Ticket to the middle class? Long term effects of Public Universities on Labor market and Financial outcomes.*

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Abstract

We construct a novel longitudinal dataset from administrative records to examine the impact of selective college education on asset accumulation, consumer credit usage, as well as short and long-term earnings. Our empirical strategy is a fuzzy regression discontinuity design that employs the admission policies of a selective public university in Colombia, relying solely on the national high school exit examination scores. Scoring above the admission threshold has no short-term effect but raises access to consumer credit by 4 percent and earnings by 24 percent eight years after college entry. While the gains in consumer credit stabilize after 11 years after college entrance, earnings returns keep growing up to 32 percent 16 years after college entry. The impacts on asset acquisition take longer to emerge as admission raises the likelihood of homeownership by 12 percent when individuals are 30 to 35 years old. The higher rates of getting graduate degrees are one reason behind the null effects in the first years. Business and engineering majors observe higher effects, likely reflecting links between college education, income growth and financial knowledge.

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1 Introduction

The earnings returns to college education receive much of the attention in the literature as the primary benefit to this human capital investment[1]. More recent papers show the effect of college education on a broader set of outcomes ranging from marriage, health and life satisfaction[2]. The effect of college education on asset acquisition and access to finance has received less attention. On top of the effect of college education through income growth, college education may directly improve individual financial decision-making by enhancing the efficiency of how individuals invest (Michael, 1972). In addition, college attendance might indirectly affect post-graduation borrowing and investment decisions through the way people finance college costs (Mezza, Ringo, Sherlund, & Sommer, 2019). Measuring the impact of college education on outcomes such as homeownership and post-college financial health might prove informative for higher education policy, particularly for publicly funded institutions.

Prior research on selective universities widely debated the causal effect of high-quality college education on earnings. The observed wage premium may reflect the selection bias arising from the correlation of unobserved characteristics with future earnings. Dale and Krueger (2002) find negligible returns for a set highly selective US universities. However, most of the recent papers find positive returns to selective universities (Anelli, 2020; Hoekstra, 2009b; Jia & Li, 2021; Sekhri, 2020). One avenue to reconcile these mixed results is to study other dimensions on which college quality might impact economic wellbeing. Arguably, attending selective universities may offer additional benefits that students value, even if resulting in moderate effects on career benefits. We focus on post-college financial behavior, with measures describing asset acquisition by households in the long term.

By providing new evidence on financial behavior outcomes, we contribute to the broader literature on the impact of selective higher education on long-term economic wellbeing. Prior research has studied the impact of financial aid and student debt (Black, Denning, Dettling, Goodman, & Turner, 2020; Scott-Clayton & Zafar, 2019) on homeownership and debt balances by observing behavior from credit score agencies. In contrast, we assemble data from administrative sources, including the entire range of lending operations reported quarterly by every bank operating in the country to the financial regulator. We create a unique dataset combined with other primary administrative sources tracking applicants' information yearly to measure the following outcomes: i) homeownership and cars approximated by outstanding mortgage and car loans. ii) usage of credit cards measures access to formal consumer credit. Moreover,

[1] Barrow and Malamud (2015) present an extensive review of papers studying college education's earnings returns.

[2] Trostel (2015) and Oreopoulos and Salvanes (2011) provide an extensive review of the impacts of college education on outcomes beyond earnings. College education leads to high-quality jobs with more benefits, reduced mortality, improved marriage matching, reduced early fertility, boosted civic engagement and life satisfaction.

we observe students' annual earnings in a panel for 18 years after college entry, allowing us to compare early and late-career effects.

We find that the impact of the flagship public university on the earnings and credit market takes time to unfold. Like most recent papers on selective public research universities (Anelli, 2020; Bleemer, 2021; Hoekstra, 2009b), we find increased medium-run earnings return by 25 percent between ages 25 and 30. However, we find no returns five to seven years after college admission, roughly two years after expected graduation. We show the effects of the flagship university on new outcomes that are understudied in the literature. Those accepted to the flagship public university are more likely to have higher credit card usage eight years after admission, more likely to purchase a car and a house through borrowing in the formal credit market in the long term. Most effects on financial outcomes are concentrated in business majors like economics and management, with coursework directly related to financial knowledge. Overall, a college education provides returns in the labor market and influences household borrowing decisions.

We construct a more comprehensive dataset than previous papers studying the impact of selective universities. Unlike related papers (Anelli, 2020; Hoekstra, 2009b), we observe the full counterfactual set of institutions that applicants end up after admission results. We observe both men's and women's earnings in the formal sector irrespective of their location in the country after college. We can also observe postgraduation outcomes from administrative sources year by year up to 18 years after college entry. First, we collect information on admission results for applicants from 2000 to 2004 to the public university. We matched the applicants to the national high school exit examination results. We combine this data with the Ministry of Education's higher education information systems to measure college enrollment and graduation from any institution in the country. Next, we construct a panel of the earnings trajectories in the formal labor market using the Social Security system from 2008 to 2019. Lastly, we measure individuals' outstanding loans using the reports on lending operations by banks to the national financial regulator from 2004 to 2019. We can separately observe mortgage loans, car loans and credit cards debt. An outstanding mortgage and car loans approximate home and car ownership[3]. This dataset presents a broader perspective of economic wellbeing in the short and long term.

Our empirical approach exploits the clear discontinuity in attendance induced by the specific admission rules for a public research university[4]. The university uses as the only admission requirement the results from the national high school exit examination. Similar to the educational systems in middle-income countries, the majority of high school students take these

[3]Mortgage credit is arguably the main channel to finance housing purchases, more common than cash and savings, not only in Colombia(Roch, 2017) but in the USA (Mezza et al., 2019).

[4]The Universidad del Valle the third largest university in Colombia with a total enrollment of 28,000 students and serving 27% of the incoming first cohort in the region.

exams. The near-universal take-up alleviates possible concerns about selection into this exam take-up motivated by previous college expectations. In addition, the admissions rely uniquely upon the results of this exam, eliminating other subjective factors considered in the admission process to other private selective universities. Unlike papers that use a sample of students who might be eligible for admission (Smith, Goodman, & Hurwitz, 2020; Zimmerman, 2014), our sample includes only students who effectively applied to this university. In our context, applicants declare the major in the application. Then, these applicants around the threshold have are comparable in ability and motivation, then address potential selection biases arising from the correlation between unobservable characteristics that affect the choice to attend a selective university and future outcomes. Finally, we use a fuzzy regression discontinuity approach because of the no perfect compliance with the admission. Further, the treatment decision generated in the jump at the cutoff affects the outcomes only through admission status. Using the admission as an instrument satisfies the exclusion restriction allowing us to interpret our estimates as local average treatment effects.

Our first set of results is the academic outcomes. Crossing the threshold for admission at the selective public university increases the probability of getting a college degree by 7 percentage points observed after 8 years of college entrance. These results confirm the impact of high-quality colleges on graduation rates evidenced in the literature examining the impact of accessing four-year colleges on college completion (Bleemer, 2021; Goodman, Hurwitz, & Smith, 2017). Scaling these estimates with enrollment, attendance to the selective public university increases graduation by 25 percentage points. Moreover, we observe the entire counterfactual college institutions for the applicants in our sample. Among the rejected, only 36 percent enroll in less-selective private universities, and 10 percent enroll in two year-programs. Gaining admission increases enrollment in this public university instead of enrolling in other less selective private institutions in their region by 27 percentage points. Having demonstrated the effects on college attendance and graduation, we next analyze the effects on earnings and credit market outcomes.

Attendance to the selective public university creates substantial long-term earnings returns, but the effects observed in the early career are negligible. When observed 5 to 7 years after college entry, the effect of crossing the threshold for admission on annual earnings is not statistically different from zero. There is also no effect on the likelihood of getting a formal job in these early years. Earnings start to grow for all the applicants around the cutoff in the early years, but the gap between admitted and non-admitted is not statistically significant until 8 years after college entry. Scoring above the admission cutoff increases earnings by 9 percent 8 to 15 years admission. By the time the students are around 35 years old, 16 to 18 years after admission, admitted students are earning 13 higher than no admitted students from the reduced form estimates. Being admitted to the public university increases the likelihood of being employed in the formal sector by 2 percentage points. Scaling up the earnings return estimates with enrollment, the return of the selective private university is 25 percent 8 to 15 years after admission and increases to 35 percent 16 to 18 years after admission.

Admission to the public university increases access to the formal credit market observed roughly around the same time students observe positive impacts on the labor market. First, we provide evidence that students are likely credit-constraint since less than 5 percent of students use a credit card 1 to 4 years after admission, the years that students are enrolled in college. Later, all applicants observe an increase in credit card usage around 5 to 7 years after graduation. However, there is no difference between the admitted and non-admitted in these early years. After 8 years of college entry, the mean of credit card usage is about 45 percent, but the students admitted to the public university now observe a statistically significant higher usage. Admission to the public university increases credit card usage by 3 percentage points 8 years after college entry. The estimated effect is around 47 percent from the instrumental variable specification. This gap in usage of credit cards does not dissipate over time and remains relatively constant for our observation period up to 18 years. The effects on access to consumer credit are economically meaningful for credit-constraint students. Next, we observe impacts on financial access relatively earlier than durable asset acquisition.

The decision to purchase cars and invest in homes will be placed later in the student's career. In the first ten years after college admission, admission to the public university does not affect the likelihood of having a car or housing loan. After 11 years after college entry, roughly 5 years after graduation, we start to see an increasing gap of around 2 percentage points between the admitted and non-admitted that becomes statistically significant at 15 years after college entry. For homeownership, public university admission only has effects after 16 years of college entrance. Admission to a public university increases the probability of being a homeowner by 12 percent, measured by outstanding mortgage loans by the time students are 35 years old. Scaling the estimate with enrollment, the point estimate of attendance to the public university is 6 percentage points with a baseline of 12 percent. The relative effect of 50 percent is sizable but reasonable since only 10 percent of adults borrow money to buy a home[5]. Finally, we show that a single outcome does not drive the results on credit market outcomes. We estimate that the effect on the financial index is also positive and statistically significant. The demonstrated effects on asset acquisition constitute new evidence for the research on how selective college education impacts later life outcomes.

In the last part of the paper, we discuss possible channels to understand why college education might boost credit market access. First, the impact of college on earnings directly improves access to finance to students that are credit-constraint during college. Students face barriers virtually impeding them from accessing the formal credit market[6]. For instance, banks

[5]Housing loan take-up in Colombia is substantially lower than in the US, where the housing loans rate for the same population is about 65 percent. Source: Global Findex Indicators, The World Bank.

[6]In addition, students in this context have very low usage of credit cards during college and once

might require proof of work contracts and a stable income stream at least three months before a credit card application. These additional barriers for credit market access directly link the Labor market with credit market outcomes beyond income growth. Our results show that the effects on consumption credit appear one year after the labor market effects start to be statistically significant. We further show that most of the results on financial behavior outcomes are concentrated in majors like business with coursework on financial literacy and knowledge. While we cannot completely disentangle the income growth link from the financial literacy link, this evidence is suggestive of the role of college education in creating a type of human capital with possible returns in asset acquisition decisions.

Our paper makes two contributions to previous research on the impact of higher education. First, it provides the first estimates of the long-run effects of a selective public university on asset acquisition and access to finance. Prior research has focused on the effects of less-selective public colleges, finding no impact on outstanding mortgage status and no impact on student debt balances (Smith et al., 2020). Students attending community colleges that receive higher state appropriations have increased home and car ownership (Chakrabarti, Gorton, & Lovenheim, 2020). Expanding this evidence, we show that a more selective public university that serves primarily low- and middle-income students positively impact homeownership and usage of formal credit market compared to less selective institutions. Another literature has focused on financial aid and student loans as instruments to increase college access and completion. The impact of higher student debt access on homeownership is somewhat mixed (Black et al., 2020; Mezza et al., 2019), while financial aid recipients exhibit higher rates of mortgage loans (Scott-Clayton & Zafar, 2019). We add to this literature by showing that the income growth generated by high-quality education effectively increases homeownership. In our context, students graduate with virtually no student debt, but relaxing the high credit barriers might improve college access and financial outcomes in the long term.

The second contribution is to provide a more detailed measure of the effect of selective public research universities in different career stages. Our work complements recent evidence for selective universities for other middle income like China (Jia & Li, 2021), India (Sekhri, 2020), Chile (Hastings, Neilson, & Zimmerman, 2013; Zimmerman, 2019), selective universities in high income countries (Anelli, 2020; Hoekstra, 2009b) and less selective universities (Smith et al., 2020; Zimmerman, 2014) . We build on the evidence that higher access to public university systems improves academic and labor market outcomes (Bleemer, 2021; Smith et al., 2020) , by showing that the public research university can affect additional outcomes capturing economic wellbeing beyond the labor market.

they enter the market they do not immediately take credit card services even if they become eligible (Franco & Mahadevan, 2021).

Previous papers studying selective universities in Colombia are limited to short-term outcomes such as bachelor completion and early career returns (Barrera-Osorio & Bayona-Rodríguez, 2019; Bayona Rodríguez & López Guarín, 2021; J. E. Saavedra, 2008). The paper is more similar to ours is a concurrent study using The Universidad del Valle in Colombia, focusing on labor market returns to STEM programs (Ng & Riehl, 2020). Our findings on earnings are comparable for the same periods of analysis. However, with our more comprehensive dataset, we show substantial gains on previously unmeasured outcomes such as homeownership and financial inclusion accrued by low-income students attending the flagship public university. These new benefits from publicly funded institutions prove to be relevant in Colombia and other settings where public education is highly subsidized, and students do not take up substantial debt to pay for college.

2 Background

In recent decades, the increase in high school completion rates raised the demand for postsecondary education in middle-income countries. For instance, enrollment rates in higher education more than doubled from 20% in 1990 to 50% in 2014 in Latin America. Despite the rise in tertiary education coverage, there is still room to achieve college attainment rates like in developed countries (Busso, Cristia, Hincapie, Messina, & Ripani, 2018). There are significant inequalities in enrollment in the region, with the top quintile being 45 pp more likely to enroll in higher education than the bottom quintile (Ferreyra, Avitabile, Paz, et al., 2017). Finally, there are concerns over the quality of newly opened institutions that could yield poor returns for students.

In this context, selective public research universities remain at the center of the region's higher education system, enrolling larger shares of low-income students than their private equivalents. The Colombian national and regional university system serves 54% of college students. However, the national government appropriation for the public university system has declined steadily from 0.54% of GDP in 1999 to 0.39% of GDP in 2013 (Rodriguez, 2014). Policy makers responsible for budgetary decisions on national appropriations for public universities often lack informed evidence about the long-term returns of this educational investment.

Despite the decline in national funds, public universities have managed to be ranked programs among the top 10% while maintaining affordable tuition fees. Public universities have a flexible tuition scheme tied to family income. The tuition fee schedule makes college costs effectively free for low-income students and affordable for middle-income families, with tuition changing proportionally to family income at admission. In addition, public institutions provide substantial supplement funds for student maintenance covering meals and transportation expenses. As a result, most of the students from public universities graduate with virtually no student debt.

Our study employs the admission criteria of a selective public university, Universidad del Valle, Colombia, to estimate the causal returns on earnings and credit outcomes. This university is the third-largest in the country, serving more than 28,000 students as of 2017, and about 27% of the region's first-year cohort. This institution is a selective university admitting only 32% of the applicants and ranked the first university in the Pacific Region. The main campus is located in Cali, the third biggest city in Colombia. There are other higher education institutions in this city, most of them less selective. The next well-recognized universities are private and considerably more expensive. There are other public higher institutions in the state, but mostly non-selective. In sum, the possible alternatives with the same academic quality are expensive private elite universities. Finally, most of the students in public university comes from low-income and middle-income families. About 51% of the incoming cohort comes from families earning less than two monthly minimum wages[7].

Admission process: The public university uses the national high school exit examination as the sole admission criterion. The near-universal take-up of this exam eliminates possible selection arising from the decision to give the exam. About 98% of all the seniors in high school take the national examination in Colombia. Almost every higher institution in the country utilized the score as part of admission. The test evaluates students in five major fields: mathematics, language, science, social sciences, and foreign language. A student gets an overall score and a score in each field.

Getting accepted to this public university requires having a score above an unknown cutoff in the admission cycle. Importantly, students declare the major in the application. Each major have a different cutoff that changes across admission cycles depending on the number of available seats. The timeline for application is the following. First, students present the exam and receive their scores. Within a month or two of receiving the scores, students start applying to college. Students can apply to only one major per admission cycle in this university. Before the admissions cycle start, the university determines the number of seats that will offer for each program. The number of seats will ultimately define the cutoff among the list of applicants.

In addition, each program assigns a weight to the test components according to the specific skills required. The admission office gives a score to each applicant based on the major-weighted score from the national examination. This university-designated score is the running variable in our stacked regression discontinuity design. Following previous papers, we stack all programs

[7] Compared with a selective private university in the region, only 23% of the incoming cohort in 2000-2004 is coming from families earning below two monthly minimum wages. However recent large-scale merit-based scholarships targeted to low-income students boosted the share of low-income students in private universities (Londoño-Vélez, Rodríguez, & Sánchez, 2020). In 2018 50% of Universidad del Valle incoming cohort is coming from families earning below two monthly minimum wages vs 40% in the Universidad ICESI, the comparable private university. Source: Ministry of Education, System for monitoring higher education (SPADIES Spanish acronym)

and admission cohorts by standardizing the scores related to the cutoff. We set the cutoff at zero and create the running variable measuring the distance in score to the cutoff.

Notably, the exact cutoff for every major is unknown. This cutoff depends on the available seats and the score distribution of the applicants in each cycle. While the admission results are public after every admission cycle, we argue that it is very difficult to predict the exact score. Figure A.1 presents a graphical depiction of the cutoff score, arranging majors in broader fields. The exact number is never the same across the admission cycle, with some numbers very close to the previous cycles.

Selectivity and counterfactual: The Universidad del Valle admits on average 30 percent of applicants in every admission cycle. However, admission rates and passing scores may vary by field. Programs like medicine and engineering require passing scores above the 75 percentile of the score distribution for the national examination. Figure A.2 presents the distribution of the global score in the 2000-second semester and marks the cutoff for medicine in the selective public university.

The rejected applicants include students who went to other colleges and individuals who never enrolled in any college in our sample. Table A.8 present the descriptive academic outcomes for admitted and rejected groups. About 37 percent of rejected applicants attended other five-year universities. Also, 45 percent attend any other higher education institution, including a two-year program. Overall, 55 percent of the individual rejected never enrolled in any college.

3 Data

3.1 Data sources

We collect data from different administrative information sources tracking applicants to the public university up to 18 years after admission. First, we scrape the admission results available online from the Universidad del Valle for 2000 to 2004. These lists contain the names of applicants, university assigned scores, cutoff points, and admission results by program and cohort. Using name and approximate date of exam take-up, we match with a dataset of high school examination test results. From here, we could find the national identification number for 83% of the applicants. Using the national identification number, we match the applicants into administrative sources for earnings and credit. [8]

The first dataset contains the national high school exit test results and demographic characteristics reported in a pre-test survey. We collect from this dataset the pre-admission covariates: gender, birth date, family income, high school type, and parents' educational attainment. The second source is the administrative report from higher education institutions to the Ministry

[8] Appendix A.1 describes the data sources, matching rates and outcomes in detail .

of Education about their student's status. This dataset contains enrollment and graduation outcomes until 2012, about ten years after admission. Then, we can only construct academic outcomes observed until that year.

The third source is the administrative records on contributions to the social security system. In these records, we observe the monthly earnings reported by employers and independent formal workers. We construct a panel of annual salaries for formal workers from 2009 to 2019. We cannot observe payments for individuals with informal jobs. This distinction is relevant for Colombia since the informality in the labor market is about 50%. Also, we construct a variable denoting having a formal job if the individual has any reported formal work income in a given year.

The fourth source is the administrative panel of credit market transactions. We observe every active lending operation reported by registered banks in the country to the Financial Regulator. Each lending operation record contains the data of the borrower. We match the applicants to a database containing all the borrowers per type of lending operation (housing, car, credit card and other consumer credit). We construct a yearly panel of indicators on outstanding consumer debt from 2004 to 2019. Each indicator is a dummy denoting if an individual appears as a borrower in a given year.

The fifth data source is the national registry for physicians and health professionals. This administrative dataset records the specialization and graduate degrees for each authorized health professional in the country. We match the applicants to health programs to the national registry and construct a variable denoting if an individual has a graduate degree or specialization in health and medicine.

3.2 Sample

The analytical sample consists of applications to five-year programs that lead to a bachelor's degree (equivalent to Bachelor's four-year programs in the US) from the admission cycles 2000-2004. This sample has 37,554 applications from 25,852 individuals to 35 programs. We exclude from the main analytical sample 7 majors belonging to teaching school. Many of them have admission rates higher than 90% in several admission cycles, leaving an insufficient sample for the RDD. In addition, teaching programs tend to attract a pool of applicants with substantially lower scores in the exam examination than applicants to other programs [9] (Elacqua, Hincapie, Vegas, & Alfonso, 2018). Students admitted to the teaching school would have been rejected in other programs. Stacking them and standardizing them around zero places them in the

[9] Regarding earnings, teaching graduates employed in the public sector have similar earnings to college graduates (J. Saavedra, Maldonado, Santibanez, & Prada, 2017). However, getting a job in the public sector is difficult because of the longer tenures of older employees, relatively fewer openings in the last decades. Teaching graduates employed in the private sector exhibit lower wages than other college graduates.

same treated group as the other programs. Nevertheless, we present the results for the main analytical sample and present the results by field in the appendix.

Our observation is the application level. Applicants may apply many times to the university in our sample. Recurrent applicants may learn better their chances for the next application, rising concerns about possible manipulation of the cutoff. We present in the annex individual level specification using just the first application.

3.3 Variables and Descriptive Statistics

Our demographic and socioeconomic covariates are the student's gender and age, high school type (public or private), family income available as multiples of the monthly minimum wage and mother and father's highest level of education. We construct the covariates from the survey administered before the examination. Other variables in the dataset, such as the number of siblings and family size, have low response rates. Our covariates already provide information correlated with family size variables while keeping the largest sample possible.

The credit outcome of most interest is the indicator of any mortgage and any car loans per year, which denotes whether the bank reported the individual as a borrower for car and housing. These measures are proxies for homeownership and car ownership since households usually purchase these assets with credit. We create a credit card usage dummy taking the value of one if the individual has an outstanding loan by credit card in a given year. Since we have several variables measuring the credit market dimension, we also create a standardized index for financial outcomes using the three indicators of outstanding loans. The index helps to reduce concerns about multiple hypothesis testing.

Next, we construct a panel following several labor market characteristics from the social security dataset with information from 2009 to 2019. First, a dummy for holding a formal job indicates that the individual contributed to social security as an employee or independent worker. We construct the annual earnings assigning a zero value if the individual reports no wage income or is not matched in these records. We also construct the log of yearly earnings but analyze the two measures because of the large share of zero values. We attempt to address the distribution's considerable percentage of individuals with zero formal income by calculating the probability of having annual income higher than two and three times the minimum wage. These values correspond roughly to the 50 and 75 percentiles of Colombia's national household income distribution. Finally, we construct a tenure measure as the number of days with the status of formal worker within a year.

Table 1 shows the characteristics of the main analytical sample. Table 1 also presents the composition of the sample in terms of admission cohort and academic fields of the majors. About 49 percent of the applicants to the public university are men, with a mean age of 17.5

years old. (Table 1 Column 1 Panel Demographics). About 47 percent of applicants come from public high schools, and 29 percent have parents with a college degree. The applicant profile is fairly similar between our main analytical sample (Table 1 Column 2) and applicants to all five-year programs (Table 1 Column1).

Next, we compare the main analytical sample vs. the sample within the optimal selected window for the annual earnings outcome. Table 1 columns 2 and 3, the RD-sample looks similar to the entire sample of applicants to five-year programs in this public university. The RD sample has a slightly higher rate of male applicants with 53 percent vs. 49 percent in the whole sample. The student's background is very similar in the covariates before admission for students around the cutoff and for students away from the cutoff.

Regarding educational measures, the average enrollment evidence the selectivity of the university, with only 30 percent of the applicants effectively enrolling (Table 1 Column 1 Panel Education). However, applicants may decide to attend other places after admission. About 50 percent of the applicants enroll in any college. Around 35 percent of applicants have a bachelor's degree when observed in a database ten years after admission. The average formal annual earnings for the applicants is COL $ 21.9 million (real values of 2018) when individuals are 30-35 years old. This income is equivalent to being above the 60 percentile of the household income distribution in Colombia.

In the credit measures, the share of applicants with a mortgage loan observed in their mid-thirties is 9 percent (Table 1 Column 1 Panel Credit.), similar to the 11 percent of adults above 25 years old with an outstanding housing loan in Colombia, reported in the Global Findex database [10]. On the other hand, the share of applicants with a consumer loan is 49 percent, well above this share for adults aged 25 years old. About24 percent of adults in the country are borrowers of consumer credit, and 18 percent hold a credit card (in the Global Findex database). Applicants to the university have higher shares of consumer financial products usage than the general adult population in the country.

4 Empirical Strategy

4.1 Estimating the returns to admission

Students declare the major at the moment of admission and each major has their own cutoff. We estimate the effects of crossing this cutoff, this is the effect of being admitted to a specific major offered by the selective university. In our setting, individuals bellow the cutoff can enroll into programs. The next choice programs can be either at the same university or in other colleges or even in other higher education institutions. Importantly, the next best choice could be not enrolling in any college. Then our estimates should be interpreted as the difference

[10]Source: The Global Findex Database 2017 (Demirgüç-Kunt, Klapper, Singer, Ansar, & Hess, 2020).

between the mean return in the admitted program and a weighted average of both the returns in next choice programs and returns of not enrolling in a college degree. Following the literature on returns to fields of study, the weights are the probabilities of being admitted to the next choice and in our context the probability of not enrolling in college.

4.2 Regression discontinuity Design

We employ a fuzzy regression discontinuity design to estimate the effect of being admitted to a public university. We benefit from the admission criteria from a selective public university in Colombia, based solely on the high school exam test results. Candidates apply to a specific academic field, declaring one major per the admission cycle. The university assigns a score that weights the individual results from the field components in the high school exit examination. The availability of seats determines the cutoff for admission by cohort and program. We stack all programs and cohorts, setting the cutoff at zero and standardizing the admission score around the cutoff. We compare individuals around the admission threshold since their admission results from slight differences in their exam scores.

We first estimate a reduced form version with a local linear regression of the form:

$$Y_{ipc} = \beta_1 A_{ipc} + \beta_2 S_i + \beta_3 + A_{ipc} \times S_i + \lambda_{pc} + \epsilon_{ipc} \quad i \in h \quad (1)$$

Where the coefficient of interest is β_1, the effect of admission to the public university. Y_{ipc} denotes the outcome (earnings and financial indicators) by the applicant i, program p and cohort c. S_i denotes the individual score assigned by the university, normalized to the cutoff in each program and cohort; A_{ipc} denotes an indicator for the individual's score being greater or equal to the cutoff for the program p and cohort c. λ_{pc} represents cohort and program fixed effects. Robust standard errors are calculated with cluster by individual, since candidates might apply more than once in our sample. Our main specification uses local linear regression with kernel weights. The local linear regression is estimated in a window around the threshold h.

Choosing the window is a critical decision in the RD design since the observations in the limit are informative under the continuity assumption of conditional expectations functions around the cutoff. Observations closer to the cutoff are the more informative but, the lower sample around the cutoff could deliver more imprecise estimates. To deal with the bias-variance tradeoff, we follow the MSE optimal approach (Imbens & Kalyanaraman, 2011) and estimate and select a data-driven window using the most recent bandwidth selectors (Calonico, Cattaneo, Farrell, & Titiunik, 2017). We choose a different bandwidth for each side of the cutoff since there is a larger sample to the left of the admission cutoff, resulting in an asymmetric RD window. In the appendix, we also present estimations for symmetric windows.

Our fuzzy approach arises from the nonperfect compliance after the admission decision because applicants still need to decide whether to attend the university. We are interested in the effect of being admitted and attending the selective public university. Conditional on the score, the admission assignment at the cutoff satisfies the exclusion restriction since affecting the outcome only through attendance. Using this local independence assumption, we estimate local effects using instrumental variables specifications. Using the admission as an instrument for enrollment in the public university, we estimate the following specification:

$$Y_{ipc} = \alpha_1 \hat{UV}_i + \alpha_2 S_i + \alpha_3 + E_{ipc} \times S_i + \lambda_{pc} + u_{ipc} \quad i \in h \quad (2)$$

$\hat{UV}_i$ represents enrollment in the public university instrumented with the admission to the university, according to equation (1). Y_{ipc} represents the outcomes of graduation, earnings and financial indicators.

We follow a continuous approach to RD design (Cattaneo, Idrobo, & Titiunik, 2020), which is based on the underlying assumption that the conditional regressions functions for potential outcomes are continuous in the vicinity of the cutoff. The cutoff by program and year are not easily predictable by the students, so it is plausible to assume no manipulation around the cutoff. In the next section, we further discuss the validity of the RD design to examine the continuity of the score density around the cutoff and the continuity of the covariates. In addition, we present falsification tests such as placebo treatment at artificial cutoff.

The main specification is a local linear regressions with a triangular kernel. For the window selection, we primarily follow the optimal data-driven window selection proposed in (Imbens & Kalyanaraman, 2011) and implemented in (Calonico et al., 2017). Because of the selectivity of this public university, many programs exhibit relatively higher shares of not admitted and low rates of admitted individuals. We use an optimal asymmetric window, to get advantage of the relative larger pool of control individuals.

4.3 RD validity checks

Continuity of the admission score: The exact cutoff is arguably unknown to the students. The public university assigns a score for each application that weights the state examination results in each field. Each major sets a specific weighting formula to give higher weights according to the skills required. The weighting formula for each program is public. Every admission cycle, the university and departments define available seats. All applicants are assigned the admission score, ordered from higher to lower. The last admitted student's score sets the cutoff according to the available seats for that cycle. Then, the exact cutoff is not previously known by applicants. However, the admission results from previous cohorts are publicly available, thus providing information to the students that might influence how many points in the national examination they should obtain. We argue that the exact cutoff is very difficult to predict, even if the students may try to obtain something similar to the previous year. They still might get rejected if the new cohort distribution is higher than the previous cohort. Figure A.1 depicts the exact cutoff in each admission cycle for every major grouped by fields. We see that even when cutoff points sometimes look close to one another, they are never exactly the same.

However, the graphical depiction of the score distribution, shows higher densities around the cutoff (Figure 1, panel A). About 25 percent of applications are within 10 points range of the cutoff and 60 percent are in the 50 points range of the cutoff. The higher densities also reflect the stacking of all programs around the cutoff. But, when estimating local polynomial density functions around the cutoff, we find no statistical difference, supporting the claim that applicants cannot manipulate the cutoff since they cannot perfectly predict the exact value. After performing a density test using local polynomial estimation of the distribution, we fail to reject the null hypothesis that the density is continuous around the cutoff, with a p-value of 0.78. Figure 1, panel B depicts the estimated local density functions on top of the distribution with 95 percent confidence intervals.

Balance of Covariates: another evidence supporting the validity of the assumption of continuity of potential outcomes is the continuity of covariates around the threshold. Continuity of covariates also supports no score manipulation since individuals around the cutoff are similar in variables that are not affected by the admission. We estimate the effect of admission on the covariates using the same reduced form RD specification as the one proposed for the outcomes. Figure 2 present the graphical evidence of balance for the set of covariates (gender, low vs. high income, private vs. public high school and parental educational attainment.) Table A.2 report the point estimates using several specifications. We present results from MSE (columns 1, 2, 4) and CER (column 3) selected windows. Column 1 presents the same specification used for the outcomes, with optimal selected MSE windows and fixed effects by program and admission cycle. With very few points estimates statistically different from zero, overall, the results in this table support the claim of the covariates' balance.

Placebo cutoff: we conduct a test for possible discontinuity in regions of the score distribution where the admission is known to be constant, using a placebo cutoff. While this exercise cannot confirm the assumption of continuity of the potential outcomes function around the cutoff, it certainly provides supporting evidence that the admission cutoff gives the only jump in the function. We present the results of this exercise in Table A.6. Columns 2 to 4 are estimated on artificial cutoff using only the applicants to the left of the cutoff and Columns 5 to 7 are estimated on artificial cutoff using only the applicants to the right of the cutoff.

4.4 RD sensitivity analysis

We examine the sensitivity of the main specification to changes in the bandwidth and functional form. For the functional form, our main specification uses a local linear approximation to the functions. We provide alternative quadratic and cubic specifications for the main outcomes in Table A.4. While our preferred specification uses asymmetric optimal selected bandwidth, we report alternative specifications with symmetric bandwidths in Table A.2, both arbitrary and optimally selected. Choosing the bandwidth is one of the most critical steps in the RD continuity approach since it directly affects the bias and variance of the points estimate (Imbens & Kalyanaraman, 2011). Recent literature suggests testing for bandwidth not far from the MSE-optimal selected (Cattaneo et al., 2020). In Table A.3 , we provide sensitivity results by changing the bandwidth around the asymmetric optimal selected with this caveat in mind. Finally, we present a donut hole analysis, excluding points closer to the cutoff in Table A.7, to examine how sensitive are the point estimators to the observations very close to the cutoff.

5 Results

5.1 Main results: educational, labor and credit market outcomes.

This section examines the effects of admission to the public university on short and long-run labor and credit outcomes. We also provide both reduced form and instrumental variables specifications in Table 2 for the academic outcomes. For the labor market (Table 3) and credit market outcomes (Table 4), we present estimates pooling years in the following groups: 5 to 11 years, 11 to 15 years and 16 to 18 years after admission. The specification in the main tables is kernel weighted local OLS regressions that include program-cohort fixed effects, within an asymmetric optimal selected window (explained in section 3) selected for the labor market outcomes and financial outcomes separately. The point estimate of interest is the admission dummy, indicating being above the cutoff. All standard errors are clustered at the individual level since the individuals can appear several times for each application recorded.

Moreover, we present the graphical evidence of discontinuity around the cutoff for the academic outcomes (Figure 3), annual earnings and formal jobs (Figure 4), and credit market outcomes (Figure 5). These figures present a visual representation of the discontinuity, plotting conditional means bins for score intervals. Specifically, we plot the conditional means of residuals on the score after controlling for program-cohort fixed effects. On top, the figures depict the best liner fit with a 95% interval. Figures that depict conditional non-residualized means obtain similar results.

Effects on college enrollment and completion

We first document that the majority of students who receive an offer of admission enroll in the public university. Figure 1 exhibits the clear discontinuity around the admission cutoff for enrollment in a public university. Notably, we can observe the enrollment of students in other institutions different from the one we study. Students who do not meet the cutoff for a given cohort program might re-apply in the next admission cycle or apply to other public universities in the country, explaining the mean of 23 percent of attendance to public universities in the control observations. Similarly, admitted students might not enroll right after admission. Table 2 shows the estimated effects on college enrollment. Having an admission offer increases enrollment in the public university by 27.7 percentage points (Column 1) and enrollment in any university (public or private) by 16.1 percentage points (Column 2). For many applicants in this region, a public university is the only option for a college education. Then if rejected, many students would have no access to a college education.

Admission to the selective public university increases college degree attainment. We measure degree attainment in a database corresponding to 8-12 years after admission. Figure 3 presents the clear graphical discontinuity and Table 2 Column 3 presents the estimated coefficients. Admission raises the likelihood of getting a degree by 8.9 percentage points (Table 2 Column 3). Scaling up this point estimate with admission as an instrument of enrollment, we find that attendance to the selective public university increases degree completion by 29 percentage points. The point estimates are similar from recent estimates of similarly selective public universities (24-34pp in Bleemer (2021)) but slightly lower than other less selective universities (37 pp in Goodman et al. (2017)) in the USA. Compared with a private selective in Colombia, the graduation effect is relatively similar (21.3 pp in Barrera-Osorio and Bayona-Rodríguez (2019) vs 29pp in our case). Overall, the selective public university increases graduation rates relative to the counterfactual institutions in the region.

Long-run labor market effects

In this section, we focus on the results observed 16 to 18 years after admission. First, admission to the public university raises the likelihood of being employed in the formal sector by 2pp and raises income by 3.41 COL$ million (13 percent above the mean) when students age is around 30-35 years old (Table 3, column 1 and 3, panel C). We also estimate the results on log-earnings getting a point estimate of 41 log points (Table 3, column 2, panel C). Figure 3 Panel A depicts the average annual earnings in bins in score range close to the optimal MSE selected window (-80,30). Figure 3 Panel B presents an analogous visualization of the proportion of having a formal job.

Scaling up this point estimate with admission as an instrument of enrollment, we find that attendance to the selective public university raises yearly earnings by 32 percent. This paper is one of the few in a developing country to measure the returns when students are around 30-35 years old. The estimated point estimates are slightly higher to previous studies from the same ages in the USA (20 pp in Hoekstra (2009a) and 20pp in Smith et al. (2020)) and Italy (41 log points Anelli (2020)). The confidence interval for the estimated point allows us to conclude that returns to selective college education are fairly similar across countries.

Long-run credit market effects

This section focuses on the results observed 16 to 18 years after college entry. Admission to the selective public university increases the likelihood of being a homeowner by 1.6 pp (13 percent of the mean) and being a car owner by 2.5 pp (25 percent of the mean) when students age is around 30 to 35 years old. Table 4 panel C presents the results pooled from 16 to 18 years after college entrance for the reduced form RD specification and instrumental variables specification with admission as an instrument for enrollment. Figure 4 panel A depicts the visual evidence of the discontinuity for the conditional probability of having a mortgage loan. Figure 4 panel C presents the visual discontinuity for the outstanding car loans. Scaling these coefficients, we find that attendance increases the probability of homeownership by 6pp (Table 4 panel C column 4). The scaled relative effect size here is more than 60 percent increase with respect to the mean. The size of this effect is large and meaningful in this context, where the average use of mortgage loans is 10 percent. The points estimates are similar to the effect of financial aid on ever being a homeowner in the USA (Scott-Clayton & Zafar, 2019).

Lastly, admission to the public university substantially raises usage of consumer credit products such as credit cards. Figure 5 panel B presents clear graphical evidence of the discontinuity on the proportion of credit card usage around the threshold. Table 4 panel C column 2 reports an estimated effect of 5.2 pp, about 10 percent relative effect relative to the mean. We also present the effect on the standardized financial index, a composite indicator of the three credit measures outcomes. Admission to the public university leads to an increase of 0.08 of a standard deviation in the financial index. This result further supports that the impact of the selective university on credit market outcomes is robust and not driven by a particular outcome.

5.2 Short run effects vs. medium and long-run effects

This section examines the effects estimated yearly for the main outcomes. We graphically depict the RD point estimates over time from the instrumental variables specifications and the predicted trajectory separated by admission status for annual earnings (Figure 6)), homeownership (Figure 8), car ownership (Figure 9) and credit card usage (Figure 7). We also present the points estimates pooled by groups, from 5 to 10 years, 11 to 15 years and 16 to 18 years after admission for labor market outcomes (Table 3) and credit market outcomes (Table 4). We can estimate results from 5 years after admission for the annual earnings up to 18 years. Notably, we can estimate effects during college for credit market outcomes, from the first year to 18 years after admission. We find significant effects for annual earnings and credit card usage starting the eight-year after admission. The relative effect for earnings increases until the 16 years after admission, while the effect on credit card usage peaks keeps constant over time. Finally, we observe statistically significant effects for car ownership after the 11 years after admission. For homeownership, the effects are observed only in the long term, 16 years after admission.

Effects on annual earnings over the formal job career.

Admission to the selective public university does not have clear effects 5 to 7 years after admission but has significant middle and late-career effects. Being admitted to the public university has close to zero point estimate on the likelihood of formal jobs and log annual earnings 5 to 7 years after admission (Table 3 Panel A columns 1 and 2, Figure 6 panel B). Roughly two years after expected graduation, both admitted and non admitted observe a growth in their income, and there is no gap among the groups (Fig 6 Panel A). Our short-term results differ from previous papers in the same time frame, finding returns for selective private universities in the short term of 5 percent in Colombia (Barrera-Osorio & Bayona-Rodríguez, 2019) and from more selective public universities 28 percent from China (Jia & Li, 2021), but coincided with the modest results for selective public universities 7 years after admission (Bleemer, 2021). Measuring the return over more extended periods could help reconcile the results, since the gap starts to be statistically significant 9 years after admission.

While there are still no effects on the probability of having a formal job, admission to the public university raises annual earnings by 30 percent 11 to 15 years after admission (Table 3 Column 4 and 5 Panel B). From the reduced form estimates, the relative effect is 10 percent for annual earnings, including zeros, but this effect is not statistically significant for the log of earnings (Table 5 Column 2 and 3 Panel B). Finally, the returns to earnings peak from 16 years after admission. Attending the selective public university raises earnings by 41 percent and the probability of formal employment by 2 percent when students are 30 to 35 years old (Table 3 Column 4 and 5 Panel C). Figure 6 panel A presents the conditional means for annual earnings plotted year by year (after controlling for program fixed effects) with a 95 confidence interval for the admitted group. The figure shows an apparent growth in earnings for both admitted and non-admitted, with a widening gap in favor of the admitted group that picks 16 years after admission.

Furthermore, we provide evidence that admission to the public university increases job tenure and job quality. Table A.10 presents the results for the number of days working in a year and three indicators denoting earnings above one two or three times the monthly minimum wage. Admission to the public university increases by 5 percent the total days worked per year(Table A.10 column 1). Additionally, admission to the public university raises the probability of earning more than three times the monthly minimum wage by 4 percentage points (Table A.10 column 3).

Credit outcomes: relaxing credit constraints over time

We first document that students were credit-constraint during college. Both admitted and non admitted groups have a rate of credit card usage lower than five percent coinciding with the first to five years after admission 7. Students loans are not typical in Colombia, and there are several barriers to accessing formal consumer credit. In addition, the perceptions around credit card usage are negative, with students not accessing credit cards immediately after graduation (Franco & Mahadevan, 2021). The impact of attending the selective public university on boosting credit market access is economically relevant for a credit constraint student population.

Around the expected time of graduation, both groups observe growth in credit card usage rates up to 35 percent. There is a clear difference for students admitted to the public university of 20 percentage points in the eight-year after admission. Both the points estimates and relative effects keep relatively constant later after. The point estimates are almost the same magnitude in Panel A, B and C Table 4 column 2, 4 to 5 percentage points in the reduced form.

The observed effects in credit card usage eight years after admission coincides with the gap in annual earnings starting to be statistically significant. Then, attaining a college degree is not the only factor that will relax borrowing barriers in the market. We observe the combined effect of college graduation and entering into the labor market. This pattern supports the idea that the impact of college education on consumer credit access is likely to be mediated by earnings growth.

Next, we examine car and homeownership outcomes. In the first two years after expected graduation, there is close to zero effect of admission on these outcomes (Table 4 Column 1 and 2 Panel A). There is faster growth in the car ownership rates between 10 to 14 years after admission figure 9, but the point estimate is not statistically significant (Table 4 Column 2 Panel B). The proportion of applicants with an outstanding mortgage loan grows up to 5 to 7 percent when students are over 27 years old, but this rate is still low compared with the 15 percent reported by Goodman et al. (2017) by the same age and type of population.

Nevertheless, admission to a selective public university has statistically significant effects after 16 years of college entrance, rising homeownership by 6 percentage points (Figure 7 and (Table 4 Column 5 Panel C). Having not attended the selected college, the proportion of housing loan take-up still grows over time but goes up to only 10 percent. These results show the importance of using long-term measures to estimate the impact of a human capital investment such as college education in outcomes that take time to materialize.

Why no short term effects: getting a graduate degree

We document that admission to the selective public university boosts the likelihood of getting a graduate degree for physicians and related health professionals Table 5. Admission to the specialization programs in medicine is very competitive in the country. Only about 30 percent of physicians get a specialization degree. Admission to the public university raises the probability of getting a graduate degree by 13 percentage points for all health professionals and 42 percentage points for physicians. Although our results are constrained to the applicants to health programs sample, these are the more selective majors in the public university with admission rates below 5 percent and also the health professionals face the greatest competition for entry into graduate programs. These results also explain that these individuals remain longer as students, taking more extended periods to observe the returns to education.

5.3 Heterogeneous Effects

Financial literacy and knowledge acquired in college is one plausible channel explaining the observed impact of college education on borrowing patterns. While we do not observe financial literacy skills out of college, we examine whether specific majors with more coursework on finance have a different effect than other majors. Students declare the major already in the application. We group all the four-year programs in 6 fields: engineering, business, health, humanities, sciences, and teaching. The business field includes majors such as management, accounting and economics. Those majors include, as required coursework, at least one course with specific basic financial principles. Other fields such as engineering have mathematical and numeracy skills training, which is highly correlated with financial literacy.

Table **??** presents the results of the reduced form specification separately by fields. The university admission effect for business majors is slightly higher in credit card usage and borrowing for housing (Table **??**, column 2). The pvalue for the hypothesis test of the difference between business and other fields is 0.0815. Then the difference is statistically different from zero at the 10% confidence level. The university admission returns on earnings are also slightly higher for business programs. For the engineering field, the estimated point effects are slightly lower than in business. But they are statistically not different from business. In sum, majors with more mathematics and financial literacy skills have higher returns on earnings and higher probabilities of using financial services than other fields. Still, we cannot disentangle direct financial knowledge effects from the income growth effect.

We examine whether admission to the public university has differential impacts for four groups according to pre-admission socioeconomic characteristics. Table 6 reports the results gender, public vs. private high school for outcomes observed between 16 to 18 years after admission. The table reports coefficients estimated separately for each group from reduced form RD specifications.

Women students have slightly higher point estimates of admission to the public university across all outcomes (Table 6 Panel A). An offer to attend a public university increases college degree attainment by 13 percentage points and increases earnings by 13 percent. Moreover, the probability of having an outstanding mortgage loan rises by 23 percent and having an outstanding consumer loan by 15 percent. However the point estimates are not statistically significant from the men results.

In addition, the estimated effects are mainly driven by students from private high schools, with significant larger coefficients on earnings, and consumer credit outcomes (Table **??** Panel B). The impact on college graduation is similar across public and private high school students. Since the share of students from private high school is balanced across the cutoff and the global score, overall academic preparation is similar for both private and public high schools in the global score. The balance on abilities before college entry and the similar impact on college graduation suggest that the heterogeneity by high school is not likely explained by college learning differences or academic preparation. To investigate further, we examine differential traits among private schools. In this context, there is also a substantial variation in tuition prices and educational quality among private high schools (**?**).

Recognizing this heterogeneity among private schools, we further explore differences by religious affiliation. Catholic private schools are among the oldest institutions in the country, providing high-quality education. Some of those religious communities also offer subsidized tuition for students coming from disadvantaged families. In Table **??**, we estimate specifications separately for private schools by religious and non-religious affiliation. The effect of college admission is larger for religious high school group on earnings and financial services usage, suggesting that students from attend religious private high school are the group benefiting the most from attending this university, even if there is no difference in getting the college degree with other high school types. This results support the channel that students from this particular group get more of attending college by social interactions, network building with the high school peers, rather than college learning Zimmerman (2019).

5.4 RD Sensitivity specifications.

Table A.2 summarizes the estimated coefficients for the main outcomes using symmetric bandwidth around the threshold. Column 1 presents the preferred specification, using asymmetric optimal selected bandwidth for reference. Columns 2 to 6 present the results using arbitrary fixed symmetric bandwidth around the threshold, going from 10 points to 50 points. All regressions come from a local linear specification for the RD reduced form over the sample of applicants to five years programs excluding teaching. The estimated impacts of being admitted to the public university on educational attainment and credit card usage remain the same and statistically significant at the 1 percent level across all window variations. The coefficient on mortgage loans varies slightly across windows but remains statistically significant at 10 percent. The estimated impact on annual earnings is robust in the symmetric windows from 30 to 50 points around the threshold, but it is imprecisely estimated from 10 to 20 points in the symmetric windows.

However, the deviation from the MSE-optimal selected window affects the bias and inference in the RD continuous setting since points estimates could be unreliable for arbitrarily selected windows (Cattaneo et al., 2020). Table A.3 focuses on asymmetric bandwidth variations closer to the MSE-optimal selected. Columns 2 to 4 present specifications for windows closer to the optimal asymmetric window. The points estimates for college graduation, annual earnings and credit card remains robust to these specifications. The points estimates for mortgage loans remains robust to most in column 2 and 3.

Table A.4 compares the estimations from lineal (Column 1), quadratic (Column 2), and cubic (Column 3) functional forms. All results come from RD reduced form over the sample of applicants to five years programs excluding teaching. The coefficients on college degree, mortgage loan and credit card outcomes remain about the same size and statistically significant. The coefficients for annual earnings is robust to the quadratic functional form but not to the cubic functional form.

Table A.5 summarizes the estimated coefficients when adding the covariates. Columns 1 and 2 compare the specification for the sample of applicants to all five-year programs that exclude the teaching field. All columns present the results from a local linear reduced form using optimal selected asymmetric bandwidth. Optimal windows may change when including the covariates, since including the covariates improves the estimation efficiency. The covariates included are gender indicating male, parental college degree dummy, low family income indicator and public high school indicator. Since covariates are balanced around the cutoff, including them should only be justified by improving the precision of the estimates. Overall, the coefficient for the four main outcomes remains similar in magnitude and statistically significant.

6 Conclusion

This paper presents evidence of the impact of selective public universities on short and long-term outcomes beyond the labor market, such as credit market access and household asset investments. We find that college education improves financial behavior, particularly boosting consumer credit usage for credit-constraint individuals during college. Having access to credit improves the ability of individuals to face economic shocks, likely protecting them from falling into poverty. Additionally, our findings evidence the gains from selective university attendance on home and car ownership in the long term. These results present a broader perspective of economic self-sufficiency as a result of college investment.

We show suggestive evidence that students were financially constrained during college then they have limited financial tools to afford the cost of the private alternatives in the region. Because of the low baseline in financial services usage, we find large gains of college education on consumer borrowing and household asset acquisition. In contrast with the USA literature where the evidence on financial outcomes is mixed, in the middle-income country with low prevalence of financial services, we observe sizable effects of college education on this financial behavior.

The findings in this paper provide evidence that investing in public higher education institutions effectively provides paths towards social mobility in developing countries. This paper contributes to the debate on alternatives for increasing college access for low-income individuals that are financially constraint to pay the cost of high-quality alternatives. Low-income students enroll disproportionately in for-profit or low-quality institutions, and penalties in the market for doing so (Camacho, Messina, & Uribe, 2017). Financing public universities with subsidized tuition should still be considered in the portfolio of policies promoting access to higher education.

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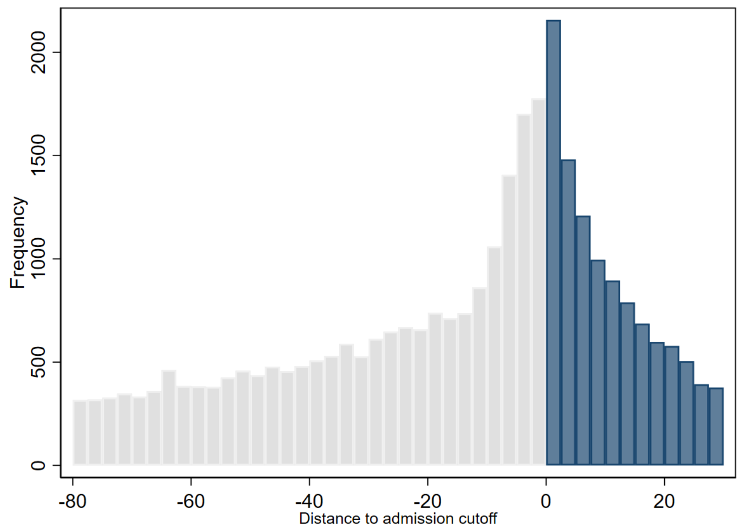
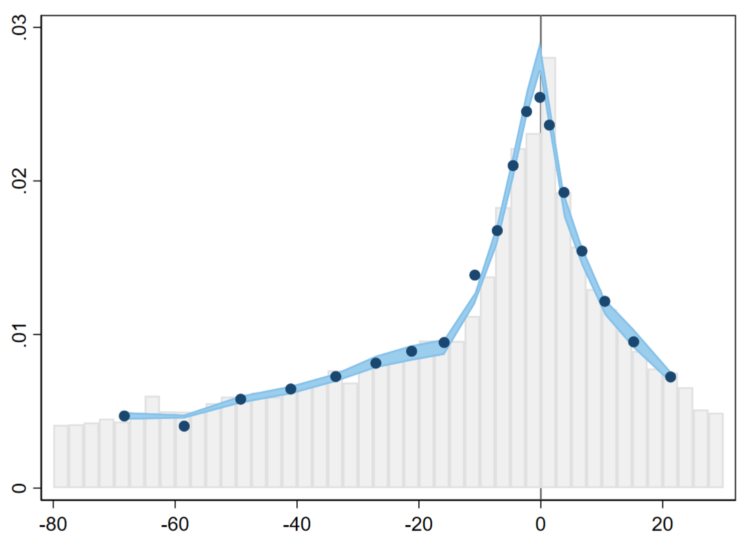
Figures

Figure 1: Score distribution



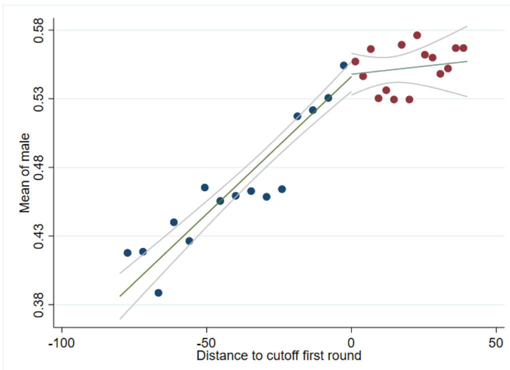
(a) Score Distribution



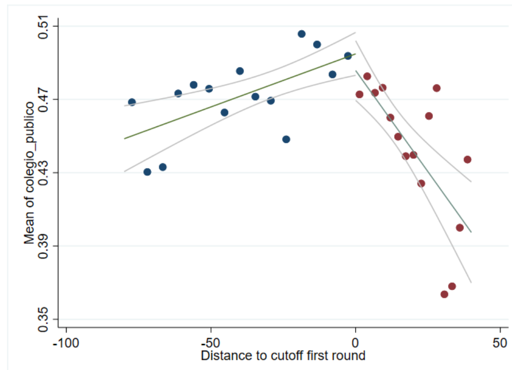
(b) Local density estimation

Notes: Sample includes applicants in the cohorts from 2000 to 2004 to a flagship Public University for all five-year programs. Figures plot the estimated density of the score around the cutoff. The score is assigned by the university to the application.

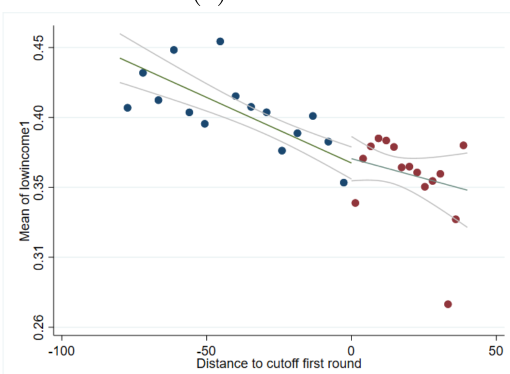
Figure 2: Covariates Balance.



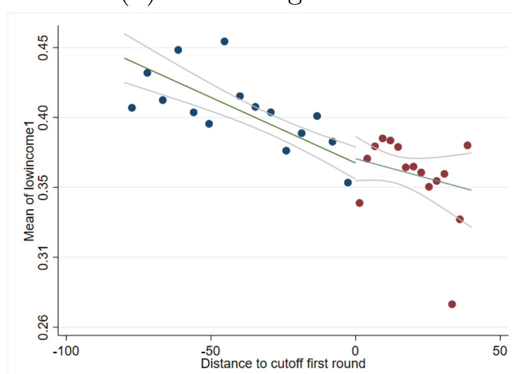
(a) Gender



(b) Public High School



(c) Low income

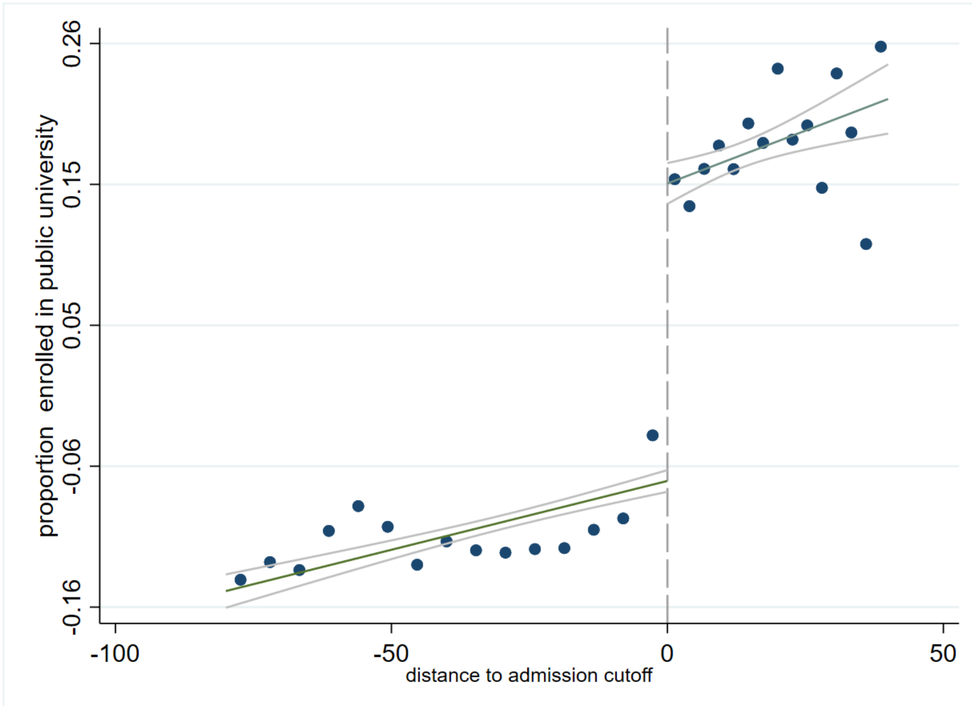


(d) Parents with college degree

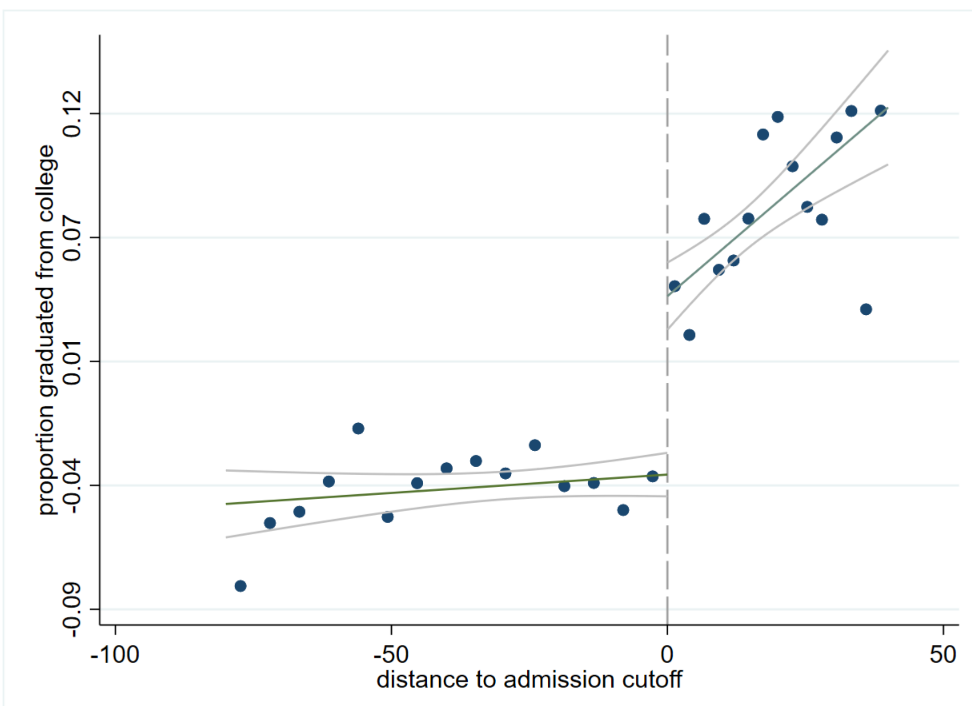
Notes: Figure presents the binned average covariates and a linear fit for both sides of the cutoff with 95% confidence intervals. Sample includes applicants in the cohorts from 2000 to 2004 for all five-year programs to a flagship Public University in Colombia. Running variable is the admission score assigned by the University to the applicant by program and cohort, stacked and standardized around zero to represent the distance to the cutoff.

Figure 3: Academic Outcomes

(a) Enrollment in the Public University



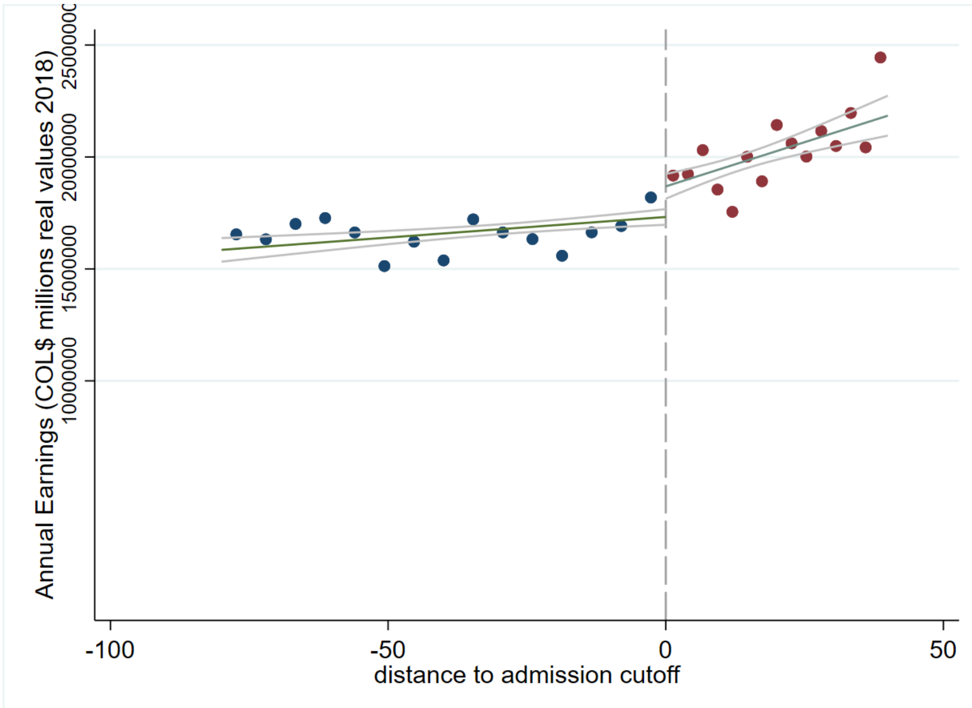
(b) Graduation from five-year programs



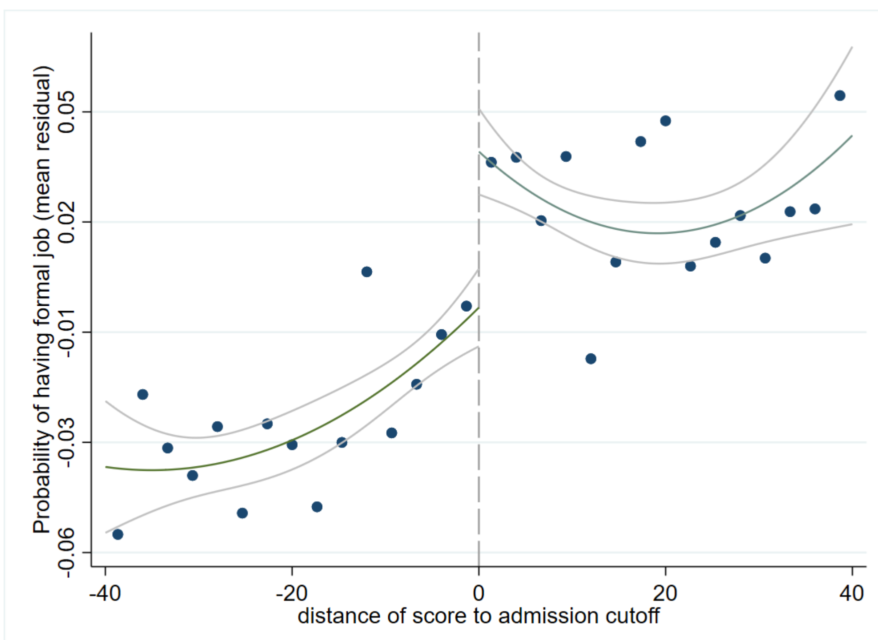
Notes: Figures presents the binned average of enrollment and graduation demeaned by program and cohort. The figure also presents a linear fit for both sides of the cutoff with 95% confidence intervals. Sample includes applicants in the cohorts from 2000 to 2004 for all five-year programs to a flagship Public University in Colombia. Running variable is the admission score assigned by the University to the applicant by program and cohort, stacked and standardized around zero to represent the distance to the cutoff.

Figure 4: Graphical Discontinuity Labor Market Outcomes

(a) Annual earnings (millions Col$ real values 2018)



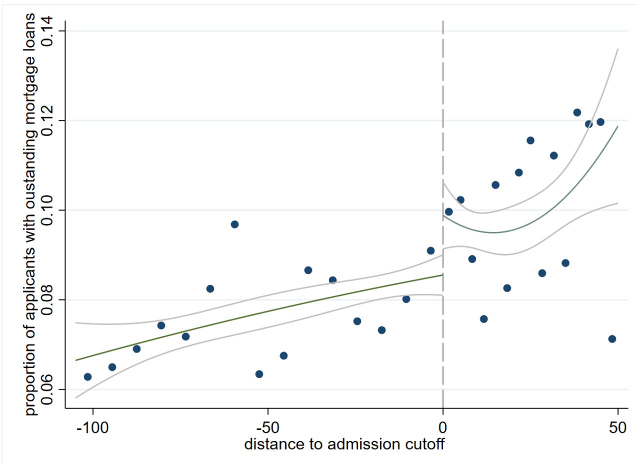
(b) Probability of having a formal job



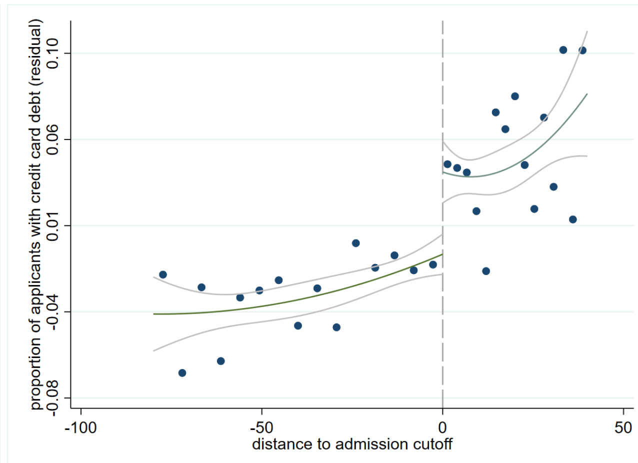
Notes: Outcomes observed 16-18 years after admission. Dots are binned average of the outcome demeaned by program and cohort. Annual earnings in Col$ millions real value of 2018. Earnings takes the value of zero when there is no formal wages observed. The figure also presents a linear fit for both sides of the cutoff with 95% confidence intervals. Sample includes applicants in the cohorts from 2000 to 2004 for all five-year programs to a flagship Public University excluding teaching school. Running variable is the admission score assigned by the University to the applicant by program and cohort, stacked and standardized around zero to represent the distance to the cutoff.

Figure 5: Graphical Discontinuity Credit Market Outcomes

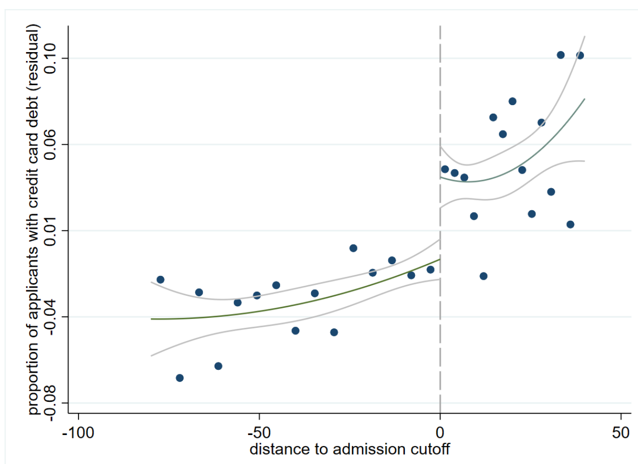
(a) Outstanding housing loan



(b) Outstanding credit card debt



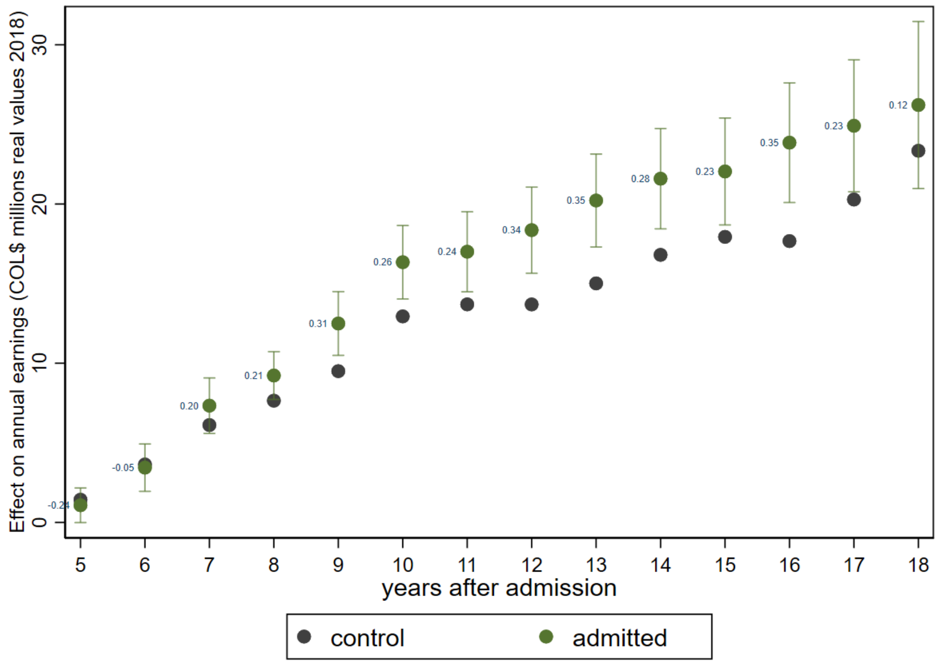
(c) Outstanding automobile loan



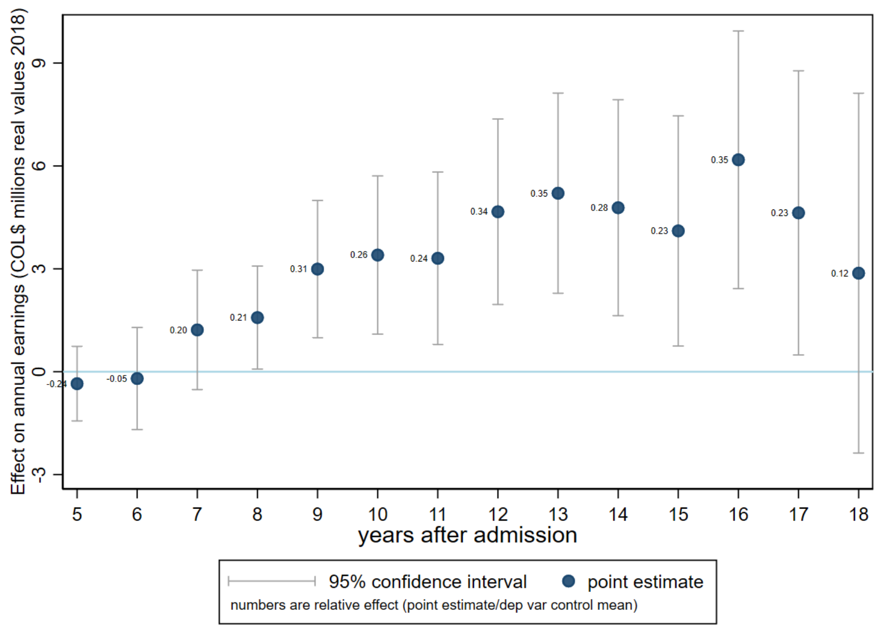
Notes: Each outcome is a dummy denoting whether an applicants have an outstanding loan 16-18 years after admission. Dots are binned average of the outcome demeaned by program and cohort. The figure also presents a linear fit for both sides of the cutoff with 95% confidence intervals. Sample includes applicants in the cohorts from 2000 to 2004 for all five-year programs to a flagship Public University excluding teaching school. Running variable is the admission score assigned by the University to the applicant by program and cohort, stacked and standardized around zero to represent the distance to the cutoff.

Figure 6: Earnings: Year by year Estimates

(a) Annual Earnings (Col$ millions)



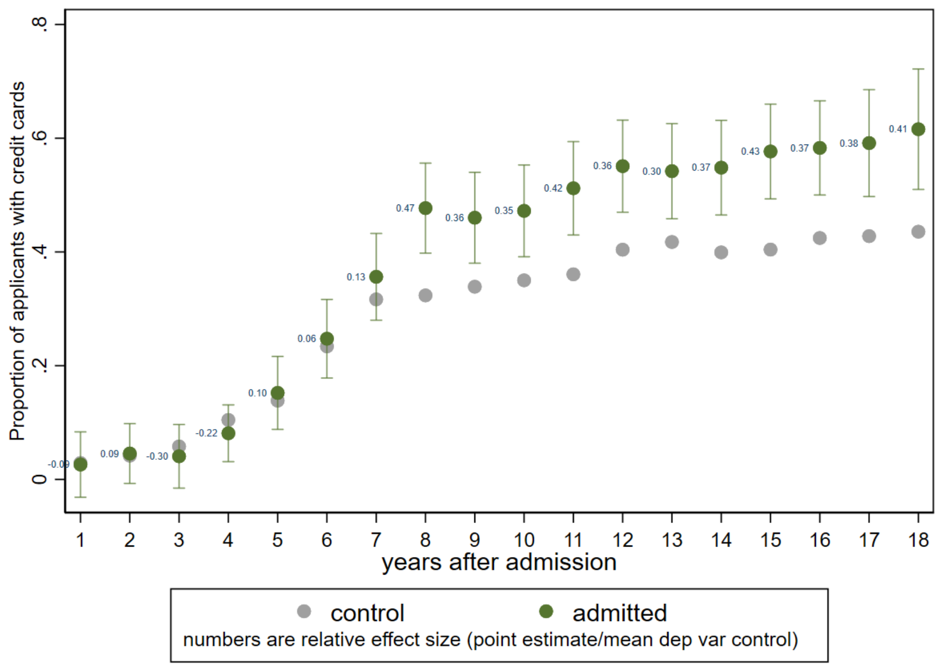
(b) Estimated effects of admission



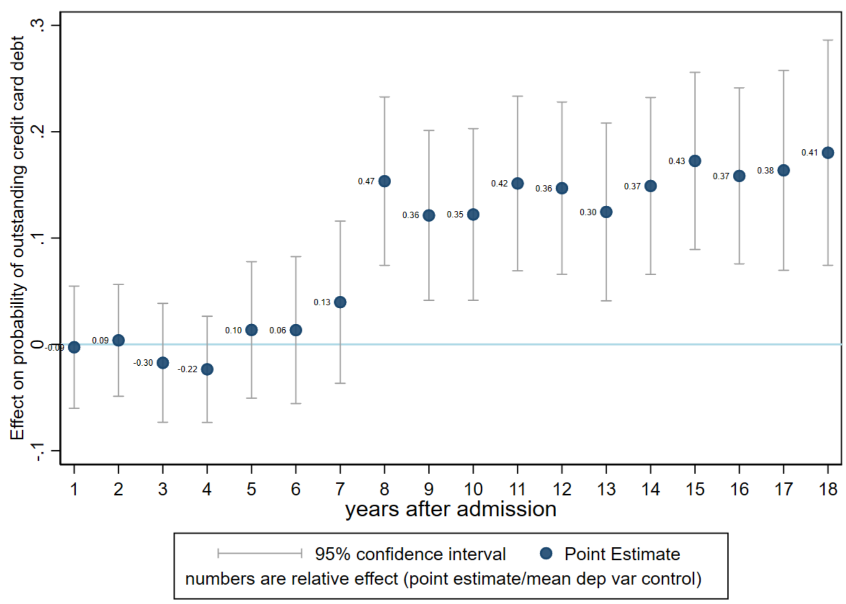
Notes: Annual earnings in the formal labor market. Units are COL$ millions real value of 2018. Figure shows the results of a local linear instrumental variable RD specification in the asymmetric optimal MSE selected bandwidth. RD regressions are separately estimated year by year using major and admission cycle fixed effects. In panel A, we plot the earnings mean for the control group and additional earnings for the group of admitted, coming from the estimated regressions year by year. In panel B, we plot the point estimates. On the left of each dot, we plot the relative effect (point estimate / mean of control group).

Figure 7: Consumer loans: year by year

(a) Proportion of applicants with credit cards.



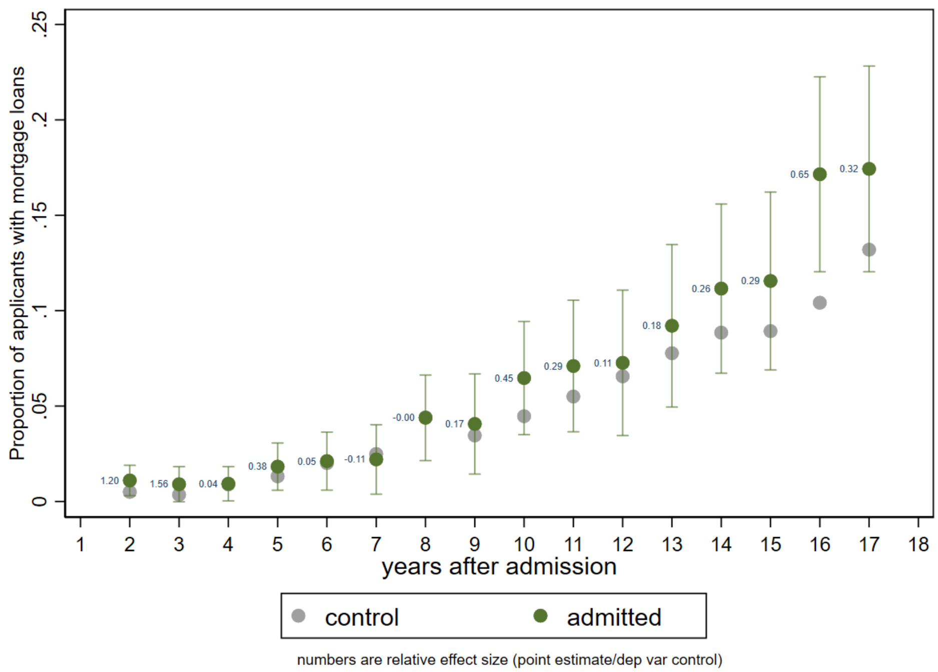
(b) Estimated effects of admission.



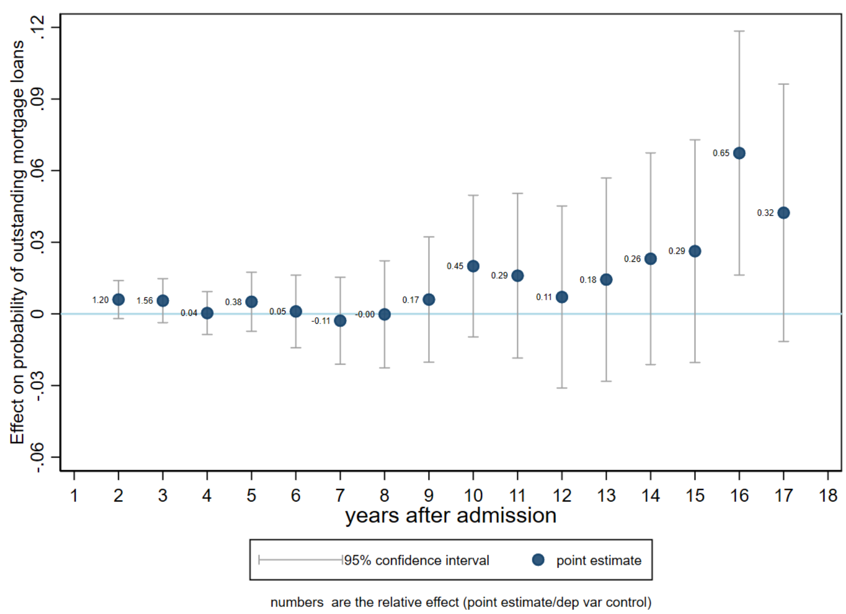
Notes: Credit card debt is a dummy denoting that the applicant has outstanding debt from credit cards with any bank in the country. Figure shows the results of a local linear instrumental variable RD specification in the asymmetric optimal MSE selected bandwidth. RD regressions are separately estimated year by year using major and admission cycle fixed effects. In panel A, we plot the proportion for the control group and additional share for the group of admitted, coming from the estimated regressions year by year. In panel B, we plot the point estimates. On the left of each dot, we plot the relative effect (point estimate / mean of control group).

Figure 8: Housing loans: year by year.

(a) Proportion of applicants with housing loans.



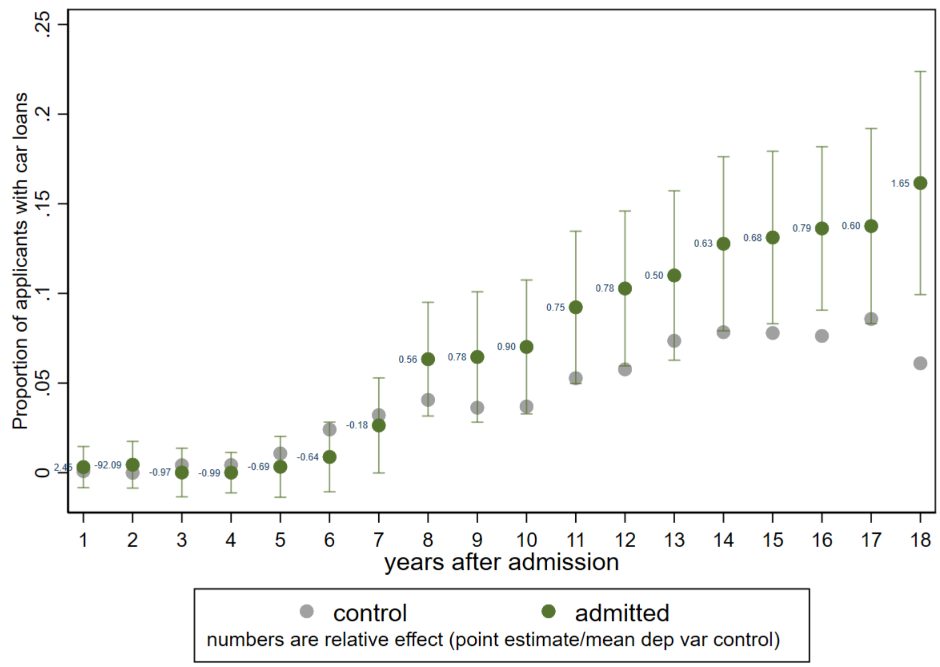
(b) Estimated effects of admission.



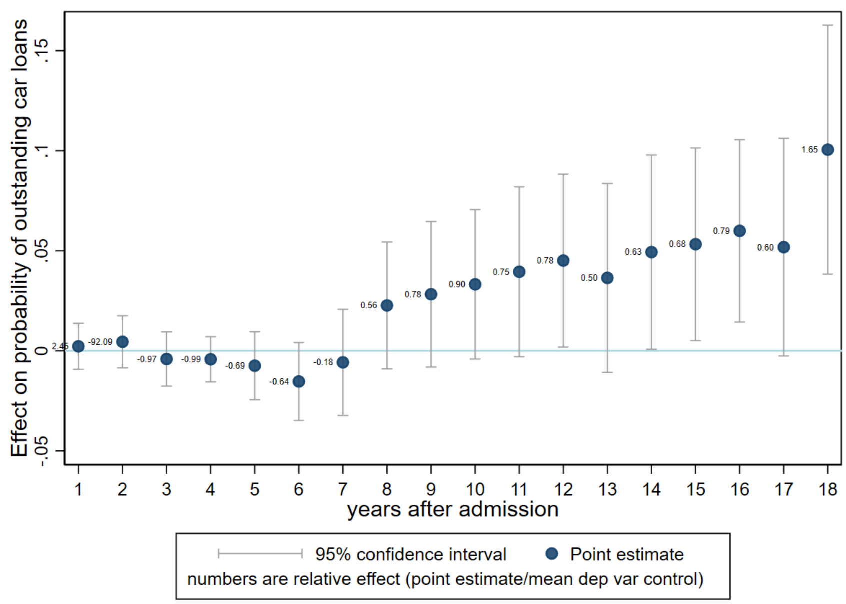
Notes: credit card debt is a dummy denoting that the applicant has outstanding debt from credit cards with any bank in the country. Figure shows the results of a local linear instrumental variable RD specification in the asymmetric optimal MSE selected bandwidth. RD regressions are separately estimated year by year using major and admission cycle fixed effects. In panel A, we plot the proportion for the control group and additional share for the group of admitted, coming from the estimated regressions year by year. In panel B, we plot the point estimates. On the left of each dot, we plot the relative effect (point estimate / mean of control group).

Figure 9: Car loans: year by year.

(a) Proportion of applicants with outstanding car loans



(b) Estimated effects of admission.



Notes: Outstanding car loans is a dummy denoting that the applicant has outstanding automobile loans with any bank in the country. Figure shows the results of a local linear instrumental variable RD specification. Local linear regressions are estimated in the asymmetric optimal MSE selected bandwidth. RD regressions are separately estimated year by year using major and admission cycle fixed effects. In panel A, we plot the proportion for the control group and additional share for the group of admitted, coming from the estimated regressions year by year. In panel B, we plot the point estimates. On the left of each dot, we plot the relative effect (point estimate / mean of control group).

Tables

Table 1: Descriptive Statistics

	All five-year programs	Five year programs (no teaching majors)	
	Full Sample (1)	Full Sample (2)	RD Sample (3)
Observations	37,554	32,253	21,994
Demographics			
Male	0.49	0.49	0.53
Age at admission	17.5	17.4	17.4
Family income *leq* 1 MW	0.39	0.38	0.37
Public High School	0.47	0.46	0.47
Parents with college degree	0.29	0.30	0.30
Educational Outcomes			
Enrolled in any five year program	0.49	0.50	0.49
Enrolled in the public university	0.28	0.28	0.31
Graduated in any five year program	0.34	0.35	0.35
Earnings and labor markets			
Annual income (in COL $ millions)	21.9	22.9	23.9
Formal Job	0.78	0.81	0.84
Credit market outcomes			
Any mortgage loan	0.09	0.09	0.10
Any credit card	0.44	0.45	0.47
Any automobile loan	0.08	0.08	0.09
Any consumer loan	0.49	0.49	0.51
Admission Cohort			
2000	0.20	0.21	0.20
2001	0.23	0.22	0.20
2002	0.28	0.28	0.27
2003	0.25	0.24	0.26
2004	0.04	0.05	0.07
Academic Field			
Business, social sciences	0.24	0.28	0.31
Engineering and sciences	0.40	0.47	0.53
Medicine and health	0.22	0.25	0.17
Teaching School and Arts	0.14	0.00	0.00

Notes: Full Sample is the list of applicants to five-year programs to the Public University from 2000 to 2004. The RD sample is the sample for the regression discontinuity specifications within the asymmetric optimal MSE selected bandwidth (closer to 70 points to the left and 30 points to the right of the cutoff) for the earnings outcomes. Observations are applications. Individuals could appear more than once. The sample of five-year programs without teaching majors excludes majors from the teaching school. Statistics of earnings and credit market are pooled 16 to 18 years after admission.

Table 2: Effects of Public University Admission on College Enrollment and Completion.

	Reduced Form			IV form
	Enrolled Public University (1)	Enrolled in any college (2)	College Degree (3)	College Degree (4)
Admitted	0.268***	0.146***	0.090***	0.315***
	(0.011)	(0.012)	(0.011)	(0.036)
Control mean	0.247	0.438	0.309	0.212
R2	0.146	0.061	0.051	0.202
N	19,859	19,859	19,859	19,859

Notes: Columns 1 to 3 present reduced form estimates from a local linear regression around the admission cutoff. Admitted represents a dummy for being above the cutoff. Column 4 presents a local linear regression estimation with admission as an instrument for enrollment in the public university. The sample consist of applications to five-year programs excluding teaching college majors. Local linear regressions are estimated in the asymmetric optimal MSE selected bandwidth (closer to 70 points to the left and 30 points to the right of the cutoff) for the earnings outcomes. Regressions include program, year, and semester of admission fixed effects. Enrollment and graduation in five-year programs are measured approximately 8-12 years after admission. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effects of Public University on Formal Earnings

	Reduced Form			IV Form	
	Formal Job	Log Earnings	Annual Earnings millions	Formal Job	Annual Earnings
	(1)	(2)	(3)	(4)	(5)
Panel A: 5-10 years after admission					
Admitted	0.00	0.01	0.53**	0.00	2.50**
	(0.01)	(0.15)	(0.21)	(0.04)	(1.14)
Mean dep var control	0.84	13.21	8.52	0.76	7.51
N	21,994	22,128	22,037	21,994	22,037
left window	-96.12	-97.79	-100.21	96.12	-100.21
right window	27.05	27.11	25.08	27.05	25.08
Panel B: 11-15 years after admission					
Admitted	0.01	0.19	1.81***	0.03	5.86**
	(0.01)	(0.15)	(0.48)	(0.03)	(2.74)
Mean dep var control	0.86	14.04	18.70	0.85	16.74
N	22,940	23,177	21,957	22,940	21,957
left window	-109.70	-121.86	-99.30	109.70	-99.30
right window	26.33	22.80	24.91	26.33	24.91
Panel C: 16-18 years after admission					
Admitted	0.02**	0.49***	3.41***	0.09**	8.94**
	(0.01)	(0.19)	(0.87)	(0.04)	(4.26)
Mean dep var control	0.79	12.93	27.12	0.74	21.77
N	20,606	20,646	21,330	20,606	15,077
left window	-103.83	-104.91	-101.63	103.83	35.35
right window	21.96	21.98	29.67	21.96	35.35

Notes: Each panel presents specifications for the outcomes pooled by years after admission. Sample includes applications for five-year programs, excluding teaching majors. Annual earnings in Col$ millions real value of 2018. Earnings takes the value of zero when there are no formal wages observed. In the log transformation, we add 1 to keep the zero valued observations. Columns 1 to 3 present reduced form estimates from a local linear regression around the admission cutoff. Columns 4 to 6 present a local linear regression estimation with admission as an instrument for enrollment in the public university. Left and right windows correspond to the asymmetric MSE optimal bandwidth calculated for each column using the rdrobust package. Regressions include major and admission cycle fixed effects. Observations are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects of Public University on Credit Market Outcomes

	Reduced Form				IV Form			
	Outstanding loan for			Financial	Outstanding loan for			Financial
	Housing	Credit Card	Car	Index	Housing	Credit Card	Car	Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 5-10 years after admission								
Admitted	-0.001	0.042***	-0.001	0.033*	-0.001	0.168***	-0.005	0.130*
	(0.005)	(0.013)	(0.006)	(0.018)	(0.018)	(0.052)	(0.024)	(0.070)
control	0.039	0.468	0.087	0.097	0.025	0.269	0.049	-0.136
N	26,823	23,942	27,665	24,138	26,823	23,942	27,665	24,138
left window	-106.7	-87.9	-106.4	-90.9	106.7	87.9	106.4	90.9
right window	24.9	19.4	31.8	18.7	24.9	19.4	31.8	18.7
Panel B: 11-15 years after admission								
Admitted	-0.003	0.040***	0.013	0.039**	-0.010	0.159***	0.050	0.154**
	(0.006)	(0.012)	(0.008)	(0.019)	(0.024)	(0.049)	(0.031)	(0.077)
control	0.072	0.549	0.140	0.260	0.059	0.428	0.043	-0.006
N	26,532	23,905	26,121	24,757	26,532	23,905	26,121	24,757
left window	-107.6	-77.6	-91.7	-87.5	107.6	77.6	91.7	87.5
right window	22.7	25.6	31.0	24.2	22.7	25.6	31.0	24.2
Panel C: 16-18 years after admission								
Admitted	0.016**	0.052***	0.025***	0.081***	0.060**	0.200***	0.093***	0.309***
	(0.008)	(0.013)	(0.008)	(0.022)	(0.030)	(0.051)	(0.029)	(0.084)
control	0.109	0.502	0.098	0.204	0.073	0.398	0.046	-0.011
N	28,512	22,729	23,993	22,611	28,512	22,729	23,993	22,611
left window	-135.0	-88.3	-93.4	-89.3	135.0	88.3	93.4	89.3
right window	22.1	22.7	27.9	21.2	22.1	22.7	27.9	21.2

Notes: Each panel presents specifications for the outcomes pooled by years after admission. Sample includes applications for five-year programs, excluding teaching majors. Housing, Credit card and car loans are dummies indicating whether the individual has an outstanding loan. The financial index is a composite indicator standardizing the three credit market outcomes. Columns 1 to 3 present reduced form estimates from a local linear regression around the admission cutoff. Columns 4 to 6 present a local linear regression estimation with admission as an instrument for enrollment in the public university. Left and right windows correspond to the asymmetric MSE optimal bandwidth calculated for each column using the rdrobust package. Regressions include major and admission cycle fixed effects. Observations are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Additional outcomes: Graduate Degree for Physicians and Health Workers.

	Graduate Degree			
	Reduced Form		IV Form	
Admitted	0.13**	0.423**	0.25***	0.729***
	(0.06)	(0.188)	(0.03)	(0.092)
Mean dep var control	0.55	0.339	0.40	0.229
N	1,818	1,818	7,123	7,123
r2	0.03	-0.017	0.09	-0.185
left window	-255.43	255.435	-159.79	159.786
right window	54.82	54.823	41.81	41.805
sample	all health	only medicine	all health	only medicine

Notes: Physician and Health Workers report to the National Registry of Health workers whether they hold a postgraduate degree or certificated specialist training. We construct a dummy denoting that these individuals graduated from this postgraduate training. The first sample includes individuals with undergraduate degree in any health field (medicine, nursery and related). The second sample includes individuals that attended the medicine school. Left and right windows correspond to the asymmetric MSE optimal bandwidth calculated for each column using the rdrobust package. Regressions include major and admission cycle fixed effects. Observations are applications; thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level.

Table 6: Effects of Public University Admission: Heterogeneous Effects

	College Degree (1)	Annual earnings (millions) (2)	Any mortgage loan (3)	Any consumer loan (4)
Panel A: Gender				
Female				
Admitted	0.13***	2.29***	0.023**	0.03***
	(0.02)	(0.43)	(0.007)	(0.01)
ci upper	0.16	3.14	0.037	0.05
ci lower	0.10	1.44	0.008	0.02
Control mean	0.29	17.90	0.04	0.40
N	11,821	29,076	58,346	49,223
Male				
admitted	0.09***	1.90***	0.01*	0.02**
	(0.01)	(0.46)	(0.00)	(0.01)
ci upper	0.12	1.44	0.02	0.02
ci lower	0.06	-0.28	-0.01	-0.01
Control mean	0.24	17.24	0.04	0.37
N	12,916	32,442	63,772	53,650
Panel B: High School				
Public High School				
Admitted	0.09***	0.58	-0.004	0.002
	(0.02)	(0.44)	(0.004)	(0.01)
ci upper	0.12	1.44	0.004	0.02
ci lowerr	0.06	-0.28	-0.011	-0.01
Control mean	0.26	17.40	0.04	0.39
N	10,019	25,311	49,458	41,624
Private High School				
Admitted	0.13***	2.96***	0.01***	0.04***
	(0.02)	(0.52)	(0.00)	(0.01)
ci upper	0.16	3.97	0.02	0.05
ci lower	0.10	1.94	0.01	0.02
Control mean	0.29	18.86	0.04	0.36
N	11,462	27,734	56,577	47,816

Notes:Outcomes are observed 16 to 18 years after admission. Sample includes applications for five-year programs, excluding teaching majors. Columns 1 to 4 present reduced form estimates from a local linear regression around the admission cutoff. Both panels present separate regression results for each subgroup. The window for all specifications is (-70,30), an asymmetric MSE optimal bandwidth calculated for the earnings outcome. Regressions include major and admission cycle fixed effects. Ci upper and lower are the 95% confidence interval. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effects of University Admission: Heterogeneous Effects by field

	Base reg (1)	Business (2)	Engineering (3)	Health (4)	Humanities (5)	Sciences (6)	Teaching (7)
College degree							
Admitted	0.091***	0.128***	0.074***	0.219***	0.041	0.057***	0.047**
	(0.013)	(0.024)	(0.016)	(0.028)	(0.025)	(0.021)	(0.019)
Dep var mean	0.280	0.322	0.331	0.323	0.302	0.169	0.193
ci upper	0.116	0.175	0.106	0.275	0.091	0.098	0.085
ci lower	0.065	0.082	0.043	0.163	-0.008	0.015	0.009
N	17,045	4,032	8,741	4,219	3,474	4,271	5,347
Annual earnings							
Admitted	3.414***	7.847***	3.865***	0.921	5.229***	0.310	1.078
	(0.867)	(1.839)	(1.348)	(2.846)	(1.811)	(1.556)	(1.104)
Dep var mean	27.124	27.715	33.976	26.519	25.806	21.104	17.011
ci upper	5.114	11.453	6.508	6.500	8.780	3.361	3.242
ci lower	1.715	4.241	1.222	-4.658	1.679	-2.740	-1.086
N	21,330	3,310	6,708	3,444	2,715	3,413	4,556
Have housing loan							
Admitted	0.016**	0.041**	0.026**	0.007	0.009	-0.013	-0.012
	(0.008)	(0.018)	(0.012)	(0.019)	(0.016)	(0.014)	(0.012)
Dep var mean	0.109	0.105	0.174	0.086	0.086	0.130	0.030
ci upper	0.031	0.076	0.049	0.045	0.041	0.015	0.012
ci lower	0.000	0.006	0.003	-0.031	-0.022	-0.040	-0.035
N	28,512	4,032	8,741	4,219	3,474	4,271	5,297
Any credit card use							
Admitted	0.052***	0.108***	0.076***	0.043	0.084***	-0.025	0.027
	(0.013)	(0.027)	(0.020)	(0.031)	(0.032)	(0.026)	(0.023)
Dep var mean	0.502	0.473	0.578	0.470	0.440	0.471	0.260
ci upper	0.078	0.162	0.114	0.104	0.147	0.026	0.073
ci lower	0.026	0.054	0.038	-0.018	0.020	-0.076	-0.019
N	22,729	3,744	7,770	4,159	3,153	3,960	5,244

Notes: Outcomes are observed 16 to 18 years after admission. Sample includes applications for five-year programs. Annual earnings in Col$ millions real value of 2018. Column 1 present the baseline specification at the true admission cutoff using the asymmetric optimal MSE selected bandwidth. Columns 2-7 present the same specification but separately by major fields. Each specification admission cycle fixed effects. Observations are applications; thus individuals could appear more than once. Ci upper and lower are the 95% confidence interval. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

A.1 Data Construction and Matching.

Data Sources We first collected all the applications records from 1999 to 2004 that were publicly available on the admission webpage of the Universidad del Valle. This first collection contains 58,817 applications with about 46,554 unique individuals. The applications from 1999 do not have the cutoff score. We drop 3,765 applications from 1999. The university offers five-year programs as well as two-year programs. We drop 8,252 applications to two-year programs. Our final main analytical sample contains 46,259 applications to 35 programs with about 37,663 unique individuals.

The application records are then merged with the national high school exit examination (Saber 11-ICFES) using the name and approximate year of the test. We matched 96 percent of applicants to this first dataset. This dataset contains information on the individual national identification number. We find the national identification number for 80.4 percent of the individuals. Using the identification number, we match the individuals with educational, earnings, and credit market administrative sources.

We access datasets coming from the following administrative information systems: **Results from high school exit test**: the high-school examinations (SABER-11, Spanish acronym) taken just before high-school graduation. The exit exam is designed and administered by the National Institute for the Evaluation of Education (ICFES, Spanish acronym). All students in Colombia are required to take this exam to be able to apply to any college. ICFES publishes the results of the exit exams to the level of the individual. In addition to scores, this dataset contains information on gender, age, high school and family background.

Information system on tertiary education : The Ministry of Education requires that every registered institution of tertiary education reports to the system (SPADIES, Spanish acronym) the status of each student from admission, enrollment, dropouts and graduation information. We use a cross-section of these educational outcomes for the year 2012, around 10 years after admission.

Information system on social security contributions: hosted by the Ministry of Health and Social Protection. Employers and independent contractors must report contributions to health and pensions through the integrated contribution liquidation format (PILA, Spanish acronym). Because employer's and employees' contributions are shares of monthly earnings, this system registers data on wages and job characteristics every month. We have access to the information on formal labor outcomes from 2008 to 2019. This dataset only characterizes the formal sector, roughly 60% of the employment in Colombia., since informal employers and informal self-employed individuals usually do not contribute to the social protection system.

Consolidated reports bank loan transactions to Financial Supervisor: Banks and credit unions are mandated to report the status of every active loan transaction with clients in a quarterly format (FORMAT 341) to the Financial Supervisor. We can observe the universe of loan transactions quarterly from 2004 to 2019. For each outstanding debt, the banks report to the supervisor information on the borrower, the total debt capital, interest rate and grade of the debt. For now, we are only using the match with this database to construct basic financial indicators.

National Registry for Health Professionals and Physicians: the health ministry keeps an administrative dataset of the physician and health professionals licensed to work in the country. This database contains information on the educational and skills formation, particularly specializations in medicine, nursery and similar graduate program for health professionals.

Matching

From the first match with the national examination results database, we recover national document identification. However, we could have young identification and adult identification. Since students take the high school exit examination before being legal adults, they presented the exam with a young identification number. The number of applications in our sample for which we found any identification (young or adult) is 45,329, with 36,866 unique individuals. This match represents 98 percent of the main analytical sample. For the subsequent merge, we try to find the adult identification required to find earnings and financial records. The number of applications in our sample for which we found national adult identification is 37,859, with 36,866 unique individuals. This is 80.4 percent of the main analytical sample.

While the matching numbers are high, we still want to verify that matching probability is not correlated with the treatment assignment. TableA.8 present the results. In this table, we run the same specification as for the main outcomes but using matching probability as the dependent variable. There is a higher probability of about 2 percentage points for the admitted to the public university to have a matched adult identification number (TableA.8, Panel adult number, Column 1). However, this coefficient is not robust to sensitivity specifications. Given the high match rate (80 percent), we consider this slight difference sufficiently small to be negligible. Since age is balanced across the cutoff, there could not be a difference in age at admission that explains the match results.

A.2 Additional Tables and Figures

Table A.1: RD Validity: Covariates Balance

Window	Asymmetric			Symmetric
Fixed effects	Yes			
Select	MSE	MSE	CER	MSE
Dependent Variable	(1)	(2)	(3)	(4)
Age				
Admitted	-0.06	0.11	0.10	0.08
	(0.08)	(0.08)	(0.08)	(0.08)
P-value	0.45	0.16	0.20	0.33
Bias corrected SE		0.09	0.08	0.09
Dep var mean	17.45	17.45		
N	21,044	21,044	18,367	17,507
left window	84.88	84.88	48.79	30.18
right window	28.62	28.62	16.90	30.18
Gender=male				
Admitted	-0.01	-0.00	0.01	0.00
	(0.01)	(0.01)	(0.02)	(0.01)
P-value	0.50	0.88	0.52	0.76
Bias corrected SE		0.01	0.02	0.02
Dep var mean	0.58	0.58		
N	18,755	18,755	15,787	18,293
left window	54.71	54.71	33.15	32.14
right window	33.73	33.73	15.50	32.14
Public high school				
Admitted	-0.03**	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)
P-value	0.02	0.19	0.51	0.38
Bias corrected SE		0.02	0.02	0.02
Dep var mean	0.50	0.50		
N	18,082	18,082	16,460	16,167
left window	79.16	79.16	49.83	33.38
right window	31.12	31.12	18.00	33.38
Parents education: primary				
Admitted	-0.03***	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
P-value	0.01	0.42	0.69	0.55
Bias corrected SE		0.01	0.01	0.01
Dep var mean	0.32	0.32		
N	20,813	20,813	18,511	17,866
left window	101.10	101.10	57.48	38.20
right window	31.46	31.46	20.52	38.20

Notes: All covariates are pre-admission family and individual characteristics. Columns 1 to 4 present estimates from a local linear regression around the admission cutoff. Admitted represents a dummy for being above the cutoff. Local linear regressions are estimated in the optimal selected bandwidth using the rdrobust package. Column 1 include major and admission cycle fixed effects. Column 1-3 use asymmetric optimal selected bandwidth. MSE =mean square error. CER= Coverage Error Rate. Observations here are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: RD Validity: Covariates Balance (cont.)

Dependent Variable	(1)	(2)	(3)	(4)
Parents education: secondary				
Admitted	0.00	-0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
P-value	0.95	0.68	0.72	0.96
Bias corrected SE		0.01	0.01	0.01
Dep var mean	0.38	0.38		
N	20,441	20,441	20,000	18,420
left window	97.84	97.84	67.10	40.79
right window	29.77	29.77	22.55	40.79
Parents education: College two-year degree				
Admitted	0.03***	0.02**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
P-value	0.00	0.02	0.33	0.30
Bias corrected SE		0.01	0.01	0.01
Dep var mean	0.10	0.10		
N	19,783	19,783	18,705	17,015
left window	91.11	91.11	61.64	34.41
right window	28.03	28.03	18.64	34.41
Parents education: College four-year degree				
Admitted	0.01	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
P-value	0.42	0.83	0.77	1.00
Bias corrected SE		0.01	0.01	0.01
Dep var mean	0.18	0.18		
N	20,779	20,779	17,922	16,516
left window	100.17	100.17	55.10	32.37
right window	31.90	31.90	18.65	32.37
Family income: $\leq$ two monthly Min. wage				
Admitted	0.01	0.01	0.00	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)
P-value	0.44	0.44	0.79	0.21
Bias corrected SE		0.01	0.02	0.02
Dep var mean	0.47	0.47		
N	23,906	23,906	17,445	17,507
left window	66.42	66.42	39.20	22.24
right window	14.31	14.31	8.45	22.24

Notes: All covariates are pre-admission family and individual characteristics. Columns 1 to 4 present estimates from a local linear regression around the admission cutoff. Admitted represents a dummy for being above the cutoff. Local linear regressions are estimated in the optimal selected bandwidth using the rdrobust package. Column 1 include major and admission cycle fixed effects. Column 1-3 use asymmetric optimal selected bandwidth. MSE =mean square error. CER= Coverage Error Rate. Observations here are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Sensitivity check: Symmetric fixed bandwidth

	Optimal	Symmetric bandwidth: points around cutoff				
	Window	50	40	30	20	10
	(1)	(2)	(3)	(4)	(5)	(6)
College graduation						
Admitted	0.091***	0.103***	0.107***	0.105***	0.089***	0.074***
	(0.013)	(0.011)	(0.012)	(0.013)	(0.015)	(0.019)
Dep var mean	0.28	0.29	0.28	0.27	0.28	0.28
N	17,045	19,197	17,392	15,195	12,065	7,953
Annual earnings						
Admitted	3.414***	2.221**	2.267**	2.099**	1.340	0.058
	(0.867)	(0.869)	(0.916)	(1.002)	(1.162)	(1.486)
Dep var mean	27.12	27.44	27.28	27.57	28.25	29.06
N	21,330	17,776	16,023	13,916	11,007	7,329
Outstanding mortgage loan						
Admitted	0.016**	0.009*	0.008**	0.011**	0.008*	0.012*
	(0.008)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)
Dep var mean	0.109	0.109	0.105	0.110	0.106	0.110
N	28,512	22,442	20,326	17,695	14,022	9,258
Any credit card						
Admitted	0.052***	0.046***	0.042***	0.045***	0.046***	0.053***
	(0.013)	(0.012)	(0.012)	(0.014)	(0.016)	(0.020)
Dep var mean	0.502	0.501	0.505	0.502	0.498	0.504
N	22,729	20,455	18,431	15,954	12,596	8,428

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Annual earnings in Col$ millions real value of 2018. Earnings takes the value of zero when there are no formal wages observed. Columns 1 present the preferred specification using the asymmetric MSE optimal selected bandwidth. Columns 2 to 6 present reduced form estimates from a local linear regression, using fixed symmetric windows around the cutoff. Admitted represents a dummy for being above the cutoff. Regressions includes program, year, and semester of admission fixed effects. Observations here are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Sensitivity check: asymmetric bandwidth

	Optimal Window	Asymmetric bandwidth		
	(1)	(2)	(3)	(4)
College graduation				
Admitted	0.091***	0.096***	0.089***	0.104***
	(0.013)	(0.014)	(0.013)	(0.011)
P-value	0.000	0.000	0.000	0.000
Dep var mean	0.280	0.279	0.289	0.295
N	17,045	13,577	16,473	21,773
right_window	23.384	15	10	20
left_window	-50.238	40	60	70
Annual earnings				
Admitted	3.414***	2.689**	2.836***	3.316***
	(0.867)	(1.065)	(0.961)	(0.820)
P-value	0.000	0.012	0.003	0.000
Dep var mean	27.124	27.470	27.540	26.905
N	21,330	12,495	15,232	20,355
right_window	29.671	15	20	40
left_window	-101.635	35	50	80
Outstanding mortgage loans				
Admitted	0.016**	0.020**	0.014*	0.009
	(0.008)	(0.009)	(0.008)	(0.007)
P-value	0.049	0.023	0.077	0.193
Dep var mean	0.109	0.107	0.109	0.111
N	28,512	20,432	23,175	29,458
right_window	22.199	15	20	40
left_window	-135.044	60	80	120
Any credit card				
Admitted	0.052***	0.054***	0.048***	0.051***
	(0.013)	(0.015)	(0.013)	(0.011)
P-value	0.000	0.000	0.000	0.000
Dep var mean	0.502***	0.506	0.500	0.501
N	22,729	14,494	17,664	23,630
right_window	22.719	15	20	40
left_window	-88.370	35	50	80

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Annual earnings in Col$ millions real value of 2018. Earnings takes the value of zero when there are no formal wages observed. Columns 1 to 4 present estimates from a local linear regression around the admission cutoff. Columns 1 present the preferred specification using the asymmetric MSE optimal selected bandwidth. Columns 2 to 4 use asymmetric windows around the optimal MSE bandwidth.Regressions includes program, year, and semester of admission fixed effects. Standard errors reported in parentheses are clustered at the individual level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Sensitivity check: parametric polynomials

	Lineal (1)	Quadratic (2)	Cubic (3)
College graduation			
Admitted	0.091***	0.106***	0.108***
	(0.013)	(0.013)	(0.012)
P-value	0.000	0.000	0.000
Dep var mean	0.280	0.287	0.293
N	17,045	24,135	29,423
right_window	23.384	45.128	57.567
left_window	-50.238	-105.020	-210.536
Annual earnings			
Admitted	3.414***	2.622***	1.532
	(0.867)	(0.942)	(1.078)
P-value	0.000	0.005	0.155
Dep var mean	27.124	27.817	28.761
N	21,330	24,114	24,732
right_window	29.671	44.555	46.468
left_window	-101.635	-127.382	-136.803
Outstanding mortgage loans			
Admitted	0.016**	0.017*	0.019*
	(0.008)	(0.009)	(0.010)
P-value	0.049	0.068	0.056
Dep var mean	0.109	0.110	0.110
N	28,512	33,200	36,213
right_window	22.199	34.504	50.180
left_window	-135.044	-192.813	-256.071
Any credit card			
Admitted	0.052***	0.057***	0.059***
	(0.013)	(0.015)	(0.016)
P-value	0.000	0.000	0.000
Dep var mean	0.502	0.507	0.509
N	22,729	28,961	31,824
right_window	22.719	32.935	45.340
left_window	-88.370	-150.888	-191.509

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Annual earnings in Col$ millions real value of 2018. Earnings takes the value of zero when there are no formal wages observed. Columns 1 present the lineal specification using the asymmetric optimal MSE selected bandwidth. Columns 2 and 3 present the quadratic and cubic reduced form estimates from a local regression, using the asymmetric optimal MSE selected bandwidth. Admitted represents a dummy for being above the cutoff. Regressions includes program, year, and semester of admission fixed effects. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Specification checks

	Base regression (1)	Regression with covariates (2)	First application only (3)
College degree			
Admitted	0.091***	0.093***	0.129***
	(0.013)	(0.014)	(0.015)
Dep var mean	0.280	0.792	0.356
N	17,045	14,366	14,354
right window	23.384	22.108	28.391
left window	-50.238	-66.035	-68.418
Annual earnings			
Admitted	3.414***	2.903***	4.132***
	(0.867)	(0.970)	(0.931)
Dep var mean	27.124	47.903	26.397
N	21,330	17,207	17,195
right window	29.671	27.402	29.555
left window	-101.635	-114.981	-119.263
Outstanding housing loan			
Admitted	0.016**	0.015*	0.016*
	(0.008)	(0.009)	(0.009)
Dep var mean	0.109	0.210	0.108
N	28,512	21,461	21,886
right window	22.199	24.761	27.719
left window	-135.044	-116.858	-123.364
Any credit card usage			
Admitted	0.052***	0.045***	0.055***
	(0.013)	(0.015)	(0.014)
Dep var mean	0.502	0.639	0.489
N	22,729	18,351	18,912
right window	22.719	22.607	31.776
left window	-88.370	-96.892	-95.806

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Column 1 present the baseline lineal specification using the asymmetric optimal MSE selected bandwidth. Column 2 present the same specification but controlling for the covariates age, gender, public high school dummy, parental education (college degree dummy) and low family education dummy. Column 3 present the same specification but with the sample of only the first application. The asymmetric optimal MSE selected bandwidth is recalculated for the presence of covariates in the estimation. Admitted represents a dummy for being above the cutoff. Regressions includes program, year, and semester of admission fixed effects. Standard errors reported in parentheses are clustered at the individual level. Standard errors reported in parentheses are clustered at the individual level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Falsification Test: Placebo cutoff

		Placebo Cutoff							
	0	5	-4	-3	-4	2	3	4	5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
College degree									
Admitted	0.091	-0.03	-0.00	-0.01	-0.03	0.04	-0.01	0.02	-0.01
	(0.013)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
p value	[0.000]	[0.16]	[0.96]	[0.69]	[0.31]	[0.24]	[0.75]	[0.47]	[0.87]
N	17,045	22,826	22,826	22,826	22,826	9,427	9,427	9,427	9,427
Annual earnings									
Admitted	3.414	4.34**	0.76	2.94	0.40	2.61	3.30	0.95	-4.04
	(0.867)	(1.92)	(1.63)	(2.21)	(2.99)	(3.18)	(2.43)	(2.36)	(3.08)
p value	[0.000]	[0.02]	[0.64]	[0.18]	[0.89]	[0.41]	[0.17]	[0.69]	[0.19]
N	21,330	22,127	22,127	22,127	22,127	8,655	8,655	8,655	8,655
Have mortgage loans									
Admitted	0.016	0.00	0.00	-0.03	-0.01	0.00	0.04	0.01	-0.06
	(0.008)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
pvalue	[0.049]	[0.83]	[0.94]	[0.16]	[0.74]	[0.86]	[0.10]	[0.56]	[0.03]
N	28,512	22,826	22,826	22,826	22,826	9,427	9,427	9,427	9,427
Have credit card									
Admitted	0.052	0.02	0.02	0.00	-0.02	-0.03	0.02	-0.02	-0.06
	(0.013)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
p value	[0.000]	[0.39]	[0.52]	[0.97]	[0.58]	[0.39]	[0.54]	[0.60]	[0.08]
N	22,729	21,851	21,851	21,851	21,851	8,523	8,523	8,523	8,523

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Annual earnings in Col$ millions real value of 2018. Columns 2 present the baseline specification at the true admission cutoff using the asymmetric optimal MSE selected bandwidth. Columns 3-10 present the placebo cutoff reduced form estimates from a local regression, using the asymmetric optimal MSE selected bandwidth. Admitted represents a dummy for being above the cutoff. Regressions includes program, year, and semester of admission fixed effects. Standard errors reported in parentheses are clustered at the individual level. P value reported in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Sensitivity Analysis: Donut Hole

		Placebo Cutoff				
	Base regression	0.1	0.2	0.3	0.4	0.5
	(1)	(2)	(3)	(4)	(5)	(6)
College degree						
Admitted	0.091***	0.095***	0.096***	0.098***	0.100***	0.101***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Dep var mean	0.280	0.278	0.276	0.273	0.272	0.271
N	17,045	16,259	16,094	15,714	15,652	15,435
Annual earnings						
Admitted	3.414***	4.058***	4.056***	4.182***	4.470***	4.645***
	(0.867)	(0.935)	(0.943)	(0.966)	(0.981)	(0.973)
Dep var mean	27.124	27.138	27.181	27.123	27.035	26.965
N	21,330	20,410	20,387	19,973	19,683	19,504
Outstanding housing loan						
Admitted	0.016**	0.015	0.016	0.017	0.017	0.020*
	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Dep var mean	0.109	0.130	0.130	0.129	0.129	0.128
N	28,512	22,636	22,017	22,759	22,650	21,753
Any credit card usage						
Admitted	0.052***	0.034**	0.038**	0.038**	0.043***	0.038**
	(0.013)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Dep var mean	0.502	0.598	0.598	0.598	0.598	0.597
N	22,729	18,631	18,352	18,131	17,897	17,927

Notes: Outcomes are pooled 16 to 18 years after admission. Sample includes applications to all five-year programs, excluding teaching school. Annual earnings in Col$ millions real value of 2018. Column 1 present the baseline specification using the asymmetric optimal MSE selected bandwidth. Column 2-6 present the reduced form estimates from a local regression, but dropping the sample in the circle radius around the cutoff. Admitted represents a dummy for being above the cutoff. Regressions includes program, year, and semester of admission fixed effects. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Robustness check: Matching

	base window	Optimal	Alternative windows 10	20	30
	(1)	(2)	(3)	(4)	(5)
Have any national ID number					
Admitted	-0.007**	-0.006	-0.007	-0.006	-0.006
	(0.004)	(0.005)	(0.007)	(0.005)	(0.004)
Control mean	0.971	0.967	0.968	0.967	0.967
	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)
N	34,608	23,230	14,565	21,268	25,928
left window	30	23.8	10	20	30
right window	-80	-23.8	10	20	30
Have adult national ID number					
Admitted	0.022**	0.016	0.020	0.017	0.017
	0.009	0.010	0.017	0.013	0.011
N	33,717	23,749	14,043	20,556	25,159
Control mean	0.8.32	0.837	0.846	0.838	0.837
left window	80	26.5	10	20	30
right window	30	26.5	10	20	30

Notes: Sample in all regressions includes applicants for all five-year programs offered. In the first panel, the outcome is a dummy denoting matching with any national id number, meaning this individual was found in the ICFES Saber records using the name and approximate date of the high school exit examination. In the bottom panel, the outcome is a dummy denoting matching with the adult national id number, required to look out the individuals in earnings and credit records. All estimations are local lineal regressions using kernel weighting. Column 1 presents the estimation in the asymmetric optimal MSE selected bandwidth for the earnings outcomes (closer to 80 points to the left and 30 points to the right of the cutoff). Columns 2 present the lineal specification using the asymmetric optimal MSE selected bandwidth specifically for matching outcomes. Columns 3 to 5 present estimation over fixed symmetric windows. Admitted represents a dummy for being above the cutoff. Regressions include program, year, and semester of admission fixed effects. Observations here are applications. Thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Descriptive Counterfactual

	Full Sample		RD Sample	
	Admitted	No Admitted	Admitted	No Admitted
	(1)	(2)	(3)	(4)
Observations	9,327	20,772	7,320	12,539
any college enrolment	0.574	0.373	0.564	0.375
public university enrolment	0.508	0.142	0.499	0.167
accredited university enrolment	0.56	0.27	0.57	0.3367
any higher education program	0.61	0.45	0.63	0.5203

Notes: Any higher education program denotes enrollment in two years (technological degree) and five-year programs (bachelor's degree). Accredited University indicates the institutions certified as high quality by the Ministry of Education. Sample is the list of applicants to five-year programs to the Public University from 2000 to 2004 excluding the teaching program. The RD sample is the sample for the regression discontinuity specifications in the asymmetric optimal MSE selected bandwidth for the earnings outcomes (closer to 80 points to the left and 30 points to the right of the cutoff). Each observation is one application, individuals could appear more than once. The sample of all-five-year programs includes applications for all majors offered by the university leading to a bachelor's degree.

Table A.10: Labor Market: Additional Outcomes

	Outcomes 16 to 18 years after admission			
	Average Days per year	Probability of earning 1× wmin	2× wmin	3× wmin
	(1)	(2)	(3)	(4)
Admitted	12.19***	0.01	0.04***	0.04***
	(4.65)	(0.01)	(0.01)	(0.01)
Mean dep var control	249.71	0.68	0.51	0.36
N	21,028	21,344	19,214	19,120
right window	22.20	26.85	24.37	23.63
left window	-109.50	-104.87	-82.56	-82.48

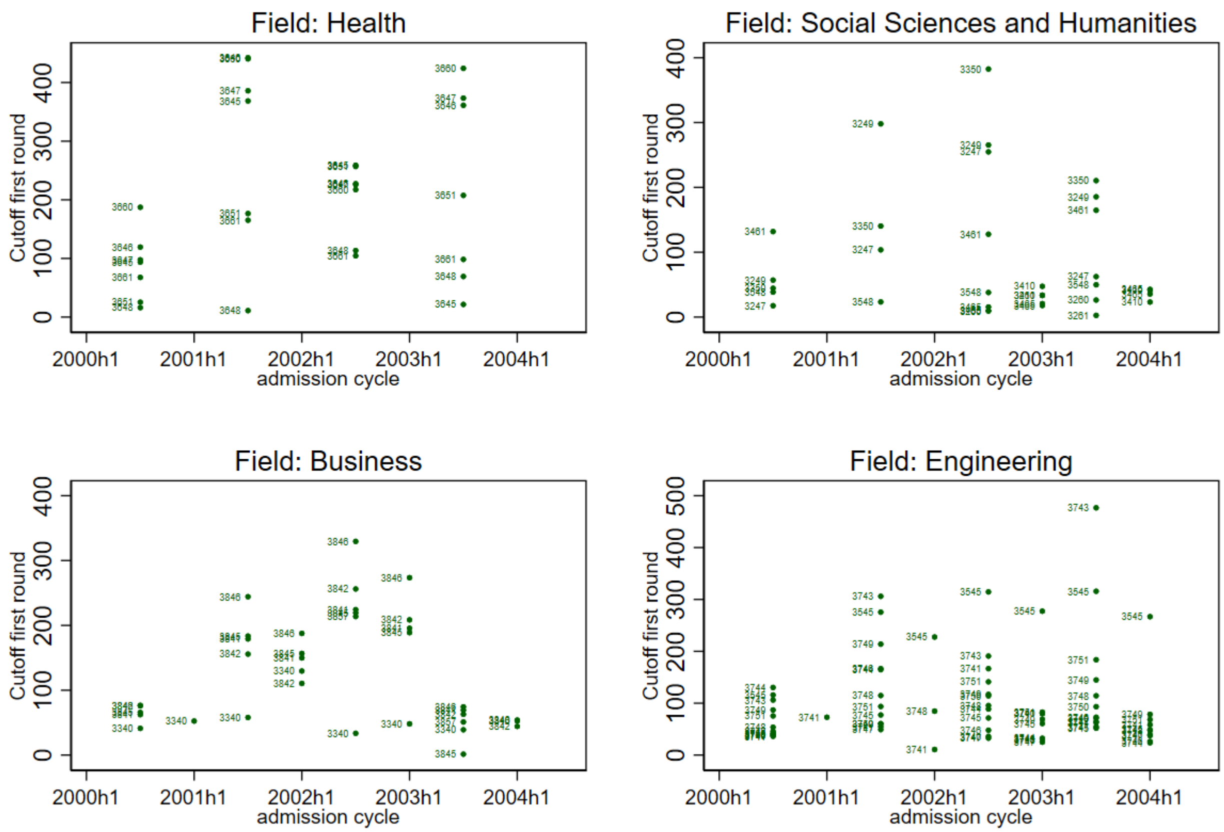
Notes: Outcomes are observed 16 to 18 years after admission. The variable days per year denote the number of days in a formal job reported to the social security within a year. W than X*wmin measures yearly income equivalent to receiving monthly more than x times monthly minimum wages. Left and right windows correspond to the asymmetric MSE optimal bandwidth calculated for each column using the rdrobust package. Regressions include major and admission cycle fixed effects. Observations are applications, thus individuals could appear more than once. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Effects of Public University Admission: Heterogeneous Effects

	College Degree (1)	Annual earnings (millions) (2)	Any housing loan (3)	Any credit card (4)
Public High School				
Admitted	0.09***	0.58	-0.004	0.002
	(0.02)	(0.44)	(0.004)	(0.01)
ci upper	0.12	1.44	0.004	0.02
ci lower	0.06	-0.28	-0.011	-0.01
Dep var mean	0.26	17.40	0.04	0.39
N	10,019	25,311	49,458	41,624
Private Religious High School				
Admitted	0.11***	5.53***	0.03*	0.06***
	(0.02)	(1.96)	(0.01)	(0.02)
ci upper	0.15	9.37	0.05	0.11
ci lower	0.07	1.69	-0.00	0.02
Dep var mean	0.28	26.31	0.13	0.55
N	6,197	4,788	6,197	5,834
Private Non-Religious High School				
Admitted	0.12***	2.71	0.02	0.05*
	(0.02)	(2.08)	(0.02)	(0.03)
ci upper	0.17	6.79	0.06	0.11
ci lower	0.08	-1.37	-0.01	-0.01
Control mean	0.32	35.06	0.22	0.42
N	3,848	3,011	3,848	3,566

Notes:Outcomes are observed 16 to 18 years after admission. Sample includes applications for five-year programs, excluding teaching majors. Columns 1 to 4 present reduced form estimates from a local linear regression around the admission cutoff. Both panels present separate regression results for each subgroup. The window for all specifications is (-70,30), an asymmetric MSE optimal bandwidth calculated for the earnings outcome. Regressions include major and admission cycle fixed effects. Ci upper and lower are the 95% confidence interval. Standard errors reported in parentheses are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

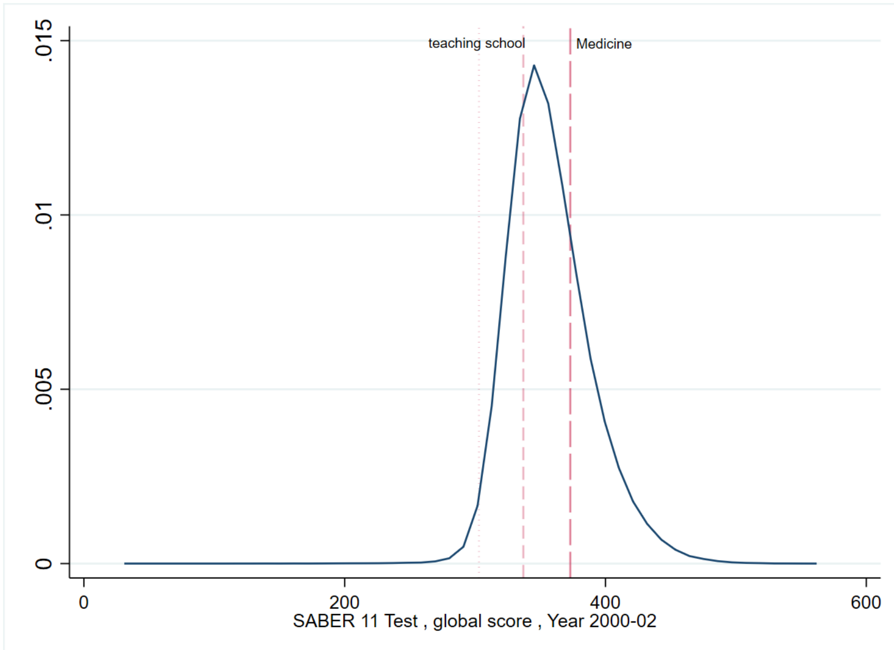
Figure A.1: Cutoff points by field and admission cycle.



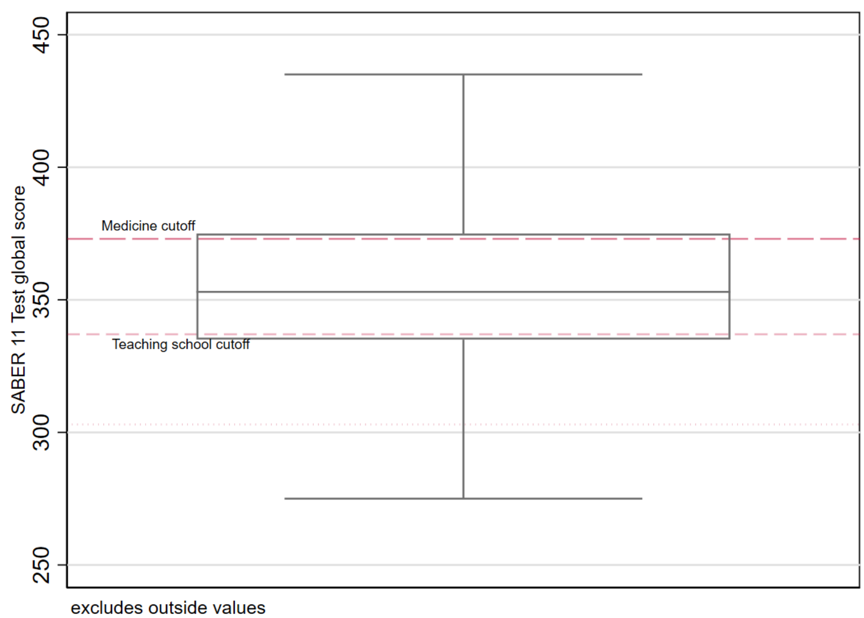
Numbers are codes for majors within each field. Dots are the exact cutoff for each admission cycle-major pair

Notes: Each dot represent a cutoff point for a major. Each graph depicts the biannual admissions cycles from 2000-01 to 2004-01. The majors are classified here by fields.

Figure A.2: Distribution of the score around the cutoff



(a) Distribution SABER 11 national examination test 2000-2



(b) Boxplot SABER 11 national examination test 2000-2

Notes: Figure in the top presents kernel estimation of the distribution for the scores in the national high school exit examination. The figure presents results for the universe of students in the last grade of high school that took the test in 2000-2. On the bottom, this figure presents the boxplot representation. In addition, the figure denotes in red the public university cutoffs for different programs.