Universal Higher Education and Upward Mobility: Degree Returns, Admission Policies and Student Sorting*

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Job Market Paper

November 17, 2024

Latest Version Available Here

Abstract

This paper examines how returns to colleges and majors, admission policies, and student sorting affect intergenerational mobility. I study this question in Denmark, where tuition-free colleges and generous living grants provide an ideal setting to investigate the sources of inequality that remain in the absence of financial constraints. Leveraging GPA admission cutoffs from a centralized matching algorithm, I apply a regression discontinuity design to examine whether students from low socioeconomic status (SES) benefit from selective degrees (college-major pairs). Scoring just above the cutoff for admission to a more selective degree raises low-SES students' income by 9% at age 30, partially closing the SES wage gap. I develop a joint model of degree selection and labor market outcomes, to disentangle the contribution of degree-specific returns from that of students' degree choices as sources of inequality. The model accounts for the impact of degree peer composition on outcomes. Estimates from the model reveal that returns to degree enrollment are higher for low-SES students than for high-SES peers across the distribution of degree selectivity. Furthermore, I find that the current GPA-based meritocratic admissions system is inefficient in terms of maximizing long-term earnings. Implementing need-affirmative admissions could reduce the SES wage gap by 15% through upward mobility of disadvantaged students, without adversely impacting displaced high-SES students. Notably, the SES wage gap could be eliminated if students selected degrees based on expected earnings returns.

*I am very grateful for the guidance and valuable comments from Atila Abdulkadiroğlu, Dan Black, Steven Durlauf and James Heckman. This research was supported by the National Research Fund of Luxembourg (FNR grant # 13572740) and a ROCKWOOL Foundation grant. I thank Jérôme Adda, Ari Anisfeld, Marianne Bertrand, Terence Chau, Michael Dinerstein, Eyal Frank, Ingvil Gaarder, Yana Gallen, Mikkel Gandil, Anders Humlum, Robert Kaestner, Dmitri Koustas, Rasmus Landersø, Sasha Lukina, Jack Mountjoy, Lesley Turner, Mythili Vinnakota as well as participants at the EEA-ESEM Congress and the Inequality Working Group for helpful comments and discussions. Any errors are my own.

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1 Introduction and Motivation

Across OECD countries, college enrollment rates and major choices differ significantly between children from high- and low-income families (OECD, 2018; Bailey & Dynarski, 2011; Patnaik *et al.*, 2021). Recognizing these trends, policies have focused on broadening college access and improving the match quality between students and majors, including through tuition-free colleges and stipends for living expenses.[1] These policies can improve long-term outcomes for students who might otherwise be unable to borrow against future earnings and have been implemented in several countries—including Denmark, the setting of this paper.[2]

In an environment without financial barriers, higher education may still uphold existing inequalities rather than foster mobility. First, the returns to colleges and majors (degrees, henceforth) may vary by SES background, depending on the nature of the education production function (Hanushek, 1971; Durlauf, 2008). If complementarities exist between degree selectivity and academic preparation, less-prepared students may experience lower returns in selective degrees, though the evidence remains mixed.[3] Second, students from low-income backgrounds may systematically sort into degrees that produce low labor market returns.[4] Finally, admission policies that rely on high school GPA or entrance exams can disproportionately disadvantage low-SES students, as these metrics may provide downward-biased measures of their underlying cognitive and non-cognitive skills (Heckman *et al.*, 2021; Sethi & Somanathan, 2022).

This paper examines how causal returns to colleges and majors, admission policies, and student sorting affect intergenerational mobility. Despite egalitarian policies from an early age, I show that substantial inequalities persist—not only in students' pre-college achievements but also in their degree choices. I find that admission policies and student sorting, rather than limited returns to selective degrees, are the primary drivers of the SES wage gap. These findings have implications beyond Denmark, as many countries already offer tuition-free higher education systems and means-tested financial aid.[5] More broadly, these results shed light on some of the fundamental sources of inequality within higher education markets, beyond financial constraints.

[1] Henceforth, I define a tuition-free system with government-funded living stipends as universal higher education.
[2] For a recent review of the impact of financial aid on outcomes, see Dynarski *et al.* (2022).
[3] See, e.g., Arcidiacono & Lovenheim (2016); Arcidiacono *et al.* (2016); Dillon & Smith (2020); Chetty *et al.* (2023).
[4] Several paper study sorting patterns in the U.S., e.g., Hoxby & Avery (2012); Chetty *et al.* (2020); Sloane *et al.* (2021).
[5] Austria, Belgium, Estonia, Finland, France, Germany, Norway, Sweden, Turkey are among OECD countries with tuition-free public institutions (OECD, 2022).

This analysis leverages several features of the Danish system. First, the higher education system's centralized admission process, based on GPA cutoffs and student-ranked degree preferences, provides an ideal setting to address challenges in estimating returns to degree selectivity. These challenges arise from multiple selection margins—such as application, admission, and matriculation—that typically complicate the comparison of students across degrees of varying selectivity.[6] I tackle these issues in two ways: first, by leveraging the GPA cutoffs that dictate admissions, and second, by using students' elicited preferences for degrees to recover selection-corrected estimates of degree-specific returns.

A second key feature is that Denmark offers all students a tuition-free higher education system with generous stipends and subsidized loans that can fully cover living expenses. This setting provides an ideal backdrop to understand the sources of the inequalities that remain. Immediate financial constraints cannot account for the SES gap in degree choice. Despite this generous financial support, there is growing evidence that such egalitarian policies enshrined in the law are often undone in practice.[7,8]

Finally, the availability of rich administrative data allows me to paint a comprehensive picture of the long-term distributional consequences of higher education degrees. To that end, I use data from the higher education system, which provides students' submitted rank-ordered lists of degrees as well as admission decisions. I combine this data with several administrative registers, to study a number of long-term outcomes of interest, including labor market outcomes, occupation, family formation, fertility and crime, by SES background. Moreover, I link each student to their parents, which enables me to characterize individual's socioeconomic backgrounds and study heterogeneity along this margin. To this end, my primary measure of students' socioeconomic status is based on parental income at the time of college application.

I begin by examining whether enrollment in more selective degrees benefits disadvantaged students, providing evidence on whether the current system can serve as a lever to reduce inequalities. I do so by applying a regression discontinuity design (RDD) in the context of the Danish

[6]Selection is also present at each school-grade transitions (see e.g., Heckman *et al.* (2018)).

[7]For instance, Eshaghnia *et al.* (2023b) examines how egalitarian policies at the level of primary schooling—tuition-free, equalized per-pupil expenditures, and standardized teacher salaries—is undermined in practice by the sorting of both students and teachers across neighborhoods, leading to unequal educational opportunities.

[8]Heckman & Landersø (2022) provide evidence of the SES gradient in college attendance in Denmark, showing strong similarities with the U.S. For instance, for the 1987 birth cohort whose parents are at the bottom quartile of the wage income distribution, college attendance stands at around 30% in both countries. At the top quartile of the income distribution, this number rises to around 50% and 60%, in Denmark and the US, respectively.

centralized college admission system to recover the marginal returns to admission and enrollment into more selective degrees across SES backgrounds. Students who apply to higher education submit rank-ordered lists of their preference for degrees. A deferred acceptance algorithm matches students to capacity-constrained degrees, where priority is determined by students' GPAs. In equilibrium, GPA-based admission cutoffs determine admission to more selective degrees. I consider students whose GPA is marginally above and below that cutoff, stacking together all cutoffs. Examining the returns to selectivity for students at this margin is highly policy-relevant, as it directly informs whether marginally increasing the representation of low-SES students in more selective degrees enhances their long-term outcomes.

My findings reveal substantial heterogeneity in the labor market impact of cutoff-crossing by SES background. Students from low-SES backgrounds reap a benefit of around 9% in pre-tax annual income, 12 years post-application. In contrast, there is no significant effect for students from high-SES backgrounds. Notably, crossing the GPA cutoff closes the gap in entering the top 1% of income earners. Both students from low- and high-SES backgrounds who marginally cross the GPA cutoff experience sharp changes in degree peer composition. Degree selectivity, as measured by averaging incoming students' high school GPA, increases by about $.3\sigma$ for low-SES students and by $.4\sigma$ for high-SES students. On the other hand, college completion, years of education or learning, as captured by college grades, remain unaffected by cutoff-crossing. University and broad field of study also remain unchanged at the cutoff. Extending the analysis beyond economic outcomes, I show that degree selectivity increases fertility for both low- and high-SES students, while having only limited effects on household structure and criminal behavior.

I also provide suggestive evidence that these results are in part driven by students from low-SES backgrounds disproportionately benefiting from exposure to better peers. I employ two strategies to estimate the effect of attending a degree with better quality peers on long-term outcomes. First, I build on an approach developed by Kirkeboen *et al.* (2016) in the context of instrumental variables with unordered treatments, which exploits variation in the quality of peers in the fallback degree. Second, I rely on within-degree, cross-cohort variation in the composition of peers, which allows me to hold constant student sorting into degrees. Both strategies provide consistent evidence on the differential role of social interactions by socioeconomic background.

These findings show substantial returns to degree selectivity for marginal low-SES students, indicating that admission policies may serve as levers to enhance social mobility. However, the

impact of such policies must account for equilibrium effects that arise from student being displaced across the system. Admission policies also alter the peer composition within each degree, which can independently influence outcomes.

Results from the RDD further reveal a persistent wage gap, even for low-SES students above the GPA cutoffs. Notably, these estimates bundle student degree choices with degree-specific returns, as the returns experienced by low-SES students may potentially reflect the poor fallback options they select. Unpacking these effects requires adding structure to separate degree-specific causal returns from student choice patterns. Estimating causal returns for specific degrees poses significant challenges, as students may self-select into degrees based on unobserved attributes.

To address these questions, I develop a model of the Danish higher education system that allows me to recover degree-specific returns, disentangling these from the effect of student degree sorting. This framework further enables the evaluation of admission policies by accounting for general equilibrium effects and the influence of degree peer composition on outcomes. To that end, I leverage features of the centralized admission system in Denmark. First, I summarize student preferences by fitting discrete choice models to students' rank-ordered lists of degrees. Due to the strategy-proof nature of the deferred acceptance algorithm used to allocate students to degrees, truthfully ranking degrees is a weakly dominant strategy (Dubins & Freedman, 1981; Abdulkadiroğlu & Sönmez, 2003). This feature enables me to recover students' true preferences for degrees. In a second step, I specify a model of earnings outcomes, which innovates upon most of the previous literature by allowing for peer effects, which accounts for the impact of peer composition at the degree-cohort level on outcomes (Abdulkadiroğlu *et al.*, 2020; Dur *et al.*, 2020; Barahona *et al.*, 2024). To identify the parameters of the model requires dealing with students self-selecting into degrees. To that end, I jointly model treatment selection and labor market outcomes using rich information on preferences elicited from students' rank-ordered choice lists. The model is identified from variation in students' ranking conditional on enrolling in the same degree.

Findings from the model reveal that the labor market returns to degree enrollment is higher for low-SES compared to high-SES students across the distribution of degree selectivity. Importantly, the model recovers estimates of the causal effect of degrees on long-run outcomes, accounting for selection on unobservables. The RDD deals with selection by holding constant the distribution of ability and preferences between students above and below the cutoff. The local average treatment

effects estimated pertains to instrument compliers situated at the cutoff.[9] In contrast, estimates from the model go beyond this margin and pertain also to students away from the discontinuity.[10]

The model provides a framework to evaluate whether alternative admission policies could enhance outcomes for low-SES students by expanding their access to more selective degrees. I consider budget-neutral policies that hold constant degree capacities. Importantly, when simulating alternative admission policies, I compute counterfactual outcomes while accounting for peer composition changes and the general equilibrium effects inherent in such policy changes. These effects are critical, as policy interventions that shift one student into a different degree generate spillover effects, displacing other students in the process and thereby altering the overall composition of students across degrees, as shown by Gandil (2023).

Simulations from the model show that departures from *ex-ante* meritocratic admissions—based on students' GPA—improves allocative efficiency, by increasing the earnings of low-SES students without harming high-SES students. Enhancing the representation of low-SES students in more selective degree reduces the SES wage gap by approximately 15%. These findings provide evidence that GPA may not be an accurate measure of the latent skills of low-SES students, since a departure from *ex-ante* meritocratic admissions increases their earnings substantially. Finally, my analysis reveals that if disadvantaged students prioritized degrees based on expected returns, the wage gap could be entirely eliminated. This highlights the role of student degree choices and admission policies, rather than degree returns, as fundamental sources in explaining the inequalities that remain.

Related Literature and Contributions. This paper contributes to four strands of the literature. First, I provide novel evidence that students from low-income households disproportionately benefit from enrollment to selective colleges and majors, relative to high-income peers. These findings build on estimates from an RDD and a model of the higher education system, contributing to our understanding of the heterogeneous nature of the returns to colleges and major selectivity. Moreover, this paper is the first, to my knowledge, to extend the analysis well beyond labor market outcomes to examine effects on asset accumulation, occupational choice, family structure, fertility, and criminal behavior, by parental income.[11] I find limited effects across these dimensions, with

[9] General equilibrium effects are also unaccounted for.

[10] Importantly, low-SES students near the discontinuities are high-achievers relative to the average low-SES student. Therefore, the returns to degree selectivity observed at these discontinuities may not generalize beyond this group.

[11] Black *et al.* (2005); Kaufmann *et al.* (2013); Humlum *et al.* (2017); Kirkebøen *et al.* (2021); Ge *et al.* (2022) also study the impact of college quality of family formation and spousal quality, without investigating the effects by parental income.

the exception of fertility, which increases across SES groups. These results contribute to the literature on long-term returns to college selectivity, which has provided mixed evidence.[12] On the one hand, a number of papers find large effects employing regression discontinuity designs (Anelli, 2020; Jia & Li, 2021), in the context of elite institutions. Others find more limited effects (Dale & Krueger, 2002, 2014; Heinesen, 2018; Mountjoy & Hickman, 2021).[13] In addition to choosing a college, students make the consequential decision of selecting a major. The evidence points to large heterogeneity in returns across majors (Kirkeboen *et al.* (2016); Hastings *et al.* (2013); Altonji *et al.* (2016) provides a review).[14] In this paper, I show that these returns to majors differ across SES backgrounds, a relationship previously understudied (Arcidiacono & Lovenheim, 2016).

Second, I provide novel evidence on the role of higher education admission policies in equalizing opportunities and fostering social mobility. To that end, I provide an empirical framework to assess the allocative efficiency of admission policies in a universal higher education systems in terms of long-term outcomes, while accounting for peer composition and supply-side capacity constraints. I show that departing from current *ex-ante* meritocratic admission policies—based solely on past performance as captured by high school GPA—could improve social mobility. Low-SES students are under-matched and reap larger benefits from being admitted to more selective degrees, even after accounting for changes in peer composition on outcomes. Displaced high-SES students are unharmed by need-affirmative admissions in terms of income. These findings underscore the limitations of high school GPA as a predictor of long-term outcomes, especially for low-SES students.[15] This contribution builds on a rich body of literature examining the range of skills that influence later-life outcomes, demonstrating that achievement relies on a broader set of skills beyond those captured by grades (Heckman *et al.*, 2006a; Borghans *et al.*, 2008, 2016; Heckman *et al.*, 2021).[16] Findings from this paper further contribute to assessing the so-called "mismatch" hypothesis, suggesting that students admitted to academically rigorous institutions

[12] A long and established literature has studied the labor market returns to college for those at the margin of attendance (see e.g., Carneiro *et al.* (2011); Oreopoulos & Salvanes (2011); Zimmerman (2014); Heckman *et al.* (2018)).

[13] Focusing on elite institutions, the literature further suggests that returns are concentrated at the tails (Chetty *et al.*, 2023) or for high-SES students (Zimmerman, 2019).

[14] In Norway, Kirkeboen *et al.* (2016) find that relative to a Teaching degree, taking up an Engineering degree results in a gain of about $75,000 in annual income. In the U.S., the premium to majors in Science, Technology, Engineering, and Math (STEM) has been increasing (Gemici & Wiswall, 2014).

[15] Almost half of OECD countries use GPA or national exams as criteria for degree admission (OECD, 2019).

[16] This is also consistent with the theoretical model by Sethi & Somanathan (2019), who argue that past accomplishments may provide only a noisy signal of the skills relevant to future performance. Group identity can then offer additional information into potential, suggesting that greater representation of low-SES students may enhance long-term outcomes. In a similar vein, Riehl (2024) shows empirically that for admission to more selective degrees to benefit disadvantaged students, entrance exams must accurately reflect their underlying ability.

through affirmative action may struggle to succeed because their academic preparation is lower than that of their peers, leading to poor outcomes (Sander *et al.*, 2012; Arcidiacono *et al.*, 2016). A recent and growing literature has re-assessed this hypothesis, finding contrasting evidence, in the context of race-based affirmative action policy (Bleemer, 2022; Barahona *et al.*, 2024). Relative to previous papers, my analysis takes into account changes in the composition of peers on realized long-term outcomes, under counterfactual admission policies.[17]

Third, I contribute to the literature on student decision-making regarding college and major choice, by relating students' observed sorting behavior to their long-term causal effects. The context of this paper provides the ideal laboratory to study these patterns given the absence of financial constraints, removing one potential candidate for differential sorting by socioeconomic background. The current research base indicates that disadvantaged students tend to enroll in colleges that do not fully align with their abilities (Griffith & Rothstein, 2009; Black *et al.*, 2015; Hoxby & Avery, 2012; Dillon & Smith, 2017).[18] Few papers directly connect college and major choices to the causal labor market returns for the specific students involved.[19] This paper advances the literature by linking student choices to their expected returns, thereby assessing whether observed undermatching has a detrimental impact on long-term outcomes. I find that students from low-SES background are less likely to apply to more selective degrees. This is the case despite the potentially large returns to more selective degrees for these students. By selecting degrees based on expected returns, disadvantaged students could substantially enhance their long-term labor market outcomes and effectively close the SES income gap.

Finally, this paper provides novel evidence on the effect of peers on long-term outcomes in higher education markets. The role of peers in shaping the choices and outcomes of individuals has produced mixed evidence in education (Barrios-Fernandez, 2023). For instance, Abdulkadiroğlu *et al.* (2014) find that students attending exam schools in New York and Boston with significantly better peers as compared to their fallback options, provides no returns in terms of their performance. Identifying the effect of peer quality on outcomes presents significant challenges, particularly given the number of educational inputs that may be correlated with better peers. Both strategies I develop in this paper provide suggestive evidence that the heterogeneous re-

[17] For instance, Machado *et al.* (2024) show how peer composition is particularly important both for students benefiting from admission policies, and those being displaced.

[18] Dynarski *et al.* (2023) provides a review of non-financial constraints to higher education.

[19] Arcidiacono *et al.* (2016); Campbell *et al.* (2022) also study mismatch on the basis of college majors, without studying the long-term causal effects on earnings.

turns I uncover at the cutoff are driven by differential returns to peer exposure. [20] These findings have implications for the impact of admission policies on outcomes through changes in degree composition, which I incorporate into my counterfactual analyses.

This paper proceeds as follows. In Section 2, I present the context, before moving on to describe three stylized facts about the Danish universal higher education system, in Section 3. Section 4 describes the data, while Section 5 turns to describing the regression discontinuity framework employed to study the returns to degree selectivity. I then outline a model of student degree choice and earnings outcomes in Section 6, presenting parameter estimates in Section 7, before considering the impact of need-affirmative admissions and student degree choices in Section 8.

2 Danish Context

Denmark implements a number of educational policies aimed at providing equal opportunities to all. This translates into generous childcare, universal high-quality pre-K, as well as free primary and secondary schools where per-pupil expenditure are equalized across schools. Below, I describe in greater detail policies pertaining to the higher education system and the Danish centralized admission system.

2.1 Tuition Free Colleges and Living Grants

Tuition at Danish higher education institutions is free for Danish and EU/EEA students. The Danish government supports students in covering living costs across a wide range of courses and studies through the State Educational Grant and Loan Scheme (SU). In 2020, over 474,000 students benefited from these forms of educational support, with an annual budget amounting to $4.2 billion, which is about 1.2% of the GNP.

As of 2024, Danish college students living away from their parents receive a monthly government stipend of DKK 6,820 (approximately $1,000). Additionally, students can apply for a supplementary loan of DKK 3,489 (approximately $500) per month. These amounts cover basic living expenses, even in more expensive cities such as Copenhagen (University of Copenhagen,

[20] These results align with recent findings from Brazil, which highlight the role of social networks in mediating the long-term effects of peers on students benefiting from affirmative action policies (Machado *et al.*, 2024).

n.d.).[21] To apply for SU, students must be enrolled in an eligible educational program and submit their application online before the end of the month for which they want to receive SU.

When a student enrolls in a university or other higher education institution in Denmark, they are entitled to SU for up to 72 months. Since most degrees (excluding medicine) typically last five years, this allows students an additional year to complete their studies or to change their major without financial penalty.

Implemented during the 1960s and 1970s, these post-secondary policies have been associated with an increase in college attainment. For cohorts born in 1955, average years of education amounted to 11.5 years. Thirty years later, this number increased to 14 years, consequently closing the gap with the U.S., where educational attainment had stayed almost constant over this period (Karlson & Landerso, 2024). Underlining the importance of these reforms, a large literature points to the high pecuniary and non-pecuniary returns to higher education (see for instance Carneiro *et al.* (2011); Oreopoulos & Salvanes (2011); Zimmerman (2014); Heckman *et al.* (2018)).

Despite the implementation of these policies, substantial inequalities can be observed in Denmark (Landersø & Heckman, 2017). Not only did educational mobility decrease in past decades (Karlson & Landerso, 2024), recent research also points to social immobility across generations in terms of life-time well-being measures (Eshaghnia *et al.*, 2021). Moreover, strong sorting is at play, with parents purposefully choosing neighborhoods, which through social interactions further amplifies the role of the family and generates inequalities in access to schools, as well as outcomes later in life (Eshaghnia *et al.*, 2023a,b). I provide descriptive evidence of significant inequalities in the context of higher education in Section 3.

2.2 Centralized College Admission System

To apply for a higher education degree in Denmark, candidates apply online though a national admission portal and submit a rank-ordered list of degrees of up to eight degrees (college-major pairs). Two application tracks can be chosen by students. Quota 1 admissions are based on a student's GPA, calculated as a weighted average of grades from nationwide-standardized oral and written exams in specific subjects taken during the final year of high school, as well as from

[21] In addition to parents, Danish students with disabilities and those facing special circumstances such as sickness or childbirth also receive additional support from the government.

continuous assessments throughout the year.[22,23] Students typically apply in July, after their high school grades are realized. Quota 2 considers additional criteria, such as work experience. Students typically apply in the Spring. Over the period studied, between 2001 and 2009, over 80% of applicants choose Quota 1.

The allocation of students to degrees is implemented through a centralized mechanism. A student-proposing deferred acceptance (DA) algorithm matches students to capacity-constrained degrees where degree capacities are set by the government. Under DA, students produce rank-ordered lists of degrees based on their preferences and submit applications to degrees. In each round, degrees tentatively accept applicants, ranked by their GPA, up to available capacity. Unassigned students then proceed to apply to their next-preferred option. This iterative process continues until either all students are assigned to a degree or their preference lists are exhausted.

Since DA is strategy-proof, truthfully ranking schools is a weakly dominant strategy for students (Dubins & Freedman, 1981).[24] Once the match is realized, students are admitted to one degree at a maximum.[25] Switching degrees requires in most cases that students reapply through the centralized admission mechanism. Heinesen (2018) provides an in-depth description of the centralized admission system in Denmark and Gandil (2023) of the matching mechanism.

3 Stylized Facts: Inequalities in a Universal Higher Education System

3.1 Differences in High School Grades at Time of Application

In Denmark, grades differences across SES backgrounds are present from a very young age, despite the free and equal provision of a host of educational programs from an early age: heavily subsidized childcare, free primary and high school education (Heckman & Landersø, 2022). These differences may reflect differences in accumulated human capital. To showcase these inequalities in the context of the higher education system in Denmark, Figure 1a depicts the relationship be-

[22]Nationwide-standardized written exams are graded by two external examiners, while oral exams are graded by the teacher alongside one external examiner. These exams carry more weight than continuous assessments in calculating GPA, with weighting further adjusted based on the difficulty level of the subject.

[23]Additionally, degree-specific grade requirements in specific high school exams may be imposed by degrees.

[24]Strategy-proofness requires the rank-ordered list to be unrestricted in length. In practice, only about 3% of students list eight degrees. This motivates my modeling approach in Section 6, which recovers student preferences by fitting a rank-ordered choice model to these preference lists.

[25]Students who are not allocated may apply for admission to some non-capacity constrained degrees or re-apply through the centralized mechanism the following year.

tween high school GPA and parental gross income pre-tax income at time of application.[26] There is a striking SES gradient in terms of grades. Across the parental income distribution, there is a $.6\sigma$ difference in grades. Figures A.1a and A.1b of Appendix A.1 further illustrates these inequalities, both in terms of skills acquired in Mathematics and in Danish during high school.[27] Due to the grade-based meritocratic admission system in Denmark, these disparities restrict the feasible degree choice set for students from disadvantaged backgrounds.

3.2 Degree Portfolio Composition and Under-Matching

Beyond differences in grades, I find a pronounced SES gradient in application patterns. The barriers to degree choice are multi-faceted (as shown by Hoxby & Avery (2012), for instance). In part, low-SES students may find it more costly to select an adequate degree portfolio ensuring adequate labor market returns from their most preferred to least preferred option.

First, I show there is a strong positive relationship between parental income and measures of degree quality. I focus here on two measures of degree quality: peer average grades and average future income. The former, henceforth degree selectivity, averages the high school GPA of all incoming students, excluding an individual's own grade. The latter is a measure of average degree income for all individuals who completed a given degree and are between 30 and 50 years old, from 2010 to 2020. Figure 1b shows that students from higher SES backgrounds tend to apply to degrees that are better in terms of peer quality, as measured by average high school grades. Differences in high school grades at time of application do not fully drive these findings. Figure A.4c of Appendix A.2 shows the relationship between degree-level peer GPA and parental gross income at time of application, by quartile of high school grades. Students from low-SES backgrounds are less likely to apply to more selective degrees than high-SES students within the same quartile of high school GPA. Figure A.5c of Appendix A.2 shows similar patterns using our second measure of degree quality, which considers average earnings at degree level.

Second, low-SES students apply to different broad fields of study. Figure A.3a of Appendix A.2 outlines student's top-ranked degree and associated field of study, by SES background. high-SES students are almost twice as likely to rank Sciences or Business as a first-best, as compared to

[26] This measure of income excludes transfers.

[27] Similar gradients exist between high school grades and parental years of education, as shown in Figures A.1c and A.1d of Appendix A.1.

low-SES students, degrees with potentially higher returns. A similar pattern arises when focusing on the second-best alternative that students rank, as shown in Figure A.3b of Appendix A.2. In fact, students' fallback options are often within the same broad field of study, as shown in Figures A.6a-A.6f and A.7, which shows the transition matrix between the top-ranked and second-best alternatives in students rank-ordered lists.

These findings echo the literature in the U.S., which studies the factors that drive student sorting into colleges of varying quality (Hoxby & Avery, 2012; Dillon & Smith, 2017). I find that students from disadvantaged background systematically choose lower quality college degrees, even after controlling for grades. These patterns of undermatching by SES background subsist, even in the absence of financial constraints.

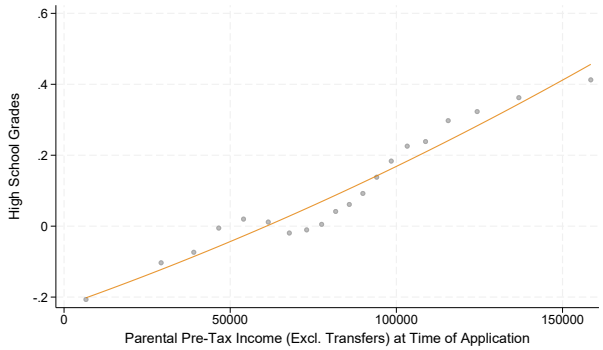
3.3 Inequalities in Later-Life Outcomes

Inequalities in terms of grades as well as portfolio composition, are potential key determinants to long-term labor market outcomes of these individuals. Figure 1c presents the correlation between wage income 12 years post-application and parental gross income at time of application. Again, we see a striking dependence between parental SES and children's outcomes, despite the strongly egalitarian education system. Figures A.8 and A.9 of Appendix A.4 further depict these inequalities in terms of a host of later life outcomes, by SES background. It showcases differences in economic and educational outcomes, and beyond, including family formation and fertility decisions, as measured 12 years after application to college. The following section aims to understand the extent to which admission to a more selective degree could indeed reduce these inequalities. I then turn to study the potential role of admission policies and student sorting patterns across degrees in fostering social mobility.

4 Administrative Data and Key Variables

This research combines several administrative datasets covering the full Danish population. I focus on first-time college applicants between 2001 and 2009. Data from the centralized system is gathered by the Danish Ministry of Higher Education. The version I was granted access to provides information on the full rank-ordered list as well as their degree assignment. However, I do

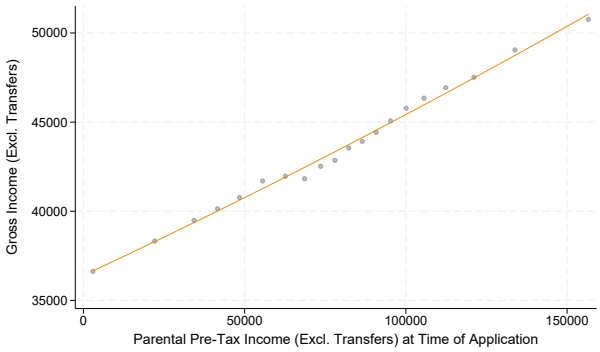
Figure 1: Three Facts



(a) High School GPA and Parental Income (USD)



(b) College Degree Quality (Measured by Average GPA of Peers) and Parental Income (USD)



(c) Student Pre-Tax Income and Parental Income (USD)

Notes: Panel (a) shows the relationship between high school grades and parental pre-tax income (excl. transfers) at time of application. Panel (b) shows the relationship between peer quality of the top-ranked degree in students' rank-ordered list and parental pre-tax income at time of application. Degree peer quality is measured by averaging over the GPA of students enrolled in that degree. Panel (c) shows the relationship between students' pre-tax income 12 years after applying and parental pre-tax income at time of application. The associated intergenerational elasticity stands at .47. The sample comprises of all Danes who apply to colleges between 2001 and 2009. Incomes are converted from DKK to 2010 USD. An exchange rate of 6.7 DKK per US dollar is used to obtain the dollar values.

not directly observe the GPA processed by the mechanism (before 2009), nor the cutoffs. To construct the running variable and cutoffs, I build on Statistics Denmark's administrative registers, which include students' subject specific grades in oral and written exams, as well as overall GPA. Together with data on degree assignment, I recover degree-specific cutoffs, which I define as the GPA for the last admitted student. The running variable and recovered cutoffs are noisy, given that the GPA I observe may in practice differ from the GPA processed by the allocation mechanism.[28] As I describe in the next section, I account for noise in the running variable by employing

[28]This can arise through different channels. For instance, students who apply directly after graduation from high school get points added to their GPA.

a doughnut RD approach, as suggested by Dong & Kolesár (2023). Appendix H shows results remain robust in specifications that do not rely on a doughnut approach.

I merge in data from several administrative registers covering the life cycle of individuals from birth up to around age 30, including information on parental attributes. These individual-level characteristics are used to test the validity of the regression discontinuity design, to capture individual heterogeneity in my model as well as to study long-term outcomes.[29]

Variables observed include income, education and origins of the parents. Parental income is measured as total pre-tax income at time of application for higher education. Parental education is captured by averaging over both parents' years of education.

Parental income, at time of application, is employed to define SES. Students are categorized into quartiles according to their parents' pre-tax income, with low-SES students identified as those in the lowest quartile and high-SES students as those in the highest quartile of the parental income distribution.

Alongside background characteristics, I use the administrative registers to link students to their socioeconomic outcomes 12 years after their first higher education application. These variables are used to explore the distributional consequences of higher education. I turn to describe these in greater detail below.

Higher Education Pipeline The data allows me to capture several aspects of the higher education pipeline, from application to completion. Beyond the application portfolio and admission recorded in the centralized admission data, I observe education spells in the education administrative register. This allows to study enrollment, time to completion, degree completion as well as years of education. College completion is defined as having undertaken over 15 years of education and graduating with at least a bachelor's degree.

Economic Outcomes The income registers provide the opportunity to examine a range of economic outcomes for individuals as they transition into adulthood. I focus on total gross income, excluding taxes and transfers, to assess earnings potential, and compare this with annual income net of taxes and transfers to evaluate the impact of redistribution in Denmark.

The data also enables me to examine the impact of higher education on the extensive margin of

[29]These variables are added as controls for ability and family background in both the choice and treatment effects model.

work. I further explore home ownership as an outcome. An individual is defined as homeowner if reporting a housing value greater than $20,000.[30] Lastly, I consider both government transfers received by individuals and taxes paid as key outcomes in the analysis.

Family Formation I further explore the effect of higher education on a several dimensions of family formation, including marital or cohabitation status, childbearing and the timing of childbearing.

Criminal Behavior Finally, I create indicators to capture criminal participation, assessing whether an individual has ever committed a crime, and specifically distinguishing severe crimes that result in incarceration.

5 Marginal Effects of Admission to More Selective Degrees

This section presents evidence on the long-term consequences of admission to and enrollment in a more selective degree compared to a next-best alternative, with a focus on differences by SES background. The objective is to provide quasi-experimental evidence on whether selective degree enrollment benefits students from low-SES backgrounds and, consequently, whether increasing their representation in selective degrees could enhance their outcomes.

I build on features of the Danish centralized college admission system and apply a regression discontinuity design. Given student priorities, preference lists and capacity constraints, the equilibrium allocation arising from the deferred acceptance mechanism, gives rise to GPA cutoffs which determine degree admissions (Azevedo & Leshno, 2016). Thus, students just above the GPA cutoff are significantly more likely to be admitted to a more selective degree than those below the GPA cutoff (as will be described in section 5.2 below).

5.1 Regression Discontinuity Design: Identification and Estimation

To identify the effect of being admitted to a more selective degree on later life outcomes, I rely on a fuzzy regression discontinuity design and use crossing the GPA cutoff as an instrument for admission. Crossing the GPA cutoff does not guarantee admission for two main reasons. First, degree-specific requirements beyond the GPA can be needed to be guaranteed admission. Second,

[30] If house is co-owned by partner, this implies a gross property value of $40,000.

students may gain admission to their target degree without meeting the GPA requirement by applying through 'Quota 2,' which considers criteria beyond GPA.

I specify the reduced-form relationship as follows:

$$Y_{ij} = f_j^s + \tau^s Z_{ij} + \beta^s X_{ij} + \gamma^s X_{ij} \times Z_{ij} + W_{ij} + \varepsilon_{ij} \tag{1}$$

where Z_{ij} is a dummy representing whether individual i is above or below the GPA cutoff for degree j. Y_{ij} is the outcome of interest. X_{ij} is the normalized GPA. f_j are degree-specific fixed effects.[31] Finally, W_{ij} represent controls, including parental income, gender, order of birth and origins. In practice, these control variables have very little effect on our estimates, and mainly serve to improve precision, as shown in Appendix H.[32] τ^s represents the returns to cutoff-crossing by SES background, indicated by superscript s.

I consider the following first-stage equation:

$$T_{ij} = g_j^s + \rho^s Z_{ij} + \psi^s X_{ij} + \phi^s X_{ij} \times Z_{ij} + W_{ij} + \upsilon_{ij} \tag{2}$$

where T_{ij} is a dummy for individual i is admitted in degree j. g_j are degree-specific fixed effects.

Each student may be facing one or several cutoffs, depending on the length of their rank-ordered preference list. Formally, my main specification follows Pop-Eleches & Urquiola (2013) and stacks each of these cutoffs across individuals.[33] τ^s and ρ^s, capture the effect of crossing the GPA cutoff to a more selective degree, for marginal applicants, relative to their next-choice option.[34] It should be interpreted as a weighted average of treatment effects around each cutoff (Fort *et al.*, 2022).

In this setting, the local average treatment effect (LATE) corresponds to the causal impact of admission or enrollment on outcomes for instrument compliers at the cutoff, τ^s/ρ^s. It is identified

[31] Fort *et al.* (2022) show that in multi-cutoff RDD induced by centralized allocation mechanisms, incorporating degree fixed effects allows to estimate the pooled average treatment effect at the cutoff—akin to what is done in the case of a stratified randomized trial.

[32] For readability, I abstract from cohort subscripts. In practice, the specification includes degree-cohort fixed effects.

[33] For example, a student applying to two capacity-constrained degrees—Economics at the University of Copenhagen and Business at Copenhagen Business School—would face two distinct cutoffs, which I stack in the analysis. Additionally, the inclusion of degree fixed effects ensures that the estimated effect leverages variation among students applying to the same degree who fall on different sides of the cutoff.

[34] Note that these more selective degrees are also more preferred. The model I build in Section 6 allows to disentangle degree-specific returns from preference.

under the following four assumptions. First, crossing the cutoff provides a strong instrument for admission and enrollment, as I show in the next section. Second, the conditional expectations of unobservables must be continuous around the cutoff. Though untestable, this is supported by the smooth density of applicants and their observable characteristics across the cutoff, for which I also provide evidence below. Additionally, the institutional context supports the exclusion restriction, where crossing the cutoff influences outcomes solely through its effect on admission or enrollment. Finally, the likely weakly positive direction of that effect for marginal applicants justifies the assumption of instrument monotonicity. Importantly, while the RDD identifies the LATE separately for low- and high-SES students, it does not identify the difference in the treatment effects between low- and high-SES students.

Focusing on students local to the cutoff is key to understanding the impact of marginal changes arising from policies that constrain or expand the supply of degree slots on outcomes. The LATE identified by the RDD allows to evaluate the impact of increasing the representation of low-SES in their target degree of choice. In other words, this analysis provides evidence on the allocative efficiency of *ex-ante* meritocratic admission policies, based on past performance, with respect to long-run outcomes. An efficient higher education system would ideally allocate students to degrees so as to maximize their potential gains, such as earnings. This will depend on properties of the education production function, which I study in greater detail in section 6.

The RDD specification allows for local linear approximations that differ arbitrarily on both sides of the discontinuity, focusing on a narrow bandwidth of one point around the cutoff.[35] Students' GPA are rounded at the first decimal in Denmark. Given the discrete nature of our running variable, I do not rely on methods that assume continuous density functions of the running variable to calculate the optimal bandwidth. I test for the sensitivity of my estimates to different bandwidth sizes and show robustness of the results. Inference is conducted by clustering the standard errors at the individual level, as suggested by Kolesár & Rothe (2018).

Finally, as explained in Section 4, I measure the running variable with noise, as I observe students' GPA from the administrative registers and not as processed by the centralized algorithm. As suggested by Dong & Kolesár (2023), I account for such noise in the running variable by employing a doughnut RD approach and drop observations around the cutoff over the interval $[-.1, .1]$, where the running variable may incorrectly classify the treatment assignment. Under this

[35]The Danish grading scale ranges from 0 to 13 until 2005. It was then replace by a scale ranging from -3 to 12.

approach, the RDD recovers the effect of cutoff-crossing for individuals at the noisily measured cutoff, assuming that the conditional means of the potential outcomes are smooth at that cutoff. These specifications and the chosen bandwidth size do not drive the results I find, as shown in Appendix H.

Before presenting results of the regression discontinuity design, I conduct two sets of validation exercises. First, I show in Figure B.1 of Appendix B that there is no manipulation of the running variable. The histogram shows that the mass on either side of the discontinuity is smooth. The slight jump at the discontinuity arises from the construction of the cutoff and the pooling across multiple cutoffs. Since each degree-specific cutoff is set at the GPA of the last admitted student, there is necessarily at least an individual at that cutoff for each degree.[36] Importantly, there is no *a priori* reasons that students would sort around the cutoff. Cutoffs are unobserved to students and vary year-on-year based on the supply and demand for each degree. I formally test the null of no manipulation around the discontinuity by conducting a version of the McCrary (2008) which allows for a discrete running variable, as developed by Frandsen (2017). This approach requires to set a parameter $k \in [0, 1]$ which determines the maximum nonlinearity in the probability mass function allowed.[37] For low-SES students, I cannot reject the null hypothesis of a smooth histogram for any values of k (p-value = .144 for $k = 0$). For high-SES students, I cannot reject the null of no manipulation at conventional levels, for values of $k > 0.06$ and after dropping individuals right at the cutoff (p-value of .15 for $k = 0.07$).

Second, I run specification 1 with pre-determined variables as dependent variables, including parental income, college attendance, gender and origins. These tests of continuity are presented in Figure B.2, which plots pre-determined variable against the running variable, and reports the coefficients of interest in the top-right corner. There is no statistically significant discontinuity in these variables at the cutoff.

Table 1 presents summary statistics on the sample used in this analysis, separately for low- and high-SES. There are large differences in parental gross income at time of application between these two groups, with parents from high-SES students having more than three times the parental income of low-SES students. Across SES background, there are also differences in parental educa-

[36] Fort *et al.* (2022) shows this can arise in RDDs in centralized admission settings. It is reminiscent to issues arising in settings with randomized waitlists, where the last unit offered treatment is by construction also always taking up the treatment (de Chaisemartin & Behaghel, 2020).

[37] A larger k allows for more deviation from linearity at the cutoff before the test rejects. A smaller k results in the test rejecting small deviations from linearity with high probability. Thus, selecting a higher k reduces the test's power.

tion, with an average of two extra years of education for high-SES students. Importantly, students' performance in school, as captured by their GPA, differs across parental income, as do the quality of the primary school attended. Furthermore, low-SES students are also much likely to be of immigrant origins. In both groups, female are more represented than males. As seen in the last row of Table 1, mean difference in wage income stands at almost 20% across both groups, 12 years after first applying to college.

Table 1: Summary Statistics

	Bottom Income Quartile	Top Income Quartile	Total
Parental Gross Income	39,699 (41,298)	163,890 (122,649)	128,233 (119,876)
Parental Gross Income (Excl. Transfers)	22,050 (40,611)	162,310 (122,551)	122,040 (123,316)
Parent College Completion	0.3 (0.5)	0.6 (0.5)	0.5 (0.5)
Parent Years of Education	12.4 (2.7)	14.7 (2.2)	14.2 (2.5)
Order of Birth	1.9 (1.1)	1.7 (0.8)	1.7 (0.9)
High School GPA	8.0 (1.2)	8.4 (1.1)	8.3 (1.1)
Peer Grades in Primary School	6.0 (0.7)	6.5 (0.6)	6.4 (0.7)
Gender			
Female	5,656	12,550	18,206
Male	2,365	7,317	9,682
Origin			
Natives	6,038	20,006	26,044
Immigrants	1,251	61	1,312
Descendants	830	92	922
Wage Income	40,502 (23,579)	47,749 (25,576)	45,669 (25,233)
Number of Observations	8,119	20,159	28,278

Notes: This table reports summary statistics of our RD sample. The sample comprises of all Danes who complete apply to college between 2001 and 2009. Incomes are converted from DKK to 2010 USD. An exchange rate of 6.7 DKK per US dollar is used to obtain the dollar values. Standard deviation in parentheses.

5.2 Degree Admission, Enrollment and Characteristics

To begin the analysis, I assess the effect of crossing the GPA cutoff on admission and enrollment patterns. This provides evidence on the first-stage relationship, presented in Equation 2. I also provide evidence on the effect of cutoff-crossing on degree characteristics to better understand the nature of the effect of scoring above the GPA cutoff for both low- and high-SES students.

These effects are depicted in Figure 2a. This figure is constructed in the following way. First, I residualize the outcome Y_{ij}, removing degree fixed effects, f_j, and covariates X_{ij}, and adding back the outcome means, for readability. I then plot the residualized mean outcomes, for each SES group, binning at the level of each discrete value of the running variable. Each figure plots in the top-right corner, the estimated effect of cutoff-crossing for low-SES students, as well as the differential effect, for high-SES students.

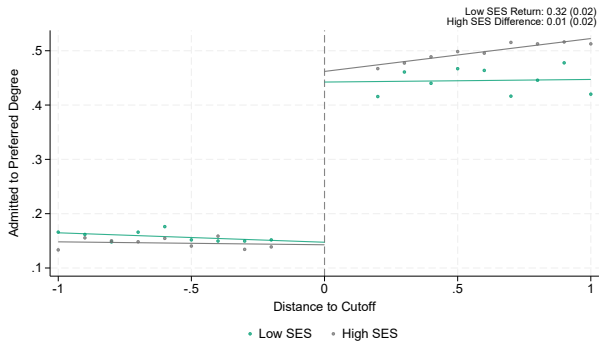
Cutoff-crossing leads to similar consequences in terms of admission across SES background. I find that admission to a more selective degree increases the probability of getting an offer by 32 percentage points.[38] Moving forward along the college admission pipeline, I find that cutoff-crossing leads to a 22 percentage point increase in degree enrollment. The effects are homogeneous across SES groups.

Finally, I show how scoring above the cutoff impacts peer composition in the admitted degree, using the two measures described in Section 3. Figure 2c shows that students marginally above the cutoff, experience a degree selectivity that is about .3 of a standard deviation higher, than students marginally below the cutoff. This effect is larger by about .1 of a standard deviation for high-SES individuals. Another approach to understand the nature of the portfolio choice is to build on income-based measures of degree quality, to capture the extent to which students from different backgrounds choose degrees with different expected labor market income. Figure 2d shows that there is a discontinuity for both low- and high-SES students in terms of degree average income, as they cross the cutoff, although the effect is more pronounced for low-SES students.

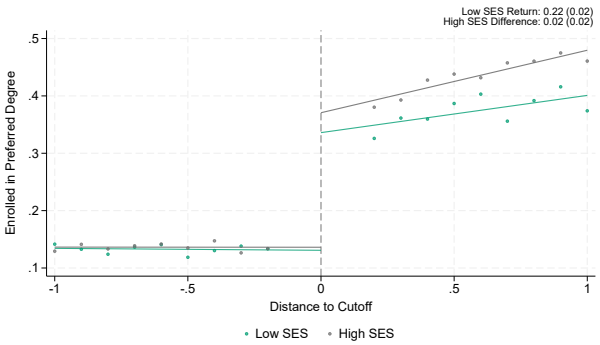
To better interpret the estimates recovered by the stacked regression discontinuity design, I describe the degree portfolio composition of students at the margin. Crossing the cutoff may lead both to degree changes within and across fields of study and university. Figures E.1-E.2 of Appendix E show that this is not the case. There are no discontinuous changes in both field of study as well as university choice. Thus, the effects estimated in the next section should be interpreted as the impact of crossing the GPA cutoff into a more selective degree within the same broad field of study and university.

[38]There are several reasons for imperfect compliance. First, degree-specific requirements beyond the GPA can be needed to be guaranteed admission. Second, the strategy aggregates all cutoffs, implying that some students who exceed a particular cutoff may not be admitted, as they could have already secured admission to a higher-preference degree. Third, the running variable is measured with noise, as discussed in Section 4. Finally, students may gain admission to their target degree without meeting the GPA requirement by applying through 'Quota 2,' which considers criteria beyond GPA.

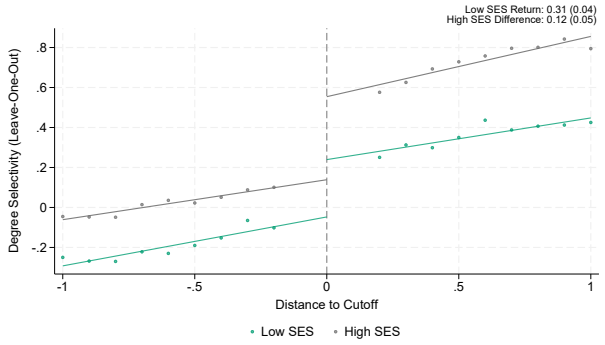
Figure 2: Degree Offer, Enrollment and Characteristics



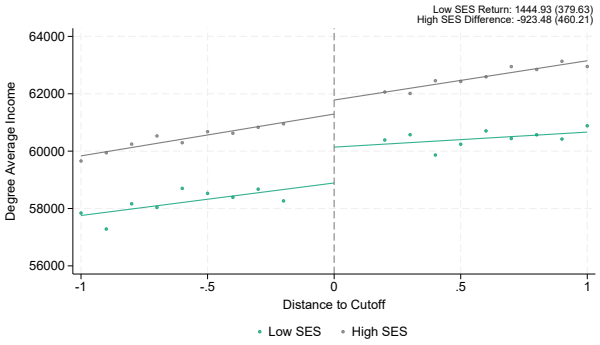
(a) Degree Offer



(b) Degree Enrollment



(c) Degree Peer Grades



(d) Degree Average Income

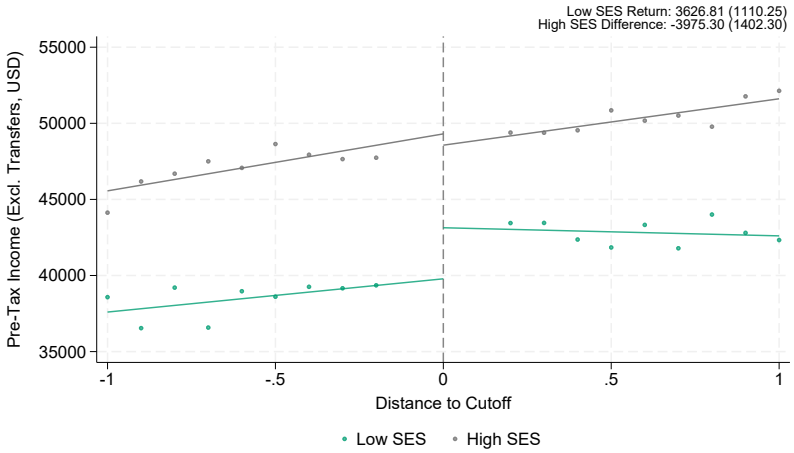
Notes: These figures present evidence on the first-stage effect of cutoff-crossing, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses. Panel (a), (b), (c) and (d) respectively outline the effect on degree offer, enrollment and degree peer characteristics, as measured by average grades and prior graduates' average income by degree.

5.3 Long-Term Outcomes

In this section, I present evidence on the long-term socioeconomic impacts of admission and enrollment in a more selective degree for instrument compliers at the margin of attendance. I proceed by reporting estimates from the reduced-form specification set out in Equation 1, corresponding to the effect of cutoff-crossing on outcomes, by SES background. To recover the LATE, these estimates can be weighted by the inverse of the first-stage estimates, as presented in the previous section. In particular, reduced-form estimates can be multiplied by a factor of about 3.1 (1/.32) to get the effect of admission and by a factor of 4.5 (1/.22) to recover the effect of enrollment in a more selective degree.

Figure 3 provides graphical evidence of the effect of cutoff-crossing on pre-tax income of individuals 12 years after college application. As students from low-SES backgrounds cross the GPA cutoff, they experience a significant increase in their income, of around $3,600 annually. This represents a jump of around 9% as compared to students just below the cutoff. Strikingly, this increase in income at the cutoff is statistically insignificant for high-SES students. Translating these effects into returns from admission and enrollment to more selective degrees, low-SES students experience an increase of around $11,000 increase in annual income from being admitted to a more selective degree, and of around $16,000 from enrolling in such degree.

Figure 3: Pre-Tax Income (Excl. Transfers), 12 years post-application



Notes: Reduced-form effect of cutoff-crossing on pre-tax income (excluding transfers), 12 years post-application. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

To explore the impact of the Danish welfare state and its redistribution through a comprehensive tax and transfer system, I consider the effect of cutoff-crossing on taxes and net income. The equalizing forces of the welfare state are at play, which reduce the gross returns by about $1,500 for low-SES students. Net of tax returns amount to around $2,100 as seen in Figure C.1b of Appendix C.1. The rise in tax contributions from low-SES students above the cutoff indicates that expanding access for disadvantaged students in selective degrees could be self-financing.

A growing literature in economics focuses on understanding the role of colleges in reaching top positions in the economy (Zimmerman, 2019; Michelman *et al.*, 2021; Chetty *et al.*, 2023). I investigate this question by studying the impact of cutoff-crossing on probability of becoming a

top income earner. Figure C.1d presents a contrasting result to Zimmerman (2019), showing that the SES gap in the likelihood of reaching the top 1% closes as low-SES students cross the GPA cutoff.

Figure C.2b further documents the differential effect on unemployment status, across SES background. The patterns presented point to larger returns for low-SES students, with a 2 percentage point reduction in unemployment. Interestingly, there no evidence that occupational sector is impacted by crossing the GPA cutoff, as shown in Figure D.1.

I also consider the impact on capital accumulation, focusing in particular on home ownership. Unlike gains in terms of income, there does not seem to be any differential returns in terms of home ownership 12 years after application, as shown in Figure C.2a of Appendix C.1. This result may reflect the fact that individuals are observed early in their career, at around age 30.

Finally, degree selectivity may have consequences beyond economic returns, including effects on family formation. For instance, Kirkebøen *et al.* (2021) demonstrates that colleges can act as marriage markets where students meet future partners. I examine patterns of family formation by SES background to assess whether these effects vary. Figure C.3 shows that cutoff-crossing increases fertility by approximately 0.08 children for both low- and high-SES students, while having no significant effect on family structure, such as cohabitation or marriage rates.

I also extend the analysis to explore the effect of degree selectivity on criminal activity, where the opportunity cost of crime may rise with increased income, particularly for low-SES students. FigureC.4 presents these findings, indicating that cutoff-crossing has no significant impact on criminal activity.

5.4 What Drives the Large Returns for Low-SES Students?

The findings thus far shed light on large differential labor market returns from attending and enrolling in a more selective college degree, for compliers at the margin of the GPA cutoff. While high-SES students obtain no gains, low-SES students benefit greatly.

This section examines several channels driving the substantial returns observed for low-SES students:

1. Educational trajectory and learning outcomes

2. Correlates of low-SES

3. Returns to exposure to higher-achieving peers

5.4.1 Educational Trajectory and Learning

This analysis starts by assessing whether differences in educational trajectories can account for the heterogeneity in returns. I evaluate this hypothesis along three dimensions—preferred college degree completion, educational attainment, and time to completion—finding no evidence of differential effects between low- and high-SES students driving the patterns uncovered, as illustrated in Figure 4.

Figure 4a illustrates the effect of crossing the GPA cutoff on the probability of completing one's preferred degree twelve years after application. High-SES students exhibit a higher likelihood of graduating from their preferred degrees, with an increase of approximately 17 percentage points, compared to 12 percentage points for low-SES students.

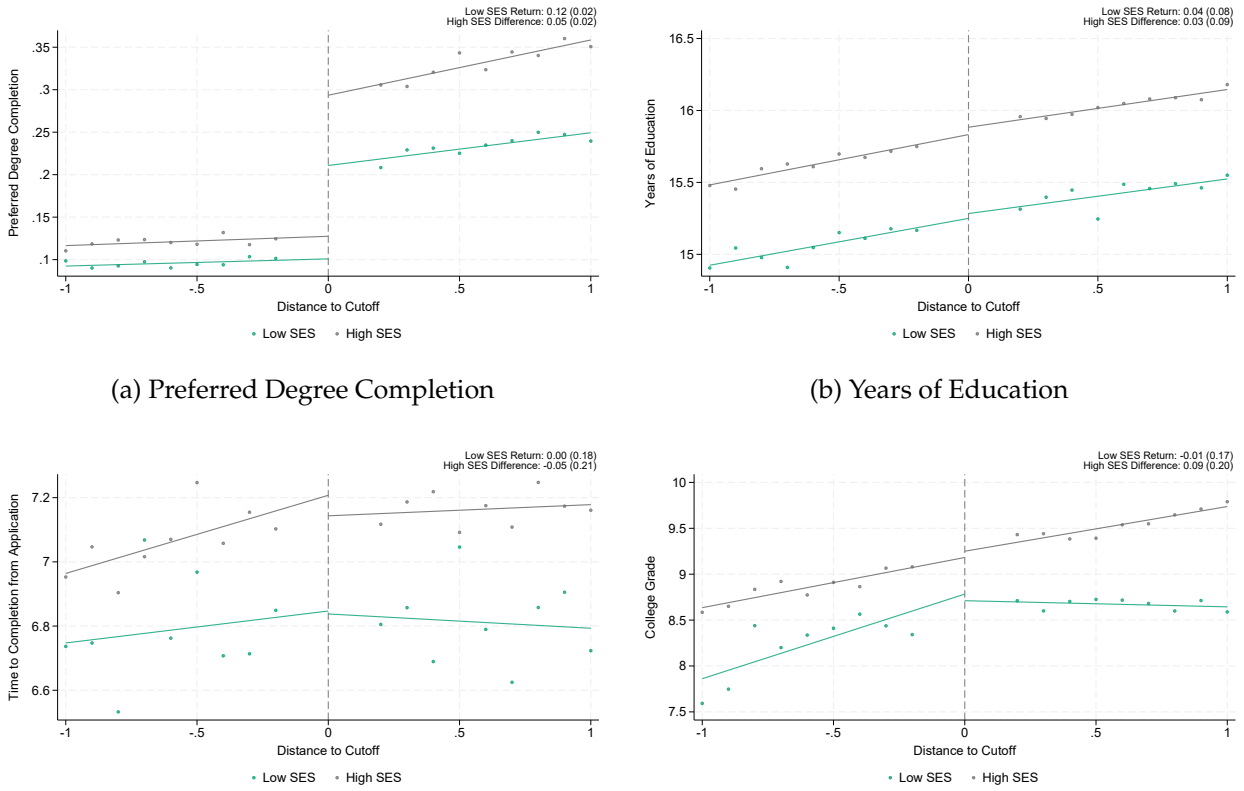
Figure 4b demonstrates that although high-SES students complete more years of education overall, crossing the cutoff has no significant effect on the number of years of education completed across SES groups. A similar pattern is observed for time to completion, defined as the number of years between application and the completion of the final degree, with no differential effect of cutoff-crossing across SES groups, as depicted in Figure 4c.

Finally, I consider the impact of cutoff-crossing on college GPA, as a means to uncover any potential heterogeneity in learning and human capital accumulation, which may drive the differential returns on income. As presented in Figure 4d, I do not find any significant effect across groups. This suggests that differences in learning, as measured by GPA, do not explain the patterns I uncover. However, it is important to note that GPA may be inversely correlated with degree selectivity, which could make it a noisy measure of learning outcomes.

5.4.2 Correlates of Low-SES and Students' Ability

Moreover, observable differences in characteristics between low- and high-SES students near the discontinuity suggest that the estimated differential effects may be disproportionately concentrated among students exhibiting these specific traits. In particular, low-SES students have sig-

Figure 4: Potential Drivers of Heterogeneous Returns



(a) Preferred Degree Completion

(b) Years of Education

(c) Time to Degree Completion

(d) Learning: College GPA

Notes: Potential mediators of the reduced-form effects of cutoff-crossing on income. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses. Panel (a), (b), (c) and (d) respectively show the effect of cutoff-crossing on degree completion, years of education, time to degree completion and college grade.

nificantly lower high school grades than their high-SES counterparts with almost a half-standard deviation difference in high school grades between low- and high-SES students.

To understand whether the effects I find are driven by effects experienced by low GPA students, irrespective of SES background, I re-estimate my main specification for students with below-median grades. I find that the differential effects across SES background remains. Low-SES students with below-median grades experience significantly greater gains compared to their high-SES counterparts with similar academic performance from cutoff-crossing, as shown in Appendix F.1. In contrast, the effects of cutoff-crossing for above-median students are close to zero across SES background.

Importantly, a unidimensional GPA provides only a noisy measure of the multidimensional nature of students' skills (see, for instance Borghans *et al.* (2016)). Differences in motivation, aspirations, or other skill dimensions may further contribute to the differential effects observed. This point raises questions about interpreting the pooled RDD, as students with varying latent abilities across choice margins are aggregated. Consequently, the average effect may obscure substantial heterogeneity in returns, as demonstrated in this paper. In ongoing work, I utilize subject-specific grades and test scores to construct a more comprehensive measure of student skills, with the goal of identifying the factors driving the observed gap in returns.

Finally, I show in Appendix F.2 and F.3, that the effect of cutoff-crossing on pre-tax earnings is more pronounced for males and students of non-Danish origins. These findings indicate that degree selectivity may offer significant economic mobility benefits for students of foreign origin.

5.4.3 Peer Effects

This section explores peer effects as a potential explanation for the differential returns. Earlier results suggest that neither educational trajectories nor ability differences are likely contributors. Moreover, portfolio composition fails to explain the observed returns, as students across the cutoff, regardless of SES, have a fallback option at the same university and in the same field as their preferred degree.

A plausible explanation is that peer effects vary by SES background. Low-SES students may benefit more from selective degrees by enhancing their social capital and building networks that could offer significant advantages in the labor market Machado *et al.* (2024). Furthermore, a high-quality peer environment may influence aspirations, potentially having a stronger impact on low-SES students.

To test this hypothesis, I employ two empirical strategies. The first leverages methods akin to those developed by Kirkeboen *et al.* (2016). The availability of students' rank-ordered preferences, as submitted to the centralized allocation mechanism, enables the construction of counterfactual degree admissions.

Specifically, for each individual, I can observe both their preferred degree and their fallback option. This allows for the estimation of counterfactual degree admission outcomes. I then link variations in peer quality across the GPA cutoff to later-life outcomes, focusing on clear margins

of choice.

I define peer quality as the average parental income of students enrolled in a given degree, which serves as a proxy for the socioeconomic background of peers and the quality of its social network. To capture the impact of peer quality differences between the preferred degree and the fallback option, ΔQ_i, I categorize these differences into tertiles. I then estimate the following model separately for high and low-SES students:

$$Y_{ij} = \left[\mu_j^s + \nu_j^s + \tau^s Z_{ij} + \beta^s X_{ij} + \gamma^s X_{ij} \times Z_{ij}\right] \times \delta^s Q_i + \varepsilon_{ij} \tag{3}$$

where μ_j and ν_j denote fixed effects for the preferred and fallback degree, respectively. The remaining variables are specified as in Equation 1.

This model is akin to running the reduced-form specification in 1, while interacting it with the difference in peer quality between the preferred and fallback option.

As described in Table 4 of Appendix G.1, peer quality improvements in the middle tertile correspond to an increase in average peer parental income of approximately \$4,200. For students in this group, the long-term impact of cutoff-crossing results in an annual pre-tax income gain of about \$8,200 (SE=\$3,600). The implied local average treatment effect (LATE) estimate is roughly \$12,600, given that the first-stage relationship between cutoff-crossing and admission stands at 65 percentage points.

The findings reveal that low-SES students disproportionately benefit from admission to degrees with higher peer quality relative to their fallback option, compared to high-SES students. These benefits are concentrated among students experiencing peer quality improvements in the middle tertile of the peer difference distribution, underscoring the non-linear nature of peer effects Brock & Durlauf (2001). In contrast, high-SES students do not experience significant income gains across any of the peer quality tertiles following cutoff-crossing.

The second identification strategy exploits within-degree variation in peer quality across cohorts. This approach relies on cohort-level differences in peer composition, controlling for individual sorting into degrees through the inclusion of fixed effects.[39] The estimated model is as follows:

[39]This identification strategy is in the spirit of Hoxby (2000) and more recently Cattan *et al.* (2023), exploiting idiosyncratic variation in peer composition in schools.

$$Y_{ijc} = \alpha + \beta S_{ijc} + \gamma F_{ic} + \rho_j + \tau_c + \varepsilon_{ijc} \tag{4}$$

where Y_{ijc} denotes later life income for individual i in degree j for a given cohort c. S_{ijc} denotes average peer parental income, while F_{ic} denotes the vector of parent-supplied inputs.

Unbiased and consistent estimation of the effect of degree peer quality rests on the assumption that changes in peer quality across cohorts within the same degree are orthogonal to unobserved factors influencing outcomes, after conditioning on the vector of covariates:

$$\text{Cov}(S_{ijc}, \varepsilon_{ijc} \mid F_{ic}, \rho_k, \tau_c) = 0 \tag{5}$$

Under this specification, variation in degree peer quality comes from changes in peers in adjacent cohorts within the same degree. Assumption (5) implies that students experiencing idiosyncratic shocks to their degree peer composition, do not endogenously sort as a response, for instance by delaying their enrollment decisions. This assumption may be plausible given information frictions regarding the exact composition of degree peers in any given cohort.

Estimates from Equation 4, reported in Table 5 of Appendix G.2, provide additional evidence on the differential peer effects by SES background. A one-standard deviation increase in peer quality—reflecting a $18,500 rise in average parental income—leads to a 6.2% increase in annual pre-tax income (excluding transfers) for low-SES students. In contrast, high-SES students do not experience any significant gains from improvements in peer quality.

Overall, the findings from both empirical strategies suggest that peer composition significantly influences labor market returns for low-SES students, whereas high-SES students appear unaffected. However, isolating the causal effect of peers remains particularly challenging given the existence of unobserved attributes correlated with peer quality. While I find that students' fallback options are within the same field of study and institution, the quality of peers may still be correlated with unobserved characteristics of the degree, such as the quality of instruction or the rigor of coursework. As a result, the findings in this section should be interpreted as suggestive rather than definitive evidence of differential peer effects.

The findings thus far offer quasi-experimental evidence on the returns to degree selectivity for low-SES students. Specifically, the results highlight that low-SES students derive substantial

benefits from admission to more selective degrees, particularly through exposure to higher-quality peers. In contrast, the lack of significant effects for high-SES students suggests that the value of degree selectivity may be less relevant for those who already possess greater social capital and access to high-quality networks.

6 A Model of the Centralized Higher Education System in Denmark

In this section, I develop and estimate a model of the Danish higher education system to investigate the sources of labor market inequalities observed among college applicants, despite the existence of a universal higher education system. As illustrated in Figure 1b, significant socioeconomic disparities remain in Denmark, as measured by the wages of students from different SES backgrounds. To study the determinants of this gap, I build a model of the centralized higher education system, which serves two main objectives. First, to evaluate whether GPA-based admission policies limit intergenerational mobility by restricting access to selective degrees for disadvantaged students who stand to benefit. Second, to explore whether improving student portfolio choices of colleges and majors could eliminate this gap. Building on prior models of student choices and outcomes under centralized admission systems (Abdulkadiroğlu *et al.*, 2020; Dur *et al.*, 2020; Barahona *et al.*, 2024), I extend this framework by incorporating the influence of average peer characteristics on students' long-term outcomes.

To achieve these objectives, the model enables me to recover student preferences and selection-corrected degree-specific returns by modeling students' degree choice behavior. This modeling approach allows to go beyond variation at the discontinuity studied in the quasi-experimental setting. Notably, these estimates bundle student degree choices with degree-specific returns, as the returns experienced by low-SES students may potentially reflect the poor fallback options they select. Unpacking these effects requires adding structure to separate degree-specific causal returns from student choice patterns. Moreover, estimating causal returns for specific degrees poses significant challenges, as students may self-select into degrees based on unobserved attributes.

Using the model, I then simulate alternative admission policies to evaluate counterfactual outcomes while accounting for the general equilibrium effects inherent in such policy changes. These effects are essential, as policy interventions that shift one student into a different degree can create a spillover effects, displacing other students in the process and thereby altering the overall com-

position of students across degrees, as shown by Gandil (2023). For each reallocation, the model accounts for changes in peer composition of degrees and their impact on outcomes.

I proceed in the following way. After describing the environment, I capitalize on the centralized college assignment mechanism in Denmark, I summarize student preferences by fitting discrete choice models to students' rank-ordered lists of degrees (cf. Section 6.2.1). In a second step, I estimate degree-specific treatment effects on long-term outcomes through a joint model of potential outcomes and treatment selection (cf. Section 6.2.2 and 6.2.3). The model will allow for parameters to vary with students' socioeconomic backgrounds, so as to understand the heterogeneity both in sorting patterns as well as returns.

6.1 Setting

Consider a set of individuals indexed by $i \in \mathcal{I} = \{1, \ldots, N\}$. Let $\mathcal{J} = \{0, 1, \ldots, J\}$ be the set of all degrees (college-major pairs) to which students can apply. The outside option, $j = 0$, represents the decision to either defer college enrollment and reapply later or forgo college attendance altogether.

Student preferences can be summarized by a strict ordering, $\succ_i$, that represents the student's preference over degrees.[40] Further consider two groups within the student population, defined by their SES, $s_i \in \mathcal{S}$. Let $\mathcal{S} = \{0, 1\}$, such that $s_i = 0$ represents low-SES and $s_i = 1$ represents high-SES students. The status s_i of each student is observable to colleges. In the model, students are classified as low-SES if their parental income falls below the median, while those with parental income above the median are categorized as high-SES.

Degrees have preference over students solely based on their GPAs a_{ij}.[41] Each degree $j \in \mathcal{J}$ has a capacity $q_j > 0$. Assume $q_0 = \infty$ for the outside option, as not attending college is available to all. A student is fully characterized by their type $\theta_i = (\succ_i, s_i, a_{ij})$, the combination of an applicant's preferences, type and GPA. I denote the set of all student types by $\Theta = \bigcup_{i \in \mathcal{I}} \theta_i$.

A deferred acceptance algorithm takes into account of student type Θ and degree capacity constraint q_j to match students to degrees (Gandil, 2023). Let $\mu : \Theta \to \mathcal{J}$ be the matching function that matches a student of a given type to a particular degree. The DA algorithm used, ensures that

[40] Student's preferences are assumed to be complete, transitive, and strict.

[41] As described in Section 2, college admission system in Denmark also considers a set of applicants based on other characteristics besides their GPA. In the model, I abstract from these students.

the assignment between students and colleges are unique and stable (Gale & Shapley, 1962).[42]

The algorithm used is key to our analysis. Under DA, truthful reporting of preferences is a weakly dominant strategy (Dubins & Freedman, 1981). This property motivates the approach presented in 6.2.1, which summarizes student preferences by fitting discrete choice models to the rank-ordered lists submitted by students.[43]

The matching, μ, can be uniquely characterized by a vector of market-clearing admission cutoffs, $c_j(\mu)$, for each degree j, as showed by Azevedo & Leshno (2016). An admission cutoff, $c_j(\mu)$, represents the minimum score a_{ij} required for admission to degree j for students with SES status s_i. Because the outside option is always available, it is assigned an admission cutoff of $-\infty$.

In line with any strict-priority mechanism, the availability of degree options varies based on students' priority scores. Let $\Omega_i(\mu) = \{j \in \mathcal{J} \mid a_{ij} \geq c_j(\mu)\}$ represent the set of feasible degree for individual i, defined as those degrees for which the individual meets the required cutoff score based on their score and SES status under the matching μ. Let $D_i(\mu) = \{j \in \Omega_i \mid j \succeq k, \text{for all}, k \in \Omega_i(\mu)\}$ denote the most preferred option in the feasible choice set $\Omega_i(\mu)$. In other words, $D_i(\mu)$ represents the degree ranked highest by individual i among the set of degrees they are eligible for. According to the stability condition, $D_i(\mu) = \mu(\theta_i)$.

The realized outcome for student i is given by $Y_i(\mu) = \sum_j \mathbb{1}\{D_i(\mu) = j\} \times Y_{ij}$ where $D_i(\mu)$ denotes the degree attended, Y_{ij} the potential outcome of interest for student i attending degree j.

6.2 Empirical Models

This section outlines the strategy used to estimate two key components of the model: student preferences and degree-specific returns. The model then enables an analysis of the effects of reallocating students across degrees according to their preferences, under varying specifications of the matching function dictated by admission policies.

[42] A stable matching is one in which there does not exist any student-degree pair (i, j), where both prefer each other to their current match under the matching.

[43] An alternative approach to recovering preferences would relax the strategy-proofness assumption and instead leverage the stability property of the DA algorithm, as shown by Fack *et al.* (2019). However, this approach relies on variation in observed choices, whereas the strategy I propose to identify the outcome equation requires variation in students' rank-ordered lists.

6.2.1 Degree Choice Model

The degree choice model presented in this section serves two purposes. First, to construct selection-corrected estimates of degree treatment effects, as described in Section 6.2.3. Second, in studying optimal allocations, these preference parameters will enable students to match with their best available degree choice, through the DA algorithm, under alternative policies.

Consider a selection model where individual i makes a degree choice j. I model student preferences using a random utility model. The utility function from enrolling in degree j, U_{ij}, is specified as follows:

$$U_{ij} = \delta_{c(Z_i)j} - \gamma_{c(Z_i)} d_{ij} + \eta_{ij} \tag{6}$$

where η_{ij} captures unobserved tastes.

The rank-ordered logit model allows for a degree specific mean utility $\delta_{j,c(Z_i)}$ and is fit separately to each cell $c(Z_i)$, where Z_i denotes a vector of individual characteristics. The following variables are dichotomized at the median, and included in Z_i: parental income and education as well as high school math and danish grades. Z_i further includes gender and tertiles of average degree income. In total, c includes 96 cells. Finally, d_{ij} denotes distance to college.

I model the unobserved taste η_{ij} as independent and identically distributed, following an extreme value type I distribution. With this assumption, Equation 6 is a rank-ordered multinomial logit model, which is estimated via maximum likelihood.[44] In particular, estimating this model recovers estimates of degree-specific mean utilities, $\delta_{j,c(Z_i)}$, which capture student preferences for a degree in each cell c.

The logit model implies the conditional likelihood of the rank list R_i is

$$\mathcal{L}\left(R_i \mid Z_i, d_i\right) = \prod_{k=1}^{\ell(i)} \frac{\exp\left(\delta_{c(Z_i)R_{ik}} - \gamma_{c(Z_i)} d_{iR_{ik}}\right)}{\sum_{j \in \mathcal{J} \setminus \{R_{im}: m<k\}} \exp\left(\delta_{c(Z_i)j} - \gamma_{c(Z_i)} d_{ij}\right)} \tag{7}$$

where $\ell(i)$ denotes the length of the list.

[44] The rank-ordered logit model is also referred to as the exploded logit model because it treats each position in the rank-ordered list as a sequential decision point, effectively decomposing the overall ranking into a series of conditional logit choices. For each rank, the model estimates the probability of selecting a specific alternative, given that higher-ranked options have already been chosen, and continues to "explode" the ranking into logit choice probabilities until all ranked alternatives are considered (Chapman & Staelin, 1982).

6.2.2 Earnings Outcomes Model

This section specifies the earnings outcomes model, whereby a given allocation between students and colleges produce an output Y_{ij}. This model will be used to recover degree-specific treatment effects, by SES, and is specified as follows:

$$Y_{ij} = \alpha_j^s + X_i' \beta_j^s + \bar{X_i}' \gamma_j^s + \varepsilon_{ij} \tag{8}$$

Let Y_{ij} denote the potential outcome for student i if she attends degree j. Potential outcomes are a function of a degree specific intercept, α_j. Moreover, I allow each degree j to have a distinct effect based on the students' characteristics X_i, which I refer to as match effects. A match effect arises from the interaction between observed and unobserved characteristics and the returns to a given degree. For instance, students may benefit more or less from a high return degree such as engineering, based on their previously acquired skills. Covariates in X_i include parental income, education, origins, mathematics and danish grades and gender.[45]

Departing from much of the existing literature, I introduce heterogeneity in degree effectiveness based on peer characteristics, denoted $\bar{X}$. This extension is critical for assessing the role of peer compositional changes on student outcomes. Indeed, as shown in Section 5.4.3, peer composition can significantly impact labor market outcomes. In this context, peer attributes are captured by the average high school grades of students, X_i, aggregated at the degree-year level, $\bar{X_i}$.[46]

I normalize X_i and $\bar{X_i}$ to have mean zero, so that α_j is the average outcome for students with average characteristics. Each of these parameters are SES-specific, denoted by a superscript s.

The mean outcome Y_i observed in the data for a given matching $\hat{\mu}$ is given by:

$$\mathbb{E}\left[Y_{ij} \mid X_i, \bar{X_i}, D_i = j\right] = \alpha_j^s + X_i' \beta_j^s + \bar{X_i}' \gamma_j^s + \mathbb{E}\left[\varepsilon_{ij} \mid X_i, \bar{X_i}, D_i = j\right]$$

A clear difficulty in identifying the population parameters α_j and β_j set out in Equation 8, is that individuals may select into degrees, based on unobserved attributes. Estimating this specification with OLS would only recover unbiased estimates under the assumption that $\mathbb{E}[\varepsilon_{ij} \mid$

[45] For the sake of readability, cohort fixed effects, while included in the model, are omitted from the discussion.

[46] The identification of peer effects on student outcomes relies on variation in peer composition across cohorts within the same degree, in the spirit of Hoxby (2000). Furthermore, using the average of past student performance to measure peer characteristics addresses simultaneity concerns inherent to the reflection problem (Manski, 1993).

$X_i, \bar{X}_i, D_i = j] = 0$. In the next section, I outline how leveraging information from students' rank-ordered lists can be used to relax this assumption.

6.2.3 Selection-Correction Approach: Identification and Estimation

To recover unbiased estimates of degree-specific treatment effects, I leverage the elicited preferences for degrees, from students' rank-ordered lists.

In particular, I account for unobserved heterogeneity by conditioning Equation 8 on the vector of unobserved tastes, $\eta_i = (\eta_{i0}, \eta_{i1}, ..., \eta_{iJ})$, thereby linking the outcome equation to the degree choice model.

Assumption 1 *The conditional expectation of Y_{ij} is specified as follows:*

$$\mathbb{E}[Y_{ij} \mid X_i, \bar{X}_j, \eta_{ij}] = \alpha_j^s + X'\beta_j^s + \bar{X_i}'\gamma_j^s + \mathbb{E}[\epsilon_{ij} \mid X_i, \bar{X}_i, \eta_{ij}] \tag{9}$$

This assumption is in the spirit of Dale and Krueger's "self-revelation" model (2002; 2014), recently revisited by Mountjoy & Hickman (2021). Under this assumption, comparing sets of students with identical covariates and rank-ordered choice lists allows us to recover the causal effects of degree enrollment. By eliciting their preferences, students reveal their unobserved "types" through the degrees they apply to, implying that degree enrollment is conditionally random among students applying to the same degrees.

Although this assumption is conceptually appealing, fully nonparametric matching based on rank-ordered lists is impractical, as very few students share identical rankings. To address this limitation, I use the structure of the logit choice model to develop a parametric approximation to the matching procedure.[47] Specifically, I adopt the following parametrization:

$$\begin{aligned} &\mathbb{E}[Y_{ij} \mid X_i, \bar{X}_i, \eta_{i1}, \ldots, \eta_{iJ}] \\ &\quad = \alpha_j^s + X_i'\beta_j^s + \bar{X_i}'\gamma_j^s + \textstyle\sum_{k=0}^{J} \psi_k^s \times (\eta_{ik} - \mu_\eta) + \varphi^s \times (\eta_{ij} - \mu_\eta),\ j = 1, \ldots, J, \end{aligned} \tag{10}$$

where $\mu_\eta = \mathbb{E}[\mu_{ij}]$ denotes Euler's constant.

[47] Alternative approaches to controlling for selection in multinomial choice settings include Lee (1983); Dahl (2002); Dubin & McFadden (1984).

As Abdulkadiroğlu *et al.* (2020) highlight, this model allows for essential heterogeneity (Heckman *et al.* (2006b)). The coefficient ψ_k^s reflects the effect of preference for degree k across all potential outcomes, allowing students with strong preferences for specific degrees to exhibit higher or lower ability. φ^s denotes a match effect of preference for degree j on the potential outcome for that particular degree.

By iterated expectations, Equation 10 implies that mean observed outcomes at degree j are

$$\begin{aligned}&\mathbb{E}\left[Y_i \mid X_i, \bar{X}_i, R_i, D_i = j\right] \\ &\quad = \alpha_j^s + X_i'\beta_j^s + \bar{X}_i{}'\gamma^s + \textstyle\sum_{k=0}^{J} \psi_k^s \lambda_k\left(X_i, \bar{X}_i, R_i\right) + \varphi^s \lambda_j\left(X_i, \bar{X}_i, R_i\right)\end{aligned} \tag{11}$$

where $\lambda_k\left(X_i, \bar{X}_i, R_i\right) = \mathbb{E}\left[\eta_{ik} - \mu_\eta \mid X_i, \bar{X}_i, R_i\right]$ gives the mean preference for degree k conditional on a student's and peer's characteristics, and preference list. The $\lambda_k(\cdot)$ functions act as control functions, addressing selection on unobservables (Heckman & Robb, 1985). These functions generalize the formulas derived by Dubin & McFadden (1984) (see Appendix I), extending them to account for the fact that I observe a ranked list of multiple alternatives rather than only the most preferred option.

The identification of the selection parameters, ψ_k^s and φ^s, hinges on the variation in preference rankings among students enrolling in the same degree, conditional on covariates. A positive ψ_k^s is inferred if students ranking degree k higher perform beyond expectation based on their observed characteristics in all degrees. A positive φ^s is inferred if these students only perform beyond expectation in degree k.

An additional source of identifying variation comes from an exclusion restriction for distance to colleges—which is included in the choice equation and not in the outcomes equation. This strategy is commonly employed in the literature on the returns to schooling (Card, 1995; Walters, 2018).

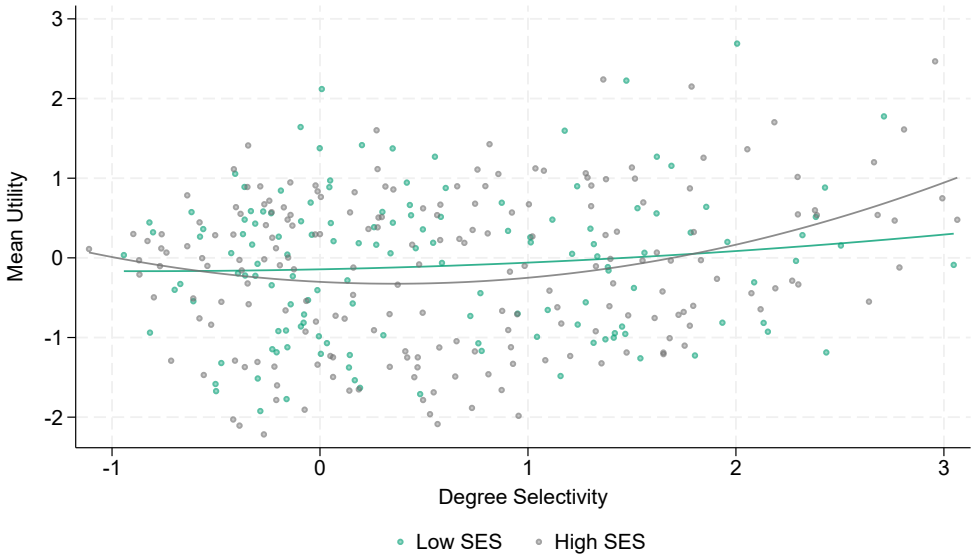
Estimation proceeds in two steps. First, I recover parameters of the choice model through maximum likelihood. These are used to construct estimates of the control functions. In a second step, I regress the outcomes of interest on dummies for degrees, interactions with student and peer characteristics, as well as the estimated control functions. This model recovers key parameters of interest, i.e. the treatment effect of each degree on outcomes, by SES.

7 Parameter Estimates

This section presents estimates from the model described above. The sample includes 13 cohorts of applicants who first applied to higher education from 1997 to 2009, and submitted their rank-ordered degree preferences through the centralized application system.[48] This amounts to 139,778 individuals who applied to 348 degrees.[49] 49,991 students are from low-SES background (about 35%), which is here defined as individuals with parental income below the median, at time of application. The outcome of interest, Y_i, throughout this analysis is wage income, 12 years post-application.

I begin by presenting the results from the degree choice model. Figure 5 plots the school-by-covariate-cell mean utility estimates $\delta_{c(Z_i)j}$ against degree selectivity. These estimates are averaged over covariate cells and residualized with respect to cell indicators. This Figure shows that students from disadvantaged backgrounds have mean utility that is only slightly positively associated with degree selectivity. In contrast, students from high-SES backgrounds seem to exhibit a steeper gradient, particularly at the upper end of the degree selectivity distribution.

Figure 5: Mean Degree Utility, by SES



Notes: This figure plots the estimates of degree-specific mean utility against degree selectivity, separately for low- and high-SES students.

[48] To maximize the size of the estimation sample, I add four additional cohorts to the RDD estimation sample.
[49] I restrict the analysis sample to degrees with more than 100 enrolled students.

I now report and analyze estimates from the outcomes model. The estimates I recover, include the degree-specific effects, α_j, and degree-specific interactions with covariates, β_j. I report the returns relative to the outside option of not enrolling in higher education in the year of application, respectively $\alpha_j - \alpha_0$ and β_j, where α_0 are estimates for the outside option. These are estimated separately for low- and high-SES students.

Table 2 reports the mean and standard deviation of these estimates across all degrees j. I find there is substantial variation in causal effects across degrees, in line with previous literature on returns to majors (Hastings *et al.*, 2013; Kirkeboen *et al.*, 2016). The larger variation in estimates among low-SES students, relative to high-SES students, underscores the significant impact that these choices have on future earnings for disadvantaged students. Moreover, there is important heterogeneity in match effects based on students' characteristics. For instance, holding average treatment effect fixed, a one standard deviation increase in degree match quality for students with higher math grades leads to about \$3,000 increase in annual wage income, while this stands at around \$2,400 for high-SES students. Finally, estimated parameters from the model reveal evidence of selection on gains, particularly for low-SES students.

Table 2: Parameter Estimates

	low-SES		high-SES	
	Mean	SD	Mean	SD
Average Treatment Effect	3037.71	11797.12	-1629.97	7951.95
Male Match Effect	7328.72	6679.70	8033.01	5268.03
Math Grade Match Effect	1504.26	2972.32	1679.34	2345.39
Danish Grade Match Effect	949.61	2861.38	811.66	2382.50
Foreigner Match Effect	-97.66	7389.19	-61.38	4613.88
Parental Income Match Effect	429.62	1115.79	76.21	394.21
Parental Education Match Effect	67.81	969.75	-80.72	799.28
Peer Grades Match Effect	-546.41	7611.90	895.55	5780.67
Preference (ψ_k)	-367.52	1378.66	-65.49	1538.33
Selection (φ)	232.30	-	115.97	-

Notes: Estimated means and standard deviations of treatment effects parameters. I report the returns relative to the outside option of not enrolling in higher education in the year of application, respectively $\alpha_j - \alpha_0$ and β_j, where α_0 are estimates for the outside option

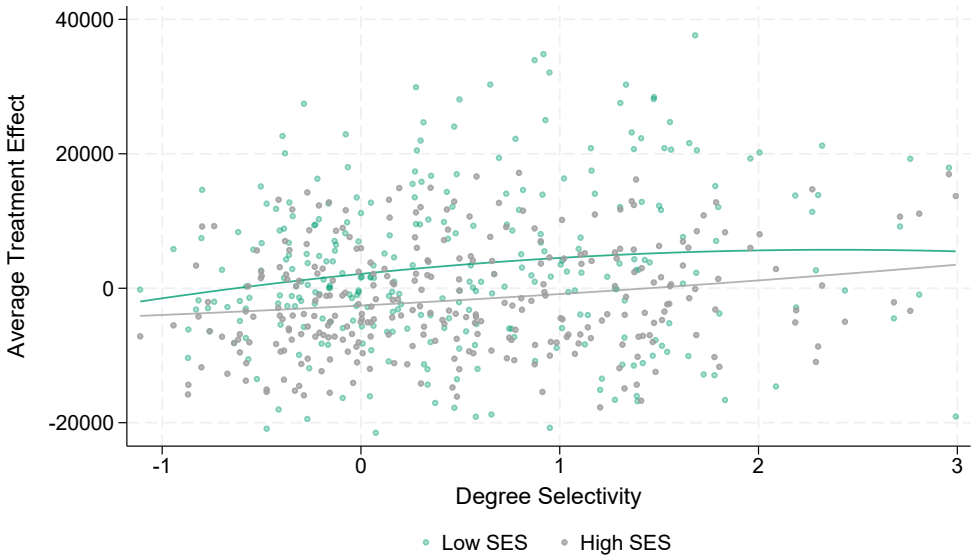
To visually illustrate the high dimensional vector of degree-specific ATEs, I plot them against degree selectivity in Figure 6. Low-SES returns are depicted in green, while high-SES returns are in gray. Interestingly, for students from disadvantaged backgrounds, the returns are positive across the distribution of degree selectivity. On the other hand, at the lower end of the degree selectiv-

ity distribution, degree returns high-SES students are in fact negative. This, in part, reflects the relatively better fallback options available to high-SES students as opposed to low-SES students.

Appendix J.2 provides graphical evidence of the correlation between degree match effects across SES background, showing weak correlations. Figures J.2f and J.5f do so for estimates arising from the model and compares them with estimates of Equation 8 with OLS, without controlling for selection. Appendix J.3 further studies the relationship between match effects against degree selectivity, separately for high and low-SES students. These figures illustrate the substantial heterogeneity in match effects across the degree selectivity.

To assess the impact of adopting a control function approach to addressing selection, Appendix J.4 provides graphical evidence on the relationship between the estimates from the model compared to estimates recovered without addressing selection. These figures show estimates that do not control for selection overestimate the returns.

Figure 6: Average Treatment Effects, by SES



Notes: Relationship between degree-specific average treatment effects and degree selectivity. The latter is measured by averaging over enrolled students' high school GPA and standardized to have mean 0 and standard deviation 1. Low-SES students are depicted in green, while high-SES students are depicted in gray. The treatment effect is relative to the outside option of not enrolling in higher education in the year of application.

8 Admission Policies and Degree Sorting

8.1 Ex-ante Meritocratic Admission Policies

The model provides a framework to assess the role of current admission practices in driving the large SES wage gap that remains amongst college applicants, despite egalitarian higher education policies. To do so, I consider a set of need-affirmative admission policies to understand the extent to which long-term labor market outcomes of low-SES students can be improved, by departing from current *ex-ante* meritocratic admission policies.[50] The choice of such policy is driven by evidence from the regression discontinuity design that low-SES students may benefit more than high-SES students from being admitted into their first-best college degree. Importantly, this model allows to estimate any potential losses from high-SES students who may be displaced from their preferred degrees, through the introduction of the policy.

The objective is to simulate student assignments under any given affirmative action (AA) schedule, utilizing the centralized matching mechanism.[51] This process begins by recovering the key inputs for the matching function $\vartheta(\Theta, q, \pi) = \mu$, where Θ denotes student types, q represents degree capacities and π the AA policy.

First, student types, $\Theta = \bigcup_{i \in \mathcal{I}} \theta_i$, where $\theta_i = (\succ_i, a_{ij}, s_i)$, are recovered. Preferences, $\succ_i$, are obtained by using estimates from the rank-ordered logit model. The remaining components of Θ, such as students' GPA, a_{ij}, and SES status, s_i, are assumed to be invariant to changes in the admission policies. This assumption—namely, the absence of behavioral responses to policy changes—enables me to recover these directly from the data. Degree capacities, $q = \{q_0, \ldots, q_J\}$, are also recovered from the data. Degree capacities are set by the government and are held constant in the simulation. After obtaining $\hat{\Theta}$ and q, I simulate the matching function as $\vartheta(\hat{\Theta}, q, \pi) = \hat{\mu}$.

With the simulated student assignments, I compute the new vector of degree peer characteristics $\bar{X}_i$ and the realized outcomes. For an individual of type θ_i, the expected outcome is given by $\mathbb{E}[\hat{Y}_i(\hat{\mu}(\theta_i)) \mid \theta_i]$, where $\hat{\mu}$ is the estimated matching function.[52] It is specified as follows, by plugging in Equation 10:

[50] By *ex-ante* meritocratic, I refer to admission criteria based on past performance, as opposed to *ex-post* meritocratic, which would be based on future returns, coinciding with an efficient allocation in terms of maximizing earnings.

[51] For the counterfactual exercises, I focus on the 2009 application cohort.

[52] For each simulation, I draw an η_{ij} from an extreme value type I distribution, repeating this process 100 times and averaging over these iterations.

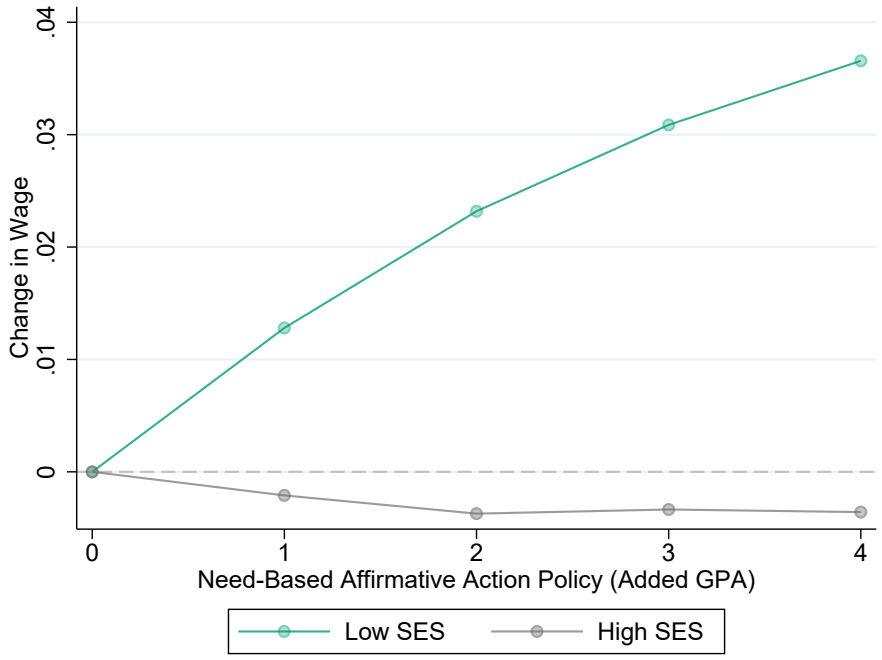
$$\mathbb{E}\left[\hat{Y}_i\left(\hat{\mu}\left(\theta_i\right)\right) \mid \theta_i\right] = \sum_j \mathbb{1}\left\{\hat{\mu}\left(\theta_i\right) = j\right\} \times \mathbb{E}\left[\hat{Y}_{ij} \mid \theta_i\right]$$

$$= \sum_j \mathbb{1}\left\{\hat{\mu}\left(\theta_i\right) = j\right\} \times \left(\alpha_j^s + X_i'\beta_j^s + \bar{X}_i{}'\gamma_j^s + \sum_{k=0}^{J} \psi_k^s \times \left(\eta_{ik} - \mu_\eta\right) + \varphi^s \times \left(\eta_{ij} - \mu_\eta\right)\right)$$

This parametrization relies on the assumption that potential outcomes are unaffected by changes in the admission practices. Importantly, it accounts for the role of peer composition in the production function of degrees, as students are being reallocated to different degrees.

I consider policies that increase the probability of admission to the preferred degrees of low-SES students. I do so by gradually increasing the GPA of low-SES, a_{ij}, from 1 to 4 additional points. This is equivalent to reducing the GPA cutoff for low-SES students.[53]

Figure 7: Long-Term Returns of Need-Affirmative Admission Policy on "Winners" and "Losers"



Notes: Effect of need-affirmative admissions on low-SES students (depicted in green) and high-SES students (depicted in gray). The policy under consideration reduces the GPA requirement gradually between 1 and 4 points. Each dot represent the average change in wage as a result of implementing the policy.

Theoretically, while low-SES students benefit by being placed into better degrees, high-SES students may be harmed by being placed into lower return degrees, due to capacity constraints

[53] Recall that in this period, the Danish grading scale ranges from -3 to 12.

in their preferred choices. Moreover, low-SES students may themselves be harmed, particularly those away from discontinuities, for whom the effects may be different than the LATEs recovered by the RDD. Finally, changes in degree peer composition may also affect outcomes. The model and simulations I conduct provide a framework to account for these three aspects.

Figure 7 presents estimates of changes in returns as need-affirmative admissions become more generous toward low-SES students. Students from disadvantaged backgrounds experience increases in their wage, 12 years after application, of around 4%, while students from high-SES backgrounds experience only slightly wage declines. These estimates build directly on the model developed earlier, which links student preferences, degree-specific returns, and the equilibrium effects of affirmative action policies. By simulating counterfactual outcomes under different policy scenarios, the model allows for an analysis of how need-affirmative admissions impacts the distribution of students across degrees and affects long-term outcomes. Figures in Appendix K.2 shows the distributional consequences of this policy, by SES status.

A key takeaway from this section is that *ex-ante* meritocratic student assignments, based solely on past academic performance, may result in inefficiencies, in terms of maximizing later life earnings in Denmark. Consistent with the quasi-experimental evidence discussed earlier, the model shows that low-SES students derive significant benefits from more generous affirmative action policies. This result highlights the potential for low-SES students to succeed in more selective degree. The findings suggest that academic metrics like GPA may not fully capture the potential of these students in selective educational environments. These findings underscore the limitations of high school GPA as a predictor of long-term outcomes, especially for low-SES students. This contribution builds on a rich body of literature examining the range of skills that influence later-life outcomes, demonstrating that achievement relies on a broader set of skills beyond those captured by GPA (Heckman *et al.*, 2006a; Borghans *et al.*, 2008, 2016; Heckman *et al.*, 2021).

This insight aligns with the theoretical framework developed by Sethi & Somanathan (2019, 2022), which posits that academic grades, particularly for low-SES students, may serve as a noisy signal of true ability. The framework suggests that not only may the variance in grades be higher for low-SES students, but these signals could also be systematically biased, underestimating the true capability of disadvantaged students. As a result, admission policies that rely heavily on these signals can lead to misallocations, where high-potential low-SES students are undermatched in less selective degrees.

By reallocating low-SES students into more selective degrees, the policy significantly boosts their future earnings potential and promotes social mobility. Notably, the model also highlights that high-SES students displaced by these policies do not experience any negative impact on their long-term returns.

8.2 Degree Choice and First-Best Allocation

Changing admission practices could reduce the SES wage gap by about 15%, as shown in Figure K.1 of Appendix K. Still, significant wage inequality remain. In this section, I study whether disparities between low- and high-SES students could be addressed by students ranking degrees by expected returns. This allocation would coincide with the first-best allocation with respect to labor market earnings, 12 years after application.

To that end, I decompose the outcome into three components, by adding and subtracting Y_{i0} from Equation 8 to get:

$$Y_{ij} = \underbrace{\alpha_0^s + X_i^{'}\beta_0^s + \bar{X}^{'}\gamma_0^s + \varepsilon_{i0}^s}_{Y_{i0}^s} + \underbrace{(\alpha_j^s - \alpha_0^s)}_{\text{ATE}_j^s} + \underbrace{X_i^{'}(\beta_j^s - \beta_0^s) + \bar{X}^{'}(\gamma_j^s - \gamma_0^s) + (\varepsilon_{ij}^s - \varepsilon_{i0}^s)}_{M_{ij}^s} \tag{12}$$

ATE_j^s denotes average treatment effect for each degree, averaged over the whole population, while M_{ij}^s denote match effects relative to the outside option.

I consider a counterfactual scenario where students submit rank-ordered list, ordered by the returns offered by each degree, based on their own characteristics. Returns here are computed as the sum of the degree average treatment effect, ATE_j and the individual-specific match effect, M_{ij}. This would correspond to an *ex-post meritocratic* allocation of students to degrees, one that is based on predictors of success, rather than past achievements.

Table 3 presents the results, disaggregated by SES background, revealing significant differences in labor market returns based on degree choices. Both low- and high-SES students experience considerable earnings gains by enrolling in their first-choice degree, but the effect is notably larger for low-SES students. Specifically, the average treatment effect of attending a first-choice degree is approximately \$26,000 for high-SES students, compared to nearly \$37,000 for low-SES

Table 3: First-best Allocation

	low-SES		high-SES	
	ATE (1)	Match (2)	ATE (3)	Match (4)
Choice 1	36,660	17,522	25,963	13,486
Choice 2	36,079	14,463	25,709	10,816
Choice 3	35,855	12,747	25,256	9,498
Choice 4	35,772	11,233	24,990	8,479
Choice 5	35,403	10,186	24,838	7,533
Choice 6	35,150	9,240	24,608	6,243
Choice 7	34,930	8,422	24,319	6,243
Choice 8	34,678	7,726	23,986	5,888

Notes: The table reports rankings of degrees based on ATE and match effects, and associated returns relative to the outside option. All values are in USD.

students. Similarly, match effects—capturing the alignment between student characteristics and degree effects—are substantial, amounting to $17,500 for low-SES students and $13,500 for high-SES students. These figures suggest that, with a ranking of degrees based on labor market returns, the SES wage gap could be fully eliminated. This is demonstrated by the fact that the $14,500 difference in returns exceeds the SES wage gap of around $10,000.[54]

These findings raise important questions about the factors influencing students' degree choices. Despite the large labor market returns associated with certain degrees, many students—particularly from low-SES backgrounds—leave significant labor market gains on the table by not prioritizing degrees with the highest returns. Importantly, this analysis does not imply that students are choosing degrees irrationally. It could well be that students value other attributes of degrees, including field of study, specific universities and location, as well as other life outcomes, including non-pecuniary aspects. Information constraints or heterogeneity in preferences could further explain these patterns.[55] Recent evidence also suggests that neighborhood and school peers, along with siblings, play a significant role in influencing both major selection and college attendance decisions (Brenøe & Zölitz, 2020; Altmejd *et al.*, 2021; Cattan *et al.*, 2023; Eshaghnia *et al.*, 2023a).

[54] This does not account for general equilibrium effects arising from changes in the supply of skills.

[55] A growing literature studies determinants of major choices, including Zafar (2013); Stinebrickner & Stinebrickner (2014); Wiswall & Zafar (2014, 2015); Patnaik *et al.* (2022). See Patnaik *et al.* (2021) for a recent review.

9 Conclusion

This paper develops a framework to evaluate the potential of higher education as a driver of upward mobility. The findings reveal that, although higher education can promote substantial mobility, disadvantaged students do not fully harness its potential. Degree sorting and admission policies restrict mobility more than the causal returns to selective degrees. The current GPA-based meritocratic admissions system is inefficient in terms of maximizing long-term earnings. By conducting this analysis in Denmark—where financial barriers are largely absent—this study isolates these sources of inequality from the effects of financial constraints.

Using rich administrative data from Denmark and the features of the centralized admissions system, I begin by estimating the labor market returns to degree selectivity for students at admission cutoffs. The findings indicate that low-SES students benefit substantially from admission and enrollment to more selective degrees, with cutoff-crossing students experiencing a 9% increase in earnings twelve years after college application. Additional analyses on various socioeconomic outcomes—including educational attainment, family structure, and criminal behavior—reveal limited impacts by SES backgrounds, except for increased fertility among both low- and high-SES students. To probe the mechanisms behind these heterogeneous returns, I employ two quasi-experimental methods to provide suggestive evidence of differential peer effects.

In addition to documenting sizable returns to degree selectivity at the margin, I develop a joint model of degree choice and earnings, incorporating peer effects, to examine the drivers of Denmark's SES wage gap. This model enables the estimation of selection-corrected, degree-specific returns and assesses the roles of admission policies and student degree sorting in shaping labor market inequalities.

Evidence from the model reveals that degree returns are larger for low-SES students relative to high-SES peers, across the distribution of degree selectivity. The results further indicate that need-affirmation admission policies could improve labor market outcomes for low-SES students without adversely impacting displaced high-SES students. Expanding access to selective degrees for low-SES students narrows the SES wage gap by approximately 15%. These findings highlight the limitations of high school GPA as a predictor of long-term outcomes, particularly for low-SES students—long-term outcomes depend on a broader range of skills beyond those measured by GPA. Crucially, if disadvantaged students prioritized degree choices based on expected returns,

the wage gap could be entirely closed. Overall, this evidence reveals that the observed disparity in outcomes is driven by differences in degree sorting and admission policies, rather than limited degree returns. Future research into the underlying determinants of students' degree choices may offer further insights into observed sorting patterns and addressing persistent inequality.

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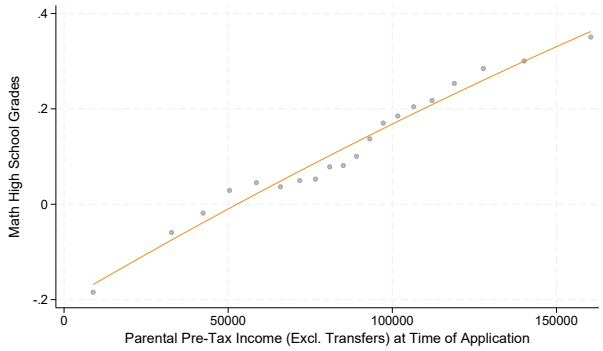
Zimmerman, Seth D. 2019. Elite Colleges and Upward Mobility to Top Jobs and Top Incomes. *American Economic Review*, **109**(1), 1–47.

A Inequalities in Universal Higher Education System

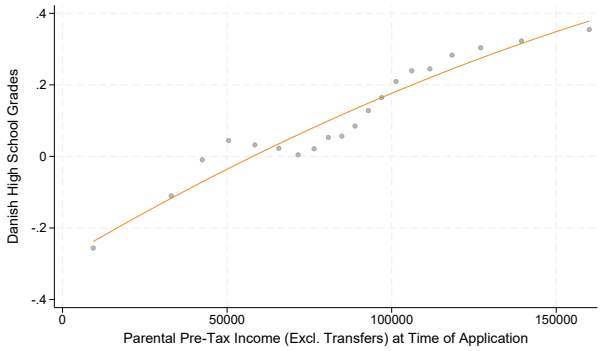
This Appendix provides further evidence on inequalities in Denmark, by parental income and education. Section A.1 focuses on inequalities in skills as measured by high school grades, with a particular focus on grades in mathematics and danish.

A.1 Skill Differences

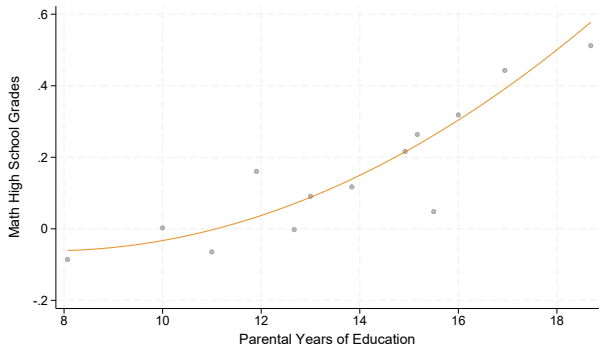
Figure A.1: High School Grades and Parental Background



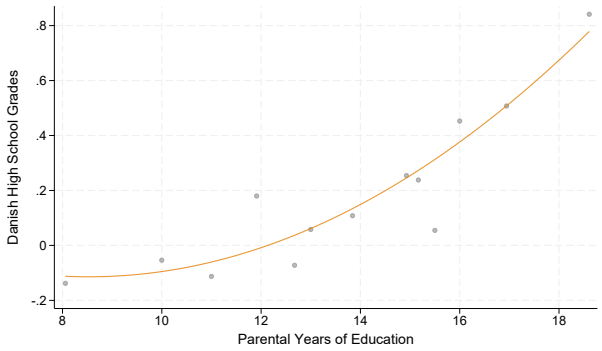
(a) Mathematics High School Grades and Parental Income



(b) Danish High School Grades and Parental Income



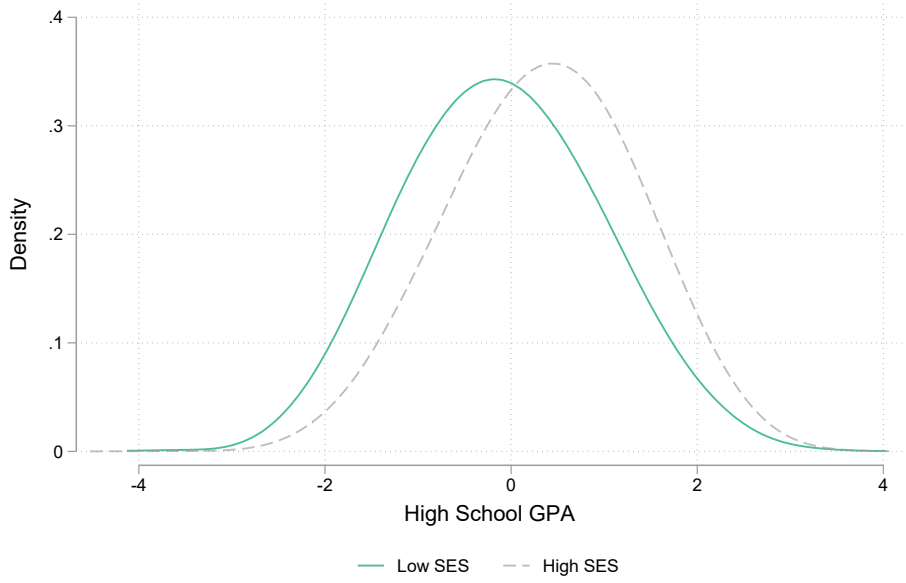
(c) Mathematics High School Grades and Parental Education



(d) Danish High School Grades and Parental Education

Notes: Relationship between student skills at time of application, proxied by mathematics and danish high school grades and parental characteristics. Panels (a) and (b) focus on the relationship between mathematics and danish high school grades, respectively, and parental pre-tax income (excluding transfers) at time of application. Panels (c) and (d) focus on the relationship between mathematics and danish high school grades, and parental education.

Figure A.2: Distribution of High School Grades



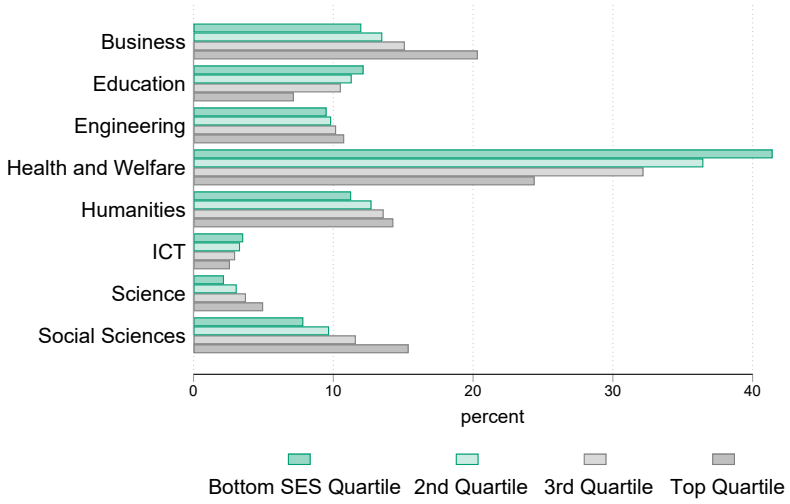
Notes: Densities of high school grades by SES background.

A.2 Degree Portfolio Composition

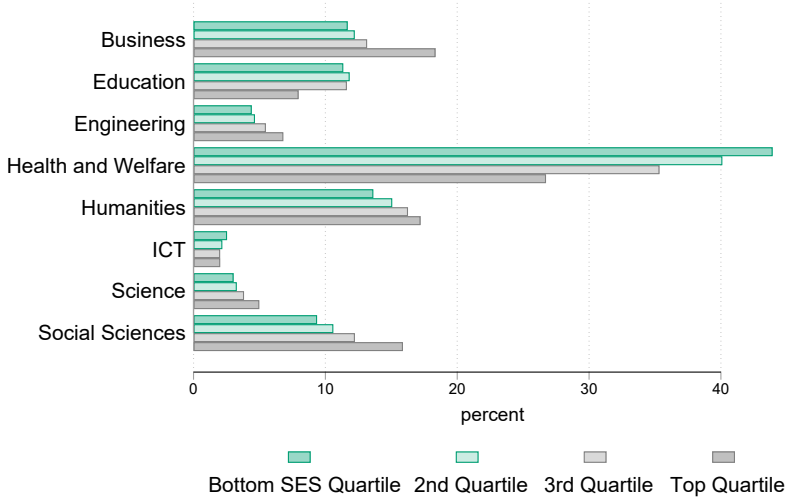
This Appendix provides evidence on differences in degree portfolio composition of students, by parental income quartile.

A.2.1 Field of Study: Top-Ranked and Second-Best

Figure A.3: Choice of Field of Study, by SES



(a) Field of Study in Top-Ranked Choice, by SES

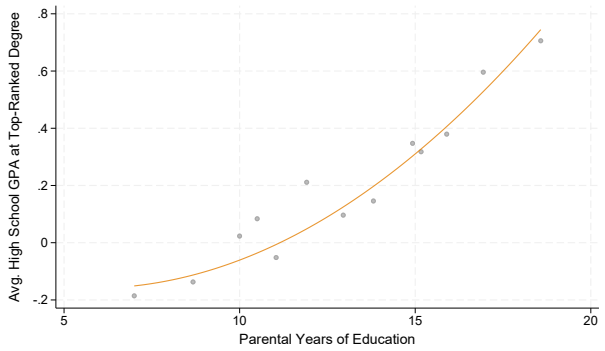


(b) Field of Study in Second-Best Choice, by SES

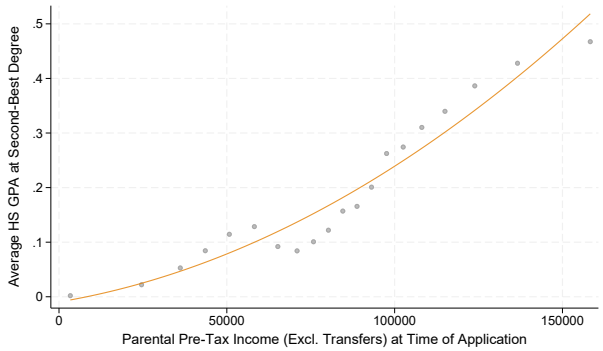
Notes: Panel (a) and (b) describe the application patterns by SES background, respectively for the top-ranked alternative in students rank-ordered list and the second-best alternative. The figures report the shares of students applying to a given field of study, by SES background.

A.2.2 Degree Quality: Top-Ranked and Second-Best

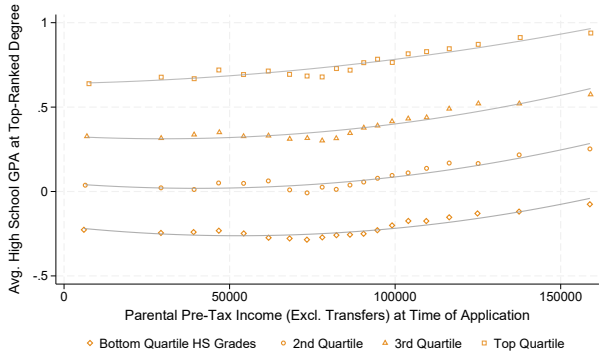
This Section provides additional facts about the quality of degrees that students are ranking, by parental education and income. Degree quality is measured by the average high school grades of incoming students. I distinguish between the quality of the top-ranked alternative and the second-best. In particular, Figure A.4c and Figure A.4d show that across the distribution of high school grades, the positive gradient between degree quality and parental SES background remains.



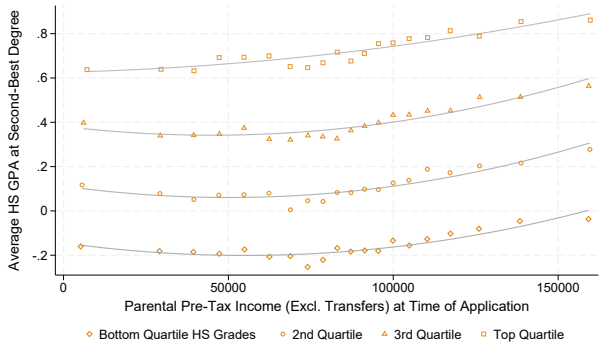
(a) Degree Average Grades and Parental Education



(b) Degree Average Income and Parental Income



(c) Degree Average Grades and Parental Education, by Grades Quartile

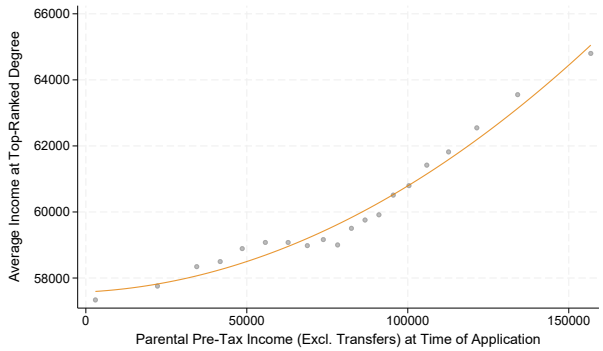


(d) Degree Average Income and Parental Income, by Grades Quartile

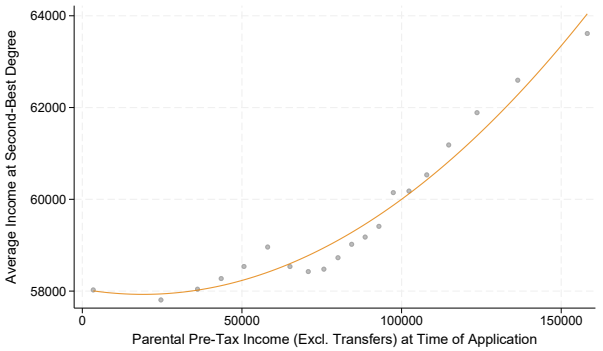
Notes: Panel (a) plots the average high school GPA of incoming students at the *top-ranked* degree chosen, against mother's years of education. Similarly, panel (b) describes the relationship between average high school grades of incoming students at the *second-best* alternative ranked by students, against parental pre-tax income. Panel (c) and (d) plot these measures of degree quality against parental pre-tax income, by quartiles of high school grades.

A.2.3 Degree Quality: Top-Ranked and Second-Best

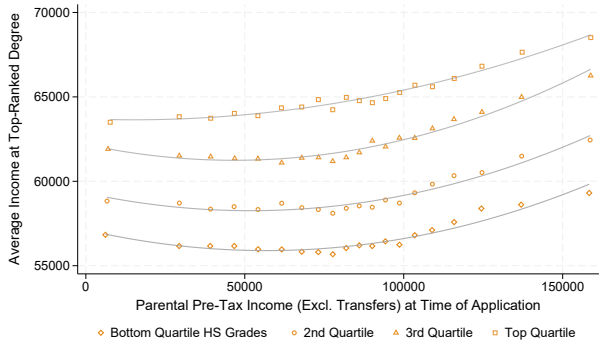
This Section reproduces the analysis of the previous Section, measuring degree quality by the average income of individuals having completed a given degree. The income for these individuals is averaged over individuals aged between 30 to 50 years old. The positive gradient between degree quality and parental background remains (see Figures A.5a and A.5b), even after controlling for students' grades, as seen in Figures A.5c and A.5d.



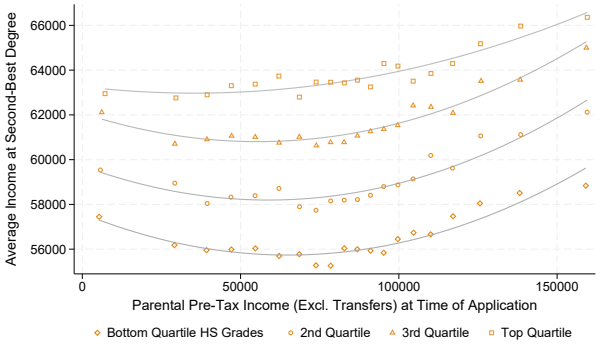
(a) Degree Average Income and Parental Income (Top-Ranked)



(b) Degree Average Income and Parental Income (Second-Best)



(c) Degree Average Income and Parental Income, by HS Grades Quartile (Top-Ranked)



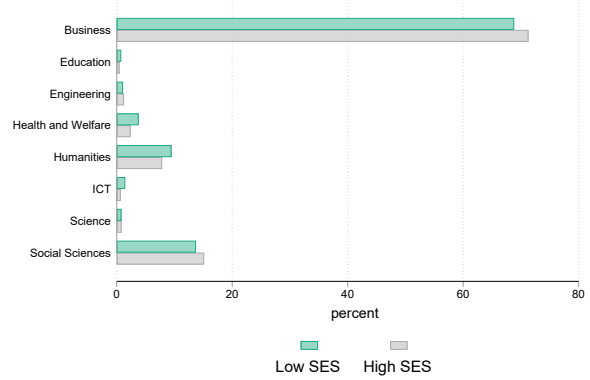
(d) Degree Average Income and Parental Income, by HS Grades Quartile (Second-Best)

Notes: Panel (a) plots the average income of students having completed the *top-ranked* degree chosen, against mother's years of education. Similarly, panel (b) describes the relationship between average income of students having completed the *second-best* alternative ranked by students, against parental pre-tax income. Panel (c) and (d) plot these measures of degree quality against parental pre-tax income, by quartiles of high school grades.

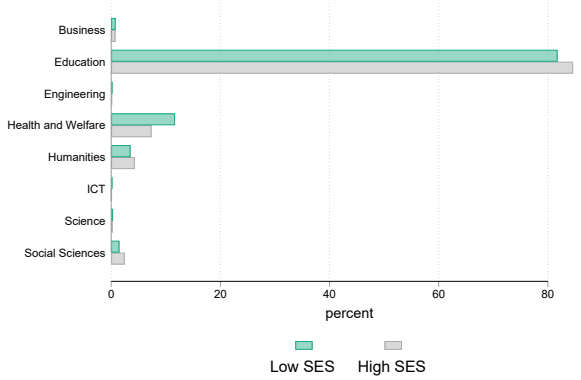
A.3 Transitions Across Fields: Top-Ranked and Second-Best

In this Appendix, I describe the relationship between the top-ranked alternative and second-best, in terms of the field of study chosen. The series of Figures presented showcase that across SES background, the field of study chosen remains largely constant between the first and second-best alternative.

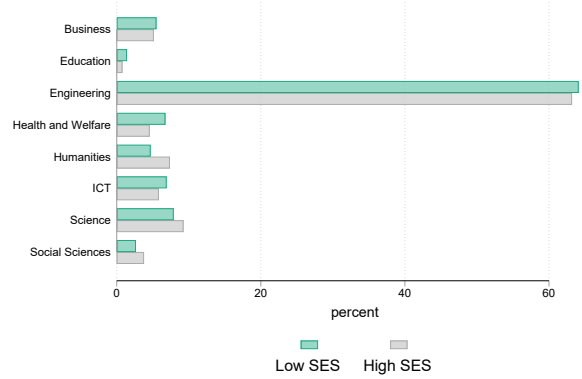
Figure A.6: Choice of Field of Study as Second-Best



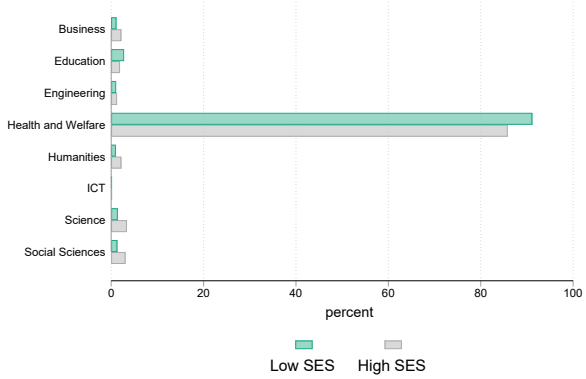
(a) Second-Best Field, Conditional on Business as Top-Ranked



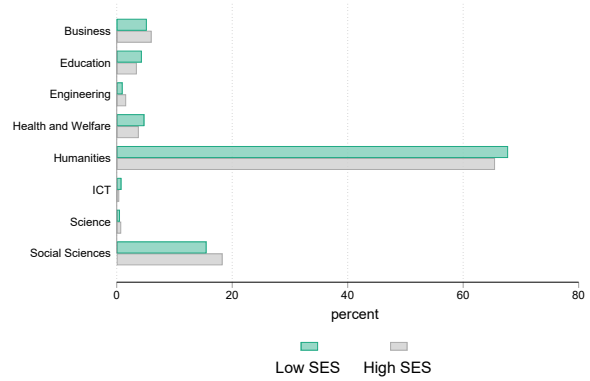
(b) Second-Best Field, Conditional on Education as Top-Ranked



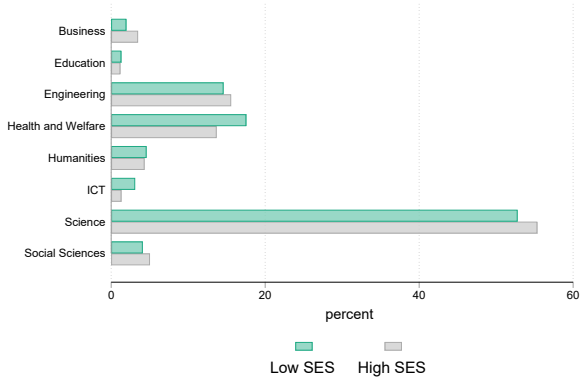
(c) Second-Best Field, Conditional on Engineering as Top-Ranked



(d) Second-Best Field, Conditional on Health as Top-Ranked



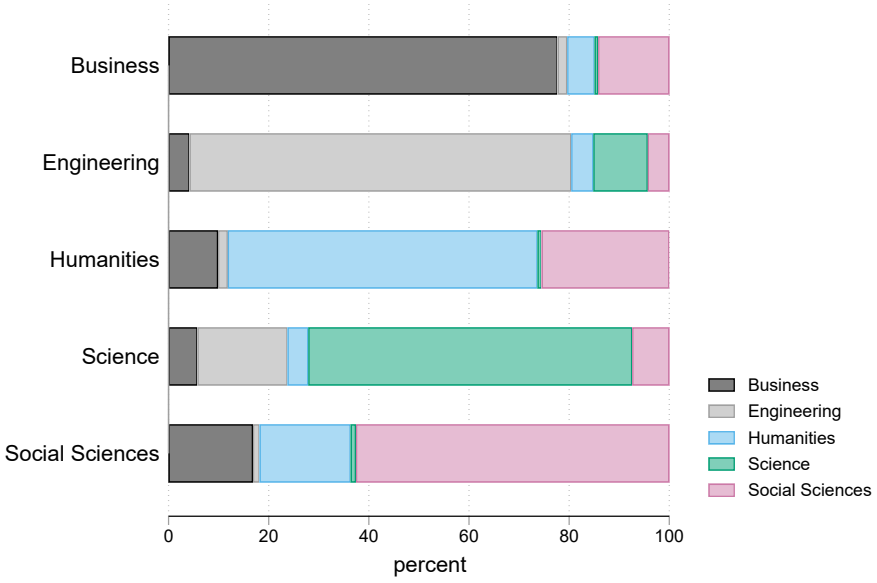
(e) Second-Best Field, Conditional on Humanities as Top-Ranked



(f) Second-Best Field, Conditional on Science as Top-Ranked

Notes: Each panel describes the percent of students choosing a field of study as second-best, conditional on a choice of first-best field, as specified in the sub-figure title.

Figure A.7: Transition Matrix: Top-Ranked and Second-Best

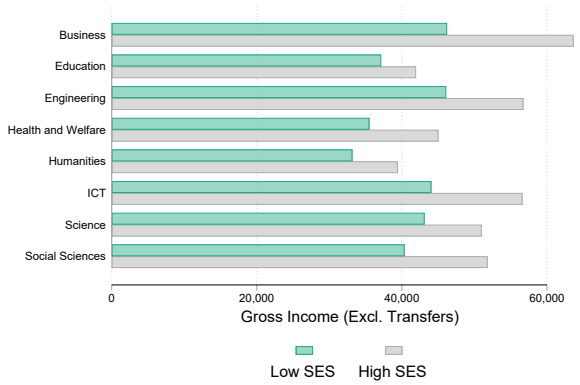


Notes: The figure depicts the transition between top-ranked and second-best alternatives in terms of field of study.

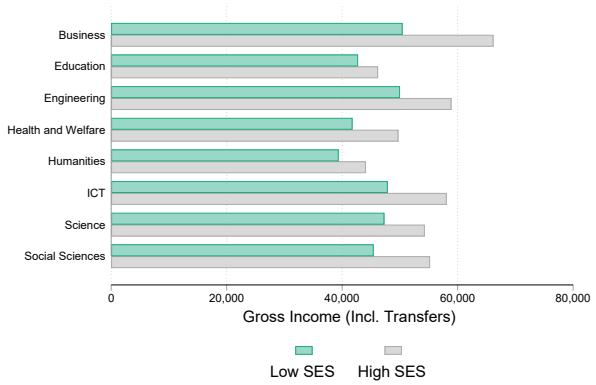
A.4 Later Life Outcomes Differences

To further study raw differences in outcomes, this Appendix depicts a number of later life outcomes, by SES background.

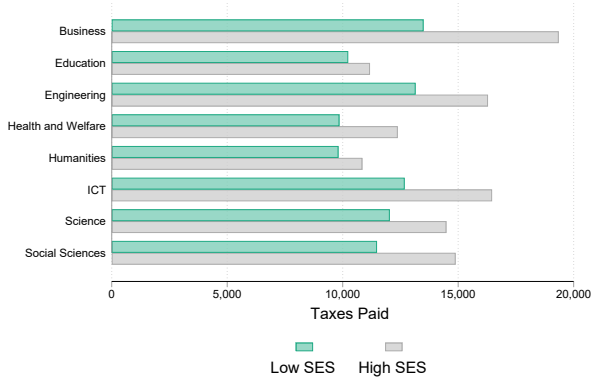
Figure A.8: Outcomes Differences



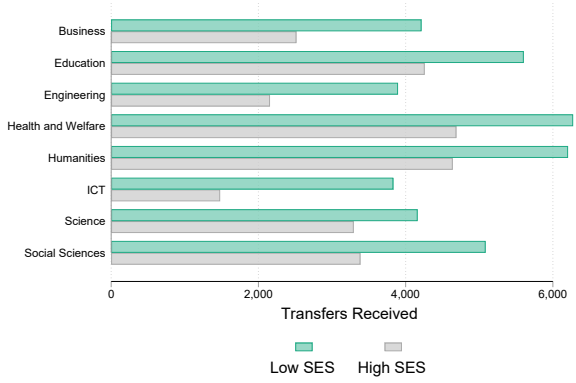
(a) Pre-Tax Income (Excluding Transfers)



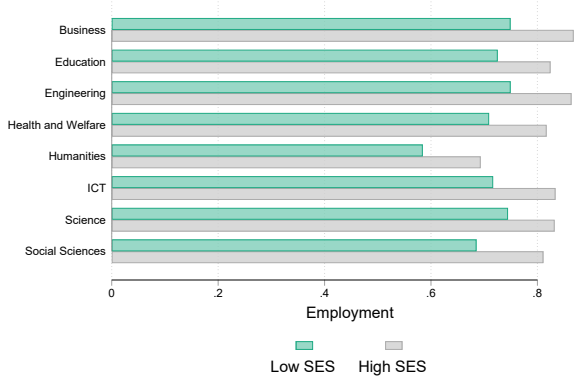
(b) Pre-Tax Income



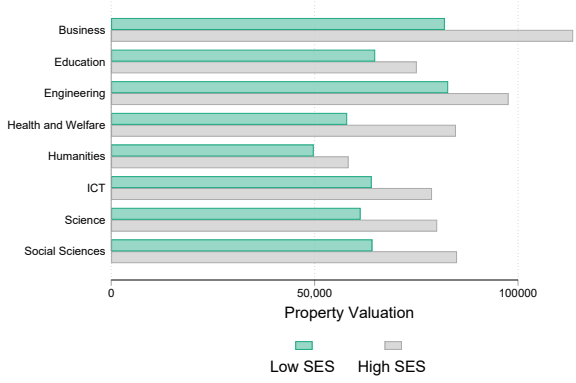
(c) Taxes



(d) Transfers



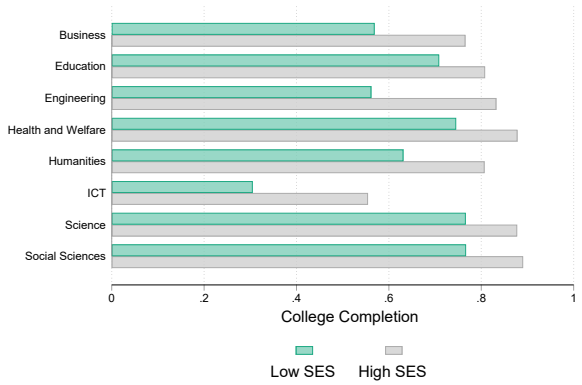
(e) Employed



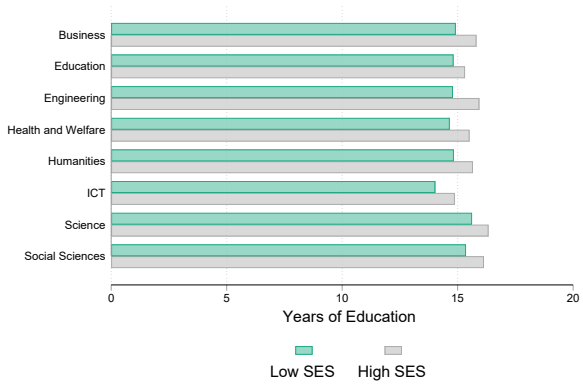
(f) Property Value

Notes: Each panel of this figure provides raw means of a given later life economic outcome by SES, as described in the title of the sub-figure.

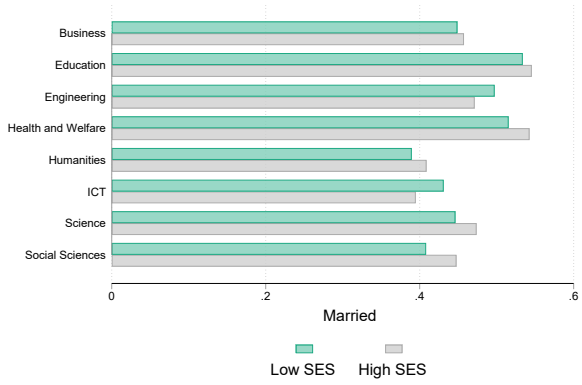
Figure A.9: Outcomes Differences



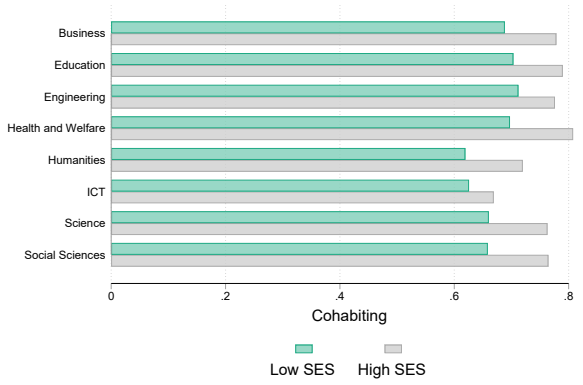
(a) College Completion



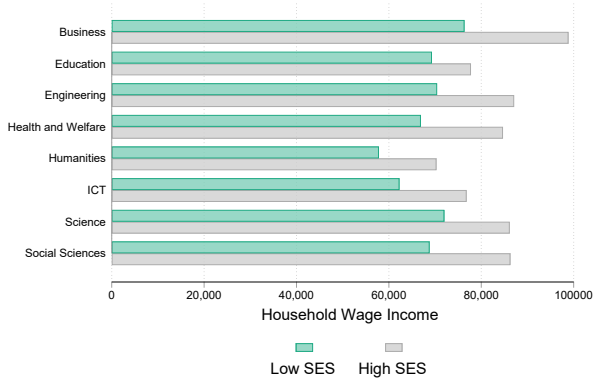
(b) Years of Education



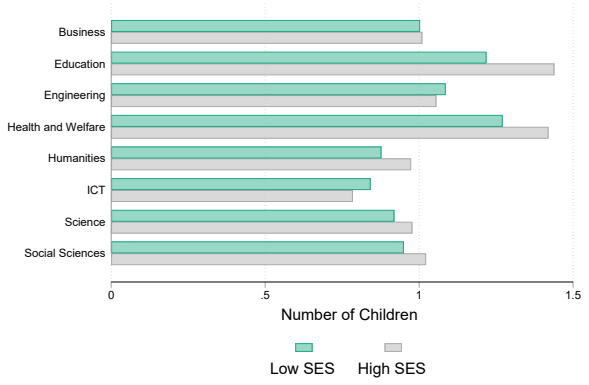
(c) Marital Status



(d) Cohabitation



(e) Household Income



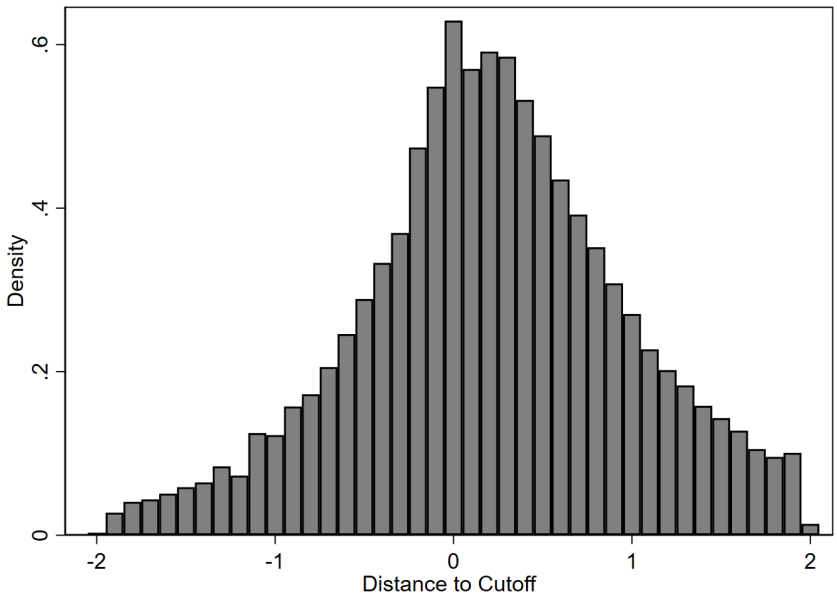
(f) Number of Children

Notes: Each panel of this figure provides raw means of a given education and household formation outcome by SES, as described in the title of the sub-figure.

B Validation of RDD

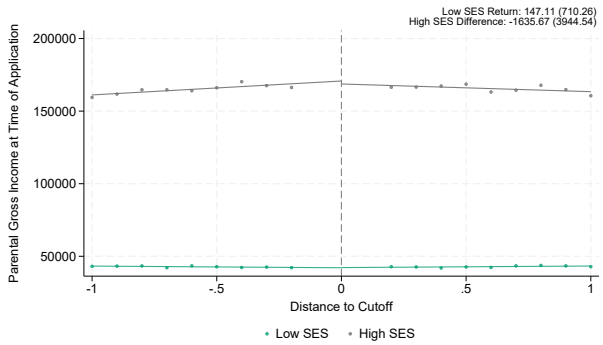
This appendix provides evidence on the validity of the RDD.

Figure B.1: Histogram of the Running Variable

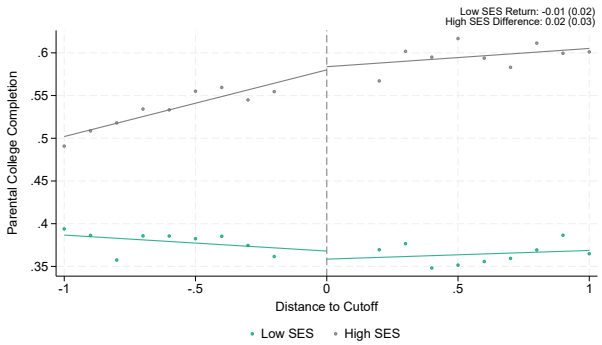


Notes: This figure provides a histogram of the discrete running variable.

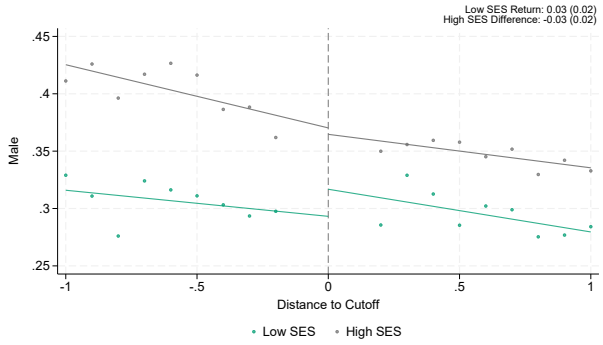
Figure B.2: Continuity of Pre-Treatment Variables



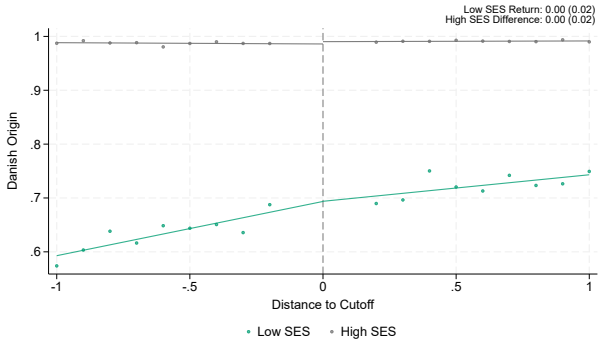
(a) Parental Income



(b) Parental College Attainment



(c) Gender



(d) Origins

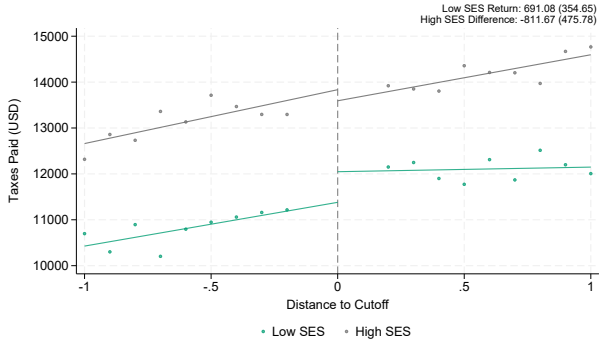
Notes: This figure provides a test of the continuity of pre-treatment variables across the cutoff. The figure depicts the effect for low-SES students (depicted in green) and high-SES students (depicted in gray). Coefficients and standard errors are reported in the top-right corner. "low-SES return" refer to the effect for low-SES students, while "high-SES difference" reports the difference in the returns between high- and low-SES students ($\tau^1 - \tau^0$).

C Other Outcomes

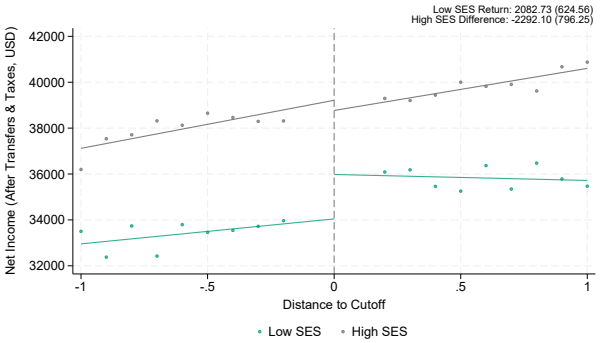
This Appendix provides additional results on the returns of cutoff-crossing on economic outcomes, household structure and criminal behavior.

C.1 Economic Outcomes

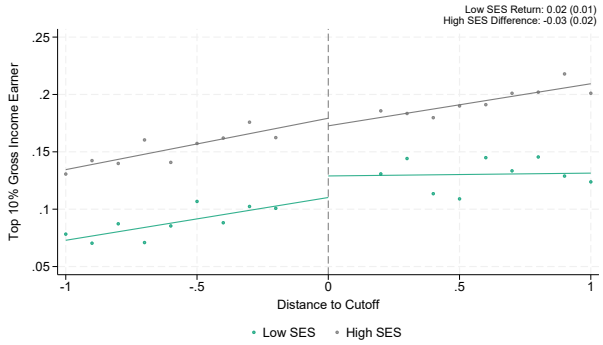
Figure C.1: Other Economic Outcomes



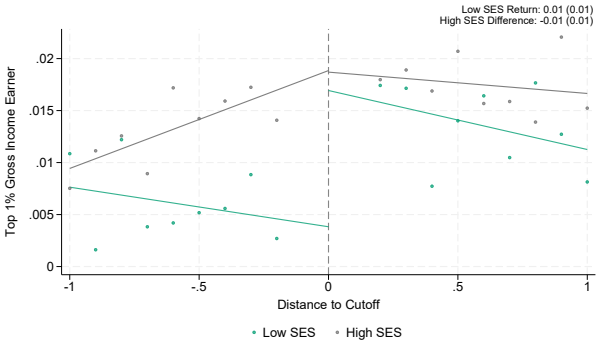
(a) Taxes Paid, 12 years post-application



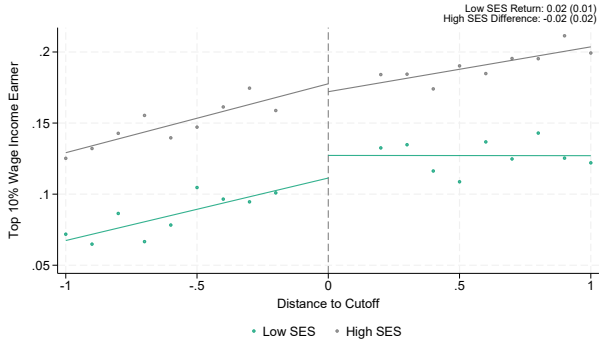
(b) Income, Incl. Taxes and Transfers, 12 years post-application



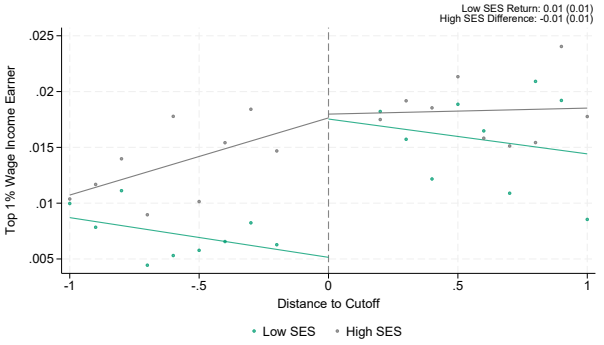
(c) Probability of Joining Top 10% Gross Income Earner, 12 years post-application



(d) Probability of Joining Top 1% Gross Income Earner, 12 years post-application



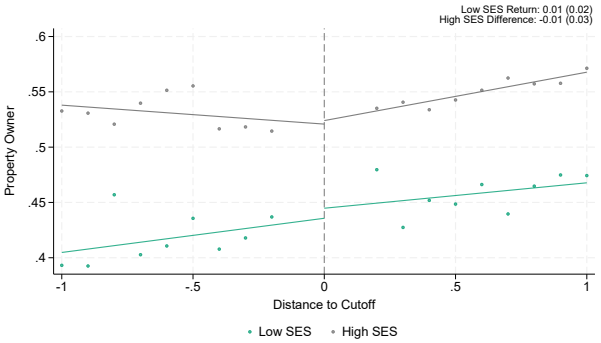
(e) Probability of Joining Top 10% Wage Income Earner, 12 years post-application



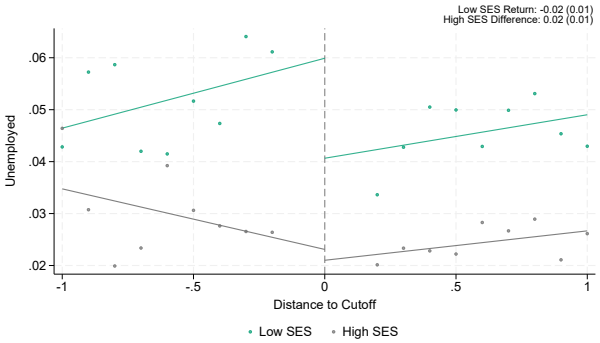
(f) Probability of Joining Top 1% Wage Income Earner, 12 years post-application

Notes: This figure presents evidence on the impact of cutoff-crossing on economic outcomes, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

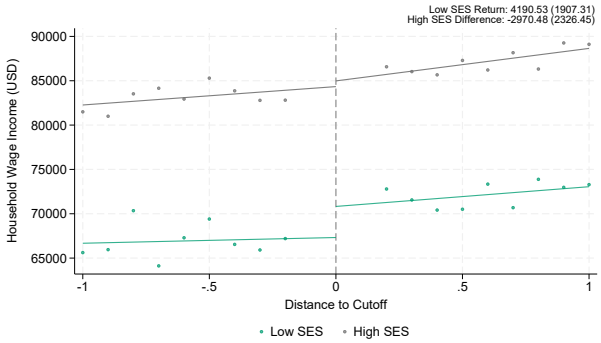
Figure C.2: Other Economic Outcomes



(a) Homeowner, 12 years post-application



(b) Unemployed, 12 years post-application

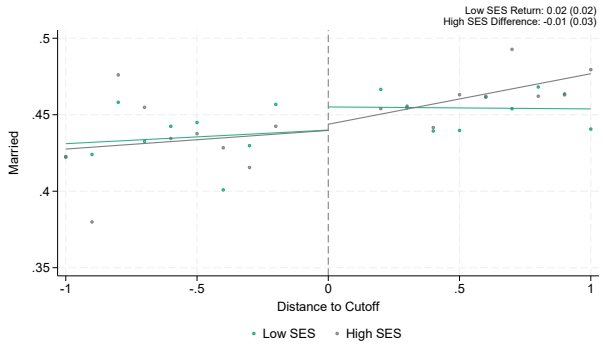


(c) Household Income, 12 years post-application

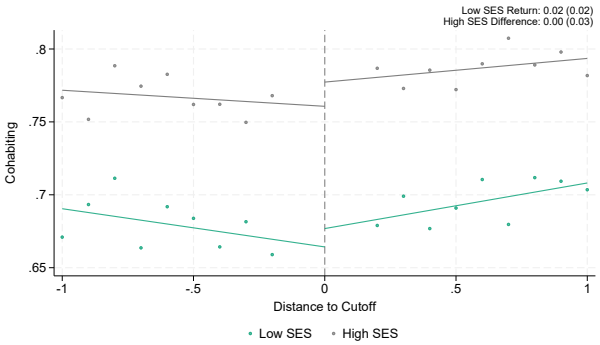
Notes: This figure presents further evidence on the impact of cutoff-crossing on economic outcomes, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

C.2 Household Structure and Family Formation

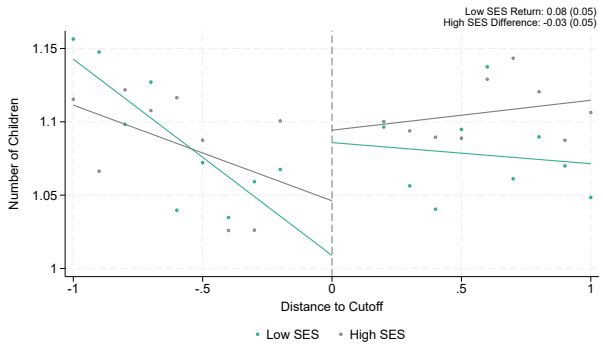
Figure C.3: Household Outcomes



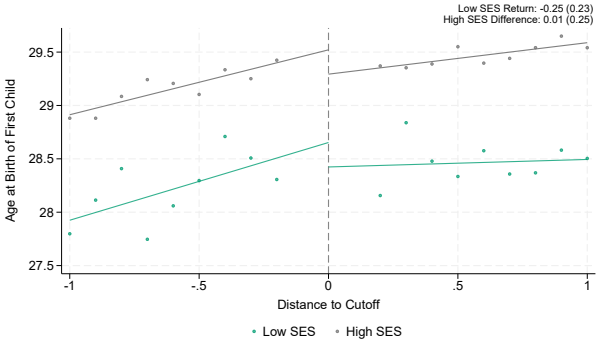
(a) Marital Status, 12 years post-application



(b) Cohabitation, 12 years post-application



(c) Number of Children, 12 years post-application

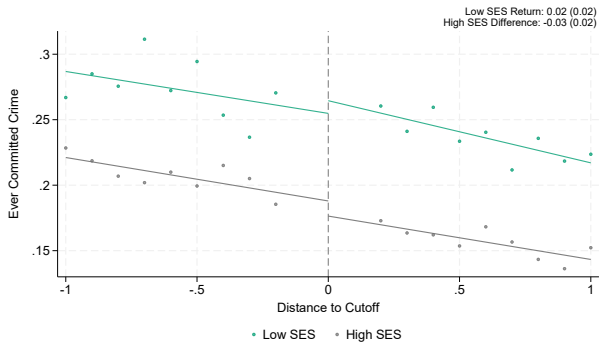


(d) Age at Birth of First Child, 12 years post-application

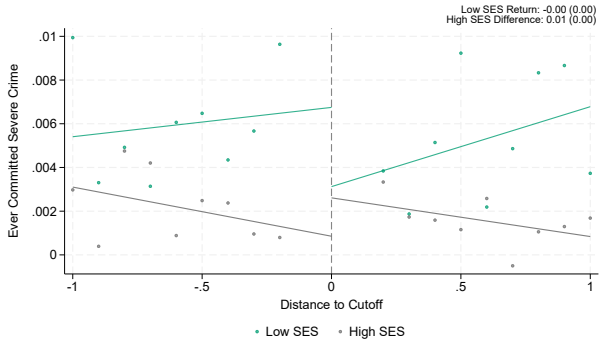
Notes: This figure presents evidence on the impact of cutoff-crossing on household structure and family formation, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

C.3 Criminal Behavior

Figure C.4: Crime Outcomes



(a) Ever Committed Crime, 12 years post-application



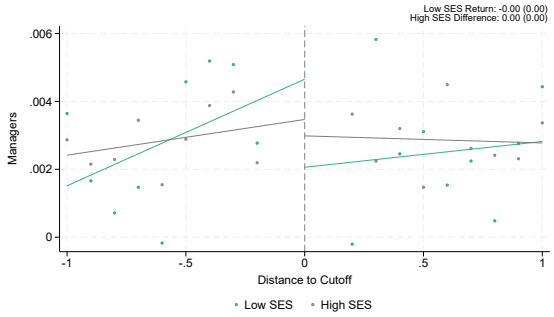
(b) Severe Crime, Incl. Taxes and Transfers, 12 years post-application

Notes: This figure presents evidence on the impact of cutoff-crossing on criminal behavior, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

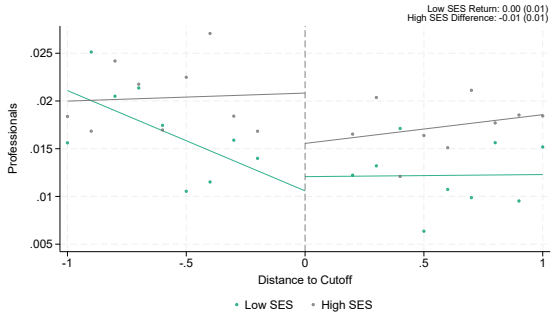
D Occupational Sectors

This Appendix provides additional results on the returns of cutoff-crossing on occupational sector.

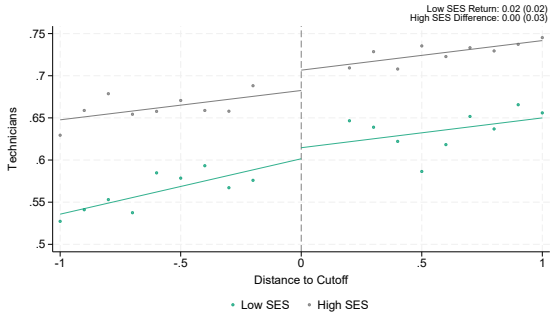
Figure D.1: Occupations



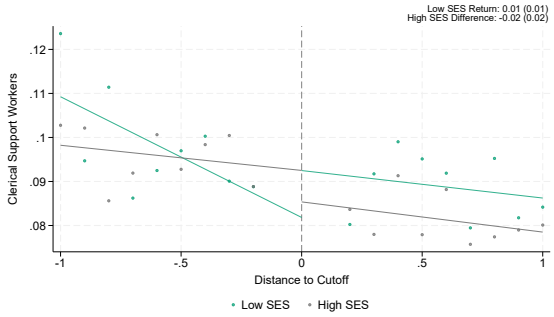
(a) Managers



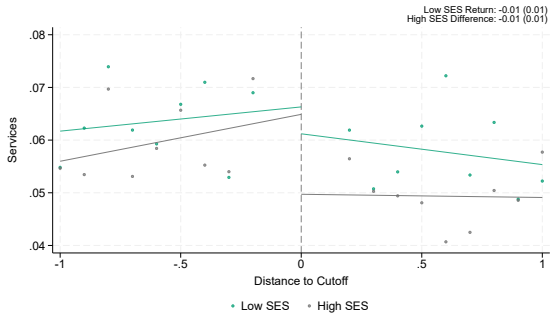
(b) Professionals



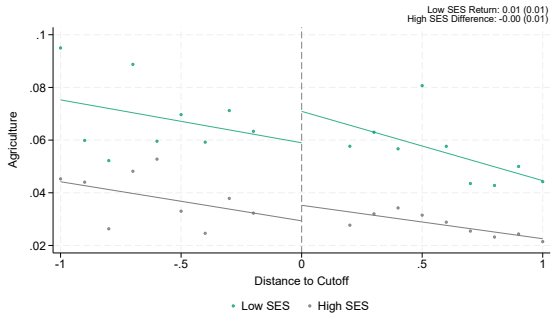
(c) Technicians



(d) Clerical Support Workers



(e) Services



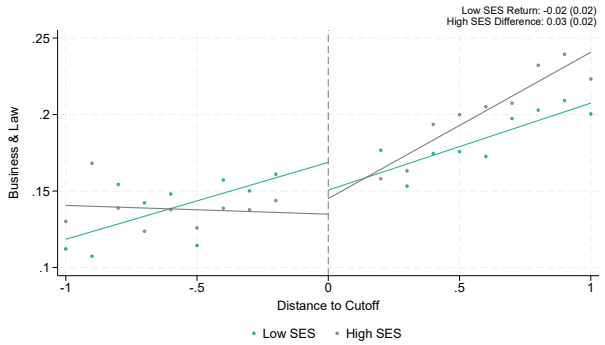
(f) Agriculture

Notes: This figure presents evidence on the impact of cutoff-crossing on occupation choice, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

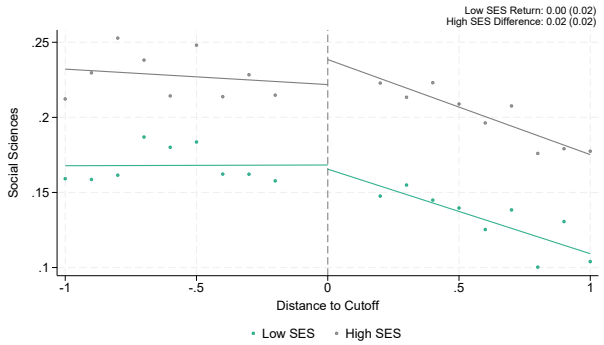
E Choice of Field of Study and Institutions

This Appendix provides additional results on the returns of cutoff-crossing on field of study and college admission.

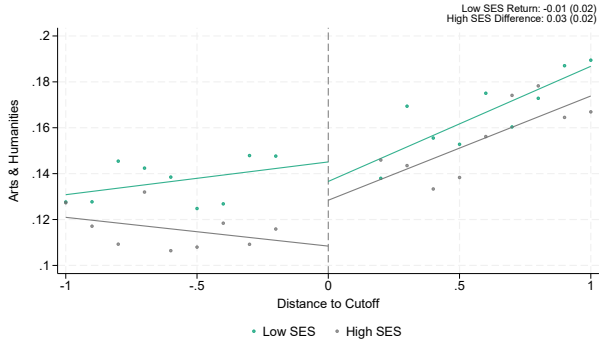
Figure E.1: Choice of Field of Study and University



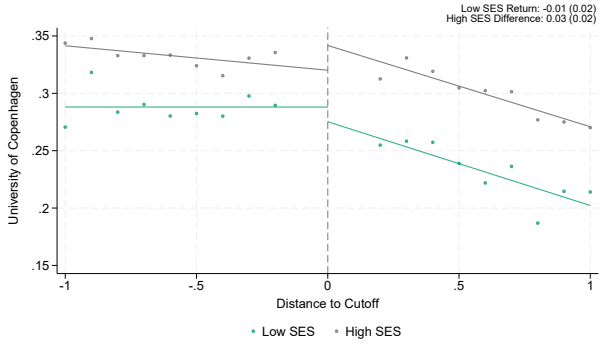
(a) Field of Study: Business & Law



(b) Field of Study: Social Sciences



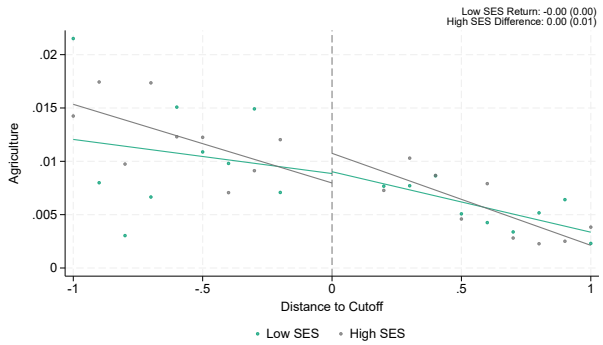
(c) Field of Study: Arts & Humanities



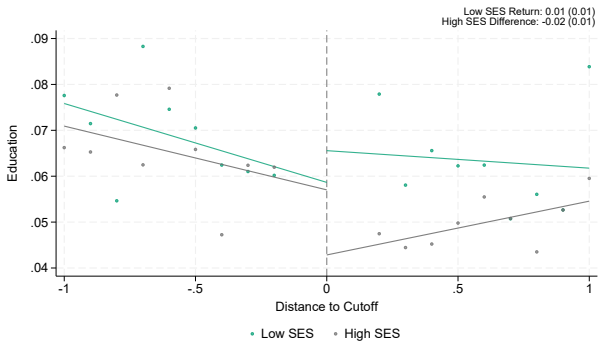
(d) Institution: University of Copenhagen

Notes: This figure presents further evidence on the impact of cutoff-crossing on field of study and college admitted, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

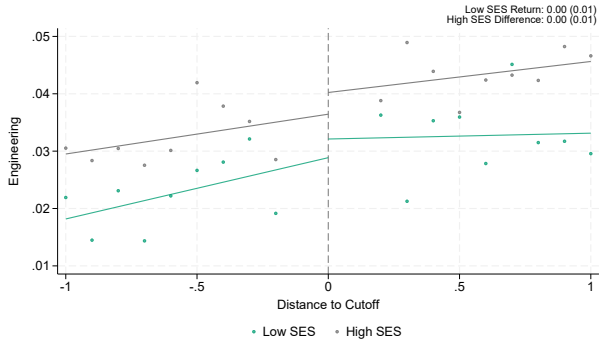
Figure E.2: Choice of Field of Study



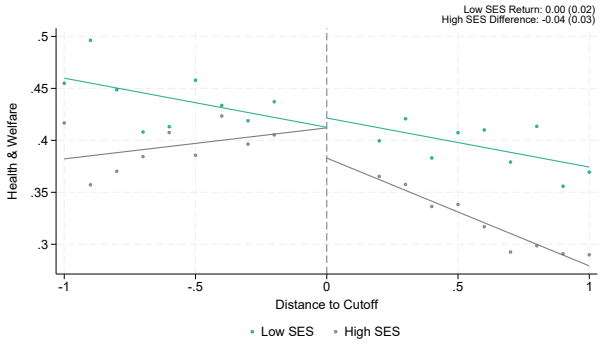
(a) Field of Study: Agriculture



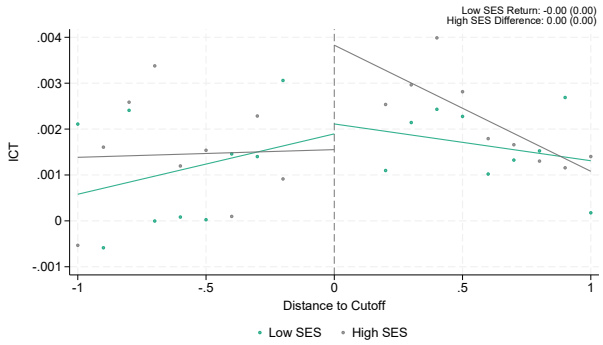
(b) Field of Study: Education



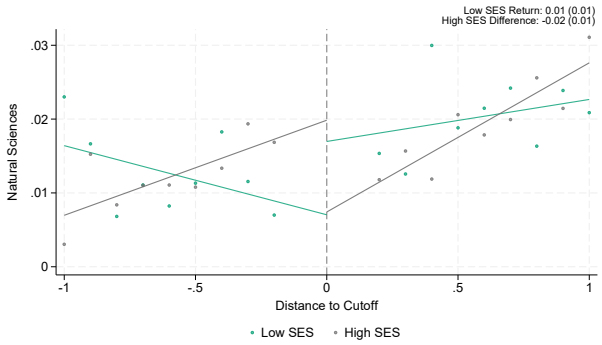
(c) Field of Study: Engineering



(d) Institution: Health & Welfare



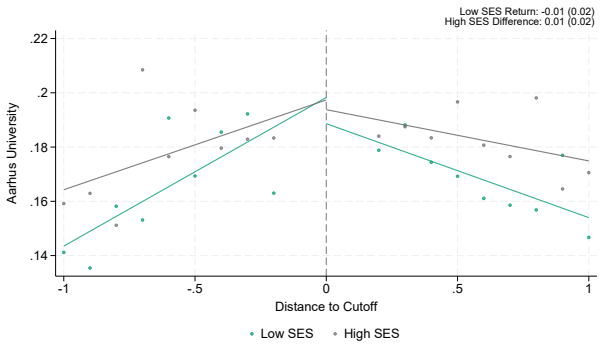
(e) Field of Study: ICT



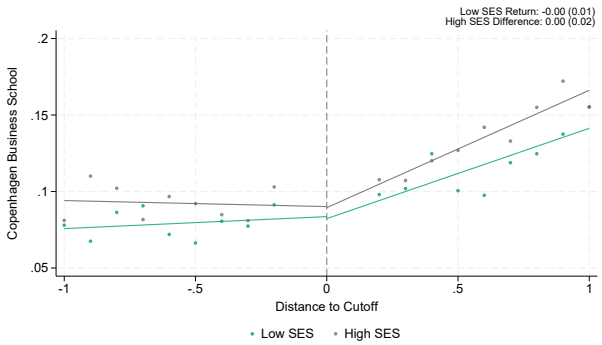
(f) Field of Study: Natural Sciences

Notes: This figure presents further evidence on the impact of cutoff-crossing on field of study, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

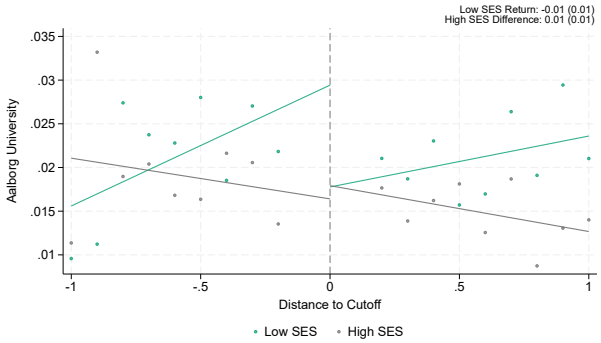
Figure E.3: Choice of University



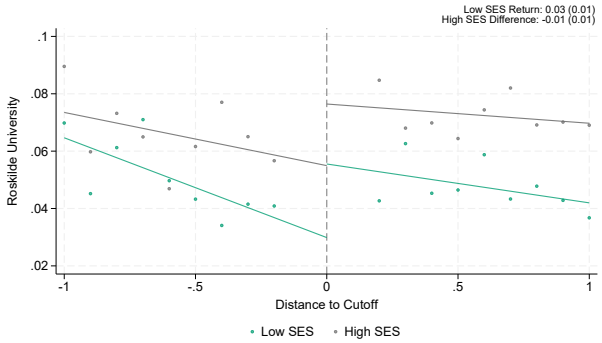
(a) Aarhus University



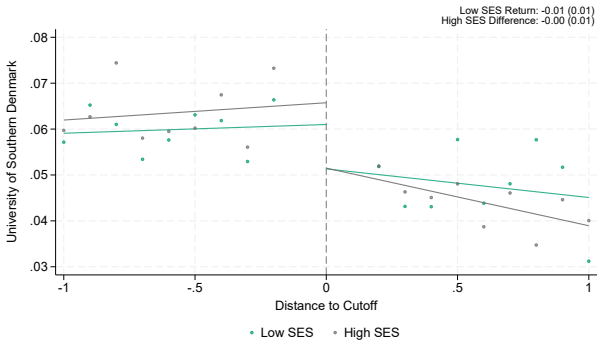
(b) Copenhagen Business School



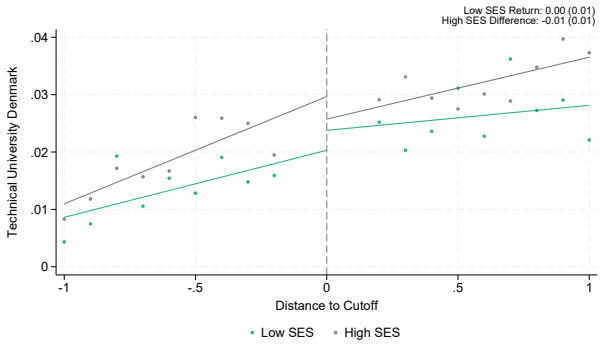
(c) Aalborg University



(d) Roskilde University



(e) University of Southern Denmark



(f) Technical University Denmark

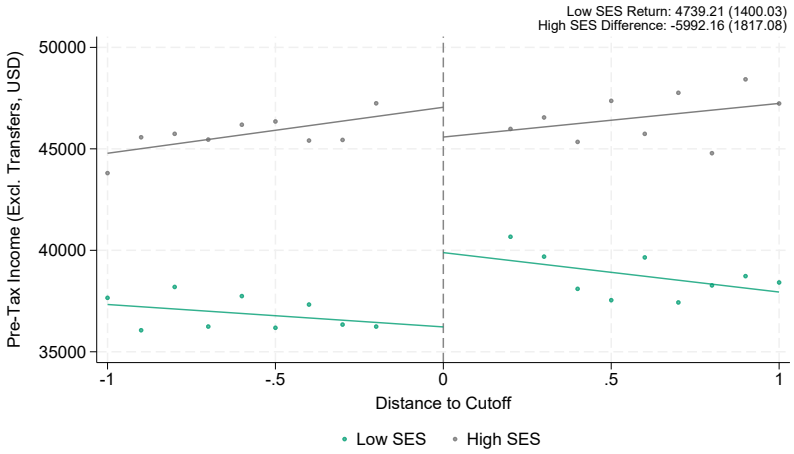
Notes: This figure presents further evidence on the impact of cutoff-crossing on the college admitted, as specified by each sub-figure title. Results are depicted separately for low-SES students (in green) and high-SES students (in gray). The top-right corner of each panel displays the estimated coefficients along with their standard errors. The term 'Low-SES return' denotes the effect for low-SES students, while 'High-SES difference' represents the estimated difference in effects between high- and low-SES students ($\tau^1 - \tau^0$). Standard errors clustered at the individual level are in parentheses.

F Heterogeneity

This Appendix provides an analysis of the heterogeneous nature of the results, based on students' GPA, gender and origins.

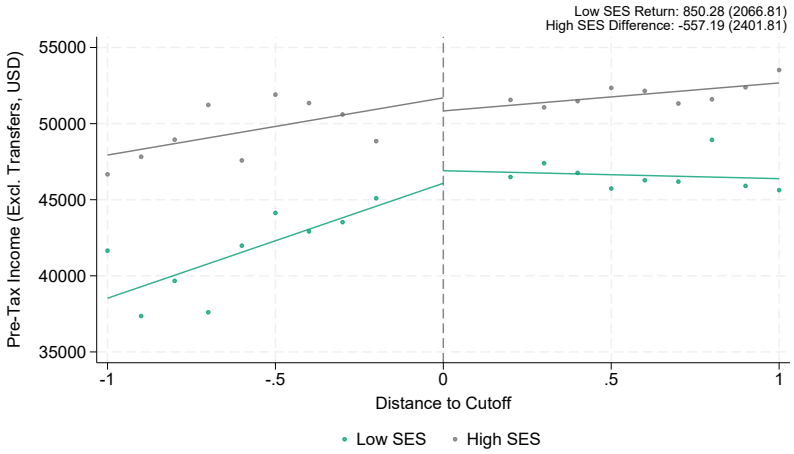
F.1 GPA

Figure F.1: Cutoff-Crossing Effect, GPA $<$ median, by SES



Notes: Reduced-form effect of cutoff-crossing on pre-tax income (excluding transfers), 12 years post-application, focusing on individuals with below median grades. The figure depicts the effect for low-SES students (depicted in green) and high-SES students (depicted in gray). Coefficients and standard errors are reported in the top-right corner. "low-SES return" refer to the effect for low-SES students, while "high-SES difference" reports the difference in the returns between high and low-SES students ($\tau^1 - \tau^0$).

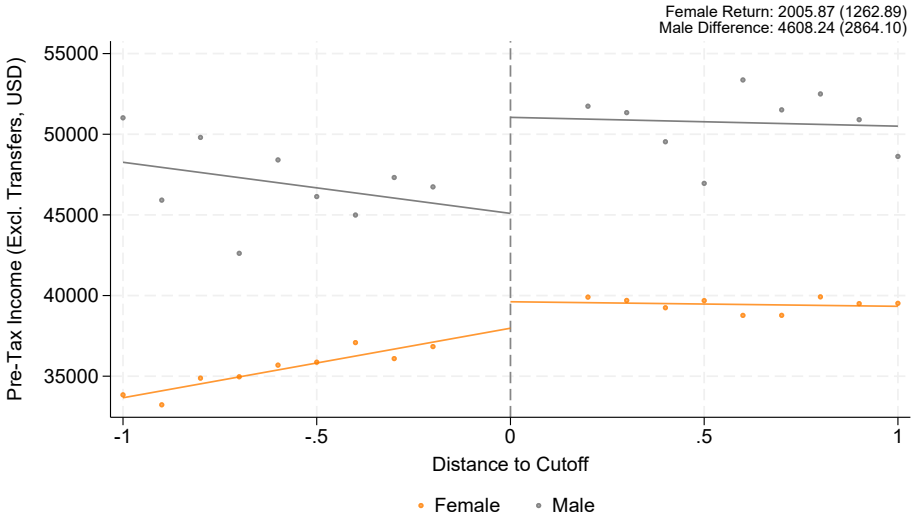
Figure F.2: Cutoff-Crossing Effect, GPA > median, by SES



Notes: Reduced-form effect of cutoff-crossing on pre-tax income (excluding transfers), 12 years post-application, focusing on individuals with above median grades. The figure depicts the effect for low-SES students (depicted in green) and high-SES students (depicted in gray). Coefficients and standard errors are reported in the top-right corner. "low-SES return" refer to the effect for low-SES students, while "high-SES difference" reports the difference in the returns between high- and low-SES students ($\tau^1 - \tau^0$).

F.2 Gender

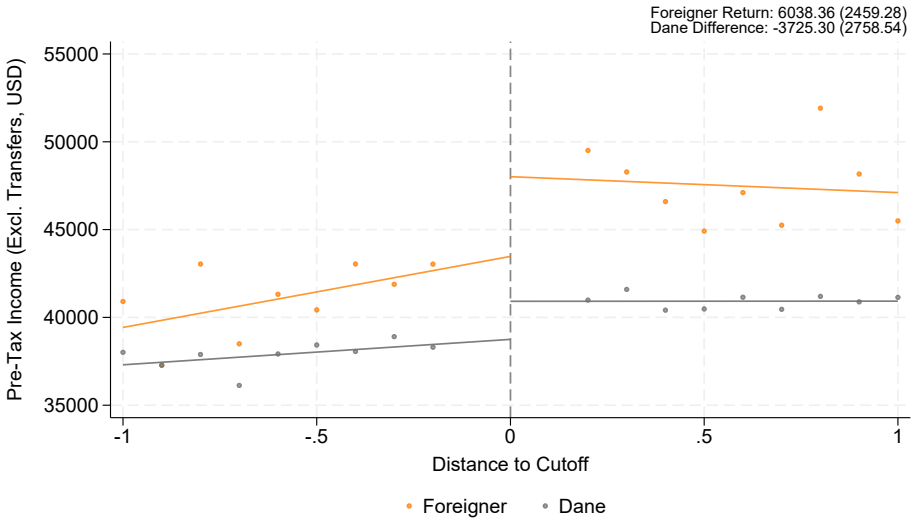
Figure F.3: Cutoff-Crossing Effect for low-SES, by Gender



Notes: Reduced-form effect of cutoff-crossing on pre-tax income (excluding transfers), 12 years post-application, focusing on low-SES students. The figure depicts the effect for female students (depicted in orange) and male students (depicted in gray). Coefficients and standard errors are reported in the top-right corner. "Female return" refer to the effect for female students, while "male difference" reports the difference in the returns between male and female students.

F.3 Origins

Figure F.4: Cutoff-Crossing Effect for low-SES, by Origin



Notes: Reduced-form effect of cutoff-crossing on pre-tax income (excluding transfers), 12 years post-application, focusing on low-SES students. The figure depicts the effect for students from foreign origins (depicted in orange) and students of danish origins (depicted in gray). Coefficients and standard errors are reported in the top-right corner. "Foreigner return" refer to the effect for foreigners, while "Dane difference" reports the difference in the returns between students of Danish and foreign origins.

G Peer Effects

This Appendix reports the regression results for the analysis on the effect of peers on outcomes.

G.1 By Tertile of Peer Quality Difference

Table 4: Tertile-Specific Coefficients

	Low SES	High SES	Tertile Mean
Bottom Tertile	2474.77	4547.86	−11512.89
	(3728.18)	(2796.70)	
Middle Tertile	6861.91	−1685.39	4217.97
	(3422.35)	(2476.59)	
Top Tertile	3127.63	98.30	21411.59
	(3969.34)	(2359.42)	

Notes: The table reports estimates of the effect of threshold crossing, by peer quality difference between preferred and fallback option. The last column shows the average difference in peer quality in each of the three quartiles I consider. Robust standard errors are in parentheses.

G.2 Within-Degree Across-Cohort Variation

Table 5: Regression Results: Peer Effects

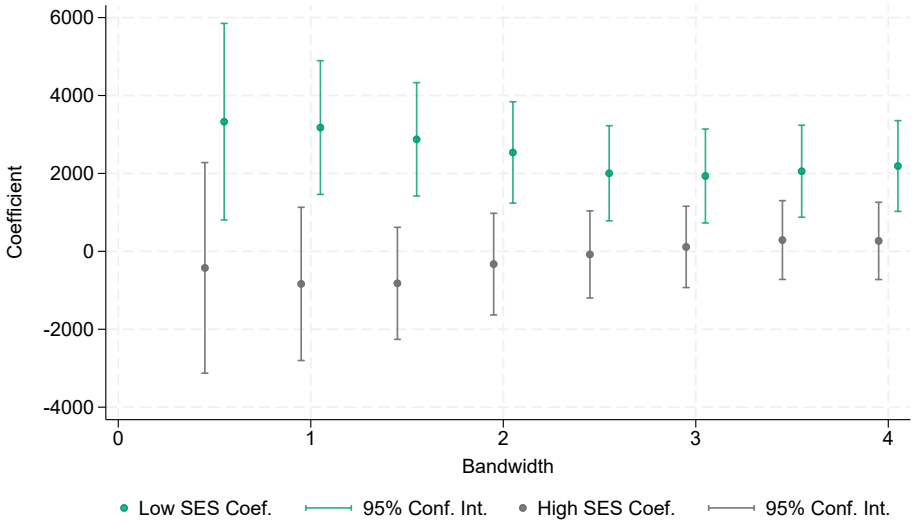
	OLS		Degree FE	
	Low SES	High SES	Low SES	High SES
Peer Quality (Parent Income)	0.201	0.220	0.062	0.016
	(0.023)	(0.047)	(0.028)	(0.028)
High School GPA	2363.2	2235.3	1466.8	2394.1
	(413.9)	(578.7)	(383.9)	(641.9)
Parental Gross Income	−0.007	0.019	0.001	0.018
	(0.023)	(0.007)	(0.018)	(0.006)
Age	−1406.9	−2437.5	−955.6	−1243.3
	(228.6)	(195.8)	(163.6)	(162.0)
Male	9584.7	13250.7	8784.7	10414.6
	(866.4)	(378.7)	(765.4)	(784.8)
Immigrants	3825.0	−4322.1	−190.8	−6685.4
	(892.7)	(2592.2)	(987.1)	(2772.9)
Descendants	3030.5	−5743.1	10.3	−5938.8
	(699.5)	(1796.2)	(685.6)	(1935.6)
Order of Birth	70.2	−621.2	−120.5	−298.5
	(185.7)	(212.5)	(151.8)	(187.5)
Parent College Completion	−1933.5	−1324.7	−1615.3	−492.0
	(654.7)	(485.7)	(355.1)	(560.4)
Constant	30429.4	53149.8	42835.6	49194.2
	(7987.6)	(9917.4)	(5993.3)	(10322.1)
Observations	7757	20201	7737	20194

Notes: The table reports estimates of the effect of peer quality on outcomes, separately for low and high SES students. The first two columns report results from OLS specifications, while the following two report parameters from specifications that include degree and cohort fixed effects. Peer quality is standardized. Robust standard errors are in parentheses.

H Robustness

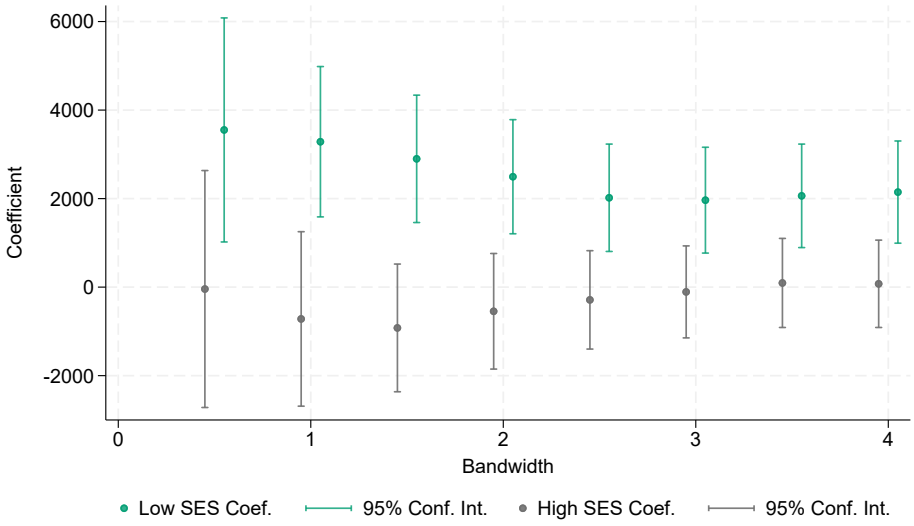
This Appendix assesses the robustness of the results by examining the role of (1) different bandwidth sizes, (2) controls, and (3) the doughnut strategy. The reported coefficients denote the effect of cutoff-crossing on pre-tax income (excluding transfers), twelve years post-application.

Figure H.1: Specifications Without Controls and Without Doughnut



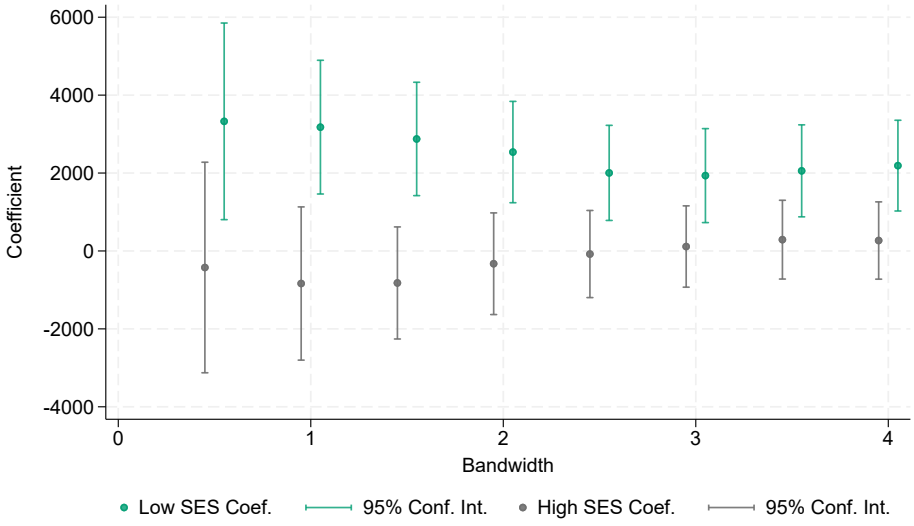
Notes: Effect of cutoff-crossing on pre-tax income, estimated with different bandwidth sizes, separately for low- and high-SES. The estimates reported come from a specification without controls and without dropping observations around the cutoff over the interval $[-.1, .1]$.

Figure H.2: Specifications Without Controls and With Doughnut



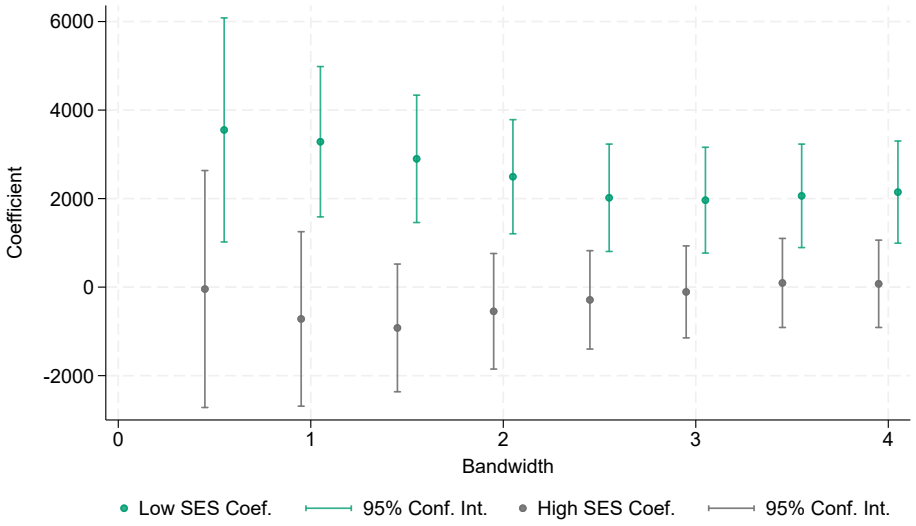
Notes: Effect of cutoff-crossing on pre-tax income, estimated with different bandwidth sizes, separately for low- and high-SES. The estimates reported come from a specification without controls and dropping observations around the cutoff over the interval $[-.1, .1]$.

Figure H.3: Specifications With Controls and Without Doughnut



Notes: Effect of cutoff-crossing on pre-tax income, estimated with different bandwidth sizes, separately for low- and high-SES. The estimates reported come from a specification with controls and without dropping observations around the cutoff over the interval $[-.1, .1]$.

Figure H.4: Specifications With Controls and With Doughnut



Notes: Effect of cutoff-crossing on pre-tax income, estimated with different bandwidth sizes, separately for low- and high-SES. The estimates reported come from a specification with controls and dropping observations around the cutoff over the interval $[-.1, .1]$.

I Control Function Derivation

This section derives the control function approach from Dubin & McFadden (1984) to provide intuition on the framework used in this paper, which follows the approach of Abdulkadiroğlu *et al.* (2020). Abdulkadiroğlu *et al.* (2020) extend the control function approach from Dubin & McFadden (1984) by allowing for rank-ordered preferences, whereas the original model by Dubin & McFadden (1984) is based on observing the preferred choice in polychotomous settings.

The unobserved factors η_j in the choice equation are assumed to have independent extreme value distributions. The density of the error term in the outcome equation, ε_1, conditional on $(\eta_1, ..., \eta_M)$ is assumed to have mean $(\sigma\frac{\sqrt{6}}{\pi})\sum_{j=1}^{M} r_j(\eta_j - \mathbb{E}(\eta_j))$ where $\sum_{j=1}^{M} r_j = 0$. r_j is the correlation of η_j and ε_1.[56] Formally, Dubin & McFadden (1984) rely on the following linearity assumption expressed in terms of the η_j:

A1- Dubin and McFadden's linearity assumption:
$\mathbb{E}(\varepsilon_1 \mid \eta_1, ..., \eta_M) = \sigma\frac{\sqrt{6}}{\pi}\sum_{j=1...M} r_j(\eta_j - \mathbb{E}(\eta_j))$,
where r_j is a correlation coefficient between ε_1 and η_j.

A1'- Dubin and McFadden's restriction:
$\sum_{j=1...M} r_j = 0$

The expected value of η_j given that alternative 1 is chosen is as follows:

$$\mathbb{E}(\eta_1 - \mathbb{E}(\eta_1) \mid V_1 > \max_{s\neq 1}(V_s), \Gamma) = -\ln(P_1), \tag{13}$$

$$\mathbb{E}(\eta_j - \mathbb{E}(\eta_j) \mid V_1 > \max_{s\neq 1}(V_s), \Gamma) = \frac{P_j}{1-P_j}\ln(P_j), \tag{14}$$

where P_j is the probability of choosing alternative j and $\Gamma = \{z'\gamma_1, z'\gamma_2, \ldots, z'\gamma_M\}$.[57] Then, imposing the assumptions from Dubin & McFadden (1984):

$$\begin{aligned}\mathbb{E}\left(\varepsilon_1 \mid u_1 < 0, \Gamma\right) &= \mathbb{E}\big[\sigma\frac{\sqrt{6}}{\pi}\sum_{j=1...M} r_j(\eta_j - \mathbb{E}(\eta_j)) \mid u_1 < 0, \Gamma\big] \\ &= \sigma\frac{\sqrt{6}}{\pi}\big[-r_1\ln(P_1) + \sum_{j=2...M} r_j\big(\frac{P_j}{1-P_j}\ln(P_j)\big)\big] \\ &= \sigma\frac{\sqrt{6}}{\pi}\sum_{j=2...M} r_j\big(\frac{P_j}{1-P_j}\ln(P_j) + \ln(P_1)\big)\end{aligned} \tag{15}$$

where $u_1 = \max\{V_{ik} - V_{il}\}$. The last equation holds because $\sum_{j=1}^{M} r_j = 0$, which means $(\sum_{j=2}^{M} r_j = -r_1)$. Selection correction in model 8 can be addressed by running least squares of the equation below:

[56] Note that η_j has unconditional variance $\pi^2/6$ and ε_1 has unconditional mean zero and unconditional variance σ^2.
[57] With the multinomial logit model, $P_j = Prob(V_j > \max_{s\neq j}(V_s)) = e^{z_j\gamma_j}/\sum_s e^{z_s\gamma_s}$.

$$Y_1 = \alpha_1 + X'\beta_1 + \bar{X}\gamma_1 + \sigma\frac{\sqrt{6}}{\pi}\sum_{j=2...M} r_j\big(\frac{P_j \ln(P_j)}{1-P_j} + \ln(P_1)\big) + w_1$$

Density of the Disturbance Terms of the Latent Models Conditionally on Alternative 1 Being Observed

The conditional density of η_1 is

$$f(\eta_1 \mid V_1 > \max_{s\neq 1}(V_s)) = f\big(\eta_1 \mid \eta_1 > \max_{s\neq 1}(z_s\gamma_s + \eta_s - z_1\eta_1)\big) \tag{16}$$

$$= \frac{g(\eta_1)}{Prob\big(V_1 > \max_{s\neq 1}(V_s)\big)} \int \dots \int 1_{[\eta_1 > (z_2\gamma_2+\eta_2)-z_1\gamma_1]} g(\eta_2)\dots 1_{[\eta_1 > (z_M\gamma_M+\eta_M)-z_1\gamma_1]} g(\eta_M) d\eta_2 \dots d\eta_M$$

$$= \frac{g(\eta_1)}{Prob\big(V_1 > \max_{s\neq 1}(V_s)\big)} \prod_{s>1} G(\eta_1 + z_1\gamma_1 - z_s\gamma_s) \tag{17}$$

where G is the cumulative of the Gumbel distribution, that is, $G(x) = exp(-e^{-x})$, with the unconditional density of $g(x) = exp(-x - e^{-x})$. Now, note that

$$\prod_{s>1} G(\eta_1 + z_1\gamma_1 - z_s\gamma_s) = exp\big(-e^{-\eta_1}\frac{\sum_{s>1} e^{z_s\gamma_s}}{e^{z_1\gamma_1}}\big)$$

After a simple transformation, we get

$$f(\eta_1 \mid V_1 > \max_{s\neq 1}(V_s)) = \frac{e^{-\eta_1}}{P_1}.exp\big(-\frac{e^{-\eta_1}}{P_1}\big) = g(\eta_1 + \log P_1)$$

where $P_1 = Prob\big(V_1 > \max_{s\neq 1}(V_s)\big) = e^{z_1\gamma_1}/\sum_s e^{z_s\gamma_s}$.

The conditional density of η_j ($j \neq 1$) is

$$f(\eta_j \mid V_1 > \max_{s\neq 1}(V_s)) = f\big(\eta_j \mid \eta_1 > \max_{s\neq 1}(z_s\gamma_s + \eta_s - z_1\eta_1)\big)$$

$$= \frac{g(\eta_j)}{P_1} \int_{\eta_1 > (z_j\gamma_j+\eta_j)-z_1\gamma_1} \prod_{s>1, s\neq j} G(\eta_1 + z_1\gamma_1 - z_s\gamma_s) g(\eta_1) d\eta_1$$

$$= \frac{g(\eta_j)}{P_1} \int_{\eta_1 > (z_j\gamma_j+\eta_j)-z_1\gamma_1} \left[exp\left(-e^{-\eta_1} - \sum_{s>1, s\neq j} exp(-\eta_1 - z_1\gamma_1 + z_s\gamma_s)\right)\right] exp(-\eta_1) d\eta_1$$

$$= \frac{g(\eta_j)}{P_1} \int_{\eta_1 > (z_j\gamma_j+\eta_j)-z_1\gamma_1} \left[exp(-\frac{1}{\tilde{P}_1^j} exp(-\eta_1))\right] exp(-\eta_1) d\eta_1$$

where $\tilde{P}_1^j = Prob(V_1 > \max_{s\neq 1, s\neq j}(V_s)) = e^{z_1\gamma_1}/\sum_{s\neq j} e^{z_s\gamma_s}$. Integrating with respect to η_1:

$$\begin{aligned}
&f(\eta_j \mid V_1 > \max_{s\neq 1}(V_s)) \\
&= \frac{\tilde{P}_1^j}{P_1} g(\eta_j)\left[1 - exp\left(-\frac{1}{\tilde{P}_1^j} exp(-(z_j\gamma_j + \eta_j) + z_1\gamma_1)\right)\right] \\
&= \frac{1}{1-P_j} g(\eta_j)\left[1 - exp\left(-\frac{1-P_j}{P_j} e^{-\eta_j}\right)\right] \\
&= \frac{1}{1-P_j}\left[g(\eta_j) - g(\eta_j) exp(e^{-\eta_j}) exp\left(-\frac{e^{-\eta_j}}{P_j}\right)\right] \\
&= \frac{1}{1-P_j}\left[g(\eta_j) - e^{-\eta_j} exp\left(-\frac{e^{-\eta_j}}{P_j}\right)\right] \\
&= \frac{1}{1-P_j}[g(\eta_j) - P_j g(\eta_j + \log P_j)],
\end{aligned}$$

where as before, $P_j = Prob(V_j > \max_{s\neq j}(V_s)) = e^{z_j\gamma_j}/\sum_s e^{z_s\gamma_s}$.

Now, the conditional expectation

$$\mathbb{E}(\eta_j | V_1 > \max_{s\neq 1}(V_s)) = \int \eta_j f(\eta_j \mid V_1 > \max_{s\neq 1}(V_s), \Gamma) d\eta_j$$

can be computed as follows. For $j = 1$

$$\begin{aligned}
\mathbb{E}(\eta_1 | V_1 > \max_{s\neq 1}(V_s)) &= \int \eta_1 f(\eta_1 \mid V_1 > \max_{s\neq 1}(V_s)) d\eta_1 \\
&= \int \eta_1 g(\eta_1 + \log P_1) d\eta_1 \\
&= \int (\omega - \log P_1) g(\omega) d\omega
\end{aligned}$$

where we use the change of variable $\omega = \eta_1 + \log P_1$ to obtain the last equation. Then,

$$\begin{aligned}
\mathbb{E}(\eta_1 | V_1 > \max_{s\neq 1}(V_s)) &= \int (\omega - \log P_1) g(\omega) d\omega \\
&= -\log(P_1)
\end{aligned}$$

For $j \neq 1$.

$$\begin{aligned}
\mathbb{E}(\eta_j | V_1 > \max_{s\neq 1}(V_s)) &= \frac{1}{1-P_j} \int \eta_j [g(\eta_j) - P_j g(\eta_j + \log P_j)] d\eta_j \\
&= \frac{1}{1-P_j} \int \eta_j g(\eta_j) d\eta_j - \frac{P_j}{1-P_j} \int \eta_j g(\eta_j + \log P_j) d\eta_j
\end{aligned}$$

Make the change of variable $\omega = \eta_j + \log P_j$. Also, note that $\int \eta_j g(\eta_j) d\eta_j = \mathbb{E}(\eta_j) = 0$. Then

$$\begin{aligned}\mathbb{E}(\eta_j | V_1 > \max_{s \neq 1}(V_s)) &= -\frac{P_j}{1 - P_j} \int (\omega - \log P_j) g(\omega) d\omega \\ &= \frac{P_j}{1 - P_j} \log P_j\end{aligned}$$

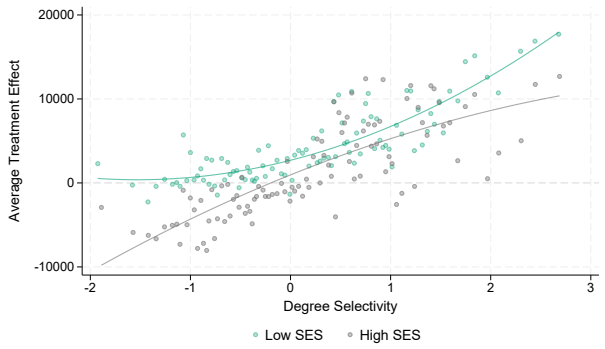
J Estimates

This Appendix provides further evidence on the relationship between degrees-specific returns, match effects and degree selectivity. It distinguishes between estimates derived from the model and those that do not account for selection, referred to as 'OLS estimates.'

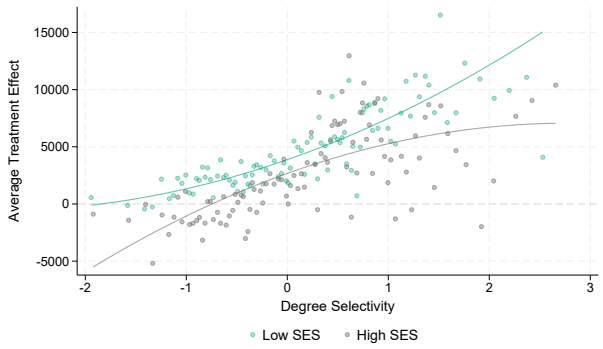
Section J.1 presents binned scatter plots on the relationship between degree-specific returns and degree selectivity. Section J.2 looks at the correlation between match effects by SES background. In Section J.3, I turn to presenting the relationship between match effects estimates and degree selectivity. Finally, Section J.4 provides a direct comparison between estimates that account for selection and those that do not.

J.1 Degree Treatment Effects

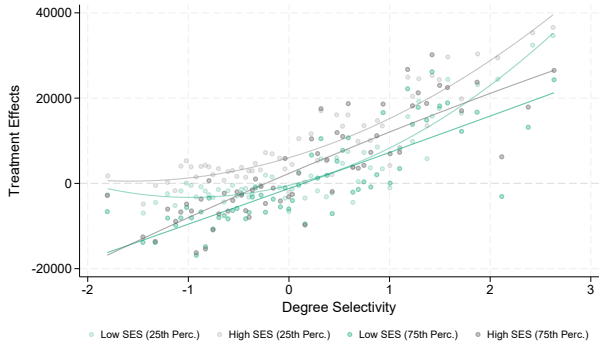
Figure J.1: Model and OLS Estimates



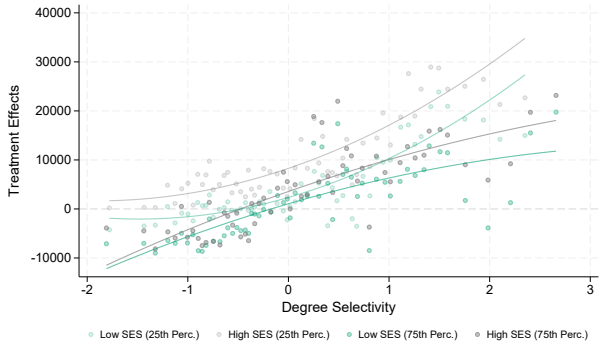
(a) Degree Treatment Effects, Model Estimates



(b) Degree Treatment Effects, OLS Estimates



(c) Degree Treatment Effects, Bottom Quartile and Top Quartile of Characteristics, Model Estimates



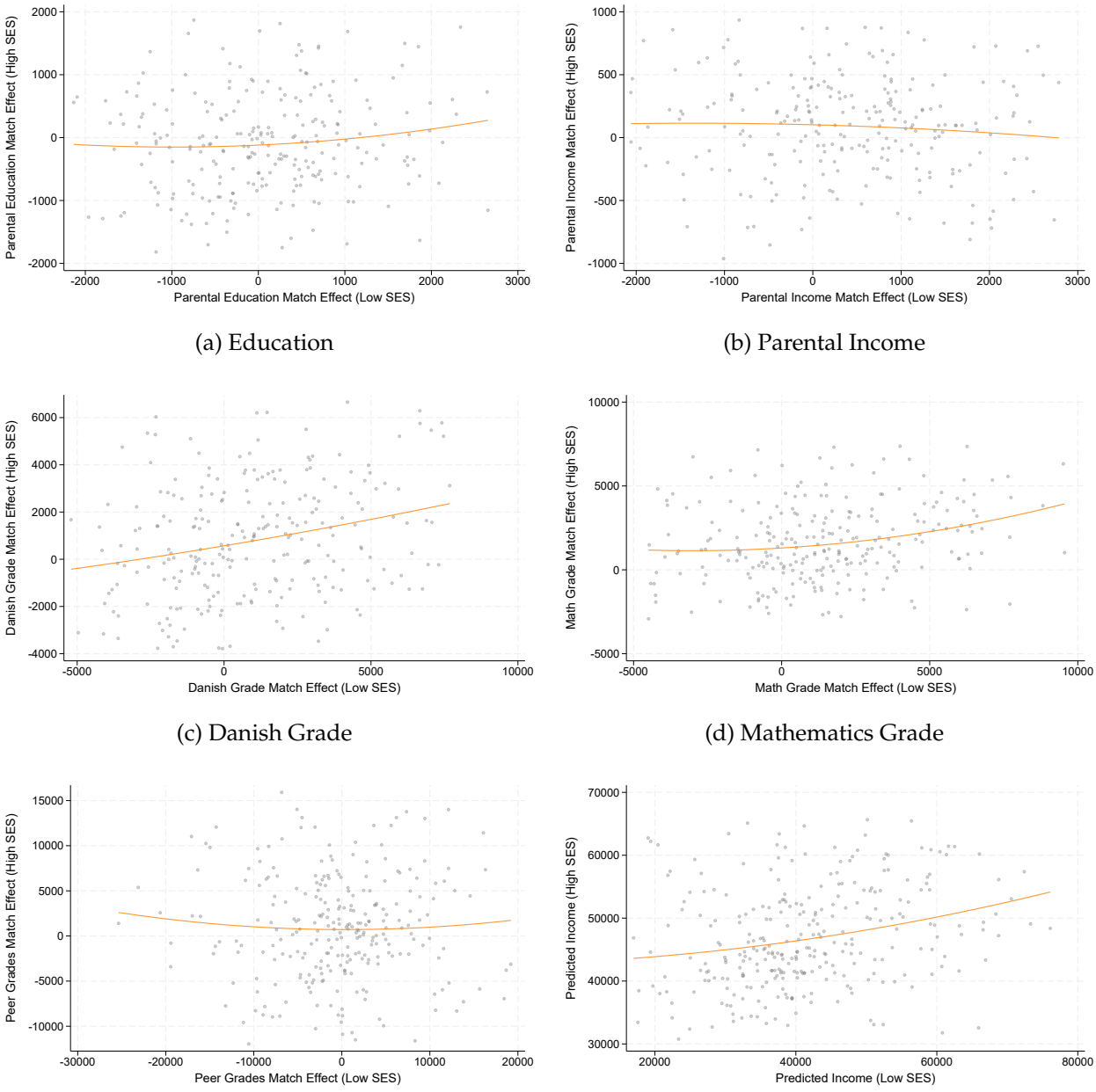
(d) Degree Treatment Effects, Bottom Quartile and Top Quartile of Characteristics, OLS Estimates

Notes: Binned scatter plots of degree-specific estimates against degree selectivity. Panels (a) and (b) present the effects at the mean levels of individual characteristics, relative to an outside option of not enrolling in a degree in the year of application. Panel (c) and (d) present the relationship between treatment effects at different levels of characteristics. Lighter shades of green and grey are used to depict students with characteristics at the bottom of their distribution, while darker shades correspond to estimates where individual characteristics stand at the top of the distribution. Low-SES students are depicted in green while high-SES students are depicted in gray.

J.2 Match Effects Correlations

J.2.1 Model Estimates

Figure J.2: Correlation Between Degree Match Effects by SES



(a) Education

(b) Parental Income

(c) Danish Grade

(d) Mathematics Grade

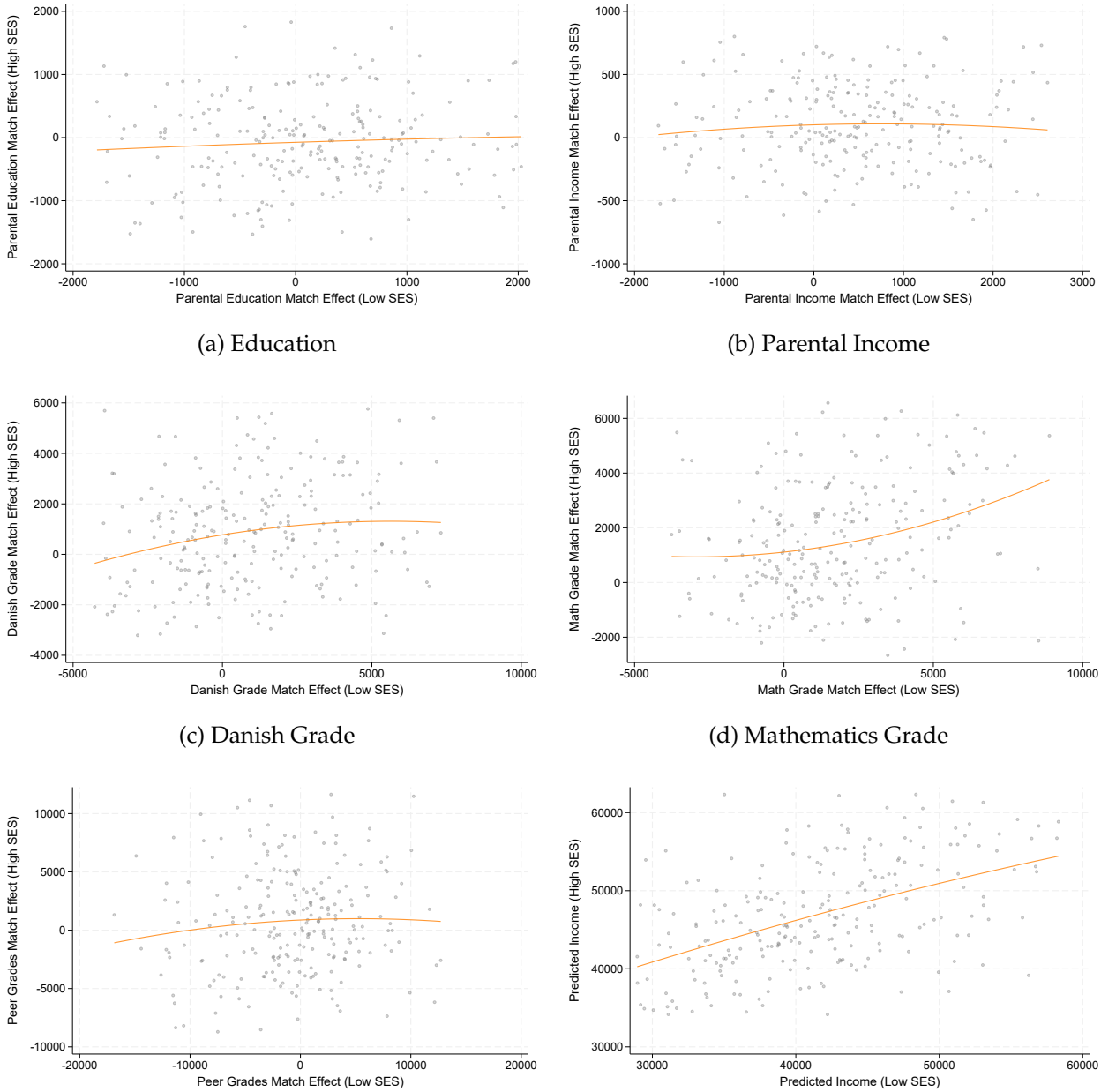
(e) Peer Grades

(f) Predicted Income

Notes: Correlations between match effects estimates from the model, across SES backgrounds.

J.2.2 OLS Estimates

Figure J.3: Correlation Between Degree Match Effects



(a) Education

(b) Parental Income

(c) Danish Grade

(d) Mathematics Grade

(e) Peer Grades

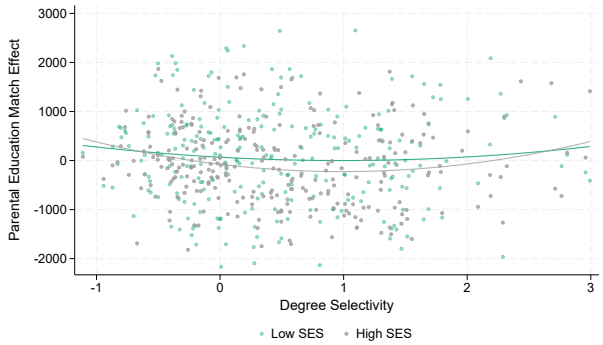
(f) Predicted Income

Notes: Correlations between match effects estimates from OLS, across SES backgrounds.

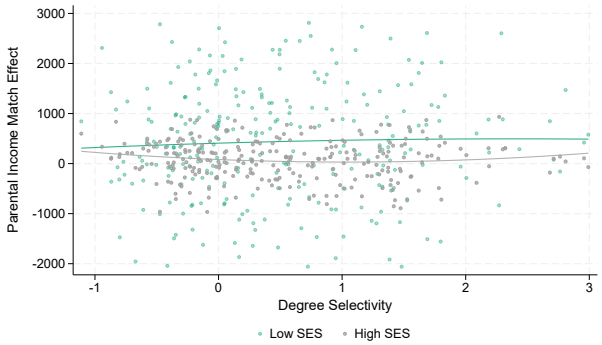
J.3 Match Effects And Degree Selectivity

J.3.1 Model Estimates

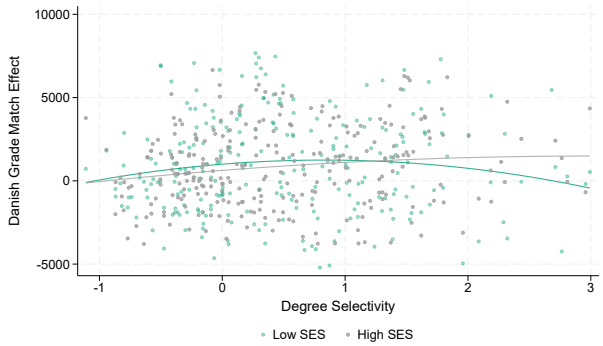
Figure J.4: Match Effects And Degree Selectivity



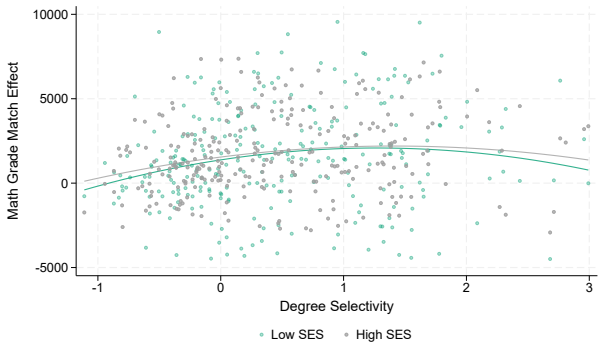
(a) Education



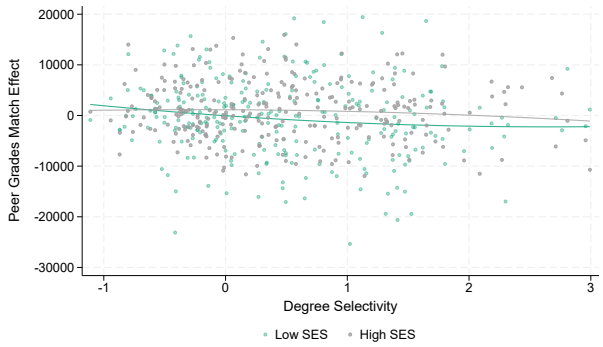
(b) Parental Income



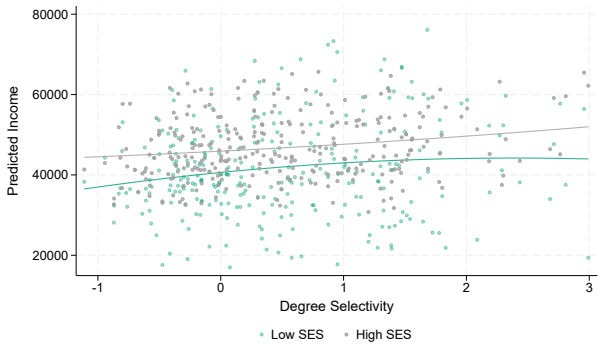
(c) Danish Grade



(d) Mathematics Grade



(e) Peer Grades

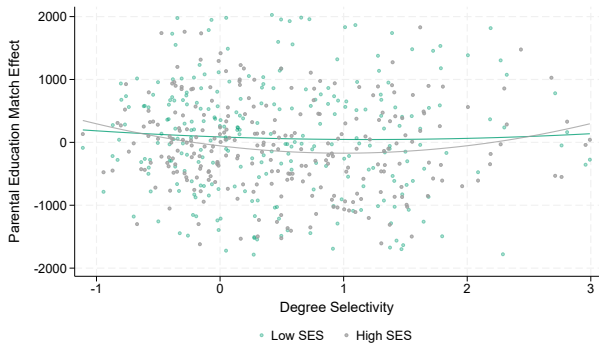


(f) Predicted Income

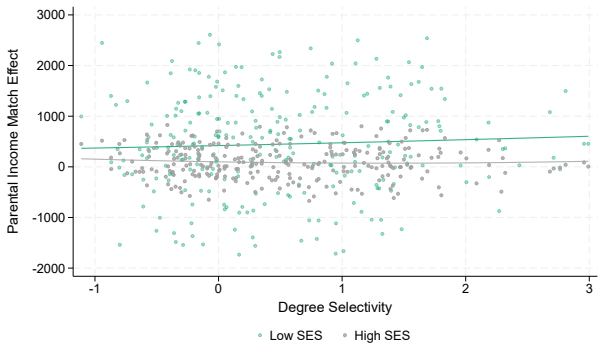
Notes: Correlations between match effects estimated from the model and degree selectivity, as measured by average high school grades of enrolled students.

J.3.2 OLS Estimates

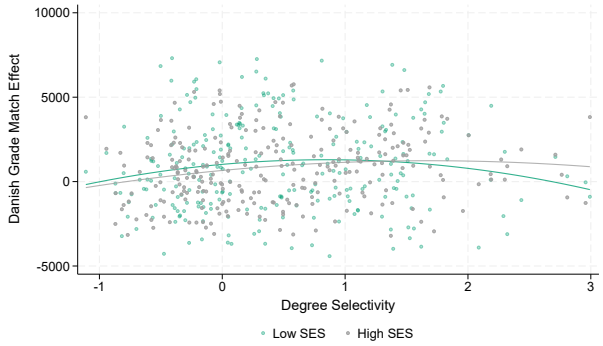
Figure J.5: Match Effects and Degree Selectivity



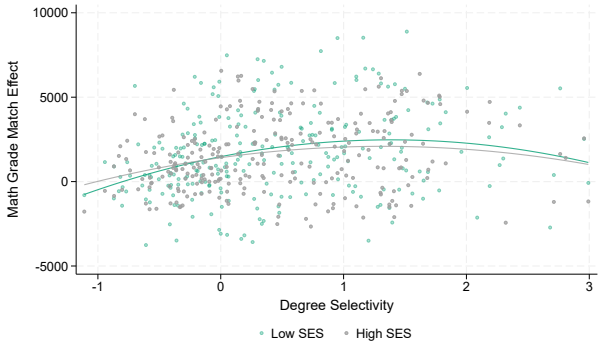
(a) Education



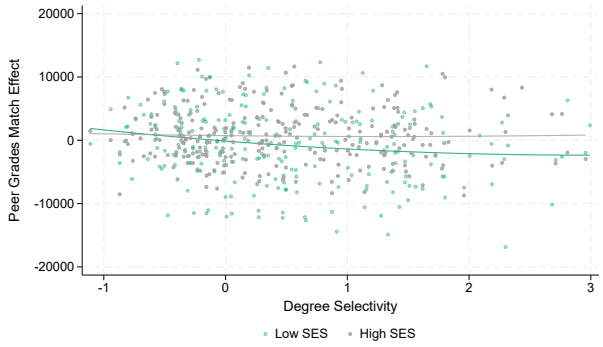
(b) Parental Income



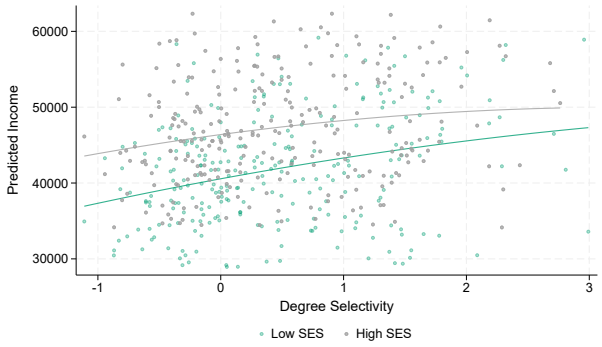
(c) Danish Grade



(d) Mathematics Grade



(e) Peer Grades

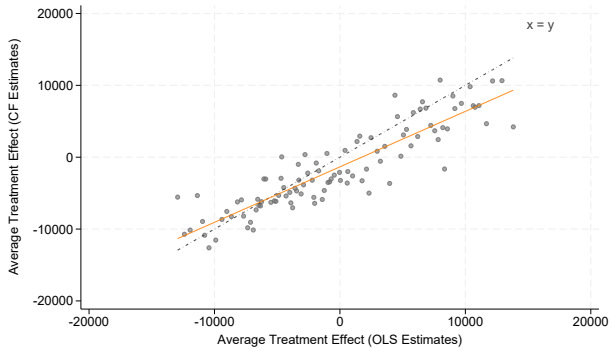


(f) Predicted Income

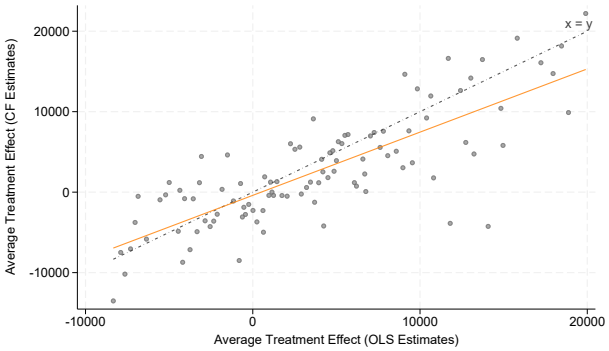
Notes: Correlations between match effects estimated by OLS and degree selectivity, as measured by average high school grades of enrolled students.

J.4 OLS vs. Model Estimates

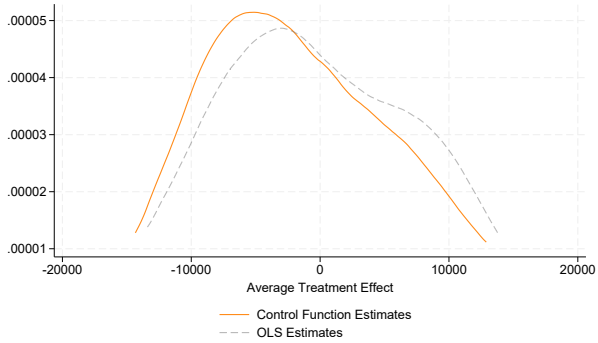
Figure J.6: Comparison of Estimates



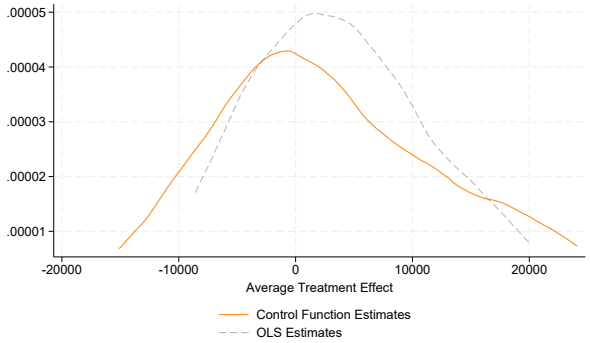
(a) Scatter Plot of Model Estimates Against OLS Estimates for high-SES Students



(b) Scatter Plot of Model Estimates Against OLS Estimates for low-SES Students



(c) Densities of Estimates for high-SES Students



(d) Densities of Estimates for low-SES Students

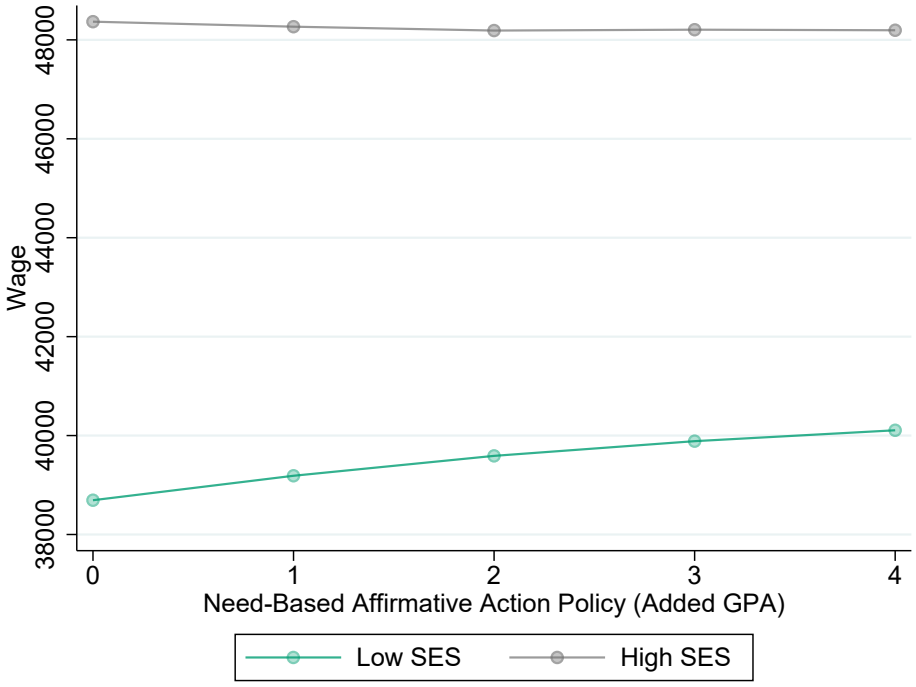
Notes: These figures compare OLS estimates with the model estimates. Panel (a) and (b) plot the degree-specific treatment effects estimates against each other, respectively for low- and high-SES students. Panel (c) and (d) depicts the distributions of estimates, respectively for low- and high-SES. The orange densities depict the Model estimates, while the dashed grey densities depict the OLS estimates.

K Counterfactuals

This Appendix shows the impact of changing admission policies on the long-term outcomes of individuals from low- and high-SES backgrounds.

K.1 Wage Income

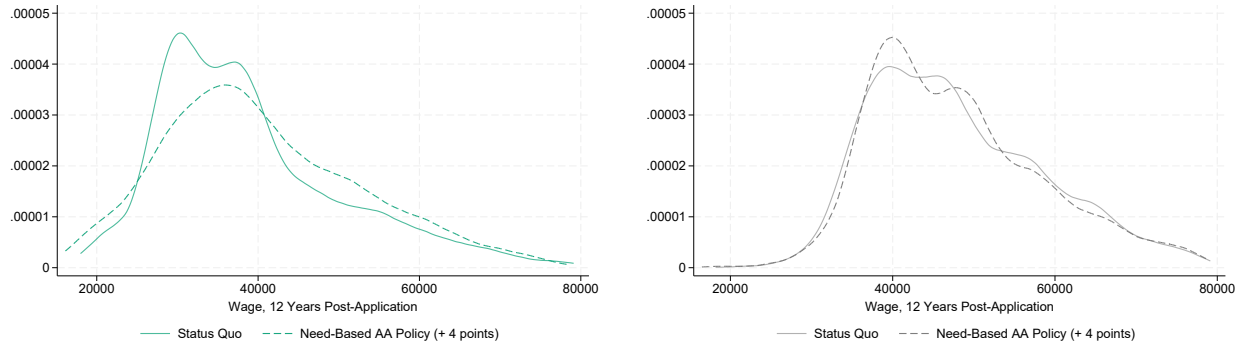
Figure K.1: Annual Wage Income (USD), Under Need-Based AA Policy



Notes: Effect of need-affirmative admissions on low-SES students (depicted in green) and high-SES students (depicted in gray). The policy under consideration reduces the GPA requirement gradually from 1 to up to 4 points. Each dot represents the average wage as a result of implementing the policy.

K.2 Wage Distribution: Before and After Policy

Figure K.2: Distributional Consequences of Need-Based Affirmative Action



(a) Wage Income Density: Before and After Policy for low-SES

(b) Wage Income Density: Before and After Policy for high-SES

Notes: These figures showcase the distribution of wages under the current status quo and affirmative action policy (dashed lined), which adds 4 additional points to low-SES students. Panel (a) focuses on low-SES students, while panel (b) presents the distributions for high-SES students.