 |
| HS Vocational Track | -0.145 | 0.023 | 0.282 | 0.012 | 0.467 | 0.025 |
| HS Academic Track | 0.009 | 0.029 | 0.349 | 0.017 | 0.620 | 0.033 |
| HS STEM Track | 0.037 | 0.031 | 0.351 | 0.020 | 0.615 | 0.036 |
| Cognitive | -1.092 | 0.012 | 0.266 | 0.005 | 0.580 | 0.009 |
| Interpersonal | | | 0.759 | 0.002 | 1.237 | 0.004 |
| 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 F.6: Estimates for Ninth and High School Choice Models (Education Choices $D_1, D_2$)

| Variable | Ninth Adv. Math | | Ninth Adv. English | | HS Voc. Track | | HS Acad. Track | | HS STEM Track | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -0.945 | 0.104 | -0.911 | 0.098 | -3.141 | 0.278 | -6.933 | 0.265 | -12.169 | 0.350 |
| Mother College | 0.606 | 0.018 | 0.492 | 0.017 | 0.420 | 0.049 | 1.060 | 0.057 | 1.404 | 0.062 |
| Mother High School | 0.297 | 0.017 | 0.254 | 0.015 | 0.440 | 0.034 | 0.747 | 0.045 | 1.080 | 0.053 |
| Mother Educ missing | 0.511 | 0.039 | 0.348 | 0.034 | 0.584 | 0.075 | 1.056 | 0.106 | 1.573 | 0.113 |
| Father College | 0.620 | 0.020 | 0.632 | 0.019 | 0.461 | 0.055 | 1.379 | 0.066 | 1.680 | 0.072 |
| Father High School | 0.384 | 0.015 | 0.335 | 0.014 | 0.373 | 0.033 | 0.808 | 0.045 | 1.237 | 0.051 |
| Father Educ missing | 0.302 | 0.034 | 0.369 | 0.029 | 0.109 | 0.064 | 0.717 | 0.088 | 0.913 | 0.100 |
| Family Income | 0.369 | 0.009 | 0.243 | 0.008 | 0.347 | 0.027 | 0.876 | 0.032 | 1.043 | 0.035 |
| School-Ave Fam Income | -0.487 | 0.030 | -0.176 | 0.027 | 0.930 | 0.069 | 0.732 | 0.081 | 0.912 | 0.088 |
| Health Endurance | 0.033 | 0.006 | 0.004 | 0.006 | 0.121 | 0.013 | -0.000 | 0.018 | 0.133 | 0.019 |
| Health Strength | -0.175 | 0.005 | -0.139 | 0.005 | -0.236 | 0.011 | -0.470 | 0.016 | -0.617 | 0.018 |
| Health missing | -0.200 | 0.032 | -0.124 | 0.028 | -0.130 | 0.060 | -0.396 | 0.078 | -0.442 | 0.092 |
| 9th GPA Bin2 | | | | | -0.541 | 0.059 | 0.058 | 0.066 | -0.140 | 0.073 |
| 9th GPA Bin3 | | | | | -1.382 | 0.083 | -0.655 | 0.094 | -0.776 | 0.103 |
| 9th GPA Bin4 | | | | | -2.529 | 0.106 | -2.013 | 0.120 | -1.935 | 0.131 |
| Took 9th Adv. Math | | | | | -0.158 | 0.053 | 0.757 | 0.063 | 2.822 | 0.094 |
| Took 9th Adv. English | | | | | -0.096 | 0.047 | 1.296 | 0.064 | 1.164 | 0.073 |
| School-Ave Adv. Math | 3.201 | 0.075 | | | | | | | | |
| Adv. Math IV | 0.201 | 0.006 | | | | | | | | |
| School-Ave Adv. English | | | 2.551 | 0.065 | | | | | | |
| Adv. English IV | | | 0.183 | 0.006 | | | | | | |
| School-Ave Vocational Track | | | | | 3.440 | 0.133 | 0.000 | 0.000 | 0.000 | 0.000 |
| Vocational Track IV | | | | | 0.076 | 0.009 | 0.000 | 0.000 | 0.000 | 0.000 |
| School-Ave Academic Track | | | | | 0.000 | 0.000 | 4.013 | 0.226 | 0.000 | 0.000 |
| Academic Track IV | | | | | 0.000 | 0.000 | 0.103 | 0.011 | 0.000 | 0.000 |
| School-Ave STEM Track | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 2.751 | 0.300 |
| STEM Track IV | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.060 | 0.012 |
| Cognitive | 0.669 | 0.012 | 0.532 | 0.011 | 0.613 | 0.025 | 1.371 | 0.035 | 1.998 | 0.041 |
| Interpersonal | 0.206 | 0.007 | 0.135 | 0.006 | 0.267 | 0.019 | 0.499 | 0.023 | 0.697 | 0.027 |
| Grit | 0.979 | 0.012 | 0.733 | 0.011 | 1.144 | 0.033 | 2.102 | 0.049 | 2.809 | 0.054 |
| Type 2 | -1.590 | 0.137 | -1.506 | 0.166 | -0.502 | 0.304 | -1.063 | 0.288 | -0.474 | 0.334 |
| Type 3 | -0.730 | 0.113 | -0.741 | 0.113 | -1.762 | 0.318 | -1.047 | 0.293 | -1.931 | 0.416 |
| Type 4 | -1.054 | 0.112 | -0.862 | 0.112 | -0.059 | 0.223 | 0.090 | 0.227 | 0.366 | 0.279 |
| Type 5 | -0.609 | 0.084 | -0.826 | 0.085 | 2.376 | 0.462 | 1.609 | 0.478 | 4.183 | 0.518 |
| Type 6 | -1.426 | 0.201 | -1.541 | 0.192 | 0.796 | 0.336 | 0.511 | 0.368 | 1.990 | 0.435 |
| Type 7 | -0.976 | 0.089 | -0.854 | 0.089 | -0.208 | 0.610 | 0.254 | 0.624 | 0.160 | 0.722 |
| Type 8 | -0.540 | 0.122 | -0.801 | 0.117 | 0.803 | 0.293 | -0.811 | 0.297 | 2.350 | 0.353 |
| N | 105913 | | 105913 | | 105913 | | 105913 | | 105913 | |

*Notes*:

Table F.7: Estimates for Apply to College, SweSAT and Enroll Models (Education Choices $D_{3a}, D_{3b}, D_{3d}$)

| Variable | Apply College | | Take SweSAT | | Total SweSAT Score | | Enroll after Admission | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -2.094 | 0.097 | -0.333 | 0.088 | 0.100 | 0.023 | 0.180 | 0.103 |
| Mother College | 0.315 | 0.016 | 0.101 | 0.018 | 0.126 | 0.004 | 0.147 | 0.023 |
| Mother High School | 0.176 | 0.015 | 0.063 | 0.023 | 0.070 | 0.005 | 0.096 | 0.029 |
| Mother Educ missing | 0.222 | 0.032 | 0.068 | 0.048 | 0.087 | 0.011 | 0.162 | 0.064 |
| Father College | 0.345 | 0.017 | 0.143 | 0.019 | 0.137 | 0.004 | 0.183 | 0.024 |
| Father High School | 0.181 | 0.014 | -0.026 | 0.020 | 0.056 | 0.005 | 0.074 | 0.026 |
| Father Educ missing | 0.191 | 0.029 | 0.062 | 0.042 | 0.075 | 0.010 | 0.042 | 0.057 |
| Family Income | 0.091 | 0.008 | 0.040 | 0.009 | 0.006 | 0.002 | 0.038 | 0.012 |
| School-Ave Fam Income | 0.003 | 0.019 | 0.144 | 0.026 | 0.084 | 0.006 | 0.048 | 0.032 |
| Health Endurance | -0.056 | 0.005 | 0.004 | 0.007 | -0.014 | 0.002 | -0.016 | 0.009 |
| Health Strength | -0.067 | 0.004 | -0.013 | 0.006 | -0.004 | 0.002 | -0.044 | 0.009 |
| Health missing | -0.175 | 0.025 | -0.013 | 0.035 | 0.028 | 0.009 | -0.037 | 0.048 |
| Took 9th Adv. Math | 0.186 | 0.026 | 0.089 | 0.024 | 0.075 | 0.006 | 0.037 | 0.034 |
| Took 9th Adv. English | 0.194 | 0.021 | 0.275 | 0.024 | 0.207 | 0.007 | 0.021 | 0.033 |
| HS GPA Bin2 | 0.365 | 0.015 | -0.021 | 0.023 | | | | |
| HS GPA Bin3 | 0.537 | 0.020 | -0.153 | 0.025 | | | | |
| HS GPA Bin4 | 0.690 | 0.024 | -0.531 | 0.032 | | | | |
| HS Academic Track | 0.829 | 0.020 | 0.659 | 0.027 | -0.069 | 0.006 | -0.078 | 0.029 |
| HS STEM Track | 1.408 | 0.030 | 0.635 | 0.029 | -0.025 | 0.006 | 0.187 | 0.036 |
| Cognitive | 0.231 | 0.010 | 0.141 | 0.011 | 0.271 | 0.002 | 0.210 | 0.011 |
| Interpersonal | 0.036 | 0.006 | 0.021 | 0.007 | -0.022 | 0.002 | -0.015 | 0.009 |
| Grit | 0.181 | 0.011 | -0.043 | 0.013 | 0.106 | 0.002 | 0.140 | 0.013 |
| Type 2 | 0.288 | 0.366 | 0.247 | 0.059 | 0.036 | 0.018 | 0.267 | 0.064 |
| Type 3 | 0.827 | 0.075 | 0.119 | 0.057 | -0.041 | 0.017 | 0.029 | 0.084 |
| Type 4 | 0.989 | 0.103 | -0.080 | 0.047 | -0.004 | 0.015 | 0.218 | 0.055 |
| Type 5 | 0.394 | 0.073 | -0.119 | 0.054 | -0.057 | 0.015 | 0.996 | 0.075 |
| Type 6 | 0.017 | 0.102 | -0.046 | 0.051 | -0.014 | 0.017 | 0.236 | 0.064 |
| Type 7 | 0.552 | 0.101 | -0.072 | 0.068 | 0.023 | 0.022 | -0.042 | 0.079 |
| Type 8 | 0.186 | 0.070 | -0.449 | 0.053 | -0.075 | 0.015 | 0.483 | 0.053 |
| 1/Precision | | | | | 0.303 | 0.001 | | |
| N | 96622 | | 45471 | | 36333 | | 35283 | |

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

Table F.8: Estimates for Major-College Application Model (Education Choices $D_{3c}$)

| Variable | 3yr non-STEM | | 3yr STEM | | 3yr Business | | Health Sci | | Educ | | Humanities | | Soc Sci | | Sciences | | Engineer | | Medicine | | Business | | Law | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 0.312 | 0.319 | -0.516 | 0.360 | -0.330 | 0.261 | 0.595 | 0.409 | 1.013 | 0.461 | -1.282 | 0.482 | 0.971 | 0.262 | -1.294 | 0.317 | -2.952 | 0.424 | -2.097 | 0.653 | -0.479 | 0.193 | 0.068 | 0.281 |
| Mother College | 0.184 | 0.054 | -0.088 | 0.046 | -0.049 | 0.055 | 0.048 | 0.080 | 0.123 | 0.074 | 0.186 | 0.082 | 0.196 | 0.046 | 0.022 | 0.047 | 0.145 | 0.052 | 0.587 | 0.112 | 0.025 | 0.042 | 0.036 | 0.061 |
| Mother High School | 0.054 | 0.067 | -0.054 | 0.055 | -0.076 | 0.063 | -0.073 | 0.090 | 0.031 | 0.077 | -0.028 | 0.109 | 0.051 | 0.055 | -0.040 | 0.051 | 0.114 | 0.066 | 0.106 | 0.171 | 0.010 | 0.050 | -0.015 | 0.078 |
| Mother Educ missing | -0.087 | 0.136 | -0.074 | 0.106 | -0.146 | 0.128 | 0.032 | 0.168 | 0.192 | 0.159 | 0.077 | 0.193 | 0.099 | 0.099 | -0.003 | 0.109 | 0.058 | 0.124 | 0.560 | 0.242 | -0.013 | 0.100 | -0.093 | 0.152 |
| Father College | -0.085 | 0.061 | -0.203 | 0.055 | -0.194 | 0.057 | 0.092 | 0.085 | 0.077 | 0.077 | -0.060 | 0.085 | 0.129 | 0.049 | 0.101 | 0.052 | 0.231 | 0.060 | 0.446 | 0.115 | 0.006 | 0.043 | 0.178 | 0.056 |
| Father High School | 0.120 | 0.057 | 0.018 | 0.050 | -0.093 | 0.057 | -0.091 | 0.075 | -0.059 | 0.068 | 0.147 | 0.095 | 0.041 | 0.051 | 0.000 | 0.050 | 0.118 | 0.053 | -0.083 | 0.141 | 0.058 | 0.046 | 0.116 | 0.070 |
| Father Educ missing | 0.189 | 0.109 | -0.154 | 0.099 | -0.107 | 0.106 | -0.053 | 0.159 | -0.387 | 0.137 | 0.082 | 0.175 | 0.087 | 0.091 | 0.090 | 0.099 | 0.215 | 0.112 | 0.145 | 0.212 | 0.120 | 0.086 | 0.293 | 0.133 |
| Family Income | -0.116 | 0.029 | -0.112 | 0.026 | 0.101 | 0.025 | -0.094 | 0.040 | -0.110 | 0.036 | -0.273 | 0.046 | -0.038 | 0.022 | -0.123 | 0.022 | 0.008 | 0.026 | 0.022 | 0.055 | 0.155 | 0.021 | 0.089 | 0.026 |
| School-Ave Fam Income | -0.280 | 0.079 | -0.334 | 0.068 | -0.136 | 0.070 | -0.405 | 0.111 | -0.696 | 0.103 | -0.405 | 0.122 | -0.161 | 0.059 | -0.023 | 0.062 | 0.143 | 0.077 | 0.125 | 0.137 | 0.128 | 0.050 | 0.012 | 0.070 |
| Health Endurance | -0.129 | 0.020 | 0.027 | 0.017 | -0.005 | 0.020 | 0.037 | 0.026 | 0.002 | 0.026 | -0.164 | 0.034 | -0.028 | 0.016 | -0.015 | 0.016 | 0.071 | 0.019 | 0.193 | 0.042 | -0.004 | 0.015 | 0.032 | 0.021 |
| Health Strength | 0.034 | 0.021 | -0.004 | 0.018 | -0.020 | 0.020 | 0.007 | 0.025 | 0.021 | 0.024 | 0.127 | 0.030 | -0.006 | 0.017 | 0.003 | 0.016 | -0.050 | 0.020 | -0.028 | 0.044 | -0.030 | 0.015 | 0.042 | 0.021 |
| Health missing | 0.005 | 0.105 | 0.084 | 0.097 | -0.632 | 0.118 | -0.151 | 0.132 | -0.011 | 0.121 | 0.099 | 0.142 | 0.110 | 0.079 | 0.167 | 0.088 | -0.059 | 0.113 | -0.108 | 0.262 | -0.116 | 0.072 | -0.092 | 0.096 |
| Took 9th Adv. Math | -0.361 | 0.072 | 0.524 | 0.065 | 0.101 | 0.076 | -0.107 | 0.091 | -0.144 | 0.075 | -0.311 | 0.095 | -0.414 | 0.068 | 0.517 | 0.076 | 0.453 | 0.078 | 0.337 | 0.206 | 0.017 | 0.062 | -0.791 | 0.093 |
| Took 9th Adv. English | 0.374 | 0.085 | -0.156 | 0.064 | -0.159 | 0.082 | 0.224 | 0.110 | 0.084 | 0.079 | 0.396 | 0.118 | -0.127 | 0.070 | 0.341 | 0.080 | -0.291 | 0.072 | 0.682 | 0.211 | -0.343 | 0.076 | -0.117 | 0.106 |
| HS Academic Track | -0.287 | 0.091 | -0.346 | 0.072 | 0.397 | 0.085 | -0.762 | 0.113 | -0.232 | 0.112 | -0.069 | 0.119 | -0.284 | 0.086 | -0.258 | 0.077 | -0.362 | 0.079 | -0.720 | 0.206 | 0.486 | 0.082 | 0.597 | 0.096 |
| HS STEM Track | -0.355 | 0.109 | 0.542 | 0.101 | -0.153 | 0.127 | -1.028 | 0.139 | 0.006 | 0.164 | 0.070 | 0.153 | -0.470 | 0.099 | 0.056 | 0.096 | 1.248 | 0.126 | 0.555 | 0.228 | 0.434 | 0.108 | 0.564 | 0.125 |
| HS GPA Bin 1 | 0.133 | 0.087 | 0.282 | 0.065 | 0.022 | 0.068 | -0.067 | 0.118 | 0.086 | 0.122 | 0.074 | 0.125 | -0.165 | 0.070 | -0.027 | 0.062 | 0.257 | 0.060 | -0.551 | 0.149 | 0.077 | 0.051 | -0.082 | 0.092 |
| HS GPA Bin 2 | -0.005 | 0.083 | 0.420 | 0.071 | -0.004 | 0.071 | -0.047 | 0.120 | 0.064 | 0.128 | 0.206 | 0.118 | -0.177 | 0.066 | -0.055 | 0.068 | 0.522 | 0.074 | -0.037 | 0.175 | 0.160 | 0.056 | 0.075 | 0.083 |
| HS GPA Bin 3 | -0.096 | 0.098 | 0.249 | 0.076 | -0.109 | 0.074 | -0.272 | 0.129 | 0.067 | 0.140 | 0.163 | 0.142 | -0.267 | 0.078 | -0.083 | 0.080 | 1.112 | 0.085 | 0.647 | 0.222 | 0.190 | 0.067 | 0.562 | 0.103 |
| HS GPA Bin 4 | -0.300 | 0.111 | -0.089 | 0.087 | -0.395 | 0.103 | -0.348 | 0.156 | -0.069 | 0.166 | 0.075 | 0.162 | -0.196 | 0.094 | 0.183 | 0.095 | 1.773 | 0.104 | 0.886 | 0.307 | 0.509 | 0.081 | 0.915 | 0.124 |
| SweSAT | 0.275 | 0.088 | -0.186 | 0.071 | -0.092 | 0.081 | -0.112 | 0.125 | 0.061 | 0.107 | 0.378 | 0.123 | 0.437 | 0.069 | 0.241 | 0.068 | 0.232 | 0.082 | -0.416 | 0.173 | 0.143 | 0.065 | 0.489 | 0.091 |
| SweSAT missing | -0.052 | 0.093 | -0.183 | 0.076 | -0.408 | 0.084 | -0.191 | 0.094 | -0.024 | 0.106 | -0.193 | 0.136 | -0.136 | 0.072 | -0.156 | 0.080 | -0.036 | 0.097 | -1.787 | 0.262 | -0.312 | 0.071 | -0.325 | 0.102 |
| Log Admit Share | 0.039 | 0.035 | -0.418 | 0.124 | -0.080 | 0.025 | -0.007 | 0.033 | -0.020 | 0.078 | 0.118 | 0.050 | 0.153 | 0.027 | 0.034 | 0.044 | 0.364 | 0.102 | 0.724 | 0.067 | 0.041 | 0.022 | 0.191 | 0.018 |
| Within-Sch-Across-Cohort IV | 0.015 | 0.016 | 0.038 | 0.012 | -0.023 | 0.018 | 0.025 | 0.020 | 0.064 | 0.027 | 0.043 | 0.021 | 0.063 | 0.013 | 0.087 | 0.012 | 0.014 | 0.012 | 0.004 | 0.025 | 0.046 | 0.010 | 0.018 | 0.013 |
| School Ave Enroll Maj | 3.874 | 1.158 | 2.457 | 0.246 | -1.655 | 0.923 | 5.281 | 1.755 | 5.413 | 0.924 | 12.182 | 2.204 | 11.742 | 1.056 | 6.250 | 0.573 | 1.553 | 0.345 | 7.762 | 3.387 | 3.415 | 0.387 | 3.922 | 1.474 |
| Min Log Distance | 0.009 | 0.017 | 0.094 | 0.014 | -0.052 | 0.015 | 0.054 | 0.022 | 0.068 | 0.020 | 0.045 | 0.025 | 0.025 | 0.013 | 0.052 | 0.013 | 0.035 | 0.016 | -0.049 | 0.030 | -0.012 | 0.011 | -0.056 | 0.017 |
| Cognitive | 0.058 | 0.039 | 0.012 | 0.035 | -0.048 | 0.037 | -0.107 | 0.060 | 0.052 | 0.055 | -0.088 | 0.063 | 0.006 | 0.033 | 0.063 | 0.032 | 0.238 | 0.041 | 0.336 | 0.090 | 0.041 | 0.030 | 0.031 | 0.040 |
| Interpersonal | -0.035 | 0.025 | -0.083 | 0.021 | 0.052 | 0.023 | 0.070 | 0.030 | 0.040 | 0.030 | -0.179 | 0.033 | 0.112 | 0.019 | -0.090 | 0.019 | 0.021 | 0.021 | 0.115 | 0.046 | 0.071 | 0.018 | 0.127 | 0.023 |
| Grit | 0.027 | 0.048 | -0.177 | 0.041 | 0.041 | 0.041 | -0.022 | 0.070 | 0.091 | 0.070 | -0.106 | 0.066 | 0.071 | 0.038 | -0.094 | 0.038 | -0.038 | 0.047 | 0.268 | 0.103 | 0.133 | 0.032 | 0.129 | 0.046 |
| Type 2 | -1.051 | 0.170 | -0.825 | 0.329 | -2.076 | 0.189 | 2.805 | 0.155 | -0.131 | 0.269 | -0.624 | 0.262 | -1.180 | 0.153 | -0.313 | 0.252 | -0.728 | 0.396 | 3.356 | 0.278 | -2.222 | 0.098 | -2.137 | 0.132 |
| Type 3 | -0.861 | 0.202 | -0.287 | 0.475 | 1.226 | 0.131 | -1.785 | 0.376 | -1.579 | 0.441 | -2.095 | 0.367 | -1.362 | 0.198 | -0.585 | 0.424 | -2.322 | 0.656 | -1.280 | 2.554 | 0.704 | 0.055 | -1.731 | 0.175 |
| Type 4 | -0.343 | 0.168 | -0.274 | 0.297 | -1.755 | 0.192 | 0.540 | 0.184 | 3.113 | 0.250 | 0.441 | 0.215 | -1.040 | 0.137 | -0.615 | 0.243 | -0.611 | 0.354 | 0.215 | 0.349 | -2.256 | 0.103 | -1.870 | 0.130 |
| Type 5 | -2.582 | 0.194 | 1.879 | 0.278 | -2.810 | 0.265 | -1.664 | 0.254 | -1.215 | 0.307 | -1.217 | 0.266 | -3.182 | 0.213 | 0.541 | 0.207 | 2.846 | 0.320 | 1.283 | 0.336 | -2.398 | 0.140 | -2.611 | 0.198 |
| Type 6 | -0.663 | 0.178 | 1.745 | 0.269 | -0.888 | 0.210 | -0.571 | 0.248 | -0.367 | 0.358 | 0.244 | 0.229 | -1.767 | 0.126 | 2.217 | 0.183 | 0.824 | 0.352 | 1.322 | 0.329 | -1.364 | 0.180 | -2.365 | 0.164 |
| Type 7 | 1.814 | 0.099 | 0.032 | 0.504 | -0.233 | 0.218 | 0.520 | 0.241 | 0.768 | 0.397 | 2.264 | 0.155 | 0.224 | 0.228 | -0.671 | 0.365 | -1.934 | 0.699 | 0.252 | 0.699 | -1.488 | 0.152 | -1.252 | 0.242 |
| Type 8 | -0.610 | 0.171 | 3.738 | 0.286 | -0.791 | 0.190 | -1.199 | 0.276 | 0.214 | 0.277 | 0.030 | 0.262 | -2.568 | 0.212 | 0.526 | 0.222 | 2.150 | 0.338 | -0.759 | 0.504 | -1.815 | 0.124 | -3.478 | 0.342 |
| N | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | | 37012 | |

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

## Table F.9: Estimates for Switch Major Model (Education Choices $D_4$)

| Variable | 3yr STEM | | 3yr Bus | | Hlth Sci | | Educ | | Humanit. | | Soc Sci | | Sci | | Eng | | Med | | Bus | | Law | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -0.597 | 0.458 | -2.656 | 0.572 | -1.124 | 0.683 | -0.307 | 0.575 | -4.266 | 0.744 | -1.234 | 0.508 | -4.274 | 0.514 | -4.385 | 0.441 | -8.234 | 1.417 | -3.242 | 0.426 | -1.770 | 0.587 |
| Mother College | -0.164 | 0.084 | -0.090 | 0.124 | 0.197 | 0.126 | 0.118 | 0.101 | 0.313 | 0.127 | 0.177 | 0.099 | -0.005 | 0.097 | 0.030 | 0.086 | 0.329 | 0.168 | 0.074 | 0.095 | 0.187 | 0.153 |
| Mother High School | 0.149 | 0.099 | 0.058 | 0.143 | 0.277 | 0.163 | 0.170 | 0.117 | 0.126 | 0.176 | 0.043 | 0.133 | 0.191 | 0.116 | 0.274 | 0.111 | -0.066 | 0.294 | 0.282 | 0.117 | -0.343 | 0.209 |
| Mother Educ missing | 0.110 | 0.201 | -0.412 | 0.307 | 0.139 | 0.357 | -0.175 | 0.228 | -0.207 | 0.349 | -0.371 | 0.255 | 0.221 | 0.244 | 0.313 | 0.233 | 0.068 | 0.513 | -0.074 | 0.239 | -0.521 | 0.423 |
| Father College | -0.353 | 0.089 | -0.381 | 0.126 | -0.176 | 0.151 | -0.165 | 0.101 | -0.072 | 0.140 | 0.016 | 0.105 | -0.222 | 0.095 | -0.079 | 0.093 | 0.171 | 0.179 | -0.156 | 0.094 | -0.040 | 0.156 |
| Father High School | -0.008 | 0.089 | -0.034 | 0.126 | -0.202 | 0.145 | 0.103 | 0.103 | 0.133 | 0.148 | 0.216 | 0.110 | 0.063 | 0.110 | 0.220 | 0.098 | 0.072 | 0.258 | -0.023 | 0.103 | 0.228 | 0.201 |
| Father Educ missing | -0.264 | 0.172 | 0.311 | 0.270 | -0.093 | 0.323 | 0.136 | 0.209 | 0.297 | 0.286 | 0.225 | 0.231 | -0.208 | 0.219 | 0.056 | 0.193 | 0.323 | 0.446 | 0.072 | 0.225 | 0.609 | 0.374 |
| Family Income | 0.031 | 0.037 | 0.076 | 0.058 | 0.055 | 0.063 | -0.023 | 0.047 | -0.027 | 0.063 | 0.029 | 0.048 | -0.020 | 0.047 | 0.107 | 0.041 | 0.138 | 0.080 | 0.211 | 0.043 | 0.111 | 0.071 |
| School-Ave Fam Income | -0.318 | 0.116 | 0.069 | 0.160 | -0.520 | 0.178 | -0.359 | 0.129 | -0.101 | 0.177 | -0.004 | 0.127 | -0.113 | 0.126 | -0.076 | 0.121 | 0.050 | 0.205 | 0.438 | 0.112 | 0.065 | 0.167 |
| Health Endurance | 0.174 | 0.031 | 0.201 | 0.052 | 0.099 | 0.048 | 0.098 | 0.038 | -0.031 | 0.053 | -0.007 | 0.040 | 0.080 | 0.038 | 0.229 | 0.035 | 0.370 | 0.070 | 0.115 | 0.038 | 0.092 | 0.063 |
| Health Strength | -0.019 | 0.032 | -0.044 | 0.046 | 0.074 | 0.052 | 0.016 | 0.037 | 0.050 | 0.046 | -0.083 | 0.042 | 0.020 | 0.038 | -0.096 | 0.035 | -0.144 | 0.082 | -0.114 | 0.036 | -0.065 | 0.063 |
| Health missing | -0.010 | 0.152 | 0.218 | 0.225 | -0.048 | 0.237 | 0.074 | 0.171 | 0.068 | 0.224 | -0.110 | 0.184 | 0.024 | 0.176 | -0.088 | 0.162 | 0.227 | 0.330 | -0.027 | 0.175 | -0.164 | 0.307 |
| Took 9th Adv. Math | 0.512 | 0.107 | 0.093 | 0.172 | 0.010 | 0.144 | 0.154 | 0.123 | 0.199 | 0.166 | -0.315 | 0.137 | 0.570 | 0.132 | 0.639 | 0.135 | 0.803 | 0.469 | 0.376 | 0.132 | -0.757 | 0.235 |
| Took 9th Adv. English | -0.154 | 0.112 | -0.302 | 0.170 | -0.002 | 0.176 | -0.006 | 0.124 | 0.164 | 0.197 | -0.249 | 0.163 | 0.004 | 0.139 | -0.225 | 0.126 | 0.130 | 0.464 | -0.362 | 0.140 | -0.173 | 0.301 |
| HS Academic Track | -0.143 | 0.107 | 0.091 | 0.152 | -0.133 | 0.156 | -0.029 | 0.118 | 0.278 | 0.159 | 0.229 | 0.140 | 0.025 | 0.127 | 0.220 | 0.133 | 0.169 | 0.314 | 0.340 | 0.123 | 0.682 | 0.243 |
| HS STEM Track | 0.173 | 0.127 | 0.134 | 0.203 | 0.014 | 0.201 | -0.137 | 0.155 | 0.056 | 0.203 | 0.352 | 0.178 | 0.571 | 0.146 | 1.199 | 0.142 | 1.339 | 0.322 | 0.371 | 0.152 | 0.920 | 0.292 |
| Enroll 3yr non-STEM | -0.937 | 0.248 | 0.000 | 0.000 | -1.913 | 0.268 | -1.792 | 0.316 | -0.307 | 0.292 | -1.725 | 0.288 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -2.077 | 0.246 | -2.333 | 0.302 |
| Enroll 3yr STEM | 5.140 | 0.237 | 1.722 | 0.216 | 1.081 | 0.255 | 0.819 | 0.315 | 0.231 | 0.420 | -0.052 | 0.319 | 4.032 | 0.217 | 4.276 | 0.170 | 0.000 | 0.000 | 1.084 | 0.223 | 0.000 | 0.000 |
| Enroll 3yr Bus | 1.626 | 0.270 | 4.885 | 0.157 | 0.000 | 0.000 | 0.138 | 0.400 | 0.000 | 0.000 | -0.151 | 0.389 | 2.134 | 0.337 | 0.000 | 0.000 | 0.000 | 0.000 | 2.211 | 0.225 | 0.000 | 0.000 |
| Enroll Hlth Sci | 0.880 | 0.336 | 0.000 | 0.000 | 5.023 | 0.244 | 0.685 | 0.384 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 2.447 | 0.311 | 0.000 | 0.000 | 0.000 | 0.000 |
| Enroll Educ | 0.993 | 0.251 | 0.000 | 0.000 | 0.617 | 0.274 | 3.980 | 0.304 | 2.216 | 0.298 | 0.244 | 0.319 | 3.263 | 0.229 | 1.746 | 0.232 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Enroll Humanit. | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.647 | 0.330 | 4.329 | 0.299 | 1.516 | 0.298 | 2.978 | 0.283 | 2.104 | 0.250 | 0.000 | 0.000 | 0.705 | 0.278 | 0.000 | 0.000 |
| Enroll Soc Sci | -0.521 | 0.293 | 0.000 | 0.000 | -0.691 | 0.305 | -0.557 | 0.348 | 0.542 | 0.357 | 2.338 | 0.268 | 1.632 | 0.271 | 0.000 | 0.000 | 0.000 | 0.000 | 0.285 | 0.222 | -0.258 | 0.238 |
| Enroll Science | 3.498 | 0.264 | 1.969 | 0.310 | 2.158 | 0.281 | 2.038 | 0.347 | 1.603 | 0.402 | 1.420 | 0.318 | 6.914 | 0.236 | 3.806 | 0.212 | 2.886 | 0.258 | 1.890 | 0.262 | 1.239 | 0.300 |
| Enroll Engineer | 2.975 | 0.239 | 0.000 | 0.000 | 0.927 | 0.290 | 1.053 | 0.305 | 0.898 | 0.387 | 0.006 | 0.318 | 3.679 | 0.225 | 5.869 | 0.176 | 2.083 | 0.251 | 1.500 | 0.238 | 0.649 | 0.279 |
| Enroll Medicine | 0.000 | 0.000 | 0.000 | 0.000 | 0.735 | 1.566 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 5.166 | 0.323 | 0.000 | 0.000 | 0.000 | 0.000 |
| Enroll Business | 1.111 | 0.269 | 3.213 | 0.155 | 0.554 | 0.285 | 0.693 | 0.326 | 0.000 | 0.000 | 1.069 | 0.294 | 3.254 | 0.220 | 2.005 | 0.230 | 0.000 | 0.000 | 3.886 | 0.204 | 0.571 | 0.231 |
| Enroll Law | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.455 | 0.346 | 2.363 | 0.411 | 0.000 | 0.000 | 0.000 | 0.000 | 1.127 | 0.278 | 4.432 | 0.212 |
| HS GPA Bin 1 | -0.043 | 0.101 | -0.030 | 0.169 | 0.120 | 0.240 | 0.009 | 0.139 | -0.138 | 0.219 | -0.215 | 0.169 | 0.079 | 0.123 | 0.216 | 0.087 | 0.563 | 0.257 | -0.132 | 0.119 | -0.022 | 0.237 |
| HS GPA Bin 2 | 0.042 | 0.106 | -0.388 | 0.162 | 0.134 | 0.237 | -0.035 | 0.134 | 0.091 | 0.189 | 0.001 | 0.140 | 0.206 | 0.136 | 0.553 | 0.103 | 0.503 | 0.275 | -0.176 | 0.133 | 0.012 | 0.226 |
| HS GPA Bin 3 | -0.016 | 0.114 | -0.483 | 0.178 | 0.059 | 0.240 | -0.187 | 0.152 | 0.001 | 0.193 | -0.115 | 0.156 | 0.296 | 0.140 | 0.756 | 0.119 | 1.283 | 0.334 | -0.153 | 0.141 | 0.346 | 0.291 |
| HS GPA Bin 4 | -0.135 | 0.122 | -0.511 | 0.199 | 0.109 | 0.273 | -0.252 | 0.163 | 0.187 | 0.215 | 0.069 | 0.183 | 0.503 | 0.160 | 1.194 | 0.139 | 1.565 | 0.406 | 0.017 | 0.163 | 0.678 | 0.343 |
| SweSAT | -0.676 | 0.108 | -0.285 | 0.165 | -0.227 | 0.153 | -0.441 | 0.129 | -0.152 | 0.178 | 0.146 | 0.136 | -0.300 | 0.122 | -0.889 | 0.118 | 0.759 | 0.256 | -0.572 | 0.124 | 0.078 | 0.212 |
| SweSAT miss | -0.225 | 0.122 | -0.410 | 0.190 | -0.675 | 0.170 | -0.133 | 0.140 | 0.391 | 0.208 | -0.403 | 0.183 | -0.256 | 0.151 | -0.772 | 0.138 | -0.204 | 0.402 | -0.836 | 0.152 | -0.866 | 0.275 |
| Cognitive | 0.103 | 0.050 | 0.056 | 0.076 | -0.052 | 0.078 | 0.022 | 0.057 | 0.153 | 0.077 | 0.079 | 0.062 | 0.107 | 0.058 | 0.219 | 0.056 | 0.138 | 0.127 | 0.199 | 0.058 | 0.031 | 0.099 |
| Interpersonal | 0.017 | 0.032 | 0.106 | 0.042 | 0.110 | 0.048 | 0.084 | 0.038 | -0.049 | 0.050 | 0.039 | 0.036 | -0.021 | 0.035 | 0.046 | 0.034 | 0.183 | 0.068 | 0.166 | 0.033 | 0.162 | 0.058 |
| Grit | -0.116 | 0.050 | 0.038 | 0.075 | -0.048 | 0.085 | -0.026 | 0.060 | 0.097 | 0.081 | 0.092 | 0.063 | -0.092 | 0.058 | -0.018 | 0.055 | 0.068 | 0.122 | 0.174 | 0.060 | 0.045 | 0.110 |
| Type 2 | 0.278 | 0.286 | -0.744 | 1.900 | 1.847 | 0.285 | 0.422 | 0.286 | 0.719 | 0.639 | -0.221 | 0.256 | 0.400 | 0.279 | 0.203 | 0.274 | 2.935 | 1.208 | -0.416 | 0.254 | -1.470 | 0.486 |
| Type 3 | -0.019 | 0.301 | 0.543 | 0.274 | 0.376 | 0.340 | -0.312 | 0.327 | 0.937 | 0.631 | -0.652 | 0.244 | 0.249 | 0.323 | -0.258 | 0.336 | -24.897 | 12.201 | 0.532 | 0.220 | -1.819 | 0.400 |
| Type 4 | -0.151 | 0.239 | 0.035 | 0.322 | 1.068 | 0.301 | 0.791 | 0.229 | 0.930 | 0.419 | -0.397 | 0.214 | -0.035 | 0.232 | -0.430 | 0.272 | 0.799 | 1.260 | -0.488 | 0.213 | -1.547 | 0.330 |
| Type 5 | 0.711 | 0.216 | 0.999 | 0.345 | 1.089 | 0.330 | 0.714 | 0.285 | 1.940 | 0.579 | 0.138 | 0.297 | 0.741 | 0.242 | 1.661 | 0.212 | 1.696 | 1.216 | 0.482 | 0.232 | -0.822 | 2.031 |
| Type 6 | 0.567 | 0.207 | 0.345 | 0.285 | 0.645 | 0.298 | 0.227 | 0.267 | 1.351 | 0.498 | -0.470 | 0.248 | 1.049 | 0.217 | 0.605 | 0.222 | 0.840 | 1.229 | -0.317 | 0.239 | -1.392 | 0.391 |
| Type 7 | -0.052 | 0.320 | -0.469 | 0.334 | 0.995 | 0.363 | 0.445 | 0.355 | 1.412 | 0.402 | 0.177 | 0.220 | -1.189 | 0.410 | -1.450 | 0.471 | -0.301 | 1.352 | -0.970 | 0.298 | -0.897 | 0.387 |
| Type 8 | 1.106 | 0.212 | 0.205 | 0.363 | 1.120 | 0.312 | 0.832 | 0.283 | 2.014 | 0.515 | -0.199 | 0.348 | 0.448 | 0.242 | 1.136 | 0.227 | 0.247 | 1.266 | 0.006 | 0.251 | -1.147 | 2.062 |
| N | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | | 37449 | |

*Notes*: Table reports estimates for the switching majors model. Enrollment in certain majors are omitted from some choices if the probability of making that transition in the data is less than 0.00025 (10 observations).

Table F.10: Estimates for Graduate College Models I (Education Choices $D_5$)

| Variable | 3yr non-STEM | | 3yr STEM | | 3yr Business | | Health Sci | | Education | | Humanities | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 0.020 | 0.262 | -0.544 | 0.214 | -1.125 | 0.467 | 0.263 | 0.410 | 0.242 | 0.276 | 0.338 | 0.622 |
| Mother College | -0.119 | 0.067 | 0.119 | 0.034 | 0.240 | 0.110 | 0.223 | 0.081 | 0.046 | 0.057 | 0.039 | 0.142 |
| Mother High School | 0.268 | 0.092 | 0.022 | 0.039 | 0.067 | 0.126 | 0.043 | 0.103 | 0.133 | 0.069 | 0.012 | 0.208 |
| Mother Educ missing | 0.221 | 0.178 | 0.077 | 0.085 | 0.392 | 0.269 | 0.164 | 0.228 | 0.335 | 0.142 | 0.053 | 0.423 |
| Father College | 0.203 | 0.069 | 0.206 | 0.035 | 0.091 | 0.119 | 0.053 | 0.089 | 0.065 | 0.061 | 0.473 | 0.147 |
| Father High School | -0.118 | 0.080 | 0.045 | 0.033 | 0.160 | 0.119 | 0.152 | 0.090 | 0.035 | 0.062 | 0.182 | 0.180 |
| Father Educ missing | -0.028 | 0.156 | 0.045 | 0.074 | 0.242 | 0.227 | 0.071 | 0.198 | -0.285 | 0.123 | 0.332 | 0.388 |
| Family Income | 0.065 | 0.035 | 0.126 | 0.018 | 0.139 | 0.052 | 0.124 | 0.045 | 0.065 | 0.033 | 0.144 | 0.073 |
| School-Ave Fam Income | 0.012 | 0.084 | 0.075 | 0.055 | 0.024 | 0.142 | -0.090 | 0.134 | -0.060 | 0.093 | -0.141 | 0.197 |
| Health Endurance | 0.036 | 0.025 | 0.004 | 0.013 | 0.072 | 0.040 | 0.072 | 0.033 | 0.035 | 0.022 | 0.008 | 0.058 |
| Health Strength | -0.062 | 0.026 | -0.107 | 0.012 | -0.099 | 0.041 | -0.079 | 0.029 | -0.116 | 0.020 | 0.067 | 0.051 |
| Health missing | 0.175 | 0.126 | -0.070 | 0.067 | 0.398 | 0.216 | -0.094 | 0.165 | -0.199 | 0.115 | -0.005 | 0.266 |
| Took 9th Adv. Math | 0.108 | 0.082 | -0.000 | 0.050 | -0.003 | 0.136 | -0.013 | 0.085 | 0.065 | 0.063 | -0.295 | 0.180 |
| Took 9th Adv. English | -0.130 | 0.099 | -0.123 | 0.040 | -0.056 | 0.147 | 0.031 | 0.091 | -0.129 | 0.071 | 0.059 | 0.232 |
| HS Academic Track | 0.127 | 0.078 | -0.003 | 0.047 | 0.141 | 0.131 | -0.122 | 0.094 | -0.042 | 0.061 | 0.159 | 0.169 |
| HS STEM Track | 0.012 | 0.099 | -0.188 | 0.040 | -0.088 | 0.158 | -0.085 | 0.118 | -0.288 | 0.077 | -0.277 | 0.198 |
| Cognitive | -0.002 | 0.030 | 0.169 | 0.017 | 0.155 | 0.052 | 0.191 | 0.039 | 0.093 | 0.026 | 0.331 | 0.061 |
| Interpersonal | 0.117 | 0.024 | 0.093 | 0.012 | 0.123 | 0.042 | 0.162 | 0.031 | 0.074 | 0.023 | 0.122 | 0.050 |
| Grit | 0.131 | 0.036 | 0.343 | 0.019 | 0.263 | 0.059 | 0.237 | 0.045 | 0.288 | 0.033 | 0.371 | 0.070 |
| Type 2 | | | 0.427 | 0.262 | | | 0.174 | 0.087 | | | | |
| Type 3 | | | 0.196 | 0.265 | 0.125 | 0.137 | | | | | | |
| Type 4 | | | -0.383 | 0.193 | | | | | 0.106 | 0.063 | | |
| Type 5 | | | -0.156 | 0.150 | | | | | | | | |
| Type 6 | | | -0.123 | 0.166 | | | | | | | | |
| Type 7 | -0.706 | 0.111 | 0.056 | 0.273 | | | | | -0.482 | 0.220 | -0.958 | 0.184 |
| Type 8 | | | -0.142 | 0.146 | | | | | | | | |
| N | 2508 | | 10234 | | 998 | | 1974 | | 3593 | | 735 | |

*Notes*: Table reports estimates for the college graduation models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.11: Estimates for Graduate College Models II (Education Choices $D_5$)

| Variable | Soc Sci | | Sciences | | Engineer | | Medicine | | Business | | Law | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | -1.159 | 0.395 | -0.058 | 0.281 | -0.510 | 0.195 | -1.769 | 2.810 | -1.172 | 0.214 | -0.920 | 0.494 |
| Mother College | 0.149 | 0.087 | 0.217 | 0.054 | 0.233 | 0.037 | 0.264 | 0.204 | 0.150 | 0.056 | 0.253 | 0.124 |
| Mother High School | 0.118 | 0.121 | 0.196 | 0.082 | 0.061 | 0.064 | -0.643 | 2.154 | 0.146 | 0.077 | 0.112 | 0.171 |
| Mother Educ missing | -0.017 | 0.275 | 0.510 | 0.163 | 0.257 | 0.118 | -0.947 | 2.498 | 0.152 | 0.166 | 0.151 | 0.312 |
| Father College | 0.151 | 0.091 | 0.200 | 0.064 | 0.191 | 0.042 | 0.227 | 0.210 | 0.085 | 0.060 | 0.144 | 0.130 |
| Father High School | 0.244 | 0.115 | 0.044 | 0.077 | -0.059 | 0.054 | -0.272 | 0.764 | 0.116 | 0.072 | 0.198 | 0.178 |
| Father Educ missing | 0.427 | 0.247 | -0.174 | 0.155 | -0.104 | 0.103 | 0.557 | 1.255 | 0.155 | 0.140 | 0.250 | 0.278 |
| Family Income | 0.070 | 0.042 | 0.061 | 0.031 | 0.145 | 0.020 | 0.197 | 0.093 | 0.063 | 0.023 | 0.135 | 0.046 |
| School-Ave Fam Income | 0.239 | 0.128 | -0.116 | 0.082 | 0.028 | 0.053 | 0.548 | 0.290 | 0.104 | 0.065 | 0.199 | 0.141 |
| Health Endurance | -0.051 | 0.036 | 0.004 | 0.024 | -0.000 | 0.016 | 0.131 | 0.078 | -0.025 | 0.022 | -0.050 | 0.050 |
| Health Strength | -0.041 | 0.037 | -0.089 | 0.024 | -0.144 | 0.017 | -0.180 | 0.089 | -0.121 | 0.023 | -0.129 | 0.047 |
| Health missing | -0.172 | 0.174 | -0.052 | 0.111 | -0.058 | 0.079 | -0.227 | 0.332 | 0.129 | 0.112 | -0.062 | 0.240 |
| Took 9th Adv. Math | -0.123 | 0.123 | -0.088 | 0.102 | -0.021 | 0.107 | 0.691 | 0.737 | 0.159 | 0.089 | 0.060 | 0.175 |
| Took 9th Adv. English | -0.081 | 0.142 | -0.140 | 0.097 | -0.083 | 0.083 | -0.133 | 1.631 | 0.039 | 0.103 | -0.136 | 0.294 |
| HS Academic Track | 0.103 | 0.111 | 0.001 | 0.081 | -0.110 | 0.083 | 0.298 | 0.885 | 0.048 | 0.086 | 0.059 | 0.185 |
| HS STEM Track | 0.157 | 0.136 | 0.241 | 0.085 | 0.022 | 0.067 | -0.330 | 0.472 | 0.134 | 0.101 | -0.214 | 0.203 |
| Cognitive | 0.126 | 0.040 | 0.129 | 0.027 | 0.147 | 0.019 | 0.136 | 0.097 | 0.102 | 0.027 | 0.179 | 0.054 |
| Interpersonal | -0.011 | 0.033 | 0.059 | 0.022 | 0.115 | 0.016 | 0.064 | 0.068 | 0.018 | 0.022 | 0.054 | 0.044 |
| Grit | 0.250 | 0.046 | 0.231 | 0.031 | 0.301 | 0.021 | 0.380 | 0.105 | 0.232 | 0.027 | 0.354 | 0.056 |
| Type 2 | | | | | | | 0.825 | 0.223 | | | | |
| Type 3 | 0.035 | 0.226 | 0.262 | 0.243 | | | | | 0.185 | 0.068 | -0.502 | 0.937 |
| Type 5 | | | -0.270 | 0.146 | 0.148 | 0.070 | | | | | | |
| Type 6 | | | -0.160 | 0.092 | 0.218 | 0.099 | | | | | | |
| Type 7 | 0.329 | 0.163 | | | | | | | -0.057 | 0.270 | -0.346 | 0.294 |
| Type 8 | | | | | 0.276 | 0.083 | | | | | | |
| N | 1428 | | 3026 | | 7960 | | 703 | | 3321 | | 969 | |

*Notes*: Table reports estimates for the college graduation models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.12: Estimates for Log Wage Models I (Outcomes $Y_{ms}$)

| Variable | HSDO | | HS-Voc | | HS-Aca | | HS-STEM | | CollDO-low | | CollDO-high | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 9.935 | 0.058 | 9.870 | 0.022 | 9.489 | 0.075 | 9.660 | 0.140 | 10.104 | 0.143 | 9.819 | 0.074 |
| Mother College | 0.015 | 0.013 | 0.024 | 0.005 | 0.053 | 0.013 | 0.027 | 0.017 | 0.012 | 0.010 | 0.063 | 0.013 |
| Mother High School | 0.013 | 0.007 | 0.015 | 0.004 | 0.023 | 0.013 | 0.017 | 0.017 | 0.042 | 0.012 | -0.011 | 0.015 |
| Mother Educ missing | 0.020 | 0.018 | 0.016 | 0.008 | 0.083 | 0.031 | 0.009 | 0.036 | 0.017 | 0.026 | 0.033 | 0.033 |
| Father College | 0.026 | 0.016 | 0.008 | 0.007 | 0.019 | 0.013 | 0.056 | 0.018 | 0.009 | 0.012 | 0.057 | 0.013 |
| Father High School | -0.002 | 0.008 | 0.015 | 0.004 | 0.030 | 0.012 | 0.036 | 0.014 | 0.041 | 0.010 | 0.029 | 0.013 |
| Father Educ missing | 0.010 | 0.015 | 0.011 | 0.007 | 0.008 | 0.025 | 0.074 | 0.031 | 0.024 | 0.022 | 0.033 | 0.028 |
| Family Income | 0.020 | 0.007 | 0.031 | 0.003 | 0.062 | 0.006 | 0.053 | 0.009 | 0.045 | 0.007 | 0.047 | 0.007 |
| School-Ave Fam Income | 0.045 | 0.018 | 0.080 | 0.007 | 0.167 | 0.028 | 0.151 | 0.025 | 0.080 | 0.017 | 0.125 | 0.018 |
| Health Endurance | 0.020 | 0.004 | 0.020 | 0.001 | 0.023 | 0.005 | 0.016 | 0.006 | 0.019 | 0.004 | 0.024 | 0.005 |
| Health Strength | -0.007 | 0.003 | -0.015 | 0.001 | -0.020 | 0.004 | -0.012 | 0.005 | -0.019 | 0.004 | -0.023 | 0.004 |
| Health missing | -0.004 | 0.016 | 0.003 | 0.007 | -0.001 | 0.022 | 0.019 | 0.031 | 0.005 | 0.022 | -0.007 | 0.026 |
| Took 9th Adv. Math | 0.041 | 0.016 | 0.005 | 0.010 | 0.027 | 0.017 | 0.034 | 0.041 | -0.007 | 0.017 | 0.020 | 0.016 |
| Took 9th Adv. English | 0.016 | 0.017 | -0.000 | 0.008 | 0.045 | 0.019 | 0.021 | 0.030 | -0.026 | 0.015 | -0.005 | 0.017 |
| HS Academic Track | | | | | | | | | 0.026 | 0.014 | 0.015 | 0.014 |
| HS STEM Track | | | | | | | | | 0.041 | 0.013 | 0.053 | 0.017 |
| Cognitive | 0.022 | 0.006 | 0.029 | 0.003 | 0.054 | 0.007 | 0.044 | 0.008 | 0.040 | 0.006 | 0.050 | 0.006 |
| Interpersonal | 0.018 | 0.004 | 0.026 | 0.003 | 0.056 | 0.005 | 0.048 | 0.006 | 0.044 | 0.004 | 0.054 | 0.005 |
| Grit | 0.000 | 0.008 | 0.030 | 0.004 | 0.054 | 0.008 | 0.049 | 0.009 | 0.051 | 0.007 | 0.056 | 0.007 |
| Type 2 | 0.077 | 0.033 | -0.084 | 0.029 | -0.069 | 0.032 | -0.094 | 0.127 | -0.351 | 0.134 | -0.187 | 0.063 |
| Type 3 | 0.313 | 0.036 | 0.618 | 0.021 | 0.512 | 0.042 | 0.579 | 0.378 | -0.146 | 0.217 | 0.311 | 0.085 |
| Type 4 | -0.154 | 0.036 | -0.034 | 0.020 | -0.038 | 0.026 | -0.021 | 0.111 | -0.380 | 0.143 | -0.214 | 0.044 |
| Type 5 | 0.862 | 0.111 | -0.176 | 0.013 | -0.349 | 0.041 | -0.017 | 0.124 | -0.096 | 0.141 | 0.003 | 0.047 |
| Type 6 | -0.053 | 0.060 | 0.059 | 0.024 | 0.091 | 0.038 | -0.013 | 0.122 | -0.209 | 0.144 | -0.044 | 0.051 |
| Type 7 | -0.182 | 0.168 | -0.223 | 0.034 | 0.028 | 0.036 | -0.134 | 0.136 | -0.275 | 0.148 | -0.225 | 0.058 |
| Type 8 | -0.024 | 0.190 | 0.252 | 0.011 | 0.053 | 0.093 | 0.049 | 0.093 | -0.116 | 0.128 | -0.081 | 0.050 |
| 1/Precision | 0.128 | 0.004 | 0.127 | 0.002 | 0.258 | 0.008 | 0.256 | 0.009 | 0.235 | 0.004 | 0.279 | 0.006 |
| N | 3183 | | 20271 | | 4112 | | 2094 | | 3745 | | 3666 | |

*Notes*: Table reports estimates for the log wage models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.13: Estimates for Log Wage Models II (Outcomes $Y_{ms}$)

| Variable | 3yr non-STEM | | 3yr STEM | | 3yr Business | | Health Sci | | Educ | | Humanities | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 9.951 | 0.111 | 10.381 | 0.087 | 9.480 | 0.279 | 10.047 | 0.075 | 10.098 | 0.041 | 10.081 | 0.150 |
| Mother College | 0.036 | 0.026 | 0.021 | 0.009 | 0.112 | 0.054 | 0.018 | 0.015 | 0.014 | 0.008 | 0.054 | 0.034 |
| Mother High School | 0.008 | 0.035 | -0.007 | 0.012 | -0.052 | 0.078 | 0.019 | 0.014 | 0.015 | 0.010 | 0.012 | 0.035 |
| Mother Educ missing | 0.021 | 0.058 | -0.018 | 0.024 | -0.042 | 0.138 | 0.059 | 0.029 | 0.016 | 0.018 | 0.039 | 0.086 |
| Father College | 0.041 | 0.026 | 0.013 | 0.010 | 0.044 | 0.062 | 0.057 | 0.016 | 0.021 | 0.009 | -0.004 | 0.037 |
| Father High School | 0.035 | 0.028 | 0.018 | 0.010 | 0.111 | 0.063 | 0.027 | 0.015 | 0.009 | 0.009 | 0.047 | 0.035 |
| Father Educ missing | 0.051 | 0.049 | 0.044 | 0.021 | 0.148 | 0.102 | -0.003 | 0.025 | 0.007 | 0.014 | 0.006 | 0.077 |
| Family Income | 0.066 | 0.015 | 0.028 | 0.005 | 0.040 | 0.021 | 0.019 | 0.008 | 0.005 | 0.005 | 0.004 | 0.019 |
| School-Ave Fam Income | 0.053 | 0.038 | 0.064 | 0.017 | 0.255 | 0.090 | 0.050 | 0.025 | 0.017 | 0.014 | -0.011 | 0.046 |
| Health Endurance | 0.029 | 0.010 | 0.013 | 0.003 | 0.069 | 0.025 | 0.019 | 0.006 | 0.010 | 0.003 | 0.012 | 0.014 |
| Health Strength | -0.038 | 0.009 | -0.017 | 0.003 | -0.037 | 0.025 | -0.008 | 0.004 | -0.004 | 0.003 | 0.001 | 0.011 |
| Health missing | -0.018 | 0.046 | 0.042 | 0.018 | -0.060 | 0.118 | 0.044 | 0.032 | 0.015 | 0.020 | 0.067 | 0.049 |
| Took 9th Adv. Math | 0.012 | 0.028 | -0.011 | 0.016 | 0.002 | 0.073 | 0.021 | 0.012 | -0.005 | 0.010 | -0.005 | 0.040 |
| Took 9th Adv. English | -0.024 | 0.036 | -0.014 | 0.013 | -0.040 | 0.084 | -0.033 | 0.015 | -0.010 | 0.011 | 0.085 | 0.048 |
| HS Academic Track | 0.038 | 0.026 | 0.007 | 0.015 | 0.002 | 0.070 | -0.025 | 0.015 | 0.012 | 0.009 | 0.010 | 0.035 |
| HS STEM Track | 0.086 | 0.034 | 0.049 | 0.012 | -0.033 | 0.094 | 0.041 | 0.020 | 0.034 | 0.011 | -0.013 | 0.043 |
| Cognitive | 0.043 | 0.010 | 0.028 | 0.005 | 0.125 | 0.028 | 0.035 | 0.007 | 0.029 | 0.004 | 0.068 | 0.015 |
| Interpersonal | 0.061 | 0.009 | 0.044 | 0.004 | 0.092 | 0.023 | 0.034 | 0.005 | 0.026 | 0.003 | 0.018 | 0.009 |
| Grit | 0.040 | 0.013 | 0.028 | 0.006 | 0.109 | 0.031 | 0.046 | 0.008 | 0.021 | 0.005 | 0.053 | 0.015 |
| Type 2 | | | -0.317 | 0.116 | | | -0.002 | 0.016 | | | | |
| Type 3 | | | -0.212 | 0.123 | 0.199 | 0.082 | | | | | | |
| Type 4 | | | -0.498 | 0.094 | | | | | 0.002 | 0.008 | | |
| Type 5 | | | -0.167 | 0.071 | | | | | | | | |
| Type 6 | | | -0.214 | 0.075 | | | | | | | | |
| Type 7 | -0.102 | 0.037 | -0.283 | 0.095 | | | | | 0.318 | 0.093 | 0.180 | 0.042 |
| Type 8 | | | -0.153 | 0.069 | | | | | | | | |
| 1/Precision | 0.292 | 0.011 | 0.200 | 0.005 | 0.348 | 0.020 | 0.191 | 0.009 | 0.128 | 0.008 | 0.197 | 0.016 |
| N | 917 | | 3578 | | 286 | | 1181 | | 1932 | | 293 | |

*Notes*: Table reports estimates for the log wage models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.14: Estimates for Log Wage Models III (Outcomes $Y_{ms}$)

| Variable | Soc Sci | | Sciences | | Engineer | | Medicine | | Business | | Law | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 9.916 | 0.168 | 10.347 | 0.098 | 10.317 | 0.076 | 10.436 | 0.182 | 9.873 | 0.116 | 9.969 | 0.150 |
| Mother College | 0.029 | 0.023 | -0.013 | 0.019 | 0.014 | 0.010 | 0.046 | 0.028 | 0.047 | 0.024 | 0.030 | 0.037 |
| Mother High School | 0.015 | 0.038 | -0.033 | 0.027 | 0.012 | 0.013 | -0.050 | 0.052 | -0.018 | 0.034 | 0.087 | 0.062 |
| Mother Educ missing | 0.145 | 0.075 | 0.065 | 0.052 | 0.003 | 0.026 | -0.011 | 0.096 | -0.112 | 0.096 | 0.020 | 0.089 |
| Father College | 0.046 | 0.026 | 0.009 | 0.019 | 0.011 | 0.010 | 0.064 | 0.028 | 0.090 | 0.027 | -0.012 | 0.039 |
| Father High School | 0.007 | 0.036 | 0.023 | 0.024 | 0.035 | 0.012 | -0.023 | 0.044 | 0.045 | 0.028 | 0.053 | 0.059 |
| Father Educ missing | -0.073 | 0.066 | -0.093 | 0.046 | 0.042 | 0.026 | 0.001 | 0.087 | 0.170 | 0.088 | 0.068 | 0.081 |
| Family Income | 0.045 | 0.013 | 0.036 | 0.011 | 0.040 | 0.005 | 0.023 | 0.009 | 0.061 | 0.011 | 0.058 | 0.017 |
| School-Ave Fam Income | 0.086 | 0.051 | -0.023 | 0.028 | 0.063 | 0.015 | -0.001 | 0.027 | 0.125 | 0.032 | 0.039 | 0.036 |
| Health Endurance | 0.031 | 0.011 | 0.018 | 0.008 | 0.018 | 0.004 | 0.014 | 0.009 | 0.043 | 0.011 | 0.029 | 0.015 |
| Health Strength | -0.011 | 0.011 | 0.000 | 0.008 | -0.018 | 0.004 | -0.018 | 0.010 | -0.025 | 0.013 | -0.037 | 0.014 |
| Health missing | 0.107 | 0.054 | 0.068 | 0.037 | 0.005 | 0.021 | 0.009 | 0.055 | -0.002 | 0.045 | 0.182 | 0.079 |
| Took 9th Adv. Math | 0.016 | 0.031 | 0.079 | 0.037 | -0.004 | 0.025 | 0.075 | 0.118 | 0.012 | 0.043 | 0.032 | 0.065 |
| Took 9th Adv. English | -0.027 | 0.038 | -0.007 | 0.035 | 0.012 | 0.018 | -0.025 | 0.152 | -0.000 | 0.050 | 0.066 | 0.107 |
| HS Academic Track | 0.039 | 0.034 | 0.080 | 0.029 | -0.058 | 0.022 | -0.023 | 0.063 | 0.045 | 0.036 | 0.067 | 0.080 |
| HS STEM Track | 0.018 | 0.043 | 0.073 | 0.027 | 0.062 | 0.017 | 0.028 | 0.060 | 0.055 | 0.046 | 0.022 | 0.087 |
| Cognitive | 0.061 | 0.013 | 0.015 | 0.008 | 0.038 | 0.005 | 0.069 | 0.012 | 0.092 | 0.012 | 0.067 | 0.017 |
| Interpersonal | 0.051 | 0.009 | 0.034 | 0.007 | 0.052 | 0.004 | 0.016 | 0.009 | 0.092 | 0.010 | 0.080 | 0.013 |
| Grit | 0.042 | 0.013 | -0.003 | 0.010 | 0.036 | 0.005 | 0.089 | 0.012 | 0.100 | 0.013 | 0.066 | 0.019 |
| Type 2 | | | | | | | 0.119 | 0.036 | | | | |
| Type 3 | 0.763 | 0.109 | 0.236 | 0.068 | | | | | 0.086 | 0.040 | 0.590 | 0.145 |
| Type 5 | | | -0.062 | 0.092 | -0.112 | 0.054 | | | | | | |
| Type 6 | | | -0.034 | 0.032 | -0.251 | 0.056 | | | | | | |
| Type 7 | -0.011 | 0.053 | | | | | | | -0.339 | 0.151 | 0.129 | 0.274 |
| Type 8 | | | | | -0.158 | 0.057 | | | | | | |
| 1/Precision | 0.217 | 0.012 | 0.241 | 0.007 | 0.239 | 0.005 | 0.223 | 0.009 | 0.346 | 0.011 | 0.272 | 0.016 |
| N | 607 | | 1151 | | 3959 | | 554 | | 1187 | | 492 | |

*Notes*: Table reports estimates for the log wage models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.15: Estimates for Log PV Disposable Income Models I (Outcomes $Y_{ms}$)

| Variable | HSDO | | HS-Voc | | HS-Aca | | HS-STEM | | CollDO-low | | CollDO-high | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 7.968 | 0.059 | 7.998 | 0.023 | 7.585 | 0.068 | 7.765 | 0.206 | 8.314 | 0.233 | 8.129 | 0.089 |
| Mother College | -0.019 | 0.013 | 0.009 | 0.005 | 0.032 | 0.013 | 0.059 | 0.022 | -0.004 | 0.014 | 0.014 | 0.016 |
| Mother High School | 0.008 | 0.009 | 0.015 | 0.004 | 0.032 | 0.013 | -0.023 | 0.021 | 0.045 | 0.017 | 0.013 | 0.020 |
| Mother Educ missing | 0.037 | 0.019 | 0.022 | 0.009 | 0.074 | 0.036 | 0.070 | 0.047 | 0.046 | 0.038 | 0.012 | 0.044 |
| Father College | 0.014 | 0.018 | 0.006 | 0.007 | 0.038 | 0.014 | 0.008 | 0.025 | 0.001 | 0.017 | 0.050 | 0.017 |
| Father High School | -0.012 | 0.008 | 0.012 | 0.004 | 0.016 | 0.012 | 0.049 | 0.019 | 0.019 | 0.015 | 0.015 | 0.018 |
| Father Educ missing | -0.012 | 0.017 | 0.005 | 0.007 | 0.019 | 0.030 | 0.033 | 0.042 | -0.030 | 0.034 | 0.025 | 0.036 |
| Family Income | 0.052 | 0.007 | 0.057 | 0.003 | 0.083 | 0.006 | 0.077 | 0.011 | 0.092 | 0.009 | 0.079 | 0.009 |
| School-Ave Fam Income | 0.063 | 0.017 | 0.072 | 0.007 | 0.148 | 0.024 | 0.140 | 0.027 | 0.032 | 0.023 | 0.052 | 0.023 |
| Health Endurance | 0.027 | 0.004 | 0.027 | 0.001 | 0.043 | 0.004 | 0.035 | 0.007 | 0.030 | 0.006 | 0.042 | 0.007 |
| Health Strength | -0.010 | 0.003 | -0.018 | 0.001 | -0.035 | 0.005 | -0.019 | 0.007 | -0.030 | 0.005 | -0.032 | 0.006 |
| Health missing | -0.007 | 0.019 | -0.028 | 0.007 | -0.013 | 0.022 | 0.026 | 0.037 | -0.075 | 0.030 | -0.091 | 0.034 |
| Took 9th Adv. Math | 0.032 | 0.017 | 0.004 | 0.010 | 0.038 | 0.018 | -0.021 | 0.048 | -0.025 | 0.026 | 0.031 | 0.025 |
| Took 9th Adv. English | -0.000 | 0.018 | -0.007 | 0.009 | 0.047 | 0.020 | 0.028 | 0.039 | -0.030 | 0.023 | -0.041 | 0.025 |
| HS Academic Track | | | | | | | | | 0.084 | 0.020 | 0.047 | 0.023 |
| HS STEM Track | | | | | | | | | 0.057 | 0.019 | 0.057 | 0.024 |
| Cognitive | 0.034 | 0.007 | 0.035 | 0.003 | 0.074 | 0.007 | 0.058 | 0.011 | 0.054 | 0.008 | 0.061 | 0.008 |
| Interpersonal | 0.031 | 0.004 | 0.037 | 0.003 | 0.089 | 0.005 | 0.076 | 0.008 | 0.087 | 0.006 | 0.089 | 0.006 |
| Grit | 0.013 | 0.009 | 0.041 | 0.004 | 0.066 | 0.008 | 0.049 | 0.013 | 0.073 | 0.010 | 0.077 | 0.009 |
| Type 2 | 0.099 | 0.048 | -0.090 | 0.029 | -0.108 | 0.042 | -0.136 | 0.323 | -0.467 | 0.220 | -0.272 | 0.119 |
| Type 3 | 0.303 | 0.029 | 0.566 | 0.021 | 0.499 | 0.042 | 0.647 | 0.490 | -0.177 | 0.294 | 0.292 | 0.087 |
| Type 4 | -0.429 | 0.103 | -0.040 | 0.021 | -0.064 | 0.030 | -0.007 | 0.159 | -0.714 | 0.274 | -0.248 | 0.054 |
| Type 5 | 0.790 | 0.064 | -0.532 | 0.026 | -0.969 | 0.032 | -0.016 | 0.217 | -0.120 | 0.219 | -0.020 | 0.057 |
| Type 6 | -0.110 | 0.105 | 0.059 | 0.024 | 0.081 | 0.037 | -0.019 | 0.187 | -0.228 | 0.231 | -0.078 | 0.062 |
| Type 7 | -1.061 | 0.116 | -1.020 | 0.019 | -0.055 | 0.045 | -0.252 | 0.301 | -0.363 | 0.247 | -0.385 | 0.094 |
| Type 8 | -0.726 | 0.161 | 0.220 | 0.010 | 0.039 | 0.089 | 0.075 | 0.150 | -0.095 | 0.207 | -0.095 | 0.065 |
| 1/Precision | 0.161 | 0.005 | 0.174 | 0.002 | 0.370 | 0.009 | 0.441 | 0.024 | 0.429 | 0.008 | 0.496 | 0.007 |
| N | 8369 | | 43958 | | 8129 | | 3890 | | 6336 | | 6198 | |

*Notes*: Table reports estimates for the log PV disposable income models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.16: Estimates for Log PV Disposable Income Models II (Outcomes $Y_{ms}$)

| Variable | 3yr non-STEM | | 3yr STEM | | 3yr Business | | Health Sci | | Educ | | Humanities | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 8.263 | 0.144 | 8.759 | 0.084 | 8.132 | 0.243 | 8.451 | 0.106 | 8.464 | 0.078 | 8.360 | 0.269 |
| Mother College | -0.022 | 0.032 | -0.010 | 0.011 | 0.067 | 0.060 | 0.029 | 0.019 | -0.014 | 0.015 | 0.062 | 0.060 |
| Mother High School | 0.082 | 0.046 | 0.004 | 0.013 | -0.004 | 0.064 | 0.002 | 0.026 | 0.043 | 0.019 | -0.057 | 0.076 |
| Mother Educ missing | 0.124 | 0.078 | 0.023 | 0.030 | -0.061 | 0.143 | 0.064 | 0.051 | 0.056 | 0.039 | 0.174 | 0.158 |
| Father College | 0.000 | 0.033 | 0.016 | 0.013 | -0.020 | 0.069 | 0.017 | 0.023 | 0.001 | 0.016 | -0.064 | 0.056 |
| Father High School | -0.020 | 0.036 | 0.022 | 0.012 | 0.077 | 0.053 | 0.013 | 0.021 | -0.004 | 0.015 | 0.094 | 0.081 |
| Father Educ missing | -0.088 | 0.068 | 0.009 | 0.026 | 0.071 | 0.114 | -0.056 | 0.050 | -0.011 | 0.037 | -0.105 | 0.138 |
| Family Income | 0.073 | 0.017 | 0.051 | 0.007 | 0.078 | 0.022 | 0.030 | 0.013 | 0.031 | 0.009 | 0.034 | 0.031 |
| School-Ave Fam Income | 0.031 | 0.046 | 0.034 | 0.019 | 0.097 | 0.069 | 0.041 | 0.035 | -0.027 | 0.024 | -0.150 | 0.085 |
| Health Endurance | 0.049 | 0.013 | 0.023 | 0.005 | 0.077 | 0.025 | 0.027 | 0.008 | 0.022 | 0.005 | 0.031 | 0.026 |
| Health Strength | -0.040 | 0.013 | -0.008 | 0.005 | -0.047 | 0.023 | -0.007 | 0.007 | 0.004 | 0.005 | 0.037 | 0.025 |
| Health missing | -0.109 | 0.059 | -0.009 | 0.025 | -0.099 | 0.121 | -0.021 | 0.039 | -0.046 | 0.033 | 0.048 | 0.105 |
| Took 9th Adv. Math | -0.007 | 0.037 | -0.015 | 0.020 | 0.023 | 0.090 | 0.041 | 0.023 | 0.009 | 0.015 | 0.065 | 0.077 |
| Took 9th Adv. English | -0.065 | 0.048 | -0.040 | 0.015 | -0.004 | 0.092 | -0.052 | 0.024 | -0.008 | 0.017 | 0.261 | 0.094 |
| HS Academic Track | 0.107 | 0.036 | 0.010 | 0.017 | 0.021 | 0.075 | -0.047 | 0.021 | -0.003 | 0.016 | 0.021 | 0.065 |
| HS STEM Track | 0.149 | 0.045 | 0.041 | 0.014 | -0.103 | 0.094 | -0.017 | 0.031 | 0.026 | 0.019 | -0.001 | 0.074 |
| Cognitive | 0.016 | 0.014 | 0.035 | 0.006 | 0.104 | 0.027 | 0.033 | 0.011 | 0.022 | 0.007 | 0.035 | 0.028 |
| Interpersonal | 0.098 | 0.012 | 0.056 | 0.005 | 0.111 | 0.026 | 0.061 | 0.008 | 0.045 | 0.005 | 0.052 | 0.019 |
| Grit | 0.022 | 0.016 | 0.041 | 0.007 | 0.123 | 0.030 | 0.041 | 0.012 | 0.024 | 0.008 | 0.026 | 0.028 |
| Type 2 | | | -0.306 | 0.148 | | | -0.002 | 0.023 | | | | |
| Type 3 | | | -0.186 | 0.115 | 0.167 | 0.077 | | | | | | |
| Type 4 | | | -1.218 | 0.210 | | | | | 0.046 | 0.015 | | |
| Type 5 | | | -0.156 | 0.064 | | | | | | | | |
| Type 6 | | | -0.207 | 0.069 | | | | | | | | |
| Type 7 | -0.140 | 0.067 | -0.260 | 0.133 | | | | | 0.362 | 0.079 | 0.324 | 0.057 |
| Type 8 | | | -0.120 | 0.061 | | | | | | | | |
| 1/Precision | 0.486 | 0.012 | 0.288 | 0.014 | 0.439 | 0.023 | 0.313 | 0.012 | 0.259 | 0.009 | 0.467 | 0.019 |
| N | 1426 | | 5192 | | 440 | | 1456 | | 2343 | | 467 | |

*Notes*: Table reports estimates for the log PV disposable income models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.

Table F.17: Estimates for Log PV Disposable Income Models III (Outcomes $Y_{ms}$)

| Variable | Soc Sci | | Sciences | | Engineer | | Medicine | | Business | | Law | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. | $\beta$ | StdEr. |
| Intercept | 8.026 | 0.167 | 8.620 | 0.122 | 8.626 | 0.082 | 8.589 | 0.198 | 8.132 | 0.118 | 7.974 | 0.163 |
| Mother College | -0.020 | 0.033 | -0.026 | 0.026 | -0.009 | 0.012 | 0.034 | 0.037 | 0.006 | 0.027 | 0.051 | 0.044 |
| Mother High School | 0.063 | 0.062 | -0.049 | 0.035 | -0.003 | 0.019 | -0.097 | 0.067 | 0.041 | 0.044 | 0.136 | 0.085 |
| Mother Educ missing | 0.025 | 0.124 | 0.013 | 0.090 | 0.028 | 0.041 | -0.043 | 0.119 | -0.133 | 0.098 | 0.134 | 0.135 |
| Father College | 0.006 | 0.036 | 0.016 | 0.027 | -0.010 | 0.013 | 0.064 | 0.043 | 0.080 | 0.033 | 0.013 | 0.047 |
| Father High School | 0.020 | 0.052 | -0.016 | 0.031 | 0.015 | 0.016 | -0.010 | 0.053 | 0.056 | 0.035 | 0.113 | 0.078 |
| Father Educ missing | -0.038 | 0.100 | -0.085 | 0.084 | -0.007 | 0.037 | 0.007 | 0.105 | 0.276 | 0.083 | 0.141 | 0.113 |
| Family Income | 0.072 | 0.016 | 0.041 | 0.012 | 0.056 | 0.006 | 0.038 | 0.013 | 0.096 | 0.012 | 0.082 | 0.019 |
| School-Ave Fam Income | 0.099 | 0.053 | -0.016 | 0.033 | 0.040 | 0.016 | 0.043 | 0.045 | 0.100 | 0.032 | 0.106 | 0.042 |
| Health Endurance | 0.054 | 0.017 | 0.040 | 0.010 | 0.034 | 0.005 | 0.011 | 0.011 | 0.023 | 0.013 | 0.043 | 0.018 |
| Health Strength | 0.004 | 0.017 | 0.007 | 0.011 | -0.019 | 0.005 | -0.013 | 0.014 | -0.016 | 0.015 | -0.034 | 0.018 |
| Health missing | 0.133 | 0.070 | 0.014 | 0.056 | -0.034 | 0.023 | -0.035 | 0.063 | 0.004 | 0.053 | 0.045 | 0.094 |
| Took 9th Adv. Math | 0.024 | 0.046 | 0.130 | 0.048 | 0.037 | 0.038 | 0.082 | 0.114 | -0.019 | 0.052 | -0.007 | 0.076 |
| Took 9th Adv. English | -0.022 | 0.061 | 0.046 | 0.049 | 0.050 | 0.032 | -0.012 | 0.125 | -0.013 | 0.055 | 0.038 | 0.096 |
| HS Academic Track | 0.082 | 0.053 | 0.047 | 0.038 | -0.058 | 0.031 | -0.058 | 0.083 | 0.025 | 0.044 | 0.020 | 0.088 |
| HS STEM Track | 0.095 | 0.067 | -0.003 | 0.036 | 0.057 | 0.024 | 0.020 | 0.080 | 0.013 | 0.052 | -0.031 | 0.096 |
| Cognitive | 0.021 | 0.018 | -0.008 | 0.013 | 0.025 | 0.007 | 0.055 | 0.016 | 0.110 | 0.015 | 0.098 | 0.020 |
| Interpersonal | 0.063 | 0.014 | 0.044 | 0.010 | 0.061 | 0.006 | 0.032 | 0.011 | 0.102 | 0.012 | 0.086 | 0.015 |
| Grit | 0.012 | 0.021 | 0.003 | 0.014 | 0.040 | 0.007 | 0.088 | 0.015 | 0.127 | 0.016 | 0.097 | 0.023 |
| Type 2 | | | | | | | 0.130 | 0.043 | | | | |
| Type 3 | 0.708 | 0.094 | 0.223 | 0.072 | | | | | 0.097 | 0.042 | 0.640 | 0.190 |
| Type 5 | | | -0.088 | 0.144 | -0.115 | 0.050 | | | | | | |
| Type 6 | | | -0.045 | 0.043 | -0.321 | 0.061 | | | | | | |
| Type 7 | -0.059 | 0.090 | | | | | | | -0.716 | 0.411 | 0.143 | 0.381 |
| Type 8 | | | | | -0.143 | 0.054 | | | | | | |
| 1/Precision | 0.396 | 0.018 | 0.398 | 0.012 | 0.370 | 0.008 | 0.290 | 0.014 | 0.470 | 0.020 | 0.401 | 0.028 |
| N | 831 | | 1632 | | 5542 | | 602 | | 1739 | | 708 | |

*Notes*: Table reports estimates for the log PV disposable income models. Imprecise loadings on the types cause problems for the simulation. In order to avoid this, we first estimate the model without constraining the loadings. We then calculate the fraction of college graduates of a certain type that are expected to graduate in a certain major. The loadings are set to zero in the graduation and outcome models if less than 0.002 of the population is predicted in that cel. The model is re-estimated pooling the low-probability cells.