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CHAPTER 1

DIRECT AND INDIRECT EFFECTS OF SCHOOLS' SCREENING UNDER SCHOOL CHOICE: EVIDENCE FROM CHILE

Abstract

Competition in educational markets can drive schools to compete for the best educational quality. Schools in practice also compete by implementing selective admission processes, known as screening, competing to attract the best pool of students while avoiding disadvantaged ones. This paper studies the prevalence of these school-side selection mechanisms in a school choice system, their direct impact on students through changes in assignments, and their spillover effects through changes in classroom composition. Using rich administrative data from Chile, evidence indicates that school-side selection in publicly subsidized private schools explains up to 20 percent of their performance gap compared to public schools. Leveraging centralized admission lotteries to simulate counterfactual distributions at individual and classroom levels, we estimate the impact of screening on students' academic performance, college enrollment, and behavioral outcomes. While this shows the value-added benefits of attending selective schools, these effects are of equal magnitude on traditionally accepted and rejected students. These findings oppose school-student fit as the primary driver for screening. In contrast, evidence supports sizable peer effects in classrooms that received lottery-induced shocks to their class composition, potentially explaining schools' implementation of screening practices.

1.1 Introduction

There are several reasons why segregation arises in educational settings. On the demand side, families apply to different schools due to their income levels, residential segregation, preferences for educational quality, and even their preferences for peers (Abdulkadiroğlu et al., 2020, Idoux, 2022). On the supply side, schools often seek to enroll high-income students due to their higher willingness to pay tuition fees, their higher non-school inputs, and flat government subsidies that induce schools to enroll students who are less costly to educate (Epple and Romano, 2008). Moreover, the presence of social interactions and imperfect school quality signals also introduce incentives for schools to implement screening practices in order to enroll students that are attractive to other families (Epple and Romano, 1998; Allende, 2019).

In part due to limitations identifying the effects of these practices, the literature evaluating the effects of school choice on the allocation of students across schools has primarily focused on the aggregate effects of school choice on students' sorting (e.g., Hsieh and Urquiola, 2006) and on demand-side factors, such as the incentives for high achieving students to switch schools (e.g., Muralidharan and Sundararaman, 2015 and Altonji et al., 2015). However, disentangling these supply and demand mechanisms is crucial when designing educational policies. For example, while commonly employed informational campaigns to aid families in their school choice decisions can be highly effective against segregation arising from demand factors, they are futile against sorting emerging from supply-side selection mechanisms, called *screening*.

This paper aims to fill this gap by assessing the prevalence of selection induced by screening, its effects on the equilibrium allocation of students into schools, and its impact on benefited and displaced students. The estimates exploit the staggered implementation of the School Admission System (*SAS*) in Chile starting in 2016, which forced all schools receiving public funding to join a centralized admission system, covering over 90 percent of the nationwide enrollment. This system implemented mandatory lotteries to allocate spots whenever a school receives more applications than their available spots, taking away schools' discretionary power to select students among their applicants.[1] The analysis shows that the introduction of the SAS reduced the baseline achievement of students enrolling in publicly subsidized private schools (*voucher* schools) and high-performing schools. This finding confirms that a portion of the performance premium of these schools comes directly from selection rather than improved school value-added. Moreover, the magnitude of the effect is sizable: the changes in incoming students' standardized scores are equivalent to 20 percent of the average test scores' gap between public and voucher schools.

The Chilean setting is particularly well suited to tackle these questions for several reasons. First, the drastic nationwide change from a largely unregulated admission system to a centralized one restricting schools' screening presents a vastly unusual scenario. In particular, Chile was one of the first to adopt a nationwide school choice system, where public schools (Public), publicly funded private schools (Voucher), and privately funded private schools (Private) must compete to fund themselves by charging tuition fees and by receiving government resources based on enrollment levels. This setting also allows us to use rich administrative data to track student and school-level outcomes over time, analyzing the applications to 31,032 classrooms in 6,123 schools across the country, sequentially reaching the entire population of students.

Sorting into schools has broadly been acknowledged as a primary mechanism for explaining the variance in student achievement (Nechyba, 2006). The proposed framework has two mechanisms to evaluate the impact of the changes in allocations induced by

1. A fraction of these schools can still engage in screening through pricing policies, restricting access to low-income students. However, conditional on their applications, schools cannot alter the selected subset of students.

screening on students' outcomes: direct effects through school enrollment and spillover effects through classroom composition. First, randomness in offers induced by oversubscription lotteries identifies the direct value-added gains of attending selective schools, as in Abdulkadiroğlu et al. (2017) and Angrist et al. (2017). Specifically, by simulating the empirical distribution of schools' admission offers under counterfactual random draws to find students with equal admission propensity to a given school but with different realized offers.[2] To test student-school mismatch theories as drivers for selection (e.g., Sander, 2004), the estimation allows for heterogeneous student-school value-added. Secondly, this methodology exploits the empirical distribution to identify classroom composition effects in a novel way. In particular, this method compares the performance of classrooms with an equivalent ex-ante empirical distribution of changes in classroom composition but with different realized shocks.

One fundamental challenge when assessing the impact of screening practices is that equilibrium allocations of students across schools depend on schools' capacity constraints: admitting a given student requires rejecting another in schools with excess demand. Consequently, evaluating changes to school admission systems requires assessing the impacts on students benefited and displaced by these policies. Defenders of these practices argue that they may improve allocative efficiency by improving the matching between schools and students, potentially benefiting all types of students. In contrast, detractors often claim that these policies introduce segregation, which can negatively impact students' development and increase inequality. The results indicate that low-income students randomly obtaining access to selective schools benefit similarly to their high-income counterparts in terms of college enrollment and standardized test scores. Nevertheless, these changes in peers' allocations affect students through classroom com-

2. Considering that students may reject their offers to apply in a second round or enroll into a pricier unsubsidized private school outside the system, admission acts as an instrumental variable for actual enrollment, as detailed in Section 1.5.1.

position: findings show that changes in peers' backgrounds affect their educational and behavioral outcomes, further enlarging the observed performance gap between selective and unselective schools.

This system implemented with the SAS is a nationwide centralized version of the Deferred Acceptance (DA) algorithm. Before the SAS, schools implemented several screening mechanisms ranging from academic selection, psychological assessments, tuition charges, religious factors, income level verification, and family background checks. Instead, in the new system, all publicly funded schools must report their slot availability before the application period and randomly assign spots among applicants in case of oversubscription. Unsubsidized private schools, which represented 7.8 percent of enrollment in 2015, can freely screen students even after the introduction of the SAS. Most public schools do not perform screening even before the reform, so their admission criteria are predominantly unaffected. Voucher schools could screen students at all levels before the reform, or at grades 7th or higher if they subscribe to a targeted subsidy program (52 percent of students enrolled in voucher schools in 2015 attended program-affiliated schools). In consequence, the SAS halted a large amount of subsidized private schools from employing screening practices.

When analyzing the impact of this screening prohibition, results indicate that the baseline standardized scores of students enrolled in selective voucher schools through the SAS decreased by 0.12 standard deviations. Conversely, the proportion of low-SES students in voucher schools increased by 8.2 percent. High-performing and highly demanded schools follow the same patterns as voucher schools, although with considerably larger magnitudes, given these schools' stricter admission policies before the reform. When interpreting these results, it is critical to consider that applicants' heterogeneity and schools' degree of oversubscription limit the changes to equilibrium allocations induced by the SAS. This constraint arises because the SAS affected the feasibility of supply-side screening but not other factors inducing demand-side differentiation. In turn, demand-side heterogeneity depends on factors such as differences in family preferences, residential segregation, and willingness to pay tuition fees, which are not directly affected by the SAS. These results are intended to complement those by Kutscher et al. (2020), who directly measure the impact of the SAS implementation on school-level segregation, finding that its impacts depend critically on local school supply and residential segregation. However, they do not disentangle supply and demand factors or measure the impact on students' outcomes, which are part of the main contributions of this paper.

Focusing on direct effects, high- and low-income students enrolling in high-performing schools improve their standardized test scores by up to 0.3 standard deviations. However, there are no significant differences between the gains for both groups. The results regarding value-added gains in college enrollment and national admission exam scores are more muted, but there are no significant differences between low- and high-income students. On the other hand, consistently with more demanding standards at high-performing schools, there is a decrease in students' GPA and grade advancement rate. This drop is slightly larger among low-income students, partially explaining the decrease in self-reported levels of motivation observed among low-income students enrolling in high-performing schools. The results are similar when focusing instead on other schools with a small proportion of low-income students or schools with more restrictive application processes, where low-income students were more likely to be rejected before the reform. The minor differences in the value-added gains obtained by high and low-income students oppose commonly held mismatch theories of school selection as drivers behind screening.

When turning our attention to spillover effects, it is essential to consider that the SAS classroom allocations play a prominent role in the Chilean system because students share all their subjects with the same classmates group, usually remaining unchanged for several years. Results indicate positive effects of high-achieving peers on college enrollment and grade advancement: an increase of one standard deviation in classmates' average standardized scores significantly increased their classmates' grade advancement by 8 percent, despite reducing their GPA ranking within the school. Similarly, improving classmates' average standardized scores increases college admission exam scores of their peers in Math and Reading college admission exams.

Besides impacting students' academic performance, increasing classmates' average standardized scores significantly decreases students reported motivation and self-confidence, reducing their school-behavior problems and increasing attendance. These results are consistent with adverse effects on motivation for low-income students attending high-performing schools, reflecting that some students may feel discouraged when participating in classrooms where their peers perform better than them.

Regarding the effects on students attending selective schools, the literature has mainly focused on higher education. In this domain, several authors have identified significant benefits of attending more selective colleges (e.g., Black et al. (2020) in Texas and Otero et al. (2021) in Brazil), although the literature is divided regarding the conditions under which these policies are effective (see Arcidiacono and Lovenheim, 2016 for a literature survey). Indeed, the efficiency consequences of redistributing slots will depend on factors such as the complementarity between students' preparation and schools' value-added (Durlauf, 2008) and private information about student-school match quality (Arcidiacono and Lovenheim, 2016). The focus on higher education is partly due to the widespread application of screening practices in higher education and the comparatively more transparent college admission mechanisms in some countries.[3] However, evidence is scarce in the context of secondary education, particularly in the US, where residential

3. Examples of this are the systems in Brazil and Chile, where precise cutoffs based on national admission exams determine higher education assignments.

and enrollment decisions are highly intertwined, and identification often requires strong structural assumptions.

These results contribute to the broad literature evaluating the impacts of school choice expansion. In particular, most of the literature has not been able to isolate the spillover effects of school choice on students remaining in public schools and those already in private schools (Muralidharan and Sundararaman, 2015). Their study provides an exception by exploiting the experimental expansion of a school choice program in India, finding null spillover effects. However, most private schools in that context are low-cost and cater to non-affluent sections of the population, which is different in Chile or the US. Altonji et al. (2015) present similar non-experimental evidence in the US focusing on the cream-skimming effects of school choice, but they do not separate demand and supply side mechanisms behind the aggregate effects. The results then contribute particularly by isolating the effects of the screening channel and cream skimming on students' stratification and performance.

These findings also contribute to the extensive literature on peer effects in education. In general, the self-selection of students and their parents into schools makes it difficult to disentangle the effects of peers from self-selection into schools. Three ways have been used in the literature to measure and identify peer effects models, experiments (Sacerdote, Sacerdote, Zimmerman, 2003, Carrell et al., 2009, Duflo et al., 2011, Carrell, Sacerdote, and West, Carrell et al., Feld and Zölitz, 2017, Garlick, 2018), quasi-experiments (Gould et al., 2009, Imberman, Kugler, and Sacerdote, Imberman et al., Jackson, 2013, Abdulkadiroğlu et al., 2014, Figlio and Özek, 2019), and social networks (Bramoullé, Djebbari, and Fortin, Bramoullé et al., Calvó-Armengol, Patacchini, and Zenou, Calvó-Armengol et al.). Although experimental peer effects studies in education have a clear identification strategy, most evidence focuses exclusively on post-secondary education in the US and often leverages the random assignment of roommates. This is problematic because peer effects seem to vary considerably depending on the social context (Sacerdote, 2014), presenting a threat to the external validity of these results. These estimates provide valuable measures in the context of a middle-income education system, exploiting a much larger sample and a richer set of outcomes than most previous studies.

The remainder of the paper is structured as follows. Section 1.2 introduces the setting and provides details about the implementation of the SAS. Section 1.3 presents the data sources. Section 1.4 measures the impact of implementing the SAS and explains the empirical approach for these results. Section 1.5 presents the estimation method and results for the direct effects of school enrollment, and 1.6 shows the estimates of the spillover effects of classroom composition. Section 1.7 concludes.

1.2 Background: The Chilean System Before The SAS

There are three types of schools in Chile: public schools, private voucher schools, and non-subsidized private schools.[4] The first two types are publicly subsidized and represent over 90 percent of schools in Chile. The voucher system consists of monthly payments per student enrolled, varying depending on the student's socioeconomic background and school attendance. Before 2015, the state fully funded all public schools, while 37.1 percent of private voucher schools had copayment systems. The copayment system allows subsidized private schools to charge fees to students on top of the public voucher. In 2019, just 18.1 percent of voucher schools charged a copayment in response to reforms to the educational system.

An essential feature of the Chilean school system is that schools must compete to attract families. Given that families cannot easily distinguish the quality of the school

4. There also exist schools with delegated administration that correspond to a separate category, representing 1.3 percent of enrollment in 2015. This group is merged into public schools in the analysis.

from the skills of the students in it, schools have powerful incentives to select students by their academic performance and economic status. Unlike educational districts in the US, families do not face restrictions in choosing a school depending on their neighborhood or residence, enhancing competition across neighborhoods. However, distance is a relevant factor in families' decisions (e.g., Gallego and Hernando, 2009). On top of this, schools may also find it easier to educate students from more advantaged backgrounds who can pay higher tuition fees, placing additional incentives to select them. This difficulty was recognized by the Chilean authorities, leading them to implement a program with larger vouchers for students from lower socioeconomic status (SEP, by its acronym in Spanish). Despite this, the preferential subsidy only differentiates students into three broad income groups, leaving plenty of space for sorting within such groups. Moreover, the extra voucher payments do not necessarily offset the additional cost of educating these students, as reflected by schools' reticence to enroll these students.

Before the school system reform, school admission policies were highly unregulated for private voucher schools and unsubsidized private schools. In comparison, most public schools could not select students based on their characteristics. In turn, private schools in Chile have been practicing school-side selection since the system's original implementation. This sorting arises directly from copayments made by families, restricting access to students based on socioeconomic status and parents' valuation of education. However, tuition fees explain only part of the observed segregation. Other screening mechanisms, such as academic selection, psychological assessments, religious considerations, and family background checks, play a role even within schools with comparable prices and affect students' sorting more obscurely.

The Chilean school system has high levels of segregation by socioeconomic status. Using the Duncan Dissimilarity Index, Valenzuela et al. (2014) estimate that in order to have a homogeneous distribution of students in the lowest 30th percentile across schools, it would be necessary to transfer between 54 and 60 percent of these low-income students from schools with high to low concentrations of disadvantaged students. They also find that school SES segregation was comparatively more elevated than Chilean residential segregation. This fact indicates that segregation cannot be explained exclusively by location factors, where factors like cream skimming can play a role in exacerbating the differences.

Schools' side selection has been controversial in Chile for several years. Following significant reforms in 2009, Chile prohibited selection based on academic or socioeconomic factors for children up to 6th grade in all schools receiving public funding (i.e., all except fully private schools). However, selection remained admissible at 6th grade or below when it was allegedly based on other factors, such as religion or adherence to the institution's values. This vague definition opens a window for blurry screening mechanisms that can maintain schools' screening based on other hidden factors, including socioeconomic level.

Since its implementation in 2009, the Preferential Subsidy Law (SEP, for its acronym in Spanish) also forbids schools voluntarily adhering to a special subsidy for low-income students to select students based on academic or socioeconomic reasons. About half of the students attending voucher schools in 2015 attended schools that opted into the program. This program places a double prohibition against screening in these schools up to 6th grade. In practice, however, the tolerance of screening by alternative motives and the difficulty monitoring have called the effectiveness of the verification mechanisms into doubt (e.g., Carrasco et al., 2014). Despite this, estimations focus on 7th grade and above to avoid comparing groups with highly imperfect compliance before the SAS implementation.

In 2015, the Chilean Ministry of Education promulgated the School Inclusion Law with a broad objective of equal access to education. This regulation changed the admission process for all publicly subsidized schools, representing over 90 percent of enrollment, implementing a series of changes in the education system. The major reforms were the gradual termination of schools' for-profit allowance, the gradual elimination of parents' copayments in voucher schools, and prohibiting selection based on social, religious, economic, or academic criteria through the implementation of the SAS. However, the deployment of the other programs followed different patterns than the SAS, allowing for more gradual adjustment periods for schools.

The School Admission System (SAS) is a nationwide system that adapts the Deferred Acceptance (DA) algorithm to Chilean law requirements. In particular, the SAS guarantees their current seats to students applying to switch schools and favors the assignment of siblings and children of parents who work in the same school. It also introduced reserved quotas by socioeconomic level, prioritizing 15 percent of vacancies for students from disadvantaged backgrounds.[5] For these adaptations, the SAS defines priority groups and runs independent lotteries on each group to break ties randomly.[6]

The Chilean Ministry of Education started implementing the SAS in 2016 with a staggering design across regions and grades. It started in the least populated region in southern Chile, and in its first year only covered pre-k, kinder, first, seventh, and ninth grades. The school assignment mechanism expanded sequentially, adding four regions in 2017 and the remaining ten in 2018, as depicted in Figure 1.1. In 2019, the SAS was entirely in place for the whole country from Pre-Kinder to 12th grade.

The introduction of the SAS switched school applications from a completely decentralized system to a unique application platform where all students must submit their rank-ordered list, including as many entrances as desired. On the other hand, schools

5. The system also considers spots for students with special education needs and high achieving students. However, these only apply to a limited subset of schools.

6. For more detailed information on the algorithm and the computational perspective, see (Correa et al., 2019) on the mechanism design of the school assignment algorithm.

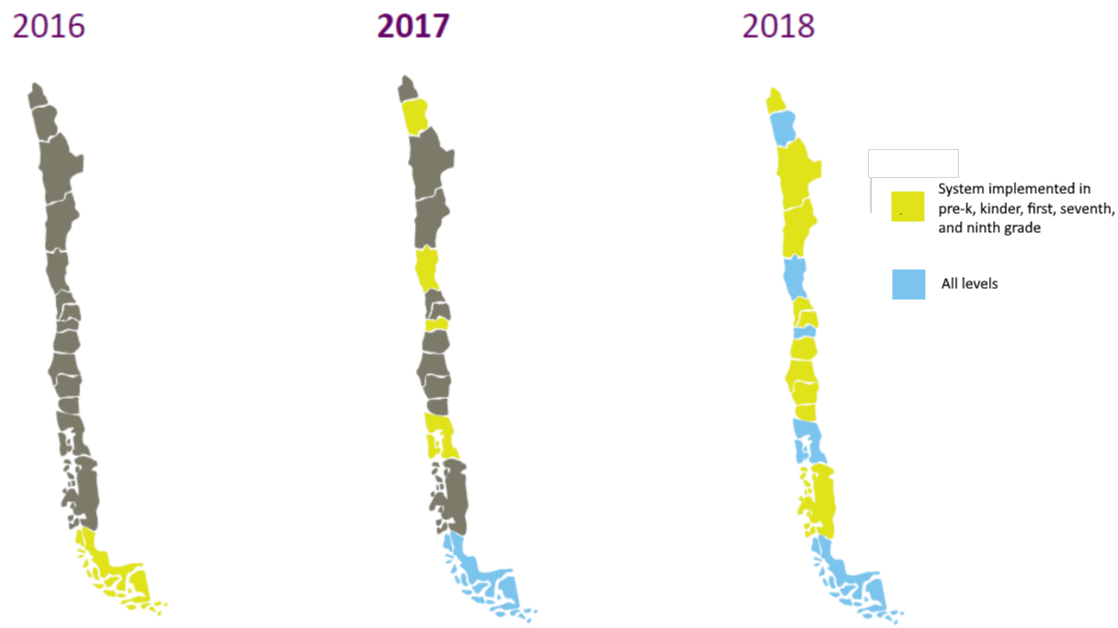


Figure 1.1: Staggered Implementation of the School Admission System (SAS)

Source: Ministry of Education of Chile. Divisions in the map represent the administrative geographical divisions of regions in Chile.

must declare their slots' availability to the Ministry of Education, and they are available on the platform at the time of application. The system then runs the DA algorithm to match schools and students, offering admission offers to students, placing them on a waitlist, or assigning them to the closest school with available spots. Once these vacancies are assigned, families can accept their allocation or participate in a second round. If families accept their admission offer, the offers become binding, and schools must enroll all those students. If families do not accept their offer, they must participate in the second stage or apply to unsubsidized schools outside the system. The process is repeated, but families must compete for unassigned vacancies after the first round. Across the first two years of the SAS implementation, 91.1 percent of students got assigned to a school in their first-round applications. Overall, 69.3 percent of students enroll in the school assigned during the first stage. Hence, the analysis focuses on the assignments from the first application stage for the remainder of the analysis.

1.3 Data

Enrollment data. Administrative panel data from the Ministry of Education, including student-level enrollment information from 2016 to 2022. The data includes records of all students in the country regardless of the type of institution. This source also contains GPA and school attendance data, SEP eligibility (targeted voucher for low SES students), and basic demographic information.

The GPA in the Chilean school system takes values between 1 and 7. Since the relative position of a student's classroom achievement changes when the new students arrive, estimates include both raw and standardized GPA. Attendance is measured from 1 to 100 and is the percentage of school days a student attended during the academic year. National standardized test scores from the SIMCE exams allow for comparison of learning outcomes across schools at 4th, 6th, and 8th grades performed between 2015 and 2017. The exams include math and language sections and a third subject that varies across years and grades. Only the former two exams are considered since they are available for all grade levels in the sample. SIMCE exam takers also respond to a household composition and socioeconomic status survey. Finally, data contains college enrollment data and college admission exam scores linkable to secondary students using anonymous identifiers.

Applicants' data. Data from the Ministry of Education containing individual-level applications' data. This data comprises the complete list of schools each student applies to, the order in which they list their preferences, and students' classification as vulnerable and high-performance. This source also includes detailed information about vacancies in each grade and school for each applicant type. Due to data availability, the analysis focuses on applications occurring in December 2017, 2018, and 2019, covering students who start the following school and calendar year in March at their new institutions (2018, 2019, and 2020 academic years). Among them, sixth-grade or below students are excluded from estimations since selection was prohibited before the reform. Across all levels, there were 76,821 applicants in 2017, 274,990 applicants in 2018, and 483,070 applicants in 2019. Among them, 30,317 applicants were above sixth grade in 2017, 107,165 in 2018, and 175,497 in 2019.

School's supply. Schools participating in the school admission system must inform the Ministry of Education of all the slots and vacancies available at each grade level. The sample's average slots per grade level are 56.5 (divided in some cases into several classrooms), and the average number of vacancies is 24.4. However, the median grade-level size and vacancies are smaller, at 40 and 12, respectively, indicating that most schools offer a single classroom per level. The number of vacancies also displays high variation across levels, mainly driven by the larger quantity offered in 9th grade by high schools. Overall, 68.8 percent of courses had at least half of their slots already occupied by current students. Moreover, 22.2 percent of the classrooms filled all their original vacancies (some new vacancies can open if current students switch to a new school).

Schools' Screening Parents' survey data identifying schools using selectivity policies before the government implemented the centralized admission system. While schools do not directly report these policies on their own, parents of students taking the SIMCE standardized exams are surveyed about the requirements they had to fulfill when applying to their respective schools. We then focus on parents of new students entering the most recently available year before the implementation of the SAS to account for the most recent admission policies within these schools. The most common types of requirements were grade certificates and parent interviews. However, since most schools require these, it becomes less informative about their selectivity.

On the other hand, psychological assessments and evaluated games are most common among voucher schools. These assessments are associated with schools that filter their students more thoroughly. One caveat is that parents' ability to recall the application process can limit the reliability of this data. Carrasco et al. (2014) survey school principals and contrast the results with those reported in the SIMCE questionnaires, finding highly consistent results in both sources. They also find that schools differ in their preferred screening mechanisms, with schools taking students from higher SES backgrounds showing more selective policies.

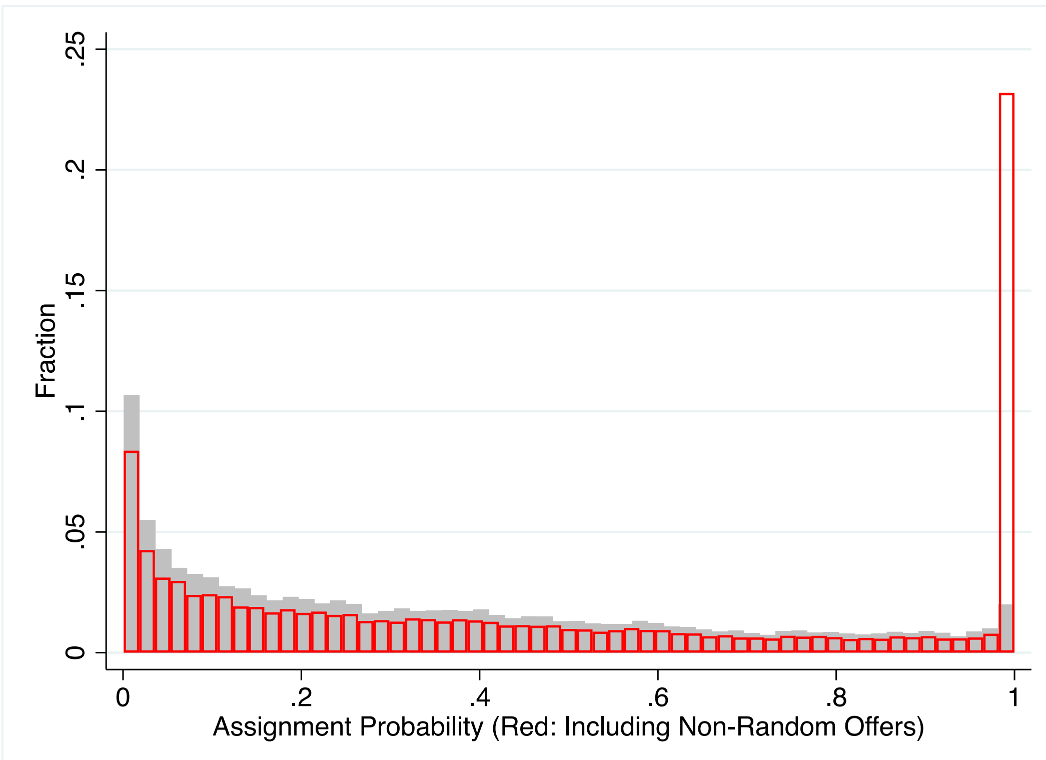


Figure 1.2: Assignments' Variability: Proportion of Assignments to a Given School

Note: the horizontal axis represents the proportion of the simulations a student gets assigned to a given school, and the vertical axis represents the fraction of occurrences of such a case. For example, students assigned to a given school in 80 percent of the simulations represent about 1 percent of the sample.

Algorithm data. The Chilean implementation of the Deferred Acceptance (DA) algorithm allows no preferences from the schools' side, forcing them to select students based on a random number whenever there is oversubscription. As a result, these lotteries introduce randomness in the admitted applicants' set in oversubscribed schools. Specifically, 52.9 percent of students have at least some variation in their assigned schools when changing the corresponding seed in the random process.[7] Figure 1.2 shows the high degree of variation in the schools to which students are assigned. For example, this figure shows that around 2.5 percent of students are assigned to one of their choices just 40 percent of the time, meaning that the remaining 60 percent get assigned to a combination of different schools.

1.4 Effects of Screening On Students' Allocation

1.4.1 Empirical Approach: Exploiting Staggered Implementation

The new admission system induced a significant shift in students' enrollment patterns. Specifically, it allowed numerous students to enroll at schools that would have rejected them before the reform. Consequently, we start by measuring the effects of prohibiting schools' side selection on enrollment patterns. Specifically, we contrast enrollment changes generated in schools forced to halt their selection practices with those schools that did not implement exclusionary practices even before introducing the new system. In particular, the SAS was initially introduced only in a subset of regions and sequentially for specific grades within these regions, as illustrated in Figure 1.1. We then estimate the following model:

$$y_{i,j,t} = \alpha + \beta Selective_j \times SAS_{g,r,t} + \gamma Selective_j + \delta SAS_{g,r,t} + \theta_j + \eta_t + \phi_g + \varepsilon_{i,j,t} \quad (1.1)$$

7. Given that the algorithm works in a staggered fashion, it is necessary to replicate the entire allocation under a different seed to compare for randomness. This is because availability may cascade depending on whether students get assigned to their higher-ranked options.

Where $y_{i,j,t}$ represent the outcomes of incoming student i in school j at time t, $Selective_j$ indicates whether the school j implemented selection practices before the SAS, $SAS_{g,r,t}$ indicates whether the SAS was functioning on grade g in region r at time t, and θ_j, η_t, and ϕ_g are school, year, and grade fixed effects. This model thus captures the differential changes in incoming students induced by the SAS in selective and non-selective grades and schools, measured by the coefficient β. In addition, by comparing different grades within the same school, we aim to isolate the effect of concurrent reforms, which did not follow a staggered implementation as the SAS.

We interpret the estimated effect as measuring the effect of supply-side responses on school enrollment. While selective schools were the most affected by the introduction of the SAS, one potential caveat to this interpretation is that the centralization of applications can also provoke changes in the demand side, leading families to submit different applications (e.g., Idoux, 2022). However, that would only represent a problem when estimating the supply side responses if the SAS implementation affected applications systematically different at those grades within a school that were exposed to the SAS at different years due to the staggered implementation. Moreover, outside options in the Chilean system are highly limited to high-income families who can pay for unsubsidized private schools since the system implementation occurred in entire regions. These schools outside the system are considerably more expensive, employ stricter screening processes, and only enroll less than 8 percent of students.

1.4.2 Estimation: Students' Sorting Across Schools

As detailed in Section 1.4.1, this specification exploits the staggered implementation of the SAS across grades and regions to measure the impact of school screening practices on students' allocations across schools. Specifically, we analyze the differential impact of the introduction of the SAS on formerly selective and unselective schools to estimate the effects of school selection.

We begin in Table 1.1 by showing the changes in the background characteristics of students enrolled in Voucher schools. Specifically, Panel A in this table shows that the introduction of the SAS significantly decreased the background achievement and income level of students enrolled in voucher schools compared to other school types. The baseline standardized scores and GPA of new students enrolled in voucher schools through the SAS decreased by 0.12 and 0.08 standard deviations. In comparison, the gap between the average standardized scores of public schools and voucher schools able to select students before the SAS was around 0.6 standard deviations, thus reducing this difference by 20 percent. Conversely, the proportion of low-income students in voucher schools significantly increases by 2.1 percent, representing an 8 percent increase compared to their pre-SAS levels. In comparison, their income per capita is 9 percent lower. This confirms that the SAS introduced voucher schools to accept higher rates of disadvantaged students.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Std. Scores SIMCE	Raw GPA [1-7]	GPA Rank	Attend. [1-100]	Low SES	Income per capita	Mother w/ High School
Panel A: Voucher Schools							
SAS Level	0.003	0.051***	0.063***	0.546***	0.056***	-0.029***	-0.010***
	(0.007)	(0.006)	(0.008)	(0.065)	(0.003)	(0.005)	(0.003)
Voucher	-0.122***	-0.095***	-0.083***	-1.075***	0.021***	-0.091***	-0.027***
× SAS Level	(0.024)	(0.013)	(0.018)	(0.090)	(0.005)	(0.009)	(0.004)
N	583,730	1,015,469	1,012,693	1,015,471	1,401,676	708,213	738,928
Panel B: High-Performing Schools							
SAS Level	0.027***	0.048***	0.061***	0.492***	0.035***	-0.054***	-0.017***
	(0.007)	(0.005)	(0.008)	(0.067)	(0.003)	(0.005)	(0.003)
High-Performing	-0.222***	-0.174***	-0.189***	-1.496***	0.041***	-0.103***	-0.023***
× SAS Level	(0.046)	(0.022)	(0.033)	(0.171)	(0.013)	(0.023)	(0.008)
N	406,142	758,618	756,610	758,616	836,523	524,171	545,475
Panel C: High Demand Schools							
SAS Level	0.007	0.056***	0.066***	0.583***	0.055***	-0.028***	-0.011***
	(0.007)	(0.006)	(0.009)	(0.069)	(0.003)	(0.005)	(0.003)
High-Demand	-0.118***	-0.107***	-0.103***	-1.136***	0.026***	-0.082***	-0.022***
× SAS Level	(0.022)	(0.012)	(0.017)	(0.092)	(0.005)	(0.009)	(0.004)
N	553,560	973,504	970,768	973,506	1,330,157	684,546	706,235

Table 1.1: SAS Adoption: Changes in New Students Enrollment by School Type

Each observation corresponds to a school switcher on a given year to compare trend changes in students enrolled at each school. Outcomes correspond to the background characteristics of the incoming students enrolled at each school. Voucher schools are publicly subsidized private schools. High-performing schools are those identified by the Ministry of Education as having good test scores given their socioeconomic composition. High-demand schools are those experiencing oversubscription at any of their classrooms during the first three years of the SAS implementation. Robust standard errors clustered at the school level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

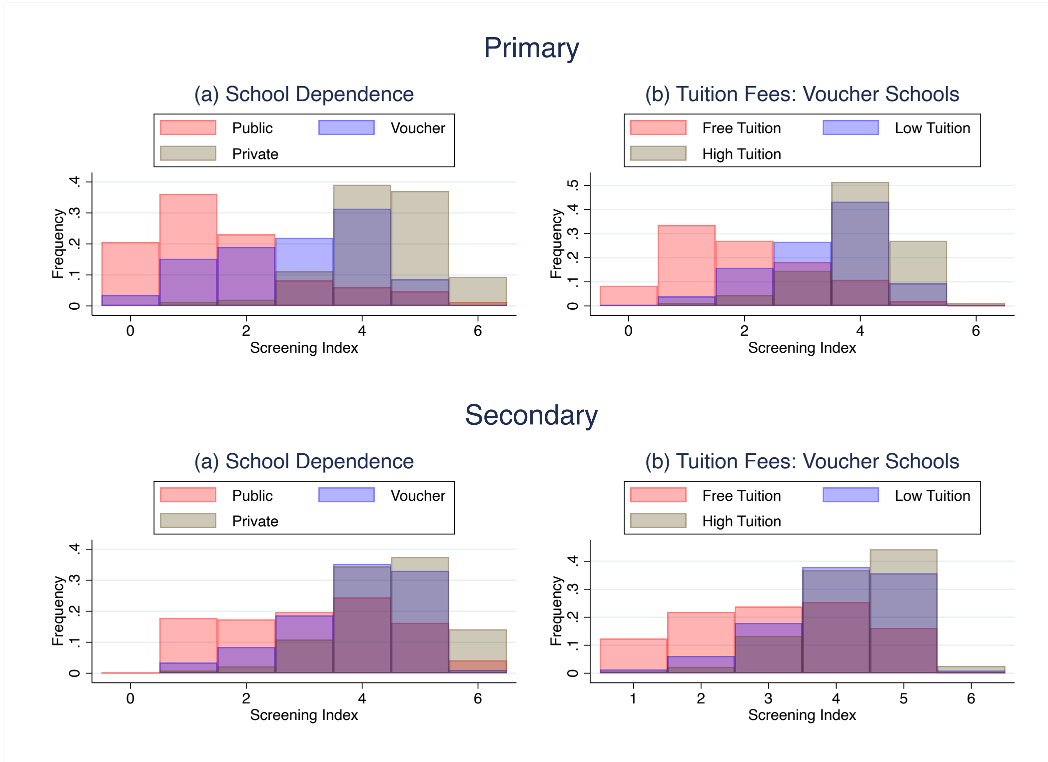


Figure 1.3: School Screening Index by Level, School Dependence, and Tuition Fees

Note: Selectivity index based on parents' response about the screening process when joining the school before implementing the centralized admission system. The index measures whether parents report having gone through a screening process including each of the following: grades certificate, personal interview, preschool certificate, admission exam, psychological assessment, and game dynamics. Panel (a) pools all school dependences, and panel (b) includes voucher schools exclusively since public schools do not charge tuition fees and private schools' admission system was not affected by the SAS.

Numerous practices associated with selective schools can act as a proxy for selectivity. Nonetheless, no single variable perfectly identifies schools that implemented exclusionary policies before preferences were collected, prior to the enactment of the SAS. Instead, we rely on a series of selective practices to construct a screening index that measures the number of screening practices families had to undergo to enter their current schools. We construct this using parents' responses to a nationwide survey implemented alongside standardized exams. Figure 1.3 illustrates this index, reflecting the high asymmetry in screening practices by school dependence, tuition fees, and educational level. In particular, private and highly-priced schools are the most selective, while secondary schools are more selective than primary schools. This pattern directly reflects the prohibition for public schools and a share of voucher schools to screen their students before 7th grade. Henceforth, we focus on 7th grade and above in the analysis.

When interpreting these results, it is crucial to consider that the variability in the characteristics of the applicants to a given school and the degree of oversubscription limits the changes to equilibrium allocations induced by SAS. This variability depends on family preferences, residential segregation, tuition fees, and local schools' supply. This intuition is confirmed when focusing on high-performing and high-demand schools in Panels B and C from Table 1.1. High-performing schools correspond to those the Ministry of Education identified as highly effective, given their socioeconomic composition. High-demand schools correspond to those receiving more applicants than their available slots at any grade during the first three years of implementation of the SAS. This definition is conservative, as some schools are slightly oversubscribed and randomize a small subset of their slots. Moreover, while most high-performing schools are oversubscribed, many oversubscribed schools are not high-performing.

The results indicate that high-performing and high-demanded schools follow the same patterns as voucher schools, although of considerably larger magnitudes. Specifically, these schools experienced a substantial decrease in their admitted students' background achievement, reflected by a decrease in the average baseline standardized scores of 0.22 and 0.12 standard deviations with the introduction of the SAS. Similarly, their lagged GPA decreased by 0.19 and 0.11 standard deviations, and their students attended class significantly less before switching to their new schools. Finally, columns (5) through (7) indicate that the proportion of low-SES students in high-performing schools increased by 410 basis points, representing a 20.6 percent increase compared to the initial proportion of low-SES students. This change is equivalent to a 9.1 percent decrease in the average income of the students getting access to spots at publicly subsidized high-performing schools. This pattern is repeated among highly-demanded schools, where the proportion of admitted low-SES increased by 2.6 percentage points, representing a 10.4 percent increase compared to the baseline levels of low-SES enrollment.

Table 1.2 inquires further into the effects of the adoption of the SAS and the prohibition of school screening on the distribution of students across schools by splitting results by tuition charges. Consistently with the results above, Panel A shows that high-priced schools are the most affected by the implementation of the SAS, decreasing the average baseline scores of their newly admitted students by 0.15 standard deviations. Mid-priced schools also experienced a decrease in the baseline SIMCE scores of their admitted students, although the size was moderate, at 0.05 standard deviations. In contrast, schools that do not charge tuition, which do not typically implement high-screening practices, did not see significant differences in their enrolled students and potentially even experienced an increase in their average income.

We complement this analysis by comparing changes in enrollment of grades that forcefully adopted admission lotteries against those that did not within a given school and year. These results are displayed in Appendix A.1. While this comparison has the appeal of controlling by school-specific characteristics that vary over time, it is also more susceptible to within-school spillovers. For instance, the mandatory adoption of the SAS at specific grades may affect admission policies at other grades within the same school. Nevertheless, the results are robust to this alternative specification, confirming the significant changes in enrollment patterns at formerly selective schools introduced by the SAS.

1.5 Direct Effect: Heterogeneous Schools' Value-Added

	(1) Std. Scores SIMCE	(2) Raw GPA [1-7]	(3) GPA Rank	(4) Attend. [1-100]	(5) Low SES	(6) Income per capita	(7) Mother w/ High School
			Panel A: High-Priced Schools				
SAS Level	0.000	0.048***	0.058***	0.506***	0.057***	-0.029***	-0.011***
	(0.007)	(0.006)	(0.008)	(0.065)	(0.003)	(0.005)	(0.003)
High-Priced	-0.148***	-0.098***	-0.057*	-1.284***	0.011	-0.137***	-0.030***
× SAS Level	(0.033)	(0.019)	(0.030)	(0.116)	(0.008)	(0.013)	(0.005)
N	578,996	1,007,044	1,004,296	1,007,046	1,387,544	703,103	733,536
			Panel B: Mid-Priced Schools				
SAS Level	-0.008	0.044***	0.057***	0.452***	0.057***	-0.037***	-0.013***
	(0.007)	(0.006)	(0.008)	(0.064)	(0.003)	(0.005)	(0.003)
Mid-Priced	-0.051**	-0.071***	-0.061***	-0.818***	0.020***	-0.042***	-0.011*
× SAS Level	(0.025)	(0.015)	(0.020)	(0.123)	(0.007)	(0.013)	(0.006)
N	578,996	1,007,044	1,004,296	1,007,046	1,387,544	703,103	733,536
			Panel C: Free-Tuition Schools				
SAS Level	-0.008	0.042***	0.057***	0.438***	0.058***	-0.042***	-0.014***
	(0.007)	(0.006)	(0.008)	(0.066)	(0.003)	(0.005)	(0.003)
Free Tuition	-0.017	-0.011	-0.027	-0.187	-0.006	0.033***	0.005
× SAS Level	(0.022)	(0.013)	(0.018)	(0.162)	(0.006)	(0.009)	(0.006)
N	578,996	1,007,044	1,004,296	1,007,046	1,387,544	703,103	733,536

Table 1.2: SAS Adoption: Changes in New Students Enrollment by Tuition Fees

Each observation corresponds to a student who switched schools at a given year to compare trend changes in students enrolled at each school. Outcomes correspond to the background characteristics of the incoming students enrolled at each school. High-priced schools charge between over 50,000 CLP monthly tuition fees, and mid-priced schools charge any tuition fee up to 50,000 CLP. Regressions control by school fixed effects, year fixed effects, and grade fixed effects. Robust standard errors clustered at the school level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

1.5.1 Empirical Approach: Exploiting Admission Lotteries

Following Angrist et al. (2017) and Abdulkadiroğlu et al. (2020), we model the potential outcomes of student i in school j are defined as:

$$Y_{ij} = \alpha_j + X_i^{'}\beta_j + f(\mathbf{X}_j^{-i}) + \epsilon_{ij} \tag{1.2}$$

$$E[Y_{ij}|X_i, \mathbf{X}_j^{-i}, S_i] = \alpha_j + X_i^{'}\beta_j + E[f(\mathbf{X}_j^{-i})|X_i, \mathbf{X}_j^{-i}, S_i] + E[\epsilon_{ij}|X_i, \mathbf{X}_j^{-i}, S_i], \quad j = 1, ..., J \tag{1.3}$$

The direct estimation of this would model give biased estimates because students self-select into schools, and these schools further select among their applicants, potentially based on the match quality measured by ϵ_{ij}. Allowing the peer effects to vary linearly depending on peers' observable characteristics, we can model the peer effects function f as:

$$E[f(\mathbf{X}_j^{-i}|X_i, \mathbf{X}_j^{-i}, S_i] = \sum_{l \in j \setminus \{i\}} X_l' \gamma_{il} \tag{1.4}$$

So the potential outcomes equation becomes

$$E[Y_{ij}|X_i, \mathbf{X}_j^{-i}, S_i] = \alpha_j + X_i' \beta_j + \sum_{l \in j \setminus \{i\}} X_l' \gamma_{il} + E[\epsilon_{ij}|X_i, \mathbf{X}_j^{-i}, S_i], \quad j = 1, ..., J \tag{1.5}$$

Following Angrist et al. (2017), we exploit the variation induced by the lotteries to obtain exogenous shifts on school assignments that are uncorrelated with potential outcomes once we account for students' preferences over schools, yielding an unbiased measure of value-added. Furthermore, we follow the method by Abdulkadiroğlu et al. (2017) to fully exploit the variation induced by lotteries in oversubscribed schools by using the entire distribution of admission offers instead of focusing on first-ranked offers. This allows us to exploit the entire assignments distribution rather than first-ranked option comparisons. In practice, the allocation probabilities have no closed-form solutions in the DA algorithm, so they must be approximated. We make this approximation by computing the assignment probability to a given school for all applicants over several runs of the algorithm with counterfactual lottery assignments. Once we calculate this, we condition on propensity score to obtain conditionally exogenous variation on school admission, producing efficiency gains over alternative methods of exploiting lottery variations.

As in Abdulkadiroğlu et al. (2017), the individual-level stratified randomization introduced by equal treatment of equals (ETE) in the DA algorithm implies that:

$$P(D_i(S) = 1 | X_i = x_i, \theta_i = \theta) = P(D_i(S) = 1 | \theta_i = \theta) = p(\theta) \tag{1.6}$$

Where $D_i(S) = 1$ is the probability that student i will be offered a spot in school j. This indicates that allocation probabilities are independent of students' characteristics X_i once we condition on students' preferences θ. In other words, lottery offers are conditionally independent of student types. Essentially, the variation exploited by this method is parallel to that exploited by propensity score matching. However, the advantage of this method is that the equal treatment of equals (ETE) in the centralized randomization lotteries guarantees the validity of the conditional independence assumption.

The ETE property implies that admission offers are a valid instrument for school enrollment after controlling for lottery assignment strata, as in Angrist et al. (2017). Given that only oversubscribed schools implement lotteries, we can only use this method to compute the value-added measurements of a subset of schools. This implies that the external validity of the value-added effects in oversubscribed schools does not necessarily extend to undersubscribed schools. However, oversubscribed schools are the policy-relevant cases since they are required to understand counterfactual assignments given the observed students' preferences where slots are disputed. The estimated model is the following:

$$Second\ \ Stage:$$

$$Y_{ij} = \alpha_j + AX_j + \epsilon_{ij} = \sum_j 1[S_i = j]1[j = Type](\alpha_j + AX_j) + \chi P_{ij} + \epsilon_{ij}$$

$$First\ \ Stage:$$

$$1[S_i = j] = \phi Admitted_{ij} \times 1[j = Type] + \chi P_{ij} + \eta_j + v_{ij}$$

We estimate this by splitting P_{ij} into bins because it is not continuous in the empirical setting. However, results are primarily unchanged when controlling by P_{ij} continuously.

1.5.2 *Estimation: Performance, College Enrollment, and Behavior*

The quality and characteristics of schools are fundamental for students' future outcomes. Consequently, the analysis in this section measures the impact of attending different types of schools. As explained in Section 1.5.1, we exploit the randomness in school admission offers to students with otherwise identical assignment probability that arise from the property of equal treatment of equals (ETE). We employ this to estimate and compare the effect of attending selective schools for different student types. Moreover, we explore the hypothesis of heterogeneous student-school value-added as a driver for screening by estimating and contrasting value-added at selective schools for benefited and displaced students.

We begin in Figure 1.4 focusing on the impacts of attending different school types on students' college enrollment and standardized test scores. We find that high-performing schools significantly increased Math scores in the national college admission exam for low-income students by 0.2 standard deviations. In contrast, the impact on Reading scores in this test is not significant on low or high-SES students, although the estimates

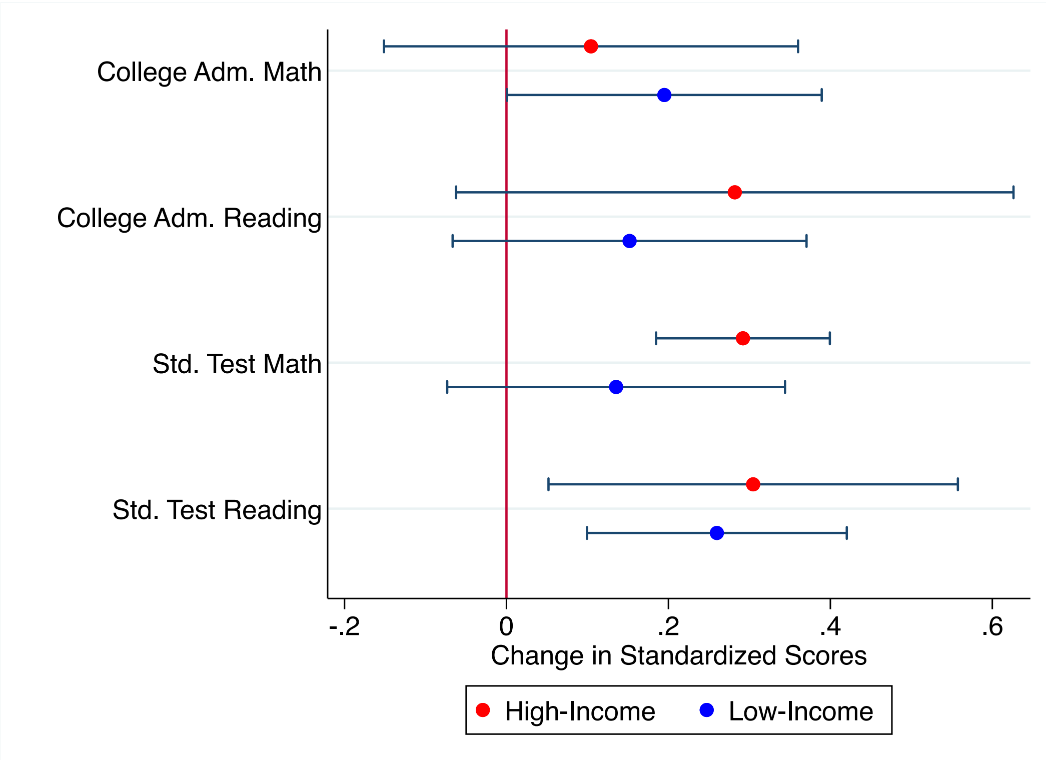


Figure 1.4: Impact of Enrolling in High-Performing Schools by Student Income Level

Note: this corresponds to the coefficient from the instrumental variables estimation as specified in Section 1.5.1

are less precise. Estimates of the effect on 8th-grade standardized scores show that all students enrolling in high-performing schools increased their test scores two years after school assignments. High-SES students significantly increased their math and reading scores by 0.29 and 0.31 standard deviations in Math and Reading. The increase in test scores is only significant in Reading for low-income students, reaching 0.26 standard deviations. These results confirm that these high-performing schools positively affect their students' performance on standardized tests. However, the differences in gains in college admission exams and test scores between high and low-SES students are not significant for any of these outcomes.

We further explore the effects of enrolling in high-performing schools in Table 1.5. The estimates show that enrollment in high-performing schools had no significant impact on the rate at which students take the national college admission exam, their percentile on the exam, and whether they enrolled in college. Consistently with the value-added estimates of high-performing schools, Panel B of Table 1.4 shows similar effects on students enrolling in quota schools. These schools correspond to those with less than 15 percent of low-income students, for which the SAS mandated priority spots for low-income students. They are the prime candidates to screen out low-SES students: over 90 percent had at least two applicants per slot reserved for low-SES students, indicating that the previous scarcity of low-income students arises partly from school-side mechanisms. These schools do not seem as highly effective at raising their students' college admission outcomes or scores as those identified as high-performing, although part of the differences comes from more noisily estimated coefficients. On the other hand, high and low-income students increase their Reading scores when attending highly segregated quota schools by 0.13 and 0.23 standard deviations, respectively. These are large effects considering these students attended their new schools for up to 2 years. However, we still do not find differences in value-added gains between low and high-income students.

	(1) Raw GPA	(2) Std. GPA	(3) Pass Year	(4) Attendance
Panel A: Selective Schools - High Performing Schools				
High-performing * High-SES	-0.166***	-0.403***	-0.030***	0.762
	(0.050)	(0.036)	(0.011)	(0.501)
High-performing * Low-SES	-0.232***	-0.582***	-0.072***	1.213***
	(0.063)	(0.057)	(0.019)	(0.449)
Difference High-Low	0.065*	0.179***	0.042***	-0.451
P-Value	0.085	0.000	0.002	0.229
N	336,912	336,591	348,263	336,913
Panel B: Segregated Schools - Affirmative Action Quota				
Quota-School * High-SES	-0.054	-0.158***	-0.007	0.468
	(0.037)	(0.034)	(0.009)	(0.428)
Quota-School * Low-SES	-0.057	-0.145***	-0.013	0.108
	(0.048)	(0.046)	(0.015)	(0.549)
Difference High-Low	0.003	-0.013	0.006	0.360
P-Value	0.922	0.724	0.553	0.402
N	336,912	336,591	348,263	336,913
Panel C: High-screening Schools				
High-Screening * High-SES	-0.096***	-0.201***	-0.011	0.299
	(0.036)	(0.033)	(0.009)	(0.459)
High-Screening * Low-SES	-0.130***	-0.259***	-0.022	-0.026
	(0.046)	(0.044)	(0.015)	(0.624)
Difference High-Low	0.034	0.058	0.012	0.325
P-Value	0.248	0.117	0.281	0.468
N	336,912	336,591	348,263	336,913
Outcome Mean	5.578	0.014	0.934	91.893
Outcome SD	0.801	0.990	0.249	10.306

Table 1.3: School Enrollment Effect: Students' Performance

Each observation corresponds to a student who applied through the SAS on a given year. Regressions contain fixed effects grouping students of equivalent SEP status (low-income indicator) and similar assignment propensity to a given classroom. Actual enrollment in the school is an instrument using random admission offers. High-performing schools are those identified by the Ministry of Education as having good test scores, given the socioeconomic composition. High-screening schools correspond to parents reporting undergoing more screening processes when enrolling at their respective schools. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

Finally, Panel C in Table 1.4 focuses on high-screening schools, defined according to parents' survey responses about the process they had to undergo to enroll at their respective schools. Again, college admission outcomes follow similar patterns from previous panels with no significant effects. Perhaps strikingly, Math test scores decrease for high-income students enrolling at high-screening schools, and Reading test scores decrease for low-income students, but these estimates are only marginally significant.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Takes Coll.	Enrolled	Exam	Coll. Adm. Exam		8th Grade Std. Test	
	Adm. Exam	in College	Percentile	Math	Reading	Math	Reading
Panel A: High-performing Schools							
High-performing * High-SES	-0.047	0.064	5.968	0.104	0.282	0.292***	0.305**
	(0.071)	(0.095)	(5.312)	(0.130)	(0.176)	(0.055)	(0.129)
High-performing * Low-SES	-0.006	-0.021	3.975	0.195**	0.152	0.135	0.260***
	(0.099)	(0.038)	(4.864)	(0.099)	(0.112)	(0.106)	(0.082)
Difference High-Low	-0.041	0.085	1.993	-0.091	0.130	0.157	0.045
P-Value	0.640	0.402	0.783	0.575	0.512	0.141	0.782
N	42,339	42,339	20,834	20,834	20,834	5,962	5,912
Panel B: Segregated Schools - Affirmative Action Quota							
Has Quota * High-SES	-0.035	0.055	10.032	0.137	0.338	0.077	0.129**
	(0.091)	(0.084)	(9.923)	(0.235)	(0.269)	(0.094)	(0.064)
Has Quota * Low-SES	-0.003	0.002	6.686	0.116	0.137	0.148	0.234**
	(0.075)	(0.057)	(10.659)	(0.237)	(0.260)	(0.110)	(0.092)
Difference High-Low	-0.032	0.053	3.346	0.021	0.201	-0.070	-0.105
P-Value	0.670	0.389	0.590	0.912	0.339	0.623	0.303
N	42,339	42,339	20,834	20,834	20,834	5,962	5,912
Panel C: High-Screening Schools							
High-Screening * High-SES	0.009	0.034	8.963	0.180	0.261	-0.242*	0.187
	(0.077)	(0.074)	(8.080)	(0.193)	(0.213)	(0.143)	(0.188)
High-Screening * Low-SES	-0.000	-0.002	5.570	0.178	0.131	-0.100	-0.600*
	(0.074)	(0.057)	(9.395)	(0.199)	(0.231)	(0.318)	(0.334)
Difference High-Low	0.009	0.036	3.394	0.001	0.130	-0.142	0.788**
P-Value	0.894	0.519	0.517	0.993	0.454	0.673	0.037
N	42,339	42,339	20,834	20,834	20,834	5,962	5,912
Outcome Mean	0.605	0.170	40.229	-0.146	-0.118	0.096	0.160
Outcome SD	0.489	0.375	26.713	0.867	0.855	0.884	0.938

Table 1.4: School Enrollment Effect: College Enrollment

Each observation corresponds to a student who applied through the SAS in a given year. Regressions contain fixed effects grouping students of equivalent SEP status (low-income indicator) and similar assignment propensity to a given classroom. Actual enrollment in the school is an instrument using random admission offers. High-performing schools are those identified by the Ministry of Education as having good test scores, given the socioeconomic composition. High-screening schools are defined according to parents' survey responses about the process they had to undergo to enroll at their respective schools. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

We continue in Table 1.5 by evaluating school enrollment's impact on students' performance. These outcomes are available for the entire sample, allowing for a more comprehensive comparison. The estimates show that low and high-SES students enrolling in high-performing schools decreased their GPA, GPA-Rank, and grade advancement rate. The raw GPA of high and low SES students enrolling in high-performing schools decreased by 0.16 and 0.22 points on the 1-7 scale used in Chile compared to students from similar backgrounds who did not enroll at these schools. Given that different schools potentially have different grading standards, we complement this with a class-standardized GPA measurement, revealing a more considerable decrease of 0.41 and 0.58 standard deviations. Similarly, the estimates also show that students enrolling in high-performing schools decreased their grade advancement rates by 2.3 percent for high-income students and 5.8 percent for low-income students, significantly affecting low-income students more than their high-income counterparts. Despite the adverse effects on GPA, low-income students increase class attendance by 1.2 percent, or 0.12 standard deviations. These performance gaps are unsurprising because the more demanding environment in high-performing schools affects low-income students more intensively than high-income students, mainly driven by the lower academic standards of their alternative schools. However, they may explain the belief that low-income students underperform at these selective schools compared to their higher-income peers despite scarce evidence of this pattern in terms of more comparable measurements such as standardized tests and college admission exams.

Further inquiring into the effect of enrollment in selective schools, Panels B and C of Table 1.5 present an analogous comparison for segregated schools that forcefully reserved spots for low-income students and schools implementing high-screening practices. The results show a similar negative effect on students' GPA when enrolling at these more demanding schools but null effects on grade advancement and school attendance.

	(1) Raw GPA	(2) Std. GPA	(3) Pass Year	(4) Attendance
Panel A: Selective Schools - High Performing Schools				
High-performing * High-SES	-0.166***	-0.403***	-0.030***	0.762
	(0.050)	(0.036)	(0.011)	(0.501)
High-performing * Low-SES	-0.232***	-0.582***	-0.072***	1.213***
	(0.063)	(0.057)	(0.019)	(0.449)
Difference High-Low	0.065*	0.179***	0.042***	-0.451
P-Value	0.085	0.000	0.002	0.229
N	336,912	336,591	348,263	336,913
Panel B: Segregated Schools - Affirmative Action Quota				
Quota-School * High-SES	-0.054	-0.158***	-0.007	0.468
	(0.037)	(0.034)	(0.009)	(0.428)
Quota-School * Low-SES	-0.057	-0.145***	-0.013	0.108
	(0.048)	(0.046)	(0.015)	(0.549)
Difference High-Low	0.003	-0.013	0.006	0.360
P-Value	0.922	0.724	0.553	0.402
N	336,912	336,591	348,263	336,913
Panel C: High-screening Schools				
High-Screening * High-SES	-0.096***	-0.201***	-0.011	0.299
	(0.036)	(0.033)	(0.009)	(0.459)
High-Screening * Low-SES	-0.130***	-0.259***	-0.022	-0.026
	(0.046)	(0.044)	(0.015)	(0.624)
Difference High-Low	0.034	0.058	0.012	0.325
P-Value	0.248	0.117	0.281	0.468
N	336,912	336,591	348,263	336,913
Outcome Mean	5.578	0.014	0.934	91.893
Outcome SD	0.801	0.990	0.249	10.306

Table 1.5: School Enrollment Effect: Students' Performance

Each observation corresponds to a student who applied through the SAS on a given year. Regressions contain fixed effects grouping students of equivalent SEP status (low-income indicator) and similar assignment propensity to a given classroom. Actual enrollment in the school is an instrument using random admission offers. High-performing schools are those identified by the Ministry of Education as having good test scores, given the socioeconomic composition. High-screening schools are defined according to parents' survey responses about the process they had to undergo to enroll at their respective schools. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

To understand the consequences of school change on students' non-academic outcomes, we present in Table 1.6 the impact of school enrollment on students' motivation, self-confidence, school satisfaction, discrimination, and behavioral problems at school. Each of these indices comprises a set of 8th-grade students' survey responses. While we do not find any statistically significant impact on high-SES students, Panel A shows that low-income students decrease their reported motivation and behavior problems by around 0.25 standard deviations. This motivation decrease is consistent with observed decreases in GPA and GPA rank within their classrooms, impacting students' motivation. On the other hand, decreases in behavioral problems at school are also concordant with increases in attendance by these low-SES students. When focusing on segregated schools forced to implement the affirmative action quota and high screening schools in Panels B and C, we do not observe any statistically significant impact on students' non-academic outcomes, except for a reduction in behavioral problems. These results suggest that part of the improvements in outcomes experienced by low-income students are likely to emerge from their better behavior due to changes in their school environment, even when the decrease in performance relative to their classmates may negatively affect their motivation.

	(1) Motivation	(2) Self-Confid.	(3) School Satisf.	(4) Discrim.	(5) Behavior Prob.
			Panel A: High-Performing Schools		
High-Perf. * High-SES	-0.017	-0.008	0.014	0.004	-0.012
	(0.027)	(0.023)	(0.014)	(0.009)	(0.010)
High-Perf. * Low-SES	-0.034**	-0.011	0.007	0.005	-0.021**
	(0.015)	(0.022)	(0.022)	(0.010)	(0.008)
Difference High-Low	0.017	0.003	0.007	-0.001	0.009
P-Value	0.335	0.765	0.558	0.931	0.367
N	6,657	6,636	6,671	6,620	6,599
			Panel B: Affirmative Action Schools		
Quota-School * High-SES	-0.012	-0.007	0.008	0.005	-0.014*
	(0.022)	(0.020)	(0.011)	(0.009)	(0.009)
Quota-School * Low-SES	-0.013	-0.005	0.004	-0.008	-0.018***
	(0.018)	(0.020)	(0.019)	(0.011)	(0.007)
Difference High-Low	0.001	-0.002	0.004	0.013	0.004
P-Value	0.925	0.844	0.751	0.328	0.657
N	6,657	6,636	6,671	6,620	6,599
			Panel C: High-Screening Schools		
High-Screening* High-SES	0.033	0.023	0.001	0.038	0.025
	(0.038)	(0.025)	(0.024)	(0.034)	(0.025)
High-Screening* Low-SES	-0.036	-0.043	-0.045	-0.004	0.064*
	(0.037)	(0.037)	(0.034)	(0.052)	(0.035)
Difference High-Low	0.069	0.067	0.046	0.042	-0.038
P-Value	0.212	0.150	0.265	0.536	0.260
N	6,657	6,636	6,671	6,620	6,599
ControlMean	0.690	0.746	0.511	0.086	0.249
ControlSD	0.138	0.123	0.104	0.122	0.086

Table 1.6: School Enrollment Effect: Students' Behavior

Each observation corresponds to a student who applied through the SAS on a given year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

These results generally confirm that enrollment in selective schools positively affects their students' performance on standardized tests and college admission exams. Although more limited in power, we find no evidence of higher performance by high-SES students, who traditionally enrolled at these schools, and low-SES students, who mostly gained access through the application of the SAS.

1.6 Spillover Effects: Changes in Classroom Composition

1.6.1 *Empirical Approach: Lottery Induced Shocks to Classrooms' Composition*

Returning to the model above, we can have that:

$$Y_{ij} = \alpha_j + \beta_j X_i + \gamma_{i,-i} X^j_{-i} + \epsilon_{ij} \tag{1.7}$$

Where $\gamma_{i,-i} = [\gamma_{i1}, \ldots, \gamma_{i,i-1}, 0, \gamma_{i,i+1}, ..., \gamma_{iN}]$ represents the usual modeling of linear effects of peers on individuals' outcomes (Blume et al. (2015)). When estimating this model, a problem arises because computing the effect of counterfactual allocations requires computing the potential outcomes that depend on school effectiveness (α_j, β_j), exogenous peer effects (Γ), and self-selection parameters (ϵ_j). Unfortunately, individual variation induced by school assignment does not allow us to separately identify the effect β_j and Γ. This is because changes to school assignments also modify the entire set of classmates X^j_{-i}. Instead, $\gamma_{i,-i}$ is identified by exploiting variation in peers characteristics X^j_{-i} induced by the lotteries, while maintaining school assignment j unaltered.

The set of applicants to any given school j is not randomly assigned. Instead, families apply to schools depending on their characteristics and their preferences. Given that the DA algorithm has several rules giving preference to individuals such as siblings or alums, no closed solution exists for the allocation probabilities. However, given the set of applications and capacity constraints, we can use the assignment algorithm under alternative random draws to obtain estimates of the empirical distribution of students across schools. This follows the same logic as Angrist et al. (2017) but expands on it by allowing the estimation of the effect of peers' backgrounds on their classmates' performance.

Similarly to the value-added estimates, we use instrumental variables to estimate the impact of the characteristics of newly enrolled peers' on their classmates in the following second-stage model:

$$\begin{aligned} Y_{i,c,t} = \alpha + \beta \bar{X}_{-i,c,t} + \gamma X_i + \rho_1 \bar{X}^{Appl}_{sg,t} + \rho_2 SAS\_prop_{c,t} \\ + \rho_3 SAS\_prop_{c,t} \times \bar{X}^{Appl}_{c,t} + \theta_{r,g,t} + \varepsilon_{i,c,t} \end{aligned}$$

Where $Y_{i,c,t}$ is the outcome of student i in classroom c and year t, $\bar{X}_{-i,c,t}$ is the average background in of classmates of student i in class c and year t, $\bar{X}^{Appl}_{j,t}$ represents applicants' average background, school j and year t, $SAS\_prop_{c,t}$ is the fraction of new students assigned by SAS on classroom c and year t, X_i are lagged standardized test-score of student i, and θ_j and τ_t are school and year fixed effects

We instrument $\bar{X}_{-i,c,t}$ with the following first stage:

$$\begin{aligned} \bar{X}_{-i,c,t} = \phi_1 + \phi_2 \bar{X}^{SAS}_{c,t} + \phi_2 SAS\_prop_{c,t} + \phi_3 SAS\_prop_{c,t} \times \bar{x}^{SAS}_{c,t} \\ + \phi_4 \bar{X}^{Appl}_{sg,t} + \phi_5 \bar{X}^{Appl}_{sg,t} \times SAS\_prop_{c,t} + \phi_6 X_i + \pi_{rgt} + u_{i,c,t} \end{aligned}$$

Where $\bar{x}^{SAS}_{c,t}$ is the mean of previous standardized test scores of student i's new classmates (randomly) assigned by SAS at classroom c in year t.

Acknowledging the non-linear nature of peer effects (Hoxby and Weingarth, Hoxby and Weingarth; Imberman, Kugler, and Sacerdote, Imberman et al.), we also estimate a more flexible model. First, we classify incumbent students by their previous achievement terciles using the most recent pre-SAS standardized SIMCE test scores. Then we estimate the peer effects for each tercile using the following specification that allows for a heterogeneous effect by incumbent student i achievement level:

$$
\begin{aligned}
y_{i,c,t} = & \sum_{k=1}^{3} (\beta_k \; tercile\_k_i \times \bar{x}_{-i,c,t}) + \gamma x_{i,t-1} + \rho_1 \bar{x}^{Appl}_{sg,t} + \rho_2 SAS\_proption_{c,t} \\
& + \rho_3 SAS\_proption_{c,t} \times \bar{x}^{Appl}_{sg,t} + \theta_{rgt} + \varepsilon_{i,c,t}
\end{aligned}
$$

Where $tercile\_k_i$ is a dummy variable that takes the value of 1 if the student i standardized test score is on tercile k on the school-year standardized test score distribution.

Section A.3 in the appendix presents an analysis of the validity of this instrument.

1.6.2 Estimation: Exogenous Peer Effects

Arguably the most affected by policies modifying the school admission system are those students whose assignment changes with the introduction of the SAS. However, the allocation of students across schools also impacts their classmates through social interactions. This is particularly relevant in the case of large-scale shifts to admission mechanisms, such as the one introduced by the SAS. Moreover, group-level interaction provides an alternative explanation for schools' high degrees of selectivity, particularly in light of the scarce value-added differentials between usually selected and rejected students. Findings from Section 1.4.2 suggest that incoming students' characteristics changed classrooms' composition in several schools. We study how these changes affected students remaining in selective and non-selective schools by measuring the impact of changes in classroom composition on their classmates' college enrollment and other academic and behavioral outcomes. We answer this by exploiting the random allocation of students to schools in oversubscribed schools to estimate a linear-in-means model of peer background effects, also called exogenous peer effects, following the specification from Section 1.6.1. In the primary estimation, we focus on changes in peers' standardized test scores, GPA-Rank within students' previous schools, and the proportion of low-income classmates.

	(1)	(2)	(3)	(4)	(5)	(6)
	School Performance				Standardized Tests	
	Raw GPA	GPA Rank	Attend.	Pass Year	Math	Reading
Panel A: Classmates' Standardized Tests Score (SIMCE)						
Classmates' Scores	0.086	-0.668***	-0.252	0.078***	0.174	0.082
	(0.094)	(0.073)	(3.235)	(0.028)	(0.248)	(0.251)
N	282,672	282,519	282,672	287,388	39,473	39,264
Panel B: Classmates' GPA-Rank (previous school)						
Classmates' GPA-Rank	0.541***	-0.584***	4.844	0.062**	0.226	0.221
	(0.149)	(0.028)	(3.323)	(0.029)	(0.198)	(0.176)
N	916,489	916,485	916,485	922,390	41,178	40,943
Panel C: Classmates's Households Income per Capita						
Household Income	1.380***	1.280***	8.127***	0.095***	0.346	0.085
	(0.194)	(0.346)	(3.050)	(0.033)	(0.381)	(0.340)
N	745,117	744,887	745,114	753,856	37,813	37,490
OutcomeMean	5.751	0.002	92.616	0.964	-0.119	-0.037
SD	0.785	0.984	9.878	0.186	0.940	0.959
IncludesLags	Yes	Yes	Yes	No	Yes	Yes

Table 1.7: Peers' Background Effect: Students' Performance

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

We start by focusing on the impact of classmates' shifts on students' school performance and standardized test scores in Table 1.7. The results in Panel A indicate that an increase of one standard deviation in classmates' average standardized scores statistically significantly reduced their classmates' GPA rank by up to 0.7 standard deviations, a direct consequence of the admission of highly competitive peers. On the other hand, they also increased their classmates' grade advancement by 8 percent. We observe similar effects in Panel B when analyzing the impact of a one standard deviations increase in classmates' average GPA-Rank in their previous schools: GPA-rank decreases by around 0.6 standard deviations in response to shifts toward students with better rankings positions in their previous schools; Grade advancement is positively affected, increasing by 0.6 percent in response to higher performing peers.

Despite confirming the relevance of high-achieving peers towards the academic achievement of their classmates, Table 1.7 also reveals that varying classmates' income levels notoriously affect their classmates' outcomes. In particular, Panel C reveals that an increase of 10 percent in average class income per capita induces an increase in GPA of 0.14 points or 0.13 standard deviations of class-standardized GPA ranking. Similarly, classmates' attendance and grade advancement rates increase by 0.8 and 0.01 percentage points in response to the same average income shift. These results then confirm the high relevance of social interactions in the educative process, partly explaining schools' screening decisions.

	(1) Motivation	(2) Self-Confid.	(3) School Satisf.	(4) Discrim.	(5) Behavior Prob.
Panel A: Classmates' SIMCE Score					
Classmates SIMCE Score	-0.080**	-0.098***	-0.060	0.030	-0.042**
	(0.033)	(0.035)	(0.037)	(0.023)	(0.020)
N	39,165	38,994	39,219	38,961	38,856
Panel B: Classmates' GPA-Rank					
Classmates' GPA-Rank	-0.038	-0.047*	-0.022	0.004	-0.030*
	(0.026)	(0.026)	(0.032)	(0.019)	(0.016)
N	45,860	45,665	45,928	45,622	45,492
Panel C: Classmates' Households Income per Capita					
Household Income	-0.174***	-0.156**	-0.174**	0.018	0.027
	(0.065)	(0.066)	(0.074)	(0.042)	(0.048)
N	39,995	39,816	40,037	39,776	39,684
OutcomeMean	0.692	0.745	0.516	0.083	0.255
SD	0.136	0.122	0.104	0.118	0.089
IncludesLags	No	No	No	No	No

Table 1.8: Peers' Background Effect: Behavior Outcomes

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Besides the impacts on academic performance reported in the previous table, we assess the effect of exogenous changes in classmates' backgrounds on self-declared behavioral outcomes of their peers in Table 1.8. We observe that an increase in their classmates' average standardized scores (SIMCE) by one standard deviation produces a decrease in their reported motivation by 0.08 index points and self-confidence by 0.098, equivalent to 0.12 and 0.13 standard deviations, respectively. Panel B shows that the impact of classmates' past GPA rank has similar impacts on students' behavioral outcomes. However, the effects are minor and not as statistically robust. On the other hand, incorporating high-performing classmates generally improved classroom behavior, as measured by the number of disciplinary faults students commit. Finally, Panel C presents strong evidence that increasing classmates' income per capita by 10 percent decreases their peers' motivation, self-confidence, and school satisfaction by 0.017, 0.016, and 0.017 index points, corresponding to 0.07, 0.13, and 0.17 standard deviations, respectively. Combined, this evidence suggests that, despite their positive effects on academic outcomes., the presence of more highly prepared peers can potentially undermine their classmates' non-academic inputs.

	(1)	(2)	(3)	(4)	(5)
	Take College	Enroll in	Coll. Exam	College Admission Exam	
	Adm. Exam	College	Percentile	Reading	Math
Panel A: Classmates SIMCE Scores					
Classmates' SIMCE Scores	0.260	0.413	34.191**	126.466**	110.551**
	(0.289)	(0.269)	(13.288)	(55.417)	(50.935)
N	71,622	71,622	44,913	44,913	44,913
Panel B: Classmates GPA-Rank					
Classmates' GPA-Rank	0.080	0.632	59.395	341.828	122.425
	(0.645)	(0.814)	(122.028)	(526.585)	(369.880)
N	199,202	199,202	137,522	137,522	137,522
Panel C: Classmates' Households Income per Capita					
Household Income per Capita	0.149	0.320	46.757***	156.560***	170.941***
	(0.223)	(0.196)	(15.057)	(59.723)	(62.381)
N	154,821	154,821	110,770	110,770	110,770
OutcomeMean	0.749	0.298	45.744	476.786	474.114
SD	0.434	0.458	28.093	122.191	127.771
IncludesLags	No	No	No	No	No

Table 1.9: Peers' Background Effect: College Enrollment

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Regarding college enrollment, Table 1.9 shows that improving classmates' average standardized scores and GPA rank by one standard deviation produces an increase in college admission exams of their peers of a similar magnitude in Math and Reading. This is equivalent to a 34 percent improvement in these students' college admission exam percentile. Moreover, point estimations of the effects of peers' GPA-rank report similarly strong responses, although the estimates are highly noisy and not significant. On the other hand, Panel C reports that enrollment of classmates with 10 percent higher household income per capita is associated with an increase in the college exam percentile of 4.7 percent points, corresponding to 0.13 and 0.09 percent in the Math and Reading exams, respectively.

	(1) Any School	(2) Public Sch.	(3) Voucher Sch.	(4) Priv. Sch.
Panel A: Classmates' SIMCE Score				
Classmates SIMCE Score	-0.099***	-0.061***	-0.036*	-0.002
	(0.033)	(0.019)	(0.021)	(0.004)
N	274,773	274,773	274,773	274,773
Panel B: Classmates' GPA-Rank				
Classmates' GPA-Rank	-0.147***	-0.061**	-0.054**	0.002
	(0.044)	(0.026)	(0.026)	(0.004)
N	866,980	866,980	866,980	866,980
Panel C: Classmates' Households Income per Capita				
Household Income	-0.731***	-0.288***	-0.393***	-0.003
	(0.094)	(0.047)	(0.055)	(0.006)
N	715,370	715,370	715,370	715,370
OutcomeMean	0.135	0.060	0.057	0.003
SD	0.342	0.237	0.233	0.053
IncludesLags	No	No	No	No

Table 1.10: Peers' Background Effect: School Switching

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

In light of the mixed impacts caused by peers, we measure in Table 1.10 the effects of changes in peers' backgrounds on school switching patterns. Specifically, as in the previous analysis, we ask whether students shift their enrollment patterns in response to classmates' scores, GPA, and household income. These results indicate that increasing classmates' average standardized scores by one standard deviation decreases school switching by 10 percent, while increasing peers' GPA rank by one standard deviation decreases school switching by 14.7 percent. Moreover, this effect arises from changes in schools switching to public and voucher schools. Finally, Panel C presents similar patterns when analyzing responses to changes in peers' per capita income: increasing average income by 10 percent reduced school switching by 7.3 percent, particularly affecting those switching to voucher schools. These results indicate that families display preferences for high-performing and high-income peers despite their adverse short-term effects on measures such as GPA rank or students' motivation.

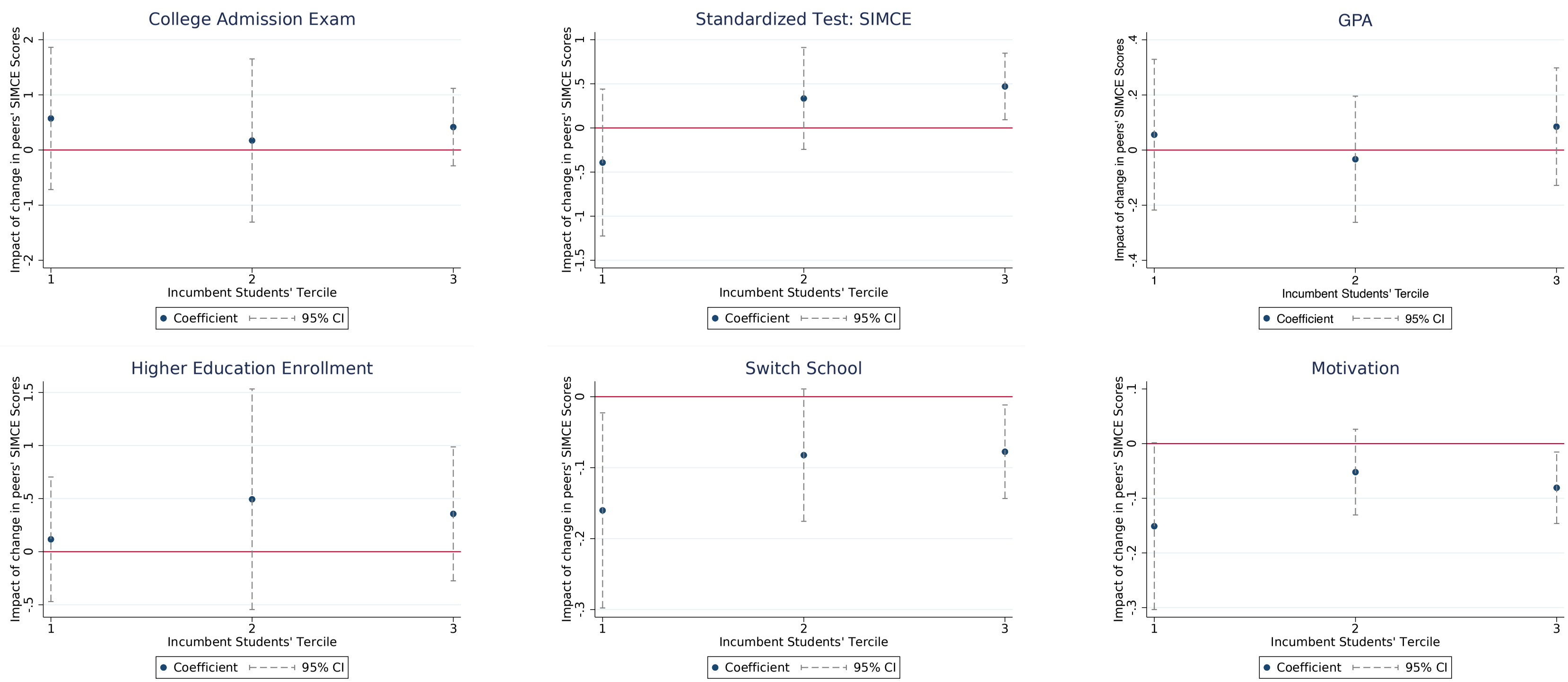


Figure 1.5: Impact of Peers' Standardized Scores - Heterogeneity by Incumbents' Test-Scores Tercile

Each observation corresponds to student-year outcomes. The X-axis corresponds to incumbent student achievement tercile Y-axis corresponds to the impact of changes on peers' average scores on standardized tests. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

To understand the heterogeneous effects of peer changes, Figure 1.5 decomposes the effects by estimating the model differentiating by students' tercile in standardized test scores. These estimations show a relatively flat effect of peers' standardized scores on college admission exam scores, higher education enrollment, and GPA. However, students from the higher-performing tercile seem to be more affected by their peers' standardized test scores.

Finally, we perform a similar exercise comparing the effects of changes in the proportion of classmates from each tercile on students' outcomes. These results are displayed in Figure 1.6, reflecting that most of the changes are driven by changes in the first and third terciles of the distribution, while mid-performing students appear to be less impactful on their classmates. Interestingly, adverse effects on college enrollment, college admission exams, standardized test scores, and school switching appear to be driven primarily by students in the lowest part of the distribution. In contrast, adverse effects on peers' motivation are driven by students from the top tercile, who possibly outperform their peers' achievement.

1.7 Conclusion

Segregation in schools extensively impacts students' academic and labor outcomes later in life, particularly among minorities. There are several reasons why this segregation may arise in educational settings. On the demand side, families apply to different schools due to their willingness to pay tuition fees, distance to schools due to residential segregation, and preferences for educational quality. On the other hand, market incentives may lead schools to implement screening practices. Specifically, these practices allow selective schools to capture students from more advantaged backgrounds who are less costly to educate, helping them attract other high-performing peers. Although

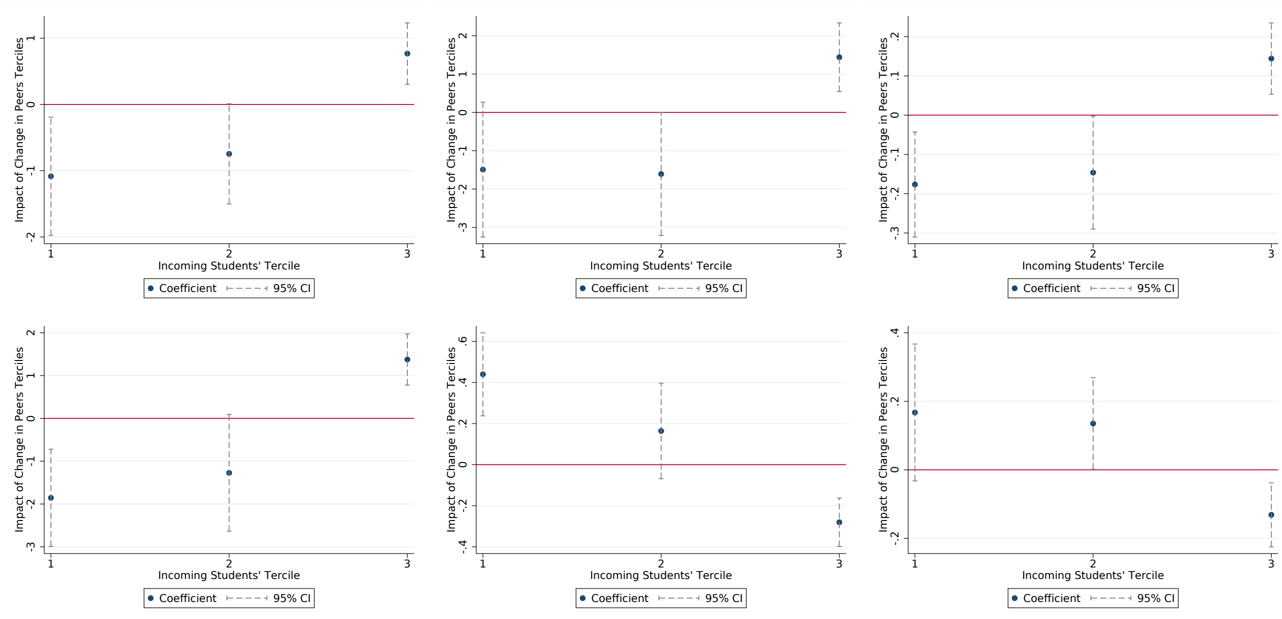


Figure 1.6: Peers' Standardized Test Scores Effect: Changes in the Proportion of Students From Each Test-Score Tercile

Each observation corresponds to student-year outcomes. The X-axis corresponds to the tercile of peers' achievement, and the Y-axis corresponds to the impact of changes in the proportion of students from that tercile. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

some literature has addressed the general existence of cream skimming (e.g., Altonji et al., 2015), this empirical setting has the advantage of isolating the effects of supply-side screening mechanisms, presenting novel evidence of this channel in a competitive market.

Disentangling these demand and supply factors behind cream skimming is crucial because it leads to different policy recommendations. In particular, school districts often attempt to alter segregation patterns through policies such as reserved spots for minority students, diminishing costs of attending selective schools through busing or scholarships, and even admission lotteries, as in Chile. However, the efficacy of these policies is limited depending on whether segregation arises from demand (families and students) or supply factors (schools), stressing the importance of distinguishing between these sources.

The results imply that supply-side cream skimming contributes to the country's sizeable socioeconomic status (SES) segregation, expanding the achievement gap between vulnerable and wealthier students. The induced segregation is problematic because research has shown that students attending more segregated schools have lower graduation, achievement, and college attendance rates (Billings et al., 2014, Johnson, 2011). Furthermore, extensive literature documents the benefits of less segregated schools for minority, low-income, and low-achieving students (e.g., Hoxby, 2000, Hanushek et al., 2009). The estimates support these patterns, showing that voucher and private schools' ability to engage in cream skimming is one of the sources of this increase in segregation and affects their classmates through classroom composition.

The efficiency consequences of redistributing slots will depend on factors such as the complementarity between students' preparation and schools' value-added (Durlauf, 2008) and private information about student-school match quality (Arcidiacono and Lovenheim, 2016). However, evidence is scarce in the context of secondary education, partly due to the difficulty of untwisting the equilibrium effects of such policies. These results present novel evidence of the effects of redistributing students across schools through a centrally designed public program, separately estimating the value-added benefits for different student types and the indirect impact of this redistribution on students through spillover effects. In particular, the estimations confirm the benefits of attending selective secondary schools in test scores and college enrollment for low- and high-income students in secondary education. However, selective practices transfer slots from lower to higher-income students without increasing overall educational achievement, based on the minor differences in value-added between students.

In this context, the lack of value-added differences between higher and lower socioeconomic students admitted into selective schools suggests that the fit of students and schools does not drive school screening practices on average. Instead, social interactions support the idea of families' preferences and group-level dynamics as a motive behind supply-side cream skimming. While it may become difficult to justify denying schooling options to high-achieving students simply because their departure from public schools affects those left behind (Ladd, 2002), it may be similarly challenging to justify rejecting high-performing students based on their low-income backgrounds simply because their characteristics are not as beneficial or attractive to their peers.

CHAPTER 2

THE BATTLE OF IDEAS: THE THREATS OF DONATIONS RELIANCE IN THE US HIGHER EDUCATION SYSTEM

Abstract

Higher education institutions in the United States receive a sizable and growing share of their resources from philanthropic contributions. The proportion of research funding provided by donations reaches up to 30 percent of funding at elite institutions, a large share of which comes from a few concentrated donors, usually through private foundations. Recent research indicates that private foundations deploy funding strategically to influence policy decisions, evidencing a mechanism through which contributors can influence universities' policies. This analysis assesses contributors' political drive in funding deployment by exploiting transaction-level data from over 75,000 private foundations from 2000 to 2018 totaling almost $100 billion, and data on individuals' political campaign contributions. The estimations indicate that increasing contributor-university ideological differences by one percent reduces donations between 1.1 and 1.5 percent, even after accounting for foundations' preferences for other attributes. The salience of political ideology is more substantial among wealthier contributors, donors supporting research and elite institutions, and donors deploying restricted-use funds. The effect is less prominent for donors supporting public schools and scholarships. Given the estimated ideological preferences of contributors, estimations show that universities face incentives to tilt towards more extreme views to accommodate donors' political preferences and increase donations. These incentives are consistent with the polarization observed in the higher education system in recent decades.

2.1 Introduction

In the last couple of decades, universities have substantially increased their financial reliance on charitable contributions, partially due to the decrease in other funding sources. According to Giving USA, total donations to education went from $40.1 billion in 2000 to $58.9 billion in 2017 dollars, a 47 percent increase. When combined with endowment income, Murray (Murray) indicates that research funding from philanthropy adds up to $7 billion a year, and donations provide almost 30 percent of the annual research funds in leading universities. In contrast, alternative funding sources such as industry contributions account for less than 6 percent of universities' research funding. While the higher education system greatly benefits from the additional resources these donations bring, they may threaten its independence.

Universities, think tanks, and other research groups are providers of non-partisan technical expertise. In contrast with some of these other institutions, universities are expected to offer a more neutral input into the lawmaking process. However, they are susceptible to external influences, like any other institution relying on outside funding. This paper measures the political leaning of boards of private foundations and faculty of higher education institutions in the U.S. by linking them to their donations to political campaigns. Moreover, we estimate the donations' sensitivity to ideological differences between donors and universities. Finally, the estimated donations' elasticity is used to inform a model to simulate the incentives universities face to shift their political leaning given the donors in their states.

In the spirit of special interest politics, as in Grossman and Helpman (Grossman and Helpman), donors may be considered to have preferences over the activities of the universities and contribute to them with a *support* motive and an *influence* motive. Donations made with a supportive motive seek to support academic activities and research in donors' interest areas. In contrast, donations made with an influence motive directly seek to affect the universities' policies. While the latter type of motive is potentially riskier, it is also more easily monitored.

Notwithstanding this distinction, if donors offer contingent contributions, both motives will confront the universities with a fundamental trade-off. If universities can increase their resources by shifting their political ideology, then, on the margin, they face an incentive to tilt their political leaning towards those of their financial supporters. For example, Bertrand, Bombardini, Fisman, Hackinen, and Trebbi (Bertrand et al.) analyze donations by charitable arms of large corporations and find evidence that non-profits are more likely to support contributing firms-backed policies after receiving donations. This evidence suggests that non-profits are influenceable by the donors who support them, consciously or otherwise. The similar threats to universities' independence faced through their funding reliance have been scarcely explored in the literature.

While it is unlikely that funders can affect the opinions of academics within a higher education institution, there are several ways in which funding could influence academics' overall ideology. For example, a conservative (liberal) donor with an influence motive could attempt to shift the political leaning of an institution to the right (left) by getting involved in the decision-making process inside the universities or offering funding contingent on the institutions performing certain activities. In principle, most universities have internal rules to avoid this, although breaching cases have occurred. On the other hand, funders can influence universities' overall ideology simply by funding departments, research centers, or academics that align with their preferred views. If several donors contribute similarly, or a limited amount of concentrated donors control a large share of resources, this mechanism could shift universities' political leaning.

Similarly, researchers are also susceptible to becoming captured by the interests of those they depend on for resources, data access, or even career and consulting perspectives (Zingales (2014)). This dependence is akin to what economists call regulatory capture, where regulators cater to the interest of those they regulate. Moreover, the threat expands when a significant proportion of funding comes from a small concentrated pool of large donors. As Zingales puts it, "Until we admit that we can be captured by vested interests as much as regulators, the risk of capture cannot be addressed. For this reason, the most important remedy is to start talking about this problem."

Private foundations are charitable tax-exempt non-profit organizations that generally get their resources from a single donor or family[1], unlike public charities that are funded by the general public. The creation and functioning of private foundations have associated costs such as required minimum expenditures and special tax filing requirements. In return, they grant their contributors significant control over the funds' use and timing. Moreover, they grant a tax subsidy by allowing the deduction of charitable contributions from income taxes.

Responses to the Voluntary Support of Education Survey conducted by CASE suggest that U.S. colleges and universities raised $49.6 billion during the 2019 academic year. Private foundations accounted for 34.3 percent of such donations, surpassing alums' support as the primary source since 2007. In comparison, federal funding to higher education was $74.8 billion in 2017, while state funding reached $87.1 billion. Overall, donations represent around 10 percent of the total funding of universities each year, with high disparities across universities. Additionally, the discretionary nature of donations leverages their influence on universities' decisions. However, researchers have neglected the study of private foundations compared to other philanthropic institutions, such as corporate foundations, despite the comparatively more significant amounts involved. In

1. An increasingly common exception to this are donor-advised funds, to which donors can contribute through a centrally managed private foundation. This legal arrangement aids donors in avoiding the high maintenance costs of private foundations and permits bypassing the annual minimum expenditure requirement of 5 percent of its investment market value. However, the donors retain control over the use of the resources, and the variations arise mainly to circumvent tax obligations.

2017, donations by private foundations totaled $66.9 billion, according to the Foundation Center, more than three times larger than donations by corporations which were $20.77 billion the same year.

The mechanisms through which private foundations' resources can shape social policy direction have been scrutinized in the literature. Despite this, most education-related research has focused on the impacts on K-12 education. Usually, studies have relied on the donations of a small subset of foundations (e.g., Reckhow (2012) and references therein). Reckhow (2012) and Shanks (2018) indicate that foundations contributing to education are increasingly adopting more strategic and selective approaches to grant-making, concentrating on fewer school districts and more willingly engaging in politics. The present study contributes by expanding the scope of the analysis to higher education. Given the role of higher education institutions' research on the policy discussion, influencing universities and colleges would allow contributors to influence the "battle of ideas." In addition, this study dramatically expands the sample's representativity compared with previous analyses focused on higher education by exploiting transaction-level data from over 87,000 foundations spanning over 18 years.

This study also contributes by estimating the political positions of faculty, which has long been debated in the literature, and private foundations, for which there is minimal evidence in the literature. First, the faculty's ideology is measured by linking the reported employers of contributors to political campaigns using Bonica (b) data from 2000 to 2018. Next, the political preferences of private foundations are inferred from each foundation's board members' contributions to political campaigns. Finally, the names of recipient institutions are matched to their official or alias names using fuzzy-matching methods. This procedure identifies 800 thousand transactions from 20,368 foundations directed to higher education institutions. The matched donations totaled $ 95 billion in 2014 inflation-adjusted dollars.

The evidence indicates that supporters contribute significantly more to those who share their political views. Estimations show that faculty and donors' ideological positions are strongly correlated: shifting faculty ideology by one standard deviation is associated with a change in contributors' ideology between 10.3 and 14.2 percent of a standard deviation, even after accounting for fixed state and time differences and several universities' features. The association between universities and donors' political ideologies is significantly stronger for universities that receive a more significant proportion of their funds from private foundations and where faculty has less diverse views. On the contrary, public schools present a more negligible donor-university views correlation. These patterns are consistent with wealthier donors operating more strategically, possibly acknowledging their higher capacity to influence their grantees. The relationship between donors' and recipients' ideology is also stronger among top-ranked colleges and universities, which are more politically influential and relevant to policy and regulatory decisions.

When individuals decide to donate to universities, they certainly weigh many factors. In particular, even donors contributing with an *influence* motive are likely to seek various objectives relevant to them, many of which are unaligned with political ideology. Unfortunately, the idiosyncratic nature of these objectives makes them hard to track since each donor's postures on a given topic are not observable to the researcher. Consequently, they do not allow for a joint assessment to compare donors. Instead, this study focuses on universities' and donors' political leaning due to its inherent importance and higher transparency.

The analysis exploits transaction-level data of donations made by private foundations to estimate the sensitivity of donations to ideological differences between universities and private foundations, defined as the absolute value of their political contribution scores. The results indicate that increasing ideological distance by one percent statistically significantly decreases a donor's contribution to a university between 1.1 and 1.5 percent. The estimation relies on comparing donations made in a given year against alternative universities in the same state. The analysis also includes university-time fixed effects capture university actions that affect all donors independently of their political views on any given year. The negative impact of ideological distance on donations holds regardless of whether we measure university views based on faculty or chair officers' views and when using donation amounts or binary donation decisions.

The preference for like-minded colleges is also stronger among donors who contribute a larger share of their funds to research and universities' current operations. However, evidence of whether this exclusively occurs in policy-relevant areas is inconclusive. This is partly due to the difficulty of classifying policy-relevant topics from the scarce available information about grants' purposes. This evidence also suggests that requesting more detailed information about the activities funded by each grant and requesting donations to be made to broadly defined areas (i.e., taking discretionary power away from donors) would diminish this channel's threat. Universities that reported receiving a more significant proportion of their donations from foundations as *restricted* for a specific goal received funding from donors that weighted university preferences more heavily.

While the initial analysis focuses on donations to individual universities, the aggregate effects will depend on the patterns that donations take into practice. For example, it is possible for the incentives generated by donations to a given higher education institution to offset each other if they rely on both conservative and liberal donors. On the contrary, if conservative and liberal donors specialize in donating to different institutions, it incentivizes these organizations to adopt more extreme postures to increase their contributions. It is unlikely that any given political ideology will produce enough incentives to shift the universities' postures on a system with highly atomized donors, as used to occur with alums donations. In practice, however, most private foundations are funded by highly wealthy donors whose views are unaligned with those of the general public. In addition, the estimated ideology-contribution elasticity suggests that many universities have incentives to adopt more extreme views, following those of their already polarized supporters.

Moreover, this goes against regulatory aims to impede tax subsidization of political voices for specific groups. While the present study focuses on universities, given data availability and their strong influence in higher education, it also sheds light on interest groups' behavior and other non-profits and foundations seeking donor funding.

The rest of the paper is organized as follows: Section 2 reviews relevant literature about regulatory special interest and political leaning of higher education institutions. Section 3 introduces the different data sources used in the paper, and Section 4 explains the empirical approach. Section 5 presents the results, separated into analyzing donor preferences, inspecting grants' purposes, and foundations' characteristics. Section 6 concludes.

2.2 Literature Review

Philanthropy has long been a significant source of resources for the U.S. higher education system. Besides supporting research, they have bolstered the system by contributing to students' financial aid and other resources necessary to universities' operations. Foundations have thus considerably sustained the development of the higher education system in the United States. Despite this, the consequences, motivations, and potential to interfere with the higher education system are not politically neutral.

In the publicly notorious cases analyzed by Skocpol and Hertel-Fernandez (Skocpol and Hertel-Fernandez) and Mayer (2017), such as the Ollin Foundation in the 1980s, Charles G. Koch Foundation more recently, these private foundations openly embraced their goal to spread free-market values in elite universities. Due to the magnitude of the amounts and number of institutions involved, different authors have analyzed these cases, such as Skocpol and Hertel-Fernandez (Skocpol and Hertel-Fernandez) and Mayer (2017), and they have also received media attention. For example, Skocpol and Hertel-Fernandez (Skocpol and Hertel-Fernandez) analyze the Charles G. Koch Foundation and reports that it has persistently supported think tanks and programs across the country adhering to libertarian ideals. Additionally, this private foundation supports college and university-based scholars and programs that promote free-market ideas and policies. The case of the Koch brothers is an exception to the norm in that no other private foundation has (openly) embarked on such large-scale politically driven operations in the higher education sector. However, no comparable study using comprehensive data on private foundations supporting higher education has been conducted to assess how widespread these practices are among these organizations.

On a smaller scale, Reckhow and Snyder (Reckhow and Snyder) analyze giving patterns for the 15 largest K-12 grantmakers. Their evidence supports the idea that foundations increasingly fund organizations that operate as "jurisdictional challengers," organizations that compete with traditional public sector institutions, such as charter schools. Moreover, as they point out, recent research shows that foundations are increasing their efforts to influence the political processes and policymaking in areas other than higher education. In particular, one of the methods through which these organizations can operate is by supporting the production of evidence favorable to their views. For example, Brulle (Brulle) show that conservative foundations have funded most philanthropic support for climate change counter-movement.

This mechanism could also open a door for other interactions. Universities play the role of experts in several topics where their research is a major input. However, institutions may be incentivized to present information influenced by their self-interest, as pointed out in the special interest literature (Grossman and Helpman (2001)). Higher education institutions must compete intensely for funding opportunities like any other organization. If universities can increase their funding resources by moving their political ideology, then, on the margin, they face an incentive to tilt their political leaning to accommodate that of their donors.

A considerable strand of literature has studied the effects of campaign finance and lobbying in politics. Some studies have found relatively minor amounts of money compared to the supposedly large return measured for these channels (Ansolabehere et al. (2003); Fowler et al. (2020)). However, donors also contribute to obtaining indirect access to politicians and policy discussions they want to affect (Fouirnaies and Hall (2018)). Evidence also suggests that preferred lobbying mechanisms depend on the context (e.g., Bombardini and Trebbi (2012)). This evidences that individuals or corporations aiming to influence political outcomes in their favor may thus do it in less obvious ways, where there is less public monitoring than direct political contributions. In this fashion, contributions to institutions supporting determined ideas can present a more stable and less issue-dependent form of influence in public opinion, as occurs with think tanks and universities.

As argued by Bertrand, Bombardini, Fisman, and Trebbi (Bertrand et al.), charitable giving by large donors can be used through foundations by wealthy donors as a tax-exempt and hard-to-trace form of influence. Unlike lobbying or campaign contributions, this form of influence is tax-deductible. [2] List (List) even cites evidence suggesting that, on the margin, taxpayers are paying \$1 through tax deductions for each \$1 contributed to philanthropy. Nevertheless, he argues that donations are not likely to be offset on a

2. Private foundations can participate in lobbying but must identify such transactions and pay a 20 percent fee over such expenditures.

one-by-one basis, based on findings from several authors. Despite this, he argues that the amount subsidized is still higher than that implied directly by the rate at which donations can be deducted for tax purposes.

Higher education politics has long been a highly debated topic, given its critical role in research and emerging new ideas, forming new professionals, and shaping students' views and ideas. The literature has mostly agreed that professors are more liberal than the general population. Moreover, their views vary across fields, states, and researcher ages. Gross and Simmons (2007), and Gross and Fosse (Gross and Fosse) find evidence consistent with this. Moreover, they show that there are as many professors who hold moderate views as there are with more liberal positions, stressing the importance of distinctions that go beyond party affiliation to measure political leaning.

The relatively low diversity in academia has also attracted extensive attention, often by conservative critics accusing bias against conservative academics or students' political indoctrination (Mariani and Hewitt (Mariani and Hewitt)). According to a survey of U.S. adults conducted in 2018 by the Pew Research Center, 79 percent of Republicans and 17 percent of Democrats with a negative view of higher education responded that professors bring their political and social views into the classroom. Regardless of whether the evidence supports this, the mere existence of a large share of the population holding this view places incentives for politicized private foundations to attempt to deliberately influence higher education political views. Moreover, universities produce a large proportion of the research on several topics. As such, impartiality and reputation represent crucial assets for these institutions. Consequently, the potential to influence universities' research threatens one of the higher education system's primary roles.

Numerous authors have corroborated the influence of researcher ideology in academic writing. Nonetheless, this is not surprising nor indicative of scientific misconduct (see Redding (Redding)). In economics, Jelveh, Kogut, and Naidu (Jelveh et al.) show that empirical results in policy-relevant parameters correlate with authors' estimated political ideology based on their campaign contributions. Chilton and Posner (Chilton and Posner) find similar results in academic writing by law professors at elite U.S. schools. Rathbun (Rathbun) shows an association between adopting different paradigms in political science and authors' ideological views. Statistically significant relationships between ideology measured by survey responses and specific economic parameters have also been reported by Carrick-Hagenbarth and Epstein (Carrick-Hagenbarth and Epstein), Mayer (b), and Caplan (2002).

Gordon and Dahl (Gordon and Dahl) show that the opinions of economists from top economics departments on current economic affairs differed in their answers and their degree of reported confidence depending on their political views. Moreover, they find that disagreements are larger on topics where the academic literature in the topic is small, for which the reported confidence is also more minor. They interpret this as differing priors remaining more determinant in cases with less evidence. Nonetheless, academic research usually focuses on topics with more limited evidence, strengthening the importance of researchers' beliefs and political ideology. One skeptical argument about the capability to affect research outcomes refers to the peer revision implemented in academic research. Nevertheless, this does not limit the capability of researchers' biases to permeate research, as reflected by studies that document such correlation even among published articles.

Another branch of the literature has focused on the effects of faculty's political ideology on students and their formation. However, the results are more nuanced than those measuring the impacts on research. As argued by Campbell and Horowitz (Campbell and Horowitz), colleges can influence students' sociopolitical attitudes in several ways, such as by learning about other cultures and worldviews and interacting with peers. Although college graduates are generally more liberal than the average population, the discussion has concentrated on whether this effect is causal or provoked by confounding factors such as family background. Kam and Palmer (2008) argue that the individual characteristics that induce students to pursue a college degree are also more likely to induce specific political postures, such as family background. Conversely, Mayer (a) find evidence consistent with educational attainment increasing political participation.

Fields outside social sciences are usually considered less subject to political biases since their study topics are often unrelated to political issues. There are numerous exceptions to such rules, however. For example, computer scientists' research can be an input to online businesses or social media regulations, and research by academics in medical departments is related to public health policies. The high expenditures on lobbying in areas connected to these departments also corroborate this intuition. Perhaps more telling, even areas related to natural sciences like medicine are subject to conflicts of interest through their financial connections. Meta-analyses by Bekelman, Li, and Gross (Bekelman et al.), Barnes (Barnes), and Lexchin, Bero, Djulbegovic, and Clark (Lexchin et al.) find a statistically significant association between industry sponsorship and pro-industry conclusions. Lexchin, Bero, Djulbegovic, and Clark (Lexchin et al.) also reports that industry funding did not appear to be correlated with quality, although it reduced publication probability.

Philanthropic donations have historically played an essential role in the U.S. higher education system, especially in comparison with other countries. Despite this, it would be misleading to assume that funding from prominent donors such as private foundations that dominate nowadays is equivalent to funding from non-partisan organizations, federal and local sources, or the general public. Besides possibly generating a governance breach, the high reliance on charitable donations implies a different level of stability than, for instance, government funds. Projects selection by universities is also not neutral to their funding sources. For example, private and public funding lead universities to produce different research types (e.g., Murray (Murray)). Furthermore, the effects of different funding types amplify if universities endogenously adjust their efforts related to alternative fundraising activities. For example, crowding-out induced by capacity constraints could occur as in Andreoni and Payne (2003), or due to donations' highly cyclical behavior (see VSE Survey Results (2018)).

Bekkers and Wiepking (Bekkers and Wiepking) conduct an extensive literature review on the motivations for giving of individuals and classifies them into the following categories: awareness of need; solicitation; costs and benefits; altruism; reputation; psychological benefits; values; efficacy. These categories arguably fit the broader category of *support* motives. However, since individual donors are commonly atomized, their potential to act with an *influence* motive is limited. This is different with larger private foundations, which size enables them to seek further-reaching objectives.

The susceptibility generated by resource constraints is particularly worrisome if those who contribute are unrepresentative of the population as a whole, as happens with campaign contributions (e.g., Bonica and Rosenthal (2018)). Thanks to their higher available income, wealthy donors contribute a larger proportion of their income. Moreover, since tax subsidies are more generous for individuals with higher incomes due to increasing tax brackets, these individuals donate a proportionally larger amount.

2.3 Data

2.3.1 Private Foundations

Private Foundations are tax-exempt non-profit organizations formally defined as 501(c)(3). They are considered charitable organizations, so they are requested to operate for the public's benefit. Unlike public charities like the Red Cross and Feeding America, private foundations' funding comes from a single source, usually an individual, family, or company. Trustees or directors appointed by the donor then manage private foundations' investments, programs, and grantmaking policies, thus permitting donors to retain control over funds expenditure.

These non-profit organizations can operate directly or through grants to other organizations, which must also be tax-exempt. Education is one of the tax-exempt areas to which they donate, taking the largest share with around 23 percent of the transactions and 26 percent of the funds in 2016. In practice, most private foundations act as grantmaking foundations, which means they fund projects from other institutions. According to IRS data, there were 82,380 grantmaking foundations with total revenue of $105 billion in 2016, holding investments valued at $800 billion. In contrast, there were only 9,092 operating foundations.

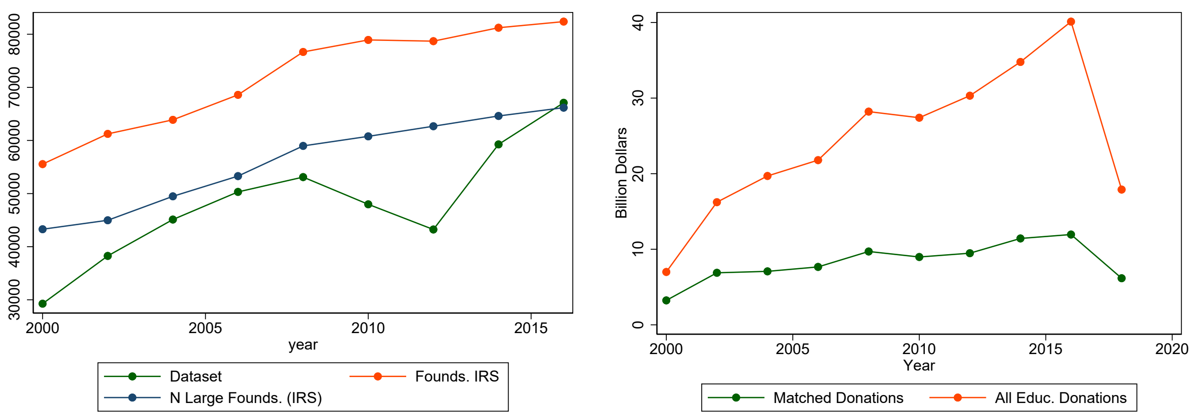
Most domestic private foundations are subject to an excise tax on their net investment income to prevent foundations from accumulating resources indefinitely without making contributions. A substantial initial endowment often funds private foundations, later depending on investment income to support their activities. The areas where private foundations can donate explicitly exclude contributions to political campaigns. Likewise, private foundations cannot "substantially" engage in lobbying but can do it under specific circumstances. In particular, private foundations are allowed to lobby in their activity area under strictly limited circumstances. [3]

The Internal Revenue Service (IRS) requires all private foundations to submit information annually. This information is considered public records since 2000, when new legislation made this information available for public access. This regulation aimed to

3. If private foundations participate in lobbying, they must pay a 20 percent tax for such expenditures, including a fraction possibly charged to managers. If the expenditures are considered substantial, private foundations risk losing their tax-exempt status.

allow for more transparency in their operation and transactions by requesting information to be filled in a form entitled "Return on Private Foundation," or *990-PF*. This form includes information about each foundation's assets and income, financial activities, trustees and officers, and most importantly, a list of all grants awarded each fiscal year and a description of the gift.

The data from financial transactions of private foundations comes from two different sources. Firstly, FoundationSearch compiles the information from filed tax forms into a single dataset containing transaction-level contributions data. This data source is complemented with the information made public by the IRS, including 990-PF Forms of all private foundations filed electronically between 2013 and 2020.



(a) IRS Data vs. Transactions Dataset (b) Matched Share

Figure 2.1: Data Coverage By Year

**Note:* IRS foundations shows the total number of grant-making foundations. Panel (b) includes exclusively transactions in the data.

FoundationSearch's dataset includes over 120,000 foundations and charitable organizations, focusing on the largest foundations in the U.S. and including transactions over $4,000. Panel (a) of Figure 2.1 contrasts the number of foundations in the dataset with those reported by the IRS using administrative data. In all years except around 2008, the number of foundations in the dataset resembles that of larger foundations in IRS data (defined as having assets over $100 thousand in assets). In this dataset, foundations are only observed if they have contributed in a given year. At the same time, IRS administrative data includes all foundations regardless of whether they are active in a given period. The decline in donations after the economic crisis of 2008 hence explains part of the difference in data coverage in that period, mainly due to donors' diminished contributions. The transactions data extract used in this study includes yearly transactions from 2000 to 2017. It has data for 13 million transactions, 3.2 million of which are classified as supporting education. This number corresponds to an average of 15.9 transactions per year per foundation, 3.77 on average going to education. The total amount adds up to $1.1 million per year per foundation (median $83K), of which $300K go to education (median $10K). Panel (b) of Figure 2.1 reveals that the average matching rate of transactions was low but stable across years. This low matching rate reflects that a large share of donations goes to K-12 education and that the matching algorithm is tuned to prioritize precision (i.e., that the identified transactions are correct) over coverage.

Although the IRS gives a unique identification number to all foundations, the 990-PF forms filled by private foundations only include the name of the institution that received the donation. The grantees' names reported in the 990-PF Forms are then matched to the official or alias name to identify transactions aimed at universities. This procedure is implemented using fuzzy-matching in three steps, striving to improve the precision of the process. First, potential matches are detected using $n-grams$ of length 4[4] combined with inverse frequency weighting of these $n-grams$. This procedure yields a set of potential matches between universities and grantees' names. [5] Finally, supervised learning

4. $N-grams$ correspond to all combinations of length n that can be extracted from each string.

5. Matches where the reported state of the potential recipient differs from that of that university are excluded from the analysis. Some of these mismatches may be effectively universities where the private foundation entered the grantee's state erroneously or inaccuracies in data transcription. Inspection of these matches reflects that a larger proportion corresponds to incorrect matches, so they are dropped from the sample.

(random forest) with a manually labeled set of matches improves matching precision. Model features include several string comparison measures, accounts for words' relative frequency, and common word abbreviations.

The name-matching algorithm identifies 807,023 transactions where universities are the beneficiaries donated by 36,614 foundations. The match rate relative to all the transactions classified as *education* is 36.7 percent and is stable across years. The average amount matched per year is $8.96 billion. In comparison, the total given to education per year averages $24.45 billion.

2.3.2 Private Foundations Ideology

The political preferences of faculty and board members of private foundations are measured by their contributions to political campaigns. Bonica (a) shows that donation-based map policy preferences for several issues and even allows discerning between the views of members of the same party. As part of the required public record of private foundations, these organizations must declare the board members' names and other key data. While the IRS collects this information annually, the dataset only has board members as of 2017-18. The matching process uses the directors' names and geographical data to match data on political ideologies, called common-space campaign finance scores (CFScores) produced by Bonica (b). Bonica's data estimates an ideal position for all political contributors based on the supported candidates' characteristics. To the extent that contributors to political campaigns pay at least some consideration to candidates' ideology, these campaign contributions should reflect the contributors' views. Since this dataset uses contributions to political campaigns with cycles lasting two years, all the analysis collapses data every two years to capture an entire election cycle.

The names-matching algorithm first matches unique names from the campaign contributions and directors dataset. More restrictive criteria are then applied to match with foundations' reported zip code, city, and state.[6] Among foundations contributing to education, 54 percent of the directors are matched to political contributors. Figure 2.2 displays the distribution of political views for board members from private foundations and the average and median at the foundation level. The figure shows that board members who contributed to political campaigns focus on candidates away from the center. As a result, their political positions are more polarized than those of the average population. The comparison of director and foundation-level data also evidences that boards tend to group directors of similar ideologies based on the dispersion observed at the foundation level.

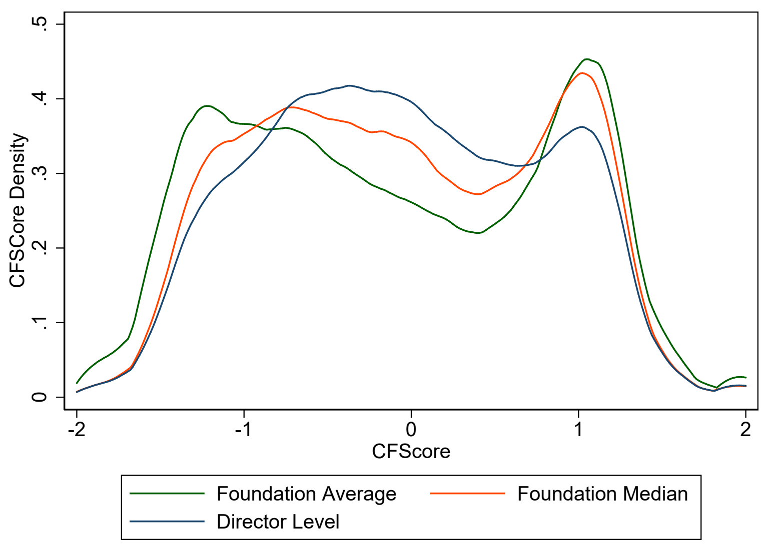


Figure 2.2: Foundations Political Ideology Distribution

**Note:* graph composed using foundations' board members in 2018. Values larger than axis limits are grouped into bordering values.

Private foundations' views are measured by the *average* of the scores of the board members. However, the results are generally robust and consistent when using the

6. Board members can live in a different area than where the foundation is located. Potential matches where location reported in the campaign contributions and private foundations data mismatch are omitted to avoid false positives unless the name has a unique match.

median instead. Directors without a match in the CFScores dataset are omitted from the final analysis. This poses the problem of maintaining in the sample those foundations whose directors are more actively involved or interested in politics, as reflected by their donations to political campaigns. However, this is precisely the group that is more prone to donate to universities in a politically driven way. Foundations that donated to higher education are generally larger (regarding assets, income, and giving), as reflected by the comparison in Table 2.1. They are also more right-leaning than the rest of the foundations and more likely to hold comparatively more extreme views.

		Mean		Difference
	Obs.	No Donation	Donated	D vs N-D
Log(Donations)	34,274	.	11.836	
Total Giving (log)	76,691	10.829	11.918	1.096***
				(0.013)
Total Assets (log)	76,411	13.320	14.340	1.078***
				(0.018)
Total Income (log)	76,145	11.849	12.951	1.141***
				(0.022)
Avg. CFScore	54,415	-0.077	-0.015	0.062***
				(0.007)
Republican (CF.avg $>$ 0.5)	54,415	0.275	0.308	0.033***
				(0.004)
Democratic (CF.avg $<$ -0.5)	54,415	0.342	0.314	-0.028***
				(0.004)
Total Directors	76,268	4.471	3.679	-0.792***
				(0.040)
Prop. of Matched Directors	76,268	0.419	0.549	0.130***
				(0.003)
No Matched Directors	76,268	0.344	0.208	-0.137***
				(0.003)

Notes: Sample size = 78,202. N Donors = 32,343. *** p$<$0.01, **p$<$0.05, *p$<$0.1. Donors classified as donating to a university at any year in the sample (2000 to 2018)

Table 2.1: Foundations Descriptive Statistics: Education Donors vs Non-Donors

2.3.3 *Faculty Positions*

The FEC regulations on contributions to political campaigns request campaign contributors that exceed $200 to report their employer, position, donated amount, and recipient. This information allows tracking of political contributions made by each university's faculty members.[7]

Despite the requirement to include employers' data, several contributors use abbreviations or poorly formatted names. To tackle this, the matching process follows the same steps used to match university and grantees' names, using $n-grams$, inverse probability weighting, and supervised learning. University-level views and then summarized using the average of all professors belonging to each institution. The median of these contributions is also used as a robustness measure, which is less sensitive to changes in contribution patterns.

Several studies focus on American professors' political views. Studies have found academics to be predominantly liberal (Gross and Simmons (2007), Klein and Stern (2005); Rothman et al. (2005)). They have also found significant variations across fields. For example, social sciences are more democratic-leaning than physical sciences, and fields like economics and political science are generally more conservative among the social sciences. Consistently with earlier results, faculty ideologies in the contributions' dataset are highly left-skewed, with most schools leaning liberal. However, since the method used in this study for linking university faculty with their institution relies on the reported employer, separating faculty by their respective departments is not viable. Instead, the analysis explores the relative importance of fields within a university and the declared use of each grant's funds to observe whether department differences can explain the perceived differences.

7. Students occasionally report their universities in the employer category. These cases are identified by the "position" field and excluded from the analysis.

2.3.4 Universities Characteristics

Data on university outcomes come from the *National Center for Education Statistics* (NCES). The data includes university-year level data from 2000 to 2018, including institutional characteristics, enrollment, demographics, admission requirements and scores, financial aid, and faculty composition. The sample used in the analysis consists of all public and private not-for-profit schools focusing on programs 2 and 4 years long. These are the primary recipients of donations, given that for-profit schools can only receive donations under very limited circumstances. Schools with programs of less than two years rarely receive donations. Since Bonica's dataset of campaign contributions is grouped as the cumulative of two years, the universities dataset is only used for even years. The final dataset contains 37,035 university-year observations, ranging between 3,610 and 4,080 per year.

Two additional sources complement the previous data. First, NCES data is linked using school identifiers with information from the *Voluntary Support for Education Survey*, made by the *Council for Advancement and Support of Education* (CASE). This survey collects data on fundraising at U.S. public and private colleges and universities. Participation is voluntary and self-reported, and it has been conducted since 1957. This dataset permits tracking factors associated with more vulnerability to universities' independence, such as higher reliance on donations or a lower endowment per student. Finally, this is combined with data from *USNews* Universities and Colleges Ranking, which collects ranking information for the whole relevant period and links the names to the NCES identifiers (*ipedsid*).

2.4 Empirical Approach

Several factors play a role in the decision of each private foundation of deciding grantee and the amounts donated to each. The following model is estimated to capture the university-level relationship between the ideologies of donors and recipients:

$$FacultyCFScore_{its} = \alpha + \beta PrivFoundCFScore_{it} + \omega X_{it} + \eta_t + \nu_s + \epsilon_i t \tag{2.1}$$

Where Y_{its} is the *outcome* of university i in year t from state s, D_{it} is the distance between the political ideology of donors and university i in year t, X_{it} are covariates of university i in year t, η_t and ν_s are year and university fixed effects, and ϵ is an error term. In this case, the exploited variation then comes from comparatively more conservative or liberal universities, contrasted to other universities or colleges within the same state. In particular, this comparison assesses whether conservative (liberal) colleges receive funding from relatively more conservative (liberal) donors within their states.

Complementary to the previous approach, the following model compares donations from private foundations with possible choices for each foundation. The choice set exploits administrative data to construct a set containing all universities within each foundation's state. Once the choice set is constructed, the following model is estimated:

$$Y_{itf} = \alpha + \beta D_{itf} + \omega_{it} + \nu_{ft} + \epsilon \tag{2.2}$$

Where Y_{itf} is the *amount donated* or a dummy indicating donations to a university i in year t by foundation f and D_{itf} is the ideological distance between donor f and university i in year t. The terms ω_{it} are university-year fixed effects to allow for potentially shared preferences for specific universities and yearly changes that affect all donors (e.g., fundraiser campaigns by universities). Resembling a conditional logit model, ν_{ft} are foundation-time fixed effects, producing comparisons within each foundation's choice set in a given year.

Several specifications include a set of covariates when indicated in the table. These regressions control by institutional characteristics, such as institution sector, size, whether it has a hospital or medical degree, HBCU states, and religious affiliation; financial aid, including the average federal, state/local, or institutional grant amounts, and average student loans per student, as well as the percent of the student receiving these benefits; selectivity, such as the number of applicants, admitted students, and enrolled students by gender; application submission requirements: GPA, high school ranking, high schools records, admission tests; quality indicators: ACT/SAT 25^{th} and 75^{th} percentiles (when requested), USNews Ranking (when available); students demographics, split by graduate and undergraduate; and the number of faculty by tenure status.

2.5 Results

2.5.1 Donors Preferences

The first step towards understanding whether there is a political consideration in contributions to universities is analyzing if universities' ideologies are predictive of their donors' ideologies. Figure 2.3 presents visual evidence supporting this idea, indicating that liberal schools receive funds from foundations all over the spectrum. In contrast, conservative schools receive most of their funds from conservative donors. This pattern is likely to occur because top-ranked schools are more liberal, driving donors to give despite the more considerable distance to their personal views. Indeed, the relationship between donors' and grantees' ideology is graphically presented in Figure 2.4, splitting faculty and donors' views according to their position in the ideologies' distribution.

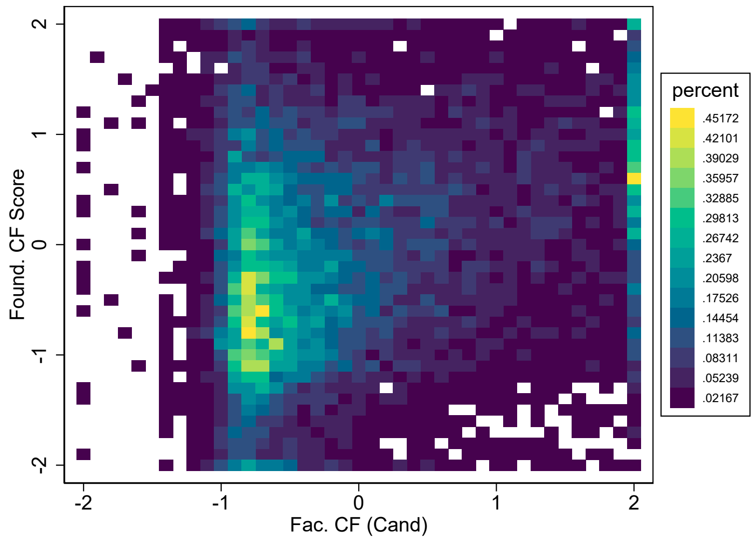
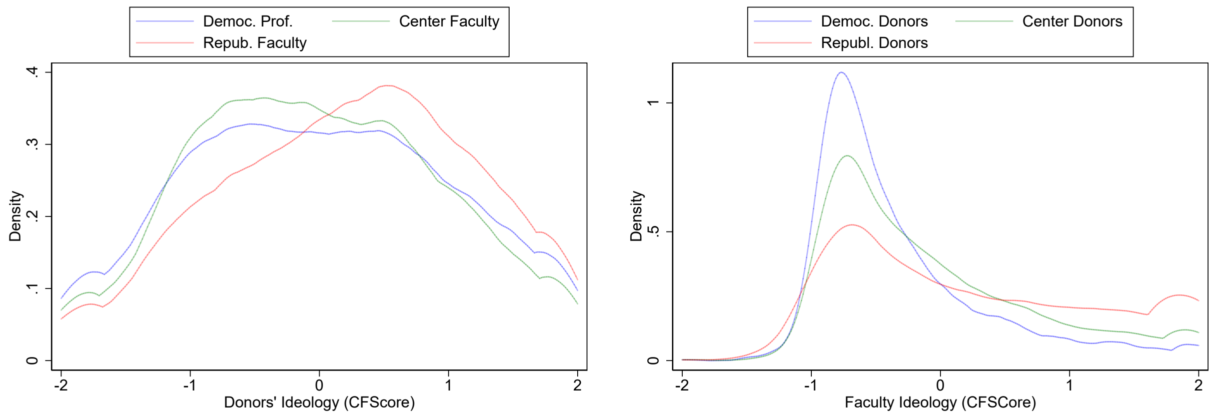


Figure 2.3: Donors vs. Recipients Political Ideologies

**Note:* figure represents the average CFScore of the foundations that donated to each university and the average CFScore of the faculty of that university. The sample includes 16,566 university-foundation observations.

Panel (a) in this figure shows that universities from the upper (lower) quartile receive contributions from donors markedly more conservative (liberal) than other higher education institutions. Conversely, Panel (b) evidences the ample explanatory power of foundations' ideology on the ideology of the colleges and universities they support.

Complementing the previous figure, Table 2.2 reports the results of regressing the weighted average of the contributors' ideology against universities' measured ideology. The first two columns show that shifting faculty's average positions by one standard deviation is associated with an increase between 10.3 and 14.2 percent of a standard deviation in donor ideology, even after accounting for state and year fixed effects and several covariates. The following two columns use the CFScore of the chief officer reported by each institution to the National Center of Educational Statistics (NCES) instead of faculty donations as a robustness measure. Although the sample is considerably smaller because not all chair officers contribute to political campaigns, the effect's magnitude is



(a) University-Grantee Names (b) Faculty Employers

Figure 2.4: University-Donors Ideologies Distribution

**Note:* figure represents the average CFScore of the foundations that donated to each university and the average CFScore of the faculty of that university. The sample includes 16,566 university-foundation observations. Democratic, center, and Republican defined as belonging to the lower quartile, the two middle quartiles, or the upper quartile of the corresponding distribution.)

similar. Finally, the last three columns present alternative specifications, including other fixed effects. The estimated effect of faculty ideology diminishes when including school fixed effects, reaching 1.9 percent. This decrease is expectable because the variation in such cases comes from within a school over time, and the nature of the political positions of faculty makes it challenging to track fluctuations and their timing.

The previous results show that the ideology of universities' faculty members has explanatory power over its donor's ideology. To inquire into what groups are more exposed to political incentives, the results in Table 2.3 analyze the intensity of this relationship in different groups depending on school-level characteristics. Consistently with what would occur if larger donors give in a more directed way that could influence institutions' outcomes (e.g., research or student formation), the association between universities and donors' views is more prominent for universities that received a more sizeable amount from foundations' donations. For example, a one percent increase in the total foundation's donations to a university increases the ideologies correlation 75

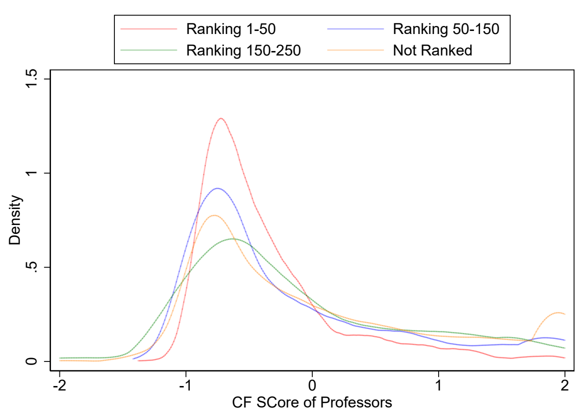
	(1) Donor Ideology	(2) Donor Ideology	(3) Donor Ideology	(4) Donor Ideology	(5) Donor Ideology	(6) Donor Ideology	(7) Donor Ideology	(8) Donor Ideology
Professors Ideology	0.142***	0.103***			0.019*		0.047***	
	(0.014)	(0.014)			(0.010)		(0.008)	
Chair Officer Ideology			0.126***	0.051*		0.036		0.065**
			(0.024)	(0.028)		(0.028)		(0.028)
r2	0.282	0.319	0.294	0.369	0.003	0.028		0.424
N	15,843	11,317	3,976	2,609	15,843	3,976	15,843	2,529
Covariates	No	Yes	No	Yes	No	No	No	No
Fixed Effects	State	State	State	State	School	School	State + R.E.	State + R.E.

Notes: Each observation corresponds to a university in a given cycle. Donors, Professors, and Chair Officers' ideology is measured by their contributions to political campaigns (CFScores, standardized). Standard errors clustered at the foundation school state level in parentheses. All regressions include cycle fixed effects. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

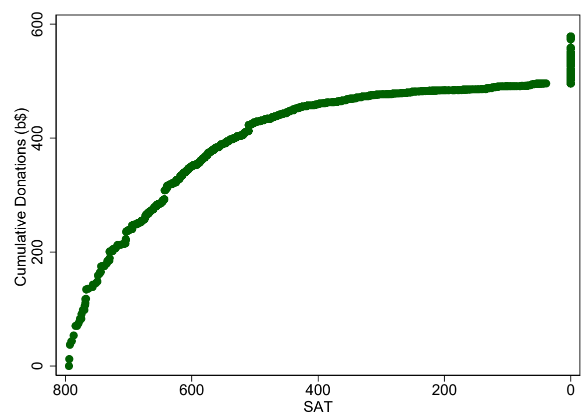
Table 2.2: Association Between Donors and Recipients Ideologies

base points, suggesting that larger donations could be deployed more strategically. Similarly, the association is smaller for universities where faculty has more diverse views, as reflected by the standard deviation of their CFScores.

The remaining columns of Table 2.3 show that public schools receive contributions from donors relatively less similar. Since public universities are usually larger, one possible explanation goes along with the faculty's higher diversity within such universities. On the other hand, these institutions rely less heavily on private donations, making them less susceptible to being influenced by their resource dependence. Since religious affiliation is often interlinked with political affiliations, an alternative source for this correlation could arise from religious affiliation. The last column in this table shows that although the association is more robust for religious schools, it is still present in the rest of the schools. Moreover, these patterns remain even when including covariates for several religious sub-denominations self-reported by the academic institutions (equivalent information is unavailable for donors).



(a) Donors Ideology by USNews Ranking



(b) Cumulative Donations by SAT Scores

Figure 2.5: Faculty Views by USNews Ranking

**Note:* Panel (a) displays the distribution of donors' ideology by USNews ranking. Ranking positions are interpolated when missing on a given year. Panel (b) presents the cumulative total donations received by universities according to their 75th percentile SAT scores.

The correlation is also higher for top schools, defined as having appeared in the top

	(1) Priv. Found. Views	(2) Priv. Found. Views	(3) Priv. Found. Views	(4) Priv. Found. Views	(5) Priv. Found. Views	(6) Priv. Found. Views
Prof. Views	-0.022	0.154***	0.138***	0.096***	0.077***	0.098***
	(0.058)	(0.023)	(0.021)	(0.014)	(0.023)	(0.014)
Prof. Views × Total Found.	0.075**					
	(0.034)					
Prof. Views × Prof. Views StDev.		-0.078***				
		(0.019)				
Prof. Views × Public			-0.067**			
			(0.027)			
Prof. Views × Religious Affil.				0.060*		
				(0.033)		
Prof. Views × Four Years					0.040	
					(0.029)	
Prof. Views × TopSchool						0.122**
						(0.046)
r2	0.319	0.325	0.319	0.319	0.319	0.319
N	11,295	10,255	11,317	11,317	11,317	11,317

Notes: Each observation corresponds to a university in a given cycle. Donors, Professors, and Chair Officers' ideology is measured by their contributions to political campaigns (CFScores, standardized). Standard errors clustered at the foundation school state level in parentheses. All regressions include covariates, the corresponding non-interacted term, and cycle and state fixed effects. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 2.3: Association Between Donors and Recipients Ideologies: Schools Characteristics

100 colleges or universities according to USNews Ranking. Concerning this last finding, Figure 2.5 indicates that top-ranked colleges and universities receive funding from more left-leaning donors, in part driven by the more liberal ideology of its faculty. Panel (b) illustrates that although the donations are concentrated in highly ranked schools, as demonstrated by the steep slope in the left-most part of the distribution, they also trickle to less renowned institutions. The analysis in Table 2.4 goes more in-depth into this finding, using three other school quality measures closely related to its prestige. Using schools' average SAT and ACT scores for the 25^{th} and 75^{th} percentiles, the analysis shows that increases in admission scores by one standard deviation increase the effect of school ideology on donations between 5.3 and 6.2 base points, consistent across the different quality measures. Again, this would be what we expected since these schools are considerably more influential in the policy domain. Indeed, their perceived political positions are more salient than in small or relatively unknown schools, where donations are more prone to have different purposes.

So far, the analysis has focused on establishing the stylized fact that donors prefer to contribute to universities whose faculty share similar ideas to their own. Despite this, several mechanisms could explain this correlation. The following section exploits transaction-level data to estimate donors' preferences for political ideologies to dig further into this issue. Table 2.5 reports the results of this analysis. Ideological distance is defined as the absolute value between the ideology of foundations' board members and faculty. The choice sets include all the universities in the sample within the same state. Finally, the analysis includes foundation-year fixed effects, university fixed effects, and university-year fixed effects. This approach compares donations from private foundations with alternatives in each university's choice set. Consequently, the parameters are estimated using variation within each year-choice set, while university fixed effects capture time-unvarying universities' characteristics and features that make them more

	(1) Priv. Found. Ideology	(2) Priv. Found. Ideology	(3) Priv. Found. Ideology	(4) Priv. Found. Ideology	(5) Priv. Found. Ideology
Fac. CF (Cand)	0.181***	0.183***	0.175***	0.177***	0.250***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.024)
SAT 75th	0.012				
	(0.019)				
Fac. CF (Cand) × SAT 75th	0.040***				
	(0.012)				
SAT 25th		0.001			
		(0.020)			
Fac. CF (Cand) × SAT 25th		0.045***			
		(0.013)			
ACT 75th			0.021		
			(0.015)		
Fac. CF (Cand) × ACT 75th			0.041***		
			(0.013)		
ACT 25th				0.004	
				(0.017)	
Fac. CF (Cand) × ACT 25th				0.031**	
				(0.015)	
Ranking					-0.016
					(0.040)
Fac. CF (Cand) × Ranking					0.042
					(0.029)
r2	0.349	0.349	0.321	0.320	0.361
N	7,873	7,874	7,774	7,776	2,067

Table 2.4: University vs. Donors Views: Quality Measures

Each observation corresponds to a university in a given cycle. Donors, Professors, and Chair Officers' ideology is measured by their contributions to political campaigns (CFScores, standardized). Standard errors clustered at the foundation school state level in parentheses. All regressions include covariates, the corresponding non-interacted term, and cycle and state fixed effects. *** p<0.01 ** p<0.05 * p<0.1.

attractive to donors independently of their political ideology.

The results in Panel (a) of Table 2.5 show that an increase of one percent in the ideological distance reduces donations' amount between 1.1 and 1.5 percent. Moreover, columns (2) and (3) show that the results are robust to adding university-level fixed effects and university-year fixed effects, indicating that the results are not driven by aggregate level preferences for each university (either fixed or time-changing). Columns (4) through (6) further show that the probability of donating to a university decreases between 30 and 40 basis points when increasing ideological distance by one percent. Furthermore, the results in Panel (b) indicate that the impact of ideology is robust to an alternative measure of university ideology, as reflected by the ideology of individuals holding high administrative roles, such as heads of departments and presidents. While the results are more nuanced, an increase of one percent in the ideological ideology decreases donations between 0.6 and 0.9 percent.

Figure 2.6 then assess the implications of the estimated ideology-contributions elasticity of private foundations. The model includes a degree 3 polynomial on distance allowing for slopes to change by donors' ideology deciles (i.e., allowing donors of different political views to value ideologically differently). In particular, the figure exploits the current distribution of education supporters to estimate the share of universities for which the model predicts that a leftward or rightward move by one standard deviation (i.e., becoming more liberal or more conservative, respectively) would statistically significantly increase their total contributions. This analysis suggests that most left and right-leaning universities would increase their donations under current circumstances if they adopt more polarized positions. This surges indirectly because of the polarized political ideologies of supporters and the comparatively scarce share of center-leaning donors. This incentivizes universities to adopt more extreme postures, permeating external donors' polarization into higher education. Given that distinct donors operate in

	(1) Donation log ($)	(2) Donation log ($)	(3) Donation log ($)	(4) Donated To Univ.	(5) Donated To Univ.	(6) Donated To Univ.
Panel (a): Faculty Average Position						
Distance (log)	-0.011***	-0.012***	-0.015***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
r2	0.051	0.055	0.056	0.051	0.055	0.056
N	32029691	32029691	32029689	32029691	32029691	32029689
Panel (b): Chair Officer Position						
Distance Chair Officer (log)	-0.006***	-0.008***	-0.009***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
r2	0.065	0.069	0.069	0.066	0.069	0.070
N	7098373	7098373	7098373	7098373	7098373	7098373
Found×Year	Yes	Yes	Yes	Yes	Yes	Yes
School	No	Yes	Yes	No	Yes	Yes
School×Year	No	No	Yes	No	No	Yes

Table 2.5: Donors Preferences: Transaction Level Analysis

Each observation corresponds to a university-foundation transaction in the choice set of a foundation in a given cycle. Distance measures the absolute value of the difference between the CFScore of the private foundation and that of the university. Standard errors clustered at the foundation state level in parentheses. All regressions include cycle fixed effect. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

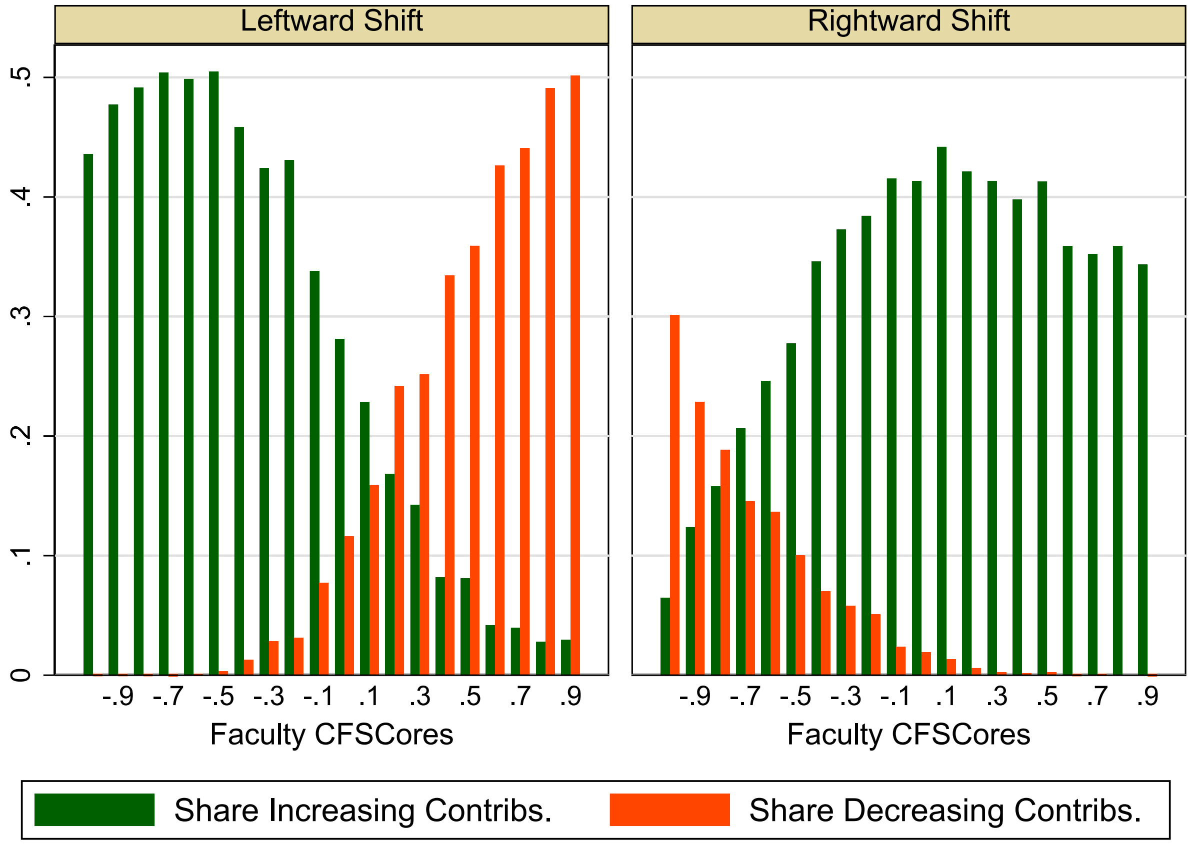


Figure 2.6: Predicted Contributions' Response to University Ideology Change

**Note:* prediction based on degree 5 polynomial on distance allowing for quantile-dependent slopes by donors' ideology. Regressions include state, individual-year, and university-year fixed effects. Standard errors clustered at the foundation state level.

different market segments or geographical areas and consequently have different choice sets, the model allows universities with similar ideologies to face different responses to a shift in their positions. Since the prediction assumes that choice sets are maintained, and only one institution changes its position at a time, the estimates represent partial equilibrium effects.

The evidence above focuses on the association between donors' and recipients' ideologies, as reflected by their contributions to political campaigns. Following the theoretical framework's insights, we expect ideology to be more relevant when the outcomes depend more on the school's ideology. To elucidate the importance of such mechanisms, one would ideally want to use department-level information on donations to observe whether this phenomenon occurs in particular areas of interest to the donor. The IRS requires private foundations to describe the objective of each grant. In the dataset, donations description is available primarily for years starting in 2010. The descriptions are manually labeled as Scholarships, Research, Medicine-STEM, Policy-relevant, and Unrestricted funds. Figure 2.7 displays the average declared destination of the funds weighted by the donation amount. The sample contains 418,326 grant descriptions, equivalent to 94 percent of the donations in the analysis subsample. Years before 2010 are excluded because data on grant descriptions has a substantially smaller coverage than previous years. [8] The most common category is unrestricted funds, which groups all descriptions that did not specify a specific goal for the funds, representing 61 percent of the donations. In contrast, the proportion reporting donations to specific areas such as Medicine-STEM or Social Sciences is small, reaching just 9 percent of the transactions altogether or 16 percent if weighted by contribution amount.

2.5.2 Grants Purpose

To understand which donors value ideological distance more highly, the results in Table 2.6 explore the strength of the association between ideological distance and donation amounts depending on the categories donors contribute more intensively. Since the classification of funds objectives can only be made for transactions that effectively occur, the classification is not computable for elements in the choice set that did not receive

8. For years before 2010, the sample contains 249,629 grant descriptions for 417,740 donations from 2000 to 2008. The proportion of transactions where grants' description is available ranges from 28 percent in 2000 to 64 percent in 2008.

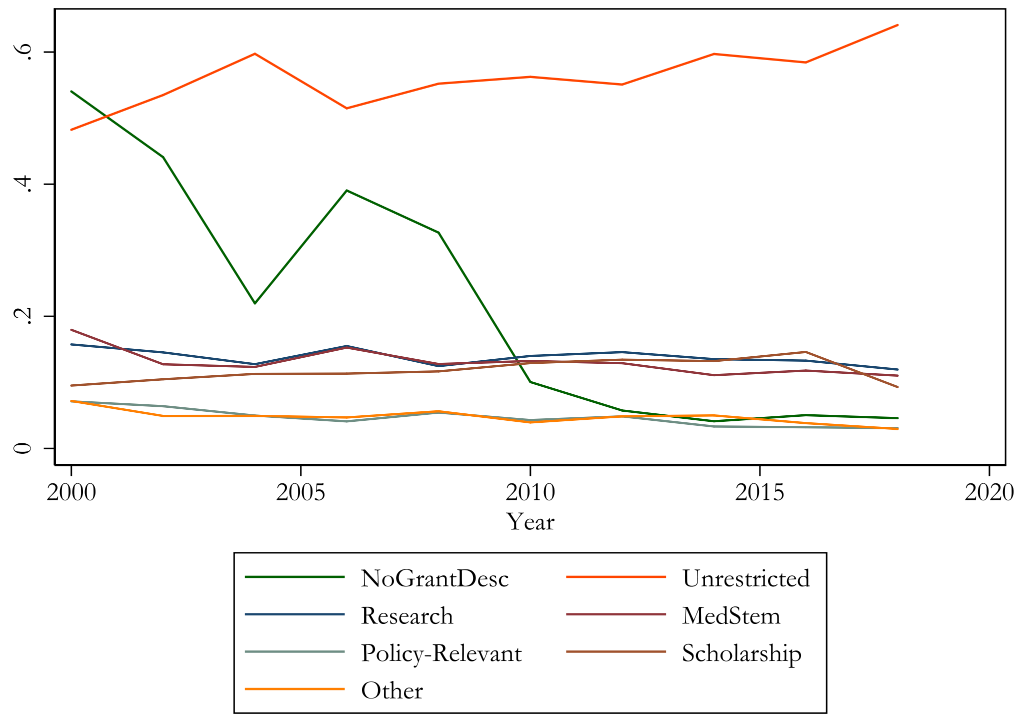


Figure 2.7: Declared Use of Funds: Evolution

**Note:* figure reports the proportion of funds linked to each area based on private foundations' grant descriptions reported to the IRS in their Form 990. Groups are not exclusive (i.e., the total adds up to more than 1).

funding in a given year. Instead, the analysis compares donors' preferences depending on whether they contributed to each area in a year. In particular, it shows the interaction of ideological distance with a dummy variable indicating if each foundation donated to a specific area each that year. [9]

The estimation in Table 2.6 shows that private foundations which give a more significant proportion to research act according to valuing ideology more deeply than other donors. However, this phenomenon appears in policy-relevant areas and fields related to exact sciences, where political opinions arguably play a minor role. In contrast, those

9. Alternatively, we could compare the donations made by each donor depending on the destination of the funds. Unfortunately, in that case, the variation would come exclusively from those donors who contributed to multiple categories.

	(1) Contribution Amount	(2) Contribution Amount	(3) Contribution Amount	(4) Contribution Amount	(5) Contribution Amount
Distance	-0.054***	-0.042***	-0.042***	-0.041***	-0.052***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.011)
Distance × Scholarships	0.036**				
	(0.017)				
Distance × Research		-0.106*			
		(0.060)			
Distance × Med-STEM			-0.075*		
			(0.040)		
Distance × Policy-Relevant				-0.156**	
				(0.074)	
Distance × Unrestricted					0.010
					(0.019)
r2	0.256	0.256	0.256	0.256	0.256
N	252,526	252,526	252,526	252,526	252,526

Table 2.6: Donors Preferences: Donors Comparison By Preferred Use of Funds

Each observation corresponds to a university-foundation transaction in the choice set of a foundation in a given cycle. Distance measures the absolute value of the difference between the CFScore of the private foundation and the university. Standard errors clustered at the foundation state level in parentheses. Contribution amounts in logs. All regressions include cycle fixed effect. *** p<0.01 ** p<0.05 * p<0.1.

donating to scholarships seem less concerned with universities' perceived ideology.

The results in Table 2.7 compare donors by the destination of foundations donations reported by universities in the Voluntary Support of Education Survey (VSE) to complement the declared use of funds. The first column of this table shows that ideological distance decreased donations an additional 0.9 percent among schools whose foundations' contributions per student to current operations are one percent higher. The second column corroborates this finding, indicating that an increase of one unit in the proportion of foundations' donations going to current operations –as opposed to capital or endowment– increases the magnitude of the preference for similar ideologies by 0.8 percent. Since current operations funds are directed toward more specific goals than endowments, this corroborates the previous funding that donors who contribute to more ideologically similar institutions target narrower areas of spending. Subsequent columns of this table further divide these expenditures according to whether the universities reported them related to research, student aid, public service, academic services, or other areas. Consistently with the results found using grants' description data, the association between donated amount and ideological distance is higher for universities that reported that foundations donated more to research. Moreover, it was also smaller for those contributing to student aid as determined when exploiting grant descriptions' data. These results are robust to examining the decision to donate instead of the donation amount.

As pointed out by the theoretical framework, a private foundation attempting to influence a school would, all else equal, target institutions more susceptible to being influenced. Table 2.8 explores this dimension by comparing universities according to their endowment levels and the size and proportion of their funding granted by foundations. This shows that universities with larger endowments receive donations from donors that are ideologically closer to them. However, this association fades if we simultaneously control whether the school can be considered a top school. The analysis also shows that ideological distance's impact is more substantial for foundations donating to schools that receive a larger proportion of their gifts from foundations. Likewise, ideology significantly influences private foundations donating to schools that receive more donations for restricted purposes. This evidence reflects what we would expect to observe if donors who are more politically active are also those who act more strategically and prefer more controlled ways of support.

2.5.3 Foundation Characteristics

The analysis so far focused on preferences of private foundations as a whole, despite considerable heterogeneity in their attributes. Private foundations present substantial differences in their total assets and income, governance practices, and openness to the public. The first two columns of Table 2.9 show the estimated change in donations in

	(1) Donation log ($)	(2) Donation log ($)	(3) Donation log ($)	(4) Donation log ($)	(5) Donation log ($)	(6) Donation log ($)	(7) Donation log ($)
Distance (log)	0.107***	-0.013***	-0.012***	-0.023***	-0.018***	-0.018***	-0.018***
	(0.020)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Distance (log) × Found. CurrOps (log $)	-0.009***						
	(0.001)						
Distance (log) × Prop. CurrOps		-0.008***					
		(0.002)					
Distance (log) × Prop. Research			-0.037***				
			(0.004)				
Distance (log) × Prop. Student Aid				0.026***			
				(0.005)			
Distance (log) × Prop. Pub. Service					0.018**		
					(0.009)		
Distance (log) × Prop. Academic Services						0.001	
						(0.003)	
Distance (log) × Prop. Others							0.001
							(0.003)
r2	0.064	0.064	0.065	0.065	0.065	0.065	0.064
N	17130275	17135542	16210881	16214345	16205261	16216763	17130275

Standard errors clustered at foundation state level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Notes: Each observation corresponds to a university-foundation transaction in the choice set of a foundation in a given cycle. Distance measures the absolute value of the difference between the CFScore of the private foundation and that of the university. Standard errors clustered at the foundation state level in parentheses. Contribution amounts in logs. All regressions include cycle fixed effect. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table 2.7: Donors Preferences: Preferred Area of Contribution

	(1) Donation log ($)	(2) Donation log ($)	(3) Donation log ($)	(4) Donation log ($)	(5) Donation log ($)
Distance (log)	0.140***	0.115***	0.102***	-0.007**	-0.008**
	(0.031)	(0.021)	(0.020)	(0.003)	(0.004)
Distance (log) × Endowment (log $)	-0.008***				
	(0.002)				
Distance (log) × Found. Total (log $)		-0.009***			
		(0.001)			
Distance (log) × Found. Restricted (log $)			-0.008***		
			(0.001)		
Distance (log) × Prop. Foundations				-0.043***	
				(0.006)	
Distance (log) × Prop. Restricted					-0.011**
					(0.005)
r2	0.062	0.062	0.064	0.059	0.064
N	20168835	20216012	17104371	18316632	17129800

Notes: Each observation corresponds to a university-foundation transaction in the choice set of a foundation in a given cycle. All interacted variables present the log-amounts per student. Standard errors clustered at the foundation state level in parentheses. Contribution amounts in logs. All regressions include cycle fixed effect. *** p<0.01 ** p<0.05 * p<0.1.

Table 2.8: Donors Preferences: University Self-Reported Destination of Foundations Funds

response to an increase of one percent in the ideological distance for different levels of assets and income, respectively.[10] This analysis shows that large donors choose universities more ideologically aligned with them. In particular, a one percent increase in ideological distance is associated with a reduction in foundations' donations of 0.8 percent among foundations with less than 500 thousand dollars in assets. In contrast, this association reaches 6 percent among foundations with more than 50 million in assets. The results are similar when measuring this in terms of income, but the differences are even starker. Moreover, these results are robust to analyzing the decision to donate or not instead of the amount of the donations.

One possible explanation for the different behavior of larger and small donors is that the former may have stronger preferences for universities' political positions. However, this is also consistent with what would occur if private foundations with larger financial capabilities internalize a higher probability of affecting the recipient institutions. On the other hand, larger foundations also donate more actively to research, while proportionally less money goes to scholarships or unrestricted funds. Specifically, the proportion of grants classified as unrestricted reaches 75 percent in the group with the smallest assets, while this is only 61 percent among the foundations with the largest assets. While Reckhow and Snyder (Reckhow and Snyder) find evidence suggesting that the largest foundations contributing to education have converged around "jurisdictional challengers," Ferrare and Reynolds (Ferrare and Reynolds) analyze a small sample of less prominent foundations and find that they have also adopted some elements of major foundations, but present much more heterogeneous strategies.

No statistically significant differences are found in the association between donors' and recipients' ideological distance when interacting with foundations' views or stan-

10. The categories used in the data are based on nine original categorical groups in the data, where adjacent groups were combined. Each group is combined to include the closest proportion to 25 percent of the sample in each group.

	Donation log ($)	Donation log ($)	Donation log ($)	Donation log ($)	Donation log ($)	Donation log ($)	Donation log ($)
Distance (log)$\times(X < 500K)$	-0.008***	-0.008***					
	(0.002)	(0.001)					
Distance (log)$\times \in (500K - 5M)$	-0.009***	-0.012***					
	(0.001)	(0.002)					
Distance (log)$\times(X \in 5M - 50M)$	-0.016***	-0.023***					
	(0.003)	(0.003)					
Distance (log)$\times(X > 50M+)$	-0.059***	-0.090***					
	(0.007)	(0.010)					
Distance (log)			-0.015***	-0.015***	-0.016***	-0.017***	-0.014***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Distance (log)× Foundation CF			0.001	0.001			
			(0.001)	(0.001)			
Distance (log)× Faculty Ideology SD					0.001		
					(0.001)		
Distance (log)× Trust						0.006***	
						(0.001)	
Distance (log)× Education Fund							-0.021**
							(0.008)
Bins Variable	Assets	Income					
r2	0.055	0.055	0.056	0.056	0.057	0.056	0.066
N	21462562	21462562	32029689	32029689	30046853	32029689	17765023

Notes: Each observation corresponds to a university-foundation transaction in the choice set of a foundation in a given cycle. Distance measures the absolute value of the difference between the CFScore of the private foundation and that of the university. Standard errors clustered at the foundation state level in parentheses. Contribution amounts in logs. All regressions include cycle fixed effect. *** p<0.01 ** p<0.05 * p<0.1.

Table 2.9: Donors Preferences: Foundation Characteristics

dard deviation in faculty views. However, this does not rule out the existence of more intricate patterns of this association. As expected, trusts display a smaller correlation between the political ideology of its board and that of its recipients. This reflects that a more significant proportion of their donations obey the decisions of individuals outside their directors' board.

2.6 Conclusion

Higher education institutions in the U.S. have sustainably relied on funds contributed voluntarily by the public to enhance their academic and research activities. A growing share of such funds comes from private foundations, reaching one-third of research funding raised in 2016 by elite universities. Unfortunately, organizations or even individuals depending on external resources are susceptible to being captured by the interest of those managing the funds. Suppose the identity or ideology of the supporters of higher education institutions is similar to that of the general population. In that case, the overall of this channel can be expected to dilute. In reality, most private foundations are funded by highly wealthy donors whose views are unaligned with those of the general public.

The evidence presented here suggests that private foundations donate to universities that share their ideology. However, more importantly, they do so more intensively when supporting research activities, enhancing their potential to affect policy decisions outside academia. In turn, the results imply that reliance on donors' contributions constitutes a mechanism through which polarization in the general society could permeate academic research and formation.

These results do not imply that universities should stop seeking or accepting funds from private foundations. On the contrary, their contributions have significantly improved U.S. higher education and hopefully will continue to do so. Instead, this aims to raise attention to this channel's potential to influence the higher education system and academic research, threatening its impartiality. Given the massive increase in donations from private foundations in previous years and the increasing societal polarization, together with reducing alternative sources such as state funding, it is expected that the relevance of these mechanisms will continue to grow in the future.

Universities aiming to reduce their dependence on particular institutions or individuals must ensure that funds originate from a larger population, usually alums, or from non-discretionary donations. The more dependent a university becomes on a small pool of donors, the more susceptible these institutions are to be captured. Likewise, the more discretionary and restrictive donors are when contributing to universities, the riskier this becomes. There are differences between donors that assign funding discretionarily to specific projects and those that donate irrespective of their specific purposes. In addition, higher reporting standards that improve accountability for tax-exempt foundations would help address this, yet only partially. While the IRS requires all private foundations to describe the grants they deploy in their tax reports, the current standard results are often uninformative. Taking together, policies in this direction could diminish this channel's threat to educational institutions' impartiality and independence.

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APPENDIX A

APPENDIX FOR CHAPTER 1

A.1 SAS Adoption: Within School Comparison

	(1) Std. Scores SIMCE	(2) Raw GPA [1-7]	(3) GPA Rank	(4) Attend. [1-100]	(5) Low SES	(6) Income per capita	(7) Mother w/ High School
	Panel A: Voucher Schools						
SAS Level	0.037***	0.125***	0.117***	0.981***	0.035***	-0.029***	-0.018***
	(0.008)	(0.006)	(0.009)	(0.096)	(0.004)	(0.007)	(0.004)
Voucher	-0.114***	-0.128***	-0.003	-1.526***	0.025**	-0.076***	0.024***
× SAS Level	(0.023)	(0.015)	(0.026)	(0.200)	(0.010)	(0.019)	(0.009)
N	580,595	1,012,627	1,009,876	1,012,629	1,398,771	703,414	734,346
	Panel B: High-Performing Schools						
SAS Level	0.053***	0.105***	0.108***	0.771***	0.029***	-0.050***	-0.015***
	(0.008)	(0.006)	(0.009)	(0.092)	(0.004)	(0.007)	(0.004)
High-Performing	-0.170***	-0.153***	-0.043	-1.757***	0.007	-0.111***	0.006
× SAS Level	(0.047)	(0.031)	(0.043)	(0.269)	(0.020)	(0.040)	(0.015)
N	404,562	756,539	754,533	756,537	834,717	521,734	543,121
	Panel C: High Demand Schools						
SAS Level	0.036***	0.122***	0.115***	0.960***	0.035***	-0.025***	-0.017***
	(0.008)	(0.006)	(0.009)	(0.098)	(0.004)	(0.007)	(0.004)
High-Demand	-0.095***	-0.123***	-0.015	-1.401***	0.018*	-0.073***	0.020**
× SAS Level	(0.023)	(0.015)	(0.025)	(0.198)	(0.010)	(0.019)	(0.009)
N	550,696	970,917	968,203	970,919	1,327,468	680,210	701,983

Standard errors clustered at classroom level in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table A.1: SAS Adoption: School Characteristics

Each observation corresponds to a student who switched schools at a given year to compare trend changes in students enrolled at each school. Regressions include year times school fixed effects to compare outcome within a school-year application period. Outcomes correspond to the background characteristics of the incoming students enrolled at each school. Robust standard errors clustered at the school level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

	(1) Std. Scores SIMCE	(2) Raw GPA [1-7]	(3) GPA Rank	(4) Attend. [1-100]	(5) Low SES	(6) Income per capita	(7) Mother w/ High School
				Panel A: High-Priced Schools			
SAS Level	0.035***	0.121***	0.114***	0.928***	0.036***	-0.027***	-0.017***
	(0.008)	(0.006)	(0.009)	(0.093)	(0.004)	(0.007)	(0.004)
High-Priced	-0.150***	-0.136***	0.039	-1.741***	0.018	-0.134***	0.022**
× SAS Level	(0.025)	(0.018)	(0.031)	(0.212)	(0.011)	(0.024)	(0.009)
N	575,892	1,004,228	1,001,505	1,004,230	1,384,665	698,350	728,999
				Panel B: Mid-Priced Schools			
SAS Level	0.025***	0.114***	0.116***	0.850***	0.036***	-0.036***	-0.016***
	(0.008)	(0.006)	(0.009)	(0.090)	(0.004)	(0.007)	(0.004)
Mid-Priced	-0.057	-0.103***	0.023	-1.506***	0.029*	-0.042	0.022
× SAS Level	(0.037)	(0.024)	(0.046)	(0.390)	(0.017)	(0.030)	(0.014)
N	575,892	1,004,228	1,001,505	1,004,230	1,384,665	698,350	728,999
				Panel C: Free-Tuition Schools			
SAS Level	0.019**	0.110***	0.119***	0.790***	0.039***	-0.038***	-0.017***
	(0.008)	(0.006)	(0.009)	(0.091)	(0.004)	(0.007)	(0.004)
Free Tuition	0.078***	0.010	-0.028	0.081	-0.030**	0.019	0.024
× SAS Level	(0.029)	(0.020)	(0.033)	(0.335)	(0.014)	(0.023)	(0.015)
N	575,892	1,004,228	1,001,505	1,004,230	1,384,665	698,350	728,999

Standard errors clustered at classroom level in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A.2: SAS Adoption: School Characteristics

Each observation corresponds to a student who switched schools at a given year to compare trend changes in students enrolled at each school. Outcomes correspond to the background characteristics of the incoming students enrolled at each school. Regressions include year times school fixed effects to compare outcome within a school-year application period. Robust standard errors clustered at the school level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

A.2 Peer Background Effect: Income Level

	(1)	(2)	(3)	(4)	(5)	(6)
	School Performance				Standardized Tests	
	GPA	GPA Rank	Attend.	Pass Year	Math	Reading
Panel A: Proportion of Low-SES Classmates						
Prop. of Low-SES Classmates	0.370	1.395***	-12.983	0.020	-1.201	0.583
	(0.439)	(0.299)	(8.028)	(0.092)	(1.735)	(1.616)
N	929,660	928,771	929,657	954,290	41,870	41,624
Panel B: Classmates's Mother High School Degree						
Mother High School Ed.	1.629***	0.177	10.282	0.214***	0.703	0.783
	(0.411)	(0.255)	(7.221)	(0.074)	(0.738)	(0.601)
N	770,535	770,291	770,531	779,651	38,852	38,536
Panel C: Classmates's Mother College Degree						
Mother College Ed.	0.817*	-0.601*	18.650**	0.043	2.289	4.226
	(0.457)	(0.312)	(8.872)	(0.076)	(2.964)	(3.804)
N	770,535	770,291	770,531	779,651	38,852	38,536
OutcomeMean	5.751	0.002	92.616	0.964	-0.119	-0.037
SD	0.785	0.984	9.878	0.186	0.940	0.959
IncludesLags	Yes	Yes	Yes	No	Yes	Yes

Table A.3: Peers' Background Effect: Income

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

	(1) Motivation	(2) Self-Confid.	(3) School Satisf.	(4) Discrim.	(5) Behavior Prob.
Panel A: Proportion of Low-SES Classmates					
Low-SES Classmates	0.021	0.042	0.094	0.061	-0.053
	(0.155)	(0.148)	(0.182)	(0.135)	(0.144)
N	47,310	47,104	47,380	47,056	46,920
Panel B: Classmates' Mother High School Degree					
Mother High School Ed.	-0.133*	-0.062	-0.048	0.071	-0.081
	(0.077)	(0.069)	(0.094)	(0.052)	(0.056)
N	41,134	40,951	41,183	40,912	40,814
Panel C: Classmates' Mother College Degree					
Mother College Ed.	0.247	-0.251	-0.274	0.235	-0.094
	(0.375)	(0.329)	(0.449)	(0.268)	(0.229)
N	41,134	40,951	41,183	40,912	40,814
OutcomeMean	0.692	0.745	0.516	0.083	0.255
SD	0.136	0.122	0.104	0.118	0.089
IncludesLags	No	No	No	No	No

Table A.4: Peers' Background Effect: Income - Behavioral Outcomes

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

	(1) Take College Adm. Exam	(2) Enroll in College	(3) Coll. Exam Percentile	(4) College Admission Exam Subject Reading	(5) Math	(6) History	(7) Science
Panel A: Proportion of Low-SES Classmates							
Prop. Low-SES	0.189	0.106	-55.833*	-183.766	-197.773*	11.683	-66.145
	(0.516)	(0.457)	(31.265)	(119.872)	(120.151)	(181.992)	(178.185)
N	209,069	209,069	142,699	142,699	142,699	142,699	142,699
Panel B: Proportion of Classmates' Mother High School Degree							
Prop. High School Deg.	0.213	-0.005	17.870	131.237	96.144	53.540	184.513
	(0.495)	(0.561)	(43.817)	(157.181)	(153.269)	(233.568)	(242.327)
N	160,507	160,507	115,259	115,259	115,259	115,259	115,259
Panel C: Proportion of Classmates' Mother College Degree							
Prop. Mother College Deg.	0.053	0.831	90.167*	237.203	433.197*	547.940*	144.829
	(0.449)	(0.602)	(51.499)	(162.998)	(222.989)	(304.876)	(233.068)
N	160,507	160,507	115,259	115,259	115,259	115,259	115,259
OutcomeMean	0.749	0.298	45.744	476.786	474.114	270.173	320.414
SD	0.434	0.458	28.093	122.191	127.771	253.378	241.765
IncludesLags	No	No	No	No	No	No	No

Table A.5: Peers' Background Effect: Income

Each observation corresponds to a student-year. Regressions control for fixed effects by grade-year, decile of applicants' heterogeneity, region, school dependence, and SEP program adherence. Actual incoming students characteristics are instrumented using deviation in each school-grade admitted set of students relative to its applicants. Robust standard errors clustered at the school-grade level in parenthesis. *** p<0.01 ** p<0.05 * p<0.1.

A.3 Peer Effects Instrument Validity

To verify the validity of this instrument, let z_i be the characteristics' vector of a student i and $Z_j = (z_1, \ldots, z_q)$ be the vector of q applicants to school j. Then the allocation mechanism will assign a subset $\mu(X_j) = [\mu_1^j, \ldots, \mu_q^j]$, where $\mu_i^j = 1$ indicates that student i was assigned to school j and $\mu_i^j = 0$ otherwise. The function μ depends on X_j to reflect that the allocations could depend on students' characteristics X under alternative assignment mechanisms. Given the limited number of spots, it has to hold that $\sum_i \mu_1^j \leq k_j \; \forall j$. Note that we can then rewrite the potential outcomes as follows:

$$Y_{ij} = \alpha_j + \beta x_i + \gamma_{(i,-i)} \mu(Z_j) Z_j^{-i} + \epsilon_{ij} \tag{A.1}$$

Given that applicants self-select when applying to schools, we have that $\mu(Z_j)Z_j^{-i} \not\perp \epsilon_{ij}$ even when spots in schools are randomly allocated among applicants. This is because the applicants' set differs for every school due to characteristics possibly related to unobservables. Consequently, a direct OLS measurement of $\gamma_{(i,-i)}$ would yield biased estimates. To overcome this, define instead $W(Z_j) = \mu(Z_j)Z_j - E[\mu(Z_j)Z_j|Z_j]$, which we refer to as classroom shocks. First, note that this is uncorrelated with the error term in the structural equation once we condition on applicants' characteristics:

$$\begin{aligned}
E[W(Z_j)'\epsilon_j|Z_j] &= E[Z_j'\mu(Z_j)'\epsilon_j - E[Z_j'\mu(Z_j)'|Z_j]\epsilon_j|Z_j] \\
&= Z_j'E[\mu(Z_j)'\epsilon_j|Z_j'] - Z_j'E[E[\mu(Z_j)'|Z_j]\epsilon_j|Z_j] \\
&= Z_j'E[\mu(Z_j)'\epsilon_j|Z_j'] - Z_j'E[\mu(Z_j)'\epsilon_j|Z_j] \\
&= 0
\end{aligned}$$

Where the first part is zero because the random assignment from DA guarantees $\mu(Z_j) \perp \epsilon_{ij}$. However, we would not expect this correlation to be zero if spots were not randomly allocated or if schools performed screening practices.

To analyze the relevance of $W(Z_j)$ as an instrument for Z_j^{-i}, we can rewrite this in the following manner:

$$\begin{aligned}
E[W(Z_j)Z_j^{-i}|Z_j] &= E[\mu(Z_j)Z_jZ_j^{-i} - E[\mu(Z_j)Z_j]Z_j^{-i}|Z_j] \\
&= E[\mu(Z_j) - E[\mu(Z_j)]|Z_j]Z_jZ_j^{-i} \\
&= V[\mu(Z_j)]|Z_j]Z_jZ_j^{-i}
\end{aligned}$$

From here, we can conclude that there are three conditions are necessary for $\mu(Z_j)$ to be a relevant instrument for classroom composition: i) that the school is oversubscribed, so that $V[\mu(Z_j)] \neq 0$; ii) that there is variation among the applicants themselves, so that $Z_jZ_j^{-i} \neq 0$; and iii) that the proportion of randomized spots is large enough.

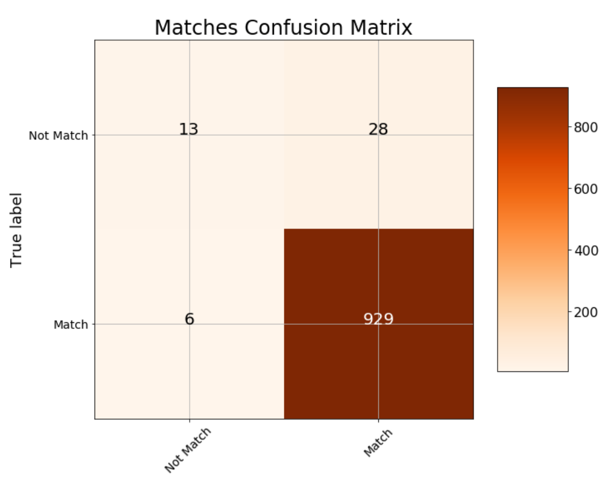
In an empirical setting, we rarely observe schools with identical characteristics and an equal number of spots and applicants. However, our estimation of the empirical distribution of new students allows us to identify schools with equivalent shock distributions. In practice, the definition of similarity will depend on the specific functional form used in the analysis. For example, in a linear-in-means model, a similar applicant pool would be one with a similar distribution of the average of admitted students. Therefore, we control by applicants' average characteristics and bins of standard deviation to produce schools with comparable admitted students distributions.

APPENDIX B

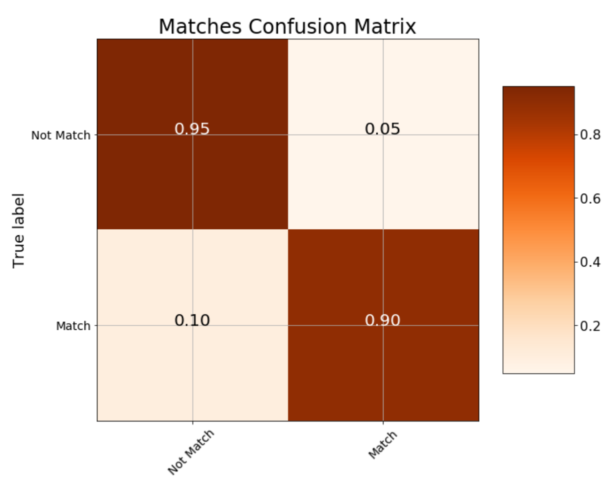
APPENDIX FOR CHAPTER 2

B.1 Matching Process

The data on faculty donations contains information about those who reported a given university as their employer. FEC respondents are required to declare the position they occupy at their current employment, but respondents are often unspecific or use abbreviations. As a results, false matches can appear. Individuals who reported to be students, teaching assistants, and research assistants were removed, but all other categories were maintained, such as administrative positions, to avoid confusion and arbitrary choices when comparing position titles from different schools. The overall distribution is hardly affected when removing categories that are less likely to represent faculty. Hence all cases are maintained to avoid noisy estimates of the school position when observing few data points for each single university.



(a) University-Grantee Names



(b) Faculty Emploers

Figure B.1: Matching Process Statistics

	(1) Contrib. Amount	(2) Contrib. Amount	(3) Contrib. Amount	(4) Contrib. Amount	(5) Contrib. Amount
Distance	-0.043***	-0.032***	-0.030***	-0.033***	-0.042***
	(0.011)	(0.010)	(0.009)	(0.010)	(0.011)
Distance × Top-School	-0.078***	-0.079***	-0.079***	-0.079***	-0.080***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Distance	0.000				
	(.)				
Distance × Scholarship	0.033*				
	(0.018)				
Distance		0.000			
		(.)			
Distance × Research		-0.076			
		(0.072)			
Distance			0.000		
			(.)		
Distance × Med-STEM			-0.108**		
			(0.044)		
Distance				0.000	
				(.)	
Distance × Policy-Relevant				-0.099	
				(0.073)	
Distance					0.000
					(.)
Distance × Unrestricted					0.009
					(0.020)
r2	0.276	0.276	0.276	0.276	0.276
N	180,194	180,194	180,194	180,194	180,194

Notes: Each observation correspond to a university-foundation transaction in the choice set of a foundation in a given cycle. Distance measures the absolute value of the difference between CFScore of the private foundation and that of the university. Standard errors clustered at foundation state level in parentheses. Contribution amounts in logs. All regressions include cycle fixed effect. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table B.1: Donors Preferences: Use of Funds - Top Schools