Extended Abstract for:
College Major and Health over the Life-Cycle

Adam Altmejd John Eric Humphries
Juanna Schrøter Joensen Gregory F. Veramendi *

March, 2025
PRELIMINARY and INCOMPLETE.
Please do not cite or circulate.

1 Introduction

The relationship between education and health represents one of the most persistent and consequential socioeconomic gradients in modern society. It is extensively documented that more educated individuals live longer and healthier lives. For example, in the United States in 2008, college graduates at age 25 expect to live about a decade longer than non-graduates – a gap comparable to the life expectancy gains achieved between 1950 and 2008 (Olshansky et al., 2012; Hummer and Hernandez, 2013). This widening gap (Pappas et al., 1993; Meara et al., 2008; Olshansky et al., 2012) represents a central policy challenge globally (Marmot, 2015; Chetty et al., 2016) as life expectancy gains are highly valued (Murphy and Topel, 2006).[1] Despite the importance of the issue and attention paid in policy and research, the complexity of the health production function combined with measurement challenges have limited our understanding of the causes of health inequalities. The literature has focused almost exclusively on levels of educational attainment rather than educational content. This is surprising given that many key predictors of health – including income, occupation, information, peers, and the environment more generally (Cutler et al., 2006; Cutler and Lleras-Muney, 2010; Galama et al., 2018; Danesh et al., 2024) – are shaped by specific education choices. Little is known about how different fields of study might differentially affect health trajectories over the life-cycle. Our main contribution is providing causal estimates of how field of study choices in higher education influence health outcomes over the life-cycle, extending both the health inequality and returns to education literatures in a novel direction.

*Altmejd: SOFI; adam@altmejd.se. 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; gregory.veramendi@rhul.ac.uk. We thank Lukas Jonsson 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] Efforts to "close the health gap" are high on the international policy agenda as exemplified by the sequence of reports by the World Health Organization (1985, 2008, 2017), as well as the EU's recent Joint Action on Health Inequalities" and the high willingness to pay to extend life, as recently demonstrated by the large expenditures to fight the COVID pandemic.

We use linked Swedish administrative labor market, education, and health records to show that field-specific health gaps sometimes exceed the gap between college and high school graduates. Our two primary health measures over the life-cycle are based on sick leave utilization and prescription drugs for chronic conditions, building on Huber et al. (2013) and Danesh et al. (2024).

We observe substantial chronic health condition gaps emerging from age 22 to 48, with differences by field of higher education comparable in magnitude to those by education level. However, patterns vary by condition type: gaps in pain medication prescriptions are larger by education level, while respiratory prescription gaps are more pronounced across fields of higher education. Generally, individuals in higher-earning fields (e.g., Engineering and Business) demonstrate better health outcomes, while those in Education fields show worse health. For example, Engineers are 5.4 percentage points less likely to have any chronic condition and 2.3 percentage points less likely to take sick leave at age 35. Medical field graduates represent a notable exception, having higher rates of prescription drug use for chronic conditions than individuals in any other field, yet without corresponding increases in sick leave usage. This raises questions about whether this pattern stems from earlier diagnosis, better understanding of treatment importance, or enhanced access to healthcare and medications.

These observed field-specific gaps, however, may reflect numerous confounding factors affecting both health and education choices. For instance, individuals pursuing nursing or medical degrees may select their education, occupation, and health behaviors based on pre-existing health attitudes. Conversely, healthcare education may naturally provide better access to health resources and diagnostic information. This makes it challenging to identify and estimate causal effects. To address these challenges, we follow the recent literature using college application data to compare individuals with similar stated preferences for college programs combined with randomness around admission cut-offs for oversubscribed college programs. This empirical strategy was first proposed by Kirkebøen et al. (2016) and has been utilized to estimate the causal effect of field of study in high school (Dahl et al., 2023) and college (Altmejd, 2018; Heinesen et al., 2022; Humphries et al., 2023) on labor market outcomes and assortative mating in the marriage market (Kirkebøen et al., 2021). We push this literature in a new direction by estimating causal effects of field of higher education on health.

Is there a causal effect of field of study on health? Our preliminary estimates on health at age 35 suggest that studying Medicine or Health Sciences causes individuals to take out more prescriptions for chronic conditions at age 35. An important caveat with our preliminarly analysis is that health gaps are only beginning to open up at age 35. We are in the process of updating our analysis with a newly acquired data on college applications and outcomes, so we can estimate causal effects for those at the margin for the cohorts entering higher education from 1977 (now from 1993) onwards and observe health outcomes until

2023 (now until 2012). This will enable us to get uniquely detail measurement of health over the life-cycle – both before and after high education choices are made – and also link these health measures to longevity as we will observe the oldest cohort through their working life until retirement age.

Prior research on the causal effect of education on health has primarily focused on education *level* rather than *field*.[2] Most studies focus on individuals at low levels of education and rely on increases in the duration of compulsory schooling for identification (Lleras-Muney, 2005; Black et al., 2015; Lager and Torssander, 2012; Meghir et al., 2018; Van Kippersluis et al., 2011; Gathmann et al., 2015; Fischer et al., 2021) and the raising of school leaving age (ROSLA) in the UK (Clark and Royer, 2013; Davies et al., 2016) and in France (Albouy and Lequien, 2009). Most of these papers find positive, but small, or insignificant causal effects of staying in school longer for those who would like to leave as soon as they can. Galama et al. (2018) review these findings and note substantial heterogeneity: effects appear larger for men than women, for older cohorts, and in poorer countries with higher baseline mortality, but are not necessarily larger in places with lower initial schooling levels. Other structured reviews (Baker et al., 2011; Byhoff et al., 2017; Hamad et al., 2018) and meta-analysis (Xue et al., 2021) similarly conclude that methodological differences explain a lot of the variation between studies, with some suggesting that education may not causally affect mortality for those who want as little education as possible. In general, who is affected by education policy seems to matter for its impact.

Research on the causal effects of education beyond the compulsory level remains scarce, but includes a few notable papers. Using a similar empirical strategy to ours, but at the high school level, Stenberg and Tudor (2024) find that admission to a preferred (Engineering) field in high school improves mental health, reducing both the incidence of antidepressant prescriptions and mental health-related hospitalizations. They suggest that the main mechanism is increased income.[3] At the college level, paper leveraging exogenous variation in the opportunity costs of college attendance (Buckles et al., 2016; Heckman et al., 2018; Fletcher and Noghanibehambari, 2021; Connolly, 2021) find that college education decreases mortality and improves a range of health outcomes. We contribute to the literature by showing that not only the level, but also the field, of higher education is an important determinant of health.

What could be driving the effects of field of study on health? The key to answering this question is understanding what changes at college admission thresholds.

To better understand the mechanisms driving these health outcomes, we explore several channels related to income, information, peer effects, occupational characteristics, and environmental factors. Education

[2] Galama et al. (2018) and Lleras-Muney (2022) provide recent comprehensive reviews of this literature.

[3] Although, also in the Swedish setting, Cesarini et al. (2016) and Lindqvist et al. (2020) find a precicely estimated zero effect of lottery wealth on mortality and psychological well-being, suggesting that in an affluent country like Sweden with an extensive social safety net, causal effects of (lottery) wealth are neither a major source of the observed wealth-mortality nor the wealth-psychological well-being gradient.

likely affects many aspects of a person's life – including earnings, cognitive abilities, socio-emotional skills, information processing, political views, and social networks – all of which may influence health behaviors and outcomes. Strong associations between college field and subsequent occupation are well-documented (Black et al., 2003; Altonji et al., 2012, 2016; Kinsler and Pavan, 2015; Altonji et al., 2016; Ransom and Phipps, 2017; Arcidiacono et al., 2020; Sloane et al., 2021), and different occupations expose individuals to varying health risks and protective factors (Case and Deaton, 2007; Fletcher et al., 2011; Kelly et al., 2014). Importantly, education might affect health through unexpected pathways. For instance, while higher education generally correlates with better health outcomes, some aspects of educated professions may have negative health consequences. Barcellos et al. (2023) find that compulsory schooling reforms in the UK led to higher blood pressure and worse inflammatory markers, consistent with more educated individuals working in more stressful or sedentary occupations. By analyzing how occupational characteristics – including hours worked, skill demands, workplace flexibility, and physical activity levels – change at college admission thresholds for marginal students, we can illuminate the complex pathways through which education choices shape both career trajectories and health outcomes.

We also contribute to the emerging literature on place-based effects on health (Deryugina and Molitor, 2020, 2021; Finkelstein et al., 2021; Kulshreshtha et al., 2022) as many have to leave their parental home and location to attend college. Danesh et al. (2024) conclude that socioeconomic and geographic factors explain most of the variation in chronic conditions over the life-cycle, but questions remain about the specific mechanisms through which place affects health. An attractive feature of our empirical strategy is that in some cases, we can hold field of study fixed while geographic location varies. For example, when individuals apply to oversubscribed Medicine programs at different universities. Since individuals are more likely to remain and work in the locations where they study, this provides us with quasi-experimental variation in geographic location conditional on field, allowing us to disentangle place effects from field effects.

Our preliminary findings suggest that the field of educational specialization may be as consequential for health outcomes as overall educational attainment. In future research, we will continue to explore these intricate relationships, including the long-term impacts of education-specific health policies and the nuanced ways different professional fields shape health trajectories. This evolving understanding moves beyond simplistic economic models, revealing health as a dynamic process influenced by a complex interplay of skills, knowledge, economic opportunities, policy environments, and technological capabilities – insights that are crucial for understanding the determinants of health inequalities and how they might be addressed through policy interventions.

The remainder of the paper proceeds as follows. Section 2 describes the Swedish institutional setting and data. Section 3 describes our empirical strategy. We then present our empirical results in Section 4.

2 Institutional Setting and Data

In this section, we describe relevant institutional details (Section 2.1) and the Swedish administrative data (Section 2.2) to put the empirical analysis into context. In Section 2.3, we present summary statistics on the enrollment field gaps in labor market and health outcomes.

2.1 Institutional Setting

College admission in Sweden is predominantly conditional on high school grade point average (GPA), but other factors also affect the admission score, including the Swedish Scholastic Aptitude test (SweSAT), high school track and course choices, and labor market experience.[4] 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.[5] Selectivity varies greatly across college majors and individual programs: the 4-year programs in medicine, law, and humanities are the most selective.[6] 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.[7]

Healthcare is universal, mostly public, and organized at the county level. Co-payments and out-of-pocket expenses are generally low and capped.[8] Although healthcare is provided primarily at the public level, private healthcare is also available in Sweden. Private healthcare can either be under contract with local/regional authorities or not be under contract. With healthcare administration being decentralized, patient fees differ across the country. Referrals from general practitioners are not required to contact a specialist, but if a patient does not have a referral, they may need to pay more and/or wait longer.

[4] 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.

[5] 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.

[6] We provide more descriptives and details in Appendix A.1.

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

[8] Act (2002:160) on Pharmaceutical Benefits (consolidated until SFS 2013:1141) reflects all changes until the end of our sample period. This law contains provisions on pharmaceutical benefits and price regulation of goods included in the benefit.

2.2 Swedish Administrative Data

NOTE: The data in this preliminary draft is the same as was used in Humphries et al. (2023) and Gallen et al. (2025). We are updating our results using recently received higher education application data going back to 1977 (vs. 1993) and outcomes through 2023 (vs. 2012), allowing us to estimate causal effects on health and mortality outcomes to 65 years old.

From the Higher Education registry, we observe the level and field of every college enrollment spell and degree since 1993. We classify all academic programs into two levels (≤ 3 years; ≥ 4 years) according to the SUN2000Niva code and nine fields (1. education; 2. humanities and arts; 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 the 3- and 4-year programs are grouped together.[9]

As discussed in the prior section, college applicants are screened based on their high school course choices and GPA. Some of them are also admitted based on high performance in the SweSAT on which we have overall test scores and sub-scores on every attempt through the Department of Applied Educational Science at *Umeå Universitet*. We have access to the complete histories of college applications and admissions from 1993 onwards through the Swedish National Archives. These include the complete set of admission scores in each admission group as we basically observe the complete data from the college admission process.

We merge several administrative registers via a unique individual identifier. Labor market data are collected and administered by Statistics Sweden (SCB). The primary source of labor market data is the longitudinal integration database for health insurance and labour market studies (LISA) that contains yearly observations during the period 1990-2013 on earnings, social transfers, employment, sector, and occupation. Our primary income measure is earnings (that most closely proxies labor market productivity).

We also plan to analyze occupation outcomes to study how occupational characteristics may influence health. We construct measures of the types of jobs in terms of, for example, skill requirements and workplace flexibility.[10] These data also include the level and field of highest completed education, information on

[9] Appendix A.1 provides more details and descriptives by college major.

[10] The first 3-digits of the Swedish occupation code (SSYK96) have an almost one-to-one mapping to the international ISCO88

enrollment in education, age, civil status, family status, and some information on household composition; including the number of children in various age-groups and the identity of the partner for married couples and for unmarried couples cohabiting with common (biological or adopted) children.

We merge education and labor market data with health data collected and administered by the National Board of Health and Welfare ("*Socialstyrelsen*"). This includes the National Cause of Death Register that provides the basis for official cause-of-death statistics in Sweden from 1970 through 2013; the Prescribed Drug Register (LMED), which includes all prescriptions from July 2005 through 2013; and the National Patient Register (NPR), which includes all in-patient care (1987-2013) and outpatient doctor visits including day surgery and psychiatric care from both private and public caregivers (2001-2013), but *not* primary care.

Our sample includes all individuals who are born between 1965-1983 and reside in Sweden.

2.3 Descriptives

We measure the health of individuals primarily through the prescription data and data on sick leave income in the LISA data.[11] We follow Huber et al. (2013) and Danesh et al. 2024 in using prescription data to identify patients with chronic conditions. Huber et al. (2013) provide a mapping between prescriptions and 22 chronic conditions that they are associated with. The four most common chronic conditions at age 35 are: psychological disorders (sleep and depression), rheumatologic conditions, chronic pain, and chronic respiratory condition.[12] These are each observed about 6-12% of the time in the 35-year old population in a given year. We create indicators for whether an individual took out a prescription in any of the 22 chronic conditions in a given year and a count variable for the number of chronic conditions observed in a year.

While sickness income ("sjuklön") for the first 14 of sickness is included in the earnings measure (*LoneInk*), income related to longer-term sickness is not. If an employee is sick for more than 14 days, they have to apply for federal sick leave benefits and these are included in *SjukPP*.[13] Our measure of sick leave utilization is thus an indicator for whether the individual was absent from work due to sickness for more than 14 days during the year.

We first investigate how health gaps vary over the lifecycle and by education. Figures 1, 2, 3, and 4 show how the probability of getting certain prescriptions vary by age and education. The left panels show how these chronic conditions vary by education level, and the right-side panels show how they vary by field. In most cases, the variation across college field is as large or sometimes larger than the variation in chronic

code that we use to merge with the O*Net data to construct measures of workplace flexibility.

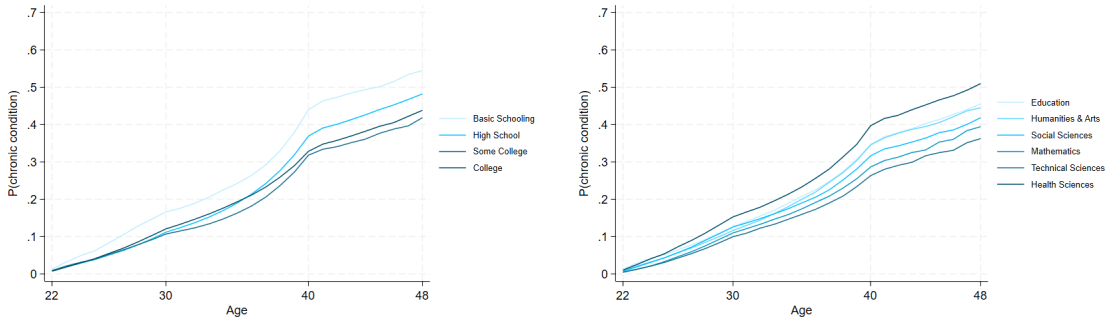
[11] In the updated data, we have also data on cause of mortality, outpatient data of diagnoses and procedures done by specialists, and diagnoses and procedures done as an inpatient at hospitals.

[12] Other chronic conditions include acid-related disorders, cardiovascular diseases, diabetes mellitus, gout and hyperuricemia, HIV, intestinal inflammatory diseases, thyroid disorders, etc. These are observed less than 1% of the time among 35 year olds.

[13] See e.g. Henrekson and Persson (2004), Johansson and Palme (2005), and Angelov et al. (2020) for more details on the sickness insurance system.

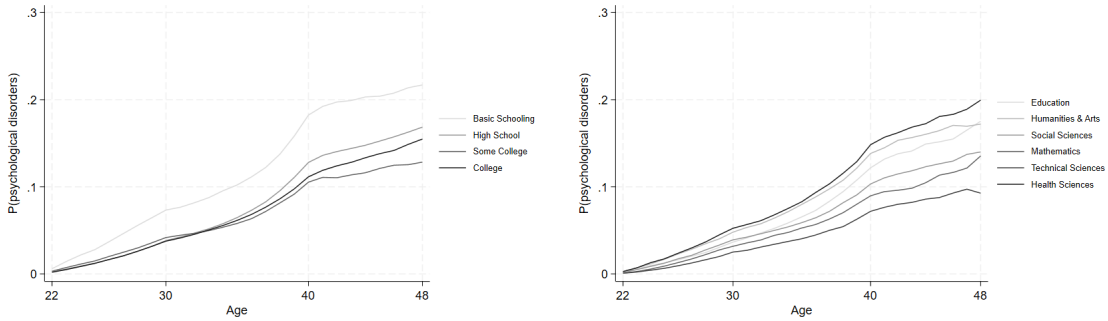
conditions across education levels. Our updated data will allow us to extend these beyond 65 years.

Figure 1: Descriptives: Education and Having Any Chronic Prescription



Notes: These figures show the fraction of the population with any chronic condition by age and education categories. The left panel shows difference in terms of levels and the right panel in terms of field for college graduates.

Figure 2: Descriptives: Education and Having a Psychological Prescription



Notes: These figures show the fraction of the population taking out a psychological prescription by age and education categories. The left panel shows difference in terms of education levels and the right panel in terms of field for college graduates.

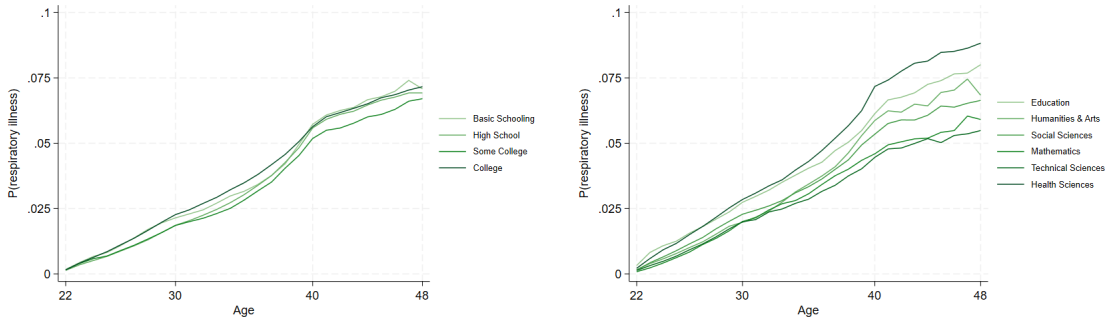
As our current application data begins in 1993 and outcome data ends in 2012, we are limited to estimating causal effects for 35-year olds. Table 1 shows how earnings and health outcomes at 35 years old vary by field of initial enrollment, with enrollment in education being the comparison category. Individuals who enroll in STEM, business, and law programs have the highest earnings at age 35. Initial enrollees in humanities degrees have the lowest earnings. We find large health gradients across fields of study. Both doctors and other health professionals take out more prescriptions, while doctors are less likely to take sick leave. Individuals who study STEM and business degrees are the least likely to be getting prescriptions for chronic conditions, while lawyers are the most likely to take prescriptions after the health professionals. On the other hand, the degrees that lead to professional careers (Law, Business, Medicine, Engineering) are less likely to take sick leave, while those who study health sciences or education are most likely to take sick leave in a given year.

Table 1: Income and Health Outcomes at 35 years old by Field of Study of First College Enrollment

	Income (1000s)	Any Chronic Condition	Number of Conditions	Any Sick Leave
STEM (3-year)	54.931***	−0.038***	−0.069***	−0.009***
	(0.934)	(0.003)	(0.005)	(0.001)
Business (3-year)	115.434***	−0.028***	−0.057***	−0.021***
	(1.717)	(0.003)	(0.006)	(0.001)
Health Sciences	0.324	0.031***	0.077***	0.040***
	(0.793)	(0.003)	(0.005)	(0.001)
Education	−15.083***	−0.008***	−0.014***	0.014***
	(0.763)	(0.002)	(0.005)	(0.001)
Humanities	−20.456***	−0.010**	−0.021***	−0.009***
	(1.493)	(0.004)	(0.008)	(0.002)
Social Sciences	25.081***	−0.005	−0.016**	−0.007***
	(1.524)	(0.003)	(0.006)	(0.002)
Science and Math	30.560***	−0.031***	−0.052***	−0.015***
	(1.180)	(0.003)	(0.006)	(0.001)
Engineering	114.650***	−0.054***	−0.098***	−0.023***
	(1.129)	(0.003)	(0.005)	(0.001)
Medicine	159.839***	0.166***	0.366***	−0.014***
	(2.138)	(0.005)	(0.013)	(0.002)
Business	101.057***	−0.035***	−0.071***	−0.021***
	(1.488)	(0.003)	(0.005)	(0.001)
Law	115.456***	0.003	0.006	−0.018***
	(1.966)	(0.004)	(0.008)	(0.002)
Observations	587,060	417,379	417,379	587,060

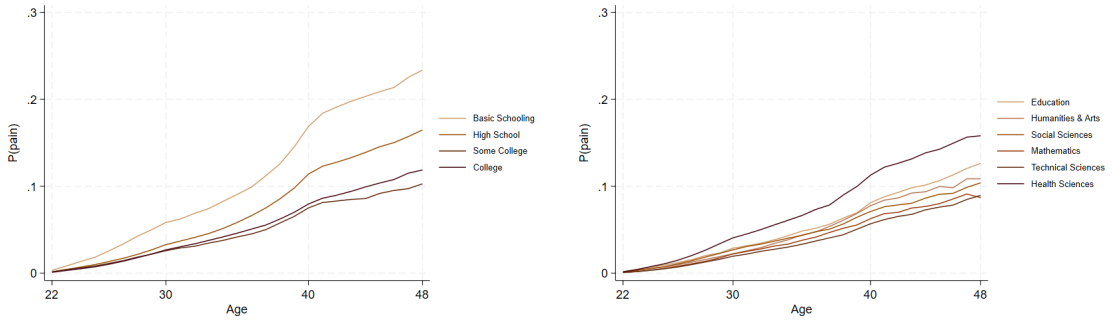
Notes: This table reports the college field gaps in income and health outcomes for individuals whose initial enrollment is in a given field. The reference category is 3-year non-STEM programs. Income is the average of the yearly earnings between ages 33 and 37 for both men and women. "Any Chronic Condition" is an indicator if an individual took a prescription associated with a chronic condition and "Number of Conditions" counts the number of different chronic conditions an individual has identified based on prescriptions. Finally, "Any Sick Leave" is an indicator for whether an individual took sick leave of at least 14 days in a year. *p<0.1; **p<0.05; ***p<0.01

Figure 3: Descriptives: Education and Having a Respiratory Prescription



Notes: These figures show the fraction of the population taking out a respiratory prescription by age and education categories. The left panel shows difference in terms of education levels and the right panel in terms of field for college graduates.

Figure 4: Descriptives: Education and Having a Pain Prescription



Notes: These figures show the fraction of the population taking out a psychological prescription by age and education categories. The left panel shows difference in terms of education levels and the right panel in terms of field for college graduates.

3 Empirical Strategy

Our empirical strategy adapts the design from Kirkebøen et al. (2016) to the Swedish setting. In particular, we take ranked lists from the centralized college application process. Similar to many centralized college application processes, individuals submit a ranked list of specific programs (fields of study) at specific institutions. Following Kirkebøen et al. (2016) and our prior work (Humphries et al., 2023), we focus on regression discontinuity analyses where we collapse application data to the field of study. Next, we consider the pairs of applications where the applicant's GPA put them near the threshold and where they would not have already been admitted to a program higher on their list. Like Kirkebøen et al. (2016), this setup gives us individuals who are just-below or just-above the threshold for being admitted to a specific major and is the top program where they could be admitted. This approach additionally allows us to look at RD estimates for admission into a particular major, conditional on the next-best major. Here we focus on the GPA admission threshold,

excluding those who have already been admitted to higher ranked programs based on any other admissions criteria.

Using this approach, we consider 2SLS regressions of the following form:

$$Y = \sum_{j \neq k} \beta_{jk} D_j + X'\delta_k + \gamma_{jk} + \epsilon_k$$
$$D = \sum_{j \neq k} \alpha_{jk} Z_j + X'\lambda_k + \eta_{jk} + \nu_{jk}, \ \forall \ j \neq k,$$

where j is the individuals' preferred field and k is the next-best field. D_j is an indicator for enrolling in field j while Z_j is an indicator for being above the GPA threshold for admissions to that major. γ_{jk} is a fixed effect for top program (j) and next-best program (k) and X is a vector of controls including birth cohort and functions of the running variable.

4 Results

In the college applications data, we see if students score above the admissions thresholds based on high school GPA or the Swedish SAT. These discontinuities result in regression discontinuities similar to those used in Kirkebøen et al. (2016). The first panel of Figure 5 shows that at the admissions threshold for a particular program there is a average jump of over 60 percentage points in being admitted. If instead of admissions we consider enrolling in the same major, we see that there is a seventeen percentage point jump at the admissions cutoff. This evidence shows that those barely missing the cutoff for admission are much less likely to be admitted to a program, and that this causes students to be less likely to enroll in that major. Table 2 shows the increase in admission, enrollment, and graduation in the same field from crossing the admission cutoff threshold for individual fields of study.

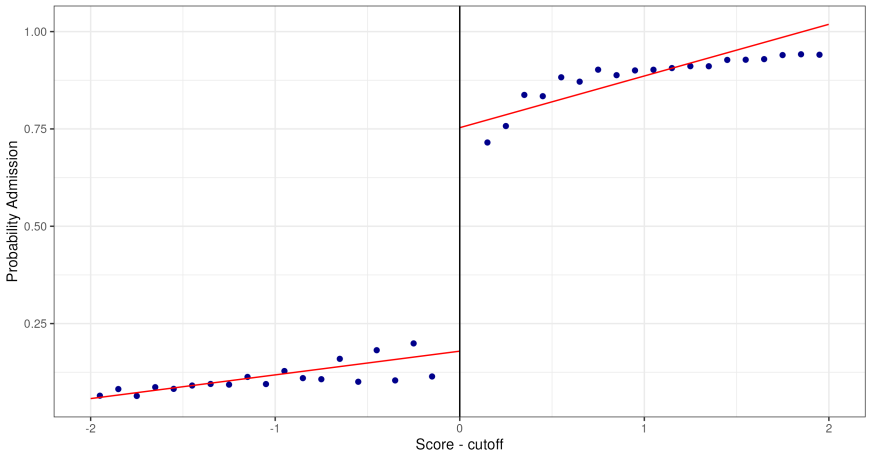
One validation of the quasi-random variation at the cutoff is checking how relevant pre-treatment variables vary across the admissions threshold. Figure 6 shows how ninth-grade GPA varies across the college admissions threshold. There is no sign of a discontinuity at the cutoff.

Table 2: Reduced Form: Education Outcomes

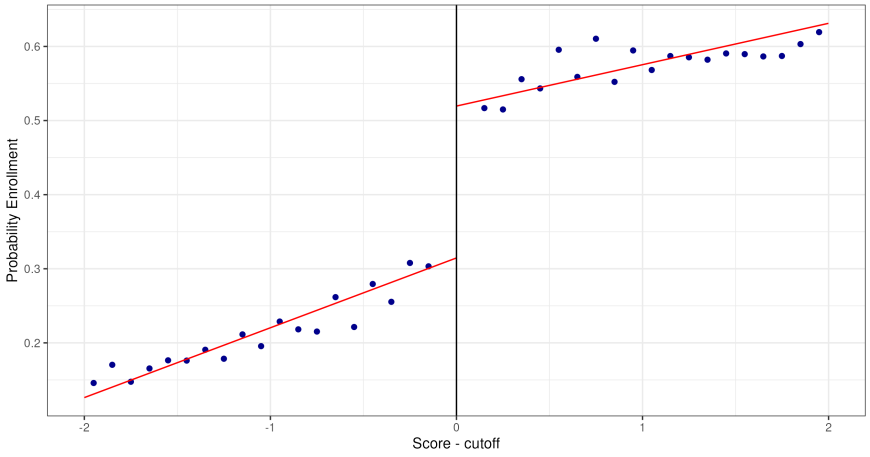
Threshold Field	Admission	Enrollment	Graduation
Non-STEM (3-year)	0.527***	0.111***	0.014
STEM (3-year)	0.575***	0.185***	0.062***
Business (3-year)	0.623***	0.214***	0.038***
Health Sciences	0.617***	0.166***	0.146***
Education	0.597***	0.124***	0.079***
Humanities	0.529***	0.114***	0.005
Social Sciences	0.615***	0.167***	0.046***
Science and Math	0.613***	0.187***	0.066***
Engineering	0.626***	0.319***	0.170***
Medicine	0.627***	0.250***	0.168***
Business	0.655***	0.206***	0.077***
Law	0.695***	0.281***	0.211***
Observations	302,795	302,795	302,795
R^2	0.490	0.131	0.093

Notes: This table shows the reduced form estimating the effect of the GPA and SweSAT admissions threshold discontinuities on admission, enrollment, and graduation in the same field. *p<0.1; **p<0.05; ***p<0.01

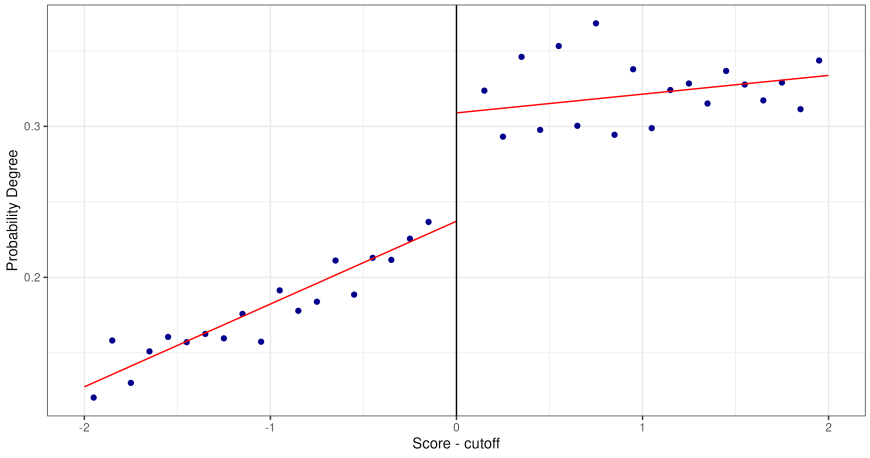
Figure 5: Reduced Form: College Outcomes



College Admission



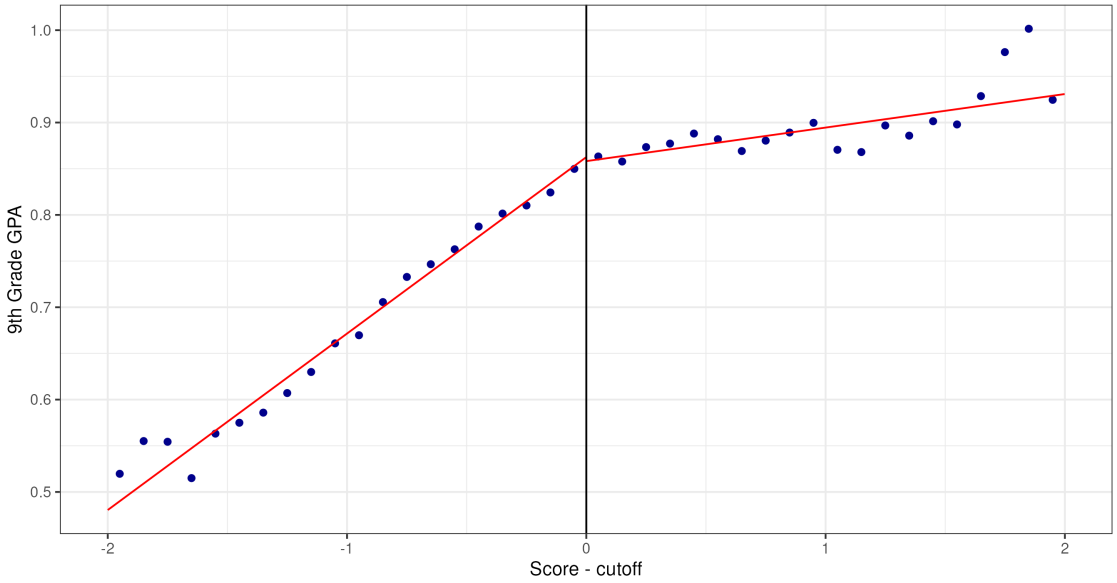
College Enrollment



College Graduation

Notes: These RD figures plot the reduced form using the GPA and SweSAT admissions threshold discontinuities on admission, enrollment, and graduation in the same field.

Figure 6: Balance at Admission Cut-offs



Notes: This figure shows how a pre-treatment measure, 9th grade GPA, varies at the admissions cutoff using the high school GPA and SweSAT admissions thresholds.

4.1 Labor Market Outcomes

Next we estimate returns to enrolling in a college field on earnings at age 35 years old. Table 3 shows two-stage-least-squares estimates of the effect of enrollment in different fields. Consistent with the literature (see e.g. Kirkebøen et al. 2016), Medicine, Law, Business, and Engineering have the highest returns, while Humanities and other short non-STEM programs have no significant causal return. The results are robust to using different functional forms of the running variable.

Table 3: Causal Effect of Enrollment Field on **Labor Income** (in 1000 SEK) at 35 years old

First Enrollment	2SLS (q=1)	2SLS (q=3)	2SLS (q=5)
Non-STEM (3-year)	−5.297	4.286	3.571
	(16.170)	(16.194)	(16.175)
STEM (3-year)	49.130**	64.575***	61.420***
	(19.837)	(19.847)	(19.837)
Business (3-year)	44.861***	54.346***	53.200***
	(17.177)	(17.207)	(17.176)
Health Sciences	13.142	21.382**	20.433*
	(10.610)	(10.679)	(10.685)
Humanities	23.210	32.445	31.550
	(25.788)	(25.878)	(25.868)
Social Sciences	45.215***	55.321***	53.940***
	(15.196)	(15.225)	(15.213)
Science and Math	25.212	41.746**	39.203**
	(16.727)	(16.707)	(16.714)
Engineering	63.357***	81.445***	78.632***
	(17.481)	(17.418)	(17.426)
Medicine	150.841***	165.100***	161.142***
	(21.480)	(21.363)	(21.350)
Business	86.159***	98.423***	96.812***
	(15.553)	(15.394)	(15.353)
Law	109.934***	122.178***	120.510***
	(17.852)	(17.819)	(17.807)
Observations	262,923	262,923	262,923

Notes: This table reports the causal effect of enrolling in a college field using the admissions cutoffs as an instrument. Income is the average of the yearly earnings between ages 33 and 37. The three columns show results assuming a local linear (q=1), a cubic (q=3), and quintic (q=5) functional form of the running variable on either side of the cutoff. We use a bandwidth of 0.5 standard deviations in GPA or SweSAT test score. *p<0.1; **p<0.05; ***p<0.01

4.2 Results on Health Outcomes

Finally, we show preliminary results of the effect of enrollment field on health outcomes. Tables 4 and 5 show the effect of enrollment field on chronic conditions using the prescription data. Table 6 shows the effect of enrollment field on the probability of taking sick leave.

In Table 4, we find significant effects of enrollment in health sciences in having more chronic conditions. The point estimates for other fields of study are negative, but imprecisely estimated. Likewise, in Table 5, we find that enrolling in a health degree makes it more likely to be taking psychological prescriptions, while the estimates for other fields are negative (more healthy) and imprecise. Our new data will allow us to estimate effects for older individuals where the gaps are larger and greater precision.

Table 4: Causal Effect of Field on **Number of Chronic Conditions** at age 35

First Enrollment	2SLS (q=1)	2SLS (q=3)	2SLS (q=5)
Non-STEM (3-year)	−0.043	−0.045	−0.039
	(0.073)	(0.074)	(0.074)
STEM (3-year)	−0.120	−0.119	−0.107
	(0.079)	(0.081)	(0.081)
Business (3-year)	−0.078	−0.069	−0.062
	(0.064)	(0.066)	(0.066)
Health Sciences	0.100*	0.101*	0.106**
	(0.053)	(0.054)	(0.054)
Humanities	0.090	0.073	0.079
	(0.118)	(0.118)	(0.118)
Social Sciences	−0.010	−0.006	0.0004
	(0.063)	(0.064)	(0.064)
Science and Math	−0.016	−0.019	−0.008
	(0.069)	(0.071)	(0.071)
Engineering	−0.059	−0.059	−0.048
	(0.071)	(0.073)	(0.074)
Medicine	0.209**	0.212**	0.225***
	(0.084)	(0.085)	(0.085)
Business	−0.064	−0.060	−0.053
	(0.057)	(0.059)	(0.059)
Law	−0.053	−0.048	−0.040
	(0.062)	(0.065)	(0.065)
Observations	243,807	243,807	243,807

Notes: This table reports the causal effect of enrolling in a college field using the admissions cutoffs as an instrument. "Number of Conditions" counts the number of different chronic conditions an individual has identified based on prescriptions. The three columns show results assuming a local linear (q=1), a cubic (q=3), and quintic (q=5) functional form of the running variable on either side of the cutoff. We use a bandwidth of 0.5 standard deviations in GPA or SweSAT test score. *p<0.1; **p<0.05; ***p<0.01

Table 5: Causal Effect of Enrollment Field on **any Psychological Disorders** at 35 years old

First Enrollment	2SLS (q=1)	2SLS (q=3)	2SLS (q=5)
Non-STEM (3-year)	−0.040	−0.040	−0.038
	(0.028)	(0.028)	(0.028)
STEM (3-year)	−0.053*	−0.053*	−0.048
	(0.029)	(0.030)	(0.030)
Business (3-year)	−0.038	−0.035	−0.032
	(0.024)	(0.025)	(0.025)
Health Sciences	0.041**	0.041**	0.043**
	(0.020)	(0.021)	(0.021)
Humanities	−0.032	−0.037	−0.034
	(0.046)	(0.046)	(0.046)
Social Sciences	−0.029	−0.028	−0.026
	(0.024)	(0.025)	(0.025)
Science and Math	−0.012	−0.013	−0.008
	(0.026)	(0.027)	(0.027)
Engineering	−0.033	−0.033	−0.029
	(0.026)	(0.027)	(0.028)
Medicine	0.041	0.042	0.047
	(0.031)	(0.031)	(0.031)
Business	−0.037*	−0.036	−0.033
	(0.021)	(0.022)	(0.022)
Law	−0.026	−0.024	−0.021
	(0.023)	(0.024)	(0.024)
Observations	243,807	243,807	243,807

Notes: This table reports the causal effect of enrolling in a college field using the admissions cutoffs as an instrument. "any Psychological Disorder" is an indicator for whether someone takes a psychological prescription in a year. The three columns show results assuming a local linear (q=1), a cubic (q=3), and quintic (q=5) functional form of the running varible on either side of the cutoff. We use a bandwidth of 0.5 standard deviations in GPA or SweSAT test score.*p<0.1; **p<0.05; ***p<0.01

Table 6: Causal Effect of Enrollment Field on **any Sick Leave Benefits** at 35 years old

First Enrollment	2SLS (q=1)	2SLS (q=3)	2SLS (q=5)
Non-STEM (3-year)	−0.017	−0.019	−0.020
	(0.023)	(0.023)	(0.023)
STEM (3-year)	−0.019	−0.020	−0.019
	(0.024)	(0.025)	(0.025)
Business (3-year)	−0.012	−0.012	−0.012
	(0.021)	(0.021)	(0.021)
Health Sciences	0.011	0.010	0.010
	(0.017)	(0.017)	(0.017)
Humanities	−0.020	−0.026	−0.027
	(0.039)	(0.039)	(0.039)
Social Sciences	−0.027	−0.029	−0.029
	(0.020)	(0.021)	(0.021)
Science and Math	−0.009	−0.011	−0.011
	(0.021)	(0.022)	(0.022)
Engineering	−0.010	−0.012	−0.011
	(0.022)	(0.023)	(0.023)
Medicine	−0.008	−0.010	−0.009
	(0.023)	(0.024)	(0.024)
Business	−0.031*	−0.032*	−0.032*
	(0.018)	(0.019)	(0.019)
Law	−0.026	−0.028	−0.028
	(0.019)	(0.020)	(0.020)
Observations	262,923	262,923	262,923

Notes: This table reports the causal effect of enrolling in a college field using the admissions cutoffs as an instrument. Any sick leave is an indicator for whether the individual taken at least 14 days of sick leave in a year. An average of the indicator between ages 33 and 37 is used as the outcome. The three columns show results assuming a local linear (q=1), a cubic (q=3), and quintic (q=5) functional form of the running variable on either side of the cutoff. We use a bandwidth of 0.5 standard deviations in GPA or SweSAT test score. *p<0.1; **p<0.05; ***p<0.01

References

Aalto, A.-M., E. Mörk, A. Sjögren, and H. Svaleryd (2019). Does childcare improve the health of children with unemployed parents? evidence from swedish childcare access reform. *IFAU Working Paper 2019:1*.

Albouy, V. and L. Lequien (2009). Does compulsory education lower mortality? *Journal of Health Economics 28*(1), 155–168.

Altmejd, A. (2018). Relative returns to swedish college fields. Technical report, Stockholm School of Economics.

Altmejd, A., A. Barrios-FernÃ¡ndez, M. Drlje, J. Goodman, M. Hurwitz, D. Kovac, C. Mulhern, C. Neilson, and J. Smith (2021). O Brother, Where Start Thou? Sibling Spillovers on College and Major Choice in Four Countries. *Quarterly Journal of Economics 136*(3), 1831–1886.

Altonji, J. G., P. Arcidiacono, and A. Maurel (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. In *Handbook of the Economics of Education*, Volume 5, pp. 305–396. Elsevier.

Altonji, J. G., E. Blom, and C. Meghir (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annu. Rev. Econ. 4*(1), 185–223.

Altonji, J. G., L. B. Kahn, and J. D. Speer (2016). Cashier or consultant? entry labor market conditions, field of study, and career success. *Journal of Labor Economics 34*(S1), S361–S401.

Angelov, N., P. Johansson, and E. Lindahl (2020). Sick of family responsibilities? *Empirical Economics 58*, 777–814.

Arcidiacono, P., V. J. Hotz, A. Maurel, and T. Romano (2020). Ex ante returns and occupational choice. *Forthcoming in the Journal of Political Economy*.

Baker, D. P., J. Leon, E. G. Smith Greenaway, J. Collins, and M. Movit (2011). The education effect on population health: A reassessment. *Population and Development Review 37*(2), 307–332.

Barcellos, S. H., L. S. Carvalho, and P. Turley (2023). Distributional effects of education on health. *Journal of Human Resources 58*(4), 1273–1306.

Black, D. A., Y.-C. Hsu, and L. J. Taylor (2015). The effect of early-life education on later-life mortality. *Journal of Health Economics 44*, 1–9.

Black, D. A., S. Sanders, and L. Taylor (2003). The economic reward for studying economics. *Economic Inquiry 41*(3), 365–377.

Bordon, P. and C. Fu (2015). College-major choice to college-then-major choice. *Review of Economic Studies 82*(4), 1247–1288.

Buckles, K., A. Hagemann, O. Malamud, M. Morrill, and A. Wozniak (2016). The effect of college education on mortality. *Journal of Health Economics 50*, 99–114.

Byhoff, E., M. C. Hamati, R. Power, S. A. Burgard, and V. Chopra (2017). Increasing educational attainment and mortality reduction: a systematic review and taxonomy. *BMC Public Health 17*(1), 719.

Case, A. and A. Deaton (2007). Broken down by work and sex: How our health declines. pp. 185–212. University of Chicago Press.

Cesarini, D., E. Lindqvist, R. Östling, and B. Wallace (2016). Wealth, health, and child development: Evidence from administrative data on swedish lottery players. *Quarterly Journal of Economics 131*(2), 687–738.

Chetty, R., M. Stepner, S. Abraham, S. Lin, B. Scuderi, N. Turner, A. Bergeron, and D. M. Cutler (2016). The association between income and life expectancy in the united states, 2001-2014. *Jama 315*(16), 1750–1766.

Clark, D. and H. Royer (2013). The effect of education on adult mortality and health: Evidence from britain. *American Economic Review 103*(6), 2087–2120.

Connolly, M. (2021). The impact of college openings on mortality: A new approach to estimating the returns to education. *Economics of Education Review 83*, 102142.

Cutler, D. M., A. Deaton, and A. Lleras-Muney (2006). The determinants of mortality. *Journal of Economic Perspectives 20*(3), 97–120.

Cutler, D. M. and A. Lleras-Muney (2010). Understanding differences in health behaviors by education. *Journal of Health Economics 29*(1), 1–28.

Dahl, G. B., D.-O. Rooth, and A. Stenberg (2023, January). High school majors and future earnings. *American Economic Journal: Applied Economics 15*(1), 351–82.

Danesh, K., J. T. Kolstad, J. Spinnewijn, and W. D. Parker (2024). The chronic disease index: Analyzing health inequalities over the lifecycle. Technical report, National Bureau of Economic Research.

Davies, N. M., M. Dickson, G. D. Smith, G. J. Van Den Berg, and F. Windmeijer (2016). The causal effects of education on health outcomes in the uk biobank. *Nature Human Behaviour 2*(2), 117–125.

Deryugina, T. and D. Molitor (2020). Does when you die depend on where you live? evidence from hurricane katrina. *American Economic Review 110*(11), 3602–3033.

Deryugina, T. and D. Molitor (2021). The causal effects of place on health and longevity. *Journal of Economic Perspectives 35*(4), 147–170.

Finkelstein, A., M. Gentzkow, and H. Williams (2021). Place-based drivers of mortality: Evidence from migration. *American Economic Review 111*(8), 2697–2735.

Fischer, M., U.-G. Gerdtham, G. Heckley, M. Karlsson, G. Kjellsson, and T. Nilsson (2021). Education and health: long-run effects of peers, tracking and years. *Economic Policy 36*(105), 3–49.

Fletcher, J. M. and H. Noghanibehambari (2021). College openings and mortality: A county-level analysis using college openings. *Health Economics 30*(5), 1082–1095.

Fletcher, J. M., J. L. Sindelar, and S. Yamaguchi (2011). Cumulative effects of job characteristics on health. *Health economics 20*(5), 553–570.

Galama, T. J., A. Lleras-Muney, and H. Van Kippersluis (2018). The effect of education on health and mortality: a review of experimental and quasi-experimental evidence.

Gallen, Y., J. S. Joensen, E. R. Johansen, and G. F. Veramendi (2025). The labor market returns to delaying pregnancy. *SSRN Working Paper No. 4554407*.

Gathmann, C., H. Jürges, and S. Reinhold (2015). Compulsory schooling reforms, education and mortality in twentieth century europe. *Social science & medicine 127*, 74–82.

Hamad, R., H. Elser, D. C. Tran, D. H. Rehkopf, and S. N. Goodman (2018). How and why studies disagree about the effects of education on health: A systematic review and meta-analysis of studies of compulsory schooling laws. *Social Science & Medicine 212*, 168–178.

Hastings, J. S., C. A. Neilson, and S. D. Zimmerman (2013). Are some degrees worth more than others? evidence from college admission cutoffs in chile. Technical report, National Bureau of Economic Research.

Heckman, J. J., J. E. Humphries, and G. F. Veramendi (2018). Returns to education: The causal effects of education on earnings, health, and smoking. *Journal of Political Economy 126*(S1), S197–S246.

Heinesen, E., C. Hvid, L. J. Kirkebøen, E. Leuven, and M. Mogstad (2022). Instrumental variables with unordered treatments: Theory and evidence from returns to fields of study. Working Paper 30574, National Bureau of Economic Research.

Henrekson, M. and M. Persson (2004). The effects on sick leave of changes in the sickness insurance system. *Journal of Labor Economics 22*(1), 87–113.

Huber, C. A., T. D. Szucs, R. Rapold, and O. Reich (2013). Identifying patients with chronic conditions using pharmacy data in switzerland: an updated mapping approach to the classification of medications. *BMC public health 13*, 1–10.

Humlum, M. K., J. H. Kristoffersen, and R. Vejlin (2017). College admissions decisions, educational outcomes, and family formation. *Labour Economics 48*, 215–230.

Hummer, R. A. and E. M. Hernandez (2013). The effect of educational attainment on adult mortality in the united states. *Population bulletin 68*(1), 1.

Humphries, J. E., J. S. Joensen, and G. F. Veramendi (2023). Complementarities in high school and college investments. *SSRN Working Paper No. 4560152*.

Joensen, J. S. and E. Mattana (2020). Student aid design, academic achievement, and labor market behavior: Grants or loans? *Available at SSRN: https://ssrn.com/abstract=3028295*.

Johansson, P. and M. Palme (2005). Moral hazard and sickness insurance. *Journal of Public economics 89*(9-10), 1879–1890.

Kelly, I. R., D. M. Dave, J. L. Sindelar, and W. T. Gallo (2014). The impact of early occupational choice on health behaviors. *Review of Economics of the Household 12*, 737–770.

Kinsler, J. and R. Pavan (2015). The specificity of general human capital: Evidence from college major choice. *Journal of Labor Economics 33*(4), 933–972.

Kirkebøen, L., E. Leuven, and M. Mogstad (2021). College as a marriage market. Technical report, National Bureau of Economic Research.

Kirkebøen, L. J., E. Leuven, and M. Mogstad (2016). Field of study, earnings, and self-selection. *Quarterly Journal of Economics 131*(3), 1057–1111.

Kulshreshtha, S., M. Salm, and A. Wübker (2022). Does population sorting through internal migration increase healthcare costs and needs in peripheral regions?

Lager, A. C. J. and J. Torssander (2012). Causal effect of education on mortality in a quasi-experiment on 1.2 million swedes. *Proceedings of the National Academy of Sciences 109*(22), 8461–8466.

Lindqvist, E., R. Östling, and D. Cesarini (2020). Long-run effects of lottery wealth on psychological well-being. *Review of Economic Studies 87*(6), 2703–2726.

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the united states. *Review of Economic Studies 72*(1), 189–221.

Lleras-Muney, A. (2022). Education and income gradients in longevity: The role of policy. *Canadian Journal of Economics 55*(1), 5–37.

Marmot, M. (2015). The health gap: the challenge of an unequal world. *The Lancet 386*(10011), 2442–2444.

Meara, E. R., S. Richards, and D. M. Cutler (2008). The gap gets bigger: changes in mortality and life expectancy, by education, 1981–2000. *Health affairs 27*(2), 350–360.

Meghir, C., M. Palme, and E. Simeonova (2018). Education and mortality: Evidence from a social experiment. *American Economic Journal: Applied Economics 10*(2), 234–256.

Murphy, K. M. and R. H. Topel (2006). The value of health and longevity. *Journal of political Economy 114*(5), 871–904.

Öckert, B. (2010). What's the value of an acceptance letter? using admissions data to estimate the return to college. *Economics of Education Review 29*(4), 504–516.

Olshansky, S. J., T. Antonucci, L. Berkman, R. H. Binstock, A. Boersch-Supan, J. T. Cacioppo, B. A. Carnes, L. L. Carstensen, L. P. Fried, D. P. Goldman, et al. (2012). Differences in life expectancy due to race and educational differences are widening, and many may not catch up. *Health affairs 31*(8), 1803–1813.

Pappas, G., S. Queen, W. Hadden, and G. Fisher (1993). The increasing disparity in mortality between socioeconomic groups in the united states, 1960 and 1986. *New England journal of medicine 329*(2), 103–109.

Ransom, M. R. and A. Phipps (2017). The changing occupational distribution by college major. In *Skill Mismatch in Labor Markets, Research in Labor Economics*, Volume 45, pp. 129–171. Emerald Publishing Limited.

Sloane, C. M., E. G. Hurst, and D. A. Black (2021). College majors, occupations, and the gender wage gap. *Journal of Economic Perspectives 35*(4), 223–248.

Stenberg, A. and S. Tudor (2024). Field of study and mental health in adulthood. *Journal of Human Resources*.

van den Berg, G. J. and B. M. Siflinger (2022). The effects of a daycare reform on health in childhood–evidence from sweden. *Journal of Health Economics 81*, 102577.

Van Kippersluis, H., O. OâDonnell, and E. Van Doorslaer (2011). Long-run returns to education: Does schooling lead to an extended old age? *Journal of human resources 46*(4), 695–721.

Xue, X., M. Cheng, and W. Zhang (2021). Does education really improve health? a meta-analysis. *Journal of Economic Surveys 35*(1), 71–105.