# Inheritance of fields of study

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## Abstract

Children are more than three times as likely to attain a university degree in the fields their parents graduated from. To estimate how much of this association is caused by the educational choices of parents, I exploit admission thresholds to university programs in a regression discontinuity design. I study individuals who applied to Swedish universities between 1977 and 1999 and evaluate if their enrollment in different fields of study increases the probability that their children later study the same topic. I find strong causal influence. At the aggregate level, children are about twice as likely to graduate in the field studied by their parent. The effect is positive for most fields, but varies substantially in size. Technology, engineering, humanities, medicine, natural science, and business have some of the largest effects, for which parental enrollment increases the likelihood to graduate with between 4.5 and 11.6 percentage points. I show that occupation choices and labor market outcomes play an important role in explaining the results. I argue that, while children who follow their parents are on average better off, their comparative advantage explains only part of the results. Parents also act as role models, as is indicated by the fact that children become less like to follow parents with really weak labor market outcomes, and that daughters more often inherit the field of their mothers, and sons the choice of their fathers.

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# 1 Introduction

Every society needs an adequate level of social mobility to be considered just. Provision of education is integral in ensuring new children are given the opportunity to advance. However, occupations are often inherited across generations. An unrelenting, strong, correlation between parents and their children's occupational and educational trajectories is observed throughout the world. Explaining this persistence and identifying ways to increase class mobility has been a key focus of social science research for decades.[1] While much attention has been given to the topic, we still know little about the causal mechanisms explaining this perceived injustice. In this paper, I study how educational choices are passed on from one generation to the next. I compare parents who apply to study the same university field but end up either above or below an admission threshold. Parents who enroll in a specific field of study cause their children to become significantly more likely to earn a degree from that field. The effect is strongest for technology, engineering, humanities, medicine, and business, and negative for almost no field.

The choice of college specialization is one of the most consequential decisions an individual makes. A degree from a university field of study is the start of a distinct career trajectory and a necessary prerequisite for many occupations. Because of the large time-span between the field of study choices of one generation and the next, a likely pathway for the intergenerational transmission of fields is occupational inheritance. I confirm that work experience is indeed a key pathway: it is mainly parents with jobs common for degree holders of a specific field that pass the field on — especially those parents who are predicted to earn well. Children follow their parents not only because they have a comparative advantage, however. Parents also act as role models: daughters are more likely to follow their mothers, and sons their fathers.

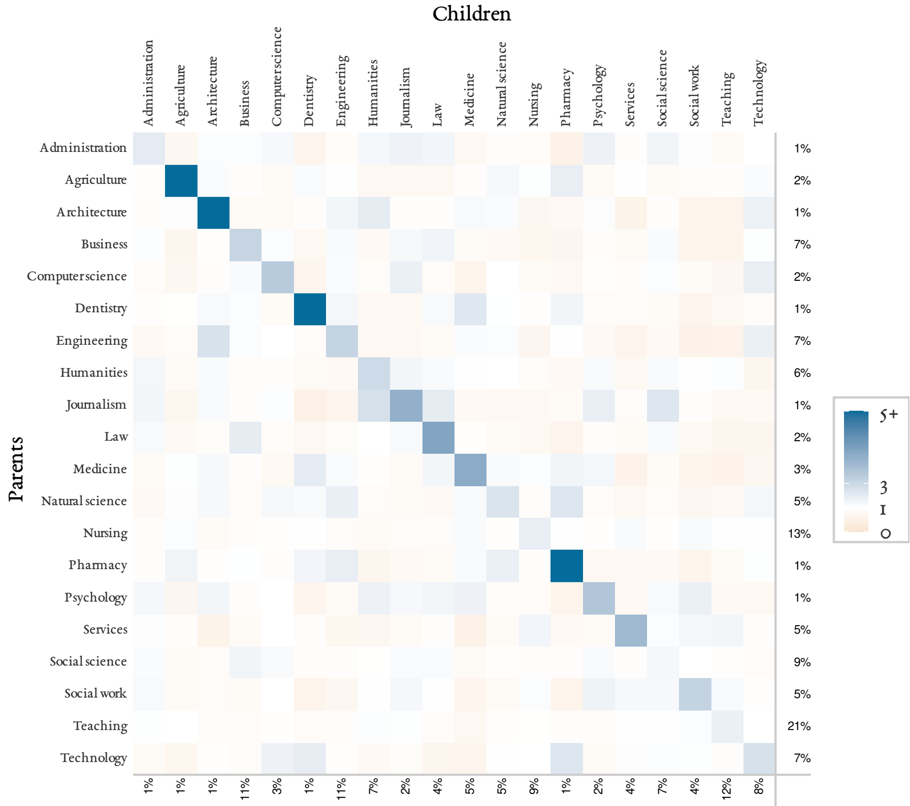
Increasing equality of opportunity is a desired objective in most liberal democracies. To understand how the correlation of educational outcomes across generations is linked to mobility and equality, it is essential to identify and estimate the size of the mechanisms through which these correlations arise. Without deep understanding of these causal pathways, it is hard to design effective policies to improve mobility. My results show that parents exhibit a considerable influence on their children, even in a relatively mobile country like Sweden.

Figure 1 presents a matrix of intergenerational associations for different tertiary degrees. The shade of each cell indicates how much more common a degree is — among children with a parent who holds a certain degree — when compared to the full population of children who graduated from college. While the blue diagonal shows how strong occupational reproduction is, it also visualizes the large variation across fields, with children of dentists earning degrees in dentistry more than 5 times as often as the general population, but children of nurses only being about 2 times as likely to become nurses. Importantly, we see no negative relationship on the diagonal. The purpose of this paper is to measure what proportion of this reproduction is actually caused by the educational choices of parents, as opposed to other factors that influence both generations. The causal effects that I find are large, but not nearly as large as the correlations. On the aggregate level, when a parent earns a degree in a specific field it causes the likelihood that their child will do so to double.

To identify this causal effect I study applicants to university programs that are quasi-randomly either above or below cutoffs to different fields, and look at the likelihood that their children also enroll

1. Since at least Becker (1964) and Coleman et al. (1966).

Figure 1. Degrees of children and parents




*Notes:* Grouped by the degree of the parents on the y-axis, the graph shows the relative popularity of different degrees among those parents' children, compared to the baseline frequency of attaining a certain degree. For example, while 4% of the children in the sample earn a degree in law, the rate is about 13% among children with a parent who has a law degree. See table B.2 for the exact values on the diagonal.

in the same alternative. In other words, I compare parents who all would like to study the same field, but where some end up not being admitted. This estimation framework allows me to identify a causal inheritance effect of parents' education on their children's preferences and outcomes. It does however mean that I identify a local average treatment effect: the estimates are valid for parents who comply with treatment and end up studying something else if they were not admitted.

This paper contributes to several large, but somewhat disparate, strands of literature. Studies of the intergenerational transmission of educational attainment, income, and health, have long attempted at identifying and measuring causal effects.[2] Since social and economic standing permeates generations, this is not a simple task. Families can live in a social stratum where higher education is valued, causing each generation to pursue university education. Such multi-generational human capital associations are even larger than measures across only two generations (Lindahl et al. 2015), but are not likely to represent direct causal effects (Braun and Stuhler 2018). Instead, to identify causal effects, many papers exploit

2. Surveyed in e.g. Björklund and Salvanes (2011) and Black and Devereux (2011).

policy changes that generate exogenous variation in parental schooling or income[3], or resort to various statistical techniques. Regression control models, instrumental variables methods, or twin relationships have often been used, but it is unlikely that these methods are able to account for all potential sources of bias.[4]

Dahl et al. (2021) is the only other paper that studies causal intergenerational transmission of fields of study specifically. Using a similar econometric design, location, and time period, they estimate causal spillover effects on high school choice across generations and between siblings. The link between high school specializations and occupations is weaker than that from university diplomas, and it is thus not surprising that their intergenerational effects are substantially smaller in magnitude than those presented here. Interestingly, they find similar effects by gender, at least for sons, who also follow their fathers high school choices twice as often. While they find mothers to mainly influence their daughters in fields that are male dominated, Table 10 in this paper shows positive maternal influence on a variety of fields, in most cases stronger for daughters.

The majority of research on intergenerational transmission and social mobility does not attempt to identify causal mechanisms, however. In sociology, measuring and understanding class reproduction is a core objective. Following a body of work that argued that a disaggregated categorization of social class into occupations is needed (Erikson and Goldthorpe 2002; Jonsson et al. 2009; Weeden and Grusky 2005), and since many modern occupations require tertiary diplomas, several recent papers address the intergenerational association of fields of study directly.[5] A common finding is that it is mainly the field of study choices of sons and their fathers that are correlated. Also, the causal effects presented in this paper are stronger for fathers and sons. I show, however, that mothers pass their education on to almost the same degree as fathers, a pattern that cannot be explained by assortative mating.

A separate body of research looks at the intergenerational association of occupation choice. A likely explanation of the strong correlations illustrated in Figure 1 is that children have a comparative advantage in choosing the same occupation as their parents. They gain this advantage through transfers of occupation-specific resources. Parental human capital can be transmitted actively at dinner table conversations, or when children help their parents with work-related tasks. It can also be passively transmitted through genetic and social endowments. Situations where social endowments are exploited to help a child advance, despite there being better qualified candidates available, are often referred to as nepotism. While all intergenerational persistence could be perceived as unfair, nepotism decreases total welfare. Labor economists have long been interested in studying occupation choice and measuring the degree of

3. Oreopoulos et al. (2006) use changes in US compulsory schooling laws to show that a 1-year increase in parental schooling decreases the probability that a child repeats a grade with 2–4 percentage points. Lundborg et al. (2014) make use of a 1950s Swedish compulsory schooling reform to show that maternal schooling improves everything from cognitive skills to health.

4. Some examples include Grönqvist et al. (2017) who show that the heritability of non-cognitive skills is almost as high as that of cognitive skills, and that it is stronger for mothers, and Björklund and Jäntti (2012) who compare the educational correlations of siblings to monozygotic twins to show that the non-genetic role of family background in determining labor market outcomes is substantial. Holmlund et al. (2011) study the causal intergenerational transmission of years of schooling. They compare results from the most common methods to their own and others' IV estimates and show that IV estimates are considerably smaller than the associations identified in control, twin, and adoption studies and argue that this is due to selection issues that have not been accounted for successfully.

5. Van de Werfhorst et al. (2001) find strong associations between fathers' and their children's choice of educational field in the Dutch Family Surveys of 1992 and 1998. Also, the association identified by Hällsten (2010) and Andrade and Thomsen (2017), on Swedish and Danish individuals respectively, is mainly between males. Similarly, Kraaykamp et al. (2013) identify a correlation between parental field of study and the level of education — mainly that sons of parents who study a technical field reach higher educational levels, while daughters to parents with a care field of study attain lower educational level. Hällsten and Thaning (2018) does the opposite, and shows 25% of the variation in field of study choice is explained by a measure of social background that includes the parental level of education.

nepotism in occupational inheritance.[6] Two studies of particular relevance to this paper address field heterogeneity directly. De la Croix and Goñi (2021) study nepotism in academia throughout history. They estimate intergenerational elasticities and show that nepotism plays a much larger role for legal and medical scholars when compared to researchers in theology and science. Aina and Nicoletti (2018) study intergenerational associations in liberal professions and find especially strong effects for occupations that have high entry barriers because of licensing and compulsory practice periods. Many of the strongest causal effects identified in this paper are also in fields that lead to occupations with high entry barriers. But the causal estimates presented here indicate that the inheritance of fields is not solely driven by comparative advantage. While uncommon, children become less likely to pick certain fields if their parents enroll. Table 8 shows large negative effects when the parent is predicted to have low earnings.

Finally, this paper contributes to the literature on the relative importance of genetic and environmental effects in explaining schooling outcomes. Any intergenerational association that is not due to genetic endowments is caused by environmental triggers, potentially interacting with genes. Heritability research has found considerable influence on educational outcomes from both genes and environmental factors (Branigan et al. 2013; Polderman et al. 2015). In these studies, all variation that cannot be tied to genetic endowments is attributed to the environment. Using the term "nurture" to describe this residual is somewhat misleading, however, as the studies say nothing about the extent to which these environmental triggers can be controlled. To the contrary, a substantial portion of the residual is likely caused by a multitude of idiosyncratic, random, events (Plomin 2011). To recommend changes to policy or individual behavior, we need to find causal pathways that can be controlled. While recent studies in behavioral genetics have identified the specific genetic markers that are responsible for as much as 10% of the variability of years of schooling (Lee et al. 2018), little progress has so far been made on the environmental side. This paper provides estimates of one such pathway. The paper examines an environmental mechanism that the parent commands, namely how parental field specialization directly influences educational preferences and degree completion of their children. While the effect identified is a miniscule part of what heritability studies would ascribe to the "environment", it entails one of the first precisely estimated environmental causal pathways.

To summarize, social scientists have long studied transmission of education from parents to their children. Because of the difficulty to attain experimental data that spans generations, the field is, until recently, void of causal analyses of these important effects. The contribution of this paper is to estimate the magnitude of the causal transmission of university fields of study and in doing so increase the understanding of how education, and more generally social status, is transmitted over generations. The findings are important for researchers, policy-makers and parents alike. Policymakers who want to increase mobility

6. Important early work includes a number of papers by Lentz and Laband. They show that children of doctors are more likely to be admitted to medical school (Lentz and Laband 1989), that lawyers transfer legal know-how to their children (Laband and Lentz 1992), that farmers tend to be sons of farmers because the experience they gain while growing up gives them a comparative advantage (Laband and Lentz 1983), and argue for an analogous mechanism explaining inheritance of entrepreneurship (Lentz and Laband 1990). Similar findings are presented in a more recent paper by Hvide and Oyer (2018), who show that male entrepreneurs are likely to start a business in an industry in which their fathers are employed — and those who do are likely to outperform other entrepreneurs in that industry, and Bell et al. (2019) who find that growing up in an area with many innovators has a causal impact on the likelihood that an individual registers a patent. Dunn and Holtz-Eakin (2000) argue that the transition to self-employment is better predicted by parental self-employment success than individual or parental financial resources. Additional important papers that identify causal effects are Bennedsen et al. (2007) who exploit the random gender of the first child to show that the appointment of a family CEO has large negative effects on firm performance, Dal Bó et al. (2009) who use discontinuities in election outcomes to show that political success builds dynasties, as well as Mocetti (2016) and Mocetti et al. (2022) who exploit deregulation in Italy to show that a decline in occupation-specific rents together with increased competition, reduces intergenerational persistence.

need to account for this self-perpetuating mechanism by providing children with additional role models to ensure they have enough knowledge about alternative careers. Some university applicants might reconsider their choices knowing how they might impact the education of their children, and parents who do not want their children to follow in their footsteps probably need to give additional attention to alternative pathways.

This paper is organized as follows. I start in Section 2 by presenting the Swedish education system, the data that I use, and how it is processed to identify the admission margins that can be used in a regression discontinuity design. In Section 3, I then describe the identification strategy and the model that I will estimate, after which I outline my main results in Section 4. I show that these results are stable and robust to various placebo checks in Section 5, and explore mechanisms in Section 6. Last, Section 7 concludes by summarizing the results and their relevance.

# 2 Institutional background and data

Swedish tertiary education is tuition-free and government run. All students are offered stipends and subsidized study-loans. Students apply through a centralized admission system. During the fall semester of 2018, 1817 different programs (at both undergraduate and graduate level) were offered at 37 institutions. Like in many other European countries, individuals apply by submitting a preference ranking of alternatives. Each alternative is a program at a specific institution. If completed, programs award the student with a field-specific bachelor's or master's degree. When a program is oversubscribed, students are sorted by previous academic performance in different admission groups and only those with the highest score are admitted. Importantly, there is no system of legacy admissions, ensuring that children have no mechanical advantage in admission probability if they apply to the same program as their parents studied.

In this paper, I use data on university applications submitted between 1977 and 2021 through the centralized application system in Sweden.[7] I study individuals who applied to university between 1977 and 1999 and match them to their children (if they have any) for which I observe applications until the end of 2021.

I use university application data from three sources. Applications from the current admission system (2008–2021) comes from Universitets- och Högskolerådet (UHR). Older applications are retrieved from the A1 (1977–1992) and H97 (1993–2005) archives at the Swedish National Archives (Riksarkivet).[8] I link the applications using individual identifiers to data from Statistics Sweden (SCB) on enrollment, degrees, high-school performance, socio-economic characteristics, and family connections, recorded up until 2021.[9]

7. It became mandatory for institutions to offer their programs through the centralized system only in 2005. While most universities participated from the start of the sample period in 1977, some joined later or only included a subset of their offered programs. Participation increased monotonically however so the programs applied to by parents will always exist in the data when I study the behavior of their children.

8. Data is unfortunately missing for the fall semester of 1992, and there is only partial data available for the years 2006 and 2007.

9. Information on degree completion comes from Utbildningsregistret (UREG), which includes both registered degrees awarded by Swedish institutions and information about highest achieved education collected through surveys and other sources. Family connections are retrieved from Flergenerationsregistret. To ensure I include all potential family members in the same family identifier (used for clustering of standard errors) I count the complete network of individuals connected through chil-

To be eligible for post-secondary education, applicants must have finished high school. Certain programs have additional requirements. Engineering programs, for example, often require completion of certain high school classes in science and math. Individuals who have not taken these courses in high school can supplement diplomas with preparatory adult education to become eligible.

Each semester has its own application period, with submission deadlines in mid-April and October. Applicants submit ordered lists of up to 12 (20 after 2005) program-institution combinations, below referred to as choices or alternatives.[10] All applicants to a given alternative are ranked by their score in the admission groups they are eligible for. The set of available admission groups varies over programs and time. For example, during a transition between high school grading systems, separate groups were used for each system — students with older high school diplomas were only competing against other students with the same kind of grades, while those with newer diplomas were admitted in a separate group. There is a specific group for admission through Högskoleprovet (a standardized non-mandatory admissions exam similar to the SAT). During 1977 to 2005, applicants who had work experience could compete in a group where the number of years they had worked gave bonus points. The number of spots reserved for each admission group is proportional to the number of eligible applicants in that group. To account for selection into these groups and that admission scores are not always directly comparable, I standardize scores separately for each group and year. In the regressions, I include cutoff fixed-effects, unique for each semester-institution-alternative-admission group combination, and separate polynomials for the running variable in each admission group.

Each application period consists of two rounds. During each round, an allocation mechanism admits students to alternatives until either all slots have been filled or all applicants have been admitted. Applicants are ranked by score in every admission group that they are eligible for and then admitted one by one. Each admission group is attributed a set of slots, decided partly by fixed rules and partly in proportion to the total number of applicants in the group. Applicants are admitted from the group that is the farthest away from having its slots filled. An applicant that is admitted in one group is removed from the queue in all other groups. After all slots are filled, applicants admitted to higher prioritized alternatives are removed from options they had ranked lower and replaced by the next individual in line from the same admission group. Once no more individuals are being admitted, the process stops and offers are sent out. Applicants then decide whether to accept their offers, and whether they want to stay on the waiting list for admission to higher prioritized alternatives. The admission procedure is then repeated in a second round.[11]

When applicants are sorted by their admission group scores, ties need to be broken. Because admission scores are coarse, 55% of admission cutoffs have more than one applicant exactly at the threshold.[12] During the period studied in this paper, three different tie-breakers were used. The two main ones prioritize applicants with identical scores either by the rank of the alternative in their application list (used during 1977–2005) or by putting applicants of the underrepresented gender first (1993–2005).[13] The or-

dren as the same family, but only biological and adoptive parents when measuring inheritance. If two divorced parents have additional children with new partners, all children are included in the same family.

10. In the current system, in use since 2005, students can apply to both degree programs and individual courses in the same application. Before 2005, only applications to degree programs where handled in the centralized system. Naturally, for parents, I therefor only look at applications to degree program. In the current system, during which most of the child applications are observed, I also include applications to individual courses for the outcome variable relating to university applications.

11. For a more detailed description of the admission algorithm see the legal case T 3897-08 from Uppsala Tingsrätt.

12. The mean number of applicants at the threshold is 3.5 and at the 99th percentile of applicants at the cutoff there are 27 individuals with exactly the same score.

13. A gender is defined as underrepresented if less than 30% (until spring 1998), or less than 40% (fall 1998–2005) of the applicants are of that gender.

der in which these two tie-breakers are implemented differs between programs and institutions. Finally, any remaining ties are broken in lotteries.

Disregarding tie-breaking, the allocation mechanism is a truncated multicategory serial dictatorship, a mechanism that is not strategy proof but still minimally manipulable (Balinski and Sönmez 1999; Pathak and Sönmez 2013). Truncation makes it rational for the applicant to add a safe option to the end of their priority ranking. Only 3.6% of applicants submit a full list with 12 ranked alternatives, however. The priority based tie-breaking creates additional motivation to include safe options. How important is incentive compatibility in our setting? It is only to support the assumption of monotonicity required for IV estimates to be interpreted as LATE (further discussed in Section 3) that we need a certain preference structure. In fact, the assumption only requires that for any pair of alternatives in the ranked list of options, the applicant prefers the alternative with a higher rank. While there are good reasons for applicants to include safe options in their application, an applicant going against this assumption would be strictly worse off, making it a highly unlikely behavior. Furthermore, I find similar results when looking only at admission to top-ranked options in Table A.3. This exercise does come at a substantial cost to statistical power, however.

After successful admission, students enroll by simply attending initial lectures. Since students need to complete academic credits each semester to not lose their stipends, enrollment and credit reception is centrally registered at the course level. I use this enrollment data both to instrument for parent admission and as an outcome variable.

Having collected enough academic credits and fulfilled various other requirements (like writing a thesis), the student can apply for a field-specific degree at the Bachelor or Master level. These degrees are registered by SCB in Högskoleregistret. I use child degree completion as the main outcome variable in the paper. Importantly, it happens that individuals get a job before finishing all requirements to apply for a degree. It is therefore likely that the effect on child enrollment is larger than that on degree completion. In combination, these outcome variables yield an interval of inheritance strength.

## 2.1 Sample construction and description

For the raw application data to be used in a regression discontinuity analysis it first needs to be processed in the following way. First, I identify cutoffs for each admission group, defined as the lowest score among all admitted students. Cutoffs are only defined for those alternatives and admission groups where there are also applicants who were not admitted at the end of the application round. I drop applicants who were admitted in non-standard admission groups and institutions that only offer practical programs, since their admission scores cannot be used for RDD analysis.

I use admission status and individual scores from the final admission round but keep individual rankings from the first round. The reason is that second round outcomes are influenced by responses to first round offers. Applicants often drop out of the waiting list for choices that they would have been admitted to if they stayed. Using second round scores to calculate cutoffs increases accuracy of the first stage greatly (because otherwise a much larger share of applicants directly below the cutoff would be admitted eventually), and is not a problem since applicants do not know what the cutoff will be when they apply or when they decide what to do after the first round. It is critical to use first-round preference rankings however, even if this decreases accuracy.[14] The reason is that there is likely selection among those who are not admitted in the first round but decide to stay. Such selection would bias the causal estimates of the RDD analysis.

14. This is the main reason why the first stage for admission, the first plot in Figure 4 does not jump from 0 to 1. A substantial portion of those above the cutoff drop out after not being admitted in the first round.

I collapse admission groups for each choice and use only the group where the applicant performed the best (had the highest relative score). If they are below the cutoff in all groups, this is the group where they would have been admitted if the cutoff was slightly lower. If they were admitted, it is the group that was used for admission. I drop dominated alternatives, where a lower ranked choice has a higher cutoff and where the applicant would thus never be admitted.

I then proceed to create observations of pairs of preferred ($j$) and counterfactual ($k$) fields and classify fields into manually constructed broad categories.[15] Furthermore, I collapse consecutively ranked options to the same field, keeping the program where the applicant performed the best (had the highest relative admission score). This could be applications to the same field at different institutions, or to different programs within the same field at one university, or both. I also show that the results are robust to a classification into much broader fields of study. In some analyses, I study additional treatment margins and collapse the individual rankings by, institutions, or institution-field combinations.

The right-hand-side data used for analysis consists of treatment pairs. An observation includes a preferred field $j$, and a counterfactual field $k$ to which the applicant would be admitted if they are below the cutoff to $j$. I keep all such combinations for each applicant. For a specific applicant, the sample can contain multiple observations where the applicant is below the cutoff to a preferred alternative $j$ but at most one where he or she is above.[16]

I merge this right-hand-side data of parent field pairs to information about children, allowing each parent's observations to be joined to all their (biological or adoptive) children. In each specification, the outcome variable is set to 1 when the child applies to, enrolls in, or graduates from the field $j$ that their parent preferred, and 0 otherwise. This includes children who do not apply to university at all during the sample period.

In the analysis, I focus on parents who apply to university during 1977–1999, are below the age of 30 when they apply, and have children who are born before the end of 1998. I include both those children who apply to university and those who don't. But since my application, enrollment, and degree completion data ends in 2021, when the youngest children included are only 23 years old, it is likely that many who have yet to follow their parents will do so in the future. This will bias the estimates downwards somewhat.

Table 1 shows summary statistics for the main sample of analysis (third column), but also how this data set differs from all applicants (below the age of 30), all applicants within a bandwidth of 1 standard deviations, and all applicants within the bandwidth who have a child that actually applies to university. Differences across the samples are small, except that children in the last two samples are much older and have a substantially higher GPA if they apply. Notice also how each parent is observed on average slightly more than two times (included separately for each child), and how the number of observations is much larger than the number of applicants (separate observations for each threshold the applicant is close to are included). Furthermore, as we will see in the regression results, the share of children who get a degree in the preferred field of their parent ($j$) is very small. There are multiple reasons why many more children enroll than earn a degree in the field of their parent. The main one is likely that most children are studying at the very end of the sample period and have yet to complete their studies. Furthermore, many students

15. Appendix D re-estimates most results in the paper using SunGrp, a classification provided by Statistics Sweden that uses information about both the topic and level of education. It is the official classification that most closely maps to different occupations. SunGrp codes are much more detailed than the classification used in the main text, with e.g. four different technology fields. This leads to large overlap in intergenerational correlations (as seen in Figure D.2), which is why I focus on broad fields.

16. This means that for each applicant there is a lowest-ranked pair where being below the cutoff to $j$ means the applicant is not admitted to any option. In total, about 75% have "nothing" as next-best field. The second most common counterfactual field is Technology with approximately 4% of the sample.

likely study the field of their parents as minor subjects, never earning a degree. A smaller part is due to dropout.

Table 1. Summary statistics

| | All applicants | In bandwidth (1 std) | Child born ≤ 1998 | Child applies |
|---|---|---|---|---|
| Application score (std) | 0.14 | 0.32 | 0.28 | 0.28 |
| | (1.02) | (0.93) | (1.01) | (0.98) |
| Parent birthyear | 1969.21 | 1969.11 | 1962.18 | 1963.51 |
| | (6.94) | (6.92) | (4.83) | (5.26) |
| Parent age at treatment | 20.93 | 20.88 | 21.58 | 21.28 |
| | (2.55) | (2.54) | (3.09) | (2.85) |
| Parent female | 57.23% | 56.30% | 59.48% | 57.89% |
| Parent foreign born | 5.09% | 4.57% | 4.09% | 3.78% |
| Grandparents foreign born | 8.23% | 7.57% | 6.71% | 6.36% |
| Grandfather's earnings (kSEK) | 364.58 | 369.81 | 363.74 | 374.17 |
| | (239.83) | (247.98) | (224.12) | (233.70) |
| Grandmother's earnings (kSEK) | 197.65 | 199.54 | 174.82 | 181.90 |
| | (109.86) | (110.88) | (102.54) | (105.32) |
| Grandfather has university education | 43.99% | 45.60% | 51.09% | 52.69% |
| Grandmother has university education | 44.47% | 46.03% | 45.05% | 47.84% |
| Child birthyear | 2002.10 | 2002.08 | 1992.01 | 1994.16 |
| | (8.62) | (8.61) | (4.71) | (5.40) |
| Child female | 48.58% | 48.59% | 48.64% | 52.53% |
| Child high school GPA | 0.45 | 0.48 | 0.48 | 0.64 |
| | (0.94) | (0.93) | (0.94) | (0.85) |
| N. treated applicants | 707 725 | 534 719 | 175 408 | 203 705 |
| N. uinique applicant × child | 1 275 611 | 968 641 | 333 691 | 352 265 |
| N. children who rank $j$ first | 119 755 | 87 059 | 69 599 | 87 059 |
| N. children who enroll in $j$ | 94 382 | 69 138 | 56 398 | 68 869 |
| N. children who earn a degree in $j$ | 30 312 | 21 705 | 21 658 | 21 439 |
| Observations | 1 969 572 | 1 337 737 | 402 649 | 432 405 |

*Notes:* The leftmost column includes all applicants to Swedish universities between 1977 and 1999 who apply through the centralized application system and are 30 years or younger at the time of application. The second column filters out those who are within the bandwidth of 1 standard deviation from either side of the admission cutoff, that is used for the main analysis in this paper. The third and fourth column focus on those applicants inside the bandwidth who have children. In the third, I summarize observations of applicants with children who were old enough to apply before the end of the sample period in 2021. It is the sample summarized in this column that is used for most analyses in the paper. In the last column, I instead limit the sample to include all children who apply to university before the end of 2021.

Table 2 shows additional results for the main sample of analysis. Here, the data set has been divided by field of study. We see that some subjects are much more common and that the first stage coefficients vary substantially. Both these factors influence the weights of each field in any aggregated results reported. Enrollment below the cutoff happens when applicants reapply and enroll within five years of being treated.

A first validation of the data can be seen in the balance plot of Figure 2. Here, whether the parent is above the cutoff is regressed on outcome variables that are all defined before treatment. A quasi-random admission of applicants should not be statistically related to these outcomes. The only variable that can be statistically distinguished from zero is the age of the parent. Admitted parents are about 3.5 weeks

Table 2. Summary statistics by field of study

| | Observations | Unique parents | Share women | Average age | Share enrolled below cutoff | First stage (parent enrolls) |
|---|---|---|---|---|---|---|
| Administration | 15 473 | 8472 | 63% | 21.71 | 29% | 14p.p.*** |
| Agriculture | 6846 | 3249 | 49% | 21.54 | 37% | 24p.p.*** |
| Architecture | 5324 | 2636 | 57% | 21.60 | 23% | 36p.p.*** |
| Business | 50 103 | 26 778 | 47% | 21.66 | 38% | 14p.p.*** |
| Computer science | 14 342 | 8041 | 42% | 22.31 | 25% | 21p.p.*** |
| Dentistry | 6577 | 3136 | 53% | 21.82 | 43% | 8p.p.* |
| Engineering | 47 304 | 25 270 | 23% | 20.63 | 48% | 11p.p.*** |
| Humanities | 12 408 | 6871 | 74% | 21.59 | 29% | 18p.p.*** |
| Journalism | 6772 | 3504 | 66% | 22.38 | 12% | 35p.p.*** |
| Law | 21 743 | 11 828 | 59% | 21.02 | 31% | 13p.p.*** |
| Medicine | 15 904 | 7333 | 43% | 22.56 | 54% | 14p.p.*** |
| Natural science | 21 250 | 11 176 | 50% | 20.81 | 40% | 13p.p.*** |
| Nursing | 5839 | 3128 | 84% | 25.07 | 39% | 14p.p.*** |
| Pharmacy | 4092 | 2097 | 84% | 20.98 | 25% | 16p.p.*** |
| Psychology | 6145 | 3020 | 69% | 23.69 | 21% | 28p.p.*** |
| Services | 7552 | 4229 | 77% | 22.13 | 10% | 14p.p.*** |
| Social science | 18 508 | 10 135 | 65% | 21.69 | 18% | 16p.p.*** |
| Social work | 27 440 | 13 959 | 81% | 22.23 | 29% | 18p.p.*** |
| Teaching | 100 598 | 51 141 | 80% | 21.38 | 45% | 11p.p.*** |
| Technology | 8429 | 5148 | 27% | 21.60 | 35% | 15p.p.*** |

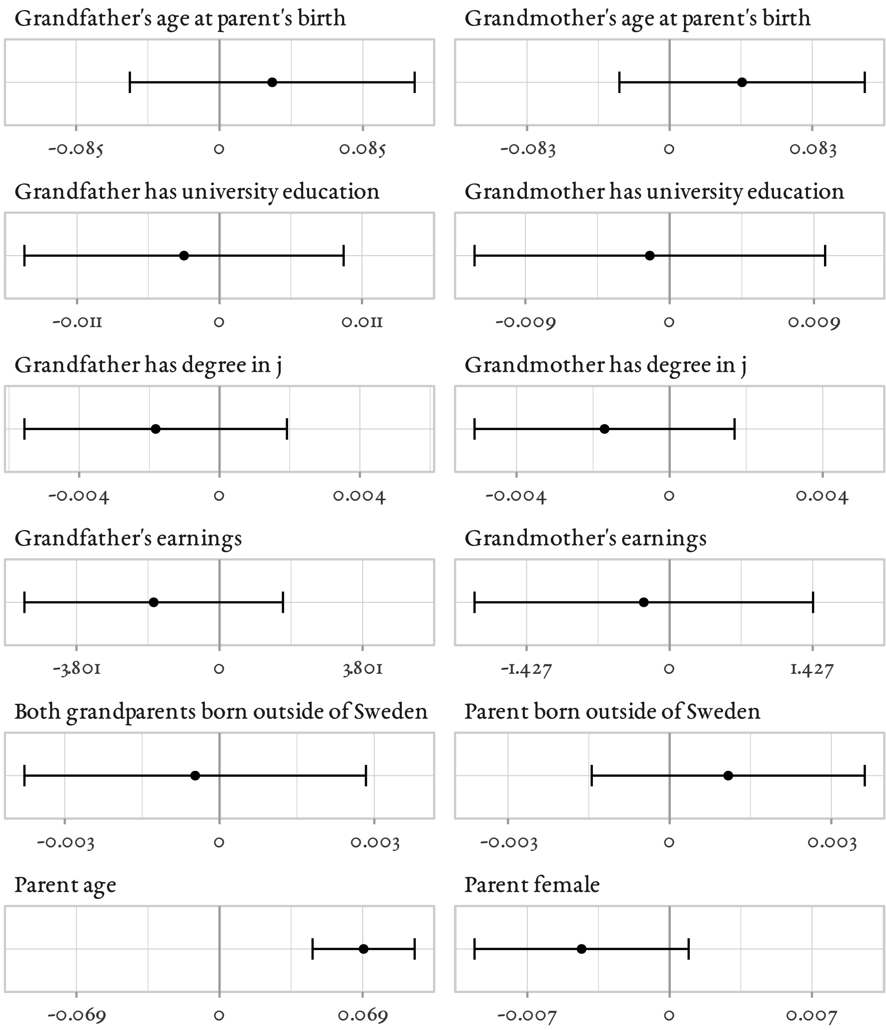
*Notes:* The table shows the main sample of analysis: parents who apply during 1977-1999, before the age of 30, are within 1 standard deviation of the admission cutoff, and who have children born before 1999. The observations are summarized separately for each field of study. The last column shows the disaggregated first stage coefficients, i.e. the increase (in percentage points) of the likelihood that the parent will enroll in their preferred field $j$ if they are above the cutoff.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

older. Since applicants could use work experience to augment their admission scores, older applicants often have mechanically higher scores. It is possible the running variable polynomials do not fully account for this, or the result is simply a statistical fluke. Nonetheless, controlling for age dummies does not change the results in any meaningful way.

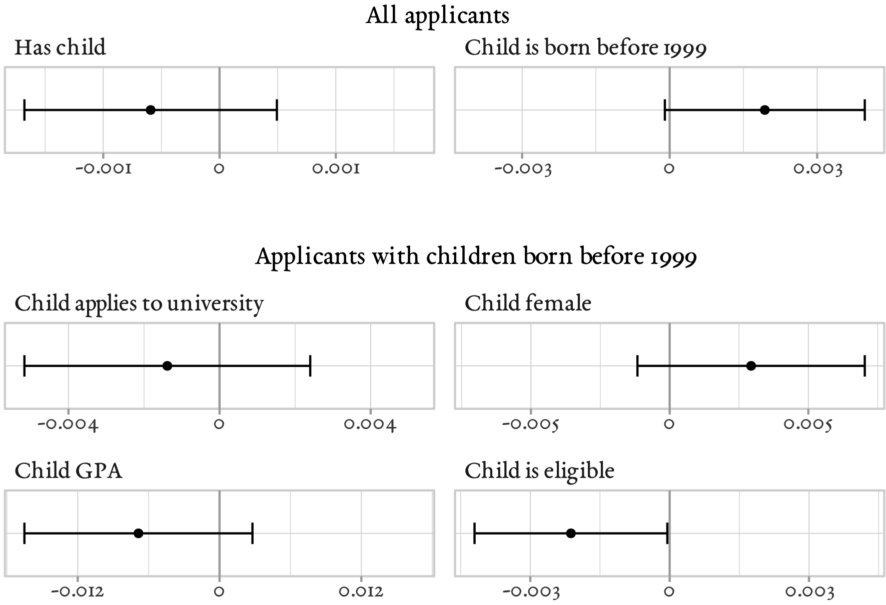
Finally, Figure 3 shows the results of a similar analysis conducted on outcome variables that are defined after treatment. Furthermore, the two topmost coefficients are estimated on the full sample of applicants, irrespective of if they have children or not. In these, we see that treatment assignment is not statistically significantly related to sample inclusion. The four final plots use the main sample to study effects on the extensive margin. University eligibility is slightly lower among children of admitted parents, but no other statistically significant effects can be discerned.

Figure 2. Covariate balance




*Notes:* The figure shows a set of coefficient plots with 95% confidence intervals for different characteristics that are defined before the parent is quasi-randomly admitted to a university program. These variables are used as outcomes in regressions that otherwise mimic the main estimation setup. They include the sample of applicants who had children born before 1999, and use cutoff fixed effects, a triangular kernel, a bandwidth of 1 standard deviation, and distinct linear polynomials for each admission group and each side of the cutoff. The plots show the estimated coefficients for the parent being above the cutoff on each of these outcomes.

Figure 3. Sample inclusion




*Notes:* The figure reports coefficients and 95% confidence intervals from a similar setup as in Figure 2 but with outcome variables that are defined after treatment. The top two plots are estimated on the full sample of applicants, while the four lower ones are estimated on the same sample that is used in the main estimation, where only those applicants who have children born before the end of 1998 are included.

# 3 Empirical framework

As we saw in Figure 1 the choices of parents and their children are strongly correlated. But this empirical correlation could be explained by external factors, and should not be understood as causal. In fact, causal transmission effects across generations are very difficult to measure. It is hard to distinguish external influences from effects directly stemming from the parents' behavior. For example, the education and income level of the grandparents could influence the field of choice for both parents and their children. A family could have a tradition of promoting medical studies going back generations. Of course, genetic factors that we know strongly influence educational outcomes most likely also have an effect on the choices of fields of study.

To correctly identify the causal effect of parental education on child preferences I employ a regression discontinuity design (RDD). RDD estimates the causal effect under fairly weak assumptions, but put strong requirements on the data (Lee and Lemieux 2010). As long as treatment assignment is not perfectly manipulable around the cutoff, RDD coefficients can be interpreted as causal effects.

I use the methodology to study individuals who apply to university between the years 1977 and 1999, and compare the behavior of the children of those parents who are above an admission threshold to the children of parents below. If the identifying assumptions hold, each admission cutoff can be seen as a separate natural experiment. I pool a large set of such experiments of admission to different education programs and institutions.

For each parent $p$, child $c$, alternative $j$, and next-best option $k$, I estimate the reduced form equation

$$\text{Child follows to } j_{pcj} = \alpha \mathbb{1}\left[a_{p\tau} \geq 0\right] + f\left(a_{p\tau}; \theta^{g}\right) + \mu_{\tau} + \kappa_{k} + \varepsilon_{pcj}. \tag{1}$$

Admission thresholds are indexed by $\tau$ with the score required for admission being $\bar{a}_{\tau}$. Note that each alternative $j$ has multiple cutoffs $\tau$. On top of each admission group ($g$) having its own threshold, $j$ can consist of multiple choices as it contains many collapsed alternatives (programs within the same field).

I control for the cutoff-centered running variable $a_{p\tau} = a_{pg} - \bar{a}_{\tau}$ with the help of a linear polynomial $f\left(a_{p\tau}; \theta^{g}\right) = \theta_{0}^{g} a_{p\tau} + \theta_{1}^{g} a_{p\tau} \mathbb{1}\left[a_{p\tau} \geq 0\right]$, that is estimated separately for each admission group $g$ and above and below the cutoff. With 20 admission groups in the main sample of analysis, a total of 40 linear polynomials are included. Estimating the polynomials at the admission group level rather than separately for each cutoff requires assuming unchanging relationships between scores and outcomes across cutoffs within the same admission group. This assumption is relaxed in Table 5, where separate polynomials are included for each cutoff. While the results stay approximately the same, this exercise decreases statistical power substantially.

$\mu_{\tau}$ are cutoff fixed effects, and $\kappa_{k}$ fixed effects for the next-best alternative $k$. In total, the main regression controls for 33 190 cutoffs and 22 next-best fields.

While the reduced form effect estimated by equation 1 is most likely to be correctly identified, it would be more interesting to understand the effect of actually studying, graduating, or even working in a specific field. To get at these measures, I employ a fuzzy design and use if the parent was above the cutoff or not as an instrument:

$$\text{Child follows to } j_{pcj} = \beta \text{Parent enrolls in } j_{pj} + f\left(a_{p\tau}; \psi^{g}\right) + \nu_{\tau} + \xi_{k} + \upsilon_{pcj}, \tag{2}$$

$$\text{Parent enrolls in } j_{pj} = \pi \mathbb{1}\left[a_{pjg} \geq 0\right] + f\left(a_{p\tau}; \phi^{g}\right) + \eta_{\tau} + \chi_{k} + u_{pj}, \tag{3}$$

and similar for degree completion. In fact, it would have been even more interesting to know the effect of whether the parent works in an occupation related to the field of study. However, as we shall see below, the further in time we get from the actual treatment (admission), the less likely it is that the assumptions allowing us to interpret the IV coefficient $\beta$ as a local average treatment effect hold. Throughout this paper, I will therefore report IV results for both enrollment and degree completion, but focus on the former, since these are more likely to be unbiased.

What are the threats to properly identifying the local average treatment effect (LATE)? The exclusion restriction holds if crossing the threshold only impacts the choices of children through enrollment (or graduation). This assumption clearly holds for enrollment, since a parent who is admitted but does not enroll has no additional knowledge about the field. Because a degree usually takes many years to complete, however, it is possible that also a parent who never earns a degree gains enough knowledge from their studies to impact the education trajectories of their children — invalidating the assumption of exclusion. However, with many years between graduation and child outcomes, the measured effect is most likely a transmission of occupational knowledge rather than education-specific information, which would ensure the assumption holds to the extent parents who drop out end up going into different occupations. This threat is even stronger if we would instrument for if the parent works in an occupation related to the field.

Since all applicants prefer $j$ over their counterfactual $k$, it is unlikely our sample includes any defiers. However, there is likely a large group of always-takers, who will enroll in $j$ later, after having reapplied. To ensure the correct treatment status is ascribed to such individuals, I count everyone who enrolls in the field within 5 years as enrolled. Then, since rankings approximately reflect true relative preferences, crossing the threshold should not make individuals more inclined to enroll in $k$, and we should not have any applicants defying treatment, ensuring that the monotonicity assumption holds.

In addition, Kirkebøen et al. (2016) show that another assumption is needed for the IV models to estimate the LATE when there are heterogeneous unordered treatments (fields of study with different next-best fields). The *irrelevance* condition holds if, when crossing the threshold to a specific alternative $j$ does not make the individual enroll or graduate in $j$, it also does not make them enroll or graduate in another field $j'$. When paired with fixed effects for the next-best alternative $k$, this assumption ensures we estimate the LATE. Does the assumption hold? Again, it seems indisputable that it holds for enrollment as admission has no other effect on an individual than through their possible enrollment. For degree completion, it is possible that admitted applicants who do not complete their studies become more likely to graduate from a related field. For example, someone who almost finishes an engineering degree can count most of their credits towards a degree in the more practical field of technology.[17]

Furthermore, even if exclusions, monotonicity, and irrelevance hold, a recent paper argues that the IV estimator, $\beta$, captures the LATE of enrolling in $j$ on child education choices if and only if the specification includes *rich covariates* (Blandhol et al. 2022). Otherwise, the IV estimand will actually contain negatively weighted always-takers. In our case, since admission is quasi-random when comparing those above and below a specific cutoff, inclusion of cutoff fixed effects ensures that the model is saturated.

To summarize, while estimates using parental enrollment can safely be interpreted as LATE, it is not certain the assumptions hold when instrumenting for degree completion. Since obtaining a degree is a central pathway through which any inheritance of fields of study must work, however, I have included estimates from the specification in the paper. These results should be interpreted with caution.

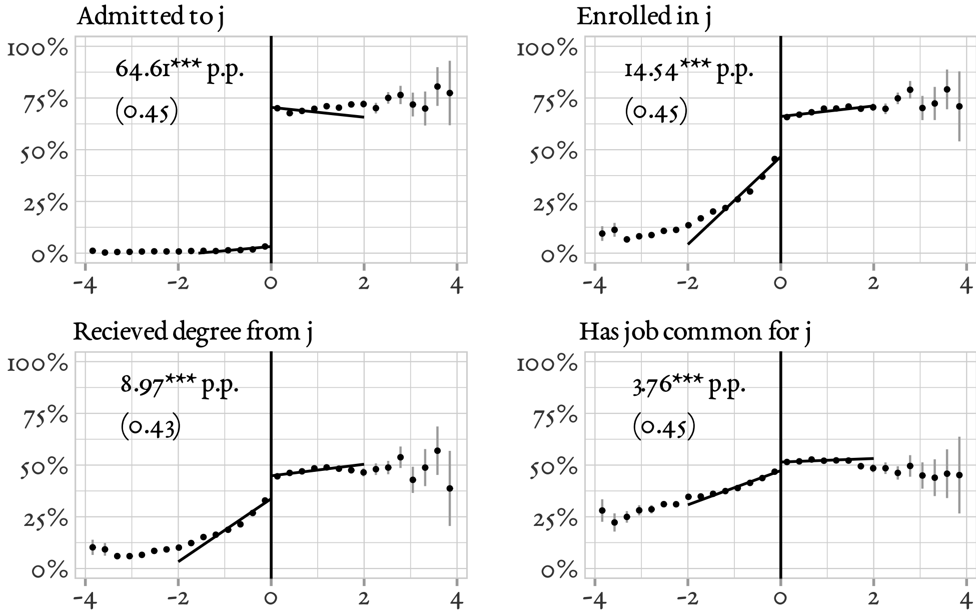
Finally, for an IV approach to be meaningful the first stage must have an adequate effect on the instrumented variables. Figure 4 and Table B.1 show clear jumps at the cutoff for parental admission, enrollment, degree completion, and employment in a field-typical job. The paper only includes results for the three first variables, since apart from the estimation likely being biased, the first stage coefficient for the last variable is quite small. All results tables in the paper report first stage Wald statistics, which are far above conventional weak instrument thresholds.

I include multiple definitions of the outcome variable to assess the strength of the transmission effect. In a weaker specification, following simply means that the child ranks $j$ highest in their own application (called "Ranks 1st" in the regression tables). I also study if the child enrolls or earns a degree in $j$.

I estimate the regressions using OLS and 2SLS by first demeaning the data by the threshold fixed effects using the R package fixest (Bergé 2018). Unless otherwise stated, I include applications with scores at most 1 standard deviation away from the cutoff. Since the results are weighted averages of a large set of cutoffs, traditional optimal bandwidth calculations do not apply. Figure 8 shows that the results are very robust to bandwidth size. In fact, some of the smallest effect sizes are found at the chosen bandwidth size.

17. It should be noted however that Kirkebøen et al. (2016) themselves, in an estimation that is very similar to what is presented in this paper, instrument for degree completion and argue that the irrelevance condition does hold.

Figure 4. Treatment take up around the cutoff




*Notes:* The plot shows admission, enrollment, degree completion, and employment in the preferred field $j$ above and below the cutoff. Admission score is standardized by semester and admission group and centered at the cutoff. Applicants with a score exactly at the cutoff but where a tie-breaking mechanism has ensured they are not admitted have been included in the bin below the cutoff. First stage coefficients from Table B.1 are reported in percentage points within each plot, with standard errors in parentheses.

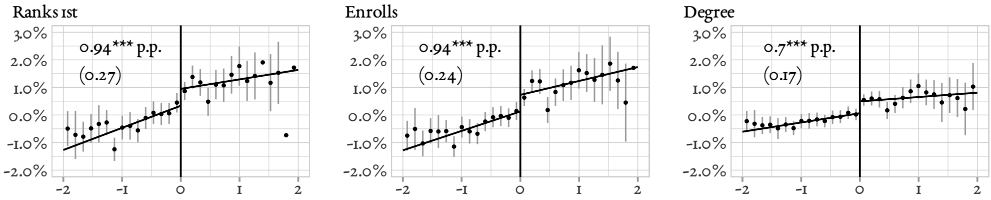
For some exercises that require substantial statistical power, I instead use all observations within 4 standard deviations. Finally, observations are weighted using a triangular kernel, giving linearly decreasing weights to observations further away from the cutoff.

# 4 Main results

We start by studying the results graphically. Figure 5 plots the three outcome variables: (1) if the child ranks field $j$ first in an application to university, (2) if they enroll in $j$, and (3) if they earn a degree from $j$. The observations are grouped in equally sized bins and plotted as functions of the running variable, demeaned for each cutoff. The sample includes all parent applicants with children born before the end of 1998. Inside each plot, the reduced form regression coefficients from Table 3 are reported. These are estimated using triangular kernels and include 20 separate linear polynomials of the running variable on each side of the threshold; one for each admission group.

Table 3 also includes estimates from the IV specifications. Parental enrollment increases the likelihood that a child will earn a degree in the same field by approximately 98% or 4.7 percentage points. We find the largest effects when scaling with degree completion instead of enrollment. When a parent earns a degree in a certain field, the likelihood that their child does the same increases with 155% or 7.5 percentage points. While this aggregate effect is large, it is substantially smaller than many of the correlations displayed in Figure 1. The effects on enrollment are somewhat smaller in relative terms, with

Figure 5. Inheritance of fields of study




*Notes:* The plots show the share of children following their parents above and below the cutoff. Linear polynomials fitted with a triangular kernel on the full width of the included data (two standard deviations) are included. Applicants with a score exactly at the cutoff but where a tie-breaking mechanism has ensured they are not admitted have been included in the bin below the cutoff. Inside the plot, coefficients from Table 3 are reported. These are fitted using separate linear polynomials for each admission group and a bandwidth of 1 standard deviation.

an effect of 6.4 percentage points (49%) for parental enrollment and 10.1 p.p. (78%) for parental degree completion. Interestingly, the change in likelihood that a child ranks the parent's field of study first in their application is exactly the same as for enrollment, but with a larger control group mean, leading to smaller relative effects (6.4p.p. or 38% for enrollment and 10.1p.p. or 61% for degree completion).

Table 3. Inheritance of fields of study

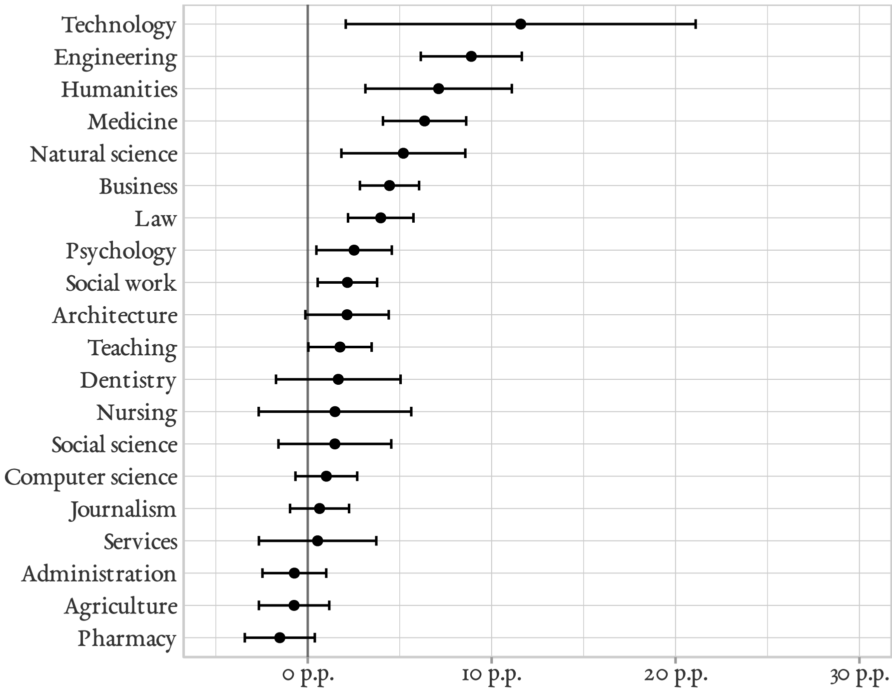
| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 0.94*** | 0.94*** | 0.70*** |
| | (0.27) | (0.24) | (0.17) |
| Parent enrolls in $j$ | 6.38*** | 6.36*** | 4.72*** |
| | (1.82) | (1.63) | (1.12) |
| Parent receives degree in $j$ | 10.07*** | 10.05*** | 7.45*** |
| | (2.88) | (2.57) | (1.78) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 946 | 946 | 946 |
| 1st stage Wald (degree) | 412 | 412 | 412 |

*Notes:* Each row reports coefficients from different models. The sample includes parents with children born before 1999. Table D.1 shows the same results but for a narrow field definition. Table A.5 instead presents results for all applicants, irrespective of if they have children or not. Coefficients and standard errors are reported in percentage points. All regressions use triangular kernel weights, and include linear polynomials of the running variables above and below the cutoff to each admission group, as well as fixed-effects for the cutoff and the next-best field. Standard errors are clustered at the cutoff and family level.

† $p \le 0.1$, * $p \le 0.05$, ** $p \le 0.01$, *** $p \le 0.001$.

The aggregate effects are weighted averages of heterogeneous treatment effects across 20 fields of study and 32 000 cutoffs. Figure 6 displays a coefficient plot of the field-level IV estimates of parental enrollment on child degree completion. The fields are sorted by the size of the point estimate.

Figure 6. Inheritance of fields of study




*Notes:* The figure reports coefficients of parental enrollment on child degree completion using the same specification as in Table 3 but with a separate coefficient estimated for each preferred field $j$ and a bandwidth of 4 standard deviations. The exact coefficients are reported in Table B.2.

Several interesting patterns can be seen in this graph. First, there is large variation in the likelihood that children follow their parents. Technology has the largest point estimate, followed by engineering, humanities, medicine, natural science, and business. Three fields have negative point estimates, but these are not significantly different from zero. When compared to the control group means displayed in Table B.2, we see that most of these relative effects are substantially smaller than the correlations reported in Figure 1. Exceptions include technology and natural science, with relative effects of about the same size as the correlations. Furthermore, the average degree completion among children whose parents were not admitted tells us something about the popularity of each field. Apart from teaching, we find all the most popular fields at the top.

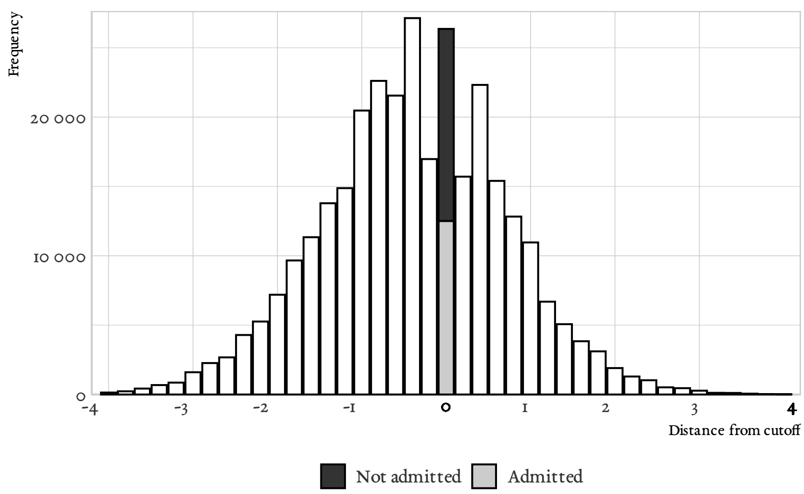
Appendix Section D presents the same analysis but with applications collapsed by the narrow fields used by SCB. The aggregate effects are only somewhat smaller in magnitude, likely because these measures do not include inheritance across closely related narrow fields, such as different engineering subfields. Figure D.2 shows, among other things, that some subfields of technology and engineering are inherited more often than others. Humanities, which is among the most commonly inherited broad fields, does in fact include the narrow field least likely to be inherited, Theology (25T). With this categorization, it is likely that many of the treated parents who have an engineering field as their preferred option, might have a different kind of engineering as their next-best alternative. This might explain why some engineering fields are imprecisely estimated. While a degree in a broad field can have many specializations, the treatment effects are more clear. As the tables in Section D show, when the main analysis is replicated using narrow fields, the robustness and overall conclusions of the paper remain unchanged.

# 5 Robustness

Regression discontinuity designs put strong requirements on the data. The main identifying assumption stipulates that the control function needs to be continuous at the cutoff. In other words, should it not be for admission, nothing would differ between applicants just above and below the cutoff. Since the exact level of the cutoff changes each year, applicants cannot know with certainty whether they will be admitted before applying, meaning that there is no way to precisely manipulate admission status. By construction, such a system ensures a continuous control function. To confirm that no other, deterministic, allocation has been used, and to verify the validity of the identification strategy, this section includes a number of robustness checks. The section also presents alternative specifications showing that the results are not sensitive to the exact choice of bandwidth or estimation strategy.

To begin, Figure 7 plots the distribution of the running variable. Applicants exactly at the cutoff (where a tie-breaker has been used) are sorted into a separate bin and their admission status is indicated in shades of gray. In the main analysis, these applicants are counted as below the cutoff whenever the tie-breaking procedure would predict them to not be admitted, and above the cutoff otherwise. The analysis in Table A.2 instead excludes these observations without much change to the estimates. In Figure 7, we see no indication of bunching on either side, or exactly at, the cutoff.

Figure 7. Histogram of the running variable




*Notes:* Histogram of the running variable around the cutoff. Applicants exactly at the cutoff are sorted separately and the shade of the middle bar indicated whether the tie-breaking mechanism admitted them or not.

We saw in Figure 2 that parental admission is not significantly related to characteristics measured before treatment assignment. An additional way to check that parents at the margin are not somehow able to select into the field they prefer is through the placebo analysis presented in Table 4. The estimation uses the same setup as the main analysis, but I instead look at the effect of child admission on parental educational outcomes. The quasi-random assignment of children to fields does not significantly affect the application, enrollment, or degree completion of parents. This indicates that the RDD estimates do not erroneously capture spurious selection into fields within families.

Table 4. Placebo

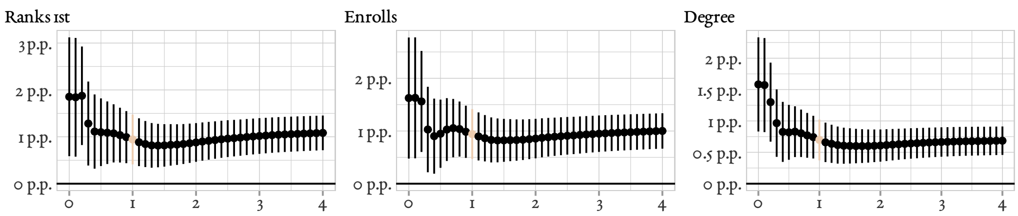
| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 0.008 | 0.02 | −0.03 |
| | (0.18) | (0.19) | (0.17) |
| Parent enrolls in $j$ | 0.04 | 0.08 | −0.16 |
| | (0.89) | (0.94) | (0.87) |
| Parent receives degree in $j$ | 0.14 | 0.30 | −0.55 |
| | (3.15) | (3.32) | (3.07) |
| Observations | 557 743 | 557 743 | 557 743 |
| Control group mean | 8.89% | 9.85% | 7.18% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 2175 | 2175 | 2175 |
| 1st stage Wald (degree) | 276 | 276 | 276 |

*Notes:* The table shows results from a placebo estimation where the admission status of the child is used to study the choices of the parent. Since the parent's application happened long before the child's, we expect to see no pattern.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Figure 8 shows reduced form results for various bandwidth choices. In choosing the bandwidth, we face the classic bias-variance trade off, where a larger bandwidth means more statistical power at the cost of potentially increasing bias. In normal RDD analysis, optimal bandwidth procedures yield balanced bandwidth choices. But since I am pooling a large set of quasi-experiments, such calculations couldn't possibly be optimal for all cutoffs. Instead, I use a bandwidth of 1 standard deviation for all aggregate analysis (marked in a lighter color in the plot), and a bandwidth of 4 when studying field-level heterogeneity. The choice of a bandwidth of 1 yields one of the smaller reduced form effects across all three outcomes. The figure clearly shows that there is little variation in the size of the effect as the bandwidth changes, except that smaller bandwidths yield even larger effects. The aggregate effect does not change much when the bandwidth is increased above 1. I exploit this fact and include all observations within 4 standard deviations in the analysis of effect heterogeneity across fields.

Figure 8. Reduced form results by bandwidth size




*Notes:* Each plot shows the main reduced form effect of a parent being above the cutoff on their child's application, enrollment, and degree completion. The leftmost bar in each plot has a bandwidth of zero and only includes applicants exactly at the cutoff where different tie-breaking mechanisms were used to allocate students. For the aggregate analysis, I use a bandwidth of 1 standard deviation, marked in a lighter color in the plot.

Applicants select into fields, but also admission groups and programs within fields. This is why I include cutoff fixed effects in all specifications. Since an applicant has one score per admission group it should be sufficient to include linear polynomials for each such group. However, this means that I am not actually estimating distinct RDD models for each quasi-experiment. To do so, the polynomial should be estimated at the cutoff level as well. Table 5 presents results from such an exercise, where a linear polynomial is fitted above and below each of the approximately 32 000 cutoffs. While this exercise is very taxing on statistical power, the estimates barely change.

Table 5. Separate slopes for each cutoff

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 0.95** | 0.93** | 0.61** |
| | (0.35) | (0.31) | (0.21) |
| Parent enrolls in $j$ | 6.58** | 6.43** | 4.24** |
| | (2.40) | (2.13) | (1.47) |
| Parent receives degree in $j$ | 10.01** | 9.79** | 6.45** |
| | (3.66) | (3.24) | (2.25) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 557 | 557 | 557 |
| 1st stage Wald (degree) | 259 | 259 | 259 |

*Notes:* The table shows the same results as in Table 3 but with distinct linear polynomials of the running variable above and below each cutoff.
† $p \leq 0.1$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Additional robustness and validity checks are performed in the appendix. Figure A.1 shows that the effect disappears as soon as the admission cutoff is moved away from zero. Table A.1 adds quadratic polynomials with little impact on results. Table A.2 shows that the results stay approximately the same (albeit become more noisy) when applicants exactly at the cutoff are removed. The results in Table A.3 are based on a sample where only those fields that were ranked first by the parent are included, to overcome potential problems with incentive compatibility. These results are again very similar to the main findings, but less precise. Next, Table A.4 includes fixed effects for the priority ranking of the application with little impact on estimated coefficients. Last, Table A.5 shows that relative effects barely change at all when I add those individuals who have no children to the sample.

# 6 Exploring mechanisms

There exists a strong and robust causal relationship between the field of study choices of parents and their children. But why and how are fields of study inherited? In this section, I try to answer this question by studying subsets and correlations across different parts of the data. I begin by analyzing the link between field of study and occupation to see if it is in fact the occupation of the parent that is inherited. I then turn to the family, to understand the role of gender and family composition. Last, I ask if it is at all beneficial for children to follow their parents' field of study choices.

Swedes often have children only after graduating from university. In the sample studied in this paper, parents are on average 22 years old when they apply to university and 50 when their children apply. In itself, this empirical fact makes it very likely that the causal effects reported in this paper work through the occupational choices of parents as well as through the knowledge they gain during their studies. There are few other pathways through which the treatment could persist for so long. For certain fields, a university degree is the only way to earn an occupational license[18], and some other occupations (like engineers and therapists) are clearly linked to university degree programs. Most occupations are not protected, however, and employees can have a number of different degrees, or sometimes no degree at all.

Figure 9 is an attempt at illustrating the complicated relationship between fields of study and occupation. Working age Swedes with university degrees are sorted by their occupation in 2017 using Swedish 3-digit SSYK occupation codes (see Table E.2 for a codebook). We see exactly the pattern described above. Graduates from fields where it is possible to gain an occupational license end up in relatively few different occupations, while e.g. social science leads to a large variety. When this figure is compared to the field heterogeneity results in Figure 6, it seems far from obvious why technology, engineering, humanities, medicine, natural science, and business should be on top.

Could the effect go through something other than the occupation of the parent? It is possible that fields like humanities make parents more inclined to actively teach their children the knowledge that they gained, sparking an interest in the topic itself. Humanities likely also has more room for nepotism, when compared to other fields, since the labor market is very saturated and success highly dependent on social capital. I cannot completely rule out this mechanism, and it seems likely it explains part of why humanities is one of the most followed subject. However, as we shall see, many of the results below indicate that the occupational pathway is indeed strong.

There seems to be no clear relationship at the field level between the fields of study that unambiguously map into occupations and the likelihood that the field is inherited. But what about the individual level? For each field, there are some occupations that most graduates work in, or where almost all workers have a degree from a specific field. I refer to these jobs "common jobs" and mark them in gray in Figure 7. These are occupations where more than 3% of the graduates work, or where more than 30% of the workforce have degrees from a specific field.[19] Table 6 shows the interaction of parental enrollment with whether the parent has a job common for field $j$ at some point when the child is between 16 and 18 years old, separately for each field. In Table 7, we look deeper at the aggregate results and evaluate if the result is strengthened if also the other parent works in a common job.[20]

While the effect is strong on the aggregate level, most field level estimates are not significant. Many of the largest interaction effects are for the most popular fields, except for technology which is barely affected at all by if the parent has a job in the field or not. The effect on law, medicine and engineering is more than doubled, perhaps because these fields of study so clearly map to occupations. In addition, the aggregate effect is only slightly strengthened if both parents work in such an occupation, as we see in Table 7.

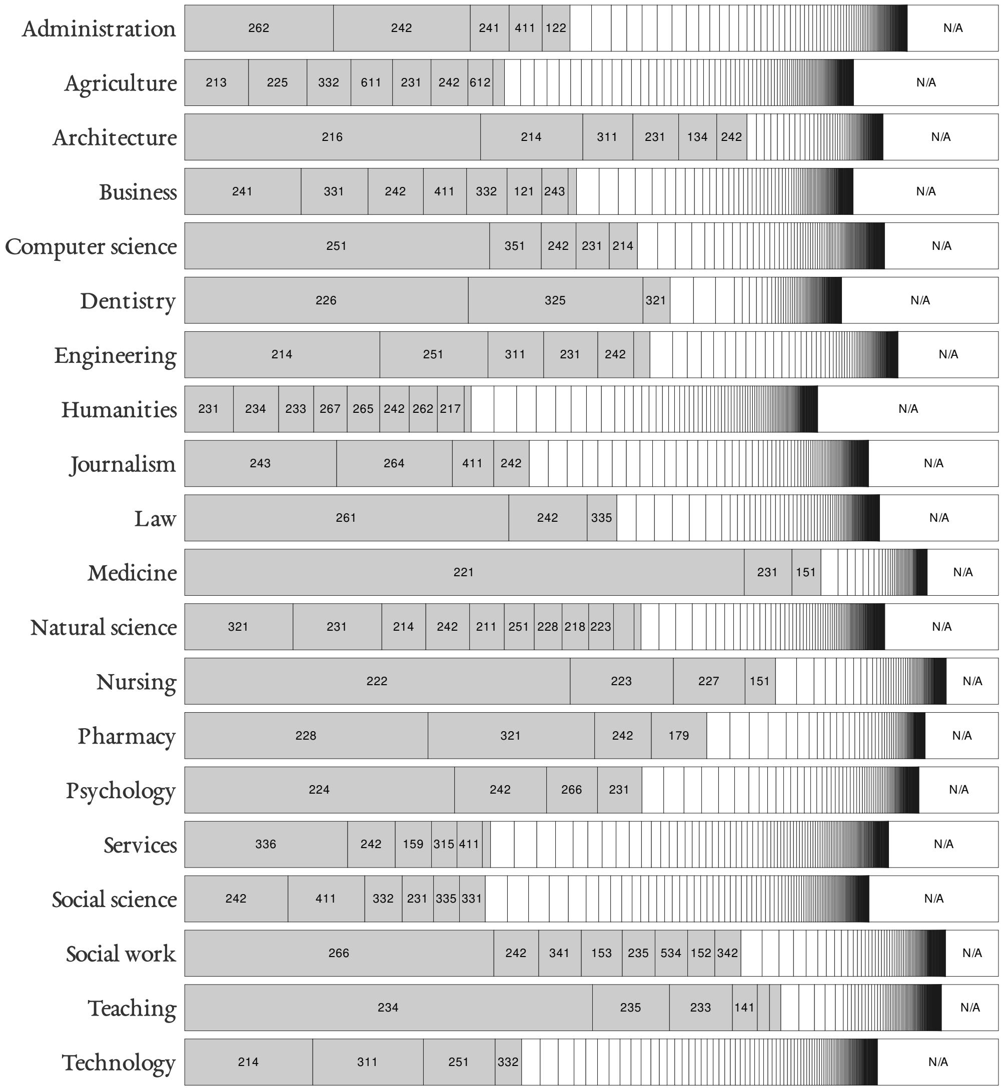
Table 8 reports an attempt to correlate the parents' labor market experience with field inheritance. It shows parental enrollment interacted with the individual-level predicted earnings of the parent should

18. For at least a part of the studied period, the following fields allowed graduates to pursue occupational licenses: medicine, nursing, law, architecture, teaching, dentistry, psychology, and pharmacy.

19. These levels are calibrated to minimize the number of wrongly classified occupations. For medicine, for example, I include medical doctors (221) and health care managers (151). For a full codebook see Table E.2.

20. I use the term "other parent" to clarify that I look at the other biological parent and disregard any post-birth family reorganization by e.g. divorce.

Figure 9. Most common occupations by field




*Notes:* For each field of study, the figure plots the share of university degree-holders among the full Swedish population who in 2017 work in different 3-digit occupation codes (SSYK 2012). Occupations highlighted in gray are counted as "most common" and include those occupations where either more than 3% of all degree-holders from the field work, or where more than 30% of workers have a degree from the field. This definition of common jobs is used in Table 7.

Table 6. Importance of parent occupation by field of study

| | Child enrollment | | | | Child degree completion | | | |
|---|---|---|---|---|---|---|---|---|
| Field | Enrolls | | × Common job | | Earns degree | | × Common job | |
| Administration | 3.56 | (4.70) | −5.61 | (6.13) | −0.67 | (1.02) | −0.28 | (1.12) |
| Agriculture | 2.09 | (1.66) | −2.42 | (1.94) | −1.00 | (0.91) | 0.41 | (1.27) |
| Architecture | −0.38 | (1.91) | 2.82 | (3.05) | 1.41 | (1.53) | −0.05 | (2.13) |
| Business | 3.81** | (1.24) | −0.07 | (1.43) | 3.66*** | (0.98) | 0.70 | (1.17) |
| Computer science | 1.44 | (1.67) | −0.58 | (2.04) | 1.15 | (1.06) | −0.74 | (1.32) |
| Dentistry | 1.08 | (2.02) | −38.26 | (40.47) | 2.25 | (1.58) | −13.48 | (23.74) |
| Engineering | 6.45* | (2.54) | 7.06** | (2.45) | 5.51** | (1.70) | 4.83** | (1.63) |
| Humanities | 20.19*** | (5.47) | 7.07 | (7.14) | 5.04* | (2.33) | 5.13† | (3.09) |
| Journalism | −0.41 | (1.38) | 1.82 | (2.00) | −0.34 | (0.96) | 1.62 | (1.53) |
| Law | 3.17* | (1.47) | 6.85*** | (1.69) | 2.33* | (1.03) | 3.79** | (1.33) |
| Medicine | 5.25*** | (1.40) | 7.64† | (4.05) | 4.43*** | (1.23) | 4.29 | (3.23) |
| Natural science | 14.23** | (4.64) | 1.37 | (5.59) | 3.96* | (1.79) | 2.53 | (2.32) |
| Nursing | 1.27 | (3.69) | 15.32† | (8.62) | 1.39 | (2.47) | −0.30 | (5.86) |
| Pharmacy | −1.10 | (1.48) | −0.79 | (2.53) | −3.10* | (1.26) | 2.61 | (1.60) |
| Psychology | 0.49 | (1.39) | 2.89 | (2.05) | 1.72 | (1.28) | 2.02 | (1.54) |
| Services | 3.60 | (2.89) | −7.59 | (5.63) | 1.08 | (1.80) | −3.96 | (3.75) |
| Social science | 0.54 | (2.46) | 1.03 | (2.77) | 0.50 | (1.86) | 2.03 | (2.13) |
| Social work | 1.84 | (1.18) | 1.15 | (1.41) | 2.44* | (0.97) | −0.99 | (1.14) |
| Teaching | 2.39 | (1.46) | −2.00 | (2.76) | 1.74† | (1.00) | −0.11 | (1.79) |
| Technology | 19.95** | (7.18) | −0.03 | (7.26) | 11.93* | (4.77) | −0.89 | (4.70) |
| Aggregate | 3.32*** | (0.92) | 3.12*** | (0.71) | 2.35*** | (0.62) | 2.26*** | (0.47) |

*Notes:* The table shows results for child degree completion. Parental enrollment is interacted with field of study and if the parent works in a job that is common for the field during the years when the child is 16-18 years old. The last row shows aggregate results. The estimation follows the same approach as Table 3, but with a bandwidth of 4 standard deviations.

† $p \leq 0.1$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

they earn a degree from $j$. The prediction is based on pre-treatment characteristics such as gender, birth year, high school GPA, immigrant status and field fixed effects to avoid capturing any direct effect of enrollment in $j$ on earnings. The estimation includes an interaction of parental enrollment with the predicted earnings of graduating from $j$. For those predicted to earn the least, the effect of parental enrollment is negative. The individuals in the sample predicted to earn the least are in the 23rd percentile of their cohort. Yet, also at that level, two out of three estimates sum to a negative effect. Looking at degree completion, for example, children only follow parents predicted to end up in the 36th percentile or higher. Also note the negative baseline, indicating that children of parents with higher predicted earnings on average have less correlated preferences.

Next, we turn to a characteristic of the fields themselves. By looking at the average GPA among those enrolled in $j$ at the same time as the treatment, we can evaluate how the likelihood that children follow their parents correlates with the popularity of the education. Table 9 reports results from this exercise. We see that while most coefficients are positive, none of the interactions are significant. Average GPA is measured in standard deviations. For the included fields, it ranges from −0.09 to 2.07. Even at these extremes, the academic quality of a parent's peers has little impact on child following.

While we observe few cases of negative effects when organizing fields by their academic popularity

Table 7. Parent occupation — both parents

| | Ranks 1st | Enrolls | Earns degree | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|---|---|---|
| Parent enrolls in $j$ | $4.52^{**}$ | $4.09^{**}$ | $3.36^{**}$ | $3.51^{*}$ | $3.18^{*}$ | $3.17^{**}$ |
| | (1.74) | (1.54) | (1.05) | (1.75) | (1.55) | (1.04) |
| × Parent has job common for $j$ | $2.77^{\dagger}$ | $4.39^{**}$ | $2.87^{**}$ | $3.39^{\dagger}$ | $4.60^{**}$ | $2.17^{*}$ |
| | (1.52) | (1.40) | (0.95) | (1.75) | (1.59) | (1.07) |
| × Other parent has job common for $j$ | | | | $5.56^{**}$ | $4.98^{**}$ | 0.99 |
| | | | | (2.04) | (1.88) | (1.22) |
| × Both parents have job common for $j$ | | | | $-5.21^{\dagger}$ | −3.68 | 1.20 |
| | | | | (3.15) | (2.92) | (2.00) |
| Parent has job common for $j$ | 1.32 | −0.63 | −0.91 | 0.23 | −1.41 | −0.93 |
| | (1.22) | (1.11) | (0.77) | (1.35) | (1.23) | (0.83) |
| Other parent has job common for $j$ | | | | $2.18^{**}$ | $1.73^{*}$ | $1.04^{*}$ |
| | | | | (0.83) | (0.76) | (0.50) |
| Both parents have job common for $j$ | | | | $3.27^{\dagger}$ | 2.48 | 0.02 |
| | | | | (1.91) | (1.77) | (1.21) |
| Observations | 402 649 | 402 649 | 402 649 | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 2647 | 2647 | 2647 | 1185 | 1185 | 1185 |

*Notes:* Parental enrollment is interacted with if the parent works in a job that is common for the field during the years when the child is 16–18 years old. Common jobs are marked in gray in Figure 9 and described in Table E.2. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table 8. Field inheritance by parent predicted earnings percentile

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | −2.88 | −1.96 | −5.25 |
| | (5.67) | (5.15) | (3.23) |
| × Predicted earnings pt. | $12.93^{\dagger}$ | $12.09^{\dagger}$ | $14.51^{***}$ |
| | (7.04) | (6.47) | (4.19) |
| Predicted earnings pt. | 1.68 | −1.29 | $-5.95^{**}$ |
| | (3.82) | (3.52) | (2.28) |
| Observations | 354 598 | 354 598 | 354 598 |
| Control group mean | 16.83% | 13.27% | 4.87% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 296 | 296 | 296 |

*Notes:* Parental enrollment is here interacted with the predicted earnings percentile of the parent. The predicted earnings percentile is calculated from a logit regression of the full population birth cohort percentile of average yearly earnings between 10 and 20 years after application on pre-treatment characteristics (gender, birth year, high school GPA, and immigrant status) and application year and field fixed-effects. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table 9. Field inheritance by average GPA among enrolled

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | 5.02$^{\dagger}$ | 5.87$^{*}$ | 4.12$^{*}$ |
| | (2.81) | (2.52) | (1.65) |
| × Avg. GPA among enrolled | 1.77 | 0.64 | 0.78 |
| | (1.98) | (1.72) | (1.15) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 551 | 551 | 551 |

*Notes:* Parental enrollment is interacted with the average standardized high school GPA among all students who enroll in $j$ during the application semester.
$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

in Table 9, using predicted earnings shows that a considerable share of children become less likely to study a field if their parents enroll. Furthermore, while not significant, many field-level interactions in Table 6 are negative, sometimes also leading to a negative total effect. If the only reason children follow their parents was because of comparative advantage we should not see such negative influence.[21] That we do points at the existence of additional mechanisms.

These findings show how important field of study choices are to understand occupational inheritance. The results underscore the importance of the labor market experience of the parent. Children do not follow parents who are predicted to have relatively bad experiences, and often become much more likely to follow parents who work in a related occupation. A result further strengthening this thesis is reported in Table B.3. When grouped by the age of the parent at child application, we see little impact of age except if the parent has reached the retirement age of 65. At this age, the effect drops substantially.

We next turn to the family. Table 10 divides the sample by parent-child gender composition. Like in Dahl et al. (2021) and several correlational studies, fathers exert a stronger influence, especially on sons. However, also the choice of mothers matter, especially for their daughters. For many fields, children are more likely to follow the parent of their own gender. There are exceptions, however. Sons follow mothers more often than fathers to engineering and medicine, while daughters follow fathers more often to engineering and law.[22] Furthermore, daughters follow their mothers to some fields where the effects for sons, as well as the aggregate results, are weak or insignificant: social work, teaching, psychology — all female dominated fields. In contrast to Dahl et al. (2021), I do not find much evidence of parents exerting a stronger influence when their field choice is not conforming to gender stereotypes. In engineering, mothers influence sons more than fathers, but fathers influence daughters more. Neither of these differences are statistically significant, however. In most cases, it seems stereotypical choices are more influential, especially for children of the same sex.

A likely explanation for why the effect is often weaker for mothers, which is echoed in several of the cited studies, is that mothers less often pursue careers in occupations related to the field that they graduated from. Since mothers are more than twice as likely as fathers to end up with a partner with a degree from field $j$ if they are quasi-randomly admitted to the field (see Table B.5), they could be directly

21. As long as enrollment in a field makes the parent more likely to work in a related occupation, which is what the fourth plot in Figure 4 indicated.

22. As can be seen in Table 10, most field-level differences across gender pairs are not statistically significant.

Table 10. Field inheritance and gender composition

| Field | Father - Son | | Father - Daughter | | Mother - Son | | Mother - Daughter | |
|---|---|---|---|---|---|---|---|---|
| Administration | −1.43 | (1.35) | −1.91 | (1.60) | −0.33 | (0.94) | −0.30 | (1.35) |
| Agriculture | −1.57 | (1.29) | −2.03 | (1.73) | −0.30 | (1.47) | 1.16 | (2.05) |
| Architecture | 1.50 | (1.74) | $4.11^{*}$ | (2.03) | 1.73 | (1.90) | 1.18 | (1.59) |
| Business | $5.85^{***}$ | (1.30) | 1.98 | (1.27) | $5.15^{***}$ | (1.22) | $4.74^{**}$ | (1.49) |
| Computer science | $3.02^{*}$ | (1.51) | −0.54 | (1.08) | 0.75 | (1.50) | 0.78 | (1.44) |
| Dentistry | $5.12^{*}$ | (2.53) | 5.76 | (3.83) | −1.62 | (2.34) | −4.27 | (3.08) |
| Engineering | $10.02^{***}$ | (2.04) | $7.43^{***}$ | (1.61) | $12.99^{***}$ | (2.40) | $6.37^{**}$ | (2.18) |
| Humanities | $7.63^{\dagger}$ | (4.23) | 6.43 | (5.37) | $6.69^{*}$ | (2.66) | $6.35^{*}$ | (2.91) |
| Journalism | $-1.64^{\dagger}$ | (0.88) | 3.83 | (2.42) | 0.62 | (1.08) | 0.15 | (1.46) |
| Law | $3.58^{**}$ | (1.38) | $5.23^{***}$ | (1.57) | $2.27^{*}$ | (1.11) | $4.78^{***}$ | (1.25) |
| Medicine | $3.71^{\dagger}$ | (1.96) | $7.07^{***}$ | (1.98) | $6.71^{***}$ | (1.83) | $8.72^{***}$ | (2.17) |
| Natural science | $5.59^{**}$ | (2.07) | $5.82^{*}$ | (2.48) | 2.48 | (2.94) | 4.84 | (3.57) |
| Nursing | 4.84 | (4.90) | 4.10 | (5.52) | 1.32 | (1.82) | −0.06 | (2.99) |
| Pharmacy | $-8.14^{\dagger}$ | (4.28) | 5.52 | (6.39) | −1.03 | (0.65) | −2.61 | (1.68) |
| Psychology | 0.55 | (1.59) | 1.29 | (2.05) | 2.10 | (1.30) | $4.66^{*}$ | (2.05) |
| Services | 0.93 | (3.55) | −4.26 | (3.60) | 2.54 | (2.60) | −0.16 | (2.29) |
| Social science | −1.09 | (2.37) | −0.79 | (2.91) | 1.99 | (1.95) | 3.99 | (2.66) |
| Social work | −1.04 | (1.15) | 2.21 | (2.18) | 1.09 | (0.75) | $4.03^{**}$ | (1.41) |
| Teaching | −0.08 | (1.15) | 2.61 | (1.73) | 1.16 | (0.91) | $2.22^{\dagger}$ | (1.25) |
| Technology | $16.16^{*}$ | (6.48) | $12.04^{*}$ | (4.98) | 2.30 | (7.72) | 11.06 | (7.62) |
| Aggregate | $5.01^{***}$ | (0.74) | $2.19^{**}$ | (0.73) | $3.40^{***}$ | (0.64) | $3.74^{***}$ | (0.72) |

*Notes:* The table reports effects for child degree completion. It shows results from a regression where parent enrollment is interacted with field as well as parent and child gender. Otherwise, the estimation follows the same approach as Table 3, but with a bandwidth of 4 standard deviations. The effects reported are linear combinations of interaction and baseline coefficients with significance levels referring to hypothesis tests against a null of no combined effects. See Table B.4 for the raw interactions.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

influencing their children even less than the previous results indicate. In Table 11 we see that there is a strong inheritance effect for mothers even if the other parent does not have a degree in the same field. With two parents with degrees in $j$ the effect is even stronger, both for mothers and fathers.

The appendix presents three additional analyses on this topic. Table B.6 shows that the effect decreases quickly and almost monotonically with birth order. Parental enrollment affects the likelihood to choose field $j$ almost 50% as much for firstborns when compared to second-borns, and has more or less disappeared for fourth-borns. Second, the analysis in Table B.7 exploits the fact that conditional on having two children, the gender of the second is random. While the table repeat how much more often first-borns follow their parents, and that daughters are slightly less affected, the gender of the second child seems to have very little, if any, effect on field inheritance. This goes against the hypothesis that female firstborns only inherit the parent's occupation if there is no later-born son who can do so instead. Finally, separately estimating the inheritance effect by the education level of the grandparents yields the results presented in Table B.8. These results are imprecise, but indicate a stronger effect for families with at least some higher level education — probably because children in such families are more likely to apply to university at all.

Appendix sections C investigates alternative margins of admission, as a way to benchmark the estimated effects. Instead of fields, the section explores inheritance of institution and location choice. Hav-

Table 11. Field inheritance and assortative mating

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | 5.29** | 5.09** | 4.44*** |
| | (1.93) | (1.77) | (1.20) |
| × Parent female | −0.82 | −0.40 | −1.06 |
| | (1.37) | (1.26) | (0.82) |
| × Other parent has degree in $j$ | 3.17 | 7.22† | 3.71 |
| | (4.38) | (4.08) | (3.12) |
| × Parent female × other parent has degree in $j$ | 2.18 | −3.22 | 2.55 |
| | (6.14) | (5.83) | (4.30) |
| Parent female | −0.32 | −0.008 | 0.51 |
| | (0.67) | (0.61) | (0.40) |
| Other parent has degree in $j$ | 7.12* | 2.45 | 0.65 |
| | (3.52) | (3.25) | (2.51) |
| Parent female × other parent has degree in $j$ | −1.09 | 2.98 | −1.49 |
| | (4.78) | (4.53) | (3.37) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 570 | 570 | 570 |

*Notes:* Otherwise, the estimation follows the same approach as Table 3.

† $p \leq 0.1$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

ing a parent enrolling in a specific institution increases the likelihood that a child earns a degree from that school with 6.51 percentage points or 108% (Table C.1). Most estimates of institution inheritance follow this pattern: the absolute effects are considerably larger in magnitude when compared to the main results, but because parents and children tend to have more correlated preferences for institutions, the relative effects are about the same. In fact, it seems inheritance of institutions is mainly driven by location choice persistence, with the measures of location inheritance in Table C.2 closely mirroring those for institutions.

The final section of this section steps away from the regression discontinuity analysis to evaluate if those children who follow their parents actually perform better. For each field, Table 12 reports how field graduation probability and earnings differ between those who have a parent with a degree in the field and those who do not. The analysis of graduation is done on individuals who have enrolled in a degree program in the field, and for earnings, I study children who have earned a degree. At the bottom, results from the aggregate analysis with fixed effects show small positive effects on graduation rate and earnings. However, these results mask substantial heterogeneity. Enrolled children are much more likely to graduate from some fields, but less likely to graduate from others. Since we are studying enrolled students only, not graduating means dropping out from the field or simply that they have not yet received the degree at the end of the sample period.

The effect on graduation probability seems to follow a different pattern than that of earnings. Out of the three fields with effects above 10, architecture, dentistry and services, only dentistry yields significantly higher earnings. Moreover, we observe large negative effects on graduation in administration and technology with weak effects on earnings, while humanities has a negative effect on earnings together with a strong effect on graduation. Considering that humanities is one of the most commonly inherited fields, these results speak to non-pecuniary explanations for why children inherit humanities so often. In

Table 12. Parent degree completion and child outcomes

| | Children who enroll in j | | | Children who receive degree in j | | |
|---|---|---|---|---|---|---|
| | Graduation probability (p.p.) | | N | Mean earnings age 30-35 | | N |
| Administration | $-6.01^{***}$ | (1.38) | 18 339 | $-0.93$ | (14.92) | 2886 |
| Agriculture | $-0.58$ | (1.79) | 6458 | $28.76^{**}$ | (10.24) | 1596 |
| Architecture | $14.58^{***}$ | (2.74) | 8699 | $-18.07$ | (14.95) | 1634 |
| Business | $-0.65$ | (0.60) | 58 112 | $57.86^{***}$ | (8.91) | 17 558 |
| Computer science | $-1.33$ | (1.74) | 22 961 | $48.97^{\dagger}$ | (25.01) | 3733 |
| Dentistry | $16.13^{***}$ | (2.32) | 4359 | $43.33^{***}$ | (11.74) | 1193 |
| Engineering | $1.55^{***}$ | (0.45) | 74 482 | $13.49^{**}$ | (4.24) | 19 735 |
| Humanities | $7.23^{***}$ | (0.79) | 29 766 | $-7.89^{\dagger}$ | (4.39) | 6914 |
| Journalism | 0.50 | (3.30) | 9994 | $-15.93$ | (31.62) | 1508 |
| Law | $3.83^{***}$ | (1.11) | 22 108 | $29.02^{**}$ | (9.23) | 6006 |
| Medicine | $2.93^{***}$ | (0.86) | 16 328 | $26.86^{***}$ | (5.51) | 7271 |
| Natural science | 1.05 | (0.93) | 27 694 | 1.81 | (5.69) | 8076 |
| Nursing | $3.91^{***}$ | (0.49) | 47 319 | $4.57^{\dagger}$ | (2.74) | 8136 |
| Pharmacy | $-1.08$ | (3.13) | 3527 | 21.43 | (20.46) | 787 |
| Psychology | $7.65^{**}$ | (2.34) | 8824 | $-1.61$ | (12.18) | 2969 |
| Services | $11.27^{***}$ | (1.37) | 10 543 | 11.87 | (9.84) | 1385 |
| Social science | $2.94^{***}$ | (0.71) | 35 034 | 6.74 | (6.50) | 5646 |
| Social work | $4.78^{***}$ | (1.10) | 18 472 | $20.10^{***}$ | (4.55) | 4144 |
| Teaching | $4.82^{***}$ | (0.36) | 75 470 | $3.92^{**}$ | (1.33) | 20 577 |
| Technology | $-7.36^{***}$ | (0.85) | 42 582 | 11.94 | (12.30) | 6286 |
| Aggregated | $2.79^{**}$ | (0.88) | 541 071 | $13.28^{*}$ | (5.26) | 128 040 |

*Notes:* This table reports results of a regression of graduation (left) and earnings (right) on parental degree completion among all children who have enrolled (left) or earned a degree (right) in each field. Earnings are measured in 1000s of 2020 SEK. The aggregate results at the bottom include field fixed effects.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

agriculture, business, computer science, dentistry, law, medicine and pharmacy, having a parent with a degree is correlated with earnings that are more than 20 000 SEK (2200 USD) per year higher. Some of these fields are among the most inherited ones (business, law, medicine), but pharmacy and agriculture are in fact the two fields least likely to be inherited. Pharmacy and agriculture are fields with large barriers to entry, ensuring high returns on parental resources. That we still see such small inheritance effects again speaks to the relative unimportance of comparative advantage. Furthermore, the coefficient for dentistry is almost twice the size of that for medicine. While healthcare is publicly funded in Sweden, the dentistry and pharmacy markets are almost completely privatized. Nepotism likely plays a role in explaining these results, since a child can start working at their parent's pharmacy or dentistry firm, for example.

# 7 Conclusion

Children are often 3–5 times more likely than average to graduate from a field that their parents have studied. This well-known pattern of intergenerational association has been shown in previous research to mainly apply to fathers and sons. In this paper, I exploited a quasi-experimental statistical design to investigate how much of this association can be attributed to causal mechanisms.

The field of study choice of a parent strongly impacts the educational trajectory of their children. I have shown that the likelihood that a child graduates from a field increases with 4.7 percentage points or 98% if the parent enrolls in that field, when compared to parents who apply to the same field but then end up studying something else. The results are robust to alternative specifications and a large set of robustness and placecbo checks.

Dissecting these results into heterogeneous effects by field of study shows that few fields see negative parental influence, but some are inherited more often than others. Parental enrollment increases graduation from technology with 11.6 percentage points (188%) but only with 2.2 percentage points (91%) in social work, and -1.5 (-213%) in pharmacy. Some of these causal effects are close to the correlations. For example, children are 177% as likely to hold a degree in technology if their parent has one. But other results are quite different. The likelihood to earn a degree in social work is 212% higher and in pharmacy the association is no less than 558%. Another interesting example is business, where preferences are so correlated across generations that even though it has one of the larger absolute causal estimates at 4.5 percentage points, the relative effect is only 52% — a fourth of the raw association of 207%.[23]

These variable patterns are the results of a complex set of differences in educational and occupational experiences across fields. Section 6 explores two key mechanisms that have been subject to extensive previous research. First, I study the importance of parental academic and labor-market experience. It takes on average 28 years between the university application of a parent and their child. Most children are not old enough to directly experience their parents time at university. Instead, the inheritance effect works indirectly, through the knowledge the parent gains from their studies, and the occupational pathways that are opened. I show in Table 6 that children are twice as likely to inherit a field if a parent works in an occupation that is representative of that field. This is especially true for the fields that are most often inherited, like law, medicine and engineering, except technology which is barely affected at all. Appendix Table B.3 further underscores connection between field and occupation inheritance by showing that the effect almost disappears for parents who have reached retirement age when their children apply to university.

Two additional results give further hints at how parental experience influence inheritance. While Table 9 shows that the quality of the education the parent applies to (in terms of average peer GPA) has a miniscule influence on inheritance, the level of earnings predicted from graduating (Table 8) has a substantial effect. So large in fact that children become *less* likely to graduate from a field if the parent is predicted to earn below the 36th percentile. The fact that we observe such negative effects, also for some field-level estimates, indicates that children follow their parents also for other reasons than their comparative advantage.

The second set of analyses looks at family composition as a way to understand how parents can act as role models for their children. Like in previous research, I find stronger inheritance for fathers, but also mothers exert strong influence. Importantly, children are more likely to follow the parent of the same sex as them, indicating that parents are in fact important role models. When studying the effect by field, it seems stereotypical choices are more influential. Daughters follow their mothers more often to fields like social work, teaching and psychology — fields with very weak aggregate inheritance. I then show that while mothers are much more likely to find a partner within the same field, the identified inheritance effect for mothers cannot be explained by assortative mating.

Are children who follow their parents better off? Section 6 ends with an analysis of earnings among degree-holders of different fields. While not causal, the analysis shows that, for certain fields of study, children who have a parent with a degree in the same field as them have substantially larger earnings than

23. See Table B.2 for a complete list of field level associations and causal effects.

those with parents without such a degree. While the difference is tiny for the aggregate measure, a large positive association with earnings can be seen for some of the most and least inherited fields. The earnings difference is a measure of the amount of rent a child can extract from their comparative advantage. That we see such weak correspondence between this earnings association and field inheritance further underscores the importance of other factors than labor market prospects when children chose what field to study.

Even in a relatively mobile country like Sweden an individual's choice of field, and, in turn, occupation, is strongly affected by the pathways chosen by their parents. For many fields, the causal findings of this paper go in the same direction as previous correlational estimates, albeit are somewhat weaker. For other fields, the causal effects are very different. Many external elements, like social norms and family traditions contribute to the spurious correlation between intergenerational education choices. This paper accounts for such factors and provides policy-relevant estimates of the direct effect of parental behavior.

These results are important to everyone working with intergenerational mobility, both at the individual and societal level. Parents who want their children to succeed need to understand how important they are as role models. Policymakers who aim at increasing equality of opportunity need to do the same. In this paper, I have identified an environmental factor influencing educational choices that can be controlled. The paper underscores the value of parental role models. To increase mobility, children from families with little exposure to tertiary education need additional role models to help them understand what educational and occupational pathways are available to them.

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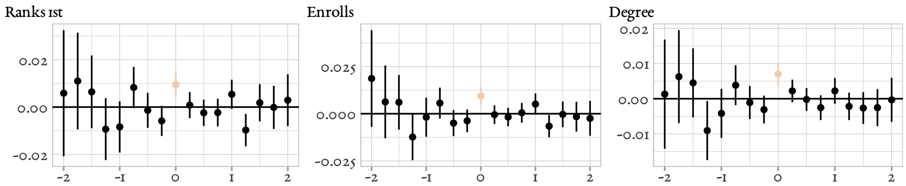
# Appendix

## A Additional robustness checks

This section includes additional robustness and validation exercises. We start with Figure A.1 where the main estimation has been conducted using various alternative cutoffs. We see that as soon as the cutoff is moved from its true position, the estimated results disappear. If for example the functional form of the running variable polynomial did not capture the effect of the score on the outcome, moving the cutoff would have had less effect on the estimated coefficients. These results further strengthen the credibility of the RDD analysis.

Figure A.1. Placebo cutoffs




*Notes:* The plot shows the reduced form effects of the main analysis while the cutoff is changed away from its true position. At $x = -1$ for example, applicants with running variables lower than $-1$ are counted as below the cutoff, while those with scores at or above $-1$ are counted as above.

The second display, Table A.1 shows the main results but using quadratic rather than linear polynomials. The effects are very close in size, but with somewhat larger standard errors.

Table A.1. Quadratic polynomials

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | $1.00^{**}$ | $0.97^{**}$ | $0.87^{***}$ |
| | (0.36) | (0.32) | (0.22) |
| Parent enrolls in $j$ | $6.29^{**}$ | $6.08^{**}$ | $5.44^{***}$ |
| | (2.24) | (2.00) | (1.36) |
| Parent receives degree in $j$ | $10.08^{**}$ | $9.75^{**}$ | $8.71^{***}$ |
| | (3.59) | (3.21) | (2.20) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 672 | 672 | 672 |
| 1st stage Wald (degree) | 284 | 284 | 284 |

*Notes:* The admission group polynomials included in the main analysis are here estimated with both linear and quadratic terms. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

As discussed in Section 2, a tie-breaking mechanism prioritizing those applicants who have ranked the alternative the highest could be a threat to the monotonicity assumption if applicants include safe options relatively high in their ranking. Since I remove dominated options when selecting $j, k$ field pairs, a more preferred field that is included below a safe option will most likely never be included as $k$. I run a number of robustness checks to ensure this potential threat to the monotonicity assumption does not have significant bearing on the results.

First, Table A.2 removes all applicants exactly at the cutoff from the analysis. In the main analysis, I use the predefined tie-breaking rules to predict admission among applicants at the cutoff. There is no indication that these applicants can manipulate their admission status, but if they could, a donut setup would help avoid the problem. Since I use triangular kernels in all analyses, applicants at the cutoff are important. While the results in Table A.2 for degree completion are somewhat smaller, the estimates for child enrollment are larger. Standard errors are almost twice as large too showing how important the applicants at the cutoff are for statistical power. However, these differences do not change the interpretation of the results in any meaningful way, speaking to the robustness of the estimates.

Table A.2. Donut

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | $0.87^{*}$ | $0.89^{**}$ | $0.40^{\dagger}$ |
| | (0.35) | (0.32) | (0.21) |
| Parent enrolls in $j$ | $8.35^{*}$ | $8.57^{**}$ | $3.81^{\dagger}$ |
| | (3.38) | (3.04) | (2.03) |
| Parent receives degree in $j$ | $13.25^{*}$ | $13.60^{**}$ | $6.05^{\dagger}$ |
| | (5.38) | (4.84) | (3.21) |
| Observations | 352 550 | 352 550 | 352 550 |
| Control group mean | 16.44% | 12.83% | 4.8% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 266 | 266 | 266 |
| 1st stage Wald (degree) | 112 | 112 | 112 |

*Notes:* In this table, the main estimation is run on a sample where applicants who are exactly at the cutoff are excluded. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Second, Table A.3 reports results where only those observations where $j$ is the highest ranked field have been included. Clearly, the applicant has no reason to rank a less preferred field first. While these coefficients are only weakly significant, the size of the point estimates does not differ much from the main results.

Third, Table A.4 includes fixed effects for the priority ranking of the target alternative. This could be important since one of the tie-breaking mechanisms is the ranking. These results are similar but somewhat larger than the main estimates.

A different threat to identification is the selection that could have been introduced by conditioning on the post-treatment outcome of having children. All main regressions are run on the sample of parents who have children born before the end of 1998. While we see no effect of admission on the likelihood of having children, this strategy could still bias the results. In Table A.5, I instead include all applicants. Those who have no children are simply assigned an outcome variable of zero. The absolute effects are much smaller, but relative to the control group mean, including all applicants barely changes the results. This exercise produces highly conservative measures of the actual treatment effects since it assumes that all future children will end up not applying to, enrolling in, or graduating from $j$.

### Table A.3. Only first-ranked $j$

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | $0.84^{\dagger}$ | 0.63 | $0.64^{*}$ |
| | (0.46) | (0.41) | (0.30) |
| Parent enrolls in $j$ | $6.35^{\dagger}$ | 4.78 | $4.84^{*}$ |
| | (3.46) | (3.08) | (2.27) |
| Parent receives degree in $j$ | $8.70^{\dagger}$ | 6.55 | $6.63^{*}$ |
| | (4.71) | (4.19) | (3.10) |
| Observations | 163 791 | 163 791 | 163 791 |
| Control group mean | 16.27% | 12.24% | 5.16% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 315 | 315 | 315 |
| 1st stage Wald (degree) | 151 | 151 | 151 |

*Notes:* The sample includes all applicants to Swedish universities before 2000 with children who apply to university no later than 2021 where the preferred alternative $j$ is ranked highest in the parent's application. There are no strategic incentives to rank anything but the most preferred alternative first. Coefficients and standard errors are reported in percentage points. All regressions use triangular kernel weights, and include linear polynomials of the running variables above and below the cutoff to each admission group, as well as fixed-effects for the cutoff and the next-best field. Standard errors are clustered at the cutoff and family level.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

### Table A.4. Priority ranking fixed effects

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | $0.86^{**}$ | $0.85^{***}$ | $0.58^{***}$ |
| | (0.27) | (0.24) | (0.17) |
| Parent enrolls in $j$ | $7.39^{**}$ | $7.28^{***}$ | $4.97^{***}$ |
| | (2.32) | (2.08) | (1.43) |
| Parent receives degree in $j$ | $11.95^{**}$ | $11.78^{***}$ | $8.04^{***}$ |
| | (3.77) | (3.37) | (2.33) |
| Observations | 402 649 | 402 649 | 402 649 |
| Control group mean | 16.58% | 12.96% | 4.82% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 596 | 596 | 596 |
| 1st stage Wald (degree) | 243 | 243 | 243 |

*Notes:* The regression reported in this table includes fixed effects for the priority ranking of $j$. Otherwise, the estimation follows the same approach as Table 3.

Table A.5. Main results: all applicants

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to *j* | 0.38*** | 0.39*** | 0.20*** |
| | (0.09) | (0.08) | (0.05) |
| Parent enrolls in *j* | 2.32*** | 2.40*** | 1.22*** |
| | (0.56) | (0.49) | (0.29) |
| Parent receives degree in *j* | 4.34*** | 4.49*** | 2.29*** |
| | (1.05) | (0.93) | (0.54) |
| Observations | 1 337 737 | 1 337 737 | 1 337 737 |
| Control group mean | 6.2% | 4.73% | 1.44% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 3611 | 3611 | 3611 |
| 1st stage Wald (degree) | 1202 | 1202 | 1202 |

*Notes:* The sample includes all applicants to Swedish universities before 2000, irrespective of if they have children or not. The outcome variable is set to 0 if the applicant has no children or has children that have not yet applied at the end of the sample period in 2021. Otherwise, the estimation follows the same approach as Table 3.

† $p \leq 0.1$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

## B Additional results

This section reports additional results and further subgroup analyses. To begin, Table B.1 reports the first stage regressions also presented in Figure 4.

Table B.1. First stage estimates

| | Parent admitted to $j$ | Parent enrolls in $j$ |
|---|---|---|
| Parent above cutoff to $j$ | 64.61$^{***}$ | 14.54$^{***}$ |
| | (0.45) | (0.45) |
| Observations | 212 336 | 212 336 |
| Control group mean | 2.11% | 36.12% |
| Bandwidth | 1.0 | 1.0 |
| | **Parent receives degree in $j$** | **Parent has job common for $j$** |
| Parent above cutoff to $j$ | 8.97$^{***}$ | 3.76$^{***}$ |
| | (0.43) | (0.45) |
| Observations | 212 336 | 212 336 |
| Control group mean | 26.08% | 43.41% |
| Bandwidth | 1.0 | 1.0 |

*Notes:* The sample includes applicants with children born before 1998, but observations are not repeated for each child. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Second, Table B.2 summarizes results from figure 1 and figure 6 showing both correlations and causal effects for each field of study.

Figure B.1 reports estimates of cross-field inheritance. While we observe a few effects with p-values lower than 0.1 (colored) away from the diagonal, many of which are negative, the number is not larger than what one would expect by chance.

Table B.3 shows inheritance by the age of the parent at the time the child applies to university. While effects are imprecise, there seems to be a strong negative effect on inheritance among parents who have reached the retirement age of 65.

Table B.4 reports the parent-child gender composition interaction terms for the results in Table 10. We see that there aggregate effects are significantly different across both parent and child genders, but few field-level interactions are significant.

Next, Table B.5 shows how the likelihood to end up having a child with a parent with a degree in the preferred field $j$ is affected by enrollment. Not only do we observe strong assortative mating, the effect is more than doubled for mothers. A woman applying to $j$ has a 6.46% likelihood to have a child with a man who holds a degree in $j$, a share that increases to 21.64% if she enrolls.

Table B.6 tabulates regression results by the birth order of each child. We see a clear, almost monotonically, decreasing effect by birth order.

Focusing on first- and second-borns, Table B.7 studies the effect the gender of the second-born has on the behavior of the first-born. In a traditional family, where the oldest son inherits the family profession, one would expect a first-born daughter to be more likely to inherit the field of a parent if her sibling is a girl. The table reports no such pattern, however. While daughters are less likely to follow their parents, the gender of the second born has little influence over this result.

Table B.2. Associations and causal estimates (child degree completion) by field

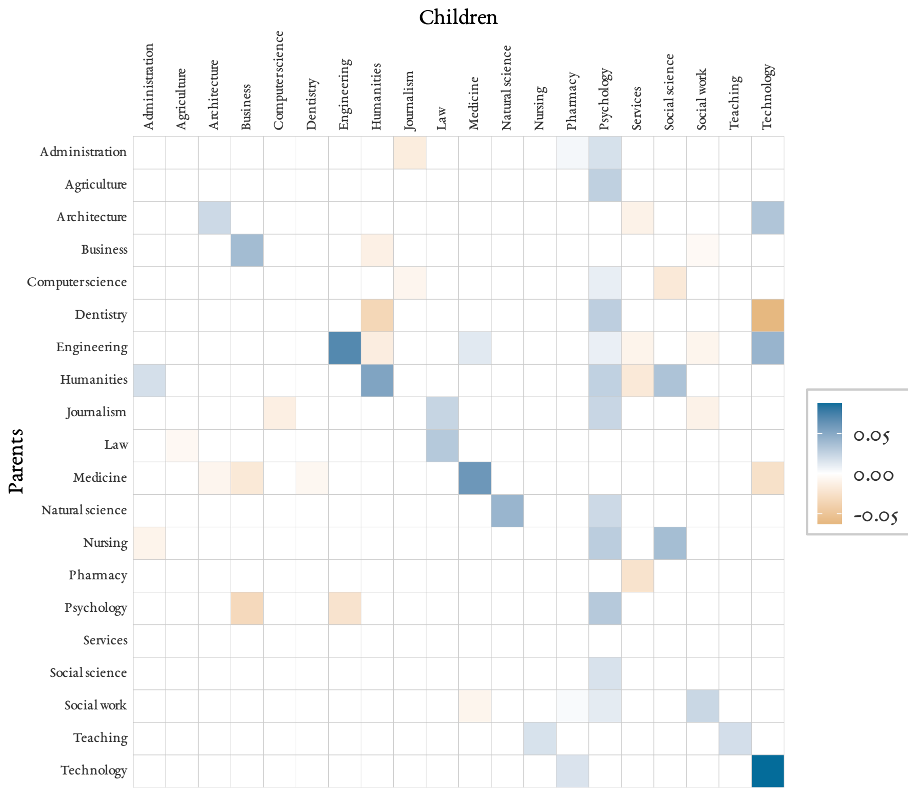
| Field | Relative popularity | Effect estimate | | Control group mean | Relative effect |
|---|---|---|---|---|---|
| Technology | 177% | 11.58p.p.$^{*}$ | (4.85) | 6.17% | 188% |
| Engineering | 210% | 8.89p.p.$^{***}$ | (1.40) | 8.09% | 110% |
| Humanities | 195% | 7.12p.p.$^{***}$ | (2.03) | 4.85% | 147% |
| Medicine | 319% | 6.35p.p.$^{***}$ | (1.15) | 5.92% | 107% |
| Natural science | 169% | 5.20p.p.$^{**}$ | (1.72) | 2.80% | 186% |
| Business | 207% | 4.45p.p.$^{***}$ | (0.82) | 8.50% | 52% |
| Law | 337% | 3.97p.p.$^{***}$ | (0.91) | 2.47% | 161% |
| Psychology | 247% | 2.52p.p.$^{*}$ | (1.05) | 1.41% | 178% |
| Social work | 212% | 2.16p.p.$^{**}$ | (0.82) | 2.36% | 91% |
| Architecture | 506% | 2.14p.p.$^{\dagger}$ | (1.16) | 1.84% | 116% |
| Teaching | 137% | 1.75p.p.$^{*}$ | (0.88) | 4.85% | 36% |
| Dentistry | 618% | 1.66p.p. | (1.73) | 1.82% | 91% |
| Nursing | 144% | 1.48p.p. | (2.12) | 4.62% | 32% |
| Social science | 119% | 1.47p.p. | (1.56) | 4.24% | 35% |
| Computer science | 235% | 1.01p.p. | (0.86) | 2.68% | 38% |
| Journalism | 307% | 0.64p.p. | (0.82) | 1.96% | 33% |
| Services | 284% | 0.54p.p. | (1.63) | 1.96% | 27% |
| Administration | 151% | −0.73p.p. | (0.89) | 0.70% | −104% |
| Agriculture | 529% | −0.74p.p. | (0.98) | 1.83% | −41% |
| Pharmacy | 558% | −1.52p.p. | (0.97) | 0.71% | −213% |
| Aggregate | 186% | 3.60p.p.$^{***}$ | (0.61) | 4.53% | 80% |

*Notes:* The relative popularity displays the numbers on the diagonal in figure 1 and is the relative share of field degree holders among children of parents with a degree in the field when compared to all children. The estimates are also reported in Figure 6 and follow the same approach as Table 3 but with separate coefficients for each field and a bandwidth of 4 standard deviations.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Finally, Table B.8 reports the results split by the education level of the grandparents. We see very weak, or even negative, effects for families where grandparents have only elementary education, but for any higher level of education, the differences are small.

Figure B.1. Cross-field inheritance matrix




*Notes:* The matrix reports regression coefficients on how quasi-random admission of parents to different fields (y-axis) affects the likelihood of children earning degrees in all different fields. Only coefficients with p-values lower than 0.1 are reported. Estimation is done using the same setup as in the main paper, but with a bandwidth of 4 standard deviations.

Table B.3. Field inheritance by parent age at child application

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | 6.83 | 9.31 | 4.04 |
| | (6.84) | (6.21) | (4.53) |
| × Parent age 41–50 | 2.29 | 0.99 | 3.93 |
| | (6.67) | (6.06) | (4.38) |
| × Parent age 51–64 | 0.99 | −2.92 | 0.14 |
| | (6.69) | (6.07) | (4.38) |
| × Parent age 65+ | −17.86 | $-21.26^{*}$ | −5.68 |
| | (11.48) | (10.48) | (6.35) |
| Parent age 41–50 | −3.72 | −3.41 | $-3.97^{\dagger}$ |
| | (3.53) | (3.20) | (2.33) |
| Parent age 51–64 | $-6.73^{\dagger}$ | $-5.52^{\dagger}$ | $-7.02^{**}$ |
| | (3.54) | (3.21) | (2.33) |
| Parent age 65+ | −0.59 | 0.41 | $-6.83^{\dagger}$ |
| | (7.27) | (6.79) | (3.92) |
| Observations | 323 481 | 323 481 | 323 481 |
| Control group mean | 20.71% | 16.14% | 5.95% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 131 | 131 | 131 |

*Notes:* The sample only includes children who have applied to university at least once before the end of the sample period. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table B.4. Field inheritance and gender composition (interaction terms)

| Field | Earns degree | | Interactions × Daughter | | × Mother | | × Mother × Daughter | |
|---|---|---|---|---|---|---|---|---|
| Administration | −1.43 | (1.35) | −0.48 | (1.76) | 1.09 | (1.38) | 0.51 | (2.13) |
| Agriculture | −1.57 | (1.29) | −0.47 | (2.08) | 1.27 | (1.43) | 1.93 | (2.67) |
| Architecture | 1.50 | (1.74) | 2.61 | (2.64) | 0.23 | (2.07) | −3.16 | (2.75) |
| Business | $5.85^{***}$ | (1.30) | $-3.87^{*}$ | (1.65) | −0.70 | (1.63) | 3.47 | (2.27) |
| Computer science | $3.02^{*}$ | (1.51) | $-3.56^{*}$ | (1.62) | −2.27 | (1.97) | 3.59 | (2.40) |
| Dentistry | $5.12^{*}$ | (2.53) | 0.64 | (4.26) | $-6.74^{*}$ | (3.18) | −3.29 | (5.53) |
| Engineering | $10.02^{***}$ | (2.04) | −2.59 | (1.79) | 2.96 | (2.63) | −4.03 | (3.27) |
| Humanities | $7.63^{\dagger}$ | (4.23) | −1.20 | (6.17) | −0.94 | (4.72) | 0.86 | (7.33) |
| Journalism | $-1.64^{\dagger}$ | (0.88) | $5.47^{*}$ | (2.46) | $2.26^{\dagger}$ | (1.25) | $-5.94^{\dagger}$ | (3.04) |
| Law | $3.58^{**}$ | (1.38) | 1.66 | (1.86) | −1.31 | (1.47) | 0.86 | (2.19) |
| Medicine | $3.71^{\dagger}$ | (1.96) | 3.36 | (2.52) | 3.00 | (2.69) | −1.35 | (3.51) |
| Natural science | $5.59^{**}$ | (2.07) | 0.24 | (2.69) | −3.11 | (3.15) | 2.12 | (4.45) |
| Nursing | 4.84 | (4.90) | −0.74 | (5.87) | −3.51 | (4.91) | −0.65 | (6.44) |
| Pharmacy | $-8.14^{\dagger}$ | (4.28) | 13.66 | (8.93) | $7.11^{\dagger}$ | (4.28) | $-15.25^{\dagger}$ | (9.25) |
| Psychology | 0.55 | (1.59) | 0.75 | (2.62) | 1.56 | (1.93) | 1.81 | (3.41) |
| Services | 0.93 | (3.55) | −5.19 | (4.35) | 1.61 | (4.28) | 2.49 | (5.60) |
| Social science | −1.09 | (2.37) | 0.31 | (3.21) | 3.08 | (2.89) | 1.69 | (4.30) |
| Social work | −1.04 | (1.15) | 3.25 | (2.22) | $2.13^{\dagger}$ | (1.19) | −0.31 | (2.61) |
| Teaching | −0.08 | (1.15) | 2.69 | (1.70) | 1.24 | (1.17) | −1.63 | (2.02) |
| Technology | $16.16^{*}$ | (6.48) | −4.12 | (4.57) | $-13.85^{\dagger}$ | (8.11) | 12.87 | (8.13) |
| Aggregate | $5.01^{***}$ | (0.74) | $-2.82^{***}$ | (0.61) | $-1.61^{**}$ | (0.57) | $3.16^{***}$ | (0.77) |

*Notes:* The table reports results from a regression where parent enrollment is interacted with field as well as parent and child gender. Otherwise, the estimation follows the same approach as Table 3, but with a bandwidth of 4 standard deviations. Table 10 reports linear combinations of the coefficients estimated in this regression.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table B.5. Assortative mating (first stage)

| | Other parent has degree in $j$ |
|---|---|
| Parent enrolls in $j$ | $6.77^{**}$ |
| | (2.35) |
| × Parent female | $8.39^{***}$ |
| | (1.69) |
| Parent female | $-3.10^{***}$ |
| | (0.91) |
| Observations | 402 649 |
| Control group mean | 9.57% |
| Bandwidth | 1.0 |
| 1st stage Wald | 373 |

*Notes:* The table shows, separately for mothers and fathers, how the likelihood that the other parent has a degree from field $j$ is affected by whether the parent enrolls in $j$ or not. It is a first stage of sorts for Table 11. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table B.6. Field inheritance by child birth order

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | $8.17^{***}$ | $8.19^{***}$ | $6.24^{***}$ |
| | (2.02) | (1.82) | (1.27) |
| × Second-born child | $-3.33^{**}$ | $-3.04^{**}$ | $-2.08^{**}$ |
| | (1.12) | (1.03) | (0.70) |
| × Third-born child | $-3.37^{\dagger}$ | $-3.63^{*}$ | $-4.35^{***}$ |
| | (1.79) | (1.59) | (1.05) |
| × ≥ Fourth-born child | $-6.59^{*}$ | $-7.00^{*}$ | $-4.04^{*}$ |
| | (3.35) | (2.98) | (1.84) |
| Second-born child | −0.16 | −0.63 | −0.61 |
| | (0.60) | (0.55) | (0.37) |
| Third-born child | −1.09 | −1.30 | −0.72 |
| | (1.00) | (0.88) | (0.59) |
| Fourth-born child | −0.22 | −0.53 | −1.63 |
| | (1.93) | (1.72) | (1.06) |
| Observations | 381 090 | 381 090 | 381 090 |
| Control group mean | 16.72% | 13.07% | 4.89% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 132 | 132 | 132 |

*Notes:* The estimation excludes children who do not have siblings. The reference group includes firstborn children. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table B.7. Field inheritance of firstborn by gender of second-born

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | 8.33** | 9.29** | 6.62*** |
| | (3.11) | (2.88) | (1.95) |
| × Child female | −1.43 | −3.50 | −1.52 |
| | (2.53) | (2.36) | (1.59) |
| × Female second-born | 0.30 | 1.28 | −0.04 |
| | (2.50) | (2.32) | (1.54) |
| × Child female × female second-born | −2.75 | −0.14 | 1.07 |
| | (3.64) | (3.37) | (2.33) |
| Child female | 3.37* | 3.67** | 2.32** |
| | (1.35) | (1.25) | (0.84) |
| Female second-born | −0.12 | −0.41 | 0.31 |
| | (1.31) | (1.21) | (0.80) |
| Child female × female second-born | 1.62 | −0.05 | −0.27 |
| | (1.92) | (1.77) | (1.21) |
| Observations | 185 389 | 185 389 | 185 389 |
| Control group mean | 17.65% | 14.11% | 5.49% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 124 | 124 | 124 |

*Notes:* The sample includes only firstborns from families with exactly two children. Otherwise, the estimation follows the same approach as Table 3.

† $p \leq 0.1$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Table B.8. Grandparents' educational level

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent enrolls in $j$ | −2.28 | −3.56 | 2.87 |
| | (4.67) | (4.20) | (2.64) |
| × Grandparent high school | 6.06 | $7.75^{*}$ | 2.09 |
| | (4.11) | (3.65) | (2.33) |
| × Grandparent lower tertiary | 6.45 | $9.09^{*}$ | 3.74 |
| | (4.73) | (4.30) | (2.69) |
| × Grandparent upper tertiary | $7.40^{\dagger}$ | $6.57^{\dagger}$ | 2.37 |
| | (4.26) | (3.84) | (2.45) |
| Grandparent high school | $-3.31^{\dagger}$ | $-3.81^{*}$ | −1.71 |
| | (1.98) | (1.77) | (1.11) |
| Grandparent lower tertiary | −3.73 | $-4.57^{*}$ | $-2.56^{*}$ |
| | (2.34) | (2.12) | (1.30) |
| Grandparent upper tertiary | −2.86 | −1.85 | −1.81 |
| | (2.09) | (1.88) | (1.18) |
| Observations | 167 347 | 167 347 | 167 347 |
| Control group mean | 16.75% | 13.13% | 4.47% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald | 58 | 58 | 58 |

*Notes:* Grandparents' educational level is defined as the highest educational level attained by any of an individual's grandparents. The reference group is grandparents with less than high school education. Otherwise, the estimation follows the same approach as Table 3.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

## C Inheritance of institution and location preferences

Instead of collapsing alternatives by field of study and looking at treatment margins where applicants are either admitted into one field or deferred to another, we can perform the same exercise but for institutions.[24] This is a useful way to gain an additional measure against which we can benchmark the results. Table C.1 reports the results of this exercise, where the outcome variables take the value 1 if the child follows to the same institution, regardless of what field of study they choose.

Just like with the transmission of education preferences between siblings (Altmejd et al. 2021), the preferences for going to the same institution across generations are a lot stronger, with as many as 18% of children enrolling in the institution that the parent applied to. The absolute effects are often more than twice as large as the ones reported in Table 3, but relative effects are only somewhat larger. The likelihood of earning a degree in a specific field increased with 98% when a parent has enrolled in it, while the corresponding effect for a child earning a degree from a specific institution is 108%.

Table C.1. Inheritance of institutions

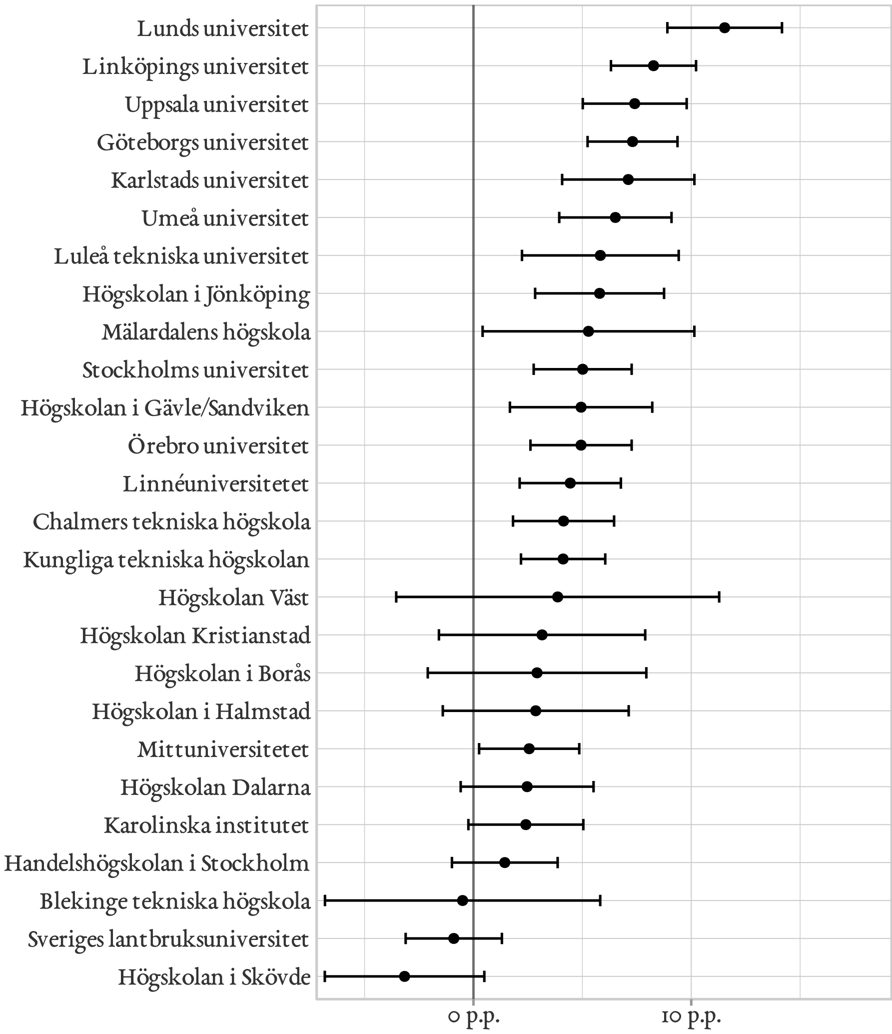
| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to *j* | 3.10*** | 2.82*** | 1.36*** |
| | (0.31) | (0.28) | (0.18) |
| Parent enrolls in *j* | 14.85*** | 13.52*** | 6.54*** |
| | (1.44) | (1.32) | (0.84) |
| Parent receives degree in *j* | 19.30*** | 17.57*** | 8.50*** |
| | (1.90) | (1.74) | (1.10) |
| Observations | 483 311 | 483 311 | 483 311 |
| Control group mean | 24.22% | 18.19% | 6.03% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 2054 | 2054 | 2054 |
| 1st stage Wald (degree) | 1355 | 1355 | 1355 |

*Notes:* Instead of collapsing consecutive options by field of study, the sample includes applications collapsed by institution. A child is thus classified as following their parent only if they pick the same institution as their parent, irrespective of what program they chose. Otherwise, the estimation follows the same approach as Table 3.

Figure C.1 presents separate coefficients for each institution. Again, we see few negative effects. The largest and most precise estimates are for big universities that offer a broad range of alternatives. The two most prestigious schools, Stockholm school of economics (Handelshögskolan i Stockholm, SSE) and the Karolinska Institute both exhibit small effects that are not significant. Interestingly, all students at SSE study business which is a field with positive inheritance. A possible reason for this is simply that both school have very high admission requirements ensuring only the most academically successful children will apply there. On the other hand, the point estimates of the two effects are very similar in size to the effect estimated by Barrios-Fernández et al. (2021), who show that children are 2.6 percentage points more likely to attend an elite college if their parents do so.

24. Many institutions have changed their names, merged, or reorganized during the period. I only include institutions that have existed during at least some part of the parent application period (1977–1999) and classify rebranded institutions with the same identifier. For example, Linnéuniversitet is a merger of Kalmar and Växjö universities. A child who goes to Linnéuniversitet is classified as following their parent no matter which of the two schools that parent applied to.

Figure C.1. Inheritance of institutions




*Notes:* The regression is run on a sample constructed by collapsing consecutive alternatives by institution rather than field. It runs same specification as the main analysis in Table 3 but with a bandwidth of 4 and with next-best fixed effects at the institution level.

Inheriting institutional preferences is likely explained by how institutions are located in different cities. Since a significant share of parents who move to a new city for their university studies stay there, admission also affects what city their children live in. Table C.2 shows results of such an exercise, where alternatives are grouped by commuting zone (2018 local labor market). This means that consecutive applications to schools in the Stockholm-Uppsala region are collapsed, for example. The results are again slightly larger but with larger baseline means, yielding similar relative effects — showing how important location is for university choice.

Table C.2. Inheritance of locations

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 3.21*** | 2.85*** | 1.39*** |
| | (0.32) | (0.30) | (0.22) |
| Parent enrolls in $j$ | 17.59*** | 15.61*** | 7.61*** |
| | (1.71) | (1.62) | (1.18) |
| Parent receives degree in $j$ | 22.18*** | 19.69*** | 9.60*** |
| | (2.21) | (2.08) | (1.51) |
| Observations | 463 579 | 463 579 | 463 579 |
| Control group mean | 29.63% | 24.78% | 9.33% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 1631 | 1631 | 1631 |
| 1st stage Wald (degree) | 1073 | 1073 | 1073 |

*Notes:* Instead of collapsing consecutive options by field of study, the sample includes applications collapsed by local labor market. A child is thus classified as following their parent as long as they choose a program at an institution in the same local labor market (commuting zone) as their parent, irrespective of what program and institution it is. Otherwise, the estimation follows the same approach as Table 3.

Last, as an additional benchmark, we can also group consecutive alternatives by their field-institution combination. Now, only consecutive options to the same field and institution are collapsed. Table C.3 reports these aggregate results. Baselines are of course miniscule here, but also the absolute effects are smaller. Parental enrollment in a field-institution combination increases graduation probability by 2.18 percentage points or 172%. That this relative effect is so much larger indicates that the effect of institution and field are complementary, and that the main results of this paper are not driven by institutions that only offer few fields of study to chose from.

Table C.3. Inheritance of field-institutions

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 1.16*** | 0.87*** | 0.54*** |
| | (0.15) | (0.13) | (0.08) |
| Parent enrolls in $j$ | 4.63*** | 3.48*** | 2.18*** |
| | (0.61) | (0.53) | (0.33) |
| Parent receives degree in $j$ | 7.11*** | 5.34*** | 3.34*** |
| | (0.94) | (0.81) | (0.51) |
| Observations | 521 268 | 521 268 | 521 268 |
| Control group mean | 5.2% | 3.62% | 1.27% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 3164 | 3164 | 3164 |
| 1st stage Wald (degree) | 1597 | 1597 | 1597 |

*Notes:* Instead of collapsing consecutive options by field of study, the sample includes applications collapsed by institution-field combinations. A child is thus classified as following their parent only if they pick the same institution as their parent, irrespective of what program they chose. Otherwise, the estimation follows the same approach as Table 3.

## D Narrow fields

The analysis in this paper is performed on a broad set of fields of study, with degree programs manually classified by the author into categories that as accurately as possible reflect distinct types of occupations. Statistics Sweden provides a classification with a similar purpose, called SUNGrp.[25] The following section presents the main results and robustness checks of the paper but using this narrow classification instead. Each field code is described in Table E.1, and Figure D.1 shows the intergenerational correlations between these narrow fields. Because fields are narrow, there are considerable spillovers between related fields. For example, codes starting with `55` are different engineering subfields, and `75V` and `75T` are dentistry and dental hygiene respectively.

The main results are presented in Table D.1. Parental enrollment increases chances that a child completes a degree in the narrow field $j$ with 2.4 percentage points or 77% — slightly lower than the 4.7p.p. (98%) of the main analysis. In Figure D.2 we see many of the same fields in the top as in the broad field categorization.

Table D.1. Inheritance of narrow fields

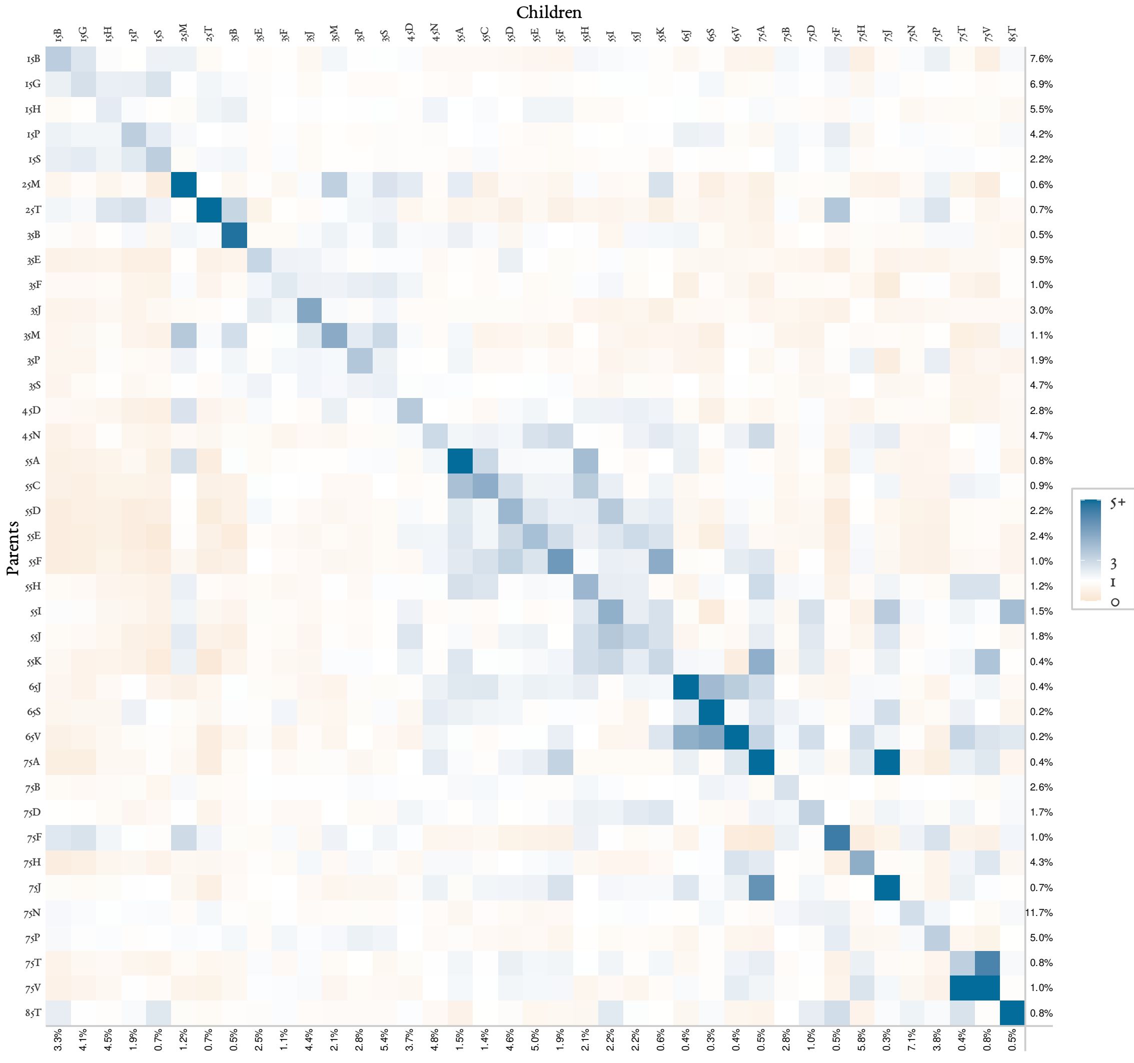
| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | $0.71^{***}$ | $0.65^{***}$ | $0.42^{**}$ |
| | (0.20) | (0.17) | (0.13) |
| Parent enrolls in $j$ | $3.98^{***}$ | $3.63^{***}$ | $2.38^{**}$ |
| | (1.12) | (0.95) | (0.74) |
| Parent receives degree in $j$ | $6.59^{***}$ | $6.02^{***}$ | $3.94^{**}$ |
| | (1.86) | (1.56) | (1.22) |
| Observations | 408 283 | 408 283 | 408 283 |
| Control group mean | 8.94% | 5.82% | 3.11% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 1362 | 1362 | 1362 |
| 1st stage Wald (degree) | 578 | 578 | 578 |

*Notes:* This table follows the same approach as Table 3 but with consecutive alternatives collapsed by the SCB's narrow field definitions described in Table E.1.

$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

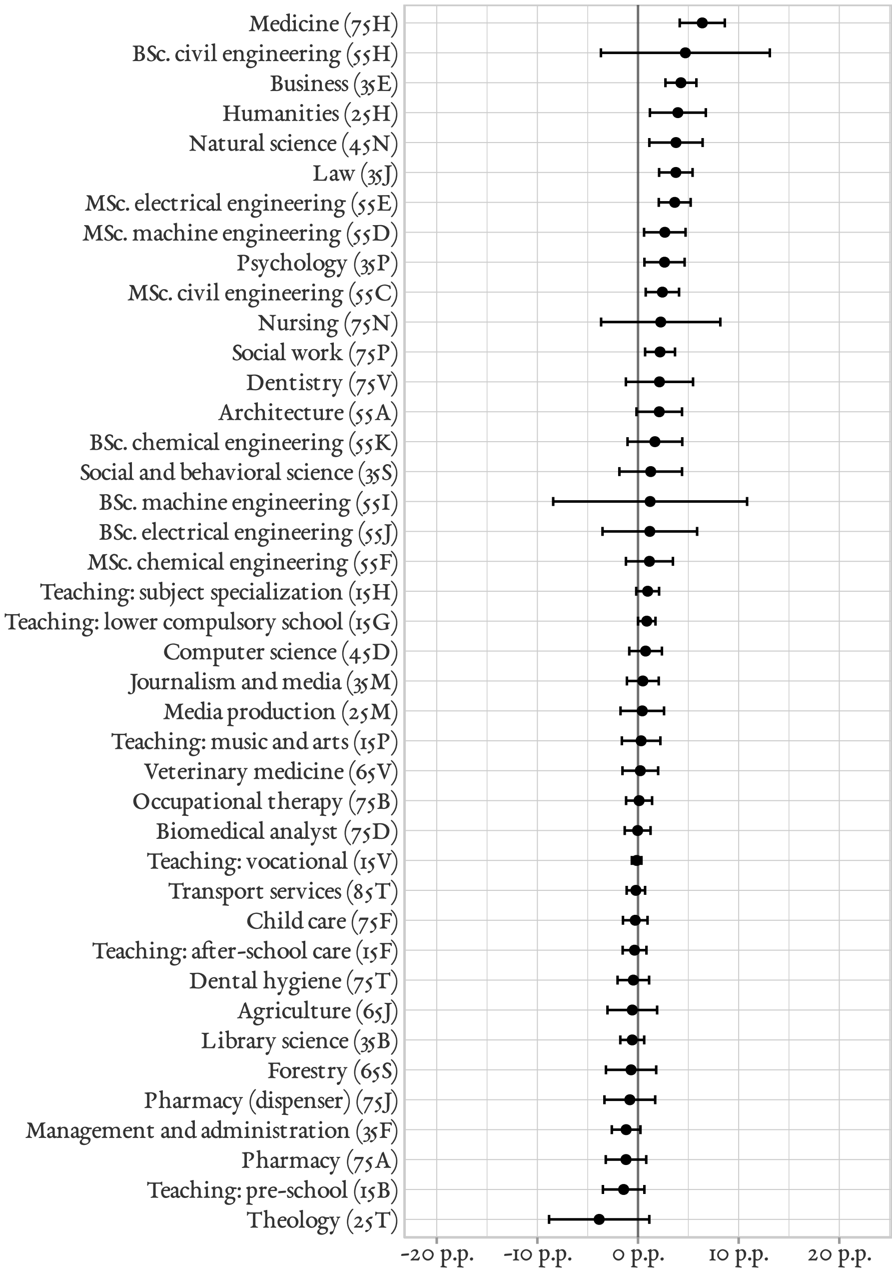
25. The broad field classification used in this paper is simply a grouping of SUNGrp codes meaning that all individuals holding a degree from a specific narrow field necessarily have the same broad field degree as well.

Figure D.1. Degrees of children and parents




*Notes:* Same as Figure 1 but with the narrow definition of fields of study. For a translation of the SunGrp codes, see Table E.1

Figure D.2. Inheritance of narrow fields




*Notes:* The regression uses the same specification as the main analysis in Table 3 but estimated separately for each narrow field.

Table D.2. Placebo (narrow fields)

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | −0.09 | −0.12 | −0.03 |
| | (0.16) | (0.16) | (0.15) |
| Parent enrolls in $j$ | −0.38 | −0.51 | −0.15 |
| | (0.69) | (0.71) | (0.67) |
| Parent receives degree in $j$ | −1.39 | −1.88 | −0.54 |
| | (2.55) | (2.60) | (2.45) |
| Observations | 539 661 | 539 661 | 539 661 |
| Control group mean | 6.98% | 6.85% | 5.35% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 2901 | 2901 | 2901 |
| 1st stage Wald (degree) | 356 | 356 | 356 |

*Notes:* This table follows the same approach as Table 4 but with consecutive alternatives collapsed by the SCB's narrow field definitions described in Table E.1.
$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

Table D.3. Separate slopes (narrow fields)

| | Ranks 1st | Enrolls | Earns degree |
|---|---|---|---|
| Parent above cutoff to $j$ | 0.70$^{**}$ | 0.63$^{**}$ | 0.36$^{*}$ |
| | (0.26) | (0.22) | (0.17) |
| Parent enrolls in $j$ | 3.96$^{**}$ | 3.54$^{**}$ | 2.05$^{*}$ |
| | (1.44) | (1.22) | (0.95) |
| Parent receives degree in $j$ | 6.43$^{**}$ | 5.75$^{**}$ | 3.32$^{*}$ |
| | (2.35) | (1.98) | (1.54) |
| Observations | 408 283 | 408 283 | 408 283 |
| Control group mean | 8.94% | 5.82% | 3.11% |
| Bandwidth | 1.0 | 1.0 | 1.0 |
| 1st stage Wald (enrolls) | 864 | 864 | 864 |
| 1st stage Wald (degree) | 371 | 371 | 371 |

*Notes:* This table follows the same approach as Table 5 but with consecutive alternatives collapsed by the SCB's narrow field definitions described in Table E.1.
$^{\dagger}$ $p \leq 0.1$, $^{*}$ $p \leq 0.05$, $^{**}$ $p \leq 0.01$, $^{***}$ $p \leq 0.001$.

# E Codebook

Table E.1. Narrow field codes and descriptions

| Code | Description | Broad field |
|---|---|---|
| 15B | Teaching: pre-school | Teaching |
| 15F | Teaching: after-school care | Teaching |
| 15G | Teaching: lower compulsory school | Teaching |
| 15H | Teaching: subject specialization | Teaching |
| 15P | Teaching: music and arts | Teaching |
| 15S | Teaching: special needs | Teaching |
| 15V | Teaching: vocational | Teaching |
| 25H | Humanities | Humanities |
| 25M | Media production | Humanities |
| 25T | Theology | Humanities |
| 35B | Library science | Administration |
| 35E | Business | Business |
| 35F | Management and administration | Administration |
| 35J | Law | Law |
| 35M | Journalism and media | Journalism |
| 35P | Psychology | Psychology |
| 35S | Social and behavioral science | Social science |
| 45D | Computer science | Computer science |
| 45N | Natural science | Natural science |
| 55A | Architecture | Architecture |
| 55C | MSc. civil engineering | Engineering |
| 55D | MSc. machine engineering | Engineering |
| 55E | MSc. electrical engineering | Engineering |
| 55F | MSc. chemical engineering | Engineering |
| 55G | MSc. engineering, other | Engineering |
| 55H | BSc. civil engineering | Technology |
| 55I | BSc. machine engineering | Technology |
| 55J | BSc. electrical engineering | Technology |
| 55K | BSc. chemical engineering | Technology |
| 65J | Agriculture | Agriculture |
| 65S | Forestry | Agriculture |
| 65V | Veterinary medicine | Agriculture |
| 75A | Pharmacy | Pharmacy |
| 75B | Occupational therapy | Nursing |
| 75D | Biomedical analyst | Natural science |
| 75F | Child care | Social work |
| 75H | Medicine | Medicine |
| 75J | Pharmacy (dispenser) | Pharmacy |
| 75L | Physiotherapy | Nursing |
| 75N | Nursing | Nursing |
| 75O | Social care | Social work |
| 75P | Social work | Social work |
| 75T | Dental hygiene | Dentistry |
| 75V | Dentistry | Dentistry |
| 85T | Transport services | Services |

Table E.2. SSYK 2012 codes of common occupations

| SSYK | Occupations | Fields |
|---|---|---|
| 121 | Finance managers | Business |
| 122 | Human resource managers | Administration |
| 134 | Architectural and engineering managers | Architecture |
| 141 | Primary and secondary schools and adult education managers | Teaching |
| 151 | Health care managers | Medicine, Nursing |
| 152 | Managers in social and curative care | Social work |
| 153 | Elderly care managers | Social work |
| 159 | Other social services managers | Services |
| 179 | Other services managers not elsewhere classified | Pharmacy |
| 211 | Physicists and chemists | Natural science |
| 213 | Biologists, pharmacologists and specialists in agriculture and forestry | Agriculture |
| 214 | Engineering professionals | Architecture, Computer science, Engineering, Natural science, Technology |
| 216 | Architects and surveyors | Architecture |
| 217 | Designers | Humanities |
| 218 | Specialists within environmental and health protection | Natural science |
| 221 | Medical doctors | Medicine |
| 222 | Nursing professionals | Nursing |
| 223 | Nursing professionals (cont.) | Natural science, Nursing |
| 224 | Psychologists and psychotherapists | Psychology |
| 225 | Veterinarians | Agriculture |
| 226 | Dentists | Dentistry |
| 227 | Naprapaths, physiotherapists, occupational therapists | Nursing |
| 228 | Specialists in health care not elsewhere classified | Natural science, Pharmacy |
| 231 | University and higher education teachers | Agriculture, Architecture, Computer science, Engineering, Humanities, Medicine, Natural science, Psychology, Social science |
| 233 | Secondary education teachers | Humanities, Teaching |
| 234 | Primary- and pre-school teachers | Humanities, Teaching |
| 235 | Teaching professionals not elsewhere classified | Social work, Teaching |
| 241 | Accountants, financial analysts and fund managers | Administration, Business |
| 242 | Organisation analysts, policy administrators and human resource specialists | Administration, Agriculture, Architecture, Business, Computer science, Engineering, Humanities, Journalism, Law, Natural science, Pharmacy, Psychology, Services, Social science, Social work |
| 243 | Marketing and public relations professionals | Business, Journalism |
| 251 | ICT architects, systems analysts and test managers | Computer science, Engineering, Natural science, Technology |
| 261 | Legal professionals | Law |
| 262 | Museum curators and librarians and related professionals | Administration, Humanities |
| 264 | Authors, journalists and linguists | Journalism |
| 265 | Creative and performing artists | Humanities |
| 266 | Social work and counselling professionals | Psychology, Social work |
| 267 | Religious professionals and deacons | Humanities |
| 311 | Physical and engineering science technicians | Architecture, Engineering, Technology |
| 315 | Ship and aircraft controllers and technicians | Services |
| 321 | Medical and pharmaceutical technicians | Dentistry, Natural science, Pharmacy |
| 325 | Dental hygienists | Dentistry |
| 331 | Financial and accounting associate professionals | Business, Social science |
| 332 | Insurance advisers, sales and purchasing agents | Agriculture, Business, Social science, Technology |
| 335 | Tax and related government associate professionals | Law, Social science |
| 336 | Police officers | Services |
| 341 | Social work and religious associate professionals | Social work |
| 342 | Athletes, fitness instructors and recreational workers | Social work |
| 351 | ICT operations and user support technicians | Computer science |
| 411 | Office assistants and other secretaries | Administration, Business, Journalism, Services, Social science |
| 534 | Attendants, personal assistants and related workers | Social work |
| 611 | Market gardeners and crop growers | Agriculture |
| 612 | Animal breeders and keepers | Agriculture |