Elite Universities and the Intergenerational Transmission of Human and Social Capital[†]

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Abstract

Do elite colleges help talented students join the social elite, or help incumbent elites retain their positions? We combine intergenerationally-linked data from Chile with a regression discontinuity design to show that, looking across generations, elite colleges do both. Lower-status individuals who gain admission to elite college programs transform their children's social environment. Children become more likely to attend high-status private schools and colleges, and to live near and befriend high-status peers. In contrast, academic achievement is unaffected. Simulations combining descriptive and quasi-experimental findings show that elite colleges tighten the link between social and human capital while decreasing intergenerational social mobility.

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1 Introduction

Do elite colleges help talented students from modest backgrounds join the social elite, or help incumbent elites retain their positions? This question is fundamental to the academic and popular debate over the social role of elite higher education, but the evidence is ambiguous. On the one hand, students from low- and middle-income families who enroll in elite colleges go on to earn more than similar students who enroll in less selective colleges. On the other hand, most students at elite colleges come from high-income families (Chetty et al., 2020), and within elite universities, students from the highest-status families are more likely to attain top incomes and top jobs (Zimmerman, 2019; Michelman et al., 2022).

A central challenge in adjudicating this debate is that it is multi-generational and multi-dimensional. Both academic and social preparation are important mediators of access to and success within elite universities (Arcidiacono and Lovenheim, 2016; Rivera, 2016; Jack, 2019). Further, elite education may shape the way both human and social capital evolve across generations. Quantifying these effects is difficult because, in addition to the standard challenges associated with causal inference, it requires measuring outcomes across multiple generations.

Chile is perhaps the only setting in which it is feasible to conduct this type of analysis at present. Three features of Chilean institutions are critical. The first feature is the availability of administrative educational records spanning more than five decades and containing family identifiers that allow us to link parents with their children.

The second feature is that Chilean universities have used an exam-based centralized admission system since the late 1960s. The centralized admission system generates sharp admission cutoffs in all oversubscribed college-by-major combinations (henceforth, "programs"). We exploit discontinuities in admissions outcomes to estimate the causal effects of admission to elite degree programs using a regression discontinuity design.

The third feature is the presence of well-studied universities and exclusive private schools that allow for clear definitions of elite college programs and proxies for social capital. On the university side, we identify eight elite degree programs at the top two Chilean universities. These programs, focused on either business or medicine, are among the most selective programs at the national level. They are associated with the highest levels of earnings, and according to Zimmerman (2019), their students account for roughly 40% of top 0.1% incomes and corporate leadership positions despite making up roughly 2% of college-eligible high school graduates.

On the high school side, we identify a set of exclusive private K-12 schools that serve as our measures of elite social capital. These schools play a central role in descriptive accounts of the Chilean social and economic elite. One way to think of them is as the Chilean equivalents of schools like Eton College in the UK or Phillips Exeter in the US. They send disproportionate shares of their graduates to elite college programs, and, conditional on enrolling in an elite program, these students are much more likely than others to attain top incomes and corporate roles (Zimmerman, 2019). Social capital is a notoriously challenging concept to pin down (Dasgupta and Serageldin, 1999; Guiso et al., 2011). However, our conception of elite private schools as loci of social capital formation lies at the intersection of several leading definitions, including Coleman (1988)'s description of social capital as "a stock of productive matter ... [that] is part of a community, [or] a network" and Bourdieu (1986)'s definition of the term as resources linked to membership of a group. Both Coleman and Bourdieu (1998) take exclusive educational institutions as leading examples of sites of the production of social capital.

To begin our empirical analysis, we establish three new facts on the intergenerational transmission of human and social capital. First, both human and social capital are highly persistent over time. A ten percentile increase in mothers' test scores is associated with a four percentile increase in children's scores, and children whose mothers attended elite private schools are 51.2 percentage points (3100%) more likely to attend such a school themselves. Second, human and social capital evolve *interdependently*. For example, children whose mothers attended a publicly subsidized school and scored in the bottom 70% of the college admissions exam distribution almost never attend elite private schools. In contrast, 10% of the children whose mothers attended a subsidized school and scored in the top 5% of the admission exam enroll in an elite private school. Third, elite college attendance predicts upward social capital mobility. Within the set of top-scoring mothers in subsidized schools, those admitted to an elite college degree program are 60% more likely to send their children to an elite private school.

Our descriptive findings suggest that parents' elite university attendance may shape childrens' human and social capital, but do not establish its causal role. Parents who select into elite universities may differ in many ways from those who do not, even holding exam scores fixed. The second part of our empirical analysis uses a regression discontinuity design to provide causal evidence on how admission to elite college programs shapes social and human capital for one's children. Using data on applications submitted to Chile's centralized assignment mechanism between 1977 and 2003, we compare children's outcomes for parents just above and below the admissions cutoffs at elite degree programs.

Our first finding is that parents' admission to an elite degree program raises children's social capital. When parents are admitted to an elite program, the chances their children attend an elite private school rise by 4.4 percentage points (20%). For parents who did not attend elite private schools, the gain is 3.4 percentage points (also 20%). In contrast, elite admission does not raise children's pre-college human capital, as measured by exam scores and grades. Despite the absence of human capital effects, parents' elite admission shifts children toward college degree programs with higher status peers. Changes in application behavior are the key channel.

Second, we unpack the mechanisms underlying the effects of elite college on social capital mobility. We find no evidence that increases in educational expenditures, changes in gender-specific role-modeling or intra-household bargaining, or differential geographic mobility explain the effects we observe. A mechanism with more support in the data is changes in marriage market matching. Low social capital students admitted to an elite degree program become more likely to marry their high-status college peers. Spouse test scores do not increase, consistent with the absence of human capital effects for children. In addition, we show that parents' elite admission shapes children's residential environments similarly to how it shapes their school environments—i.e. by shifting them towards higher status peers but not more expensive areas.

In the third part of our empirical analysis, we expand our focus to the full set of higher education programs in Chile and bring in data on applicants' full lists of preferences over programs. The expanded dataset lets us separate the effects of different elements of the bundle of attributes available at elite colleges and consider the importance of these attributes across the broader higher education system. We focus on exposure to high human capital peers, exposure to high social capital peers, and the marriage market exposure of low social capital students to high social capital students. Our results show that marriage market and social capital exposure, rather than human capital exposure, are key drivers of upward social capital mobility for one's children. Linking these data to survey records provides direct evidence that parent admission to degree programs with high status peers raises the status of their children's friend groups.

To conclude, we assess the magnitude of elite universities' effects on intergenerational mobility using two complementary approaches. The first is a stylized vector autoregression (VAR) model of college attendance, spouse selection, and capital transmission. Similar in spirit to Kremer (1997)'s study of assortative matching or Chetty et al. (2019)'s forward projection of racial income gaps in the US, the goal of this exercise is to ask whether reasonable estimates of mobility parameters are consistent with a large or small role for elite universities as a causal determinant of mobility. In the model, human and social capital shift college "eliteness," and then all three factors shape spouse human capital, social capital, and college quality, which combine with one's own attributes to determine child human and social capital. We calibrate the effects of college eliteness using regression discontinuity estimates, and set other parameters using OLS regressions.

We find that, compared to a counterfactual in which elite university admission has no effect on children's social capital, the observed elite university effects raise the correlation between parent and child social capital by 49% and increase the within-generation correlation between human and social capital by 37%. Elite universities thus decrease intergenerational social capital mobility but also allocate social capital more meritocratically in the sense that they tighten its link to human capital.[1]

The second exercise asks how giving an admissions score bonus to lower SES students would shape the inter- and intra-generational allocation of social capital. We use students' application rank lists to simulate assignments under different bonus regimes and compute counterfactual children's outcomes under each regime using regression discontinuity estimates of the effects of exposure to elite college peers.

We find that plausible changes in admissions policy yield substantial tradeoffs between mobility and meritocratic objectives. For example, a score bonus similar in size to recent affirmative action policies in the Chilean admissions system reduces the intergenerational correlation of social capital by 5%, thus raising mobility. However, it also reduces the intragenerational correlation between social and human capital by 5%.

[1]We use the term "meritocracy" to refer to the allocation of rewards on the basis of academic achievement. While this definition is common (e.g., Markovits, 2019), others are possible. Sen (2000) notes that meritocracy is "underdefined" because the concept of merit depends on what one considers a good society.

The bottom line is that elite universities play a quantitatively important but double-edged role in the intergenerational transmission of social capital, simultaneously shifting social capital towards high achievers and increasing its persistence across generations. Admissions policy changes shift the balance society strikes between these two objectives, but do not produce allocations that are both more mobile and more meritocratic.

This paper contributes to several strands of literature. First, we demonstrate that multi-generational effects are crucial to understanding the way elite universities shape upward mobility to the very top. Several recent papers explore how elite universities affect access to top jobs and top incomes over a single generation (Zimmerman, 2019; Michelman et al., 2022; Chetty et al., 2023). Evidence from contemporary Chile and the historical US indicates that elite universities expand inequality in access to top positions by baseline social status and that social interactions between high-status individuals at elite universities are an important reason why (Zimmerman, 2019; Michelman et al., 2022). Our findings support the idea that elite universities increase intergenerational persistence and that social mechanisms are important. However, we also show that, over multiple generations, elite universities can provide a path for talented lower-status families to join the elite group, even when single-generation effects point in the other direction.

Second, we advance the literature on the distribution of economic returns across colleges. Our finding that exposure to academically high achieving peers does not promote intergenerational upward mobility is consistent with previous studies showing that colleges' "value added" to earnings is weakly related to peer *academic* quality (Dale and Krueger, 2002, 2014; Hoxby, 2020; Chetty et al., 2020; Mountjoy and Hickman, 2020). Abdulkadiroğlu et al. (2014) make a similar point for academically selective public high schools in the US. We go beyond this work by exploring intergenerational effects, by showing that peer *social* status is a much stronger correlate of intergenerational gains, and by showing that social capital is itself an important output of elite education.

Third, our findings elevate a string of papers on intra-family and intergenerational "spillover" effects by showing that these effects are quantitatively important for long-run outcomes. Previous research uses similar designs to examine sibling spillovers on college, major, and school choice in education settings (Altmejd et al., 2021; Dustan, 2018), and to study the transmission of high school field of study from parents to children (Dahl et al., 2020). We similarly contribute to work on the marriage market effects of higher education by quantifying the link between marriage outcomes and intergenerational social capital transmission (Kirkebøen et al., 2021; Ge et al., 2018).

The closest paper to ours in this vein is Kaufmann et al. (2021). This study uses data on 1990-93 applicants to five selective Chilean universities to study how admission affects marriage and child outcomes. We innovate relative to this work in several ways. First, we access data on both parent and child social status, which allows us to to examine the intergenerational transmission of social capital and its interaction with human capital mobility. Second, we bring to bear data on a broader set of institutions, a longer time span, and full student preference lists. These data allow us to generate new insights. For example, access to more data allows us to focus on the small set of elite degree programs that Zimmerman (2019) shows generate a disproportionate share of top outcomes, while access to data on preference lists allows us to unpack the key role that peers in the social as opposed to academic elite play in driving intergenerational social capital transmission.

Fourth, our results speak to a broader literature on intergenerational persistence in earnings, schooling, and IQ (Solon, 1999; Anger and Heineck, 2009; Black and Devereux, 2010; Grönqvist et al., 2010; Chetty et al., 2014, 2017; Hertz et al., 2008; Lundborg et al., 2018). We provide evidence on the causal role of elite education and highlight how social capital shapes the human capital outcomes that are the focus of many papers. The focus on elite formation distinguishes our work from previous research examining shifts between lower levels of educational attainment and prestige (Amin et al., 2015; Behrman and Rosenzweig, 2002; Holmlund et al., 2011; Pekkarinen et al., 2009).

Finally, we bring credible quantitative evidence to a canonical question in the literature on social capital. Much of the economics literature on social capital focuses on how civic engagement and social trust affect well-being (Guiso et al., 2011). However, Bourdieu's initial conception of social capital emphasized its role in social reproduction, with elite universities as fulcra of elite reproduction (Bourdieu, 1972, 1986, 1998). Our findings support the idea that elite universities help reproduce incumbent elites, but also qualify it by showing that, over time, elite universities change who the incumbents are by strengthening ties between social and human capital.

2 Institutions

2.1 Secondary schools and social capital

Primary and secondary students in Chile attend three types of schools: public schools, subsidized voucher schools, and non-subsidized private schools. Public schools are government-run, free, and funded through student vouchers. Voucher schools are privately run but publicly subsidized through the voucher system. Non-subsidized private schools rely on tuition fees only and are considerably more expensive than voucher schools. See Hsieh and Urquiola (2006) for more details. In the class of 2018, 40.0% of students attended a public school, 49.6% a voucher school, and 10.3% a private school.

We distinguish between two types of unsubsidized private schools: elite and non-elite. To classify private schools, we expand the approach from Zimmerman (2019). Focusing on the cohorts graduating from high school and entering college in the 1970s and 1980s, we identify a set of seven schools that consistently place their alumni in elite business and political positions.[2] Until recently, these seven elite private schools enrolled only male students. To extend the classification system to cover female students, we augment the elite group with the seven most popular schools among the sisters of male elite students, relying on family links available for recent cohorts (2004–2018). Each of these seven schools historically admitted only women, although two have become coeducational since

[2]To identify these schools, we relied on three reports produced by a head hunting firm—Seminarium—that characterized the education trajectories of business and political leaders in 2003 and 2010. The schools we classified as elite consistently rank among the 15 most popular among individuals in different elite occupations. Online Appendix B provides further details.

the 1970s. Finally, to extend the classification system through the present, we identify eight private schools founded in the 1980s or later by organizations associated with the traditional elite schools. In the 2018 class, students graduating from these 22 elite private schools represented 1.1% of their cohort.

We take attendance at an elite private school as our main measure of social capital. This is an important choice to justify, because elite private schools may differ from other schools on many dimensions, including price and academic quality. Our basic argument is that the main way elite private schools stand out from other expensive private schools is in the social pedigree of their students, the social insularity of the educational experience, and the long-run importance of the social relationships that are formed there, not price or academic excellence. This argument has strong qualitative and quantitative support.

The production of social capital at elite private schools starts at the point of admission. Admission to an elite private school typically requires some sort of exam for the child, but also interviews with parents and in many cases letters of recommendation from members of the school community. Applicants whose parents graduated from elite schools have admission advantages similar to legacy enrollment policies in the US. Entering these schools is difficult for children without an elite background.

The social consequences of admissions decisions at elite private schools are magnified by a distinctive feature these schools share: unlike most of the other schools in the country, students are admitted when they are four years old and attend the same institution until graduating from high school. This means that students attending elite private schools spend 14 years of their lives together.

The social distinction of elite private schools is clearly visible in descriptive statistics. For each school we compute indices of social pedigree based on the last names of the students who attend. Following Abramitzky et al. (2020)'s approach for identifying Jewish names in Census data, we compute a prestige score for each last name by comparing the share of individuals with that name in the population to the share with the name in either a) Chile's most exclusive polo club, the Club de Polo y Equitación San Cristóbal, or b) historical "Who's Who" lists of prominent Chileans from de Ramon (2003). For each name, we compute the prestige index E as

$$E = \frac{\text{Share in the club}}{\text{Share in the club} + \text{Share in the population}},$$

so that E is zero for names that never appear in membership lists and approaches one for names that are common in membership lists but rare in the population. People in Chile have two last names (on their mother's and father's side), so we compute individual scores by averaging over the two names, and compute school scores by averaging over individuals in the school. We also compute average tuition fees, average scores on the college admissions exam, and test score value added for each school. Our measure of test score value added conditions on students' age and gender, parental education, household income, and the availability of different educational inputs (such as books) at home. See Online Appendix C for details on our value added and tuition measures.

Table 1 reports how measures of price, quality, and prestige vary by school type. All variables are standardized to have mean zero and standard deviation one. Private schools are expensive, and elite private schools are among the most expensive private schools in the country. Their prices are on average 8.6 standard deviations above the non-private mean, compared to 4.3 standard deviations for non-elite private schools. However, elite private schools are not uniquely expensive. We identify a set of 35 non-elite private high schools with tuition fees at least as high as the least expensive elite school. Average tuition in this group is similar to what we see for elite private schools. Panel (a) of Figure 1 displays a histogram of the tuition distribution that identifies different school types.

On measures of academic performance, private schools outperform subsidized schools, while elite and expensive non-elite private schools score similarly. Elite private schools and non-elite expensive schools have average scores and value added about 2 standard deviations above the population mean. The gap between elite private schools and non-elite private schools is only about 0.2 to 0.3 standard deviations.

Where gaps between elite private schools and non-elite expensive schools are most pronounced is in the social prestige measures. Elite private schools score 5.7 standard deviations above the population mean on the polo club index and 6.1 standard deviations above the mean on the Who's Who index. Both values are about four standard deviations above expensive non-elite schools. Panel (b) of Figure 1 displays a histogram of the polo club prestige index. 20 of the 30 highest scoring schools are in the elite private category.

Social inputs at elite private schools matter in the long run for access to top jobs and positions in society. On the qualitative side, Warner (2014) describes his experience searching for investment banking jobs in Santiago, during which he is repeatedly asked about where he attended high school. Warner views his Harvard PhD as the more relevant credential, but recruiters seem less interested. Huneeus (2013) interviews the founder of a Chilean investment bank, who emphasizes the importance of school background for social interactions in elite spaces:

> *"We have meritocracy as an objective in our firm, but only to a certain extent, because there are codes [...] when a guy has attended certain [elite] k-12 schools, those codes are built in."*

On the data side, Zimmerman (2019) shows that social ties between college classmates from high-status Chilean high schools are an important determinant of long run corporate leadership. Pairs of students from elite private schools who are college peers are more than four times more likely to hold top corporate jobs at the same firms than pairs of students from private high schools in general.

The bottom line is that elite private schools are academically strong schools, and they are expensive schools. But where they most stand out is in the social pedigree of the students they admit, the duration of the time students spend there, and the long-run influence of the social ties between their students. The way students are chosen and the time they spend together cultivates what Coleman (1988) refers to as "closure of the social structure"—the idea that links within a social group are common, and ties to non-group members less common—and identifies as critical for the development of social capital through norms, networks, and exchange relations.

There is of course some fuzziness at the margin of our elite/non-elite classification. As we discuss later, our findings hold under alternate groupings and when we take continuous measures based on name indices as the outcomes of interest.

As a final point, we emphasize that there are many forms of social capital that we are not attempting to measure. Past work defines social capital broadly, as "productive matter" (Coleman, 1988) or "beliefs and values that facilitate cooperation" (Guiso et al., 2011) within some linked group, which could be a school community, but also a neighborhood, an ethnic group, a business partnership, and so on. Our claim is not that we measure all types of social capital, but that we credibly measure a type of social capital that is salient among Chilean economic and social elites and plays an important role in access to top positions in the economy and in society.

2.2 Higher education and human capital

Most Chilean universities select their students through a centralized admissions system. Students take a national university admissions exam and then submit a ranked list of degree programs to the admissions authority.[3] They are allocated to programs based exclusively on scores and preference rankings using a deferred acceptance algorithm.

We take performance on the university admissions exam as our main measure of human capital. This exam has been offered since the late 1960s and consists of required math and reading sections plus additional subject-specific tests required for certain programs. Taking the university admission exam and applying to universities is free for students from subsidized high schools, and college financial aid programs are available to low-income applicants. Online Appendix B provides more detail on college finance in Chile; see also Solis (2017) and Bucarey (2018). We focus on the average of math and reading scores and consider not taking the admissions exam as an outcome of potential interest.

The two most prestigious universities in Chile are the University of Chile (UC) and the Catholic University of Chile (PUC). Both universities have participated in the centralized admissions system since its beginning. As with elite private schools, the alumni of these two universities make up a large share of business and political elites. Within these universities, programs in business, law, engineering, and medicine are the most selective and highest paying. Zimmerman (2019) provides evidence on this point. Following Zimmerman (2019), we focus our analysis of elite degree programs on these four fields at UC and PUC.

Students from high-status backgrounds are overrepresented at elite universities. Among the freshmen starting at UC and PUC in 2019, 53.5% came from subsidized schools, 36.1% from non-elite private schools, and 10.1% from elite private schools. The over representation of non-elite and elite private school alumni was even larger in the business, law, medicine, and engineering programs, where they represented 43.5% and 17.4% of first year enrollment, respectively. Relative to the population of high school graduates, elite private school graduates are overrepresented at elite degree programs by a factor of 16. The degree of over-representation we observe for elite private school students at elite degree programs is similar to the over-representation of children with family incomes in the top 1% at Ivy+

[3]During our sample period, students could rank either eight or ten programs, depending on the year.

universities in the US (Chetty et al., 2020, 2023).[4]

3 Data

3.1 Data sources

We draw on archival and administrative data from two public agencies: the Chilean Ministry of Education and the Department of Evaluation, Assessment, and Educational Records of the University of Chile (DEMRE). DEMRE is the agency in charge of the university admission system.

DEMRE provided individual-level records of admissions exam scores for the years 1968 through 2018 and of college applications for the years 1977 through 2018. We digitized these records from hard copies for application cycles in 2003 and earlier. In each year, we observe exam scores for all test takers. From 1977 on, we observe ranked lists of admitted and marginally rejected students at each degree program, including the score the degree program used to evaluate the student. These lists form the basis of our main empirical design, which compares just-admitted to just-rejected applicants at elite programs.

For many but not all application cycles we also obtain records of applicants' submitted preference rankings and the rules used to score those applications. With these records, available from 1977 to 1979, 1981 to 1989, and from 2000 onward, we are able to reconstruct the application process and identify individuals at the margin between specific degree programs, for example someone who is applying to medicine at PUC and has medicine at UC as their fallback option if they are rejected. These records form the basis for an alternate design that compares outcomes for people crossing thresholds between different target and fallback options.

The data also contain demographic information. We observe the high school each applicant attended. In addition, from 2004 onwards we observe self-reported socioeconomic characteristics and the national identification number of applicants' parents.

The Ministry of Education records that we use in this project cover the period 2002 to 2018. They include the universe of students enrolled in primary and secondary education and contain information on the schools students attend and their academic performance. The Ministry of Education also granted us access to a dataset identifying siblings attending school at the same time between 2002 and 2015. We combine these sibling links with the parent links provided by DEMRE to identify members of the same family.

We use these data to create two analysis samples: the intergenerational correlations sample (IC) and the elite colleges sample (EC).

3.2 Intergenerational correlations sample (IC)

To build the IC sample, we identify students reaching their senior year of high school between 2003 and 2017. We link these students to their scores on the university admissions exam and to the university and major in which they first enroll. About 85% of high

[4]Note that elite private school graduates are conceptually distinct from top 1% students. Elite private school graduates are not just from rich families, they are from rich and socially connected families.

school seniors take the admissions exam. We then use information on parent and sibling identifiers, together with registers from the Ministry of Health that link children born between 1992 and 2010 with their mothers, to identify the students' parents. We identify at least one parent for 81% of the students in our sample.

Finally, we link students' parents to their admissions exam and college enrollment records. We are able to link 30% of students with at least one of their parents' scores. That this rate is far from 100% makes sense given that college attendance in Chile rose rapidly between the parent generation and the child generation.[5] We consider both parents and students who did not take the test in many of our analyses.

Panel A of Table 2 describes the IC sample. Column (1) looks at all high school graduates and column (2) looks at graduates who register for the university admission exam. Columns (3) and (4) zoom in on students for whom we observe a parent identifier and students whose parents took the university admissions exam, respectively. Students' gender and age composition do not change much across columns. Differences are larger when we look at students' academic and socioeconomic characteristics. Children of parents who also applied to college are more likely to graduate from the academic track in high school and perform better both in high school and in the university admission exam. They are also more likely to enroll in college in general and in elite college programs in particular. In terms of family background, they are more likely to graduate from private high schools, to come from high-income households, and to have at least one parent who completed a university degree.

3.3 Elite colleges sample (EC)

To build the EC sample we identify applicants near the admission cutoff for an elite degree program between 1977 and 2003. We use the information on family links to match these applicants with their children. We identify at least one child for 41.1% of applicants. We add information on the secondary schools these children attend, their admissions exam scores, and the college degree programs in which they enroll.

Panel B of Table 2 presents summary statistics for this sample. Column (1) characterizes all college applicants in our sample, while column (2) examines applicants that we are able to link to children. Columns (3) and (4) focus on the subset of individuals applying to elite college programs and scoring close to the admissions cutoff, which we define as being within 25 points on the standardized admissions score. Column (3) characterizes below-cutoff applicants, while column (4) looks applicants who score above the cutoff. Individuals applying to elite college programs are balanced in terms of gender. Not surprisingly, their scores in the admission exam are higher than those in the broader population and they have a higher chance of being admitted to college. They are also more likely to have graduated from private high schools.

[5]The share of college-age individuals enrolled in higher education rose from 12% in 1977, the first year of our sample, to 38% in 2018, the last year (UNESCO Institute for Statistics, 2022).

4 Intergenerational correlations

We begin our empirical analysis by describing the joint evolution of social and human capital across generations and how it relates to elite university attendance. Our central findings here are a) that both human and social capital are highly persistent across generations, b) that human and social capital evolve interdependently, so that social capital levels predict human capital mobility, and vice versa, and c) that elite college attendance predicts upward mobility in both human and social capital.

Figure 2 presents intergenerational correlations between mothers' admissions test score ranks and children's academic outcomes.[6] To construct this figure, we locate each applicant's score from the first time they take the admissions exam and compute his or her rank using the known score distribution. Scores on the college admission exam are normalized to follow a normal distribution with mean 500 and standard deviation 110. The extremes of the distribution are truncated, but the minimum and maximum scores are below the first percentile and above the 99th percentile, respectively. We place individuals who do not take the college admission exam in a different category that for expositional purposes we call percentile 0. When estimating these correlations, we omit mothers who we do not observe taking the exam. The maroon square at the bottom left corner of each panel reports outcomes for this group. We split the sample by mother's high school type, our proxy for social capital.

We find that human capital is persistent across generations. Panel (a) of Figure 2 shows that the rank-rank relationship between mothers' and children's admissions exam scores is approximately linear in the full sample. The slope is 0.41, meaning that a ten percentile increase in mother's rank increases a child's predicted rank by 4.1 percentiles.

Social capital mediates the intergenerational transmission of human capital. Panel (b) of Figure 2 again reports the rank-rank relationship between mother's and child's admissions exam scores, this time splitting by mother's high school type. The slopes of the rank-rank relationship decrease with social capital. For children of subsidized-school mothers, the slope of child's score rank in mother's score rank is 0.40, while for non-elite private school mothers it is 0.35 and for subsidized school mothers it is 0.30. The intercepts increase with social capital, from a rank-zero intercept of 44 percentiles for subsidized-school mothers to a rank-zero intercept of 61 percentiles for elite private school mothers. The result is differences in child mean score rank by mother's social capital that are large at the bottom of the score distribution and decline toward the top. The 17 percentile gap between elite private and subsidized school mothers at rank zero is equal to what would be expected from a 45-percentile increase in test score rank for subsidized school mothers. The gap across school type for elite private and subsidized school mothers in the top percentile of the exam distribution is 7 percentiles, or the expected gain from an 18 percentile increase in scores for subsidized school mothers.

Patterns of intergenerational persistence and interdependence are similar for social

[6] Online Appendices D.1, D.2, and D.3 report results that use alternate measures of child human capital and that relate children's score to father's or parent-average scores rather than mother's scores. Results are similar to those we present here.

capital. Panel (c) of Figure 2 plots the share of students who attend elite private schools by mother's exam rank, split by mother's high school type. Differences by social capital are stark. 65% of students whose mothers scored at the top of the college admission exam distribution and attended an elite private school go on to attend an elite private school, compared to only 10% of children whose mothers had the same scores but attended subsidized schools. Children of the lowest-scoring elite private school mothers are more likely to attend an elite private school than children of the highest-scoring subsidized-school mothers. At the same time, rates of social capital mobility vary with parent human capital. For example, children of subsidized-school mothers with scores below the 70th percentile on the admissions exam almost never attend an elite private school. As scores for subsidized-school mothers rise, however, the share of their children attending elite private schools also rises, reaching 10% by the top of the score distribution.

Parents' elite higher education predicts children's social and human capital even after controlling for parents' pre-college social and human capital. Among mothers in the top 1% of the admissions test score distribution, for whom attending an elite degree program is a realistic option, elite attendance is associated with better human and social capital outcomes for children at all levels of mothers' social capital. For example, as shown in panel (d) of Figure 2, subsidized school mothers who are admitted to an elite college program are around 50% more likely to send their children to elite private schools, 30% more likely to have children with top 1% test scores, and 20% more likely to have a child who enrolls in an elite college program. Online Appendix Figure A.I reports equivalent statistics for mothers who attend elite and non-elite private schools.

These descriptive patterns suggest that elite college programs may play a role in mediating the persistence of human and social capital across generations. However, it is also possible that the relationship between parents' elite attendance and children's outcomes is driven by selection into elite colleges on the basis of attributes that we do not observe. The next section explores the causal role of elite colleges in more detail.

5 Using admissions discontinuities

5.1 Specification

We use a regression discontinuity design to isolate the causal effect of admission to elite degree programs on intergenerational human and social capital transmission. This approach compares outcomes for children whose parents apply to elite degree programs and fall just above or just below the cutoff for admission.

Our main RD specifications have the form

$$E_{ijct} = \beta_0 + \beta_1 A_{jct} + f(S_{jct}; \theta) + \mu_{ct} + \varepsilon_{ijct}, \tag{1}$$

where E_{ijct} is an educational outcome for child i whose parent j applied to the college-major combination c in year t. A_{jct} is an indicator for parent j's admission status to college-major c in year t, $f(S_{jct}, \theta)$ is a linear function of the application score S_{jct} whose slope is allowed to change at the admission cutoff, and μ_{ct} is a fixed effect for interactions between target college-major combination c and application year t. Because target degree program and application year are balanced across the admission threshold, the μ_{ct} fixed effects are not required for the identification of causal effects. We include these covariates to increase precision and because they correspond to the level at which each admissions quasi-experiment takes place.

Intuitively, these specifications aggregate information from many cutoff-specific quasi-experiments by stacking the data across all cutoffs (Pop-Eleches and Urquiola, 2013). As discussed in Zimmerman (2019), the use of stacked data means that parents may show up in the data more than once, if, for example, their score falls just below the cutoff at their first-ranked choice and just above the cutoff at a lower-ranked choice. In addition, each parent may have multiple children, and children may have multiple parents who apply to elite degree programs. When conducting statistical inference, we account for the presence of multiple observations of parents and children by clustering standard errors two ways, at the child and parent level.[7]

Several points related to estimation procedure and sample selection are important to highlight. First, when estimating this specification we pool mothers and fathers, but we also present results that split by parent gender. Second, our main estimates focus on parents whose application scores are within 25 points of the admission cutoff. This is the same window used in Hastings et al. (2013)'s analysis of Chilean admissions data, and is similar to optimal bandwidth values computed as in Calonico et al. (2014). Our findings are not sensitive to the use of alternate bandwidths. Finally, we restrict our sample to the first time a parent applies to college, eliminating test re-takers from the data.

5.2 Validity

For the regression discontinuity design to generate informative results, crossing the threshold for elite admission needs to generate variation in the degree programs parents attend. Though data on college enrollment are not available for our full sample period, we can test this proposition using data from 2006 through 2017, for which population enrollment records are available.

Figure 3 illustrates the relationship between admission and enrollment in elite college programs for individuals applying to college during the 2006-2017 period. Panel (a) shows the sharp change in admission probability at the cutoff. Only students above the admissions cutoff receive an offer through the centralized admission system. Panel (b) shows how the admissions discontinuity translates to enrollment. We observe a jump of 76 percentage points from a base of 12%. The change in probability is less than one because not all students accept the admissions offer. This means that above-cutoff enrollment rates are below 100% and that in some cases initially rejected students can move up off of a waitlist and enroll. Also, in recent years both UC and PUC have introduced some special admission programs for talented students from disadvantaged backgrounds. The number

[7] Note that this stacked specification does not draw on information about where a degree program falls on a parent's rank list. In section 6.3 we use data on applicants' full preference rankings to explore the effects of crossing admissions margins between different types of target- and next-option degree programs.

of places offered through these programs is small, but they allow some applicants under the regular admission cutoff to enroll in elite college degrees.

The bottom line here is that, despite some non-compliance with centralized assignment, threshold-crossing induces a large discontinuity in enrollment. The fuzziness in the discontinuity design means that the effects of attending an elite college program are somewhat larger than the estimated admissions effects we present.

Interpreting regression discontinuity estimates as causal effects requires the assumption that "treated" units just above the cutoff are comparable to "control" units just below in terms of the observable and unobservable determinants of outcomes of interest. Standard tests of balance pass easily. We report results from these tests in Figure 4.

Panel (a) of Figure 4 shows the distribution of the running variable in the range of the cutoff. There is no visual evidence that students manipulate their scores to fall just above the cutoff. This makes sense given the structure of the admissions process, in which cutoffs depend only on centrally assigned exam scores, are determined endogenously by the demand for seats and the supply of spots, shift from year to year, and are not known to applicants until admissions results are revealed. The statistical test for manipulation suggested by Cattaneo et al. (2018) fails to reject the null of no manipulation (p=0.356).

Panel (b) of Figure 4 shows that crossing the admissions threshold does not affect selection into the sample of parents. In principle, admission to an elite college program could affect the probability that applicants go on to have children. This would create a censoring problem, requiring additional assumptions on what outcomes for "missing" children would have been. It turns out, however, that admission does not affect the probability that an applicant becomes a parent. Online Appendix E.1 shows that the count of children is also stable across the threshold.

Panel (c) of Figure 4 looks within the sample of parents to examine the effects of threshold-crossing on potential confounders. We find no evidence of discontinuities in the gender of the parent, the kind of high school the parent attended, the gender of the child, the birth year of the child, or the family size reported by the children when registering for the admission exam. A joint test of the null that the coefficients on each of these parent and family characteristics are zero fails to reject at conventional levels (p=0.615).

5.3 Interpretation

Changes in outcomes across the cutoff result from shifts in the bundle of program and peer attributes available at the target program relative to the mix of applicants' next-best alternatives. Table 3 describes how the observable attributes of the degrees where students enroll change when they gain admission to an elite program, splitting out the sample by the kind of high school the student attended.

Students marginally admitted to specific elite degree programs become much more likely to attend any elite degree program, and attend college with peers who are higher scoring and more likely to have attended high-status private high schools. Students who are admitted to elite degree programs become 75 percentage points more likely to enroll in their target degree program, 52 percentage points more likely to enroll in any elite degree program, and 27 percentage points more likely to enroll in any degree program at an elite college (UC or PUC). The average score of their peers on the admissions exam rises by about 26 points (0.76 standard deviations), the share of their college peers from elite private high schools rises by 4.8 percentage points (37%), and the elite name index of the high schools attended by their college peers rises by 0.52 standard deviations. We see similar effects across most outcomes for students from elite and non-elite schools.

In short, the elite admission treatment involves changes in a variety of institution and peer characteristics. In section 6.3, we use additional data on applicants' preference lists to break out the importance of specific program attributes.

6 Results

6.1 Elite colleges, human capital, and social capital

We now turn to the effects of parents' elite admission on children's human and social capital accumulation. Table 4 reports estimates from regression discontinuity specification (1).

Our first finding is that parents' elite admission raises children's social capital. As reported in Panel (a) of Table 4, parents who are admitted to elite college programs are 4.4 percentage points more likely to send their child to an elite private school, a 20% increase relative to the below-threshold mean of 22.3%. For parents who did not attend elite high schools, the gain is 3.35 percentage points, 20% of the below-threshold mean of 16.6%. Gains are similar (but less precisely estimated) for children of parents who attended elite high schools, for whom the below threshold mean is much higher, at 65.7%.

The right columns of Panel (a) of Table 4 report results for an alternate measure of social capital: the polo club elite name index at the schools children attend. This index increases by 0.33 standard deviations across the cutoff.

These discontinuities are visually obvious. Figure 5 shows regression discontinuity plots for (the children of) parents who attended non-elite high schools. Panel (a) shows the discontinuity in the rate at which children attend elite private schools. Panel (b) shows the discontinuity in the name index.[8]

Parents at the admissions margin substitute between elite and non-elite private schools for their children, not between private schools and subsidized schools. As we report in Online Appendix E.2, the effects of threshold-crossing on non-elite private attendance have roughly the same size as the elite private effects, but opposite signs.

Our second finding is that parents' elite admission does not affect children's human capital accumulation. As reported in Panel (b) of Table 4, parents' elite admission does not raise children's high school GPA or mean scores on the college admissions exam. These results hold in full sample and in splits by parent high school type. They are also precisely estimated. For example, we can rule out a 4.5 point (0.04 standard deviation) increase in mean scores in the full sample. Panels (c) and (d) of Figure 5 present visual evidence that these outcomes are smooth through the cutoff. Results reported in Online Appendix E.2

[8] Online Appendix E.2 displays a version of Figure 5 using the full parent sample. This figure closely resembles Figure 5.

show that rates of exam-taking are also smooth through the cutoff.

Consistent with the absence of human capital gains, we observe that the academic quality of the schools children attend does not change across the cutoff. Panel (e) of Figure 5 illustrates this result, taking exam value added of the high schools that children attend as the outcome of interest. This dovetails with descriptive findings from section 2 showing that the elite private schools students substitute towards at this margin stand out mostly for social pedigree, not academic quality.

Our third finding is that parents' elite admission shapes their children's higher education trajectories. As reported in Panel (c) of Table 4, children whose parents cross the admission threshold enroll in college programs where their classmates are 0.97 percentage points (10%) more likely to have elite private school backgrounds. These peers, however, do not obtain significantly higher scores on the college admission exam. Panels (f) and (g) of Figure 5 provide regression discontinuity plots for these outcomes. Panel (h) of Figure 5 shows a large discontinuity in the polo club elite name index for a child's college peers.

Panel (d) of Table 4 focuses on elite colleges and elite degree programs. When parents cross the elite admissions threshold, their children become 2.4 percentage points (7.5%) more likely to enroll in elite colleges (i.e., UC or PUC). Panel (i) of Figure 5 illustrates this result. In contrast, children's likelihood of enrolling in an elite *program* within these elite colleges does not change. These findings parallel the results reported in Panels (b) and (c). To attend an elite degree program, children must clear a formidable academic hurdle, and, if they do attend, they will have high-scoring peers who have also cleared this hurdle. Panels (b) and (c) show that parents' elite admission does not raise students' own test scores and does not cause students to attend degree programs with higher-scoring peers. In contrast, as discussed in Section 2, there are other degree programs at elite colleges where admissions requirements are not as stringent but where students are still disproportionately drawn from high-status backgrounds. It is these other degree programs towards which parent elite admission shifts child college attendance.

An interesting feature of these findings is the presence of higher education effects in the absence of exam effects. Because admissions depend only on academic performance, the implication is that the higher education effects arise from changes in application behavior, with higher social capital students applying to colleges with higher-status peers. Results presented in Online Appendix E.2 show that the effects of parent elite admission on the rates at which children *apply* to elite colleges are roughly equal to the elite college enrollment effects reported in Table 4. This parallels findings on college "undermatch" in the US (Hoxby and Turner, 2013; Dynarski et al., 2021).

Our findings are robust to alternative estimation approaches. Our main results persist over a wide range of bandwidths, including optimal bandwidths computed as in Calonico et al. (2014, 2020). Our findings are also robust to alternate control sets, sample selection procedures, and high school classification schemes. See Online Appendix F for details.

6.2 Mechanisms and heterogeneous effects

6.2.1 Gender and role modeling

We now turn to the mechanisms underlying the effects of elite admission on children's social and human capital. We first consider mechanisms related to child and parent gender. In principle, gender may mediate the effects of parents' elite admission through channels such as gender-specific role model effects (Dahl et al., 2020) or gender differences in preferences over investment in children's outcomes (Duflo, 2003). However, when we split our analysis of admissions effects by parent and child gender, we find little evidence of effect heterogeneity. We report these findings in Online Appendix Table A.I. Gender match is not a first-order determinant of the effects we see.

6.2.2 Educational expenditures

Income effects are another plausible mechanism. Parents may earn more and increase their educational expenditures in general, with children's elite private attendance being one manifestation of that increase. This story, in which social capital follows from financial success, is quite different from causal stories in which social relationships formed at elite institutions drive intergenerational capital transmission. To test the role of increasing educational expenditures as a driver of increased elite attendance, we place measures of educational expenditures on the left side of equation (1). We find that parents' admission to an elite college modestly increases educational expenditures, but that this increase is driven by increased rates of attendance at elite private schools, and not by increased enrollment at other expensive private schools. See Online Appendix E.3 for details.

That generic expenditure effects do not drive our findings is consistent with results from previous work indicating that income effects are likely limited for non-elite parents gaining admission to elite college programs. Zimmerman (2019) shows admission to the elite business, engineering, and law programs in our sample only increases earnings for men graduating from private high schools. We *do* find effects when focusing on the children of women and applicants who did not attend private K-12 schools, suggesting that our findings are not primarily driven by income effects.[9]

6.2.3 Regional mobility

All of the elite private high schools are in the Santiago region. Admission to an elite degree program in Santiago may make parents from other regions more likely to live in Santiago as adults, expanding elite high school access for their children by virtue of geographic proximity. We test this hypothesis by re-estimating our main specifications separately for parents from Santiago and for parents from other regions. We find no evidence that mobility across regions is an important mechanism. See Online Appendix E.5 for details.

[9] Zimmerman (2019) finds that elite medical programs do significantly increase earnings for male and female students who graduated from both subsidized and private schools. In Online Appendix E.4 we show that our results persist even when we focus on the sub-group of non-elite parents applying to elite business, engineering and law programs (i.e., on parents who do not experience earnings gains).

6.2.4 The marriage market

The fourth type of mechanism we consider is changes in parents' social environment in college and beyond. We start by focusing on a specific channel through which peer inputs may shape intergenerational outcomes: the marriage market. The identity and attributes of one's spouse are particularly important when studying children because both partners contribute genes, childcare, and family inputs. As described in Section 3, we do not directly observe marriages, but we can identify couples through their children. We use these data to estimate regression discontinuity specifications with spouse attributes as outcomes.

Because the focus of the analysis is on parents, we use a slightly different sample than in our analysis of child outcomes. We create a sample in which each observation corresponds to a parent's application, rather than an application-child, and cluster standard errors at the parent level instead of at the family level. We continue to limit the sample to the main group of interest: applicants who did not themselves attend elite high schools.

Table 5 reports our findings. As a preliminary step, we verify that the rate at which we observe applicants' spouses is smooth through the cutoff. This proves to be the case: we match 55% of marginal parents to spouse records, with no discontinuity in rates at the point of admission. Since our coverage of mothers is better than our coverage of fathers in the child data, we are able to identify more wives than husbands.

Our first result is that non-elite applicants admitted to elite colleges become more likely to partner with people in their program. The share of parents whose spouse attended their target program rises by 8.6 percentage points when they cross the threshold for admission, roughly doubling the below-threshold mean rate of 9.4%. Panel (a) of Figure 6 displays this result. The rates at which applicants marry individuals in any elite program and individuals in any elite college rise by somewhat less than the target program effect, indicating substitution towards the target program from other elite college programs. For example, as shown in Panel (b) of Figure 6, the share of applicants marrying individuals who attend any elite degree program rises by 4.3 percentage points across the cutoff.

Our second result is that marital matches generated by admission cross boundaries defined by baseline social capital. The rate at which applicants not from elite high schools marry someone from an elite private school rises by 3.15 percentage points when they cross the admissions cutoff, a 46% increase over the below-threshold mean of 6.84%. Panel (c) of Figure 6 shows the regression discontinuity plot for this finding. The shift towards partners from elite private high schools is part of a broader pattern of substitution towards higher-status private school partners and away from subsidized school partners. As shown in panel (d) of Figure 6, the rate at which applicants marry someone from any private school (elite or non-elite) rises by 6.3 percentage points (15%). Effect sizes are broadly similar for male and female applicants (columns (2) and (3) of Table 5 illustrate these findings).

Our third result is that spouse test scores do not rise across the admissions cutoff. Table 5 illustrates this finding. Elite admission helps non-elite applicants match to high social capital partners, but it does not raise their partner's human capital.

Our findings on marriage market effects parallel our findings on children's outcomes, in the sense that we find large effects of admission on the social capital but not the human capital of one's partner. These findings provide qualitative support for the idea that changes in the social environment at college are an important driver of long-run effects for children, and raise the possibility that changes in marriage partners may themselves be a quantitatively important driver of children's outcomes.

6.2.5 Social capital in the neighborhood

Schools are leading sites of social capital formation, but they are not the *only* sites of social capital formation. To better understand the changes in children's social lives that result from parent's elite admission, we place attributes of children's neighborhood peers on the left side of equation (1). We define neighborhood peers as high school graduates with residential addresses within 100 meters of one's own address. These data are available for residents of the three largest regions of Chile. See Online Appendix C for details.

Children of parents admitted to elite degree programs grow up in neighborhoods where their peers have higher social and human capital. Table 6 reports these results. Panel A shows that children of parents just above the cutoff for elite admission live in neighborhoods with peers who score about 0.23 to 0.25 standard deviations higher on the polo club name index. This effect is similar in size to the effect of parents' elite admission on the polo club name index of children's school peers reported in Table 4. As shown in Panels B and C, children also shift towards neighborhoods where peers pay higher school tuition and score better on the college admissions exam.

Despite increases in the human and social capital of residential peers, we see little evidence that children live in more expensive neighborhoods. As reported in Panel D of Table 6, the census block level price per square meter (a standard index of home price in Chile) does not change much across the admissions threshold, and we cannot rule out zero effects at conventional levels.[10]

We draw two conclusions from this exercise. First, parents' admission to elite degree programs reshapes children's social lives both at home and at school. The joint shift in neighborhood and home environment may augment social capital development. As Coleman (1988) points out, school communities develop stronger shared norms and trust relationships when social ties extend beyond the school. Second, as we found in our analysis of educational expenditures in section 6.2.2, simply spending more money does not appear to be the main mechanism underlying the shift in social environment.

6.3 Academic vs. social vs. marriage market inputs

6.3.1 Beyond elite degree programs

Our findings thus far show that admission to elite degree programs shapes intergenerational mobility in social capital but not human capital, and that changes in parents' social lives, including matching to high social capital spouses, may be an important reason why.

[10]Prices per meter are measured in Unidad de Fomento (UF), the inflation-adjusted unit of account typically used to describe real estate values in Chile. Due to limited precision we cannot rule out meaningful increases for this outcome. For non-elite students the upper bound on the 95% CI for the admissions effect is about 2.5UF, or roughly 5% of the below-threshold mean.

We also show that admission to an elite college shifts a bundle of educational inputs simultaneously, including both peer academic skill and peer social pedigree. We now ask which components of this bundle—academic inputs, peer social pedigree, or access to high social capital marriage partners—drive the effects we see, while also expanding our field of view to the full set of degree programs in the Chilean higher education system.

To do this, we augment our base dataset on admissions outcomes at the eight elite degree programs in two ways. First, we bring to bear data on applicants' full preference rankings. In our parent sample, these records are available for 1977-1979, from 1981 through 1989, and then from 2000 through 2003. Preference ranking data allow us to identify applicants on the margin between pairs of degree programs with different attributes. We can then isolate the impact of observable elements of the elite college bundle, holding others fixed.

Second, we use data on all degree programs, not just elite degrees. This expands the sample size dramatically, which is helpful given the restriction on application cycles. It also allows us to exploit all of the variation in peer attributes in the higher education system, not just variation generated by elite admission. More fundamentally, it allows us to explore the determinants of social and human capital mobility in the broader higher education system, not just at top programs.

Motivated by our analysis of elite degree programs, we focus on three program attributes: academic quality Q, social pedigree or "eliteness" E, and elite marriage market access M. We define academic quality as the mean admissions exam score of admitted students, and social pedigree as the share of admitted students who attend an elite school. We define elite marriage market access as the share of non-elite students at the program who marry alumni of elite private schools. To avoid having one's own outcomes affect measured degree attributes, we use a cohort-level leave-out procedure in which the attribute of a degree program in a given application cohort is computed using data from all other cohorts. We combine measured degree attributes with the application list data to compute the difference between the attributes of the target and next option for each submitted application, and label these differences ΔQ, ΔE, and ΔM, respectively.[11]

6.3.2 Differential effects by changes in degree attributes

Figure 7 shows results from a simple initial exercise, in which we split up applications from non-elite parents (separately) by quartiles of ΔQ, ΔE, and ΔM, and estimate versions of equation 1 within each sample. Panels (a) through (c) report "first stage" effects. These effects are large. For example, when applicants in the top quartile of ΔQ gain admission to their target degree, the academic quality of their peers rises by 62 points (1.24 standard deviations of the college degree average test score distribution); when applicants in the bottom quartile gain admission to their target degree, the mean academic quality of their

[11] ΔQ, ΔE, and ΔM each measure attributes of students' college degree programs. ΔM differs from the other two variables in that there is a natural first-stage outcome through which one might claim the effects of changes in M on child social capital should operate: whether a given non-elite student goes on to marry an alumnus of an elite private school. In Online Appendix C.4 we show that cross-threshold changes in observed marriage outcomes for students are proportional to cross-threshold changes in M.

peers falls by 47 points (0.96 standard deviations).

The lower panels of Figure 7 show how human and social capital accumulation change with admission in each sample. We find that the probability one's children attend an elite private school tracks gains and losses in peer elite high school shares and in elite marriage market access. As in our analysis of elite programs, effects are large relative to base rates. When parents in the top quartile of ΔM gain admission to their target degree, the chance their child attends an elite high school rises by 2.4 percentage points, or 17%. When parents in the bottom quartile of ΔM are admitted, the chance their child attends an elite high school falls by 2.3 percentage points. In contrast, the relationship between peer academic quality and social capital mobility is, if anything, negative. We see no evidence that any of these variables are associated with changes in children's human capital.

A challenge in interpreting these findings is that changes in degree attributes may be correlated with one another. People with high values of ΔE may have lower values of ΔQ, for example. We address this issue by running parametric specifications that control simultaneously for the effects of academic, social, and marriage market variables. These specifications have the form

$$\begin{aligned} E_{ijct} = &\beta_0 + \beta_1 A_{ijct} + \beta_2 A_{ijct} \times \Delta E_{ijct} + \beta_3 A_{ijct} \times \Delta Q_{ijct} + \beta_4 A_{ijct} \times \Delta M_{ijct} \\ &+ \beta_5 \Delta E_{ijct} + \beta_6 \Delta Q_{ijct} + \beta_7 \Delta M_{ijct} + f(S_{ijct}, \mathbf{\Delta X}_{ijct}; \theta) + \mu_{ct} + \varepsilon_{ijct}. \end{aligned} \tag{2}$$

E_{ijct} is an outcome for child i of parent j applying to program c in cohort t and A_{ijct} is an indicator for i's admission to c in year t. β_1 is the main effect of admission to the target degree relative to an observably identical next choice. β_2, β_3, and β_4 are coefficients on the main regressors of interest—interactions between admission and the change in degree-specific peer attributes across the cutoff. Controls include main effects of $\mathbf{\Delta X}_{ijct} = [\Delta E_{ijct}, \Delta Q_{ijct}, \Delta M_{ijct}]$, as well as a continuous linear function of S_{ijct} that is allowed to vary above and below the cutoff and to interact linearly with the $\mathbf{\Delta X}_{ijct}$. We include fixed effects for parent target degree $c \times$ application cycle t.

Table 7 reports the results of these regressions for our main outcomes. When reporting coefficients, we standardize the $\mathbf{\Delta X}_{ijct}$ to have mean zero and standard deviation one.

Results confirm the visual intuition from Figure 7. Social capital gains for children depend on private school peer share and elite marriage rates at the colleges where parents are admitted. For example, admission to a program with a one standard deviation higher elite marriage rate raises the chances one's child attends an elite school by 1.05 percentage points, 16% of the mean. In contrast, holding peer social status and elite marriage rate fixed, admission to a degree with a one standard deviation higher average exam score reduces the chance one's child attends an elite school by 0.78 percentage points (12% of the sample mean).

Turning to human capital, peer social status and elite marriage rates do not affect children's exam performance. Peer academic performance has a negative and marginally significant effect on average exam scores or high school GPAs.

For higher education, we see positive effects of parents' peer elite high school share on children's elite college and elite degree program attendance. These effects are economically meaningful. For example, admission to a college degree with a one standard deviation higher elite peer share raises the chances one's child attends an elite degree program by 1.81 percentage points, just over 25% of the mean rate of 0.072. We observe similar positive effects on measures of the social capital of children's classmates in the same college program, such as the share of college peers from elite private high schools and the elite name index at the college program (columns 8 and 9), but do not observe positive effects on the human capital of children's college classmates (column 7).

We see no evidence that parents' admission to a college with higher peer human capital or better marriage market opportunities raises the quality of the college their children attend, holding parent elite peer share fixed. Coefficients on the interactions between admission and the ΔQ and ΔM variables are zero or negative for each of the higher education outcomes.

The key theme emerging from Figure 7 and Table 7 is that admission to degree programs with high-end peer social inputs drives the intergenerational transmission of social capital, while admission to programs with stronger academic peers if anything reduces upward social mobility and does not raise human capital either. Together with our evidence on marriage matching for students admitted to elite degree programs, these findings suggest that college social inputs are crucial drivers of long-run social capital mobility.

Because college social inputs are not randomly assigned, the above analysis does not rule out the possibility that the social capital gains associated with admission to degree programs with higher status peers arise not from exposure to those peers but instead from changes in some other degree attribute with which exposure is correlated (and which is not correlated with peer *academic* achievement). One way to assess this possibility is to allow for heterogeneous effects by additional observable degree attributes and see whether the social input effects persist. Online Appendix Table E11 reports results from specifications that allow for heterogeneity based on cross-threshold changes in field of study, an important determinant of earnings that is strongly correlated with student demographics (Hastings et al., 2013). This does not affect our findings.

6.4 High school type and friendship formation

Our discussion thus far takes the kind of K-12 school a child attends as a proxy for social capital accumulation. This approach has a strong basis in studies of Chilean elite formation. However, a possible concern is that children whose parents did not attend elite K-12 schools themselves may have difficulty acquiring social capital even if they attend elite high schools, perhaps because of challenges integrating into the school's social environment. In the terminology of Chetty et al. (2022), friending bias may limit social capital accumulation even if exposure to high-status peers rises.

We provide direct evidence on the social integration of friend groups across and within K-12 schools and on how children's friend groups are shaped by their parents' college admissions outcomes. Our approach relies on a link between application records and data from the Longitudinal Study of Tobacco, Alcohol, and Drug Consumption. This study followed a group of roughly 4,500 students starting seventh grade in 2008 over the course of four years (see Valenzuela and Ayala, 2011, for further details). A survey implemented at the beginning of the study asked each student to identify their closest friends. We use these records to compute the average elite name index among students' friends. We then place this variable on the left-hand side of regression discontinuity specifications. We summarize the results of this exercise here, with details in Online Appendix G. Notably, we find no evidence of differential selection into survey reporting or differences in the number of friends reported.

Figure 8 illustrates our main findings. Panels (a) and (b) present regression discontinuity plots where the outcome is the mean elite name index of children's friends. The sample—limited to survey participants whose parents did not attend an elite K-12 school and are marginal applicants—is split by whether the share of elite peers at the parent's target degree program is higher ($\Delta E > 0$, panel (a)) or lower ($\Delta E < 0$, panel (b)) than in the next option program.

Children's friends rise in status when their parents gain admission to programs with higher-status peers, and fall in status when their parents gain admission to programs with lower-status peers. On average, children whose parents cross the threshold for admission to college degree programs with higher elite peer shares report an increase of 0.03 in the elite peer index value for their own friends. This is equal to 30% of a standard deviation of the friends' elite name index in the survey sample and is statistically indistinguishable from the cross-threshold shift in the peer elite name index for the high schools children attend.

These findings confirm that parents' admissions outcomes shape children's social groups and that the identities of the K-12 schools children attend are effective proxies for social effects. Friending bias does not appear to be a first order determinant of how children's friend groups shift when their parents gain access to socially elite degree programs.

7 Quantifying the contribution of elite universities

7.1 A VAR calculation

How much do the elite college effects we document shape the intergenerational and cross-sectional correlations between human and social capital? To get a sense of the quantitative importance of elite college for intergenerational mobility, we combine our descriptive and regression discontinuity estimates using a stylized vector autoregression (VAR) model that incorporates capital accumulation, elite college attendance, and marriage market matching. We are interested in intergenerational and cross-sectional correlations given the data we see and under different assumptions about the causal effects of elite college.

The assumptions we invoke when specifying the model are strong. We therefore view the exercise as an extended back of the envelope calculation, in the spirit of Kremer (1997)'s analysis of neighborhood effects or Chetty et al. (2019)'s forward projection of racial income gaps in the US. Given our best guesses at the parameters governing the intergenerational evolution of social and human capital, how much do elite colleges matter?

We model dynasties that evolve over time. Dynasties are endowed in each period with social and human capital. Given these values, they choose the "eliteness" of the college they attend. After college, they match to a spouse who is also characterized by human capital, social capital, and college eliteness. The social and human capital of the next generation in the dynasty are then determined as a function of parents' average social capital, human capital, and college eliteness.

This conceptual setup gives rise to the following VAR:

$$S_{it} = \alpha_0 + \alpha_1 \overline{S}_{it-1} + \alpha_2 \overline{H}_{it-1} + \alpha_3 \overline{E}_{it-1} + e_{1t} \tag{3}$$

$$H_{it} = \beta_0 + \beta_1 \overline{S}_{it-1} + \beta_2 \overline{H}_{it-1} + e_{2t} \tag{4}$$

$$E_{it} = \gamma_0 + \gamma_1 S_{it} + \beta_2 H_{it} + e_{3t} \tag{5}$$

$$S^s_{it} = \delta_0 + \delta_1 S_{it} + \delta_2 H_{it} + \delta_3 E_{it} + e_{4t} \tag{6}$$

$$H^s_{it} = \phi_0 + \phi_1 S_{it} + \phi_2 H_{it} + e_{5t} \tag{7}$$

$$E^s_{it} = \psi_0 + \psi_1 S_{it} + \psi_2 H_{it} + \psi_3 E_{it} + e_{6t} \tag{8}$$

S_{it}, H_{it}, and E_{it} are social capital, human capital, and college eliteness for dynasty i in generation t. We continue to measure human capital using entry exam scores. We measure social capital as the polo club name score eliteness of the high school an individual attends. As discussed in sections 2 and 6.1, this is a continuous analog of the binary "elite high school" categorization. We measure college "eliteness" as the average value of social capital for students who attend, as in section 6.3. S^s_{it}, H^s_{it}, and E^s_{it} are the same variables for the spouse, and $\overline{S}_{it}$, $\overline{H}_{it}$, and $\overline{E}_{it}$ are average values of the individual and the spouse. The e_{jt} are error terms, which we assume are statistically independent with mean zero and variances to be estimated.

A few restrictions are worth noting. First, we allow the direct effects of elite college to enter only through peer social capital. This is motivated by our findings in section 6.3 that the academic quality of college peers does not produce upward social or human capital mobility. Second, we restrict the college eliteness effects on child's human capital and spouse human capital to be zero. This choice is motivated by null effects in our regression discontinuity analysis for these outcomes. Third, we impose separability across all inputs and do not distinguish between mothers and fathers or daughters and sons. These choices are motivated by our finding of limited heterogeneity in elite college effects by baseline social capital and by parent and child gender.

Our approach to calibrating the model is to estimate the parameters governing elite colleges' role in production and matching using instrumental variables specifications that parallel the regression discontinuity designs in section 6.3. We then fill in the remaining parameters using OLS regressions similar to our analysis in section 4, restricting college effects to the estimated values from the discontinuity designs. Finally, we compute the variance and autocovariance matrices of S_{it} and H_{it} as functions of model parameters, using both the estimated values and counterfactual assumptions on the parameters governing the causal effects of elite colleges (α_3, δ_3, and ψ_3) and selection into elite colleges on the basis of social capital (γ_1). Online Appendix H describes the procedure in detail.

We emphasize that our approach involves many simplifications. To highlight a few, our instrumental variables specifications impose strong exclusion restrictions on the channels through which attending an elite college shapes long-run outcomes. We assume that treatment effects are homogeneous and apply them away from the admissions cutoffs where they are estimated. We impose strong functional form assumptions. We assume that parameters governing the process remain stable across generations, even though the Chilean economy and education system change over the period we study. Finally, when conducting counterfactual exercises, we assume that descriptive relationships governing other relationships in the data are stable even as the effects of college change. We interpret our findings as a back-of-the-envelope variance decomposition, not as a precise prediction about what might happen in the future under different policy regimes.

Our main finding is that elite colleges play a quantitatively important role in making social capital both more persistent across generations and more closely correlated with human capital within generations. That is, elite colleges tend to reduce social capital mobility while also allocating social capital more meritocratically, in the sense that the social capital reward becomes more closely linked to academic achievement.

The first column of Table 8 reports baseline results based on observed parameter values, while the second column reports results from a counterfactual in which the causal effects of college on both social capital accumulation and marriage market matching are set to zero, i.e. where $\alpha_3 = \delta_3 = \psi_3 = 0$. Looking first at autocorrelations, in the base model the intergenerational correlation of social capital within a dynasty is 0.3420. This falls by 33% to 0.2299 in the no college effects counterfactual. At the same time, elite colleges tighten the link between academic and social success: in the base model, the cross-sectional correlation between social and human capital is 0.1761. Under the counterfactual no college effects model, this value falls by one fourth, to 0.1286. We see a similar result for "intergenerational meritocracy": the correlation between *parent* human capital and child social capital falls by roughly one third when we zero out college effects.

These effects are large relative to the simulated effects of other kinds of policies. The third column of Table 8 reports results from a counterfactual exercise that leaves elite college effects at their base levels but eliminates the effect of social capital on selection into elite colleges by setting $\gamma_1 = 0$. The idea is to eliminate "undermatch" of low social status students. We find that eliminating undermatch has effects that are similarly signed to the effects of eliminating elite college effects entirely, but slightly smaller. For example, the intergenerational correlation of social capital falls from 0.342 at baseline to 0.250, and the cross-sectional correlation of social and human capital falls from 0.176 to 0.163.

We also use the model to understand the extent to which the quantitative impacts of elite college are driven by marriage market effects. To do this, we consider counterfactuals that alternately a) set $\alpha_3 = 0$ and thereby eliminate the direct effect of elite college on social capital accumulation while keeping marriage market effects fixed, or b) set δ_3 and ψ_3 equal to zero, thereby eliminating matching effects while keeping the direct effect fixed. We report results from these exercises in columns 4 and 5 of Table 8. We find that direct effects are the more important channel. When we set $\alpha_3 = 0$, the intergenerational correlation in social capital falls to 0.2345, 96% of the way from the base case to the full no college effects counterfactual in column 2. When we set δ_3 and ψ_3 equal to zero, the same intergenerational correlation falls to 0.3378, 6% of the way from the base case to the full no college counterfactual.

7.2 Admissions policy and the mobility-meritocracy tradeoff

The VAR exercise considers the role of elite universities in society by shifting their causal impacts from the observed values to zero. We now ask what our findings say about the effects of marginal changes to existing policy on mobility and meritocracy.

We consider two types of marginal policy changes. The first type seeks to promote intergenerational mobility by providing admissions score bonuses to college applicants from subsidized schools. This resembles affirmative action interventions adopted by Chilean higher education policymakers starting in 2007.[12] The second type of policy provides score bonuses to students from elite private high schools. This exercise captures the flavor of admissions policies at elite US universities, where admissions chances are higher for high-status students at a given level of academic achievement.[13]

Our goal here is to address three related questions. First, given the applications students submit and our estimates of the effects of assignment to degree programs with elite classmates, can changes to admissions policy have meaningful effects on intergenerational social capital mobility? Second, how sharp a tradeoff between mobility and the meritocratic allocation of social capital do these policies pose? Third, how does the meritocracy-mobility tradeoff depend on the role of elite college peers in the production of social capital?

The exercise proceeds as follows. In the first step, we use the rules of the assignment algorithm and students' submitted application rank lists to simulate the allocation of students to programs under a series of counterfactual scoring rules in which students from subsidized (or elite private) schools receive progressively larger bonuses on their application index score, ranging from five to fifty points in five point intervals. In the second step, we compute counterfactual human and social capital outcomes for each child under the new assignment h using the rule

$$Y_{ij}^h = Y_{ij} + \gamma(E_j^h - E_j), \tag{9}$$

where Y_{ij}^h is the outcome under counterfactual assignment h for child i of parent j, Y_{ij} is the observed outcome for child i of parent j, E_j^h is the share of elite college peers for parent j under counterfactual assignment h, and E_j is the share of elite peers observed in the data. γ is a parameter reflecting the effect of parents' elite peer share on child outcome, estimated using RD specifications that parallel equation 2 but restrict the effects of college admission to operate only through a main effect and through peer elite high school share.

[12] These policies effectively reduced admissions cutoffs for subsidized school students. The size of the cutoff reduction varied across programs, with the middle 80% of the distribution ranging from five to 112 points. See DEMRE (2023) for further details.

[13] Arcidiacono et al. (2019) report that Harvard applicants in the high-status "legacy, donor, or child of faculty" (LDC) category receive higher scores on the personal, athletic, and extracurricular components of their applications than other students, and are more likely to be admitted than non-LDC students who receive the same academic rating.

In the third step, we compute correlations between parent and child social capital as well as between child human capital and child social capital under the observed allocation and under each counterfactual allocation. See Online Appendix I for details.

This exercise maintains the exclusion restrictions and homogeneous effects assumptions from the VAR analysis. However, it relaxes assumptions on the functional form of intergenerational relationships and stays much closer to the existing policy regime in the counterfactuals it considers. A crucial remaining assumption is that submitted applications remain the same under the counterfactual policies. We view this assumption as reasonable for small point bonuses.

Figure 9 reports our findings. The horizontal axis reports the correlation between children's social and human capital. The vertical axis reports the intergenerational social capital correlation. The axis is reverse scaled so that moving vertically up the graph corresponds to lower intergenerational correlations and higher social capital mobility. Each point represents the outcome from a counterfactual simulation and is labeled with the size of the score bonus for the listed group.

Focus first on the solid-filled points, which describe counterfactuals in which the causal effect of assignment to each degree adjusts to reflect the share of elite students in the degree program. Blue circles report results from score bonuses for subsidized-school students. Green squares report results for score bonuses to elite private school students. In these counterfactuals, the social capital production function depends on who your college peers are, so counterfactual outcomes change from baseline for two reasons: because students are assigned to different degree programs, and because degree programs have different shares of elite students and therefore have different effects on social capital accumulation.

The first finding here is that admissions bonuses for lower social capital students can have quantitatively important effects on social mobility, but that these gains reduce the correlation between children's social and human capital. A ten-point bonus reduces the intergenerational correlation of social capital by 5%, from 0.526 to 0.500. This score bonus also reduces the correlation between children's social and human capital by 5%. The slope of the mobility-meritocracy tradeoff is approximately constant over the range of subsidies for low social capital students we consider, with a one-unit increase in the correlation between child social and human capital corresponding to a 2.7 unit decrease in intergenerational social capital mobility.

The second finding is that, perhaps surprisingly, score subsidies for elite high school students *also* pose a tradeoff between mobility and meritocracy, provided the subsidies are fairly small. As score bonuses for elite students rise from zero to 25 points, social capital mobility falls, while the correlation between children's social and human capital rises. At bonus levels above 25 points, both social capital mobility and the social capital-human capital correlation fall. What is happening here is that score bonuses for elite school graduates distort the allocation of college slots in a way that tends to reduce the human capital-social capital correlation, all else equal. However, bonuses for elite students also increase the share of elite students in top programs, which raises the effects of access to elite college programs on social capital accumulation for all admitted students, pushing up the correlation between social and human capital. At low subsidy levels, the latter effect dominates, but as subsidies get bigger, the former effect becomes more important. The implication is that if social capital production depends on access to elite peers, a planner placing high value on meritocracy might reasonably implement modest admissions subsidies for high-status applicants.

The hollow points on the figure report results from a parallel set of counterfactuals in which degree effects are held fixed at baseline values, so changes in outcomes result only from changes in degree assignments, not changes in the causal effects of assignments. In these simulations, bonuses to elite school graduates reduce both mobility and meritocracy at all subsidy values. This is because gains for students from exposure to peers with higher social capital are shut down. Bonuses for subsidized schools graduates follow a steeper slope than in the first set of simulations: a ten point score bump reduces the intergenerational correlation of social capital by 2.5% and the intragenerational human capital-social capital correlation by less than 1%. Shifting the mix of students towards those with subsidized school backgrounds does not reduce the gains to attending an elite program, so mobility gains can be achieved at a smaller cost to meritocratic objectives.

The conclusion from both the local admissions counterfactuals and the VAR decomposition exercise is that elite universities play quantitatively important roles in *both* shaping the transmission of social capital across generations *and* shifting the allocation of social capital towards academic high achievers. Plausible changes to admissions policy can increase the intergenerational mobility of social capital *or* increase the degree to which it is meritocratically allocated, but the tradeoffs between these two objectives are substantial.

8 Conclusion

This paper uses five decades of data linking parents' and children's educational outcomes in Chile to obtain three main results. First, we show that access to elite colleges helps talented students from lower-status families expand access to social capital for their children. Second, we show that the key mechanisms underlying this effect are social, not academic. Third, we show that elite colleges play a quantitatively important role in the intergenerational transmission of elite social capital. Elite colleges create a social elite that is both academically higher-achieving and intergenerationally stickier, highlighting a tension between ideas of fairness centered on meritocracy and ideas centered on opportunity.

The point that meritocracy need not expand opportunity dates to Young (2017)'s coinage of the term. Nevertheless, our finding that elite college admission expands access to elite social capital in the second generation paints a more optimistic picture than recent studies showing that elite college students from lower-status backgrounds are less likely to reach top positions in business and society than their high-status college peers (Zimmerman, 2019; Michelman et al., 2022).

Our findings on the social links between elite universities and elite high schools apply most straightforwardly to settings such as the US and UK, where elite private high schools channel students into elite universities and then to top roles in business and government (Cookson and Persell, 2008; Sutton Trust and Social Mobility Commission, 2019; Chetty et al., 2023), and less directly in countries like France, where many traditional elite high schools are state-run (Van Zanten and Maxwell, 2019). Stepping back from the specific institutional structure, we view our findings as an existence result. Elite universities can provide a long-run path to elite social capital even in high-inequality settings such as Chile, where concerns about elite entrenchment sparked protests in 2019 (Taub, 2019; Flores et al., 2020). Intergenerational effects may be even larger in settings where baseline social divisions are less stark.

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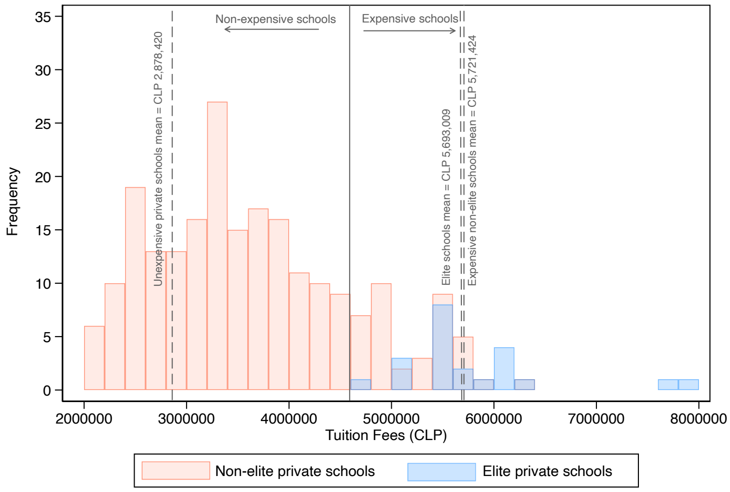
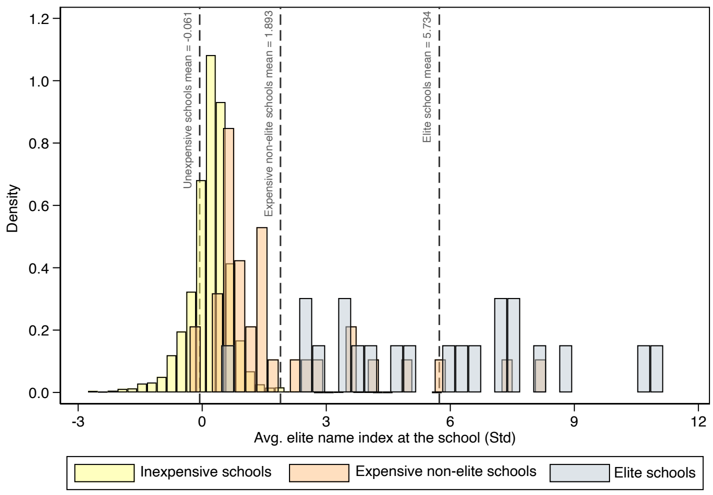
Figure 1: Characteristics of private K-12 schools



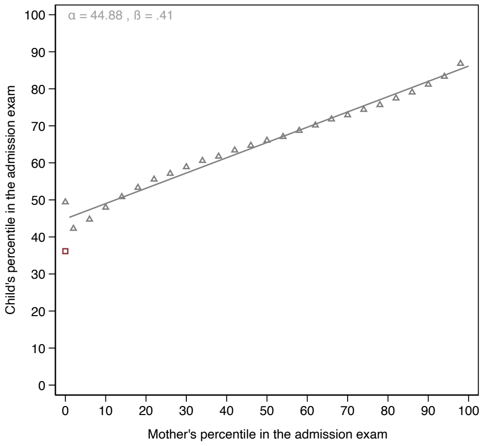
(a) Distribution of tuition fees



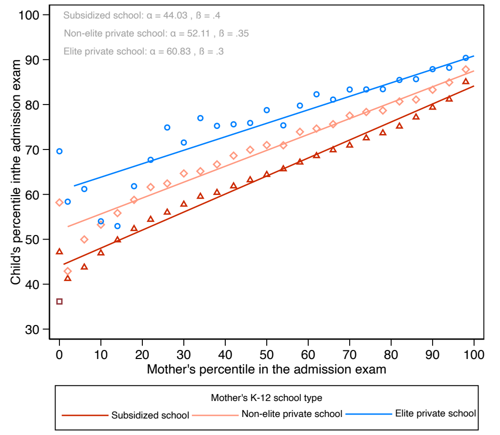
(b) Distribution of polo club elite name index

Panels (a) and (b) in this figure describe inexpensive, expensive non-elite, and elite K-12 private schools along two dimensions: tuition fees and the polo club elite name index. Panel (a) illustrates the distribution of tuition fees charged by private schools. Panel (b) illustrates the distribution of the polo club elite name index. See section 2.1 for details.

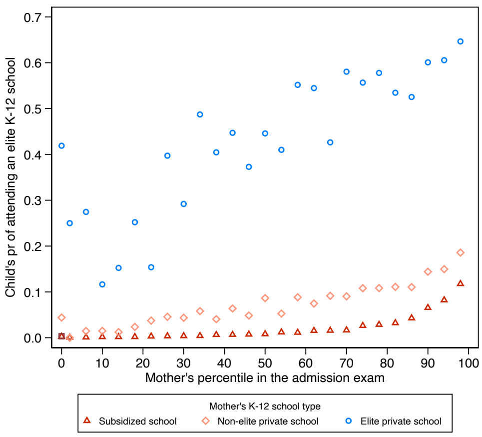
Figure 2: Correlations between mothers' scores and children's outcomes



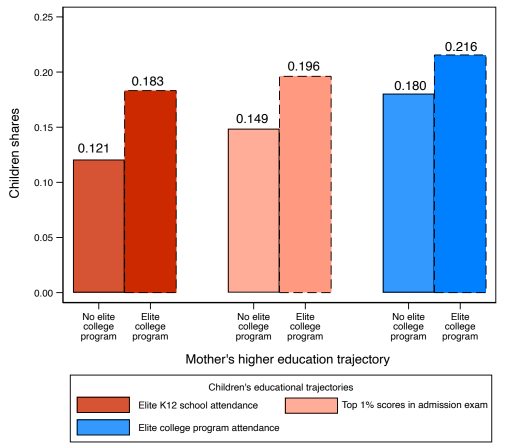
(a) Rank-rank exam score correlations in the whole sample



(b) Rank-rank exam score correlations by mother's high school type



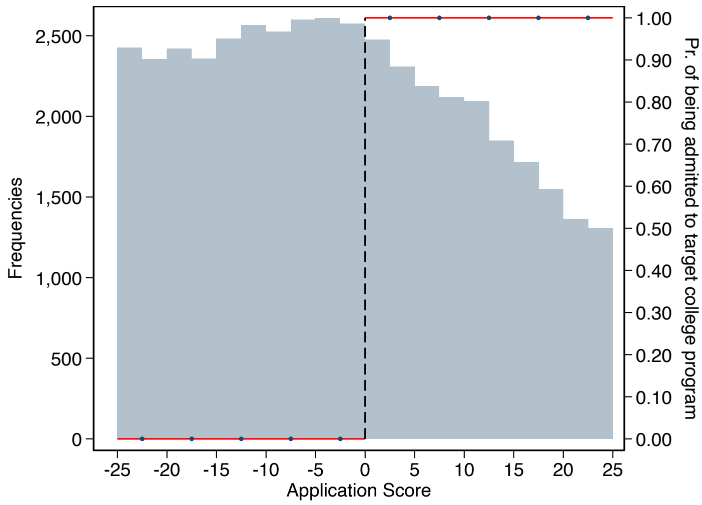
(c) Probability child attends an elite K12 school



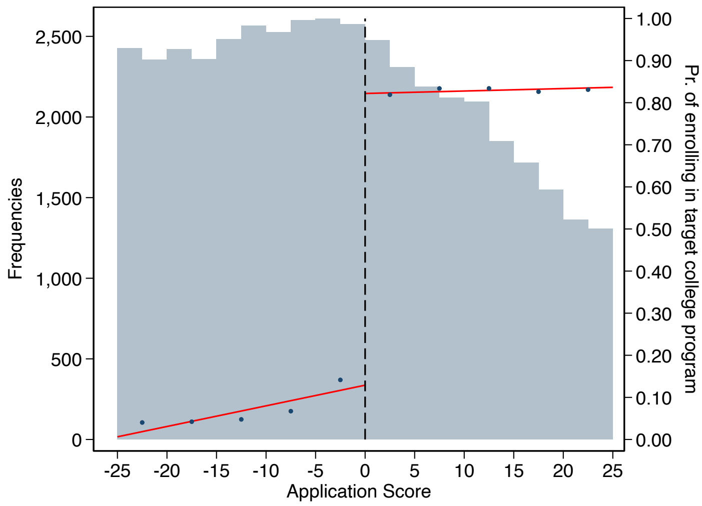
(d) Children outcomes by mother's higher ed trajectories (mothers from subsidized high schools scoring in the top 1%)

Panels (a) to (c) in this figure illustrate correlations between children's outcomes and their mothers' percentile in the university admission exam. Panel (a) illustrates the relationship between mothers' and children's percentiles in the university admission exam for the whole sample. Panel (b) replicates this exercise, splitting the sample by mother's high school type. Panel (c) shows the probability that a child attends an elite high school by mother's high school type. Maroon squares in panels (a) to (c)—at lower left—illustrate cases in which we do not observe mothers' high school and scores. Linear fits in panels (a) and (b) exclude observations where mothers' scores are not observed. Panels (a) and (b) include cases in which children did not take the admissions exam; these children are treated as having zero rank. Panel (d) focuses on mothers who attended a subsidized high school and scored in the top 1% of the university admission exam. It shows how their children's outcomes change depending on whether or not they attended an elite college program. The red bars on the left illustrate differences in children's attendance to elite K12 schools, the pink bars in the middle illustrate differences in children's probability of scoring in the top 1% of the university admission exam, and the blue bars on the right illustrates differences in children's probability of attending an elite college program themselves. See section 4 for details.

Figure 3: Changes in admission and enrollment outcomes around the admission cutoff



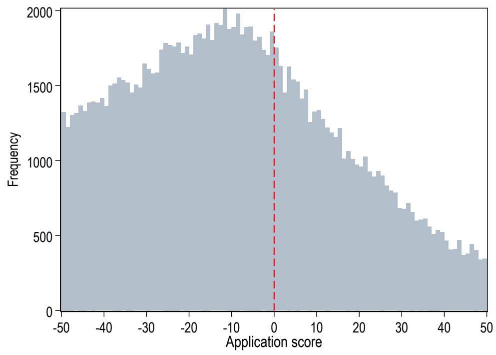
(a) Admitted to target college program



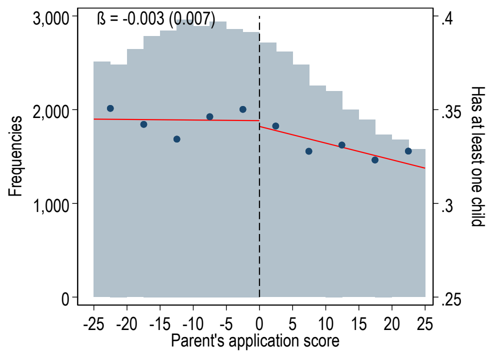
(b) Enroll in the target college program

Panel (a) illustrates how the probability of receiving an offer to an elite college program through the centralized admission system changes around the admission cutoff. Panel (b) illustrates the change in the probability of enrolling in the target elite college program. This figure uses data from the 2006 through 2017 application cycles. These are the years for which we observe enrollment data. The blue bars in the background illustrate the distribution of the running variable (i.e., application scores). Blue dots represent outcome means at different levels of the running variable. The red lines correspond to linear regressions and are independently estimated at each side of the cutoff. See section 5.2 for details.

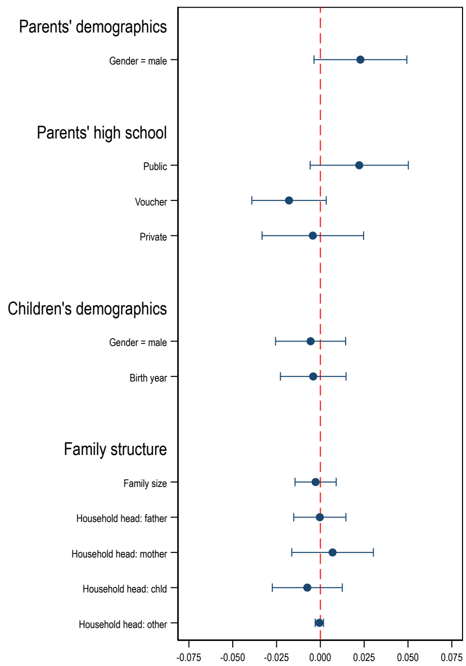
Figure 4: Regression discontinuity validity tests



(a) Distribution of application score



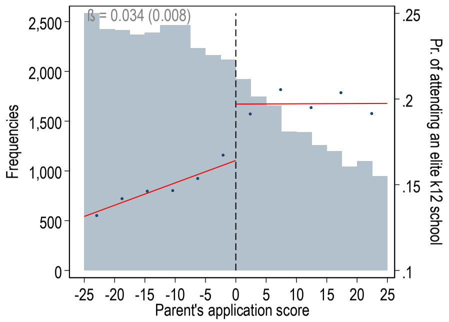
(b) Pr. of having a child



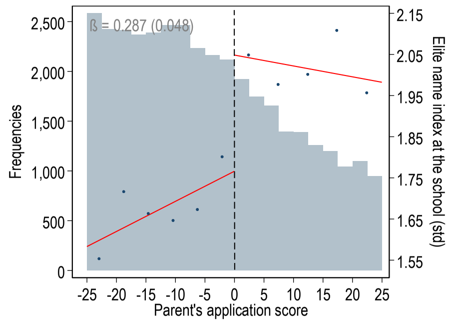
(c) Discontinuities in potential confounders

This figure presents the results of several tests of the validity of the regression discontinuity design. Panel (a) illustrates the distribution of application scores of individuals applying to elite college programs between 1977 and 2003 (i.e., the years in which we observe parents). Panel (b) uses the same sample to study how admission to an elite college program affects the probability of observing an applicant's child in our sample. Panel (c) reports regression discontinuity estimates of how threshold-crossing affects predetermined covariates. The estimates in Panel (c) come from running specification 1 taking the predetermined covariates as outcomes. Blue dots represent point estimates. Blue lines are 95% confidence intervals. See section 5.2 for details.

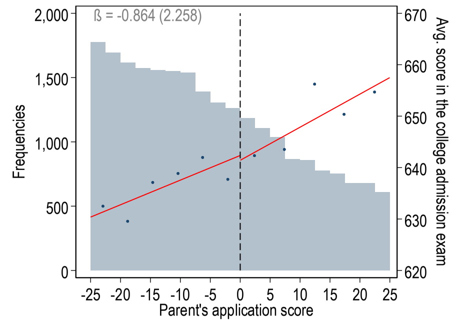
Figure 5: Effect of non-elite parents' admission to an elite college program on children's outcomes



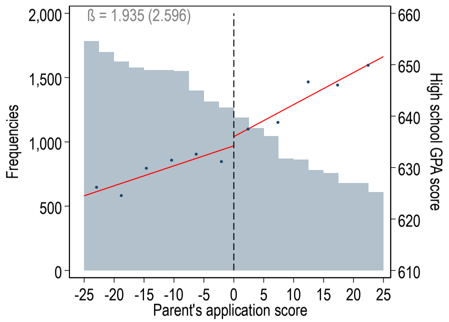
(a) Child attends elite K-12 school



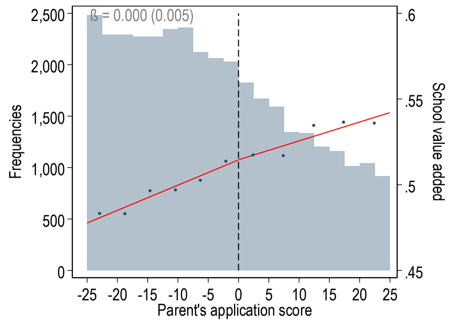
(b) Name index in child's school



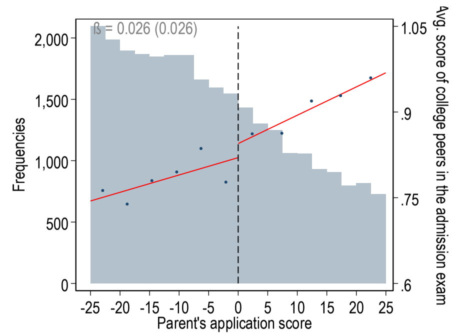
(c) Child's admissions exam score



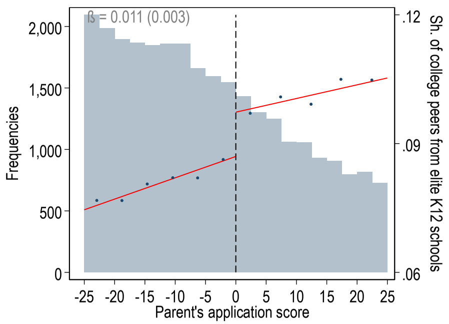
(d) Child's high school GPA



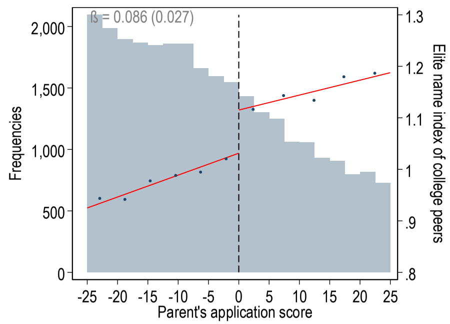
(e) Child's K-12 school value added



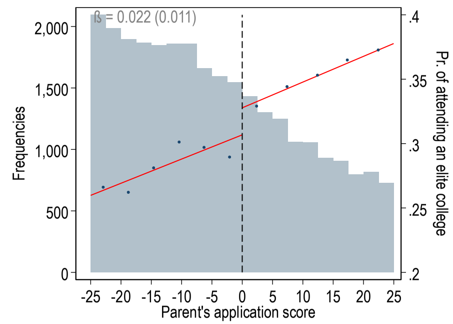
(f) Child's college peers test scores



(g) Child's college peers from elite schools



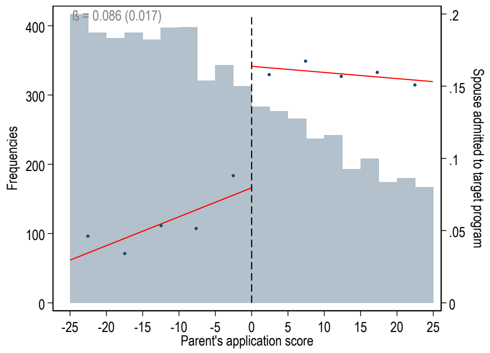
(h) Child's college peers name index



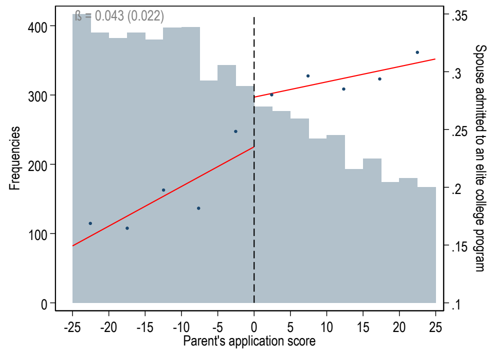
(i) Child attends an elite college

This figure illustrates how children's outcomes change when one of their parents gains admission to an elite college program. The sample is limited to parents applying to elite college programs who did not themselves attend an elite private K-12 school. Panel (a) shows the probability that the children attend an elite K-12 school; panel (b) the elite name index at the children's K-12 school; panel (c) children's average score in the college admission exam; panel (d) children's high school GPA; panel (e) the value added of children's K-12 school; panels (f) to (h) characterize children's college peers in terms of test scores and of their social pedigree; finally panel (i) describes children's probability of attending an elite college (i.e., University of Chile or Catholic University). The running variable—i.e., parent's application score—is centered around the admission cutoff of the parent target degree. Each dot represents outcome averages at different levels of parents' application score. The red lines are fitted values from linear regressions, fit separately on each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable in the estimation sample. See section 6.1 for details.

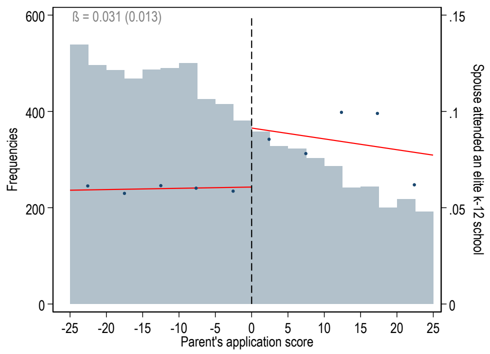
Figure 6: Effects of admission to an elite college program on spouse characteristics



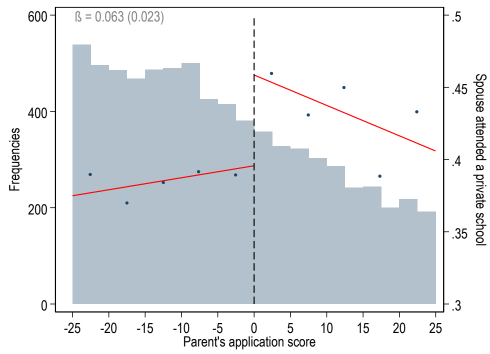
(a) Spouse admitted to target degree program



(b) Spouse admitted to any elite program



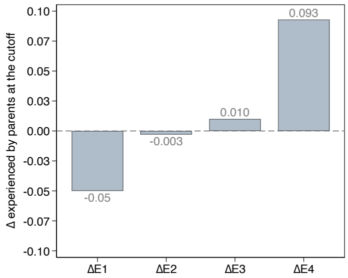
(c) Spouse attended an elite K-12 school



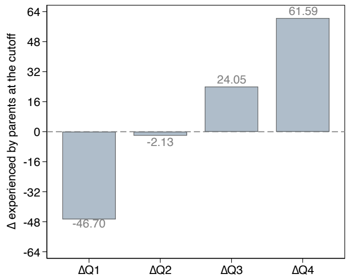
(d) Spouse attended any private K-12 school

This figure illustrates how admission to an elite college program changes the characteristics of spouses. Panel (a) shows the probability of marrying someone admitted to the target (i.e., above-threshold) degree program. Panel (b) shows the probability of marrying someone admitted to any elite college program. Panel (c) shows the probability of marrying someone who graduated from an elite private K-12 school, and panel (d) shows the probability of marrying someone who graduated from any private K-12 school (includes non-elite and elite private schools). The running variable in all cases corresponds to a parent application score. It is centered around the admission cutoff of his/her target program. Each dot represents the mean of the outcome variable at different levels of the parent's application score. The red lines illustrate the slope of the running variable and its 95% confidence interval. The slope is independently estimated at each side of the cutoff using a linear regression. The blue bars in the background show the distribution of the running variable. See section 6.2.4 for details.

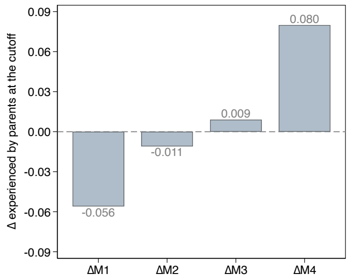
Figure 7: RD estimates of effects of parents' college exposure to elite peers (E), college exposure to high-scoring peers (Q), and college marriage prospects (M) on children's outcomes



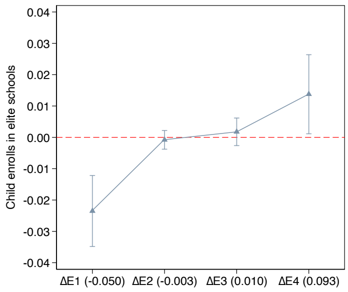
(a) E experienced by parents by ΔE



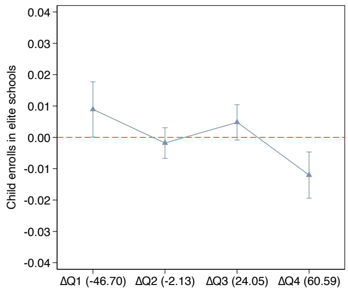
(b) Q experienced by parents by ΔQ



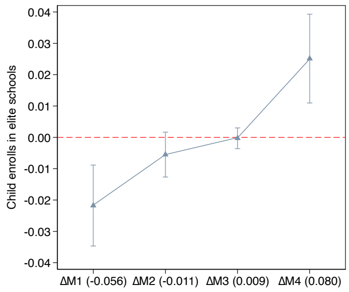
(c) M experienced by parents by ΔM



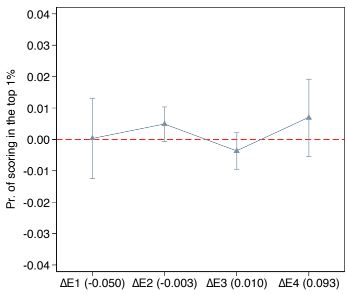
(d) Child attends an elite HS by ΔE



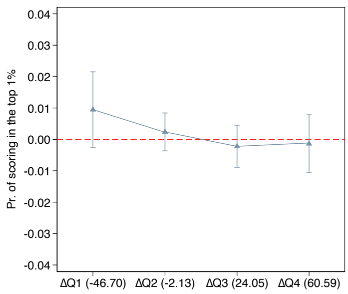
(e) Child attends an elite HS by ΔQ



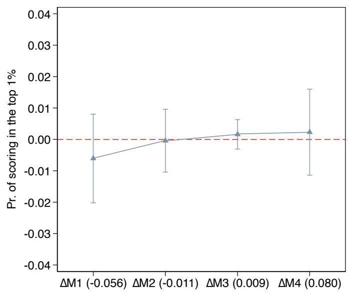
(f) Child attends an elite HS by ΔM



(g) Child scores in top 1% by ΔE



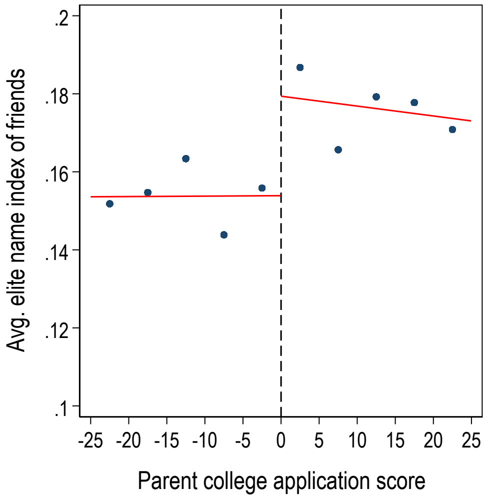
(h) Child scores in top 1% by ΔQ



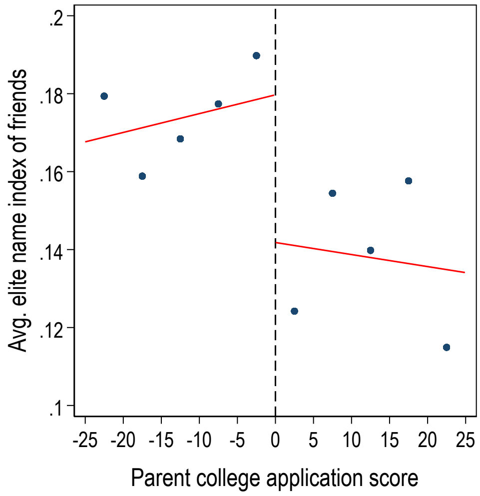
(i) Child scores in top 1% by ΔM

This figure illustrates how outcomes for children change when their parents cross admissions thresholds that shift them between different kinds of college degree programs. All results reported in this table are regression discontinuity estimates of equation 1, splitting the sample by attributes of the target and next option degree programs. The effect of parents' admission to their target college program is allowed to vary depending on the difference in the share of alumni of elite K-12 schools (ΔE), in peers' average score in the college admission exam (ΔQ), and in the share of non-elite students marrying alumni of elite K-12 schools (ΔM) in the target and next best college program. We split the sample in quartiles by ΔE, ΔQ, and ΔM. We then estimate equation 1 in each sub-sample. Each reported estimate represents the crossing threshold effect that being admitted to a target college program has on the outcome variable in the panel title for the listed quartile of ΔE, ΔQ and ΔM. The sample consists of parents who did not themselves attend elite private high schools applying to college degree programs in the centralized system with binding admissions constraints. Panels (a) to (c) illustrate the changes that parents experience at the cutoff in exposure to elite peers (E), in peer academic quality (Q), and in marriage market prospects (M). Panels (d) to (f) show changes in children's probability of attending an elite private K-12 school. Panels (g) to (h) show changes in the probability that the children score in the top 1% of the college admission exam. Vertical intervals in lower two rows are 95% confidence intervals. See section 6.3 for details.

Figure 8: Parents exposure to elite peers in college and elite name index of children's friends in grade seven



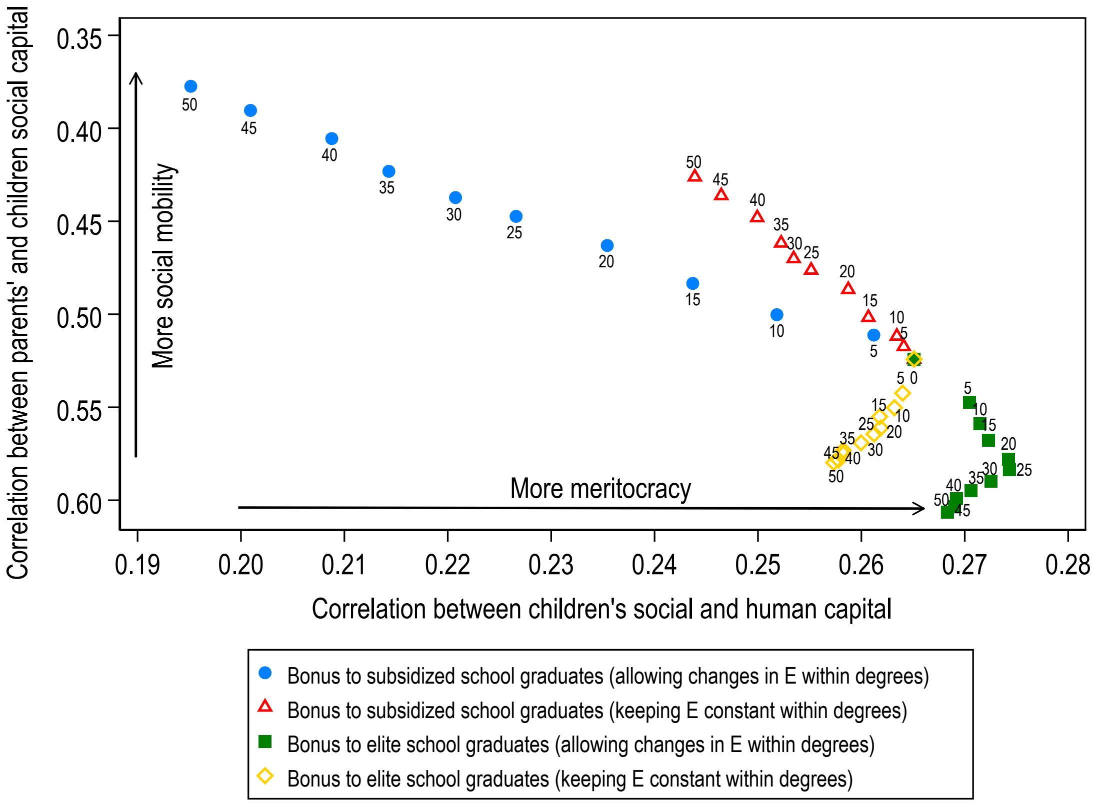
(a) $\Delta E > 0$



(b) $\Delta E < 0$

This figure illustrates how parent exposure to alumni of elite K-12 schools during college affects the social status of the friends of their children. Panel (a) illustrates the change experienced by children whose parents were marginally admitted into degrees that increased their exposure to alumni of elite K-12 schools. Panel (b) illustrates the change experienced by children whose parents were marginally admitted into degrees that decreased their exposure to alumni of elite K-12 schools. Blue dots represent outcome means at different levels of the running variable. The red lines correspond to linear regressions and are independently estimated at each side of the cutoff.

Figure 9: The mobility-meritocracy trade-off under simulated admissions policies



This figure illustrates the relationship between the intergenerational correlation of social capital and the intragenerational correlation of human and social capital under simulated admissions policies. The scale of the y-axis—which plots the intergenerational correlation of social capital—is reversed. Each point is calculated from a counterfactual admissions simulation in which students from a given kind of high school (noted in the legend) receive an admissions score bonus of the amount listed next to each point. All simulations hold fixed submitted application lists, program capacity constraints, and admissions process rules and procedures (other than the changes in score calculations for selected groups). Effects of assignment to different degree programs on children's outcomes are based on regression discontinuity estimates of gains from exposure to high-status peers in college. The solid-filled points allow the effects of parents' assignment to a given degree on children's outcomes to adjust as peer composition shifts, while the hollow points show results from counterfactuals in which degree causal effects are fixed, so that all changes in outcomes reflect differences in assignments. See section 7.2 for details. The blue circles and red triangles show results from simulations that give score bonus to (low-SES) graduates of subsidized schools, while the green squares and yellow diamonds show results from subsides given to (high status) graduates of elite schools.

Table 1: K-12 school characteristics

	Subsidized schools (1)	Non-elite private schools (2)	Non-elite expensive schools (3)	Elite schools (4)
Standardized tuition fees	-0.152	4.170	8.528	8.484
Standardized admission exam scores	-0.067	1.342	1.812	2.018
Standardized value added	-0.058	0.961	1.748	2.017
Standardized elite name index (Polo club)	-0.102	0.789	1.893	5.734
Standardized elite name index (Who's Who)	-0.084	1.125	2.489	6.107
Observations	9383	451	35	22

Notes: The table characterizes different types of K-12 schools in terms of the tuition fees they charge, the average scores their students obtain in the college admission exam, their value added, and their eliteness. The eliteness of schools is measured by two elite-name indexes based on the last names of their students. The first one uses as reference the last names of the members of an exclusive club in Chile, "Club de Polo y Equitación San Cristóbal", while the second one uses the last names of prominent individuals in Chilean history identified in de Ramon (2003). Column (a) describes subsidized schools, column (b) non-elite private schools, column (c) non-elite expensive schools, and column (d) elite schools. See section 2.1 for details.

Table 2: Sample construction

	A. Intergenerational Correlations Sample			
	All high school graduates	High school graduates registered for the admission exam	High school graduates registered for the admission exam and reporting parents id	High school graduates registered for the admission exam with parents also taking the exam
	(1)	(2)	(3)	(4)
A.1 Demographic characteristics				
Female = 1	0.52	0.53	0.54	0.52
Age in grade 12	17.88	17.83	17.82	17.79
A.2 Academic characteristics				
High school track: academic	0.57	0.65	0.66	0.84
High school gpa	5.60	5.68	5.69	5.80
Registers for the exam	0.82	1.00	1.00	1.00
Takes the exam	0.75	0.89	0.90	0.96
Math score	499.46	499.87	503.18	544.88
Reading score	495.32	495.68	499.04	539.93
Attends college	0.39	0.47	0.48	0.65
Attends an elite college	0.01	0.02	0.02	0.03
A.3 Socioeconomic characteristics				
Public school	0.44	0.40	0.39	0.25
Voucher school	0.47	0.49	0.50	0.53
Non-elite private school	0.08	0.09	0.10	0.19
Elite private school	0.01	0.01	0.01	0.03
Low income ($< CLP270,000$)	0.52	0.49	0.47	0.28
Mid income ($CLP270,000 - CLP834,000$)	0.34	0.36	0.37	0.42
High income ($> CLP834,000$)	0.14	0.15	0.16	0.30
Parental Ed. = Less than high school	0.15	0.13	0.12	0.00
Parental Ed. = Completed high school	0.52	0.52	0.51	0.36
Parental Ed. = Completed a vocational he degree	0.14	0.15	0.15	0.25
Parental Ed. = Completed a university degree	0.19	0.20	0.21	0.40
Observations	2955112	2430011	2173416	980366
	B. Elite Colleges Sample			
	All college applicants (1977 - 2003)	College applicants with children	Elite college applicants with children (below the admission cutoff)	Elite college applicants with children (above the admission cutoff)
	(1)	(2)	(3)	(4)
B.1 Demographic characteristics				
Female = 1	0.46	0.67	0.50	0.51
B.2 Academic characteristics				
Math score	610.22	599.44	670.91	696.83
Reading score	583.82	574.68	656.25	676.63
Admitted to any college	0.70	0.65	0.83	1.00
Admitted to an elite college	0.04	0.03	0.06	1.00
B.3 Socioeconomic characteristics				
Public school	0.44	0.48	0.31	0.25
Voucher school	0.26	0.23	0.15	0.13
Non-elite private school	0.22	0.19	0.35	0.38
Elite private school	0.03	0.02	0.08	0.13
Observations	878240	360492	8473	6603

Notes: Panel A presents summary statistics for students reaching their high school senior year between 2003 and 2017. Column (a) describes all the students in the sample, column (b) those who register for the university admission exam after completing high school, column (c) students who report their parents ID number, and column (d) students with at least one parent taking the university admission exam between 1968 and 2003. Panel B presents summary statistics for individuals applying to college between 1977 and 2003. Column (a) describes the whole sample, column (b) those for whom we find children, and column (c) and (d) those who in addition to having children applied to top college programs and were near the admission cutoff. Column (c) focuses on those who did not gain admission, while column (d) focuses on those who did gain admission. See section 3 for details.

Table 3: Effects of elite college admission on enrollment outcomes and peer environment

	All Schools (1)	Non-Elite Schools (2)	Elite Schools (3)
Pr. of being admitted to target program	1.0000	1.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)
Pr. of enrolling in target program	0.7543	0.7356	0.8555
	(0.0448)	(0.0474)	(0.0313)
Pr. of enrolling in any elite program	0.5236	0.5222	0.5364
	(0.0837)	(0.0842)	(0.1006)
Pr. of enrolling in any elite college	0.2682	0.2818	0.2010
	(0.0546)	(0.0557)	(0.0695)
Observations	34798	29405	5393
Avg. peer score in admission exam	26.2668	25.7381	29.5320
	(3.0607)	(3.1836)	(2.8564)
Sh. of peers from elite K-12 schools	0.0481	0.0518	0.0288
	(0.0087)	(0.0074)	(0.0219)
Elite name index of college peers (P)	0.5155	0.5161	0.4901
	(0.1068)	(0.0822)	(0.2551)
Observations	30851	26127	4724

Notes: This table presents regression discontinuity estimates from equation (1) of changes in college applicants' enrollment outcomes and college peer environments when they cross the threshold for admission to an elite degree program. We use data on individuals applying to elite college programs between 2007 and 2018, the years for which we observe enrollment. The titles in each row indicate the outcome variable. "Elite name index of college peers (P)" is the polo club elite name index. The first four columns use the full set of applications to elite college programs within a bandwidth of 25 points around the admission cutoff. The last three columns only focus on applications for which we observe a next best option. Columns reflect estimates in different samples, determined by student high school type. See section 2 for details. An observation corresponds to an individual × college program application. Standard errors clustered at the applicant level are reported in parentheses.

Table 4: Effect of parent admission to an elite college program on children's outcomes

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.0439	0.0335	0.0440	0.3272	0.2871	0.0515
	(0.0079)	(0.0077)	(0.0242)	(0.0503)	(0.0475)	(0.1623)
Observations	42694	37266	5422	42694	37266	5422
Counterfactual mean	0.2231	0.1656	0.6572	2.2277	1.7993	5.4565
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.2770	1.9345	2.0234	0.2175	-0.8636	3.2941
	(2.4256)	(2.5962)	(7.0567)	(2.1070)	(2.2577)	(5.9947)
Observations	26779	23887	2881	26675	23783	2881
Counterfactual mean	635.9329	634.0054	654.7350	643.1954	640.4561	667.9947
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.0282	0.0258	0.0088	0.0097	0.0106	-0.0033
	(0.0245)	(0.0261)	(0.0760)	(0.0031)	(0.0032)	(0.0114)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.8424	0.8232	1.0154	0.0977	0.0878	0.1844
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.0238	0.0218	0.0202	0.0064	0.0061	0.0065
	(0.0105)	(0.0112)	(0.0336)	(0.0083)	(0.0087)	(0.0283)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.3174	0.3065	0.4144	0.1500	0.1407	0.2320

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). Standard errors clustered two ways at the parent $\times$ child level are in parentheses. "Counterfactual means"are below-threshold mean values of the dependent variable for running variable values between -5 and 0. See Section 6.1 for details.

Table 5: Effects of parents' admission to elite college programs on marriage market outcomes

	All Parents (1)	Mothers (2)	Fathers (3)
Spouse observed = 1			
Admitted into target program = 1	0.0087	0.0167	-0.0005
	(0.0132)	(0.0173)	(0.0174)
Counterfactual mean	0.5483	0.3297	0.8266
Spouse was admitted into target program = 1			
Admitted into target program = 1	0.0860	0.1367	0.0626
	(0.0169)	(0.0369)	(0.0168)
Counterfactual mean	0.0938	0.1592	0.0525
Spouse was admitted into an elite college program = 1			
Admitted into target program = 1	0.0435	0.0986	0.0352
	(0.0221)	(0.0446)	(0.0230)
Counterfactual mean	0.2277	0.3837	0.1325
Spouse was admitted to an elite college = 1			
Admitted into target program = 1	0.0620	0.0546	0.0793
	(0.0262)	(0.0460)	(0.0327)
Counterfactual mean	0.4723	0.5061	0.4500
Spouse attended an elite school = 1			
Admitted into target program = 1	0.0315	0.0191	0.0373
	(0.0132)	(0.0291)	(0.0148)
Counterfactual mean	0.0684	0.0861	0.0611
Spouse attended any private school = 1			
Admitted into target program = 1	0.0630	0.1028	0.0532
	(0.0233)	(0.0465)	(0.0276)
Counterfactual mean	0.4030	0.3934	0.4074
Spouse's performance in admission exam = 1			
Admitted into target program = 1	-0.8679	-0.7716	1.508
	(4.8778)	(7.9386)	(5.8999)
Counterfactual mean	585.5686	640.0642	558.3246
Observations	7294	2049	5229

Notes: The table presents regression discontinuity estimates of specification (1) with spouse attributes as the outcome of interest. The sample is mothers and fathers applying to elite degree programs who did not attend elite high schools themselves. Rows are outcomes and columns are sample splits. Column (1) pulls mothers and fathers together, column (2) focuses on mothers, and column (3) on fathers. Standard errors clustered at the applicant level are in parentheses. Counterfactual means are below-threshold means of the dependent variable. See section 6.2.4 for details.

Table 6: Effect of parents' admission to an elite college program on children's neighborhood

	All parents (1)	Non-elite parents (2)	Elite parents (3)
	Panel A - Elite name index		
Parent admitted in target program	0.2513	0.2312	0.2499
	(0.0842)	(0.0842)	(0.3091)
Observations	9422	8576	829
Counterfactual outcome mean	2.0717	1.8910	3.9138
	Panel B - Avg. tuition fees		
Parent admitted in target program	140,460.14	133,057.92	-4,767.46
	(48115.25)	(49564.91)	(134097.59)
Observations	9422	8576	829
Counterfactual outcome mean	1,669,936.2	1,572,111.5	2,674,398.4
	Panel C - Avg. scores in the college admission exam		
Parent admitted in target program	6.7244	6.5716	-0.0611
	(2.2263)	(2.3445)	(5.0404)
Observations	9421	8575	829
Counterfactual outcome mean	600.2215	596.4495	638.4723
	Panel D - Census block square meter average price (UF)		
Parent admitted in target program	0.9763	0.6480	1.5210
	(0.9139)	(0.9696)	(1.7674)
Observations	8474	7663	794
Counterfactual outcome mean	53.9813	52.4459	68.3682

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on the characteristics of the neighborhood in which they lived when their children completed high school. We split the sample by parents' high school type as noted in columns. Outcomes are listed in panel sub-headers. We only observe addresses for children completing high school in the Santiago, Valparaiso, and Biobio regions. More than 60% of the student population attends school in one of these three regions. While the analyses presented in panels A to C focus on characteristics of neighbors living in a 100 meter radius, the analysis in panel D focuses on the average square meter price in a census block. In urban areas, a census block coincides with an actual block. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual outcome means are below-threshold mean values of the dependent variable for running variable values between -5 and 0. See section 6.2.5 for details.

Table 7: Effects of attributes of parents' college programs on children's outcomes

	Pr. of attending an an elite K12 school	Elite name index in K12 school	Avg. score in the admission exam	High school GPA	Attends an elite college	Attends an elite college program	Avg. peer score in college program	Sh. of college peers from elite K12 schools	Elite name index among college program peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent admitted in target major=1	-0.0008	0.0049	0.8318	-0.6976	-0.0006	-0.0007	-0.0038	-0.0004	-0.0033
	(0.0017)	(0.0122)	(0.7537)	(0.8662)	(0.0030)	(0.0021)	(0.0077)	(0.0008)	(0.0066)
Parent admitted in target major=1 × ΔE (STD)	0.0068	0.1377	-0.3881	-0.0871	0.0181	0.0087	0.0091	0.0043	0.0360
	(0.0042)	(0.0306)	(1.2615)	(1.4185)	(0.0059)	(0.0043)	(0.0139)	(0.0017)	(0.0144)
Parent admitted in target major=1 × ΔQ (STD)	-0.0078	-0.0508	-1.9746	-1.1474	-0.0038	-0.0013	-0.0151	-0.0016	-0.0156
	(0.0019)	(0.0135)	(0.9338)	(1.0787)	(0.0037)	(0.0025)	(0.0095)	(0.0009)	(0.0078)
Parent admitted in target major=1 × ΔM (STD)	0.0105	0.0039	0.4406	-0.1086	-0.0103	-0.0004	-0.0077	-0.0006	-0.0071
	(0.0037)	(0.0271)	(1.1776)	(1.3343)	(0.0053)	(0.0038)	(0.0128)	(0.0015)	(0.0129)
Observations	350767	286567	242276	244091	286567	286567	286563	286563	286563
Counterfactual outcome mean	0.0643	1.0291	601.0341	604.0711	0.1835	0.0712	0.5924	0.0447	0.6618

Notes: This table presents estimates from parametric regression discontinuity specification (2) of the effects of attributes of the programs to which parents are admitted on outcomes for children. Each column is a single specification. Reported coefficients are the main effect of admission to the target program and interactions between admission and differences between the attributes of the target and next-option degree program. We consider differences along three dimensions: share of college peers from elite high schools (ΔE), average college peer exam scores (ΔQ), and share of non-elite college peers who marry alumni of elite K-12 schools (ΔM). All the Δ variables are in standard deviation units. Samples vary across columns due to data availability. Columns (1) and (2) focus on children old enough to observe attending primary education (i.e., born before 2014). The rest of the columns focus on children old enough to observe applying to college (i.e., born before 2001). The elite name index is the polo club elite name index. We control for a linear polynomial of the running variable, the slope of which is allowed to change at the cutoff. The slope of the running variable on both sides of the cutoff is allowed to vary with ΔE, ΔQ and ΔM. The main effects of ΔE, ΔQ, and ΔM are also included in the specification. We also control for parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are presented in parentheses. Counterfactual outcome means are mean below-threshold value of the dependent variable. See section 6.3 for details.

Table 8: Inter- and intra-generational correlations between social and human capital

	Baseline model	No direct effect of elite colleges on social capital or on the marriage market ($\alpha_3 = 0, \delta_3 = 0, \psi_3 = 0$)	No direct effect of social capital on elite college attendance ($\gamma_1 = 0$)	No direct effect of elite colleges on social capital ($\alpha_3 = 0$)	No direct effect of elite colleges on marriage market ($\delta_3 = 0, \psi_3 = 0$)
	(1)	(2)	(3)	(4)	(5)
$Corr(S_{it}, H_{it})$	0.1761	0.1286	0.1634	0.1311	0.1729
$Corr(S_{it}, S_{it-1})$	0.3420	0.2299	0.2499	0.2345	0.3378
$Corr(H_{it}, H_{it-1})$	0.2830	0.2780	0.2815	0.2793	0.2815
$Corr(S_{it}, H_{it-1})$	0.2844	0.1950	0.2853	0.1989	0.2810
$Corr(H_{it}, S_{it-1})$	0.1217	0.1039	0.1125	0.1060	0.1192

Notes: The table presents correlations obtained from the VAR model described in Section 7. The figures on the first column come from the baseline model. The figures in columns (2) to (5) come from restricted versions of the model. Restricted versions of the models make some parameters equal to zero, but keep the variance-covariance matrix estimated for the baseline model unchanged.

Elite Universities and the Intergenerational Transmission of Human and Social Capital

Online Appendix

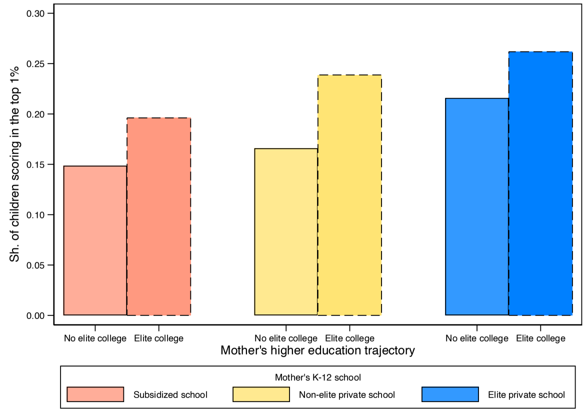
Andrés Barrios-Fernández Christopher Neilson Seth Zimmerman

August 11, 2024
Latest Version

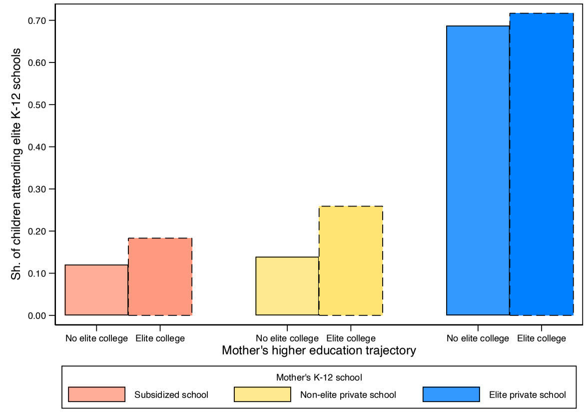
Contents

A Additional figures and tables

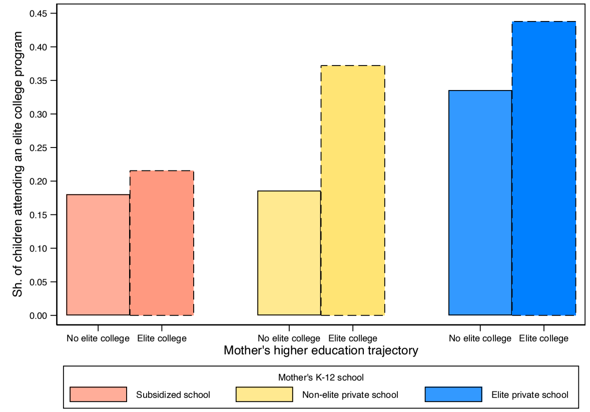
Figure A.I: Children's outcomes by mother's elite college program attendance



(a) Pr. child has top 1% score



(b) Pr. child attends elite high school



(c) Pr. child attends an elite college program

This figure illustrates how children's outcomes relate to whether their mothers attended elite college degree programs. All mothers in the sample used to build this figure scored in the top 1% of the university admission exam. The colors of the bars denote the type of high school attended by the mother. Light bars with solid borders illustrate means for children whose mothers did not attend an elite college program. Dark bars with dashed borders illustrate the means for children whose mothers did attend an elite college program. Panel (a) shows the probability that a child scores in the top 1% of the university admission exam distribution. Panel (b) shows the probability that a child attends an elite high school. Panel (c) shows the probability that a child attends an elite college program. See section 4 for details.

Table A.I: Effect of parent admission to an elite college program on children's outcomes by parents' and children's gender

	All children (1)	Daughters (2)	Sons (3)	All children (4)	Daughters (5)	Sons (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Non-elite parent admitted to target degree = 1	0.0335	0.0405	0.0254	0.2871	0.2154	0.3604
	(0.0077)	(0.0109)	(0.0109)	(0.0475)	(0.0669)	(0.0682)
Observations	37266	18547	18708	37266	18547	18708
Counterfactual mean	0.1656	0.1614	0.1699	1.7993	1.8445	1.7540
Non-elite mother admitted to target degree = 1	0.0314	0.0306	0.0329	0.2528	0.0831	0.4325
	(0.0114)	(0.0160)	(0.0163)	(0.0684)	(0.0963)	(0.0986)
Observations	16868	8418	8441	16868	8418	8441
Counterfactual mean	0.1706	0.1661	0.1751	1.7932	1.8434	1.7431
Non-elite father admitted to target degree = 1	0.0355	0.0519	0.0207	0.3265	0.3521	0.3127
	(0.0104)	(0.0149)	(0.0147)	(0.0663)	(0.0936)	(0.0950)
Observations	20393	10120	10255	20393	10120	10255
Counterfactual mean	0.1605	0.1570	0.1651	1.8056	1.8486	1.7619
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Non-elite parent admitted to target degree = 1	1.9345	1.1314	2.3373	-0.8636	-0.4110	-1.6691
	(2.5962)	(3.5187)	(3.7909)	(2.2577)	(3.1058)	(3.2881)
Observations	23887	11905	11963	23783	11841	11924
Counterfactual mean	634.0054	644.4243	623.3063	640.4561	632.6736	648.6326
Non-elite mother admitted to target degree = 1	5.7027	5.8628	4.0025	2.4630	3.9668	1.4470
	(4.2504)	(5.7425)	(6.2709)	(3.6434)	(5.0532)	(5.2783)

B Institutions: Further Details

B.1 Elite schools and elite occupations

This section of the Online Appendix provides additional detail on the Chilean primary and secondary education system, extending the discussion in section 2 of the main text. The Chilean school system is organized in two education cycles: primary education—grades 1 to 8—and secondary education—grades 9 to 12. Education is provided by three types of schools: public schools, voucher schools, and non-subsidized private schools. Public schools are free and are funded through student vouchers.[14] Voucher schools are private, but they are publicly subsidized through the voucher system. These schools were able to charge tuition fees on top of the voucher between 1994 and 2015. However, the amount of the voucher they received decreased as their tuition fees increased. Non-subsidized private schools are fully funded through tuition fees and are considerably more expensive than voucher schools.

According to the registers of the Ministry of Education, in the class of 2018—the last one we observe in our data—40% of the students attended a public school, 50% a voucher school, and 10% a private school. For this paper we further divide private schools in two categories: non-elite private schools and elite private schools.

To identify elite private schools we follow an approach similar to Zimmerman (2019). We focus on the cohorts graduating from high school and entering college in the 1970s and 1980s and identify a set of seven schools that consistently place their alumni in elite business and political positions. To identify these schools we rely on three reports produced by a head hunting firm—Seminarium (2003a,b, 2013)—that characterized the education trajectories of business and political leaders in 2003 and 2010. The business leaders characterized in these reports correspond to owners and corporate executives of firms with turnovers above USD 250 million. The political leaders include presidents, ministers, vice ministers, senators, and representatives. When ranking schools according to their representation in different elite occupations, seven traditional elite private schools consistently appear in the top 10. These seven schools are Colegio Craighouse, Colegio de los Sagrados Corazones de Manquehue, Colegio del Verbo Divino, Colegio San Ignacio El Bosque, Colegio Tabancura, Saint George College, and The Grange School. Figure B.I illustrates the share of individuals in elite occupations and in the whole population by type of high school. Alumni of non-elite private and elite private schools are overrepresented in elite occupations, but this phenomenon is particularly pronounced for the latter group. Despite representing 1% of the high school graduates, their shares in elite occupations fluctuate between 15% (among representatives) and 45% (among large firms owners).

The traditional elite private schools historically enrolled only male students, and some are still male only. Further, many new private schools opened in the 1980s and later, and some of these may now be "elite" in their own right. We therefore extend our definition of elite private schools to include both traditional elite schools for women and new elite

[14] In the early 1980s the Chilean school system suffered a major transformation. Public schools were transferred from the Ministry of Education to the municipalities. In addition, the funding system was changed and a voucher system was introduced.

schools.

We identify traditionally elite women's schools in a data-driven way, by looking at schools where the sisters of male students in traditional elite schools enroll. For this exercise we rely on family links available for recent cohorts (i.e., 2004-2018). Using these links we ranked schools according to the share of sisters of elite boys enrolling in them. Table B.I presents this ranking. The list includes some of the traditional elite schools that used to be only for men (e.g., The Grange School), traditional elite female schools (e.g. Villa Maria Academy), and a set of schools founded in the 1980s or later (e.g. Colegio Cumbres, founded in 1986). We end up with a list of seven schools that were and in many cases still are female-only. These schools are Dunalastair, Sagrado Corazon de Apoquindo, Villa Maria Academy, Santa Ursula, Colegio Los Andes, Colegio Huelen, and La Maisonnette.

We identify the new elite schools by compiling a list of eight schools that grew out of traditional elite schools in the 1980s or later. These schools were founded either by alumni of the traditional elite schools or by the same organizations (such as religious groups) that run traditional elite schools. These eight schools are Colegio Apoquindo, Colegio Cordillera, Colegio San Benito, Colegio Cumbres, Colegio Los Alerces, Colegio Monte Tabor y Nazareth, Colegio Everest, and Colegio Huinganal.

Our finding from Table 1 of the main text that elite private school students differ dramatically from other students in terms of social capital name indices suggests that our approach to classification—which did not take name indices into account—is a reasonable one. Data on the schools attended by the children of graduates from traditional elite schools provides further support for our approach. We identify the high schools where graduates from traditional elite schools scoring near the admission cutoff to an elite college program send their children.

Table B.II reports the 25 most common such schools, which together account for 74% of the children of parents who attended the traditional elite schools. Schools in our elite group make up the top 12 most common schools in this set, and 19 of the top 25. Later in this Online Appendix we show that the main results of the paper are robust to different definitions of elite schools. We show that the results hold when focusing only on the 14 "traditional elite schools" and also when using a slightly broader definition of elite schools (i.e., all the schools in Table B.II).

Table 1 in the main text describes the distribution of college entrance exam scores by high school type. Figure B.II provides more detail. Students completing their secondary education in elite private schools perform better in the college admission exam than those who complete their secondary education in subsidized and non-elite private schools. Indeed, very few students from subsidized schools score at the very top of the college admission exam. The difference is less pronounced when looking at the graduates of non-elite private schools. Many of them are able to obtain very high scores in the college admission exam.

In section 2.2 of the main text, we discuss the overrepresentation of elite private school graduates at selective universities and elite degree programs. Figure B.III provides more detail on this point, and how it relates to elite application and enrollment. Elite private school graduates perform better in the college admission exam. However, even after conditioning on students' performance in the college admission exam, the graduates of elite private schools are considerably more likely to apply and to be admitted to elite college programs. When looking at students in the top 5% of the college admission exam, we find that the graduates of elite private schools are 15 percentage points more likely to apply to an elite college program than the graduates of non-elite private schools. When comparing them with the graduates of subsidized schools, we find a difference of around 25 percentage points.

These differences affect the composition of the student body of elite colleges and elite college programs. Among the freshmen starting in any of the elite universities—i.e., University of Chile and Catholic University of Chile—in 2019, 53.46% came from subsidized schools, 36.07% from non-elite private schools, and 10.47% from an elite private school. The overrepresentation of non-elite and elite private school alumni is even larger in the most prestigious programs—i.e., business, law, engineering and medicine—where they represented 43.48% and 17.43% of the first year enrollment respectively. As illustrated in Figure B.IV, it is 16 times more likely to find an elite private school graduate in these programs than in the whole population. Table B.III shows that the overrepresentation of elite private school graduates is highest at the University of Chile and the Catholic University of Chile. When looking at the composition of the student body of other selective universities in the country, the shares of elite private school graduates drop dramatically. These results suggest that elite private schools influence their alumni education trajectories in ways that go beyond human capital.

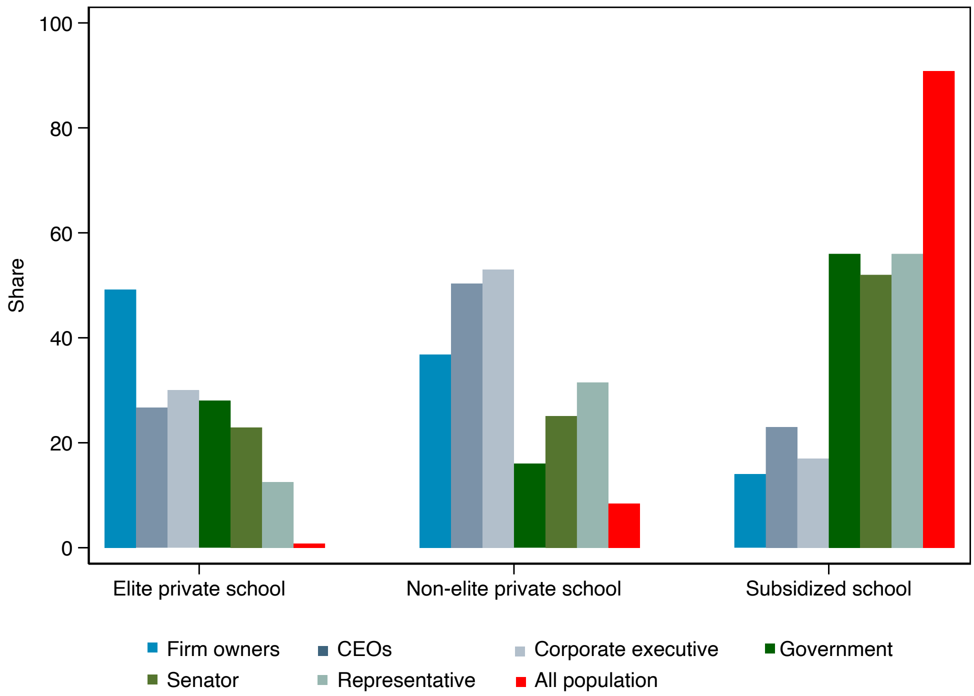
Figure B.V further characterizes schools in terms of their location, fees, social pedigree, and academic results. Panel (a) illustrates the location of non-elite and elite schools in Santiago. The elite schools are concentrated in the north-east, which not surprisingly is also the most expensive area of the city. As Panels (b) and (c) show, elite schools are among the most expensive in the country. However, there are a few similarly expensive non-elite private schools. According to Panels (c) and (d) the graduates of these elite schools obtain very high scores in the college admission exam. Nevertheless, the graduates of some non-elite schools obtain similarly high scores. The dimension in which elite schools really stand out is the social pedigree of their students.

B.2 Elite colleges and higher education finance

This section supplements section 2.2 of the main text with some additional detail on elite universities and higher education finance in Chile. In the main text we note that alumni of UC and PUC make up a large share of business and political elites. As reported in Figure B.VI, more than 60% of the individuals in business or political elite positions come from one of these two institutions.

Turning to college finance, taking the university admission exam and applying to universities is free for students graduating from subsidized high schools (i.e., public and voucher schools). In addition, since tuition fees in Chile are relatively high, there are generous funding programs available for students. Eligibility for different types of financial aid depends on socioeconomic and academic criteria. Subsidized student loans, for instance, are currently available to everyone whose average score in the reading and math section of the admission exam is above the 40th percentile. The largest scholarship programs currently require a higher score and are only available for students in the bottom 70% of the income distribution.[15]

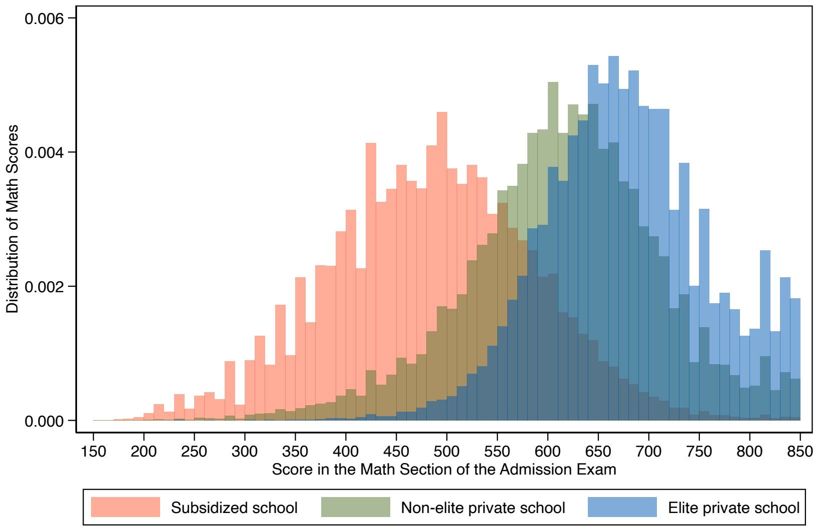
Figure B.I: Share of individuals in elite occupations by type of high school



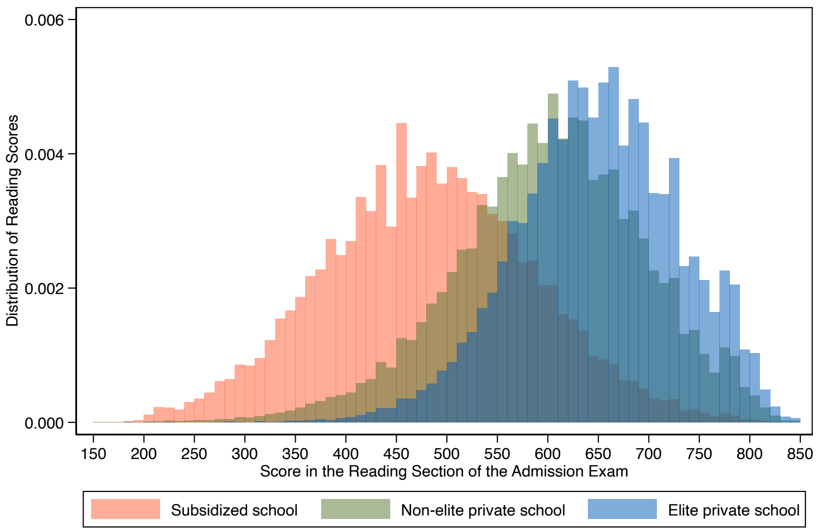
This figure illustrates the share of individuals graduating from elite private, non-elite private and subsidized high schools in different elite occupations and in the whole population. Elite occupations include leadership positions in business and politics. The data for figures comes from three reports developed by Seminarium—a specialized head hunting consulting firm—in 2003 and 2010. See section B.1 for details.

[15]The financial aid system has experienced important transformation in recent years. In addition to making some existing benefits available to more students, new programs have been introduced. For instance, starting in 2015, students in the bottom 60% of the income distribution were eligible for free higher education. Regardless of their scores on the admission exam, if a university that has agreed to participate in the free higher education program admits them, they do not need to pay fees. Universities receive from the government a reference tuition fee for each student admitted under this program.

Figure B.II: Distribution of Scores in the College Admission Exam by Type of School



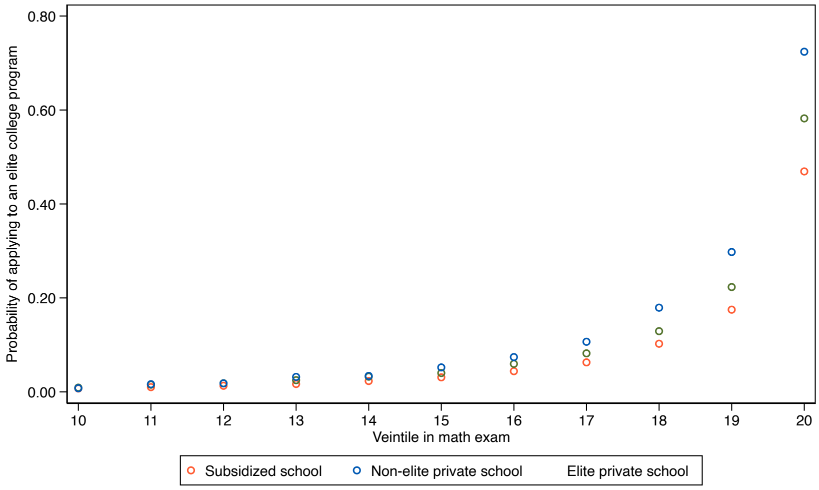
(a) Mathematics Scores



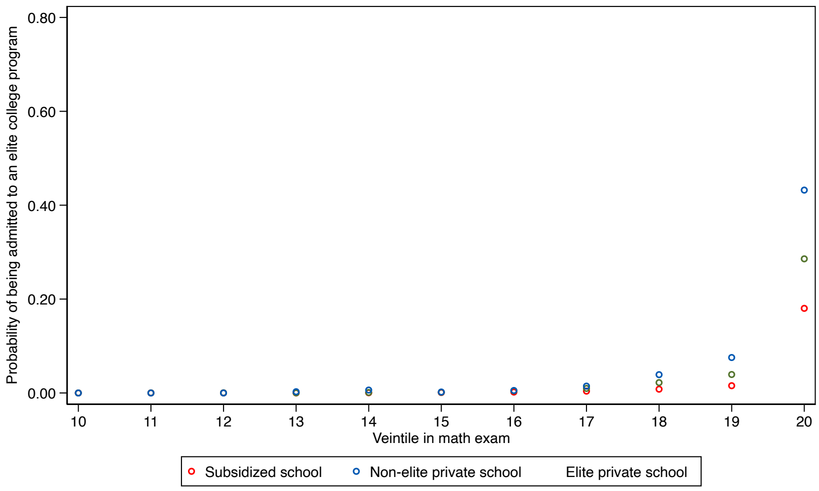
(b) Reading Scores

This figure illustrates the distributions of math and reading scores in the college admission exam distinguishing by the type of school that applicants attended. The plotted distributions only include applicants taking the exam between 2002 and 2017.

Figure B.III: Probability of Applying and being Admitted to an Elite College Program by Type of School



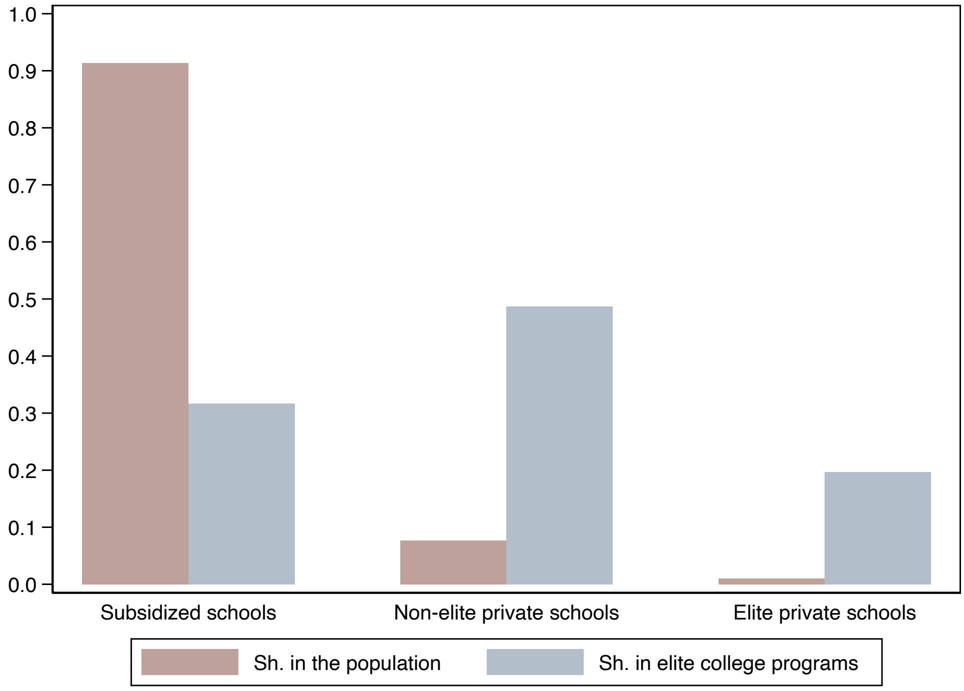
(a) Pr. of applying to an elite college program



(b) Pr. of being admitted to an elite college program

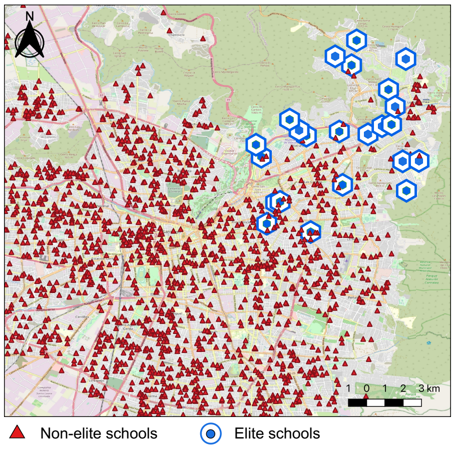
This figure illustrates the probability of applying and being admitted to a top college program for students at different levels of the academic performance distribution. The figure allows these probabilities to vary depending on the type of school in which applicants completed their secondary education. The plotted distributions include students graduating from high school between 2002 and 2017.

Figure B.IV: Share of individuals in elite college programs by type of school

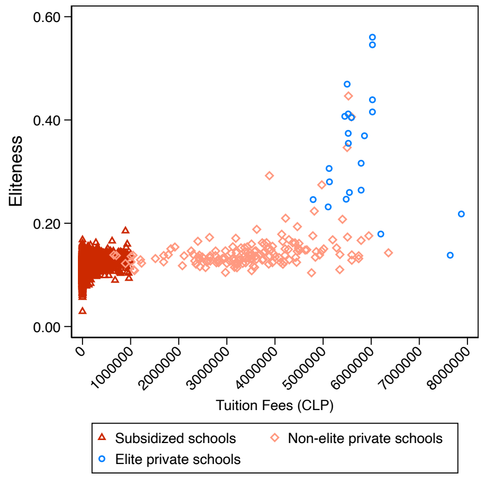


This figure illustrates the share of individuals graduating from different types of schools admitted to elite college programs. The figure also presents the shares that different types of schools represent in the population. The data in this figure comes from individuals completing high school between 2003 and 2017.

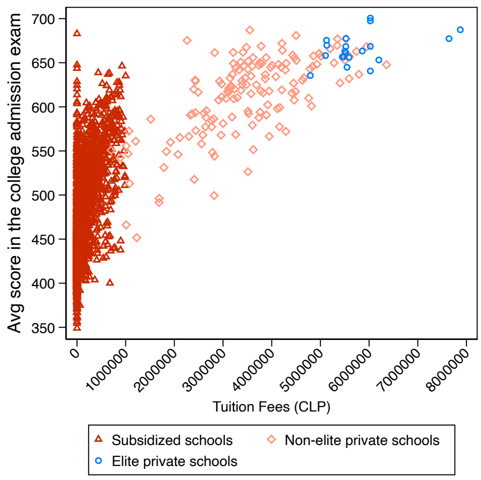
Figure B.V: Characteristics of K-12 schools



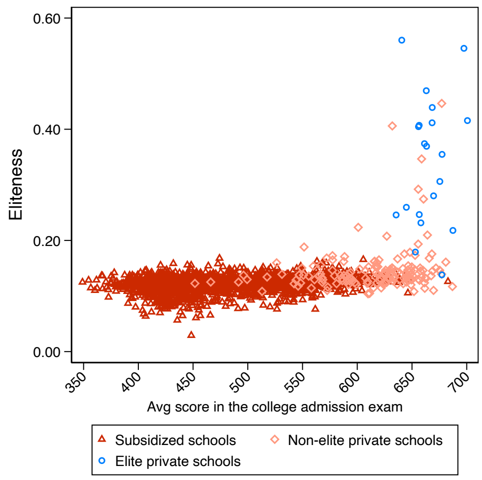
(a) Geographic distribution of schools



(b) Elite names index and tuition fees



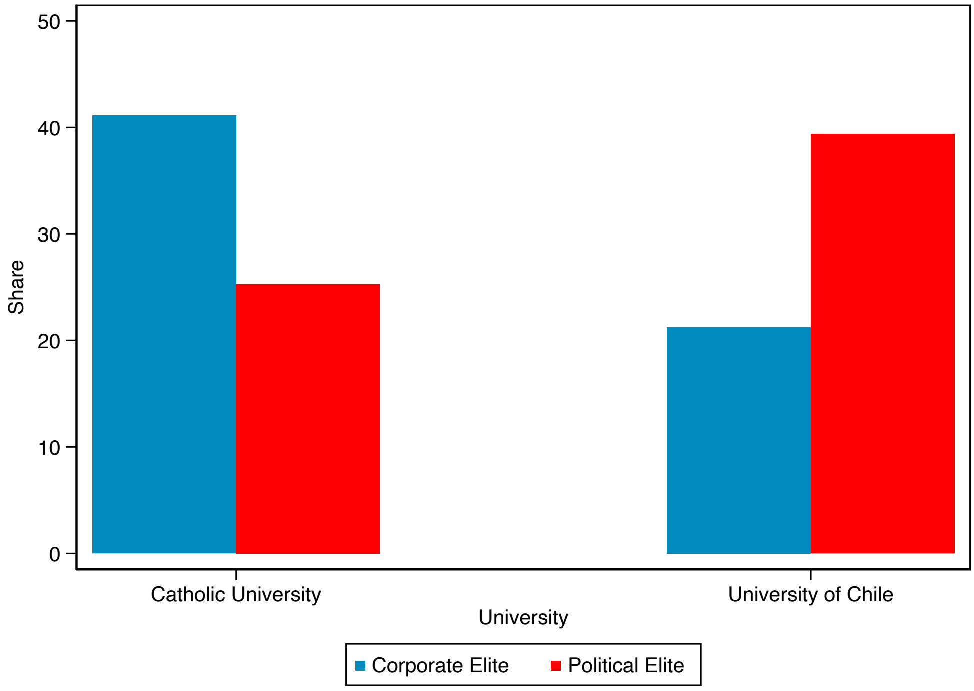
(c) College admission exam and tuition fees



(d) Elite names index and admission exam

This figure describes subsidized, non-elite private and elite private K-12 schools along four dimensions: location, tuition fees, elite names index, and scores in the college admission exam. Panel (a) illustrates where non-elite and elite schools are located in Santiago, the capital city of Chile. Panel (b) illustrates the relationship between tuition fees and the elite last name index discussed in the paper. Panel (c) illustrates the relationship between tuition fees and average performance in the college admission exam. Finally, panel (d) illustrates the relationship between average performance in the college admission exam and the elite names index. See section B.1 for details.

Figure B.VI: Share of individuals in elite occupations by university



This figure illustrates the share of individuals graduating from the two most selective universities in Chile—i.e., Universidad de Chile and Universidad Católica—and their participation in elite business and politics occupations. The data behind these figures comes from three reports developed by Seminarium—a specialized head hunting consulting firm—in 2003 and 2010. See section B.2 for details.

Table B.I: Schools attended by sisters of boys enrolled in traditional elite K-12 schools

Rank (1)	School (2)	Share of sisters (%) (3)
1	Colegio Cumbres	11.86
2	Colegio Los Andes de Vitacura	11.78
3	Colegio Everest	7.68
4	Colegio Villa Maria Academy	7.57
5	Colegio Los Alerces	7.24
6	Colegio Tabor y Nazareth	7.14
7	Colegio del SC de Apoquindo	6.17
8	Colegio Saint George College	5.03
9	Colegio San Benito	4.77
10	Colegio Huelén	4.54
11	SS.CC. de Manquehue	3.78
12	Colegio Santa Úrsula	3.75
13	Colegio The Grange School	3.06
14	Colegio Apoquindo	1.56
15	Colegio Dunalastair	1.38
16	Colegio La Maisonnette	1.10
Total		88.41

Notes: The table presents the schools most commonly attended by the sisters of boys enrolled in traditional elite K-12 schools. We compute the shares using the universe of high school graduates registering for the university admission exam between 2003 and 2018. See section B.1 for details.

Table B.II: K-12 schools attended by children of parents who attended older elite K-12 schools

Rank (1)	School (2)	Share of children of elite parents (%) (3)
1	Colegio Cumbres*	6.66
2	Colegio Everest*	6.66
3	Colegio del Verbo Divino*	5.22
4	Colegio Saint George*	5.17
5	Colegio San Benito*	4.99
6	Colegio The Grange School*	4.75
7	Colegio Villa Maria Academy*	4.54
8	Colegio Tabancura*	4.37
9	Colegio Tabor y Nazareth*	3.90
10	Colegio Los Andes*	3.43
11	Colegio Cordillera*	2.63
12	Colegio Los Alerces*	2.40
13	Colegio San Anselmo	2.35
14	Colegio SS.CC. de Manquehue*	1.98
15	Colegio Santiago College	1.88
16	Colegio San Isidro	1.79
17	Colegio Santa Úrsula*	1.65
18	Colegio Padre Hurtado y Juanita de los Andes	1.58
19	Colegio San Ignacio El Bosque*	1.51
20	Colegio SC de Apoquindo*	1.48
21	Colegio Huelén*	1.41
22	Colegio Craighouse*	1.08
23	Colegio The Newland School	1.03
24	Colegio Francisco de Asís	0.96
25	Colegio La Maissonette*	0.96
Total		74.39

Notes: The table presents the schools most commonly chosen by elite parents (those who attended older elite K-12 schools) near the admission threshold of an elite college program for their children. The stars indicate schools that we identify as elite private schools using our classification scheme. See Online Appendix B.1 for details.

Table B.III: Representation of Students from Elite Schools in Different College Programs

College	Business/Economics (1)	Civil Engineering (2)	Law (3)	Medicine (4)
Universidad Católica de Chile	29.7	22.6	25.3	11.8
Universidad de Chile	13.9	6.0	9.5	6.7
Universidad de Concepción	0.4	0.1	0.7	0.5
Universidad Católica de Valparaíso	2.9	1.6	3.8	
Universidad Técnica Federico Santa María	3.3	3.9		
Universidad de Santiago	7.6	4.4		3.6
Universidad Austral	0.6		0.4	0.3
Universidad de Valparaíso	0.6	2.0	0.5	1.9

Notes: The table illustrates the representation of elite school students in different college programs. For instance, the figure at the top left corner of the table indicates that a 29.7% of the students admitted to Business and Economics at the Universidad Católica de Chile come from elite private schools. Figures were computed using individuals applying to college between 1978 and 2003. See Online Appendix B.1 for details.

C Variable construction

This section provides additional details on variable construction.

C.1 Tuition fees

School tuition fees were obtained from two sources. First, from the Ministry of Education we obtained information on the tuition fees charged by voucher schools. Voucher schools were allowed to charge tuition fees on top of the voucher between 1994 and 2015. We normalized these tuition fees so they reflected the 2021 level of prices. The information on the tuition fees charged by private schools was manually collected. To reduce the number of schools for which we needed this information, we focused on the private schools attended by the children of individuals applying to elite college programs whose scores put them within the bandwidth we use in our main analyses. In most cases, this information was available on the websites of the schools. If the tuition fees on the website did not correspond to 2021, we adjusted them so they would reflect 2021 price levels. In a few cases, however, we directly called the schools to inquire about their prices. Combining these different sources we were able to collect data on the tuition fees charged by the schools attended by more than 80% of the children in our sample. As reported in Table E3 in the main text, there is no change at the cutoff in the probability of observing the tuition fees that parents paid for their children's K-12 schools.

C.2 K-12 school value added

One of the variables we use to characterize the K-12 school that the children of elite college program applicants attend is the school value added. To build this variable we exploit the fact that in Chile there is a standardized test—SIMCE—that is regularly applied to primary and secondary education students. For this exercise, we focus on the test scores that students obtain when they are in grade 10 (this is the only high school grade in which the standardized test is applied). We combine the test scores with a rich vector of socioeconomic and demographic characteristics and estimate the following specification:

$$Y_{it} = \beta_0 + \Sigma_{k=1}^{K} \beta_k X_{kit} + \mu_t + \mu_{s(it)} + \varepsilon_{it}$$

where Y_{it} is the average of the scores that students obtain in the reading and math section of the exam, X_{kit} is one of the K controls we include in this specification, μ_t is a year fixed effect, and μ_s is a school fixed effect. Our measure of school value added is given by μ_s.

The controls X_{kit} include gender, dummies for birth year, dummies for parental education (less than high school, completed high school, vocational higher education, university education), dummies for three household income categories (low, middle, high), dummies for three categories of books at home (less than 10, 10 to 50, more than 50), and two dummies indicating the availability of a computer and of Internet at home.

C.3 Neighborhood characteristics

In Section 6.2.5 we study how parents' admission to elite college programs affects the neighborhood in which they live when their children complete high school. To characterize neighborhoods, we compute the average elite name index, tuition fees, and college admission exam scores of children within a 100- and 200-meter radius of each child's home address, excluding the reference child. We identify neighbors using data from Barrios-Fernández (2022). This data contains geocoded addresses of students completing high school between 2004 and 2012 in three regions of Chile: the Metropolitan Region of Santiago, the Valparaiso Region, and the Biobio Region. More than 60% of the student population comes from one of these three regions. We match children in our sample with his/her neighbors completing high school between 2004 and 2012. We build this measure only for children old enough to complete high school between 2004 and 2012 in one of the three regions in which we observe addresses. On average, these children have 38.65 neighbors in a 100-meter radius, and 128.50 neighbors in a 200-meter radius.

We do not have information on the characteristics of the houses in which children live with their parents, but we do observe the value of the square meter at the census block level. Census blocks are the smallest geographic unit used in the Chilean census, and in urban areas they coincide with actual city blocks. As in the case of the variables described in the previous paragraph, we build this variable for children completing high school between 2004 and 2012 in the three regions for which we observe addresses. The land prices used in this section are reported in an inflation-adjusted account unit, UF.

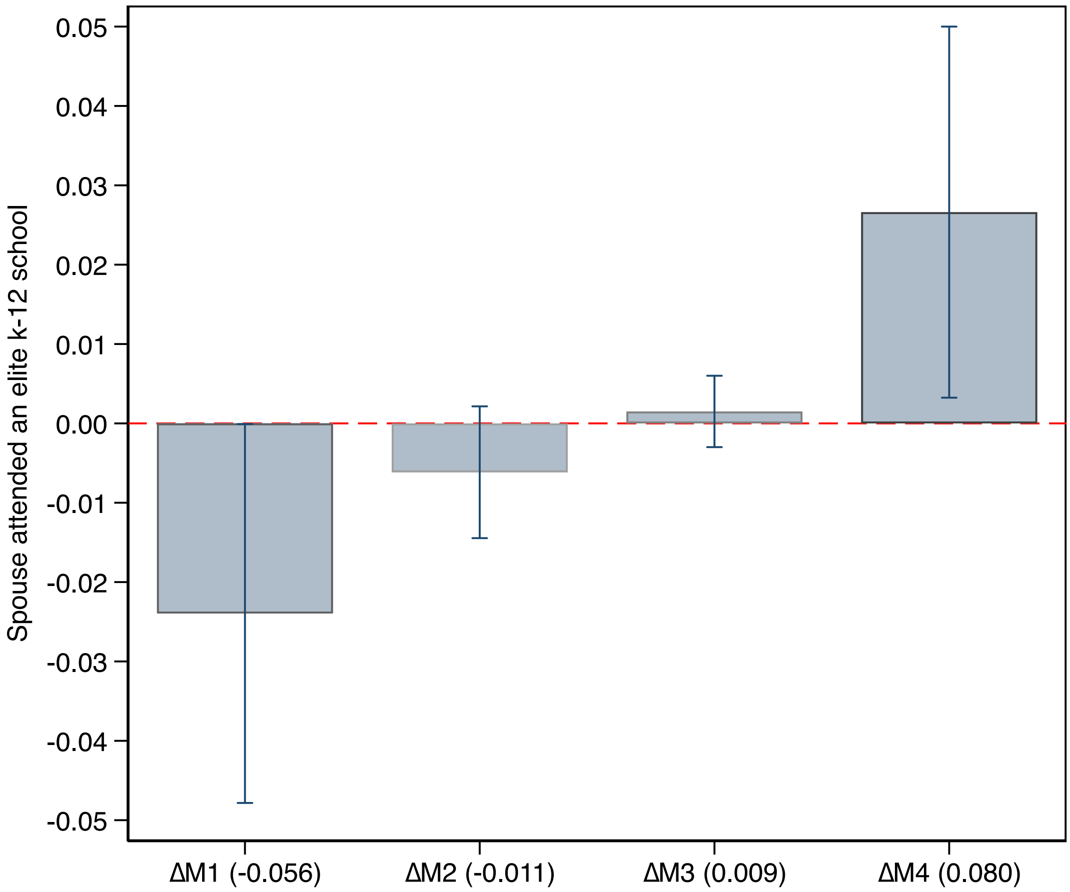
C.4 Marriage market strength in college degree programs

In section 6.3 we develop program-specific measures of marriage market prospects. The goal is to capture variation in the likelihood that non-elite individuals admitted to specific college programs will marry elite individuals. We build a measure M_{dt} that is equal to the share of non-elite admitted students marrying elite individuals for each college program d and each application year t. When computing these shares for individuals applying to college in year t we only used applicants from other years t^{-}.

The point of this measure is that admission to degrees with higher values of M_{dt} should raise the rate at which non-elite students go on to marry elite students. We test its performance by estimating regression discontinuity specifications of the form given in equation (1), splitting by quartile of ΔM—the difference between the value of M_{dt} at the target and next-option degree for a given individual. For context, panel (c) of Figure 7 in the main text reports how values of M_{dt} at the degrees where students are admitted change across the cutoff. For students in the top quartile of ΔM, admission to the target degree raises M_{dt} at the degree where they are admitted by 0.08. Changes in M_{dt} are close to zero in the middle two quartiles, and negative in the bottom quartile. If actual marriage outcomes track our measure of marriage market opportunity, we should observe similar patterns, though perhaps different magnitudes.

We report results in Figure C1, with each bar representing a regression discontinuity estimate. We observe an increasing pattern across quartiles of ΔM, with negative effects in the bottom quartile, approximately zero effects in the middle two quartiles, and positive effects in the top quartile. In short, the change applicants experience in the probability of marrying into the elite is proportional to ΔM_{dt}. We interpret this as evidence that our measure of marriage market opportunity does a credible job of predicting changes in marriage market experiences for individuals randomized into different degree programs.

Figure C1: Effect of admission to an elite college program on marriage market outcomes



This figure reports regression discontinuity estimates from equation 1 where the outcome is an indicator for whether one's spouse attended an elite private high school, splitting the sample by cross-threshold changes in our measure of degree-specific marriage market prospects M. Each bar is a regression discontinuity estimate and the sample is split by quartiles of ΔM, from the bottom quartile on the left to the top quartile on the right. Numbers in parentheses on the horizontal axis the mean values of cross-threshold changes in M within the quartile as reported in Panel (c) of figure 7. Vertical bars are 95% CIs. See section C.4 for details.

D Intergenerational correlations

D.1 Alternate human capital measures

The rank-rank correlations between child and parent scores in the main text are based on college admissions exams. However, not all children take the college admission exam. As reported in Table 2, the college admission exam is taken by 75% of high school graduates, and by around 90% of children for whom we identify parents. In this section we complement the results in the main body of the paper by estimating rank-rank correlations that use children's performance on a standardized test taken by all students at the end of grade 10 rather than their college entrance exam scores. The grade 10 standardized test is known as the SIMCE. The downside of the SIMCE measure is that the test is not administered every year. Thus, these rank-rank correlations only include children who were in grade 10 in 2001, 2003, 2006, 2008, 2010, 2012, 2013, or 2015.

We find similar patterns to those reported in the main text. Panel (a) of Figure D.I displays rank-rank correlations between children and mothers, while panel (b) displays correlations between children and fathers. Although the slopes are slightly smaller than those obtained using the admissions exam data for children's ranks, a clear positive correlation remains. In addition, the children of parents who attended elite private high schools obtain on average higher scores, with convergence across social status groups as mother's test scores rise but not as father's test scores rise. The correlation between SIMCE scores and college admissions exam scores for students for whom we observe both scores is 0.75.

D.2 Intergenerational correlations between fathers and children

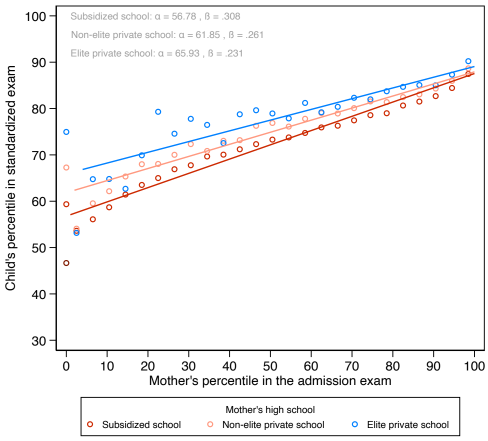
In section 4 we discuss correlations between mothers' outcomes and outcomes for children. This section presents a parallel analysis of correlations between fathers' outcomes and children's outcomes. Figure D.II presents results similar to those in Figure 2 but using data for fathers rather than mothers. Panel (a) presents rank-rank correlations between fathers' and children's performance on the college admission exam. As in the case of mothers, we find a positive rank-rank correlation of between 0.3 and 0.4. An important difference we observe is that slopes are similar across different levels of fathers' social capital. Unlike what we observed for mothers, there is little convergence at the top of the score distribution. Results for other outcomes parallel those in Figure 2.

Figure D.III replicates A.I but using data for fathers rather than mothers. Qualitative patterns are similar across the board.

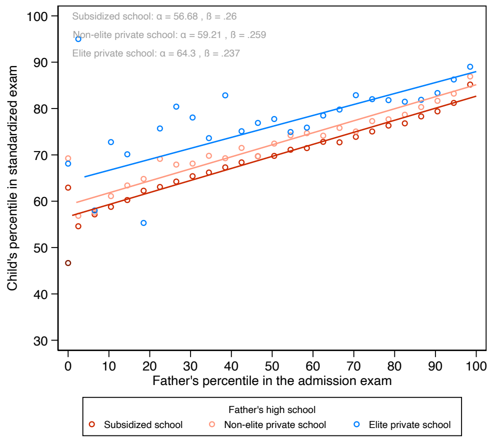
D.3 Intergenerational correlations between parents and children

Figure D.IV reproduces main text Figure 2, replacing outcomes for mothers with average outcomes for both parents. The sample is limited to children for whom we have college admissions exam data for both parents. Broad patterns are similar to those reported in the main text. Panel (a) in Figure D.IV presents rank-rank correlations between parents and children's performance on the college admission exam. We find a positive rank-rank correlation of between 0.3 and 0.5. The slopes estimated when focusing on parents who attended subsidized or non-elite private K-12 schools are larger than when looking independently at mothers or fathers. Other measures of children's human and social capital also improve with parents' average performance on the college admission exam.

Figure D.I: Correlations between Parents' Scores in the College Admission Exam and Children's Scores in SIMCE



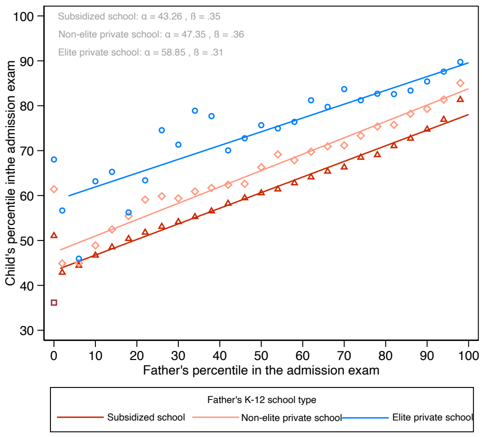
(a) Mothers



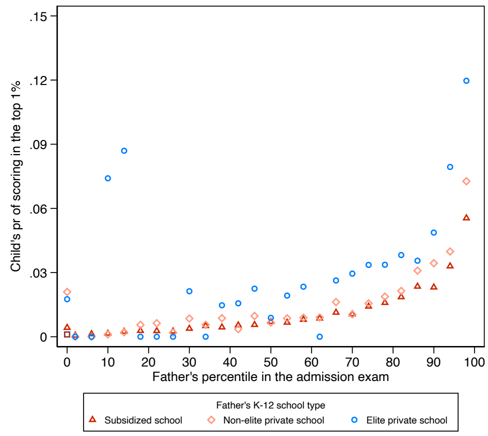
(b) Fathers

This figure illustrates rank-rank correlations between parents' scores in the college admission exam and their children scores in the SIMCE. The SIMCE is a standardized test that students take at the end of grade 10. We allow the correlations to vary depending on the type of high school attended by the parents. Panel (a) focuses on correlations between mothers and children, while panel (b) between fathers and children.

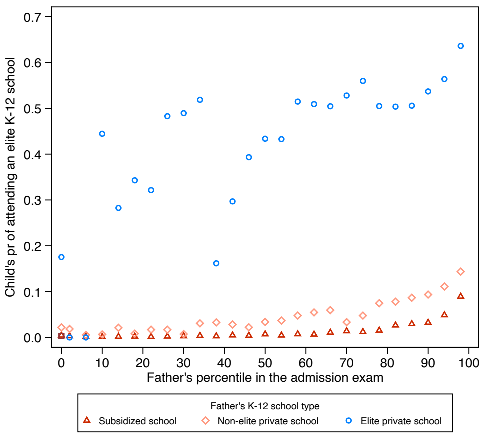
Figure D.II: Correlations between Fathers' Scores and Children's Outcomes by father's K-12 school type



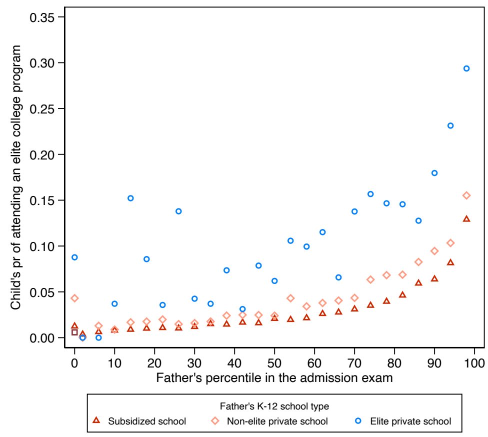
(a) Rank-rank correlations



(b) Child scores in top 1%



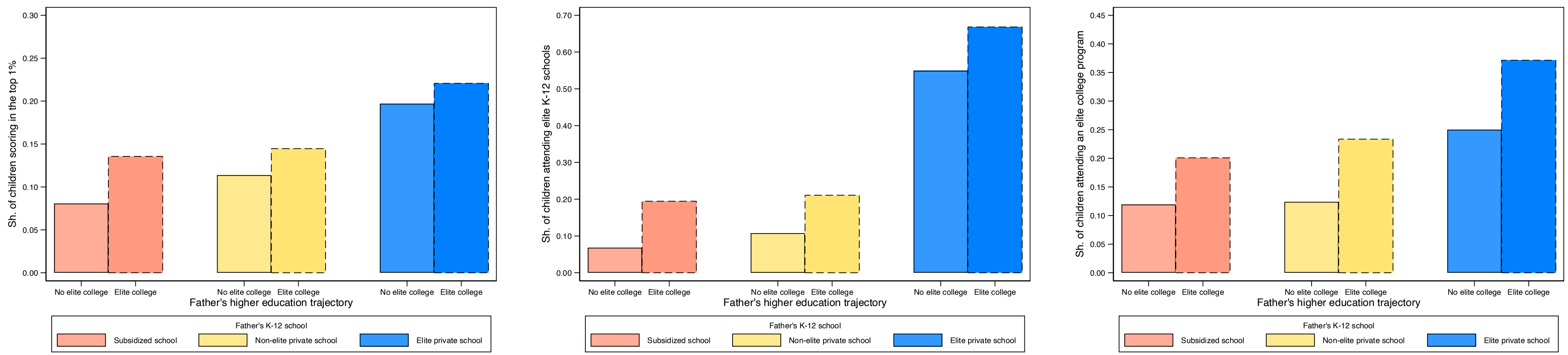
(c) Child attends elite high school



(d) Child attends elite college program

This figure illustrates correlations between different children outcomes and their fathers' percentile in the university admission exam distribution. For each outcome we allow the relationship to vary depending on the type of high school attended by the father. Panel (a) illustrates the relationship between fathers' and children's percentiles in the university admission exam. Panel (b) focuses on the probability that a child reaches the top 1% in the university admission exam distribution; panel (c) on the probability that a child attends an elite school; and panel (d) on the probability that a child attends an elite college program. The linear relations illustrated in panel (a) ignore zeros. Maroon circles in all panels illustrate cases in which we do not observe fathers' high school and scores. See section D.3 for details.

Figure D.III: Child outcomes by father's elite college attendance.



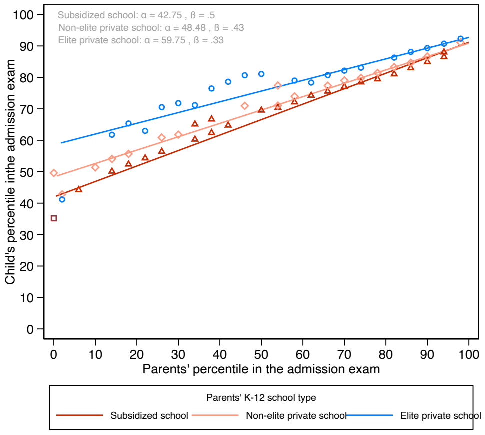
(a) Child scores in top 1%

(b) Child attends an elite high school

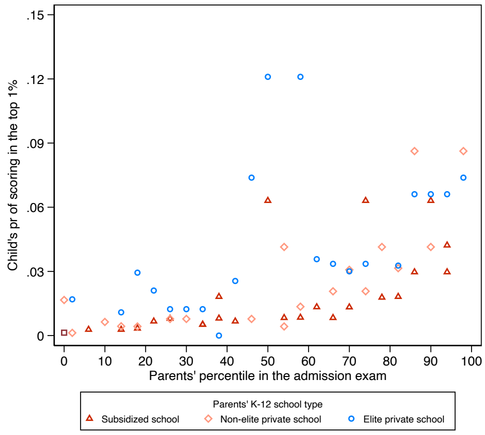
(c) Child attends elite college program

This figure illustrates how children's outcomes relate to whether their fathers attended elite college degree programs. All fathers in the sample used to build this figure scored in the top 1% of the university admission exam. The colors of the bars denote the type of high school attended by the father. Light bars with solid borders illustrate means for children whose fathers did not attend an elite college program. Dark bars with dashed borders illustrate the means for children whose fathers did attend an elite college program. Panel (a) shows the probability that a child scores in the top 1% of the university admission exam distribution. Panel (b) shows the probability that a child attends an elite K-12 school. Panel (c) shows the probability that a child attends an elite college program. See section D.3 for details.

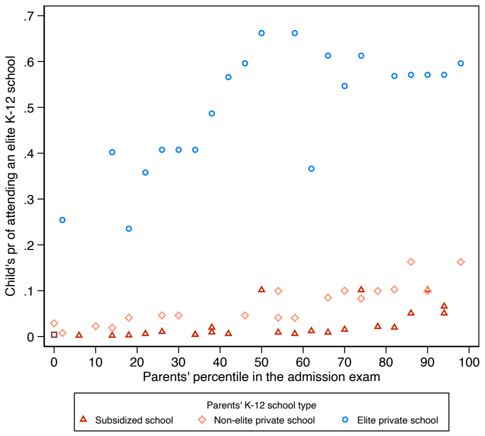
Figure D.IV: Correlations between Parents' Scores and Children's Outcomes



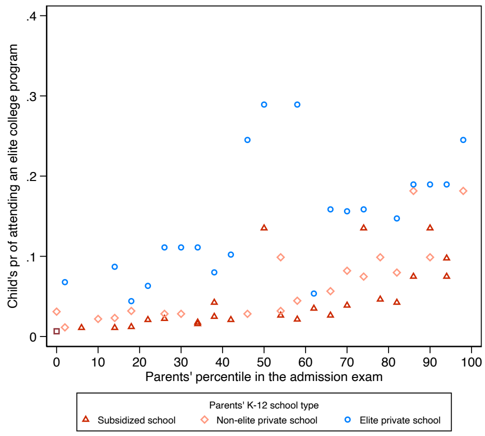
(a) Rank-rank correlations



(b) Child scores in top 1%



(c) Child attends elite high school



(d) Child attends elite college program

This figure illustrates correlations between different children outcomes and their parents' percentile in the university admission exam distribution. For each outcome, we allow the relationship to vary depending on the type of high school attended by the parents. We classify children's social background based on the most exclusive of their parents' high school. Panel (a) illustrates the relationship between parents' and children's percentiles in the university admission exam. Panel (b) focuses on the probability that a child reaches the top 1% in the university admission exam distribution; panel (c) on the probability that a child attends an elite school; and panel (d) on the probability that a child attends an elite college program. The linear relations illustrated in panel (a) ignore zeros. Maroon circles in all panels illustrate cases in which we do not observe parents' high school and scores. See section D.3 for details.

E Additional results

E.1 Changes in fertility at the cutoff

Figure 4 in the main text reports that parents' chances of having at least one child do not change when they cross the cutoff for admission to an elite degree program. Figure E1 expands this exercise by looking at all college applicants and by studying changes in the number of children applicants have as the outcome of interest. We see no evidence of a change in the probability of having a child or in the number of children across the admissions cutoffs that we study.

E.2 Regression discontinuity estimates for additional educational outcomes and sample definitions

This section provides figures and tables that supplement our main analysis of the elite college regression discontinuity in section 6.1 of the main text.

Figure E2 reproduces main text figure 5 using the full elite college applicant sample rather than restricting to parents not from elite high schools.

Tables E1 and E2 report estimates of equation 1 for outcomes beyond those reported in main text Table 4. Key results are as follows. Panel (a) of Table E1 reports estimated effects of parent elite admission on children's attendance at non-elite private schools. The effects here are almost identical in magnitude to the effects of parent admission on children's elite private school attendance, but with negative signs. The primary margin of substitution at the cutoff is between elite and non-elite private schools. This panel also reports results for an alternate measure of child social capital: the "Who's Who" elite name index at the high school the child attends. Effects for this index are very close to the effects for the polo club index that we report in the main text.

Panels (b), (c), and (d) of Table E1 report results for additional human capital measures. These measures are the probability of taking the college admission exam, scoring in the top 1% or top 5% on the college admissions exam, being admitted to any college participating in the centralized admission system, and achieving a combination of grades and test scores high enough to permit admission to some program in an elite college or an elite program in an elite college. We observe null effects across all of these outcomes.

Panel (a) of Table E2 shows that parent elite admission raises children's chances of applying to an elite college by roughly 77% of the increase in elite college enrollment reported in main text Table 4 (the enrollment effect is 0.0218 in the non-elite parents sample; the application effect is 0.0168). The finding that application patterns change rationalizes the increase in enrollment despite null effects on the human capital measures that determine admissions outcomes. We do not see effects on applications to elite college programs (consistent with null effects on enrollment in these programs).

Panels (b) and (c) of Table E2 describe how parents' elite admission shapes alternate measures of children's educational trajectories. Average test scores of children's college peers do not change. However, they are more likely to have college peers from elite K12 schools and the elite name indices of their college peers rise. These effects are present in the full sample and for children of non-elite parents; results for children of elite parents are noisily estimated. Children become more likely to follow a comprehensive "elite trajectory"—from an elite high school to an elite college—when their parents are admitted to an elite degree program (d).

In Table E4 we replicate the analyses looking at changes in children's college peers, but focusing only on children who are actually admitted to a college that participates in the centralized admission system. The estimates we obtain are very similar to the ones presented in panel (b) of Table E2, in which we include non-admitted children in the sample and assign them college peer values based on averages among non-admitted students. That the treatment of non-admitted students does not affect our findings makes sense given that children's rates of admission to any college are high and do not change when parents cross the admissions cutoff.

E.3 Further details on educational expenditure

This section provides additional details relating to our discussion of educational expenditure effects in main text section 6.2.2. Our main finding is that parents' admission to an elite college modestly increases educational expenditure, but that this increase is driven exclusively by increased rates of attendance at elite private schools, and not by increased enrollment at other private schools. Reading across Table E3, column 1 shows that admission to elite degree programs does not change the probability that we observe a tuition value at the schools children attend. Column 2 shows tuition at the schools where children enroll rises by 145,207 Chilean Pesos (CLP) at the cutoff, or about 4% of the below-cutoff mean. Columns 3, 4, and 5 show that the probability children attend an "expensive" school—defined as in section 2—rises by 4.1 percentage points across the cutoff, and that this effect is driven entirely by increased rates of attending elite private high schools, not non-elite expensive private schools. Column 6 takes as the dependent variable the type-specific average price tuition at the school the child attends, where type is either "elite private" or "other." This value rises by CLP 96,343, 66% of the total increase we find, indicating that most of the increase in tuition is driven by the shift towards elite private schools.

Figure E3 shows regression discontinuity plots for key outcomes reported in Table E3. We see a clear discontinuity in educational expenditure but no increase in the rate at which students attend non-elite expensive schools. The discontinuity in the school-type based expenditure index is clear. As reported in the main text, the shift towards elite private schools explains most of the overall increase in educational expenditures.

E.4 Heterogeneity by high school and degree type

We extend the elite college regression discontinuity analysis by digging deeper into heterogeneity by high school type and college degree program. We first consider splits within the sample of non-elite parents by breaking out parents who attended subsidized public and voucher schools from parents who attended non-elite private schools. Figure E4 reports estimated regression discontinuity effects that split the non-elite sample in this way. We observe similar effects on elite high school attendance and on high school elite name index for children of parents from subsidized and non-elite private high schools. Effects on scores in the college admission exam are null in both groups. Effects on the elite name index of the college degree that children attend are again fairly similar across non-elite groups. Table E5 replicates the main analyses distinguishing between children whose parents attended subsidized schools and those whose parents attended non-elite private schools. Both groups of children are affected by their parents' admission to elite college programs in similar ways.

In Figure E5 we study whether the effects documented in the main body of the paper are driven by parents being admitted to business-oriented programs or to medicine. This distinction is potentially important, because Zimmerman (2019) shows that the distributional effects of admission are very different for business-oriented and medical programs. Business-oriented programs help students from private school backgrounds reach the very top of the income distribution and top corporate leadership roles but have limited effects for students from other backgrounds. In contrast, medical programs raise average income for all students but do not help them reach the very top of the income distribution.

As reported in Tables E6 and E7, we find that admission to both types of elite college programs raises the chances that children of non-elite parents of attend elite private high schools, but that effects for medical programs are somewhat larger than for the business-oriented programs (0.058 vs. 0.026).

E.5 Parents from Santiago vs parents from other regions of the country

Because all of the elite K-12 schools and colleges are located in Santiago, one hypothesis worth studying is whether the effects we document for children are driven by parents moving to Santiago to attend college. To explore this hypothesis, we replicate our main analyses and split the sample depending on whether parents attended K-12 schools located in Santiago or in other cities. The idea is that for parents living in Santiago before college, the geographic mobility effects of attending college in Santiago are likely more limited. Tables E8 and E9 present our results.

We find that attending an elite college program makes parents more likely to send their children to an elite K-12 school regardless of whether they (the parents) attended high school in Santiago or not. The estimated coefficient is slightly larger for parents who attended K-12 schools in Santiago, suggesting that parents' migration to Santiago is not an important driver of our results.

Paralleling our findings for the pooled sample, we find no human capital gains in either geographical group. When splitting the sample between parents from Santiago and from other cities, the increase we find on children's probability of attending an elite college becomes not significant. However, the coefficients are very similar to the ones documented in the main body of the paper.

E.6 Additional results on children's neighborhood

This section shows that the results presented on Section 6.2.5 on changes in neighborhood characteristics are robust to using a 200-meter radius instead of a 100-meter radius to define a child's neighborhood. Table E10 presents the estimates from this exercise.

E.7 Effects of attributes of parents' college programs on children's outcomes

We expand the analyses presented in Section 6.3.2 by allowing parental admission effects to vary depending on the target and next-option field of study. For this exercise we classify each degree in our sample in ten fields of study following the International Standard Classification of Education (ISCED-F 2013).[16] We define the fields of study at the two-digit level, with the exception of *Business administration and law*. In this case, we separate *Business and administration* from *law*. Based on this classification, we generate a variable that identifies the target and next-option field of study (F_{ijct}) and estimate the following specification:

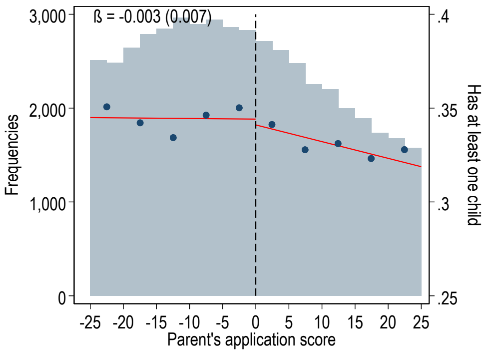
$$\begin{aligned} E_{ijct} =& \beta_0 + \beta_1 A_{ijct} + \beta_2 A_{ijct} \times \Delta E_{ijct} + \beta_3 A_{ijct} \times \Delta Q_{ijct} + \beta_4 A_{ijct} \times \Delta M_{ijct} \\ &+ \beta_5 \Delta E_{ijct} + \beta_6 \Delta Q_{ijct} + \beta_7 \Delta M_{ijct} + \Sigma_f \gamma_f A_{ijct} \times 1(F_{ijct} = f) \\ &+ f(S_{ijct}, \mathbf{\Delta X}_{ijct}, F_{ijct}; \theta) + \mu_c + \mu_{c'(ijct)} + \mu_f + \mu_t + \varepsilon_{ijct}. \end{aligned} \tag{10}$$

E_{ijct} is an outcome for child i of parent j applying to program c in cohort t and A_{ijct} is an indicator for i's admission to c in year t. β_1 is the main effect of admission to the target degree relative to an observably identical next choice. β_2, β_3, and β_4 are coefficients on the main regressors of interest—interactions between admission and the change in degree-specific peer attributes across the cutoff. In addition, we allow the threshold crossing effect to vary depending on the target and next-option field of study. Controls include main effects of $\mathbf{\Delta X}_{ijct} = [\Delta E_{ijct}, \Delta Q_{ijct}, \Delta M_{ijct}]$, as well as a continuous linear function of S_{ijct} that is allowed to vary above and below the cutoff and to interact linearly with the $\mathbf{\Delta X}_{ijct}$ and with F_{ijct}. We include fixed effects for target degree c, next option degree c', target $\times$ next-option field of study, and application cycle.

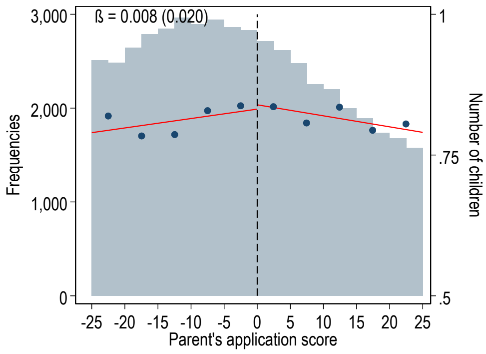
Table E11 reports the results of these regressions for our main outcomes. When reporting coefficients, we standardize the $\mathbf{\Delta X}_{ijct}$ to have mean zero and standard deviation one. Results are similar to those reported in Table 7. Allowing for differential effects depending on the fields of study chosen by parents does not change the conclusions discussed in the main body of the paper.

[16] Visit this link for further details

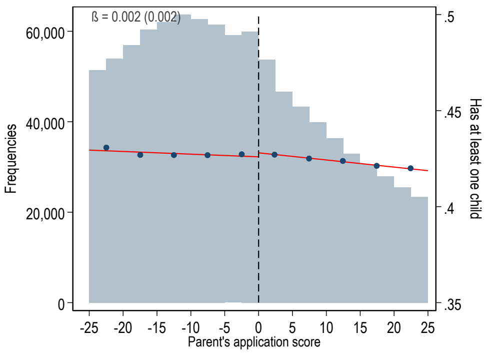
Figure E1: Admission to elite college programs and fertility



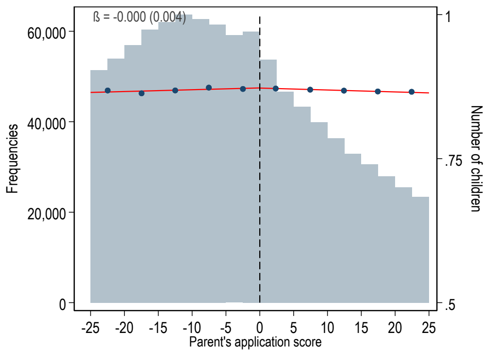
(a) Pr. of having a child - Elite college applicants



(b) N. of children - Elite college applicants



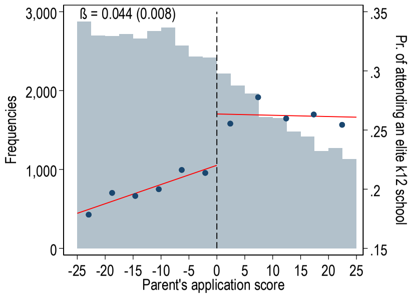
(c) Pr. of having a child - All applicants



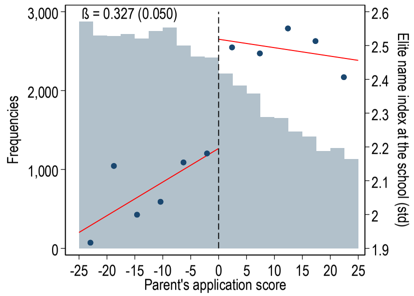
(d) N. of children - All applicants

This figure illustrates changes on the probability of having a child and on the number of children at the admission cutoff of elite college programs (panels a and b) and of all oversubscribed programs in the centralized admission system (panels c and d). Panels (a) and (b) focus on individuals applying to elite college programs between 1976 and 2002. The running variable corresponds to individuals' college application score. It is centered around the admission cutoff of their target college program. Each dot represents outcome averages at different levels of individuals' application score. The red lines correspond to linear regressions and were independently estimated at each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable—i.e., individuals' application score—in the estimation sample. Panels (c) and (d) replicate the previous exercises, but focusing on individuals applying to any oversubscribed college program. See section E.1 for details.

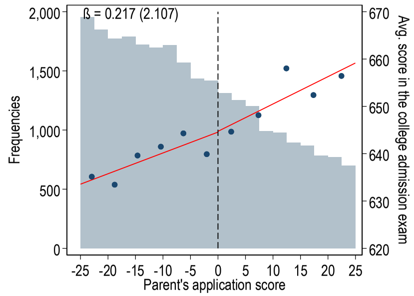
Figure E2: Effect of parents' admission to an elite college program on children's outcomes– full sample



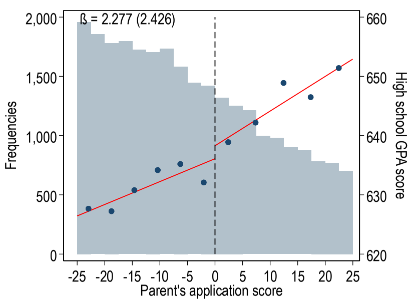
(a) Child attends elite K-12 school



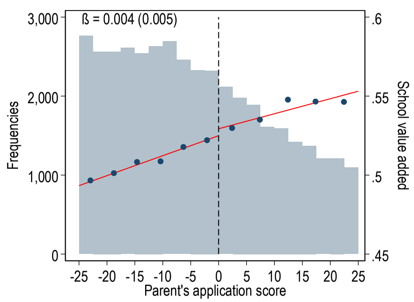
(b) Name index in child's school



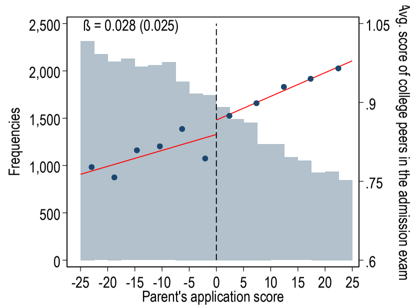
(c) Child's admissions exam score



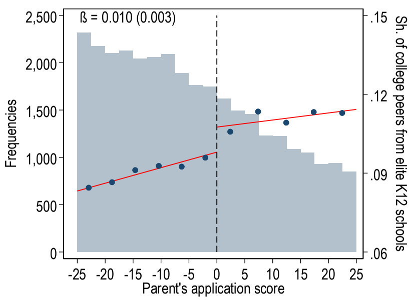
(d) Child's high school GPA



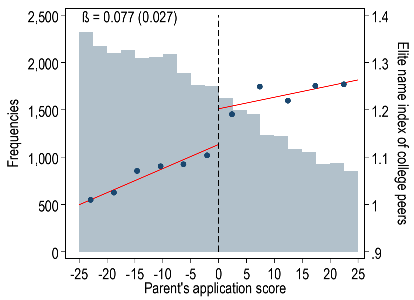
(e) Child's K-12 school value added



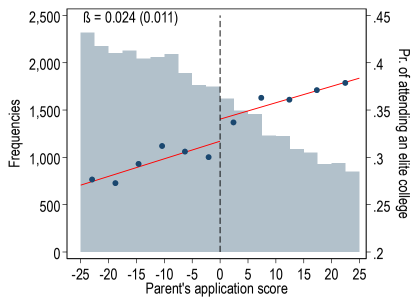
(f) Child's college peers test scores



(g) Child's college peers from elite schools



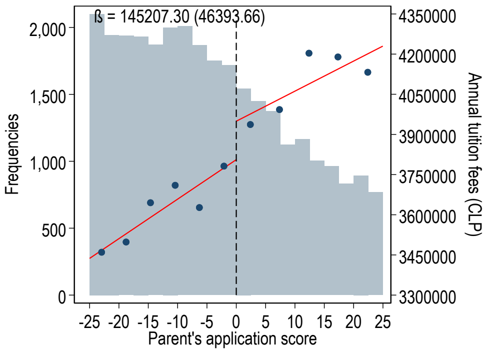
(h) Child's college peers name index



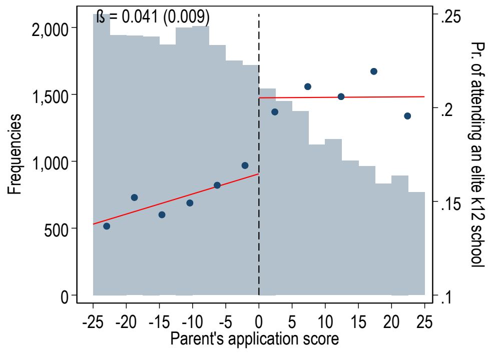
(i) Child attends an elite college

This figure illustrates how children's outcomes change when one of their parents gains admission to an elite college program. The sample is limited to parents applying to elite college programs. Panel (a) shows the probability that the children attend an elite K-12 school; panel (b) the elite name index at the children's K-12 school; panel (c) children's average score in the college admission exam; panel (d) children's high school GPA; panel (e) the value added of children's K-12 school; panels (f) to (h) characterize children's college peers in terms of test scores and of their social pedigree; finally panel (i) describes children's probability of attending an elite college (i.e., University of Chile or Catholic University). The running variable—i.e., parent's application score—is centered around the admission cutoff of the parent target degree. Each dot represents outcome averages at different levels of parents' application score. The red lines are fitted values from linear regressions, fit separately on each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable in the estimation sample. See section E.2 for details.

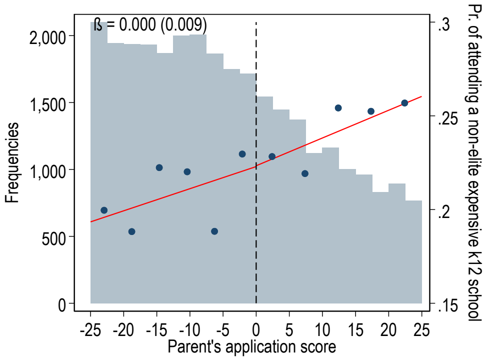
Figure E3: Effect of parents' admission to an elite college program on educational expenditure



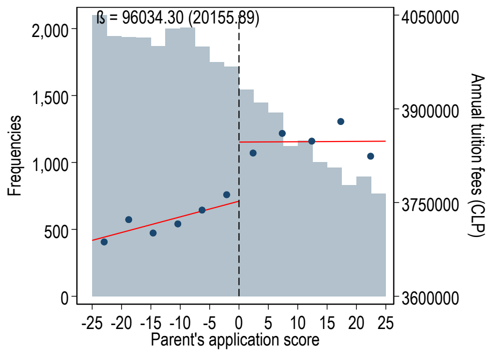
(a) Tuition fees



(b) Pr. of attending an elite K-12 school



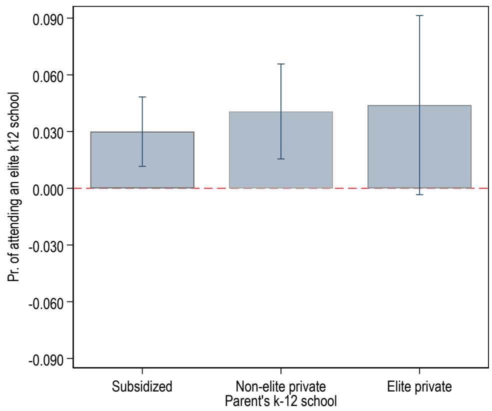
(c) Pr. of attending a non-elite K-12 expensive school



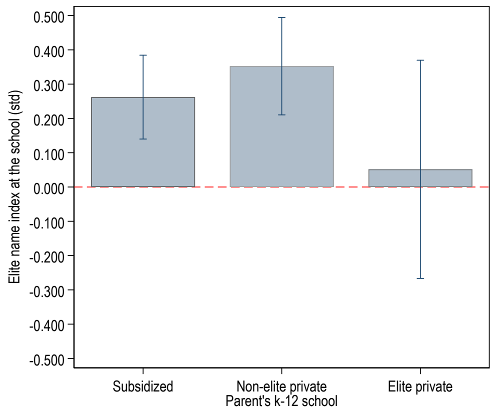
(d) Δ in tuition fees explained by Δ in elite schools attendance

This figure shows how parents' admission to an elite college program changes their expenditures on their children's education. Panel (a) illustrates the change in annual tuition fees paid by parents marginally admitted to an elite college program in their children K-12 schools. Panels (b) and (c) show how the probability of sending children to an elite and non-elite expensive private K-12 school changes at the cutoff. Finally, panel (d) studies how much of the increase in tuition fees documented in panel (a) is explained by parents becoming more likely to send their children to an elite K-12 school. To implement this exercise, we replaced the actual fees charged by elite and non-elite schools by the average fee on each category. In all cases, the running variable corresponds to parents' application score to elite college programs. It is centered around the admission cutoff of their target programs. Each dot represents the mean of the outcome variable at different levels of parents' application score. The red lines correspond to linear regressions and were independently estimated at each side of the cutoff. The blue bars in the background illustrate the distribution of the parents' scores in the estimation sample. See section E.3 for details.

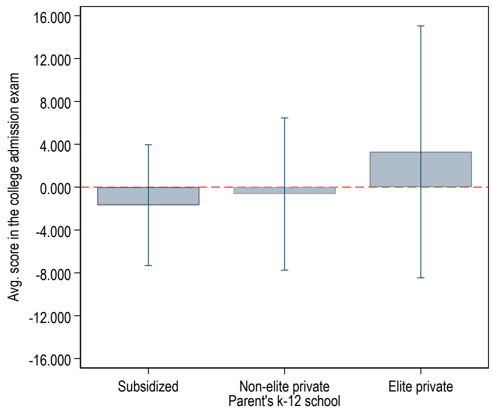
Figure E4: Effect of parents' admission to an elite college program on their children's outcomes–alternate high school splits



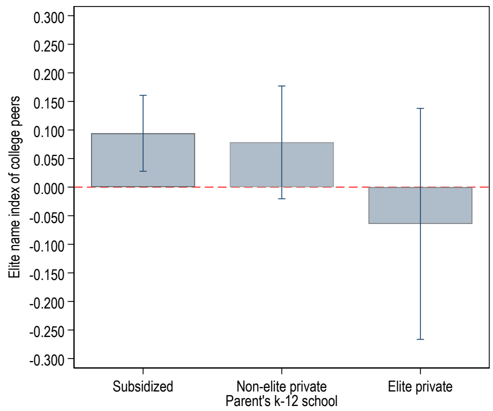
(a) Child attends elite K-12 school



(b) Elite name index at K-12 school



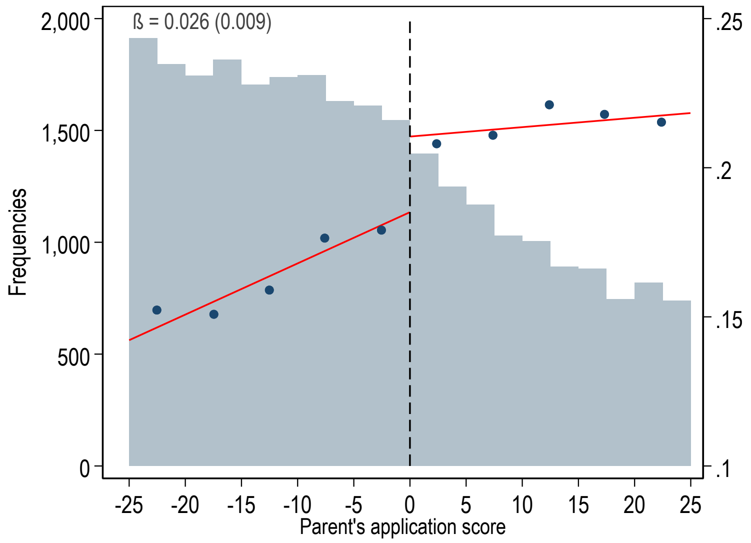
(c) Avg. score in the college admission exam



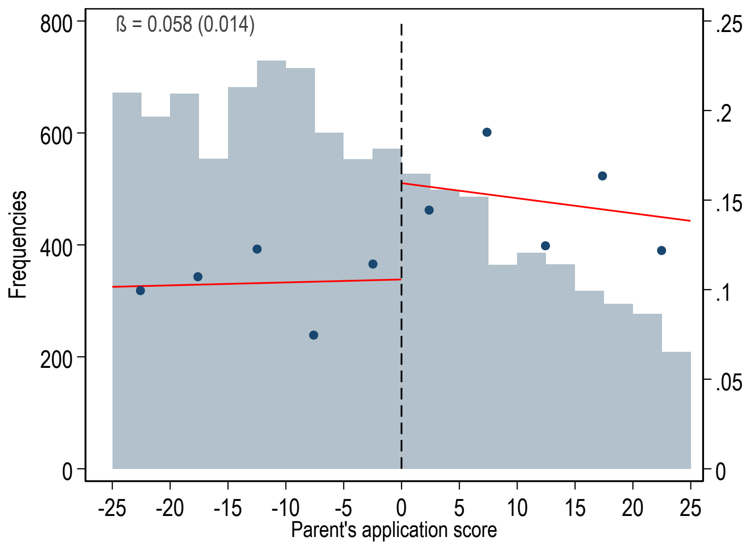
(d) Elite name index of college peers

This figure illustrates the effects of parents' admission to elite college programs on their children's educational trajectories depending on the type of K-12 school attended by the parent. In panel (a) the outcome is children's probability of attending an elite K-12 school. In panel (b) the outcome is the elite name index of the K-12 school of the children. In panel (c) the outcome is children's average score in the college admission exam. In panel (d) the outcome is the elite name index of the college degree attended by the children. Each coefficient is estimated using our main specification in the set of parents who attended subsidized, non-elite private, and elite private schools, respectively. See section E.4 for details.

Figure E5: Effect of parents' admission to an elite college program on their children's K-12 school type, split by parents' field of study



(a) Business and Law



(b) Medicine

This figure illustrates how the probability of attending an elite private school changes for the children of non-elite parents when one of their parents gains admission to a top college program. Panel (a) focuses on cases in which parents gain admission to top business and law programs, while panel (b) on cases in which parents gain admission to top medical schools. The running variable corresponds to the parents' application score to top college programs. It is centered around the admission cutoff of their target program. Each dot represents the share of children going to university at different levels of parents' application score. The red lines correspond to linear regressions and their 95% confidence intervals and were independently estimated at each side of the cutoff. The blue bars in the background illustrate the distribution of the parents' scores in the estimation sample. See section E.4 for details.

Table E1: Parents' admission to an elite college program and children's outcomes—additional outcomes

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending a non-elite private school			Elite name index in K-12 school (WW)		
Parent admitted to target degree = 1	-0.0440	-0.0358	-0.0591	0.3151	0.2653	0.0989
	(0.0092)	(0.0096)	(0.0238)	(0.0492)	(0.0469)	(0.1534)
Observations	42694	37266	5422	42694	37266	5422
Counterfactual mean	0.6403	0.6809	0.3339	2.6320	2.2127	5.7946
	Panel B - Effects on child's pr. of taking the admission exam and scoring in the top 1%					
	Pr. of taking the college admission exam			Pr. of scoring in the top 1% of the admission exam		
Parent admitted to target degree = 1	-0.0003	0.0018	-0.0126	-0.0045	-0.0067	0.0051
	(0.0082)	(0.0086)	(0.0263)	(0.0078)	(0.0081)	(0.0267)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.8092	0.8116	0.7928	0.1346	0.1260	0.2099
	Panel C - Effects on child's admission exam and on college admissions					
	Pr. of scoring in the top 5% of the admission exam			Pr. of being admitted to any selective college		
Parent admitted to target degree = 1	0.0017	-0.0011	0.0077	0.0022	0.0049	-0.0129
	(0.0105)	(0.0112)	(0.0333)	(0.0079)	(0.0083)	(0.0260)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.3251	0.3164	0.4006		0.8259	0.7928
	Panel D - Effects on child's eligibility for elite colleges					
	Pr. of being eligible for an elite college			Pr. of being eligible for an elite college program		
Parent admitted to target degree = 1	0.0004	-0.0006	0.0035	0.0178	0.0137	0.0445
	(0.0105)	(0.0113)	(0.0311)	(0.0108)	(0.0115)	(0.0341)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.6370	0.6337	0.6685	0.3519	0.3463	0.4033

Notes: The table presents estimates obtained from specification (1) that illustrate the effect of elite and non-elite parents' admission to an elite college program on their children's education trajectories. The sample varies across panels. Panel A focuses on children old enough to have enrolled in primary education (i.e., born before 2014). Panels B to D focus on children old enough to have applied to college in the period we observe (i.e., born before 2001). Standard errors clustered two ways at the parent × child level are presented in parentheses. See section E.2 for details.

Table E2: Parents' admission to an elite college program and children's outcomes—additional outcomes

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's college applications					
	Pr. of applying to an elite college			Pr. of applying to an elite college program		
Parent admitted to target degree = 1	0.0187	0.0168	0.0124	0.0013	-0.0002	0.0029
	(0.0111)	(0.0118)	(0.0334)	(0.0103)	(0.0109)	(0.0329)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.4836	0.4726	0.5801	0.2854	0.2763	0.3674
	Panel B - Effects on child's college peers' test scores and school of origin					
	College peers' avg test scores (std)			Share of college peers from elite K-12 schools		
Parent admitted to target degree = 1	0.0282	0.0258	0.0088	0.0097	0.0106	-0.0033
	(0.0245)	(0.0261)	(0.0760)	(0.0031)	(0.0032)	(0.0114)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.8424	0.8232	1.0154	0.0977	0.0878	0.1844
	Panel C - Effects on college peers' elite name index					
	Polo elite name index in college program			WW elite name index in college program		
Parent admitted to target degree = 1	0.0768	0.0862	-0.0468	0.0833	0.0929	-0.0492
	(0.0267)	(0.0272)	(0.0993)	(0.0294)	(0.0301)	(0.1076)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	1.1224	1.0374	1.8651	1.1224	1.2008	2.0871
	Panel D - Effects on child's whole educational trajectory					
	Pr. of attending an elite K-12 school and an elite college			Pr. of attending an elite K-12 school and an elite college program		
Parent admitted to target degree = 1	0.0289	0.0213	0.0661	0.0058	0.0047	0.0090
	(0.0073)	(0.0068)	(0.0328)	(0.0057)	(0.0053)	(0.0279)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.1101	0.0827	0.3481	0.0647	0.0477	0.2127

Notes: The table presents estimates obtained from specification (1) that illustrate the effect of elite and non-elite parents admission to an elite college program on their children education trajectories. All the results in this table were estimated focusing on children old enough to have applied to college in the period we observe (i.e., born before 2001). Standard errors clustered two ways at the parent × child level are presented in parentheses. See section E.2 for details.

Table E3: Effect of parents' admission to elite college programs on educational expenditures for children

	Pr. of observing tuition fees (1)	Tuition fees (CLP) (2)	Pr. of attending an expensive school (3)	Pr. of attending an expensive elite school (4)	Pr. of attending an expensive non-elite school (5)	School type specific mean tuition (CLP) (6)
Parent admitted to target degree = 1	0.0006	145207.30	0.0416	0.0413	0.0004	96,343.01
	(0.0080)	(46,393.66)	(0.0107)	(0.0086)	(0.0093)	(20,155.89)
Observations	37266	30244	30244	30244	30244	30244
Counterfactual mean	0.8101	3.78e+06	0.3904	0.1710	0.2194	3.77e+06

Notes: Notes: The table presents regression discontinuity estimates obtained using specification (1). The sample is limited to children a) whose parents applied to elite degree programs and did not themselves attend elite private high schools and b) who attend schools for which we observe annual tuition fees (with the exception of the first column). Expensive schools are defined as those charging the same or more than the cheapest elite private school (i.e., CLP 4,790,000). This means that we classify all elite schools in our sample as expensive schools. "Type-specific mean tuition"is the mean value of tuition for the type of school the child attends, where type is either elite private or other. Standard errors clustered two ways at the parent $\times$ child level are reported in parentheses. "Counterfactual means" are below-threshold means of the outcome variable. See section 6.2.2 for details

Table E4: Parents' admission to an elite college program and children's peers in college—Only children admitted to college

	All parents	Non-elite parents	Elite parents	All parents	Non-elite parents	Elite parents
	(1)	(2)	(3)	(4)	(5)	(6)
	Child's college peers' avg test scores (std)			Child's share of college peers from elite K-12 schools		
Parent admitted to target degree = 1	0.0316	0.0219	0.0576	0.0114	0.0117	0.0015
	(0.0246)	(0.0262)	(0.0708)	(0.0035)	(0.0036)	(0.0123)
Observations	26963	24064	2888	26963	24064	2888
Counterfactual mean	1.1273	1.0967	1.4064	0.1180	0.1055	0.2320

Notes: The table presents estimates obtained from specification (1) that illustrate the effect of elite and non-elite parents admission to an elite college program on the college peers of their children. All the results in this table were estimated focusing on children old enough to have applied to college in the period we observe (i.e., born before 2001) and who were actually admitted to college. Standard errors clustered two ways at the parent $\times$ child level are presented in parentheses. See section E.2 for details.

Table E5: Effect of parent admission to an elite college program on children's outcomes by parent high school type

	All non-elite parents (1)	Subsidized school parents (2)	Non-elite private parents (3)	All non-elite parents (4)	Subsidized school parents (5)	Non-elite private parents (6)
Panel A - Effects on child's K-12 school						
		Pr. of attending an elite private school			Elite name index in K-12 school	
Parent admitted to target degree = 1	0.033	0.030	0.041	0.287	0.262	0.352
	(0.008)	(0.009)	(0.013)	(0.048)	(0.062)	(0.072)
Observations	37266	22091	15164	37266	22091	15164
Counterfactual mean	0.166	0.139	0.201	1.799	1.669	1.974
Panel B - Effects on child's human capital						
		High school GPA			Avg. score in the college admission exam	
Parent admitted to target degree = 1	1.934	-0.125	3.449	-0.864	-1.682	-0.600
	(2.596)	(3.291)	(4.271)	(2.258)	(2.876)	(3.624)
Observations	23887	15414	8454	23783	15338	8426
Counterfactual mean	634.01	627.58	645.57	640.46	634.56	651.01
Panel C - Effects on child's college program characteristics						
		Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college	
Parent admitted to target degree = 1	0.026	0.004	0.059	0.011	0.011	0.011
	(0.026)	(0.033)	(0.044)	(0.003)	(0.004)	(0.006)
Observations	28482	17812	10648	28482	17812	10648
Counterfactual mean	0.823	0.826	0.820	0.088	0.078	0.103
Panel D - Effects on child's type of college and program						
		Pr. of attending an elite college			Pr. of attending an elite college program	
Parent admitted to target degree = 1	0.022	0.014	0.034	0.006	-0.001	0.014
	(0.011)	(0.014)	(0.018)	(0.009)	(0.011)	(0.015)
Observations	28482	17812	10648	28482	17812	10648
Counterfactual mean	0.306	0.305	0.310	0.141	0.135	0.150

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. "Counterfactual means"are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table E6: Effect of parent admission to an elite college program on children's outcomes—parents applying to business oriented elite programs

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
Panel A - Effects on child's K-12 school						
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.044	0.026	0.061	0.342	0.274	0.075
	(0.010)	(0.009)	(0.025)	(0.062)	(0.059)	(0.174)
Observations	31899	27164	4732	31899	27164	4732
Counterfactual mean	0.247	0.182	0.671	2.435	1.941	5.618
Panel B - Effects on child's human capital						
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	1.486	1.010	0.657	-0.086	-1.357	3.764
	(2.860)	(3.103)	(7.597)	(2.482)	(2.699)	(6.321)
Observations	19528	17027	2493	19466	16963	2495
Counterfactual mean	629.575	626.785	651.689	638.359	634.882	664.711
Panel C - Effects on child's college program characteristics						
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.031	0.028	0.015	0.011	0.012	-0.006
	(0.028)	(0.031)	(0.080)	(0.004)	(0.004)	(0.012)
Observations	23648	20444	3196	23648	20444	3196
Counterfactual mean	0.807	0.778	1.025	0.101	0.088	0.193
Panel D - Effects on child's type of college and program						
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.022	0.021	0.002	0.015	0.015	0.006
	(0.012)	(0.013)	(0.035)	(0.010)	(0.010)	(0.030)
Observations	23648	20444	3196	23648	20444	3196
Counterfactual mean	0.317	0.302	0.432	0.144	0.132	0.229

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parents' admission to an elite business, engineering, or law program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. "Counterfactual means"are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table E7: Effect of parent admission to an elite medical program on children's outcomes

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.045	0.054	-0.081	0.301	0.333	0.023
	(0.014)	(0.013)	(0.077)	(0.079)	(0.075)	(0.428)
Observations	10795	10102	690	10795	10102	690
Counterfactual mean	0.150	0.121	0.571	1.601	1.401	4.429
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	4.274	4.008	13.698	1.028	0.351	0.095
	(4.575)	(4.732)	(19.189)	(3.981)	(4.115)	(19.209)
Observations	7251	6860	388	7209	6820	386
Counterfactual mean	653.901	653.057	673.795	656.986	655.284	688.705
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.017	0.018	-0.083	0.007	0.008	0.014
	(0.049)	(0.050)	(0.239)	(0.005)	(0.005)	(0.032)
Observations	8514	8038	472	8514	8038	472
Counterfactual mean	0.943	0.943	0.959	0.0889	0.086	0.135
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.028	0.024	0.151	-0.018	-0.017	-0.002
	(0.021)	(0.021)	(0.107)	(0.016)	(0.017)	(0.081)
Observations	8514	8038	472	8514	8038	472
Counterfactual mean	0.317	0.318	0.308	0.168	0.163	0.250

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite medicine program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual means are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table E8: Effect of parent admission to an elite college program on children's outcomes—parents from Santiago

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.055	0.041	0.044	0.358	0.305	0.052
	(0.010)	(0.010)	(0.024)	(0.064)	(0.056)	(0.162)
Observations	26463	21035	5422	26463	21035	5422
Counterfactual mean	0.247	0.153	0.657	2.357	1.646	5.457
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.580	1.983	2.023	-0.548	-2.628	3.294
	(3.154)	(3.554)	(7.057)	(2.746)	(3.101)	(5.995)
Observations	15692	12799	2881	15622	12729	2881
Counterfactual mean	634.024	630.033	654.735	643.871	638.901	667.995
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.022	0.019	0.009	0.006	0.007	-0.003
	(0.032)	(0.036)	(0.076)	(0.004)	(0.004)	(0.011)
Observations	19245	15563	3668	19245	15563	3668
Counterfactual mean	0.828	0.790	1.015	0.102	0.085	0.184
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.023	0.019	0.020	0.010	0.010	0.007
	(0.014)	(0.015)	(0.034)	(0.011)	(0.012)	(0.028)
Observations	19245	15563	3668	19245	15563	3668
Counterfactual mean	0.323	0.305	0.414	0.147	0.130	0.232

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite medicine program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual means are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table E9: Parents' admission to an elite college program and children's outcomes—parents from outside Santiago

	(1)	(2)
	Panel A - Effects on child's K-12 school	
	Pr. of attending an elite K-12 school	Elite name index in in K-12 school
Parent admitted to target program = 1	0.029	0.308
	(0.012)	(0.079)
Observations	16221	16221
Counterfactual mean	0.183	1.998
	Panel B - Effects on child's human capital	
	High school GPA	Avg. score in the college admission exam
Parent admitted to target program = 1	0.187	0.519
	(3.873)	(3.353)
Observations	11071	11036
Counterfactual mean	638.613	642.298
	Panel C - Effects on child's college program characteristics	
	Avg. score in the college admission exam	Sh. of peers from elite K-12 schools in college
Parent admitted to target program = 1	0.029	0.015
	(0.039)	(0.005)
Observations	12889	12889
Counterfactual mean	0.864	0.091
	Panel D - Effects on child's type of college and college program	
	Pr. of attending an elite college	Pr. of attending an elite college program
Parent admitted to target program = 1	0.024	-0.001
	(0.017)	(0.013)
Observations	12889	12889
Counterfactual mean	0.309	0.155

Notes: The table presents estimates obtained from specification (1) that illustrate the effect of non-elite parents' admission to an elite college program on their children education trajectories. Only parents from outside the Santiago region are included in this table. Panel A focuses on children old enough to have enrolled in primary education (i.e., born before 2014). Panels B to C focus on children old enough to have applied to college in the period we observe (i.e., born before 2001). Standard errors clustered at the family level are presented in parentheses. See section E.5 for details.

Table E10: Effect of parents' admission to an elite college program on children's neighborhood (200m radius)

	All parents (1)	Non-elite parents (2)	Elite parents (3)
	Panel A - Elite name index		
Parent admitted in target program	0.2076	0.1808	0.2896
	(0.0765)	(0.0765)	(0.2671)
Observations	9422	8576	829
Counterfactual outcome mean	2.0348	1.8750	3.6601
	Panel B - Avg. tuition fees		
Parent admitted in target program	114004.32	102306.93	141217.12
	(43843.15)	(45222.15)	(121028.77)
Observations	9422	8576	829
Counterfactual outcome mean	1604436.9	1520828.4	2452935.4
	Panel C - Avg. scores in the college admission exam		
Parent admitted in target program	5.5764	4.5261	9.1817
	(2.124563)	(2.2441242)	(4.3073314)
Observations	9421	8575	829
Counterfactual outcome mean	596.1825	592.6519	631.9401
	Panel D - Census block square meter average price (UF)		
Parent admitted in target program	0.9763	0.6480	1.5210
	(0.9139)	(0.9696)	(1.7674)
Observations	8474	7663	794
Counterfactual outcome mean	53.9813	52.4459	68.3682

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parents' admission to an elite college program on the characteristics of the neighborhood in which they lived when their children completed high school. We split the sample by parents' high school type as noted in columns. Outcomes are listed in panel sub-headers. We only observe addresses for children completing high school in the Santiago, Valparaiso, and Biobio regions. More than 60% of the student population attends school in one of these three regions. While the analyses presented in panels A to C focus on characteristics of neighbors living in a 100 meter radius, the analysis in panel D focuses on the average square meter price in a census block. In urban areas, a census block coincides with an actual block. The specification includes parents' application-year fixed effect and parents' target program fixed effect. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual means are below-threshold mean values of the outcome of the dependent variable. See section 6.2.5 for details.

Table E11: Effects of attributes of parents' college programs on children's outcomes

	Pr. of attending an elite K12 school	Elite name index in K12 school	Avg. score in the admission exam	High school GPA	Attends an elite college	Attends an elite college program	Avg peer score in college program	Sh. of college peers from elite K12 schools	Elite name index among college program peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent admitted in target major=1 × ΔE (STD)	0.0098	0.1582	-0.8022	-0.3337	0.0184	0.0092	0.0117	0.0049	0.0400
	(0.0042)	(0.0309)	(1.3039)	(1.4661)	(0.0060)	(0.0044)	(0.0143)	(0.0017)	(0.0147)
Parent admitted in target major=1 × ΔQ (STD)	-0.0072	-0.0658	-1.8960	-0.9162	-0.0068	-0.0028	-0.0117	-0.0015	-0.0143
	(0.0020)	(0.0146)	(1.0371)	(1.1982)	(0.0041)	(0.0027)	(0.0106)	(0.0010)	(0.0085)
Parent admitted in target major=1 × ΔM (STD)	0.0079	-0.0059	0.4826	0.1740	-0.0088	0.0009	-0.0081	-0.0007	-0.0084
	(0.0037)	(0.0268)	(1.2162)	(1.3746)	(0.0054)	(0.0038)	(0.0131)	(0.0015)	(0.0130)
Observations	350767	286567	242276	244091	286567	286567	286563	286563	286563
Counterfactual mean	0.0643	1.0291	601.0341	604.0711	0.1835	0.0712	0.5924	0.0447	0.6618

Notes: This table presents estimates from parametric regression discontinuity specification 10 of the effects of attributes of the programs to which parents are admitted on outcomes for children. Each column is a single specification. Reported coefficients are interactions between parental admission to target degree and differences between the attributes of the target and next-option degree program. We consider differences along four dimensions: share of college peers from elite high schools (E), average college peer exam scores (Q), and share of non-elite college peers who marry alumni of elite K-12 schools (M). In addition, we allow the effect to vary depending on the fields of the target and next-option degree. We distinguish between ten fields following the ISCED-F 2013 definitions. Thus, the specification includes fixed effects defined by the target and next-option field of study combination, as well as interactions between these effects and scoring above the admission cutoff. All the variables are in standard deviation units. Samples vary across columns due to data availability. Columns (1) and (2) focus on children old enough to observe attending primary education (i.e., born before 2014). The rest of the columns focus on children old enough to observe applying to college (i.e., born before 2001). Elite name index in K12 school and among college peers is the polo club elite name index. We control for a linear polynomial of the running variable, the slope of which is allowed to change at the cutoff. The slope of the running variable on both sides of the cutoff is allowed to vary with E, Q and M. It is also allowed to change depending on the target and next-option field of study combination. The main effects of E, Q, and M are also included in the specification. Standard errors clustered two ways at the parent-child level are presented in parentheses. Counterfactual means are mean below-threshold value of the dependent variable.

F Robustness checks

We test the robustness of our main findings to a variety of alternative specifications.

F.1 Varying the set of controls

This section shows that our results are robust to varying the set of controls that we use.

Table F1 reproduces key analyses from main text Table 4 but adds a set of predetermined covariates as control variables. These covariates are parent's gender, parent's type of K-12 school, child's gender, child's birth year, self-reported household earnings, and self-reported family size. Adding these controls does not affect our findings.

In Table F2 we also reproduce the key analyses from main text Table 4 but removing all the fixed effects. As discussed in Section 5, since parents' target degree progam and application year are balanced across the admission threshold, the fixed effects—i.e., μ_{ct}—that we add in specification (1) are not required for the identification of causal effects. The results in the Table confirm this by showing that removing these fixed effects does not affect our findings. Thus, we include these covariates to improve precision and because they correspond to the level at which each admissions quasi-experiment takes place.

F.2 Alternative bandwidths

Figure F1 illustrates how the effect of parent elite admission on children's social capital depends on the bandwidth used to estimate the regression discontinuity specification. We vary the bandwidth used in five point intervals from 10 points to 40 points (i.e., 15 points on either side of our main bandwidth of 25 points). Effects in the full sample and for non-elite parents are stable. Effects for elite parents become somewhat larger at narrow bandwidths, suggesting that the estimates we report in the main text for this group are if anything conservative.

In addition, in Tables F3 to F6 and Figures F2 to F4 we replicate the main tables and figures of the paper, but this time using optimal bandwidths computed according to Calonico et al. (2014, 2020). To keep the estimation samples comparable across related specifications while also allowing for different optimal bandwidths for different outcome types, we computed optimal bandwidths for three primary outcomes, one for each outcome type—child high school outcomes, child college outcomes, and parent marriage market outcomes. The three primary outcomes are: (i) child's probability of attending an elite K12 school, (ii) child's probability of attending an elite college, and (iii) parent's probability of marrying someone from their target degree. We then replicated Tables 4 to 7 and Figures 5 to 7 using these alternative bandwidths. We use optimal bandwidths computed for child's probability of attending an elite K12 school when looking at outcomes that we observe for children prior to college. We use the optimal bandwidths computed for a child's probability of attending an elite college when looking at outcomes that we observe for children old enough to attend college. Finally, we use the optimal bandwidths computed for parent's probability of marrying someone from their target degree to study all marriage market outcomes. We allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff.

We find that the optimal bandwidth when the outcome is children's elite K12 school attendance is 16.9 points to the left and 22.95 points to the right of the admission cutoff faced by the parent. Similarly, the optimal bandwidth when the outcome is children's elite college attendance is 18 points to the left and 31.5 points to the right of the admission cutoff faced by the parent. Finally, the optimal bandwidth when the outcome is an indicator for a parent's marriage to someone from their target degree is 13.23 points to the left and 29.14 points to the right of the admission cutoff they face. These bandwidths are similar to the one we use in the main body of the paper, though generally slightly shorter to the left and similar or larger to the right.

Estimating RD specifications within these bandwidths, we find results very similar to those in the main text. The only exception is the result on spouses' probability of attending any elite program. For this outcome we now obtain a small and non-statistically significant effect. That most results coincide with the ones presented in the main text is not surprising given that the optimal bandwidths are similar to the 25-point bandwidth for which results are reported in the main text.

F.3 Placebo cutoffs

We conduct an additional "placebo cutoff" robustness exercise. We create placebo cutoffs at 10 point intervals from 30 points below to 30 points above the true cutoff, and re-estimate the regression discontinuity specifications at each placebo value. We focus on children's elite private school attendance as the outcome of interest. Figure F5 reports results from this exercise. The zero value on the horizontal axis corresponds to the true cutoff—i.e., the actual treatment.

In the full sample and in the sample of non-elite parents, the placebo estimates are universally small and do not differ statistically from zero at conventional levels. In the smaller elite parent sample, estimates are noisy and in all but one case do not differ statistically from zero.

F.4 Alternative elite K-12 school definitions

We consider two alternative ways of identifying elite private schools. The first approach limits elite schools to only the traditional elites, as defined in Section B.1. The second approach defines as elite the 25 most popular schools among the children of parents who themselves graduated from elite schools, as listed in Table B.II.

Tables F7 and F8 present results from these exercises. Our main results do not qualitatively change when using these alternative elite definitions.

F.5 Polynomial of degree two

Regression discontinuity specifications in the main text use linear controls for the running variable. Linear specifications are standard in the regression discontinuity literature, but we nevertheless assess the robustness of our findings to quadratic controls. Figures F6 and F7 display regression discontinuity plots using quadratic controls. We find similar results to our main specifications. Outcomes related to children's K12 schools remain remarkably similar, with the one exception being that we find larger effects for elite parents. Point estimates for children's human capital and college type effects are all similar under this alternate specification, though in some cases less precisely estimated (see Table F9 for further details). We do see somewhat smaller effects for the attributes of children's college peers. Overall, these findings support our main claims that parents' elite admission shapes children's social but not human capital.

F.6 Other sample definitions

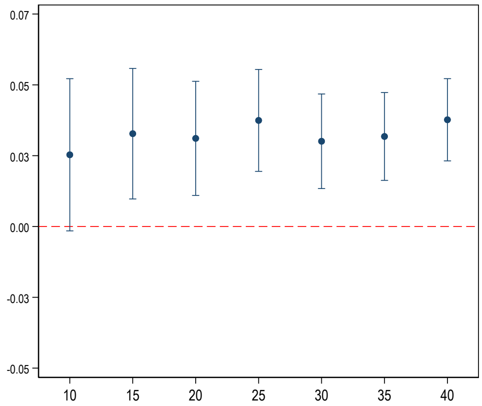
We consider three alternative approaches to sample construction. First, our main analysis limits the sample to parents' first time applying through the centralized system. Table F10 eliminates the first application restriction, considering all applications. As in the main analysis, we find that parents' elite admission raises child social capital and changes the attributes of college degree programs, but doesn't increase human capital accumulation. Our results for children's social capital, children's human capital, and the observable attributes of children's college programs (Panels A through C) are very similar to those reported in the main text. The effects on children's K12 trajectory and on peers from elite K12 schools in college are somewhat larger in this sample. We do observe a small decline in the "attend an elite college" coefficient (Panel D, left side) relative to the main text. This coefficient remains positive but is not statistically significant at conventional levels.

Second, we consider specifications that focus on the set of parents who can be matched to Ministry of Health birth records. As described in section 3, we construct parent-child links using datasets from DEMRE, the Ministry of Education, and the Ministry of Health. While the Ministry of Health data provide mother-child links for all children born in the country, family links show up in the Ministry of Education and DEMRE data only if at least one of the children in the family registers for the college admission exam between 2003 and 2018. As we describe in sections 3 and 5, the vast majority of children do participate in this process, and we see no evidence of imbalance in selection into the sample on the basis of treatments of interest. Nevertheless, it is interesting to ask whether our results would look different if we considered only parents whose (potential) children would show in the Ministry of Health data. These data cover mothers who give birth between 1992 and 2010, so we focus on women who applied to college between 1990 and 2003.

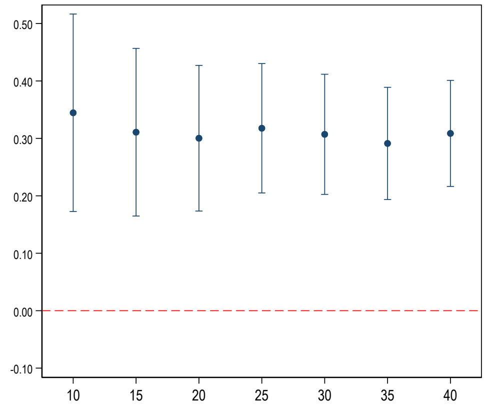
Table F11 presents results from this exercise. The sample is dramatically reduced relative to the main text because of the cohort restriction and restriction to female applicants. The full sample count for school type falls from 42,696 in Table 4 to 6,588. However, we still find that parent admission to elite college raises child social capital, with somewhat larger effects than in the main analysis (Panel A). For human capital (Panel B), we use elementary grade SIMCE scores rather than admissions exam scores because very few children in this sample are old enough to have participated in the college admissions process. As in the main text, we find null effects. We do not report results for college outcomes because few children in this subsample have applied to college.

Finally, we perform a similar analysis, but focus on the set of college applicants who applied to college before 1988. This is the set of college applicants for whom we are more likely to find a child because they have completed their fertility in time for all children to be included in our sample. We link 65% of them with at least one child. This match rate is 58% larger than the match rate in our main sample. The results of this exercise are presented in Table F12. The estimates we obtain when focusing on this sample are remarkably similar to the ones presented in the main body of the paper.

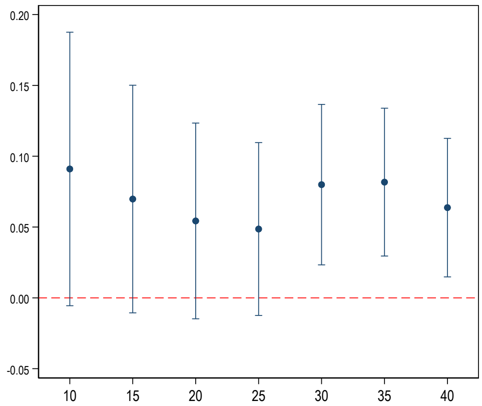
Figure F1: Effect of parents' admission to an elite college program on children's K12 school—alternative bandwidths



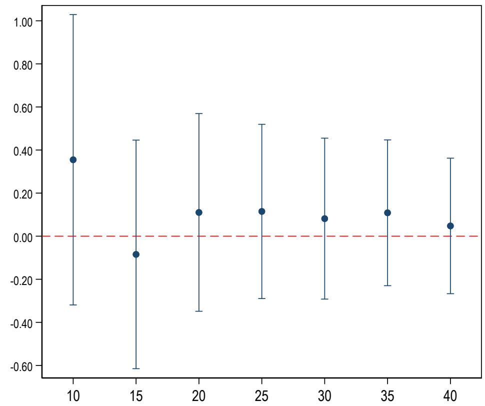
(a) Elite K12 school attendance (Non-elite parents)



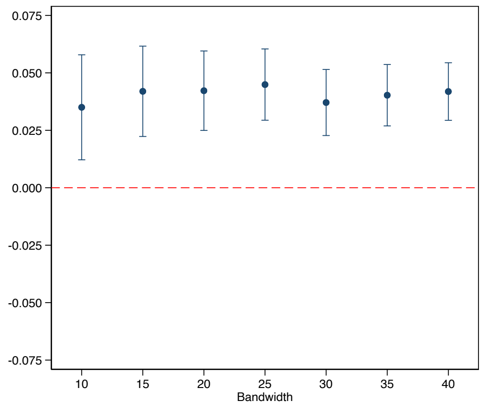
(b) Name index in K12 school (Non-elite parents)



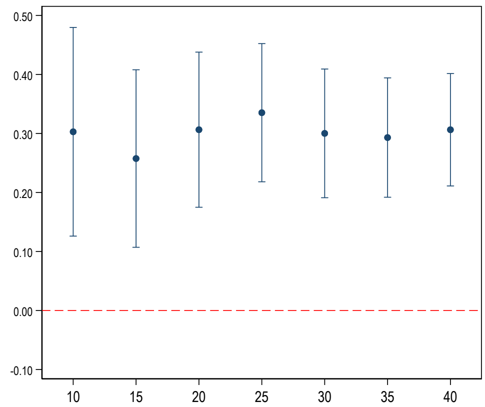
(c) Elite K12 school attendance (Elite parents)



(d) Name index in K12 school (Elite parents)



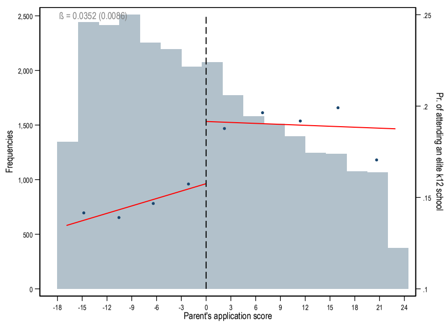
(e) Elite K12 school attendance (All parents)



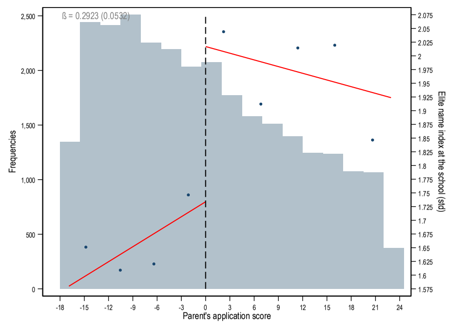
(f) Name index in K12 school (All parents)

This figure presents estimates of equation 1 for a variety of alternative bandwidths beyond our main bandwidth of 25 points. We study two outcomes. The first one is an indicator for whether their child attends an elite private school. The second one is the elite name index of their child school. Each point corresponds to a regression discontinuity estimate obtained running our main specification with a different bandwidth. Panels (a) and (b) use the sample of non-elite parents. Panels (c) and (d) use the sample of elite parents. Panels (e) and (f) use the full sample of parents. Confidence intervals are computed using standard errors clustered two ways at the parent × child level. See section F.2 for details.

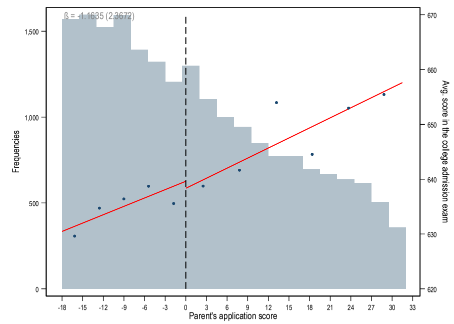
Figure F2: Effect of non-elite parents' admission to an elite college program on children's outcomes - Optimal bandwidth



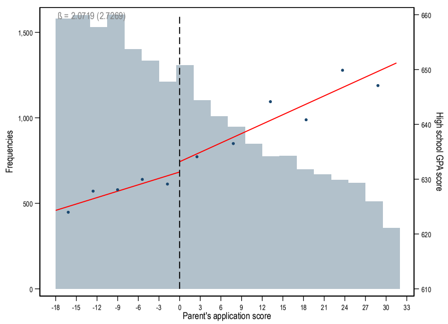
(a) Child attends elite K-12 school



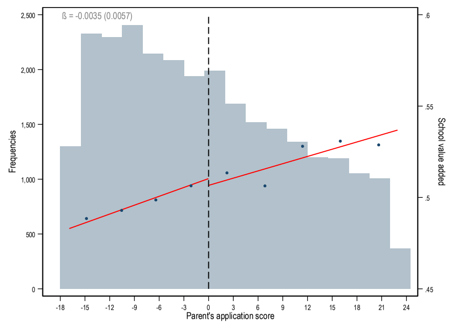
(b) Name index in child's school



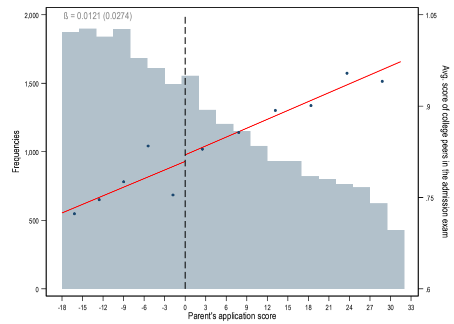
(c) Child's admissions exam score



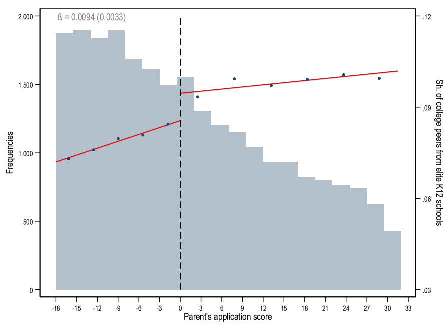
(d) Child's high school GPA



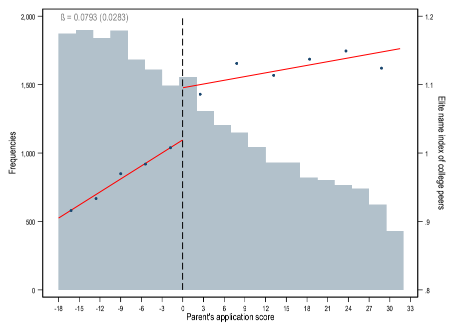
(e) Child's K-12 school value added



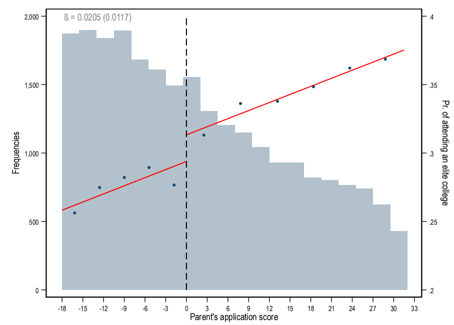
(f) Child's college peers test scores



(g) Child's college peers from elite schools



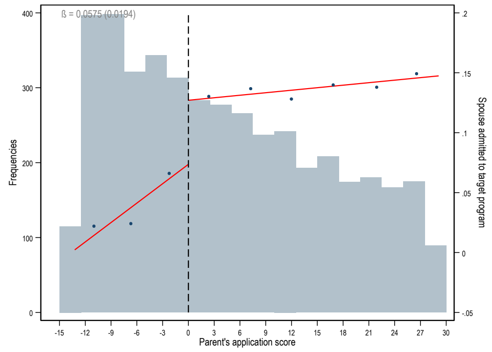
(h) Child's college peers name index



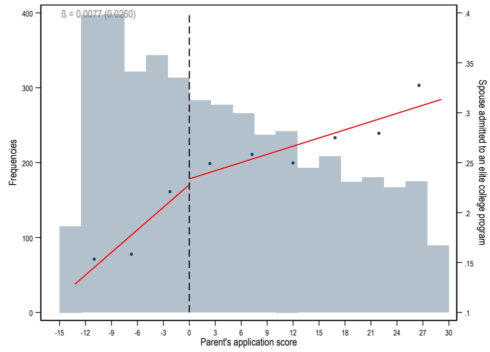
(i) Child attends an elite college

This figure illustrates how children's outcomes change when one of their parents gains admission to an elite college program. The sample is limited to parents applying to elite college programs who did not themselves attend an elite private K-12 school. Panel (a) shows the probability that the children attend an elite K-12 school; panel (b) the elite name index at the children's K-12 school; panel (c) children's average score in the college admission exam; panel (d) children's high school GPA; panel (e) the value added of children's K-12 school; panels (f) to (h) characterize children's college peers in terms of test scores and of their social pedigree; finally panel (h) describes children's probability of attending an elite college (i.e., University of Chile or Catholic University). The running variable—i.e., parent's application score—is centered around the admission cutoff of the parent target degree. Each dot represents outcome averages at different levels of parents' application score. The red lines are fitted values from linear regressions and their 95% confidence intervals, fit separately on each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable in the estimation sample. Figures focus on optimal bandwidths computed for child's probability of attending an elite K12 school when looking at outcomes that we observe for children prior to college. They focus on optimal bandwidths computed for a child's probability of attending an elite college when looking at outcomes that we observe for children old enough to attend college. We compute these optimal bandwidths following Calonico et al. (2014, 2020) and allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. See section 6.1 for details.

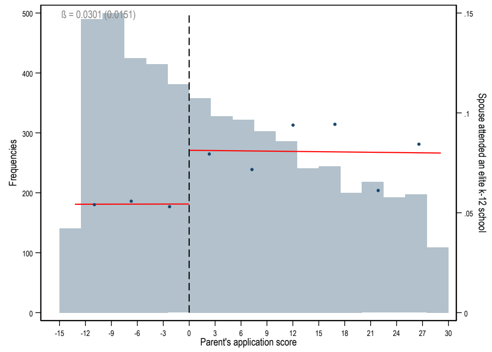
Figure F3: Effects of admission to an elite college program on spouse characteristics - Optimal bandwidths



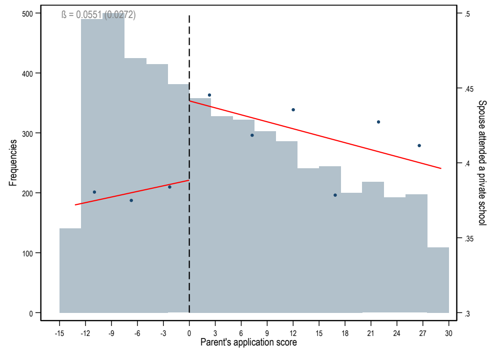
(a) Spouse admitted to target degree program



(b) Spouse admitted to any elite program



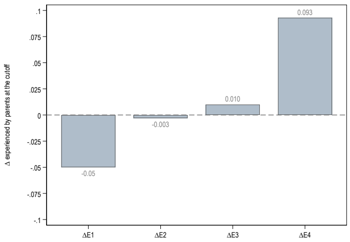
(c) Spouse attended an elite K-12 school



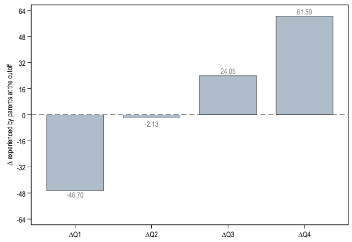
(d) Spouse attended any private K-12 school

This figure illustrates how admission to an elite college program changes the characteristics of spouses. Panel (a) shows the probability of marrying someone admitted to the target (i.e., above-threshold) degree program. Panel (b) shows the probability of marrying someone admitted to any elite college program. Panel (c) shows the probability of marrying someone who graduated from an elite private K-12 school, and panel (d) shows the probability of marrying someone who graduated from any private K-12 school (includes non-elite and elite private schools). The running variable in all cases corresponds to a parent application score. It is centered around the admission cutoff of his/her target program. Each dot represents the mean of the outcome variable at different levels of the parent's application score. The red lines illustrate the slope of the running variable and its 95% confidence interval. The slope is independently estimated at each side of the cutoff using a linear regression. The blue bars in the background show the distribution of the running variable. We use the optimal bandwidths computed for parent's probability of marrying someone from their target degree to study all marriage market outcomes. We allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. See section 6.2.4 for details.

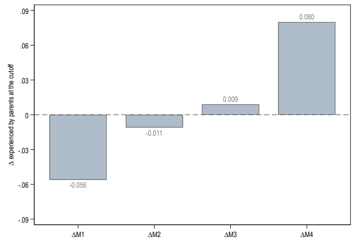
Figure F4: RD estimates of effects of parents' college exposure to elite peers (E), college exposure to high-scoring peers (Q), and college marriage prospects (M) on children's outcomes



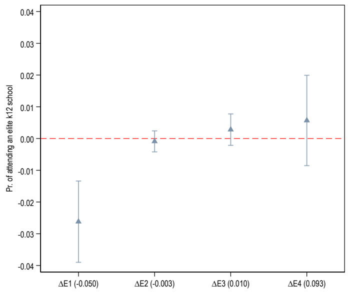
(a) E experienced by parents by ΔE



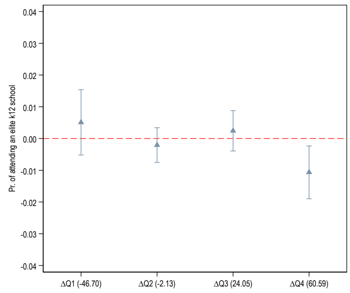
(b) Q experienced by parents by ΔQ



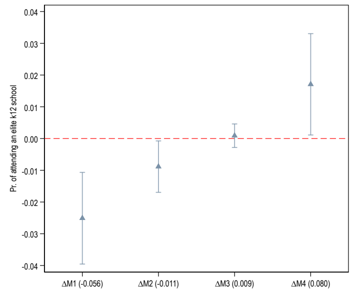
(c) M experienced by parents by ΔM



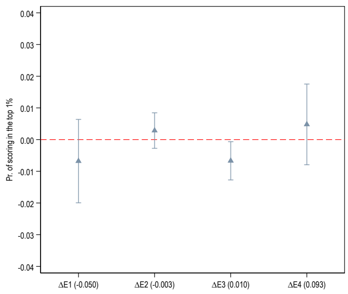
(d) Child attends an elite HS by ΔE



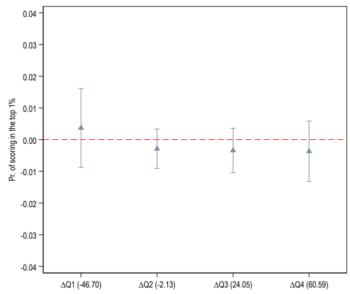
(e) Child attends an elite HS by ΔQ



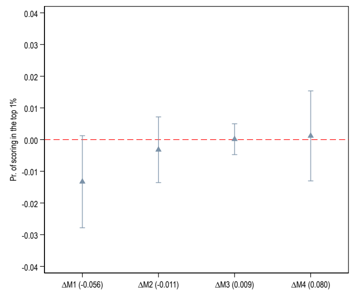
(f) Child attends an elite HS by ΔM



(g) Child scores in top 1% by ΔE



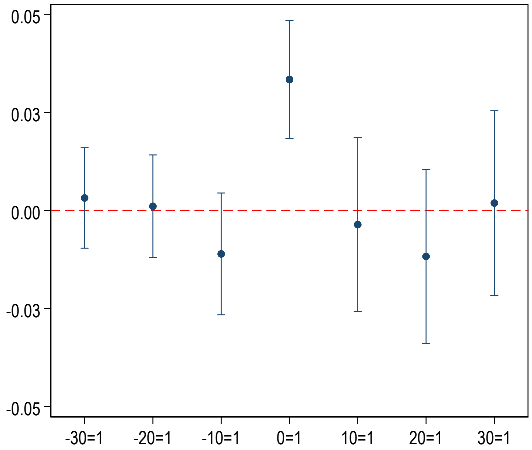
(h) Child scores in top 1% by ΔQ



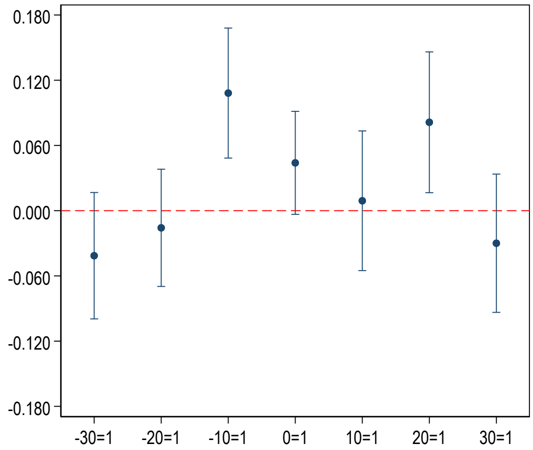
(i) Child scores in top 1% by ΔM

This figure illustrates how outcomes for children change when their parents cross admissions thresholds that shift them between different kinds of college degree programs. All results reported in this table are regression discontinuity estimates of equation 1, splitting the sample by attributes of the target and next option degree programs. The effect of parents' admission to their target college program is allowed to vary depending on the difference in the share of alumni of elite K-12 schools (ΔE), in peers' average score in the college admission exam (ΔQ), and in the share of non-elite students marrying alumni of elite K-12 schools (ΔM) in the target and next best college program. We split the sample in quartiles by ΔE, ΔQ, and ΔM. We then estimate equation 1 in each sub-sample. Each reported estimate represents the crossing threshold effect that being admitted to a target college program has on the outcome variable in the panel title for the listed quartile of ΔE, ΔQ and ΔM. The sample consists of parents who did not themselves attend elite private high schools applying to college degree programs in the centralized system with binding admissions constraints. Panels (a) to (c) illustrate the changes that parents experience at the cutoff in exposure to elite peers (E), in peer academic quality (Q), and in marriage market prospects (M). Panels (d) to (f) show changes in children's probability of attending an elite private K-12 school. Panels (g) to (h) show changes in the probability that the children score in the top 1% of the college admission exam. Vertical intervals in lower two rows are 95% confidence intervals. We use optimal bandwidths computed for child's probability of attending an elite K12 school when looking at outcomes that we observe for children prior to college. We use optimal bandwidths computed for a child's probability of attending an elite college when looking at outcomes that we observe for children old enough to attend college. These optimal bandwidths were computed following Calonico et al. (2014, 2020) and are different above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. See section 6.3 for details.

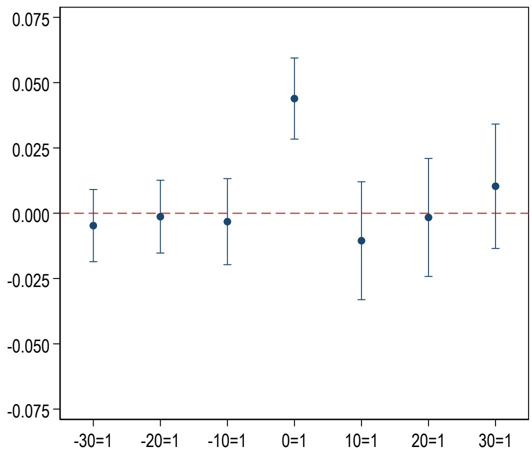
Figure F5: Effect of parents' admission to an elite college program on children's elite high school attendance—placebo cutoffs



(a) Placebo cutoffs (Non-elite parents)



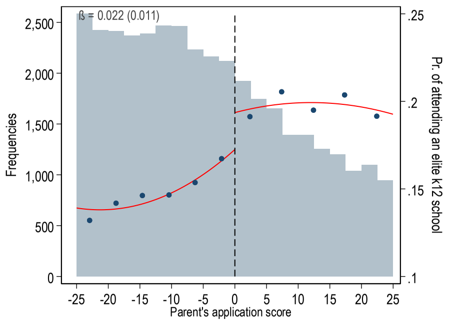
(b) Placebo cutoff (Elite parents)



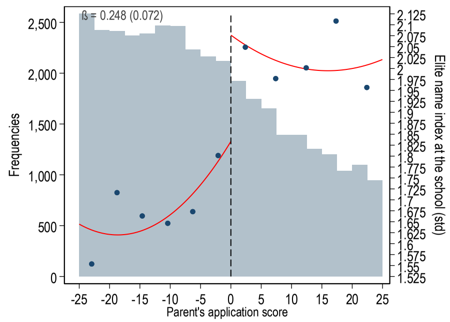
(c) Placebo cutoff (All parents)

This figure illustrates estimates for the effects of parents' admission to an elite college program on their children's probability of attending an elite school. Each point corresponds to an estimate obtained using equation 1, but changing the location of the admission cutoff used in estimation to a variety of false "placebo" values. The numbers on the x-axis indicate the distance between placebo cutoffs and the actual cutoff. Panel (a) focuses on non-elite parents, panel (b) on elite parents, and panel (c) on the full sample of parents. Confidence intervals are computed using standard errors clustered two ways at the parent × child level. See section F.3 for details.

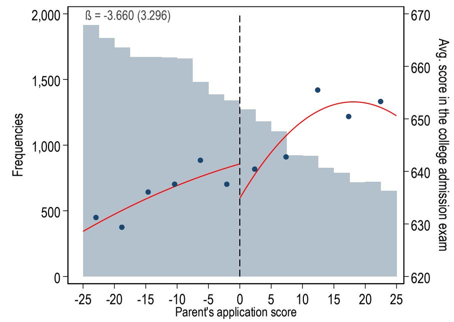
Figure F6: Effect of non-elite parent admission to an elite college program on children's outcomes—polynomial of degree 2



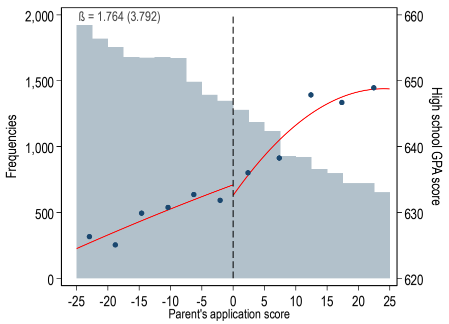
(a) Child attends elite K-12 school



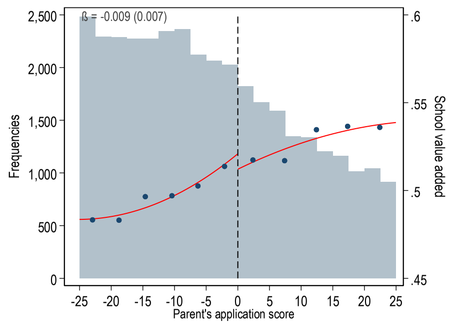
(b) Name index in child's school



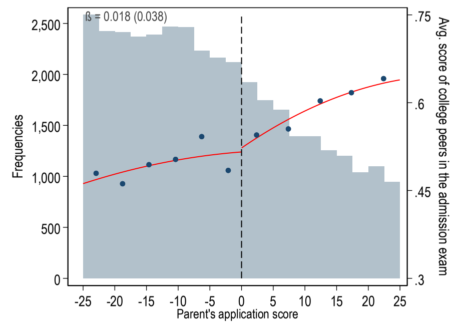
(c) Child's admissions exam score



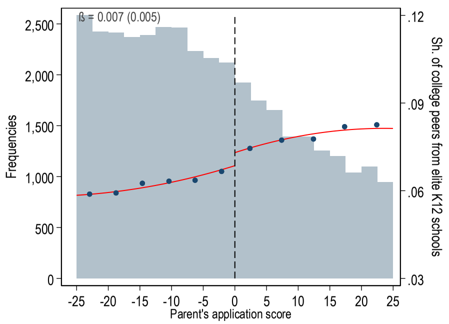
(d) Child's high school GPA



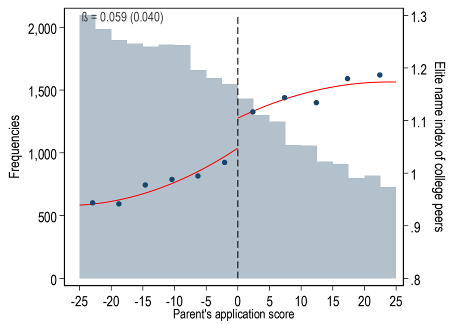
(e) Child's K-12 school value added



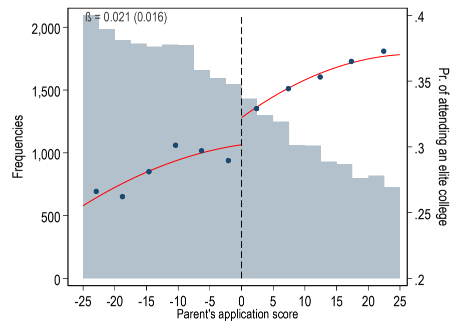
(f) Child's college peers test scores



(g) Child's college peers from elite schools



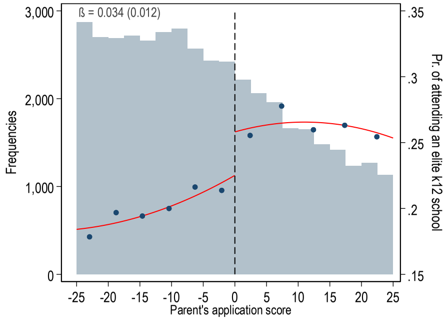
(h) Child's college peers name index



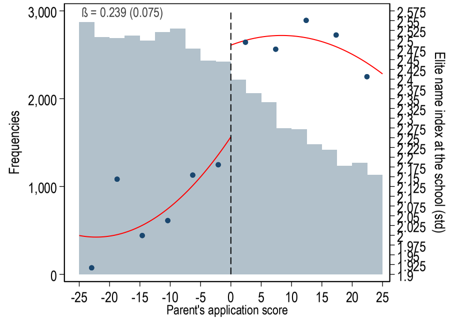
(i) Child attends an elite college

This figure illustrates how children's outcomes change when one of their parents gains admission to an elite college program. The sample is limited to parents applying to elite college programs who did not themselves attend an elite private K-12 school. Panel (a) shows the probability that the children attend an elite K-12 school; panel (b) the elite name index at the children's K-12 school; panel (c) children's average score in the college admission exam; panel (d) children's high school GPA; panel (e) the value added of children's K-12 school; panels (f) to (h) characterize children's college peers in terms of test scores and of their social pedigree; finally panel (h) describes children's probability of attending an elite college (i.e., University of Chile or Catholic University). The running variable—i.e., parent's application score—is centered around the admission cutoff of the parent target degree. Each dot represents outcome averages at different levels of parents' application score. The red lines are fitted values from quadratic regressions, fit separately on each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable in the estimation sample. See section F.5 for details.

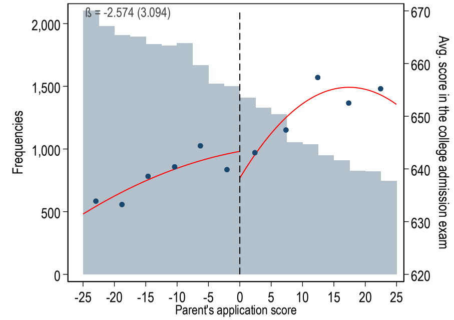
Figure F7: Effect of parent admission to an elite college program on children's outcomes—polynomial of degree 2



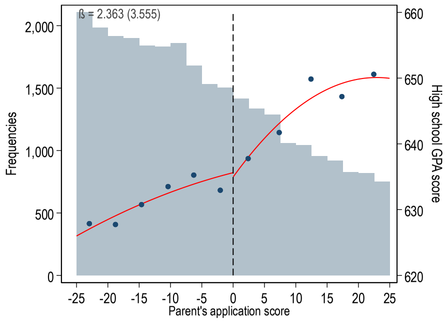
(a) Child attends elite K-12 school



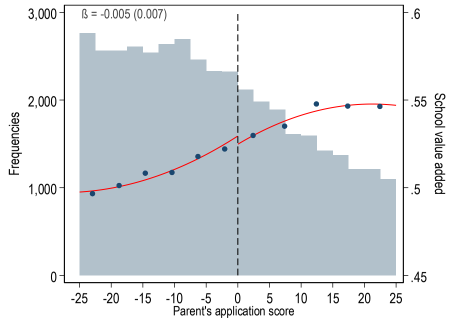
(b) Name index in child's school



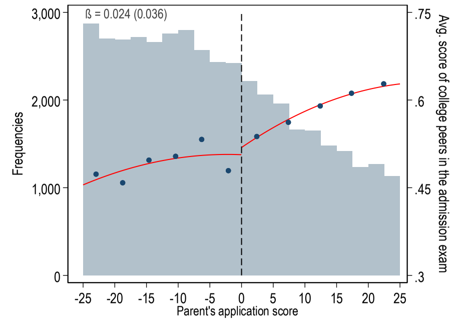
(c) Child's admissions exam score



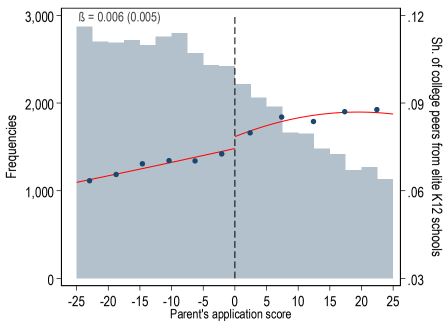
(d) Child's high school GPA



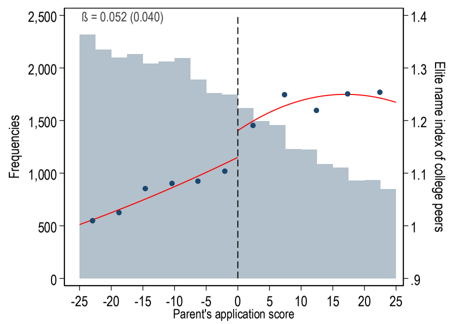
(e) Child's K-12 school value added



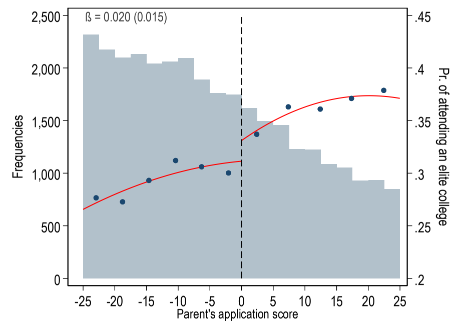
(f) Child's college peers test scores



(g) Child's college peers from elite schools



(h) Child's college peers name index



(i) Child attends an elite college

This figure illustrates how children's outcomes change when one of their parents gains admission to an elite college program. Panel (a) shows the probability that the children attend an elite K-12 school; panel (b) the elite name index at the children's K-12 school; panel (c) children's average score in the college admission exam; panel (d) children's high school GPA; panel (e) the value added of children's K-12 school; panels (f) to (h) characterize children's college peers in terms of test scores and of their social pedigree; finally panel (h) describes children's probability of attending an elite college (i.e., University of Chile or Catholic University). The running variable—i.e., parent's application score—is centered around the admission cutoff of the parent target degree. Each dot represents outcome averages at different levels of parents' application score. The red lines are fitted values from quadratic regressions, fit separately on each side of the cutoff. The blue bars in the background illustrate the distribution of the running variable in the estimation sample. See section F.5 for details.

Table F1: Effect of parent admission to an elite college program on children's outcomes—additional controls

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.038	0.032	0.085	0.301	0.307	0.196
	(0.009)	(0.009)	(0.033)	(0.055)	(0.056)	(0.219)
Observations	28726	25735	2980	28726	25735	2980
Counterfactual mean	0.208	0.161	0.651	2.094	1.781	5.030
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.378	2.061	4.158	0.438	-0.634	5.646
	(2.351)	(2.520)	(6.945)	(2.017)	(2.164)	(5.924)
Observations	26776	23884	2881	26674	23782	2881
Counterfactual mean	635.933	634.005	654.735	643.195	640.456	667.995
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.034	0.024	0.088	0.011	0.012	0.005
	(0.024)	(0.026)	(0.069)	(0.003)	(0.003)	(0.012)
Observations	26960	24061	2888	26960	24061	2888
Counterfactual mean	1.127	1.097	1.406	0.118	0.106	0.232
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.029	0.025	0.052	0.008	0.006	0.034
	(0.012)	(0.012)	(0.039)	(0.010)	(0.010)	(0.035)
Observations	26960	24061	2888	26960	24061	2888
Counterfactual mean	0.386	0.371	0.526	0.182	0.170	0.295

Notes: The table presents estimates obtained from equation 1 augmented to include additional covariates. The specification controls for a linear polynomial of the running variable—i.e., parents' application score—which slope is allowed to change at the cutoff. The specification also includes parents' application-year and parents' target college program fixed effect. The specification also controls for parent's gender, parent's type of K-12 school, child's gender, child's birth year, household earnings, and family size. Household earnings and family size are self reported by students when registering for taking the college admission exam at the end of high school. Earnings are reported in broad categories. The sample only includes children born before 2001 who are old enough to register for the exam and report variables used as controls. Standard errors clustered two ways at the parent × children levels are presented in parentheses. See section F.1 for details.

Table F2: Effect of parent admission to an elite college program on children's outcomes - No fixed effects

	All parents	Non-elite parents	Elite parents	All parents	Non-elite parents	Elite parents
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.0435	0.0341	0.0248	0.3343	0.3123	-0.0806
	(0.0083)	(0.0080)	(0.0237)	(0.0535)	(0.0501)	(0.1625)
Observations	42696	37268	5428	42696	37268	5428
Counterfactual mean	0.2231	0.1656	0.6567	2.2277	1.7993	5.4560
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.0392	2.2100	-0.7695	-0.0040	-0.5285	3.0487
	(2.4531)	(2.6239)	(6.6991)	(2.1273)	(2.2784)	(5.5941)
Observations	26791	23899	2892	26687	23795	2892
Counterfactual mean	636.0213	634.0237	654.0350	643.2666	640.4840	668.0486
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.0337	0.0422	-0.0472	0.0099	0.0118	-0.0135
	(0.0247)	(0.0263)	(0.0731)	(0.0032)	(0.0032)	(0.0110)
Observations	32173	28493	3680	32173	28493	3680
Counterfactual mean	0.8424	0.8232	1.0083	0.0977	0.0878	0.1830
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.0246	0.0262	0.0037	0.0057	0.0067	-0.0100
	(0.0106)	(0.0112)	(0.0318)	(0.0083)	(0.0087)	(0.0269)
Observations	32173	28493	3680	32173	28493	3680
Counterfactual mean	0.3174	0.3065	0.4110	0.1500	0.1407	0.2301

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). No fixed effects are included. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual means are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table F3: Effect of parent admission to an elite college program on children's outcomes - Optimal Bandwidths

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.0420	0.0352	0.0497	0.2734	0.2923	-0.1420
	(0.0089)	(0.0086)	(0.0277)	(0.0568)	(0.0532)	(0.1874)
Observations	32855	28529	4316	32855	28529	4316
Counterfactual mean	0.2231	0.1656	0.6566	2.2277	1.7993	5.4533
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	3.1182	2.0719	12.0084	0.6544	-1.1635	11.9601
	(2.5490)	(2.7269)	(7.5224)	(2.2113)	(2.3672)	(6.3975)
Observations	23202	20505	2684	23104	20409	2682
Counterfactual mean	635.9728	634.0054	655.0704	643.2245	640.4561	668.1976
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.0252	0.0121	0.0991	0.0089	0.0094	0.0033
	(0.0257)	(0.0274)	(0.0806)	(0.0033)	(0.0033)	(0.0121)
Observations	28023	24578	3431	28023	24578	3431
Counterfactual mean	0.8424	0.8231	1.0154	0.0977	0.0878	0.1844
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.0236	0.0205	0.0257	0.0055	0.0058	0.0099
	(0.0110)	(0.0117)	(0.0357)	(0.0086)	(0.0090)	(0.0301)
Observations	28023	24578	3431	28023	24578	3431
Counterfactual mean	0.3174	0.3066	0.4144	0.1500	0.1407	0.2320

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effect. We use optimal bandwidths computed for child's probability of attending an elite K12 school when looking at outcomes that we observe for children prior to college. We use optimal bandwidths computed for a child's probability of attending an elite college when looking at outcomes that we observe for children old enough to attend college. We compute these optimal bandwidths following Calonico et al. (2014, 2020) and allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. Standard errors clustered two ways at the parent × child level are in parentheses. "Counterfactual means"are below-threshold mean values of the outcome of the dependent variable. See Section 6.1 for details.

Table F4: Effects of parents' admission to elite college programs on marriage market outcomes - Optimal bandwidth

	All Parents (1)	Mothers (2)	Fathers (3)
Spouse observed = 1			
Admitted into target program = 1	0.0217	0.0256	0.0088
	(0.0153)	(0.0195)	(0.0204)
Counterfactual mean	0.5466	0.3294	0.8247
Spouse was admitted into target program = 1			
Admitted into target program = 1	0.0575	0.1385	0.0333
	(0.0194)	(0.0420)	(0.0190)
Counterfactual mean	0.0938	0.1585	0.0526
Spouse was admitted into an elite college program = 1			
Admitted into target program = 1	0.0077	0.0962	-0.0074
	(0.0260)	(0.0520)	(0.0268)
Counterfactual mean	0.2292	0.3862	0.1328
Spouse was admitted to an elite college = 1			
Admitted into target program = 1	0.0510	0.0921	0.0419
	(0.0305)	(0.0532)	(0.0386)
Counterfactual mean	0.4738	0.5081	0.4511
Spouse attended an elite school = 1			
Admitted into target program = 1	0.0301	0.0297	0.0308
	(0.0151)	(0.0319)	(0.0174)
Counterfactual mean	0.0688	0.0854	0.0599
Spouse attended any private school = 1			
Admitted into target program = 1	0.0551	0.1470	0.0220
	(0.0272)	(0.0516)	(0.0328)
Counterfactual mean	0.4038	0.3902	0.4082
Spouse's performance in admission exam = 1			
Admitted into target program = 1	-7.4294	-8.3078	-4.5922
	(5.7010)	(9.2131)	(6.9320)
Counterfactual mean	586.2626	640.4345	558.4727
Observations	5296	1471	3809

Notes: The table presents regression discontinuity estimates of specification (1) with spouse attributes as the outcome of interest. The sample is mothers and fathers applying to elite degree programs who did not attend elite high schools themselves. Rows are outcomes and columns are sample splits. Column (1) pulls mothers and fathers together, column (2) focuses on mothers, and column (3) on fathers. Standard errors clustered at the applicant level are in parentheses. Counterfactual means are below-threshold means of the dependent variable. We use the optimal bandwidths computed for parent's probability of marrying someone from their target degree to study all marriage market outcomes. We allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. See section 6.2.4 for details.

Table F5: Effect of parents' admission to an elite college program on children's neighborhood - Optimal bandwidth

	All parents (1)	Non-elite parents (2)	Elite parents (3)
	Panel A - Elite name index		
Parent admitted in target major	0.2376	0.2374	0.1758
	(0.0967)	(0.0969)	(0.3646)
Observations	7020	6360	645
Counterfactual outcome mean	2.0717	1.8910	3.9138
	Panel B - Avg. tuition fees		
Parent admitted in target major	147,259.14	157,372.66	-15,375.159
	(55,398.31)	(57,141.56)	(15,4321.62)
Observations	7020	6360	645
Counterfactual outcome mean	1,669,936.2	1,572,111.5	2,674,398.4
	Panel C - Avg. scores in the college admission exam		
Parent admitted in target major	7.0023	7.1505	1.6358
	(2.5629068)	(2.7062079)	(5.8103109)
Observations	7019	6359	645
Counterfactual outcome mean	600.2215	596.4495	638.4723
	Panel D - Census block square meter average price (UF)		
Parent admitted in target major	1.0714	0.9859	0.7774
	(1.0431378)	(1.1132509)	(1.8327701)
Observations	6344	5709	619
Counterfactual outcome mean	53.9813	52.4459	68.3682

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on the characteristics of the neighborhood in which they lived when their children completed high school. We split the sample by parents' high school type as noted in columns. Outcomes are listed in panel sub-headers. We only observe addresses for children completing high school in the Santiago, Valparaiso, and Biobio regions. More than 60% of the student population attends school in one of these three regions. While the analyses presented in panels A to C focus on characteristics of neighbors living in a 100 meter radius, the analysis in panel D focuses on the average square meter price in a census block. In urban areas, a census block coincides with an actual block. The specification includes parents' application-year × parents' target program fixed effect. As these neighborhood' characteristics are observed pre-college, we use optimal bandwidths computed for child's probability of attending an elite K12 school. To compute these optimal bandwidths we follow Calonico et al. (2014, 2020) and allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual outcome means are below-threshold mean values of the outcome of the dependent variable. See section 6.2.5 for details.

Table F6: Effects of attributes of parents' college programs on children's outcomes - Optimal bandwidths

	Pr. of attending an an elite K12 school	Elite name index in K12 school	Avg. score in the admission exam	High school GPA	Attends an elite college	Attends an elite college program	Avg peer score in college program	Sh. of college peers from elite K12 schools	Elite name index among college program peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent admitted in target major=1	-0.0013	-0.0029	1.1524	-0.6178	-0.0037	-0.0016	-0.0023	-0.0007	-0.0048
	(0.0019)	(0.0126)	(0.7763)	(0.8898)	(0.0031)	(0.0021)	(0.0080)	(0.0008)	(0.0068)
Parent admitted in target major=1 × ΔE (STD)	0.0050	0.1192	0.4445	0.5410	0.0189	0.0095	0.0040	0.0043	0.0333
	(0.0047)	(0.0316)	(1.3009)	(1.4670)	(0.0060)	(0.0044)	(0.0143)	(0.0017)	(0.0148)
Parent admitted in target major=1 × ΔQ (STD)	-0.0071	-0.0526	-1.8978	-1.3291	-0.0064	-0.0034	-0.0114	-0.0016	-0.0153
	(0.0021)	(0.0140)	(0.9634)	(1.1065)	(0.0038)	(0.0025)	(0.0098)	(0.0009)	(0.0080)
Parent admitted in target major=1 × ΔM (STD)	0.0115	0.0209	0.0893	-0.6802	-0.0094	0.0017	-0.0017	-0.0001	-0.0022
	(0.0041)	(0.0276)	(1.2044)	(1.3665)	(0.0054)	(0.0038)	(0.0131)	(0.0015)	(0.0131)
Observations	267129	244581	206445	207953	244581	244581	244579	244579	244579
Counterfactual outcome mean	0.0643	1.0292	601.0368	604.0762	0.1835	0.0712	0.5926	0.0447	0.6619

Notes: This table presents estimates from parametric regression discontinuity specification (2) of the effects of attributes of the programs to which parents are admitted on outcomes for children. Each column is a single specification. Reported coefficients are the main effect of admission to the target program and interactions between admission and differences between the attributes of the target and next-option degree program. We consider differences along three dimensions: share of college peers from elite high schools (ΔE), average college peer exam scores (ΔQ), and share of non-elite college peers who marry alumni of elite K-12 schools (ΔM). All the Δ variables are in standard deviation units. Samples vary across columns due to data availability. Column (1) focuses on children old enough to observe attending primary education (i.e., born before 2014). The rest of the columns focus on children old enough to observe applying to college (i.e., born before 2001). is the polo club elite name index. We control for a linear polynomial of the running variable, the slope of which is allowed to change at the cutoff. The slope of the running variable on both sides of the cutoff is allowed to vary with ΔE, ΔQ and ΔM. The main effects of ΔE, ΔQ, and ΔM are also included in the specification. We use optimal bandwidths computed for child's probability of attending an elite K12 school when looking at outcomes that we observe for children prior to college, such as test scores and school attributes. We use optimal bandwidths computed for a child's probability of attending an elite college when looking at outcomes that we observe for children old enough to attend college. We compute these optimal bandwidths following Calonico et al. (2014, 2020) and allow for different bandwidths above and below the cutoff. We do this because the distribution of the running variable is less dense at higher values (i.e., very high scores are rare) so sample sizes tend to be larger below than above the cutoff. Standard errors clustered two ways at the parent × child level are presented in parentheses. Counterfactual outcome mean are mean below-threshold value of the depend variable. See section 6.3 for details.

Table F7: Parents' admission to an elite college program and children's outcomes—traditional elite schools only

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
			Panel A - Effects on child's K-12 school			
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.044	0.036	0.043	0.327	0.287	0.143
	(0.008)	(0.008)	(0.024)	(0.050)	(0.048)	(0.157)
Observations	42694	36886	5800	42694	36886	5800
Counterfactual mean	0.223	0.162	0.640	2.228	1.767	5.343
			Panel B - Effects on child's human capital			
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.277	1.776	1.087	0.217	-1.040	3.857
	(2.426)	(2.616)	(6.570)	(2.107)	(2.278)	(5.530)
Observations	26779	23579	3188	26675	23475	3188
Counterfactual mean	635.933	632.943	660.508	643.195	639.486	672.135
			Panel C - Effects on child's college program characteristics			
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.028	0.026	-0.007	0.010	0.010	-0.003
	(0.025)	(0.026)	(0.072)	(0.003)	(0.003)	(0.011)
Observations	32162	28120	4028	32162	28120	4028
Counterfactual mean	0.842	0.814	1.070	0.098	0.086	0.188
			Panel D - Effects on child's type of college and program			
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.024	0.020	0.021	0.006	0.005	0.008
	(0.011)	(0.011)	(0.032)	(0.008)	(0.009)	(0.027)
Observations	32162	28120	4028	32162	28120	4028
Counterfactual mean	0.317	0.303	0.431	0.150	0.137	0.248

Notes: This table presents estimates obtained from equation 1 that illustrate the effect of parents' admission to an elite college program on children's outcomes. In this case, the schools used to define elite and non-elite parents and elite and non-elite schools for children include only the traditional elite schools, a sub-sample of those used in the main body of the paper. Samples vary across panels. Panel A focuses on children old enough to have enrolled in primary education (i.e., born before 2014). Panels B and C focus on children old enough to have applied to college in the period we observe (i.e., born before 2001). Standard errors clustered two ways at the parent × child level are presented in parentheses. See section F.4 for details.

Table F8: Parents' admission to an elite college program and children's outcomes—extended elite schools

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.044	0.035	0.046	0.327	0.272	0.197
	(0.008)	(0.008)	(0.023)	(0.050)	(0.048)	(0.148)
Observations	42694	36075	6615	42694	36075	6615
Counterfactual mean	0.223	0.158	0.609	2.228	1.743	5.088
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.277	1.965	-0.650	0.217	-0.611	0.962
	(2.426)	(2.636)	(6.224)	(2.107)	(2.295)	(5.194)
Observations	26779	23276	3493	26675	23175	3490
Counterfactual mean	635.933	632.536	661.014	643.195	638.885	674.011
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.028	0.029	-0.018	0.010	0.011	-0.004
	(0.025)	(0.026)	(0.068)	(0.003)	(0.003)	(0.010)
Observations	32162	27691	4453	32162	27691	4453
Counterfactual mean	0.842	0.810	1.071	0.098	0.085	0.188
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.024	0.022	0.016	0.006	0.007	0.003
	(0.011)	(0.011)	(0.030)	(0.008)	(0.009)	(0.026)
Observations	32162	27691	4453	32162	27691	4453
Counterfactual mean	0.317	0.301	0.433	0.150	0.135	0.252

Notes: This table presents estimates obtained from equation 1 that illustrate the effect of parents' admission to an elite college program on children's outcomes. In this case, the schools used to define elite and non-elite parents and elite and non-elite schools for children include all the schools in Table B.II. Samples vary across panels. Panel A focuses on children old enough to have enrolled in primary education (i.e., born before 2014). Panels B and C focus on children old enough to have applied to college (i.e., born before 2001). Standard errors clustered two ways at the parent × child level are presented in parentheses. See section F.4 for details.

Table F9: Effect of parent admission to an elite college program on children's outcomes—second degree polynomial

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.034	0.022	0.100	0.239	0.248	0.176
	(0.012)	(0.011)	(0.036)	(0.075)	(0.072)	(0.247)
Observations	42694	37266	5422	42694	37266	5422
Counterfactual mean	0.223	0.166	0.657	2.228	1.799	5.457
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	2.363	1.764	10.916	-2.574	-3.660	7.974
	(3.555)	(3.792)	(10.586)	(3.094)	(3.296)	(9.018)
Observations	26779	23887	2881	26675	23783	2881
Counterfactual mean	635.933	634.005	654.735	643.195	640.456	667.995
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.024	0.018	0.098	0.006	0.007	0.011
	(0.036)	(0.038)	(0.115)	(0.005)	(0.005)	(0.017)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.842	0.823	1.015	0.098	0.088	0.184
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.020	0.021	0.000	0.004	0.012	-0.048
	(0.015)	(0.016)	(0.051)	(0.012)	(0.013)	(0.043)
Observations	32162	28482	3668	32162	28482	3668
Counterfactual mean	0.317	0.306	0.414	0.150	0.141	0.232

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. Counterfactual means are below-threshold mean values of the outcome of the dependent variable. See section 6.1 for details.

Table F10: Effect of parents admission to an elite college program on children's outcomes (Multiple applications)

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.0330	0.0258	0.0278	0.2506	0.2252	0.0035
	(0.0068)	(0.0065)	(0.0250)	(0.0424)	(0.0400)	(0.1628)
Observations	54636	49073	5552	54636	49073	5552
Counterfactual mean	0.1963	0.1513	0.6711	1.9869	1.6662	5.3688
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	0.9791	1.1522	-3.3726	-0.0089	-0.5941	-0.6370
	(1.9579)	(2.0803)	(5.9743)	(1.7010)	(1.8089)	(5.0523)
Observations	41734	37650	4074	41537	37452	4075
Counterfactual mean	633.2926	630.6301	662.7506	639.2589	636.3474	670.4808
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.0224	0.0241	-0.0369	0.0079	0.0086	-0.0074
	(0.0195)	(0.0207)	(0.0634)	(0.0024)	(0.0024)	(0.0095)
Observations	50100	44977	5111	50100	44977	5111
Counterfactual mean	0.8383	0.8163	1.0765	0.0913	0.0818	0.1917
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.0108	0.0105	-0.0096	0.0025	0.0018	0.0030
	(0.0083)	(0.0088)	(0.0280)	(0.0064)	(0.0067)	(0.0236)
Observations	50101	44978	5111	50101	44978	5111
Counterfactual mean	0.3188	0.3075	0.4397	0.1465	0.1366	0.2515

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. It differs from the main text analysis in that it includes parents applications across multiple application cycles, not just the first one. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2001). The specification also includes parents' application-year fixed effect, parents' target program fixed effect, and parents' next best program fixed effect. Standard errors clustered two ways at the parent × child level are in parentheses. are below-threshold mean values of the outcome of the dependent variable. See section F.6 for details.

Table F11: Effect of mother admission to an elite college program on children's outcomes (Mothers applying to college between 1990 and 2002)

	All mothers (1)	Non-elite mothers (2)	Elite mothers (3)	All mothers (4)	Non-elite mothers (5)	Elite mothers (6)
			Panel A - Effects on child's K-12 school			
		Pr. of attending an elite private school			Elite name index in K-12 school	
Parent admitted to target degree = 1	0.0729	0.0450	0.1278	0.4795	0.3895	0.1587
	(0.0196)	(0.0191)	(0.0440)	(0.1243)	(0.1059)	(0.3053)
Observations	6588	5126	1456	6588	5126	1456
Counterfactual mean	0.2459	0.1525	0.6364	2.3798	1.5436	5.8672
			Panel B - Effects on child's human capital			
		Avg. score in 4th grade standardized exam			Pr. of scoring in the to 1% in 4th grade standardized exam	
Parent admitted to target degree = 1	-0.1753	-2.2304	6.4985	-0.0155	-0.0191	-0.0100
	(1.8465)	(2.1840)	(3.6547)	(0.0165)	(0.0185)	(0.0391)
Observations	4405	3386	1015	4558	3500	1054
Counterfactual mean	316.2843	315.6174	319.0954	0.0934	0.0840	0.1333

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of mothers admission to an elite college program on outcomes for their children. In these analyses, we focus on women applying to college between 1990 and 2002. Since we observe all mother-children links for births taking place in Chile between 1992 and 2010, we are likely to observe all children being born before 2010 for most of these women. Note that the youngest cohorts of women in this sample—i.e., those applying for college in 2002—are unlikely to have completed their fertility by 2010 as on average, they were 26 years old. We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panel B focuses on children old enough to have reached grade 4 in 2002 or between 2005 and 2018 (i.e., the years in which we observe SIMCE scores). The specification also includes mothers' application-year × mothers' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. "Counterfactual means"are below-threshold mean values of the outcome of the dependent variable. See section F.6 for details.

Table F12: Effect of parent admission to an elite college program on children's outcomes (Parents applying to college between 1977 and 1988)

	All parents (1)	Non-elite parents (2)	Elite parents (3)	All parents (4)	Non-elite parents (5)	Elite parents (6)
	Panel A - Effects on child's K-12 school					
	Pr. of attending an elite private school			Elite name index in K-12 school		
Parent admitted to target degree = 1	0.0386	0.0353	0.0504	0.3368	0.3519	0.1349
	(0.0098)	(0.0095)	(0.0323)	(0.0619)	(0.0599)	(0.2175)
Observations	29450	26258	3192	29450	26258	3192
Counterfactual mean	0.2241	0.1746	0.6594	2.2194	1.8850	5.1577
	Panel B - Effects on child's human capital					
	High school GPA			Avg. score in the college admission exam		
Parent admitted to target degree = 1	1.7181	1.3973	2.1550	-0.1884	-1.1835	2.4788
	(2.5000)	(2.6678)	(7.3043)	(2.1658)	(2.3152)	(6.1601)
Observations	25363	22702	2660	25266	22605	2660
Counterfactual mean	636.9981	635.2226	653.0375	644.4249	641.9089	666.8625
	Panel C - Effects on child's college program characteristics					
	Peer avg score in the college admission exam			Sh of peers from elite K-12 schools in college		
Parent admitted to target degree = 1	0.0344	0.0296	0.0371	0.0099	0.0109	0.0017
	(0.0259)	(0.0274)	(0.0810)	(0.0033)	(0.0034)	(0.0122)
Observations	29450	26258	3192	29450	26258	3192
Counterfactual mean	0.9037	0.8824	1.0917	0.1029	0.0924	0.1950
	Panel D - Effects on child's type of college and program					
	Pr. of attending an elite college			Pr. of attending an elite college program		
Parent admitted to target degree = 1	0.0252	0.0228	0.0311	0.0073	0.0067	0.0153
	(0.0112)	(0.0118)	(0.0366)	(0.0089)	(0.0093)	(0.0311)
Observations	29450	26258	3192	29450	26258	3192
Counterfactual mean	0.3356	0.3233	0.4437	0.1593	0.1490	0.2500

Notes: The table presents estimates of regression discontinuity specification (1) that describe the effect of parent admission to an elite college program on outcomes for their children. In these analyses, we focus on individuals applying to college before 1988. We match a 65% of these college applicants with at least one child old enough to enroll in K12 school (i.e., born before 2014). We split the sample by parent's high school type as noted in columns. Outcomes are listed in panel sub-headers. Samples vary across panels. Panel A uses data on children old enough to have enrolled in primary education within our sample period (i.e., born before 2014). Panels B to D use data on children old enough to have applied to college in our sample period (i.e., born before 2002). The specification also includes parents' application-year × parents' target program fixed effects. Standard errors clustered two ways at the parent × child level are in parentheses. "Counterfactual means"are below-threshold mean values of the outcome of the dependent variable. See section F.6 for details.

G Changes in children's friends

This section studies whether parent admission to elite college programs affects the social status of the friends that their kids make in K-12 school. To implement these analyses we rely on data from the Longitudinal Study of Tobacco, Alcohol, and Drug Consumption carried on by the Catholic University of Chile between 2008 and 2011 (see Valenzuela and Ayala, 2011, for further details). This study followed a group of roughly 4,500 students starting seventh grade in 2008 over the course in four years. A survey implemented at the beginning of the study asked each student to report the number and identity of their closest friends at school. With the support of the Ministry of Education we were able to link the data collected through the survey with our administrative records and compute for each individual the social status of their closest friends based on the elite name index introduced in Section 2.

Using this data we implement two types of analyses. First, we present descriptive evidence that the relationship between an individual's social status and the social status of his/her friends is almost entirely explained by the K-12 school he/she attends. Panels (a) and (b) in Figure G1 show the distribution of the elite name index in the whole student population and in the survey. Although private schools are overrepresented in the survey, the distribution of the elite name index in the survey is similar to its distribution in the population.

Panel (c) in Figure G1 illustrates the relationship between the average elite name index of friends and own elite name index. When plotting the raw relationship between these variables, we find that average social status of friends grows with an individual's own social status, particularly at the top of the distribution. However, this positive relationship goes away when controlling for school fixed effects.[17]

These findings suggest that the eliteness of one's friends is not that strongly related to one's own family prestige, *conditional on the high school one attends*. We interpret our descriptive results as support for the idea that the identities of the high schools that students attend are strong predictors of social capital accumulation.

Our second exercise directly tests the effects of parents' admission to colleges with higher shares of elite peers on children's propensity to become friends with high-status peers in high school. Our approach is to estimate versions of the regression discontinuity specifications from equation 1 that take the eliteness of children's survey-reported friend groups as the outcome variable.

We modify this specification in several ways to fit the size and design of the survey sample. First, we drop the fixed effects for parent target degree that are included as controls in equation 1. Including these controls is not feasible in our survey-based specifications because many degrees in our much smaller survey sample have only a few parents listing them as a target. These controls were included in equation 1 for precision and removing them does not compromise the regression discontinuity design.

[17]Specifically, we regress own and friends elite name index on a set of school indicator dummies, compute the residuals from these regressions, and plot the relationship between the residuals of own and friends' elite name index. We add the sample mean back to the residuals for visual comparability.

Second, we adopt a weighting scheme to accommodate the survey's sampling procedure. The survey oversampled students from private and elite K-12 schools. For instance, although in 2008 only 0.77% of seventh grade students were enrolled in an elite K-12 school, in the survey this group of students represented 4.56% of the sample. We reweight using inverse sampling probability by high school type, so that shares of students in public, voucher, private, and elite K12 schools in the reweighted survey sample match shares in the full population.

Third, and finally, we focus on stripped-down specifications that split by the value of ΔE at parents' target and next choice options. This follows from our findings in Table 7 that changes in college elite peer shares are key drivers of intergenerational social capital accumulation as measured by high school type. In cases where ΔE is positive, we estimate standard regression discontinuity specifications and report the effects of admission to the target program. However, in the cases where ΔE in exposure to alumni of elite K-12 schools is negative, we redefined the indicator of admission as a dummy variable taking the value one for individuals scoring *below* the score of the last applicant admitted to the target degree, and multiply the running variable by minus one. That is, the admission indicator in these specifications always indicates admission to the degree program with the higher share of elite students. This allows us to estimate in a single specification the effect of parent admission to a degree that increases his/her exposure to alumni of elite K-12 schools, pooling across all admissions margins where the elite peer share changes.

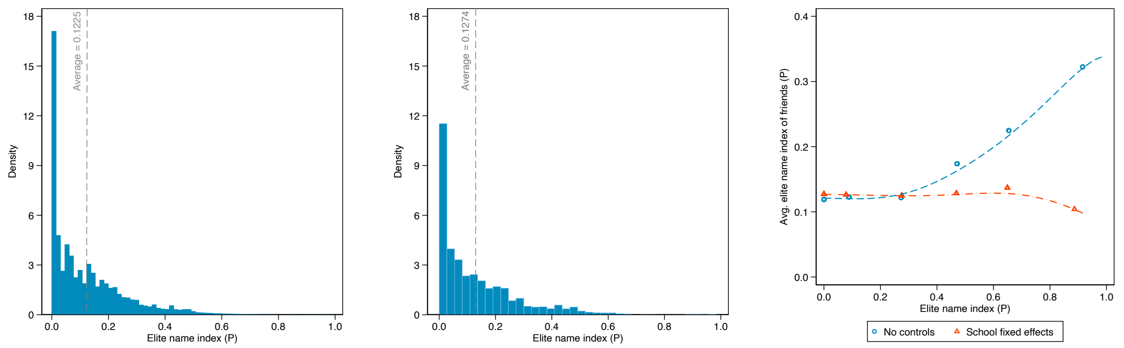
Figure 8 shows how the average elite name index of kids' friends changes with parent admission to a target college program that increased (panel a) or decreased (panel b) exposure to alumni of elite K-12 schools during college relative to the next option. Discontinuities are visually clear in both graphs. Parents who target and are admitted to programs with higher shares of elite peers go on to have children with higher-status friends. Parents who target and are admitted to programs with *lower* shares of elite peers go on to have children with *lower* status friends.

Table G1 pools the two panels into a single regression specification, with the admission indicator always equal to one at the degree with the higher value of E, as described above. The first column reports the effect of admission on the probability that a child appears in the friendship survey. This probability is very low, since relatively few students are surveyed. Changes in magnitude across the threshold are small and statistically insignificant, mitigating concerns related to differential censoring. The second column limits the sample to the surveyed population and reports the effect of admission on the probability that a child has more than five friends. Here again we do not see meaningful effects.

The third column in Table G1 reports our key results: parent admission to programs with higher elite peer shares raises the average elite name index of children's friends. The index value rises by 0.03, roughly a 30% of a standard deviation of the average elite name index of friends in the whole sample. As shown in the fourth column, these children also experience an increase in the average elite name index of the K-12 school they attend. This increase represents more than two-thirds of the increase we find on the elite name index of their friends, suggesting that an important part of the latter effect is driven by the K-12 school they attend.

Finally, the fifth column of Table G1 reports the effects of parent admission to a program with higher-status peers on the probability a child attends an elite school. The effect here does not differ statistically from zero at conventional levels (p=0.12) but is almost identical in size to what we report for parent admission to elite college programs in Table 4.

Figure G1: Own vs friends' elite name index



(a) Elite name index distribution in the whole population

(b) Elite name index distribution in the survey

(c) Avg. elite name index of friends vs own elite name index

This figure illustrates the distribution of the elite name index in the whole student population (panel a) and in the survey data (panel b). It also illustrates the relationship between the average social status of friends and and individual own social status (panel b). Social status is measured by the elite name index introduced in Section 2 of the paper. Blue circles and blue dashed lines illustrate this relationship with no controls. Red triangles and orange dashed lines illustrate the relationship after partialling out school fixed effects from both variables. After partialling out school fixed effects, we added the mean of each variable to their residuals for illustration purposes. The lines correspond to local polynomials fitted using a Gaussian kernel and a bandwidth of 0.2 elite name index points. Results are very similar when using lowess regressions instead. These results are available upon request

Table G1: Parents exposure to elite peers in college and children's friends in grade seven

	Pr. of observing children's friends (1)	Pr. of having more than 5 friends (2)	Avg. elite name index of children's friends (3)	Avg. elite name index of children's K-12 school (4)	Pr. of attending an elite K-12 school (5)
Parent admitted to degree that increases ΔE	0.0003 (0.0002)	-0.0067 (0.0699)	0.0299 (0.0148)	0.020 (0.010)	0.0308 (0.0200)
Observations	812530	1066	1066	1066	1066
Counterfactual outcome mean	0.002	0.568	0.161	0.169	0.159

Notes: This table presents the results of a specification that studies whether parent admission to a degree that increases his/her exposure to alumni of elite K-12 schools affects the number and characteristics of their kids' friends. As in the rest of the paper, these specifications use a bandwidth of 25 points. All specifications in odd columns control for a linear function of the running variable which slope is allowed to change at the cutoff. Column (1) looks at changes in the probability of having data on children's friends, column (2) looks at changes in the probability that children have five or more friends, column (3) look at changes in the average elite name index of children's friends, column (4) at changes on the average elite name index in children's K-12 school, and finally, column (5) looks at changes in children's probability of attending an elite K-12 school. The standard deviation of the average elite name index of friends in the survey sample is 0.1025. Thus, the effect reported in column (3) represents an increase of 30% of a standard deviation in the average elite name index of friends.

H VAR model

This section provides further detail on the back of the envelope calculation presented in Section 7 of the main text. We model dynasties that evolve over time. Dynasties are endowed in each period with social and human capital. Given these values, they choose the "eliteness" of the college they attend. After college, they match to a spouse who is also characterized by human capital, social capital, and college eliteness. The social and human capital of the next generation in the dynasty are then determined as a function of parents' average social capital, human capital, and college eliteness.

This conceptual setup gives rise to the following VAR:

$$S_{it} = \alpha_0 + \alpha_1 \overline{S}_{it-1} + \alpha_2 \overline{H}_{it-1} + \alpha_3 \overline{E}_{it-1} + e_{1t} \tag{1}$$

$$H_{it} = \beta_0 + \beta_1 \overline{S}_{it-1} + \beta_2 \overline{H}_{it-1} + e_{2t} \tag{2}$$

$$E_{it} = \gamma_0 + \gamma_1 S_{it} + \gamma_2 H_{it} + e_{3t} \tag{3}$$

$$S^s_{it} = \delta_0 + \delta_1 S_{it} + \delta_2 H_{it} + \delta_3 E_{it} + e_{4t} \tag{4}$$

$$H^s_{it} = \phi_0 + \phi_1 S_{it} + \phi_2 H_{it} + e_{5t} \tag{5}$$

$$E^s_{it} = \psi_0 + \psi_1 S_{it} + \psi_2 H_{it} + \psi_3 E_{it} + e_{6t} \tag{6}$$

S_{it}, H_{it}, and E_{it} are social capital, human capital, and college eliteness for dynasty i in generation t. We continue to measure human capital using entry exam scores. We measure social capital as the polo club name score eliteness of the K-12 school an individual attends. As discussed in sections 2 and 6.1, this is a continuous analog of the binary "elite K-12 school" categorization. We measure college "eliteness" as the average value of social capital of the college peers of an individual, as in section 6.3. S^s_{it}, H^s_{it}, and E^s_{it} are the same variables for the spouse, and $\overline{S}_{it}$, $\overline{H}_{it}$, and $\overline{E}_{it}$ are average values of the individual and the spouse. The e_{kt} are error terms, which we assume are statistically independent with mean zero and variances to be estimated.

Our approach to calibrating the model is to estimate the parameters governing elite colleges' role in production and matching using instrumental variables specifications that parallel the regression discontinuity designs in section 6.3. We then fill in the remaining parameters using OLS regressions similar to our analysis in section 4, restricting college effects to the estimated values in from the discontinuity designs.

We start by creating instruments based on the characteristics of the target and fallback options of parents, following our approach in section 6.3. We characterize each college-major combination in terms of the social capital of the students it admits and of the social capital of the spouses of these students. We then construct measures ΔE and ΔE^{spouse} based on the gap between the peer eliteness and spousal eliteness of each marginal applicant's target and fallback college program.

To calibrate equation 1, we estimate an IV specification of the following form:

$$S_{ijc\tau} = \alpha_1 \overline{S}_i + \alpha_3 \overline{E}_i + \mathbf{D_{ijc\tau}} \Gamma + \mu_{c\tau} + \varepsilon_{ijc\tau} \tag{7}$$

$S_{ijc\tau}$ is the social capital of child i of parent j applying to program c in application cohort

τ. The endogenous regressors are parent average social capital $\overline{S}_i$ and parent average college eliteness $\overline{E}_i$. We instrument for these variables using the admission interactions $A_{ijc\tau} \times \Delta E$ and $A_{ijc\tau} \times \Delta E^{spouse}$. $\mathbf{D_{ijc\tau}}$ is a vector of controls that includes the main effects of ΔE and ΔE^{spouse}, linear terms in admissions score $Score_{ijc\tau}$ that may vary above and below the cutoff, interactions between the $Score_{ijc\tau}$ terms and the ΔE and ΔE^{spouse} terms, and the main effect of admission $A_{ijc\tau}$. The $\mu_{c\tau}$ are fixed effects for target degree times application cohort, as in main text equation 2. We estimate this specification in the sample of college applicant parents for whom we observe spouse and child outcomes.

This specification is an IV analogue of main text equation 2. Intuitively, crossing an admissions threshold where the value of ΔE is large raises one's own college eliteness, which in turn raises couple-average college eliteness $\overline{E_i}$. If individuals who attend more elite colleges are more likely to marry spouses who also attend elite colleges, this will also raise $\overline{E_i}$. Crossing an admission threshold where the value of ΔE^{spouse} is large raises spouse social capital which in turn raises couple-average social capital $\overline{S}_i$. Own social capital is by definition fixed at the time of application. The exclusion restriction imposed here is that couple-average social capital and couple average college eliteness are the only channels through which admission to degree programs with high levels of E or E^{spouse} shape child outcomes.

This approach recovers estimates of the social capital and college eliteness parameters in equation 1, α_1 and α_3. Note that although equation 1 also includes a human capital term, we cannot estimate it using the IV approach because, as we report in Table 5 of the main text, elite admission does not affect spouse human capital, and own human capital as defined here is fixed at the time of admission. We therefore recover the human capital coefficient α_2 using restricted OLS. Specifically, we estimate

$$S_{it} = \alpha_0 + \hat{\alpha}_1 \overline{S}_{it-1} + \alpha_2 \overline{H}_{it-1} + \hat{\alpha}_3 \overline{E}_{it-1} + e_{1it} \tag{8}$$

restricting coefficients α_1 and α_3 to the values recovered from the IV specification. We use the residuals from this specification to compute an estimate of the variance of e_{1t}. We estimate this specification in subset of the IGC sample for whom we observe human and social capital outcomes for both parents.

We calibrate equation 2 in a similar way. We first obtain an estimate for β_1 by running an IV specification in which $\overline{S}_i$ is instrumented with an interaction between $A_{ijc\tau}$ and ΔE^{spouse}. Then, we obtain estimates for β_0 and β_2 by running an OLS specification in which β_1 is restricted to take the value obtained in the IV specification.

We follow this approach for equations 4 and 6 as well, using the sample of parents for whom we observe spouses. For equation 4, we first obtain an estimate for δ_3 from a specification in which we instrument E_{it} with an interaction between A_{jt} and ΔE_{jt}. We then recover δ_0, δ_1 and δ_2 via an OLS specification in which we restrict δ_3 to take the value obtained from the IV specification. The right hand side variables on equation 6 are the same as in equation 4, so we follow the same approach to calibrate it.

We estimate the two remaining equations, equations 3 and 5, using OLS. We estimate equation 3 using the full sample of children, and we estimate equation 5 using the sample of parents for whom we observe spouses.

Table H1 presents results from the above estimation steps. The column number matches the equation in the VAR. Rows are independent variables. We indicate with the superscript "2SLS" estimates obtained through 2SLS, and with the superscript "OLS" estimates obtained from constrained OLS regressions. The row at the bottom of the table presents the estimates of the variance of the error terms e_{it}.

With these parameter estimates in hand, we use standard VAR techniques to obtain the MA(∞) representation of the VAR(1) process, and use the MA representation to obtain expressions for the variance and autocovariance matrices of S_{it} and H_{it} as functions of model parameters. In addition to computing variance and autocovariance matrices for estimated parameter values, we compute these matrices under counterfactual assumptions about the causal role of college attendance.

Table H1: VAR parameters estimation

	Children's outcomes			Spouse's characteristics		
	S_{it}	H_{it}	E_{it}	S^s_{it}	H^s_{it}	E^s_{it}
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{S_{it-1}}$	0.357^{2SLS}	0.115^{2SLS}				
	(0.251)	(0.052)				
$\overline{H_{it-1}}$	0.281^{OLS}	0.465^{OLS}				
	(0.004)	(0.004)				
$\overline{E_{it-1}}$	0.423^{2SLS}					
	(0.085)					
S_{it}			0.472^{OLS}	0.271^{OLS}	0.097^{OLS}	0.073^{OLS}
			(0.002)	(0.004)	(0.003)	(0.001)
H_{it}			0.382^{OLS}	0.116^{OLS}	0.265^{OLS}	0.076^{OLS}
			(0.003)	(0.004)	(0.004)	(0.002)
E_{it}				0.057^{2SLS}		0.039^{2SLS}
				(0.014)		(0.003)
Observations	553,839	553,839	157,352	88,976	88,976	88,976
Cragg-Donald Wald F statistic	16.134	431.737		3853.52		3853.52
Var(e)	0.620	0.641	0.651	0.820	0.542	0.092

Notes: The table presents estimates from 2SLS and OLS regressions described in Section H. We use these regressions to calibrate the VAR describing the evolution of human and social capital across generations introduced in Section H. Column numbers match the equations on the VAR. We indicate with the superscript 2SLS estimates obtained from 2SLS regressions in which we instrument the endogenous variable with an interaction between crossing and admission threshold and ΔE or ΔE^s. These regressions focus only on parents scoring near a college admission cutoff and as in the main body of the paper control for the running variable—i.e., a parent application score—and by parent application year and parent target degree fixed effects. We indicate with the superscript OLS estimates obtained from constrained OLS regressions in which some of the parameters were forced to take the values obtained by the 2SLS. In equations (1) and (2) standard errors are clustered at the child level; while in equations (4) to (6) at the parent level. In equation (3) we simply use heteroskedasticity robust standard errors. The final row presents estimates for the variance of the random terms associated with each equation of the VAR.

I Admissions policy changes and intergenerational mobility

This section provides further details on the exercise we implement to study the potential consequences of changes in admissions policy on the persistence of social capital across generations. Specifically, we study the consequences of programs that boosts the application scores of students from different kinds of high schools (either subsidized or elite) by giving them a bonus that ranges between 5 and 50 points (i.e., between 15% and 135% of the application score's standard deviation).

I.1 Auxiliary model

Our goal is to understand how shifts in the allocation of parents to degree programs shape social and human capital outcomes for children. We focus on parents' share of college peers from elite high schools as the causal channel of interest. This follows evidence from Table 7. Let Y_{ij} denote the outcome for child i of parent j observed in the data, and Y_{ij}^h denote the same outcome under counterfactual degree assignment h. We let

$$Y_{ij}^h = Y_{ij} + \gamma(E_{ij}^h - E_{ij}), \tag{1}$$

so that the counterfactual outcome rises and falls with the change in the share of elite peers at the parents' college degree program, $E_{ij}^h - E_{ij}$. Y_{ij} and E_{ij} are observed, so the challenges here are 1) to recover E_{ij}^h, the counterfactual assignment, and 2) to recover γ, the effect of college elite peer share on outcomes of interest.

I.2 RD estimation

We recover γ using a simplified version of specification (2) that studies how parents' elite peer share impacts children's social capital (measured by the Polo elite name index introduced in Section 2) and children's human capital (measured by the average of reading and mathematics scores in the college admission exam). Specifically, we estimate the following specification:

$$\begin{aligned} Y_{ijct} =& \alpha + \beta A_{ijct} + \gamma A_{ijct} \times \Delta E_{ijct} + \delta \Delta E_{ijct} \\ & + f(S_{ijct}, \mathbf{\Delta E}_{ijct}; \theta) + \mu_c + \mu_{c'(ijct)} + \mu_t + \varepsilon_{ijct} \end{aligned} \tag{2}$$

Y_{ijct} is the outcome for child i of parent j who applied to degree c in year t and A_{ijct} is an indicator for parent j's admission to degree c in year t. β is the main effect of parent admission to his/her target degree relative to an observably identical next choice. γ is the coefficients on the main regressor of interest—interactions between admission and the change in degree-specific exposure to alumni of elite K-12 schools across the cutoff. Controls include the main effect of ΔE_{ijct}, as well as a continuous linear function of S_{ijct} that is allowed to vary above and below the cutoff and to interact linearly with $DeltaE_{ijct}$. We include fixed effects for target degree c, next option degree c', and application cycle.

This specification strips down equation (2) to focus on the share of peers from elite high schools as the driver of children's outcomes. Table I1 summarizes results from this step. As in Table 7 we show that parent admission to degrees with higher elite peer shares has a large effect on child social capital but not human capital.

I.3 Assignment simulations and counterfactual outcomes

We recover E^h_{ij} for different counterfactual h using simulation exercises. Each exercise has two steps.

In the first step, we simulate program assignments in the parent generation under a given score bonus for students from subsidized high schools, holding fixed both applicants' submitted rank lists and the count of spots available in different programs. Several features of this exercise are important to note:

- We restrict attention to application years for which we observe the full list of preferences submitted for each applicant. These years are 1977, 1978, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 2001, 2002, and 2003.
- Chile uses the deferred acceptance algorithm to assign college applicants to programs.
- Our understanding of the assignment process is strong enough and the quality of data high enough to recreate essentially all observed assignments. Our code replicates the allocation for 99.99% of the college applicants in our sample.
- We simulate ten counterfactual scenarios in which we increase the application score of students from subsidized schools between five and fifty points in intervals of five points. Program assignments are fully determined by seat availability, rank lists, and application scores.

Let $c(i,h)$ denote the program assigned to i under counterfactual h, and $E(c,h)$ be the share of elite K-12 students assigned to c under h. We then compute the individual-level elite shares of interest E^h_{ij} as $E^h_{ij} = E(c(i,h),h)$, that is, the share of elite peers under counterfactual h at the degree to which the student is assigned under h. In addition, we compute an alternate counterfactual share measure $\tilde{E}^h_{ij} = E(c(i,h),h_0)$, where h_0 denotes the observed baseline scenario. This alternative counterfactual is equal to the *observed* share of elite peers at the program to which i is assigned under counterfactual h; it effectively holds the causal impact of each degree fixed while reassigning students across programs.

I.4 Correlations

We compute correlations between social capital and child social capital and between child human capital and child social capital under the observed allocation and under each counterfactual allocation. Figure 9 plots the results of these calculations under our main counterfactuals (i.e., the E_{ij}, in filled points) and under counterfactuals that hold degree effects fixed (the $\tilde{E}_{ij}$, in hollow points). Each point is labeled with the size of the point bonus that students of the listed type receive. Note that the vertical axis is reversed, so that intergenerational mobility rises as one moves vertically up the graph.

Table I1: Effects of parent exposure to alumni of elite K-12 schools in college on children's outcomes

	Elite name index in child's school (P)	Avg. score in college admission exam
	(1)	(2)
Parent admitted in target major=1	0.0192	0.0171
	(0.0106)	(0.0074)
Parent admitted in target major=1 × ΔE (STD)	1.3411	-0.0018
	(0.3739)	(0.1482)
Observations	350983	276984
Counterfactual mean	0.9470	0.2058

Notes: This table presents estimates from parametric regression discontinuity specification (2) of the effects of parent exposure to alumni of elite K-12 school in college on outcomes for children. Each column is a single specification. Reported coefficients are the main effect of admission to the target program and interactions between admission and differences between the share of alumni of elite K-12 schools of the target and next-option degree program. The ΔE variable is in standard deviation units. Samples vary across columns due to data availability. Column (1) focuses on children old enough to observe attending primary education (i.e., born before 2014). The second column focuses on children old enough to observe applying to college (i.e., born before 2001). "Elite name index in child's school (P)" is the polo club elite name index. We control for a linear polynomial of the running variable, the slope of which is allowed to change at the cutoff. The slope of the running variable on both sides of the cutoff is allowed to vary with ΔE. The main effect of ΔE is also included in the specification. We also control for parents' application-year and parents' target program and next option fixed effects. Standard errors clustered two ways at the parent × child level are presented in parentheses. Counterfactual mean is the mean below-threshold value of the dependent variable.

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