Switching costs in school choice systems

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Abstract

Chilean households value academic quality and have access to detailed information about schools' characteristics. However, they seldom react to relative changes in the quality of schools and their potential competitors by switching schools. Why do students not switch more often despite their ability to do so each year? I document that families' preferences for schools exhibit inertia, which deters them from switching. To quantify this inertia, I estimate a discrete choice model combining rich administrative data and two sources of identification. First, some students are forced to switch because of schools' grade level configuration, which disrupts their inertia. Second, the introduction of a centralized assignment mechanism reduced search costs earlier for some students than for others. I find that families are willing to switch only if the destination school is substantially better than their current school. Further, I investigate the microfoundations of this inertia by surveying a random sample of parents. My findings indicate that attributes that develop through the schooling experience and that are difficult to modify through market forces or policy interventions, such as the learning environment and personal relationships, are relevant. This implies that the demand for schools is to some extent captive, which dilutes the incentives for schools to compete in attracting enrollment and could limit quality improvements in school choice systems.

Keywords: School choice system, switching costs, peer effects, deferred acceptance algorithm
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1 Introduction

School choice systems, which allow students to choose their school each year, have been growing in popularity around the world (Patrinos et al., 2009). In such systems, the freedom to choose –*and switch*– schools is the key channel of demand-side pressure for schools to compete with each other to attract enrollment (Friedman, 1962). If families hesitate to switch when their schools worsen or when potential competitors improve, then the demand becomes captive and the incentives for all schools to improve (and thus retain or attract other schools' students) are diluted. As a consequence, this could limit overall quality in school choice systems. Given the growing ubiquitousness of policies granting room for choice, understanding the extent to which households are willing to switch schools is key to judge the potential success of these policies in improving the quality of education.

In this paper, I document that families' preferences for schools exhibit inertia, which deters them from switching schools. I formalize the above argument by drawing an analogy with the literature on switching costs (or inertia), which investigates, in different contexts, why agents do not react to changes in the market environment that would benefit them (Farrell and Klemperer, 2007). In schooling, inertia might arise because students form relationships that are deleterious to break or because searching for a new school is costly (if parents have to gather information or fill out paperwork). If these costs are high, they might deter families from leaving poorly performing schools or seeking to enroll in better ones. On top of weakening the incentives to compete, the presence of inertia could explain why families do not necessarily choose the "best" schools, an observation that the literature has attributed to a lack of preferences for quality (Abdulkadiroğlu et al., 2020) or inaccurate information about what the best schools are (Ainsworth et al. (2022), Allende et al. (2019)).[1]

I proceed in five steps. First, I present descriptive evidence on the existence of inertia. I show that every year a minor share of students chooses to switch schools, that the probability of switching does not change after changes in the relative quality of their schools and the (geographically) closest competitor, and that the introduction of a website that alleviated search costs increased mobility. In the second step, I study the consequences of switching for cognitive and noncognitive outcomes. This step is key because a school choice system requires that families be willing to switch schools (to strengthen demand-side pressure on schools); if the costs of doing so outweigh the benefits, encouraging mobility might hurt switchers. I find weakly positive effects of voluntary switches. Third, I explore the consequences of school mobility for nonswitchers. This is relevant because having new peers each school year might affect performance in ways that are not immediately obvious. In addition, any policy aimed at encouraging mobility should take into account the potential externalities for nonswitchers; I find that these are negative but mild. Steps 1, 2 and 3 pose a puzzle: families could be better off by switching schools while inducing only mild externalities for the students who receive new classmates. Why, then, do they not switch more often? In the fourth step, I offer an explanation by investigating the factors that drive families to seek a new school. To do so, I estimate a demand for schools that incorporates inertia combining a discrete choice model with data on students' choices and schools' attributes. Finally, to decompose inertia in different potential sources, I show the results of directly surveying a random sample of parents to inquire about their reasons for not switching.

In the first step, I show descriptive evidence of the presence of inertia in the Chilean school system. First, I show that a every year only a minor share of students switch schools. Second, I show that the marginal effects on the probability of switching after changes in the cognitive and noncognitive outcomes

[1] Note that these are features of the demand that weaken the incentives to compete and give schools market power. On the supply side, schools might gain market power if they differentiate themselves from competitors horizontally by offering alternative learning programs, becoming imperfect substitutes (Gilraine et al., 2021).

of the closest competitor schools are precisely estimated zeros. In other words, students do not react to changes in the market environment even though, in principle, switching to better-performing schools would make them better off. Third, I estimate an event study leveraging the staggered roll-out of a school choice system that alleviated search costs by centralizing in a single web-platform all the information and paperwork that families had had to collect on their own before its introduction. I find that switching rates increased by 1.5 percentage points in grades in treated administrative regions over the rates in untreated ones. This suggests that part of the inertia is due to search costs.

In the second step, I study the consequences for switchers in terms of both cognitive and noncognitive outcomes. Answering this question is challenging because of the unobserved nature of the underlying switching decision process and the likelihood that it might be related to the very outcome on which its impact is being measured. For example, if students whose parents advocate for a better education are more likely to switch schools, a positive effect of switching may arise due to parental support, thereby biasing the effect of switches. I overcome this challenge in two ways. First, I leverage the fact that some Chilean schools have grade configurations that do not offer 9th grade, forcing their 8th-grade students to switch schools. Being enrolled in a school that does not offer the following grade increases the probability of switching schools only for those in such schools while not necessarily impacting students' outcomes per se. Second, I leverage the fact that the centralized school choice system (CSCS) allocates students to schools using the deferred acceptance algorithm with embedded lotteries when there are ties among applicants at oversubscribed schools. This allows me to recover the probability of a student's being offered a seat at a new school, conditional on which such offers are independent of unobserved determinants of outcomes (Abdulkadiroğlu et al., 2017).

I find that, two years after switching, students forced to switch (but allowed to choose where to re-enroll, given the school choice system) perform approximately 0.2σ lower than students who are not forced to switch schools on cognitive outcomes and approximately 0.14σ lower in noncognitive outcomes. However, I find that, one year after the switch, students who voluntarily switch schools perform 0.3σ better in reading (and not different in math) than those who also applied to switch but were denied a seat in a new school by chance. Heterogeneity analyses indicate that the positive effects in reading are stronger among students who performed above average before voluntarily switching than among nonswitcher students who also performed above average. Similarly, noncognitive outcomes remain unchanged across the four alternative available measures. In this case, the heterogeneity analysis indicates that self-esteem deteriorates considerably among students who scored above average in this dimension before switching. Taken together, these results suggest that the consequences of switching schools are, at the very least, not harmful for voluntary switchers.

In the third step, I study the consequences for nonswitchers, i.e., those who remain in their current schools and experience the arrival of new classmates. Addressing this question presents the challenge that the proportion of new entrants is likely correlated with unobserved determinants of school quality, which, in turn, can affect students' outcomes. As a consequence, any cross-sectional estimation of the effect of the share of new entrants on outcomes comparing students facing different shares in different schools would be biased in the direction of the correlation between the share of new entrants and the unobserved determinants of students' outcomes. To address this issue, I build upon Hoxby (2000) and exploit the variations in the new entrants share within the same school to compare students at different grade levels who are similar in observed characteristics and school environment but who face different exposure levels to new classmates. Such variation can be considered idiosyncratic after I control for a rich set of individual characteristics.

I find that turnover has a small negative impact on the cognitive outcomes of nonswitcher students. An increase equivalent to one standard deviation in the share of new entrants leads to a decrease of 0.007σ and

0.015σ in math and reading test scores, respectively. Additionally, turnover hinders noncognitive outcomes, with effects ranging between 0.004 and 0.02σ (depending on the noncognitive dimension) following an increase of one standard deviation in the share of new classmates. The heterogeneity analyses reveal that the negative effects are concentrated among students with lower baseline performance, and for cognitive outcomes, this effect is more pronounced among girls. In the case of noncognitive outcomes, the negative impact is stronger for boys. The composition of the share of new entrants proves to be a key factor, as the better (worse) the outcomes of new students, the more positive (negative) are the effects on both cognitive and noncognitive outcomes of nonswitcher students. Additionally, when a higher proportion of new entrants is of a disadvantaged background, the negative effects on nonswitcher students become more pronounced.

These three preceding steps pose a puzzle: why despite the potential benefits of switching to preferred schools students do not switch more often? In the fourth step, I study the causes of school mobility by estimating a demand for schools with switching costs. The inclusion of these costs captures the idea that students become locked in after enrolling in a given school and, thus, deter them from switching. I incorporate two sources of inertia to account for the fact that, after considering other relevant schools' observed attributes (e.g., alternative measures of quality or peer SES), students might hesitate to switch schools. The first source arises from the hassle of having to look for alternative schools, visit them to find out about educational projects and complete paperwork (a search cost). The second source captures a bundle of other potential sources of inertia such as leaving friends or specific teachers behind (a fixed cost). Both of these costs might deter families from switching schools even if there are better alternatives available, if they are informed about these, and they value academic and non academic quality.

To separately identify these two sources of inertia, I extend the argument in Luco (2019) to the Chilean school system context. In particular, different Chilean students face different switching costs depending on two dimensions. The first dimension is whether students have to actively choose a school; this dimension generates two groups of students. The first group is composed of those entering the system for the first time (i.e., rising 1st-grade students) and those transitioning to a grade level that their status-quo school does not offer (most of them in 8th grade due to the common 1st-to-8th-grade configuration in Chile); I call these active students. The second group is composed of students already enrolled in the system who can passively remain in their status quo by default (e.g., students in 4th grade in a school that offers 5th grade); I call these passive students. The second dimension is whether students apply to switch schools through the centralized school choice system, which, given the roll-out of the system, depends on the grade in which the student is seeking to enroll and the administrative region in which the school is located. The intersection of these two dimensions generates four types of students: passive students exposed to the CSCS; passive students not exposed to the CSCS; active students exposed to the CSCS; and active students not exposed to the CSCS.

Passive students both exposed and not exposed to the CSCS can avoid both the search and the fixed costs by remaining in their status quo schools. Active students exposed to the CSCS can avoid only the search cost, as the CSCS eliminates the hassle of having to collect information on different alternative schools but not other costs associated with leaving a school, such as leaving behind a community. If the fixed costs are high enough, passive students subject to the CSCS will remain in their status quo schools. Thus, comparing the choices of this group with those of active students subject to the CSCS identifies the fixed costs. On the other hand, active students not exposed to the CSCS incur both costs upon (obligatorily) switching schools. Thus, the comparison of the choices of this group and those of active students exposed to the CSCS identifies the search costs.

The demand estimates show that, after I account for a set of relevant schools' attributes such as peers' socioeconomic characteristics, out-of-pocket fees and academic and nonacademic quality, families derive

high disutility from switching schools. Specifically, the search cost equals 0.2σ of the school average test score in math (1.4σ of a noncognitive test). In other words, families are willing to "pay" the search cost only if moving from a median school to one in the 60th percentile of the school-average math test score distribution. These estimates are higher for disadvantaged students (0.33σ), which implies that this group of the population does not exercise choice effectively. Overall, these results imply a weak demand-side pressure channel over schools to improve quality, provided that families' school choices show substantive inertia. To obtain an idea of what schools' responses are to this inertia, I calculate value added among schools that offer primary only versus those that offer secondary only. The former, which face arguably less pressure to offer quality (as their students must switch at the end of 8th grade and, thus, they face no incentives no retain them) provide significantly less value added than the latter, which face more pressure (as these must attract and retain them.)

In the fifth step, I address two potential concerns about my switching costs estimates. First, the fixed cost is a bundle of multiple factors –e.g., friendships, school community and its environment– that are impossible to disentangle with the administrative data only (this concern is common in the switching costs literature but is often disregarded). Second, its quantification depends on an inference from parents' revealed preferences for schools' attributes that might be imperfect if parents' choices are constrained for any reason. To deal with these concerns, further decompose the sources of inertia in its microfoundations, and directly quantify switching costs, I conduct a survey on a random sample of parents of students in primary education.

To nonswitchers, I ask them to choose reasons for not switching schools among a closed set of possible reasons. I find that distance to school, academic quality and the educational project (presented to parents as the "learning environment, educational project and values") are the three main reasons cited. However, parents also rank the "specific teachers" (65%) and "friendships" (45%) as important factors. These are all attributes that develop with the schooling experience and that are difficult to change by market forces or policy interventions. For switchers, I ask them to evaluate the importance of different attributes when choosing a new school. I find that the most important ones are academic quality and the educational project. Finally, I quantify switching costs building upon Becker et al. (1964). I present hypothetical schools to both groups of parents to infer their "willingness to switch" by sequentially improving these alternative –bu otherwise very similar– schools on three dimensions: increasing values of academic outcomes, a discrete improvement in nonacademic outcomes, and increasing amounts of lump-sum cash transfers. I find that even when parents are offered sizable hypothetical improvements in academic outcomes or lump-sum cash transfers, they are unwilling to switch. However, they do seem willing to switch in exchange for improvements in nonacademic outcomes.

This paper contributes to three different strands of the literature. First, it adds to the ongoing debate on the determinants of families' preferences for schools. In particular, I focus on the tension between the valuation of quality versus information availability in school choice contexts. The literature on this matter has adopted what I call a "static" view of school choice, and the debate can be summarized by considering the following two recent papers.[2] Abdulkadiroğlu et al. (2020) and Ainsworth et al. (2022) both estimate the preferences of one cohort of rising 9th graders in New York and Romania, respectively. The former argues that, conditional on peer quality, preferences are unrelated to value added. The latter argues that families "leave value added on the table" when not choosing the most effective schools (as observed by the researchers) because they are misinformed and provides evidence that information interventions can help families choose slightly better. Hence, these two papers put forward two different mechanisms to explain the fact that families seem not to prioritize academic quality when choosing schools. This paper

[2]The literature on this matter is extensive. See, for example, Hastings et al. (2009), Burgess et al. (2015) and Beuermann et al. (2023).

studies preferences with a panel of students who can potentially switch schools between two consecutive years but face a cost to do so arising from inertia.[3] This mechanism could explain why parents do not choose the "best" schools despite valuing quality even though they are, in principle, well informed about schools' quality.[4]

Second, this paper adds to the literature on switching costs. For instance, the markets for health insurance and retirement pension funds have been studied as ones in which enrollees tend to be nonreactive to the existence of better plans even though they could be better off by switching (Handel (2013), Luco (2019)). Similarly, in marketing, switching costs have been proposed as an explanation for brand loyalty in consumption of different goods (Dubé et al. (2009), Osborne (2011)). This paper extends this argument to families' school choices, a context in which individuals "experience the good" on a daily basis but can choose once a year. Thus, switching costs acquire a different meaning but play a similar role in producing persistence in families' choices. Concretely, through the schooling experience students get used to a learning environment and people. Since there is a cost associated with ending these relationships, students get locked in their schools. This paper uses identification arguments analogous to those used in the literature on switching costs using variations that are common in educations system around the world (e.g., to look at periods when individuals must actively choose a different school due to grade configuration), thus providing a guide for similar studies elsewhere and adding to the literature on the role of inertia in agents' decisions. Furthermore, by surveying nonswitchers' parents about their reasons to not switch, I shed light on the microfoundations of switching costs, something that very few papers in the literature have attempted before (Miravete and Palacios-Huerta (2014), Hastings et al. (2017)).

Finally, this paper adds to the literature on the effects of school mobility in the context of a school choice system. This is relevant because quality in such systems rely on parents seeking the best schools for their kids and, therefore, the ex-post consequences of switches must be taken into account by policies seeking to promote mobility as a way to encourage schools to provide quality.[5] The literature has heavily focused on events such as school closures (Engberg et al. (2012), Brummet (2014)), natural disasters (Sacerdote (2012)), grade configurations (Schwerdt and West (2013), Jackson (2010), Schwartz et al. (2017)), and desegregation policies (Domina et al. (2021), Hill et al. (2023)). These allow to deal with endogeneity, but the estimates they produce out of forced switches are conceptually different from -and not as policy relevant as- those studying switches that occur because families actively decide that another school becomes preferred than the status quo one. Only two papers have aimed to recover a causal estimate of voluntary switches: Hanushek et al. (2004) and Schwartz et al. (2017). None of these papers, though, explore the effects on non-cognitive outcomes. In this study, the use of two instrumental variables approaches allow me to rely on milder assumptions than the ones in these two studies are forced to impose to claim causality (i.e., that the costs of switching sunk after one year Hanushek et al. (2004)), and preserve the relevance of the interpretation of switches that occur out of families will.

The rest of this paper is organized as follows. Section 2 describes the institutional context and explains why it is suitable to answer the research questions. Section 3 describes the data sources. Section 4 shows some descriptive facts of the Chilean educational system. Section 5 studies the consequences of school mobility. It explains three reduced form approaches taking advantage of different sources of

[3] Since I rely heavily on the data collected through the CSCS, this paper also adds to the growing literature using preference data from centralized assignment mechanisms to understand the determinants of preferences (Agarwal and Somaini (2018), Kapor et al. (2020)).

[4] The Chilean school system makes consistent efforts to inform parents about schools' academic quality and its evolution. Furthermore, the web platform of the CSCS contains information on a wide range of characteristics, which alleviate information frictions, something that I will exploit when estimating switching costs in Section 6.

[5] The US, where most of the existing research has taken place, is not an ideal setting to study this issue as school choice is still limited and most of mobility is residential (Rumberger, 2003).

variation in the data. Section 6 studies the causes of school mobility; it explains how I define a demand for schools that incorporates switching costs and my strategy to identify its coefficients. It also describes the survey I conduct to further elucidate the content of switching costs. Section 7 concludes.

2 Institutional Context

Chile introduced a universal school vouchers system in 1981 aiming to increase enrollment and improve quality by incentivizing the existing traditional public schools to compete against the entry of privately-owned schools. In its current form, every student in the country is entitled to a government voucher that allows them to attend any school of their choice with no constraints (such as place of residency or socioeconomic status) except for fully private schools which do not accept vouchers.[6] Also, students are allowed to switch schools every school year with little restrictions.[7] There are three main types of schools. Public ones -which account for 36 percent of the national enrollment- are ran by municipalities, the smallest political-administrative division in the country.[8] Private voucher (P.V.) schools -which account for 54 percent of the national enrollment- are owned and managed by private entities that can administer one or more schools of the same type at the same time. Finally, fully private schools -that account for 9 percent of the national enrollment- are privately managed and funded exclusively on the basis of families' out of pocket fees.

Public and private voucher schools compete for vouchers to fund their operations with them.[9] The amount of the voucher does not depend on the type of school; it varies depending on educational level, on whether it offers special programs or not, rural status, and students' "disadvantaged" status (for whom the school receives twice the value of the regular voucher since 2008). As a consequence, conditional on school and students' characteristics, public and private voucher schools receive the same public funding. Differences in total funding, though, can arise due to the ability of P.V. schools to charge out-of-pocket fees (allowed since the mid-90s in secondary education as a way to complement schools' funding); while both types of schools are allowed to charge them, in practice 20% of them did so before their gradual prohibition in 2016, and virtually all of them were private voucher.

In 2016, a reform introduced three important changes. The most important one -for this project- was the introduction of a centralized school choice system. Before it, families would shop for schools, seek information on vacancies and educational projects and visit them to get a sense on schools quality. In the new system, families find all that information in a web platform and through it submit a rank-ordered list of preferences for schools; then, the Deferred Acceptance algorithm allocates available seats to applicants based on the preferences submitted and the system's priorities. Second, the reform forbid out-of-pocket fees, which critics of the status-quo argued contributed to socioeconomic segregation of the system by cream-skimming the demand (Valenzuela et al., 2014). In practice, the government is gradually increasing the voucher amount over time so the gap between the current voucher and schools' sticker price will close and all schools will become free of charge in full regime around 2030.[10]Third, it forbid for-profit schools in

[6]In practice, the government pays a monthly amount per each enrolled student as long as the student reaches a monthly attendance level. To ensure that schools truthfully report attendance levels, the government randomly monitors schools throughout the year.

[7]The main constraints that a student may face when seeking to switch to a particular school is the availability of vacancies at that school and their family's ability to pay in case the school charges out-of-pocket fees.

[8]This local administration is being replaced by a centralized one since 2017, but logistical and political difficulties have slowed the implementation.

[9]The vouchers are funded through general taxes revenues and private educational projects -for instance religious schools- are allowed to receive them.

[10]The law froze the real price of schools so that these could not increase it indefinitely.

an aim to better align incentives towards the provision of quality. With this change, previously for-profit ones must decide whether to become fully-private, and give up government vouchers to remain for profit, or change their legal status to "educational societies" and re-invest any surplus they could obtain.

The Centralized School Choice System

The Centralized School Choice System (SAE, *Sistema de Admisión Escolar*, by its acronym in Spanish) organizes the admissions and matching process of students and schools. Its introduction was staggered over four years and across the 16 administrative regions of Chile.[11] The system consists of a web platform in which families find a range of relevant information on schools (e.g., administrative dependency, religious orientation, price(if applicable), number of vacancies, location, school average standardized test scores, among others) and through which each applicant must submit a rank-ordered list of preferences for schools.[12] These lists can have as many schools as families wish to include. Upon receiving applications, the Deferred Acceptance mechanism assigns students to their top choice provided that are enough seats available. If there are not, students whose parents work in the school, whose siblings are enrolled in the school, who are disadvantaged and who are former students of the school (in that order) receive a special priority when deciding who gets to enroll in each school. If there are ties, a lottery number drawn at the school level breaks them. Appendix A provides further details about the Chilean D.A. algorithm.

Consider year 2019 as an example of how during a typical year the process works. That year (for school year 2020) the system remained open between mid-August (with little variations in the specific dates by regions) and September the 10th.[13] During this window families navigated the platform and submitted their preferences. Results of the main round of applications were made public in early November and families enrolled (physically, not online) at their assigned schools between December 13th-20th. The school year starts in early March and SIMCE tests are taken in October of each year. Timeline in Figure 14 of Appendix F summarizes the main milestones of the centralized school choice system process.

3 Data

I use four data sources. First, to measure cognitive outcomes, I use SIMCE (*Sistema de Medición de la Calidad de la Educación*) data which corresponds to Math and Reading test scores from the official Chilean testing system. Second, to measure non-cognitive outcomes I use IDPS (*Indicadores de Desarrollo Personal y Social*), which contain four standardized measures capturing social and personal development of students. Both SIMCE and IDPS are jointly collected for the period I analyze and have universal coverage for the grade levels that have to take it in Chile each year (except for 2nd grade, which I do not use). Third, I use publicly available administrative records of both school and student characteristics from the Ministry of Education.[14] Fourth, I use the data arising from the centralized school choice system which contain the rank ordered lists of preferences of families for schools and the system's priorities for different students. The student and school identifiers available in all these data-sets allow me to merge them. I provide further details below.

[11] The first one entered the system in 2017 and the last one in 2020. The map in Figure 11 in the Appendix depicts the roll-out of the system.

[12] Figures 16 and 17 in the Appendix contain screenshots of the website to get a sense of what families see online while looking for a school.

[13] Previous and subsequent years followed a very similar calendar.

[14] See http://datosabiertos.mineduc.cl/.

1. **Cognitive Outcomes.** I use data from the System of Education Quality Measurement (hereafter SIMCE, its acronym in Spanish) containing Reading and Mathematics test scores for students in the cohort(s) that take it each year. SIMCE tests are taken by the universe of students in the grade that has to take it each year, following a calendar that is publicly known in advance. These tests are not high stakes for students; their goal is to asses overall school quality, and individual results are never publicly disclosed (only researchers are granted access; only school averages are made public, partly to inform parents on schools' quality). I use the tests for different 19 cohort/years between 2014 and 2019. I standardize these for each subject, grade and year to have mean equal to zero and standard deviation equal to one. See Table 14 in Appendix D for a calendar detailing which grades take the tests what years.

2. **Non-cognitive outcomes.** I use data from the Indicators of Personal and Social Development. These correspond to standardized tests designed to measure aspects of social and personal development of students. They measure four dimensions (i.e., one test per each of them): self-esteem and school motivation, school coexistence climate, participation and civic education, and habits of healthy life. Importantly, they are designed in such a way that schools can influence them, for instance through positive interactions, teachers supporting students, through school regulations against bullying, etc.(MINEDUC, 2019) All of them apply questionnaires to students; additionally, the second dimension also considers questionnaires for parents and teachers while the third one only students and parents. Each of the four tests are measured in a scale between 0 and 100 (at the student-level), which I standardize to have a mean equal to zero and a variance equal to one for each indicator, grade and year. Further details on what of each dimension captures can be found in Appendix G.

3. **Administrative records.** At the student level, these data contain basic characteristics related to their school progress, including attendance, grades, school enrolled both at the beginning and at end of the school year. They also contain gender, disadvantaged status (*prioritario* in the system's nomenclature) and age. At the school level, these data contain geographical region, administrative dependence (either public, private voucher or fully private), grades offered, whether it is religious or not, out-of-pocket fees (if it charges), and geographic coordinates.

4. **Centralized school choice system.** These data contain the rank-ordered lists of students applications. Given the staggered roll-out of the system, the universe of students observed in the data grows over time. For a given region, the first year of implementation considered only grades pre-kinder, kinder, 1st, 7th and 9th; from the second year on, students of all grades had to apply through the CSCS. However, once a student is enrolled through the system any given year, I do not observe their preferences in subsequent years because enrolled students are not required to re-apply unless they want to switch schools. Importantly, these data also contain the geographic coordinates of the student's household (with some random error added by the Ministry of Education to preserve anonymity.)[15]

4 Descriptive Facts

In this section, I show some patterns of the data that help to clarify aspects of the Chilean environment and also further motivate my research questions.

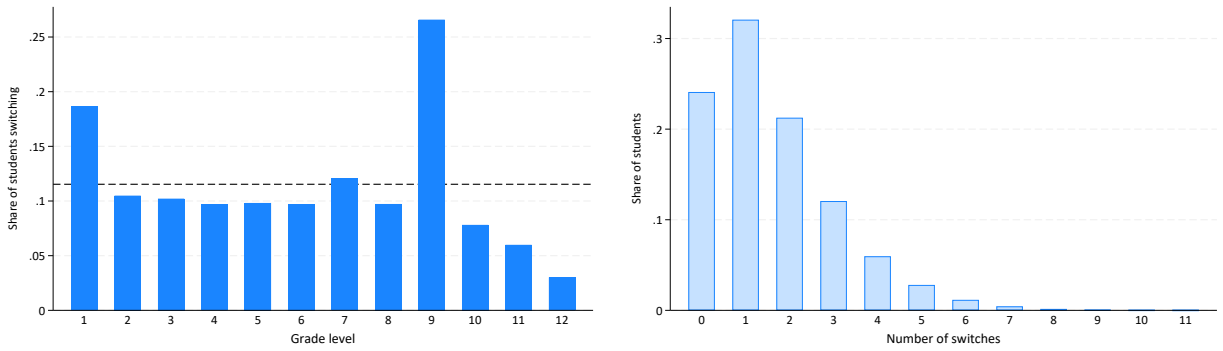
[15]Distance to school, though, is not a variable in the assignment algorithm.

Fact 1: *A minor share of students choose to switch schools each year. However, over their school-life, 70% of students switch schools at least once*

Panel (a) of Figure 1 shows, for every grade level, the percentage of students that were in a different school the previous year. On average 12%, of students switch schools each year. Students in Kinder, 6th and 8th grade are those most likely to switch schools when moving on to 1st, 7th and 9th grades, respectively. The sample in both panels is restricted to students in schools that offer the full set of grades (Figure 12 in Appendix F replicates the same figure considering all students regardless of their schools' grade configuration). This means that these correspond to voluntary switches, as opposed to forced switches due to grade configurations. Noticeably, though, the jumps in the rates do coincide with the most common arrangements, which in Chilean schools is 1th-8th (primary) and 9th-12th (secondary).[16] This implies that students might still want to switch when "natural" cycles are over.[17] Importantly, although Panel (a) shows that a small share of students switch every year, this is not by itself evidence of inertia. Fact 2 provides a more formal test about it.

Panel (b) splits the cohort of students entering the school system in 2010 (graduating in 2021) according to the number of times they switched schools during their time in school. 24% of them remained in the same school they enter in 1st grade. 33% switched only once; almost 20% switched twice and around 20% switched more than 3 times. The figure shows that school switches are a prevalent from the point of view of students, and that a sizable share of students switch more than once during their lifetime.

Figure 1: Switching rates in Chile, all grades



(a) Flow (b) Cumulative within cohort

Note: Panel (a) shows the share of students in each grade which school is different from the one enrolled the previous year. Each share is calculated as the average of switchers per grade over years 2010-2019. Panel (b) follows the cohort of students that entered 1st grade in 2010 and graduated in 2021; it plots the share of students in the cohort that switched any given number of times in their school life. In both panels only students in schools that offer all grades are included.

Fact 2: *Switching decisions are uncorrelated with current schools' closest competitors' observed quality*

Figure 2 shows the marginal effects of a Logit regression seeking to predict students' switching behaviour with pre-switching characteristics of both the current school and the geographically closest school, conditional on students' characteristics.[18] Panel (a) shows the marginal effects of lagged current

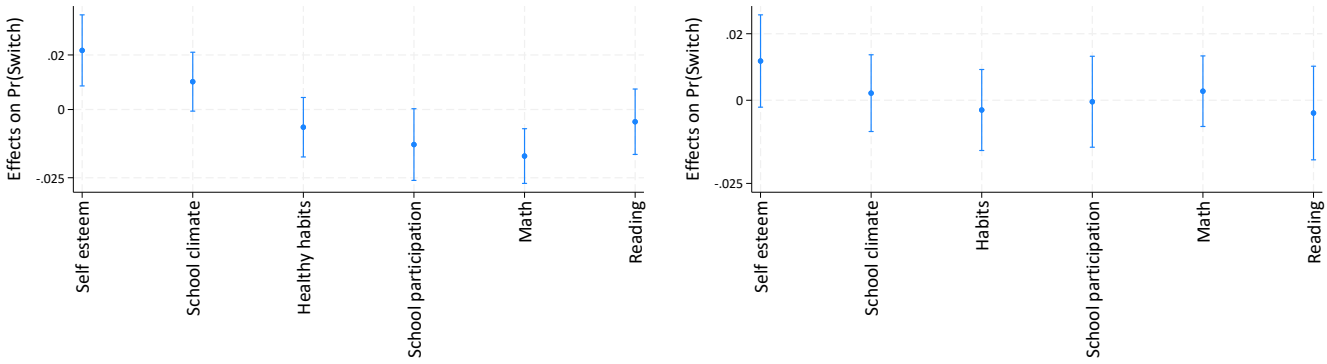
[16] Less common but not rare are schools that offer 1th-6th and 7th-12th.

[17] More importantly, this feature of switching behavior implies that schools might face demand-side pressure when competing to attract enrollment at particular grade levels.

[18] This exercise assumes that students' outside option is the school that is closest to the one they are currently enrolled at.

school's average outcomes in the four non-cognitive and the two cognitive outcomes. Panel (b) plots the same using, for each student, the nearest school's outcomes. Panel (a) suggests that the better a school's performance in Math is, the less likely to switch a student will be; this doesn't occur with Reading performance nor three of the non-cognitive outcomes. While these results are not conclusive, they lean towards the view that families are not very reactive to changes in own schools' performance. Panel (b) shows that the effects of changes in the closest competitor's average cognitive and non-cognitive outcomes are precisely estimated zeroes. This means that no matter how better potential substitutes schools' become, students remain in their status quo schools; in turn, this suggests to some extent the presence of inertia in the preferences for schools.

Figure 2: Predicting switching behaviour with own and alternative school's average outcomes



(a) Currently enrolled school's outcomes

(b) Nearest school's outcomes

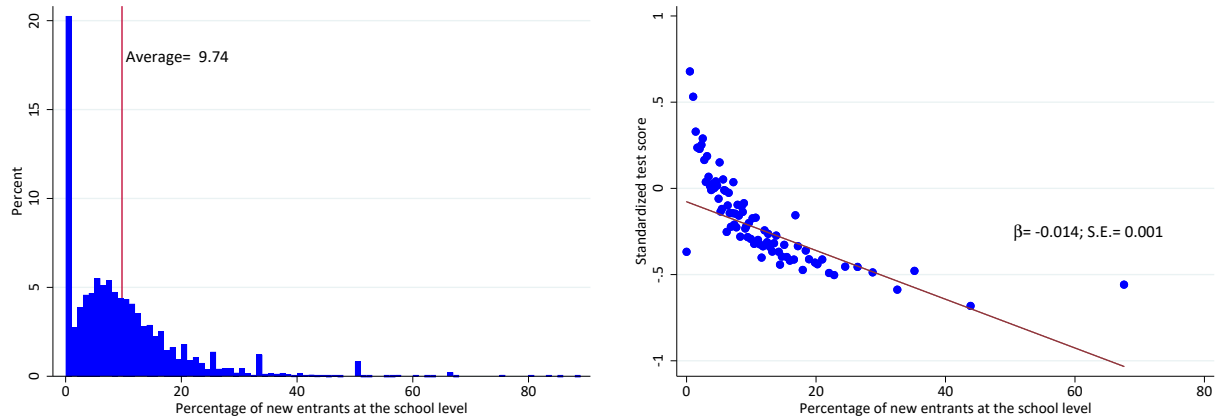
Note: Marginal effects from one logit regression on a panel of students in all grades (1st to 12th) between 2014 and 2019. The dependent variable is an indicator that equals one if the students is in a school different from the one observed in the previous year. Covariates include gender, disadvantaged status, grade level and twelve lagged outcome variables (six for the current and six for the nearest school). Standard errors clustered at the school level.

Fact 3: *Most schools have a share of new students in the range between 0 and 20% each year. This influx of new classmates is negatively correlated with academic and non-academic outcomes*

Panel (a) of Figure 3 shows the distribution of the percentage of new students at the school-level for year 2018, the last year there is available SIMCE data for all grade levels. It shows that while 20% of schools don't have new students, the majority of them do, and that there is a lot of dispersion on the share of new students across schools. The average influx level –considering all schools– is 9.74%, although most of the schools have a turnover in the range [0,20%]. Panel (b), on the other hand, shows that at least on the surface appears to be a negative relation between the percentage of new students in the school and math tests scores. In Section 5 I study how much of this relation –which also holds in Reading and in non-cognitive outcomes (see Figure 13 in Appendix F)– can be taken as causal.

Such assumption can be supported in the observation that, among all the preferences listed by students applying to switch through the CSCS, 45% of these preferences contain a school that is one of the 5 closest schools to the one the student is currently enrolled at. Also, the closest competitor is determined considering the relevant grade for each student. This is, if a student is enrolled in 5th grade, and the closest school is one with a [9th-12th] grade configuration, then the closest competitor is not the actually geographically nearest school.

Figure 3: The school-level share of new students and its correlation with academic performance, 2018



(a) Distribution of school-level share of new students

(b) Turnover and Math performance

Note: Panel (a) depicts the distribution of the proportion of students that are new at the school level, by taking the average of the switchers share of 6th and 10th grades in 2018. Panel (b) shows a binscatter plot with the proportion of new entrants at the school level together with the standardized math test score of 6th and 10th graders in 2018.

Fact 4: *The introduction of a centralized school choice system that alleviated search costs encouraged school mobility*

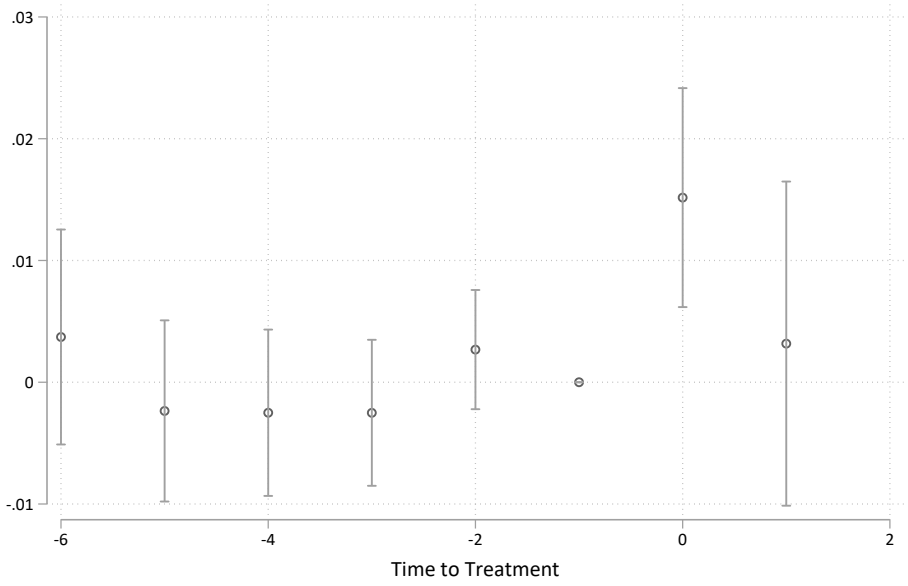
The introduction of the CSCS might have had increased switching rates, as it might have eased the access to different schools (e.g., by reducing search costs as families could access a range of information, pictures of schools, etc., in a single website). The system was staggeredly introduced across the different Chilean administrative regions and over time, thus naturally creating control and treatment regions and offering the possibility to evaluate its impact on switching rates in a direct way. To estimate the effect of its introduction I run the following event study:

$$\text{Switches}_{igrt} = \alpha + \sum_{k=T_0}^{-2} \beta_k \times \text{Treated}_{grt} + \sum_{k=0}^{T_1} \beta_k \times \text{Treated}_{grt} + \Gamma \mathbf{x}_{it} + \gamma_t + \lambda_r + \varepsilon_{igrt} \quad (1)$$

where Switches_{igrt} is an indicator value that takes the value of one if student i, in grade g, in administrative region r is in a new school in year t. Treated_{grt} is the absorbing state treatment and equals one for the regions, grades and years for which the CSCS is in place. γ_t and λ_r are year and region fixed effects, respectively. Coefficients β_k capture the difference in switching rates between treated and untreated grades k periods relative to the year just before the introduction of the CSCS.

Figure 4 shows the resulting β_k coefficients. I find a sizable jump in switching rates right after the introduction of CSCS that fades away in the second year of implementation, while no pre-trends are appreciated, thus lending credibility to the parallel trends assumption. These results imply that the CSCS did increase mobility, most likely by reducing some of the (pecuniary and non-pecuniary) costs of switching schools. Interestingly, the effect of the system's introduction seems to be short-lived, as after two years of being in place there are no differences between treated and control grade/regions. However, the fact that I observe few observations post-treatment might be reducing the significance of a point estimate that is somewhat positive.

Figure 4: Event study on switching rates



Note: Estimates of β_k parameters in Equation 1 and 95% confidence intervals shown. Standard errors clustered at the grade and region level.

5 Understanding the consequences

In this section my goal is to characterize the consequences of school mobility. Given its importance as a channel of demand-side pressure on schools, it is key to find out whether promoting mobility with the goal of strengthening incentives is also beneficial or not for students' individual outcomes. I proceed by seeking answers to the following questions: (i) what is the effect of forced switches?, (ii) what is the effect of voluntary switches?, and (iii) what is the effect on non-switchers? In all cases, the outcome variables are cognitive (math and reading) and four dimensions of non-cognitive outcomes.

The effect of forced switches

My first approach to estimate the effect of switches is to exploit an instance in which students are forced to switch. This idea has been used before in the literature and allows to break the endogeneity caused by the fact that switching is a decision of families. I recover the causal effect of switching schools by instrumenting it with fact that students enrolled in 8th grade at schools that do not offer 9th grade must forcefully switch to a different school. In other words, I seek to compare students that remained in the same school between 8th and 10th grade to students that switched between these two same grades due to exogenous reasons. I implement this strategy by estimating the following system:

$$Y_i^{10th} = \beta_0 + \beta_1 \widehat{\text{Switch}}_i + \beta_2 Y_i^{8th} + \beta_3 \mathbf{x}_i + \varepsilon_i \quad (2)$$

$$\text{Switch}_i = \gamma_0 + \gamma_1 \text{Terminal grade}_i + \epsilon_i \quad (3)$$

where Y_i^{10th} is either a cognitive or non-cognitive outcome of a student observed in 10th grade, and Switch_i is an indicator that equals one if the student is observed in 10th grade in a school different from the one

he or she was enrolled in 8th grade[19]. The instrumental variable Terminal grade$_i$ is an indicator that takes the value of 1 if student i attended 8th grade in a school which terminal grade was 8th grade. It satisfies the exclusion restriction as attending such a school should not impact outcomes per-se; it satisfies the relevance restriction as it forces these students to enroll in a different school in 9th grade. As dependent variable I use the outcomes observed in 10th grade in 2016 and 2017 while controlling for lagged tests scores observed in 8th grade in 2014 and 2015, respectively.

The effect of forced switches: results

Result 1: *Forced switches induce a reduction of around 0.2σ in cognitive outcomes and around 0.14σ in non-cognitive outcomes two years after switching*

Table 1 shows the 2SLS results. Column (1) shows that the probability of switching schools is 80% higher among students in terminal grade school than for students whose schools allow them to continue to the next grade level; this confirms empirically that the instrument is relevant. Columns (2) through (5) show the β_1 effects of Equation 2 effect on non-cognitive outcomes. Self-esteem and Habits of healthy life are the only outcomes that deteriorate -0.14σ and 0.15σ, respectively- two years after switches. These are the only ones that interview students only, which could explain the finding. School coexistence climate (Column(3)) and Participation and civic education (Column(4)) do not experience deterioration. The cognitive outcomes of students forced to switch are considerably lower than those not forced to do so. In math I find a -0.2σ effect and in reading a -0.23σ effect. To put this figures in context, Schwartz et al. (2017) finds similar magnitudes, but after 1 year of forcefully switching.

Table 1: The effect of forced switches

	First Stage		Non-Cognitive			Cognitive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Switch	S.E.	S.C.	P.C.E.	H.H.L.	Math	Reading
Terminal grade	0.804***						
	[0.00567]						
Switch		-0.139***	-0.0178	0.0356**	-0.148***	-0.204***	-0.231***
		[0.00958]	[0.0180]	[0.0146]	[0.0177]	[0.0141]	[0.0134]
Obs	236791	235446	182726	184205	234862	241457	236791
F-statistic	7361.066						

Note: 2SLS estimates of system in equations 2 and 3. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. S.E.: Self-esteem; S.C.: School coexistence climate; P.C.E.: Participation and civic education; H.H.L.: Habits of healthy life. Covariates include students' age, gender, disadvantaged status, and indicator variables for schools in rural areas and administrative dependency. Sample consists of students observed in 10th grade in 2016 and 2017 with non-missing lagged tests scores in 8th grade in 2014 and 2015, respectively.

The effect of voluntary switches

Forced switches are useful to deal with endogeneity and benchmark my estimates with the literature, and although students are still choosing their destination school, the previous section estimates can not

[19] I use these particular grades because I do not observe scores in 9th grade due to the calendar of evaluations in Table 14 of Appendix D.

inform the effect of *choosing* to leave the current school. To deal with this, I exploit the quasi-random assignment embedded in the centralized school choice system. In concrete, any student aiming to switch submits a rank-ordered list of preferences for schools. Then, whether he or she actually switches is mediated by the allocation of students to schools generated by the assignment mechanism. Thus, in principle I can instrument the endogenous *switching* using the offer of a seat to a different school through the CSCS (a *re-allocation*), which induces switches but does not affect outcomes, only except through them. Notwhithstanding that, reallocations depend on (all) students' preferences, the priority that the system gives to each of them, the number of vacancies at each school, and the random number the D.A. algorithm gives every applicant at each school. All these variables shape the probability of reallocations; thus, reallocations are conditionally independent of switches only after accounting for these probabilities. Abdulkadiroğlu et al. (2017) call this probability that emerges from multiple runs of the D.A. algorithm the "Deferred Acceptance Propensity Score" (D.A.P.S.) and show that controlling for it leads to causal comparisons between treated and untreated units. Intuitively, this strategy compares the outcomes of students that sought to switch, among whom some of them could do so as a result of a winner lottery ticket.

To obtain the D.A.P.S. of re-allocation for each student I run the assignment algorithm 1,000 times each year using different random tie-breaking number draws while holding students' preferences, the system priorities and the schools' vacancies constant. In each of these simulations I store the number of times a student is allocated to a different school from the one currently enrolled; then, I divide this number by 1,000 to obtain the D.A.P.S. which represents the probability of being re-assigned to a new school in each enrollment process. Figure 15 in Appendix F shows an histogram of the estimated D.A. Propensity score (pooling all grades and years) by assignment status; reassuringly, the distribution of the D.A.P.S. is skewed to the right for students that are re-allocated and to the left for those that are not. The overlap of both distributions allows me to compare the outcomes of re-assigned and non re-assigned applicants with similar propensity scores.

Once I obtain the D.A.P.S., I estimate the following system of equations pooling students in different grades and years:

$$\text{Score}_i = \alpha + \beta \mathbf{x}_i + \rho \widehat{\text{Switch}}_i + \phi \hat{p}_i + \varepsilon_i \quad (4)$$

$$\text{Switch}_i = \mu + \gamma \mathbf{x}_i + \pi \text{Re-allocated}_i + \psi \hat{p}_i + \nu_i \quad (5)$$

where Score_i corresponds to the test score in either Reading, Mathematics or four alternative non-cognitive measures of performance of student i. I standardize the tests each year/grade to have mean equal to zero and standard deviation equal to one. Switch_i is an indicator for switching school and Re-allocated_i is an indicator for being re-allocated by the D.A. algorithm to a different school. $\mathbf{x}_i$ is a vector of observed characteristics including gender, age, and an indicator for rural schools; $\hat{p}_i$ is the D.A. propensity score.

To maximize power, I pool observations from multiple grades (4th, 6th, 8th, and 10th grades) and different years (2018 and 2019.)[20] The empirical strategy corresponds to a two-stages least squares - augmented by the D.A. Propensity Score- where the "Re-Allocated" instrument satisfies the exclusion restriction, in theory, as it increases the actual enrollment probability but does not impact on academic or non-academic achievement. Empirically, I show that this first stage is valid in the next section. Under the assumption that after conditioning on observed characteristics any remaining variation in tests scores

[20] Table 14 clarifies the timing of evaluations and the availability of the D.A. propensity score generated by the CSCS. Note that on top of the coincidence of SAE and the evaluations, the size of the sample depends critically on the fact that there actually is a non-degenerate probability that a student is assigned to a different school from the one currently enrolled at.

is random, I interpret ρ in Equation 4 as the causal effect of switching school, relative to remaining in the status quo school, one year after switching.

Assessing the validity of the Deferred Acceptance Propensity Score

The D.A.P.S. allows me to rule out the influence of unobserved determinants of switching on both academic and non-academic achievement. To prove that its use can indeed yield to a causal comparison between switchers and non-switchers that have an equal probability of being re-allocated, I conduct two balance tests.

First, I run a set of regressions using re-allocation as dependent variable and a set of observed characteristics as independent ones on different samples, as shown in Table 2, and check whether they predict school switches or not. In Column (1) I include all students in the available grades (4th, 6th, 8th and 10th) that aimed to switch schools through the CSCS (i.e., with a D.A.P.S. $\in [0, 1]$); the estimates show that students' age and gender, along schools' rural status predict switching. In Column (2) I use the subset of students for whom I obtain an estimate of the D.A. Propensity Score that is strictly between zero and one and non-missing tests scores, which will correspond to the estimation sample; in this sub-sample, observed characteristics still predict the probability of assignment. In Column (3) I control for the D.A. propensity score. Doing so further reduces the size of the point estimates and erases significance. I use this sub-sample of students with a D.A.P.S strictly between zero and one in the estimations, for whom the assignment variable is unrelated to observed characteristics.

Second, I estimate one regression with each observed characteristic as dependent variable and both the indicator for re-allocation by the algorithm and the D.A.P.S. as independent variables to check whether the observed characteristics are balanced across both groups of students (re-allocated or not). Table 15 in the Appendix reports the coefficient on the "Re-Allocated" indicator in each of those different regressions. In Columns (1), (3) and (5) I show that there are indeed differences in the means of age, the share of students in rural schools and the share of males between the groups of re-allocated and non-reallocated. However, when including the D.A.P.S. as covariate, points estimates become very small and there are no statistically significant differences in any of the observed characteristics. All in all, the conclusion is that after conditioning on the D.A. Propensity Score, both groups are comparable in observed characteristics and plausibly comparable in unobserved ones.

The effect of voluntary switches: results

Result 2: *Voluntarily switching schools improves Reading performance but has null effects on Math performance*

Table 1 shows the results of estimating the 2SLS system of equations 4 and 5 on cognitive outcomes. The sample consists of students in 4th, 6th, 8th and 10th grade (although 89% of them are in 8th grade) observed one year after they switch schools.[21] All specifications control for students' gender and age, an indicator for schools in rural areas, and the Deferred Acceptance Propensity Score; throughout all specifications I report Eicker–Huber–White standard errors.[22] Column (1) shows the first stage estimated with a linear probability model; being reallocated (i.e., being offered a seat to a different school from the one currently enrolled at) by the CSCS significantly increases the probability of switching schools by 41% relative to students not reallocated. Coupled with an F-statistic of 37.52, this shows that the instrument is

[21] Students enter a new school in March of each year and SIMCE tests are taken in October of each year.

[22] Although clustering S.E. at the school level would appear more intuitive as one would expect unobserved shocks to tests would be correlated within schools, I observe few students per school.

Table 2: Probability of switching school as a function of students' characteristics

	(1) All students	(2) Pscore (0,1)	(3) Pscore (0,1)
Age	0.0470***	0.0408***	-0.00277
	[0.00700]	[0.0138]	[0.0121]
Rural school	-0.0519*	-0.128**	-0.0351
	[0.0313]	[0.0649]	[0.0521]
Female	-0.0582***	-0.104***	-0.0352
	[0.0172]	[0.0322]	[0.0274]
D.A.P.S.			0.852***
			[0.0340]
Obs	2752	946	946
Adj R2	.02	.022	.309

Note: Columns (1)-(3) report the results from regressions using the assignment indicator as dependent variable and the reported set of variables as covariates. Eicker–Huber–White standard errors in brackets. Column (1) uses the sample of students that aimed to switch schools; it includes those with a D.A.P.S. $\in [0, 1]$. Columns (2) and (3) use only students with a D.A.P.S. $\in (0, 1)$.

empirically valid. Columns (2) and (3) show the results of the effect of being reallocated by the algorithm to a new school (i.e., the Intent to Treat); it has a null impact on the Math test and a 0.128 S.D. in the Reading test. More importantly, columns (4) and (5) show the second stage results, after instrumenting switches with re-allocations through the algorithm. Switching has no impact on Math performance and has a sizable 0.31 S.D. impact on the Reading test.[23]

Table 3: The impact on switchers' cognitive outcomes

	First Stage	Reduced Form		2SLS	
	(1)	(2)	(3)	(4)	(5)
		Math	Read	Math	Read
Re-allocated	0.413***	0.0397	0.128*		
	[0.0363]	[0.0706]	[0.0704]		
Switch				0.0960	0.310*
				[0.170]	[0.169]
Obs	946	946	931	946	931
F-statistic	44.525				

Note: 2SLS estimates of system in equations 4 and 5. Eicker–Huber–White standard errors in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Covariates include students' age and gender, and an indicator variable for schools in rural areas. Sample consists of students in 4th, 6th, 8th and 10th grade.

Result 3: *Voluntary switches do not affect non-cognitive outcomes*

[23] The 90% confidence interval for the effect of switching is [0.03, 0.586].

Table 4 shows the results of estimating the 2SLS system again, but using the four different non-cognitive tests scores results. Column (1) shows that the first stage remains valid with the sample of students for whom I observe these tests scores. Columns (2) through (5) show the second stage instrumenting switches with re-allocations. I find a negative effect on the Self-esteem test that is non-significant; in all the other tests the effect is positive but non-significant. In other words, for the students that decide to switch schools, doing so does not affect nor positively nor negatively their non-cognitive outcomes after one year of switching, on average.

Table 4: The impact on switchers' non-cognitive outcomes

	First Stage	2 Stages Least Squares			
	(1)	(2)	(3)	(4)	(5)
		Self esteem	School coexistence	Particip. civic educ.	Healthy habits
Re-allocated	0.413***				
	[0.0362]				
Switch		-0.107	0.203	0.224	0.0311
		[0.201]	[0.201]	[0.201]	[0.207]
Obs	960	960	956	960	959
F-statistic	43.986				

Note: 2SLS estimates of system in equations 4 and 5. Eicker–Huber–White standard errors in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade. Covariates include students' age and gender, and an indicator variable for schools in rural areas. See Appendix G provides details on the specific content of each non-cognitive test

Result 4: *Students whose past outcomes were above average experience the greatest gains in Reading but the greatest deterioration in Self-esteem*

Given these findings, I next conduct a heterogeneity analysis to uncover where the effects are focused. I split the sample in two: students whose past test scores were above versus students whose past scores were below the (past scores distribution) average, for each of the six available tests. Table 5 shows the results of estimating the effect on cognitive outcomes. For students whose past performance was below average, switching schools does not lead to any gain or loss in Math or Reading performance (columns (1) and (2)); for students whose past performance was above average (columns (3) and (4)), the effect remains to be null in Math and positive in Reading (and stronger than in the baseline specification).

Table 5: The impact on switchers' cognitive outcomes

	Below average		Above average	
	(1)	(2)	(3)	(4)
	Math	Read	Math	Read
Switch	-0.0165	0.0988	0.0629	0.360*
	[0.221]	[0.244]	[0.203]	[0.197]
Obs	382	375	564	556

Note: 2SLS estimates of system in equations 4 and 5. Eicker–Huber–White standard errors in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Covariates include students' age and gender, and an indicator variable for schools in rural areas. Sample consists of students in 4th, 6th, 8th and 10th grade.

Table 6 performs the analysis using non-cognitive outcomes. In this case all coefficients are statistically insignificant but the one for the test on self-esteem for students with an above-average baseline score; this is, students whose past self-esteem was above average suffer a deterioration in their self-esteem upon switching schools, compared to students who also scored above average but did not switch schools. All in all, these findings suggest that switching schools might have great benefits for a subset of the population on cognitive outcomes (i.e., those who were already high-performers before switching) while not inducing considerable harm, except for those whose self-esteem was high before switching.

Table 6: The impact on switchers' cognitive outcomes

	Below average				Above average			
	(1) Self esteem	(2) School coexistence	(3) Particip. civic educ.	(4) Healthy habits	(5) Self esteem	(6) School coexistence	(7) Particip. civic educ.	(8) Healthy habits
Switch	0.693	0.609	0.596	-0.307	-0.446**	0.0391	0.105	0.0907
	[0.428]	[0.441]	[0.456]	[0.510]	[0.227]	[0.219]	[0.217]	[0.218]
Obs	397	354	329	384	563	602	631	575

Note: 2SLS estimates of system in equations 4 and 5. Eicker–Huber–White standard errors in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Covariates include students' age and gender, and an indicator variable for schools in rural areas. Sample consists of students in 4th, 6th, 8th and 10th grade.

The effect on non-switchers

To answer the question of whether schools' turnover affects non-switchers' outcomes or not, I exploit the fact that by design the standardized tests in Chile are taken by at least three different grades every year. This means that I can use the variation in the share of new students across grades to identify its impact on tests scores while keeping all their school-level determinants fixed (Hoxby, 2000). This strategy seeks to alleviate the key concern that –in the cross-sectional data– the share of new entrants is likely correlated with unobserved determinants of school-level quality. Under the assumption that the relevant margin of selection is at the school-level (for instance, if students seek to enroll in a new school because most of their graduates entered to college, or because a new gym was built), then the variation in the share of new entrants between two different grades in the same school can be regarded as idiosyncratic.

To implement this approach, I compare the outcomes of non-switchers 6th graders to those of non-switchers 10th graders in the same school in 2018; the outcomes of 4th, 8th and 10th graders in 2017; those of 4th, 6th and 10th graders in 2016; those of 4th, 6th, 8th and 10th in 2015; and those of 4th, 6th, and 8th in 2014. (See the Calendar of evaluations in Table 14 in the Appendix for a visual clarification) Formally, I estimate the following equation:

$$\text{Test Score}_{igst} = \alpha_t + \gamma_s + \beta_1 \text{Inflow \%}_{gst} + \beta_2 \text{Outflow \%}_{gst} + \beta_3 \mathbf{x}_{it} + \varepsilon_{itgs} \tag{6}$$

where Test Score_{igst} is either the cognitive or non-cognitive test score of student i in grade g in school s and year t; α_t and γ_s are year and school fixed effects, respectively; $\mathbf{x}_{it}$ is a vector of student characteristics including an indicator for students who self-identify as being from an ethnic minority group, an indicator for male and four dummies for different levels of mother's education. Outflow $\%_{gst}$ corresponds to the number of students that left the grade/school the previous year as a proportion of the number of students currently enrolled in the grade/school. Inflow $\%_{gst}$ is the variable of interest and corresponds to the

students in the grade level that are new in the school as a share of the total number of students in the grade in the school, expressed as a number between 0 and 100. The coefficient of interest is β_1, which corresponds to the impact of the proportion of new classmates on non-switchers performance.

This approach utilizes within-school grade-to-grade variation in the share of switchers while controlling for a rich set of observed characteristics, thus addressing a number of concerns. First, the school fixed effects allow me to deal with the possibility that switchers might attend specific schools due to sorting, which is particularly critical in the case of Chile given the high levels of segregation observed in the system. By comparing students' performance in the same school, I can isolate the influence of school-level time-invariant characteristics such as location and overall quality. Second, the switchers share that I build is at the grade as opposed to the classroom level, which I could feasibly build. The rationale for constructing the indicator at this level of granularity is that schools may choose to assign new students to different classes (of the same grade) and target resources differently, thus generating unobserved determinants of performance linked to the (classroom-level) switchers share that I could not account for.

Assessing the validity of the school fixed effects approach

For Equation 6 to yield a causal estimate of β_1, the identifying assumption is that the differences in the share of switchers in two (or more) different grades within the same school is as good as random. Empirically, this assumption can be supported by checking whether the relation of students' characteristics and the share of switchers disappears when fixed effects are included. Indeed, Table 16 in the Appendix shows that this is the case; while students characteristics (in particular, the controls used in my preferred estimation) predict the share of new entrants in the cross sectional variation (Column (1)), when including school and year fixed effects to exploit the within-school variation in the switchers share (Column (2)), the point estimates of the coefficients are much smaller and in some cases loose significance. This is particularly notorious in the case of the categorical variables for income ranges and suggests that the within-school variation in the switchers share is uncorrelated with unobserved determinants of test scores.

Lastly, since my identification strategy exploits year-to-year variation in the percentage of new entrants, it is crucial that this percentage actually vary between cohorts in the same school, which is not necessarily obvious ex-ante. To confirm that such variation exists, I estimate a regression in which the dependent variable is the share of new students and the independent variables are all covariates (I exclude the relevant dependent variable in my regression of interest, i.e., test scores) and school fixed effects. The residuals of this regression, shown in Figure 18 in the Appendix, show that there is still enough variation to identify the effect of the switchers share on test scores.

The effect on non-switchers: results

Result 5: *Turnover slightly worsens non-switchers' cognitive outcomes*

In this subsection I describe the results of estimating different specifications of Equation 6. In all of them I restrict the sample to students enrolled in the same school they were in the previous year, observed in 2014 (grades 4th, 6th and 8th), 2015 (4th, 6th, 8th and 10th), 2016 (4th, 6th, and 10th), 2017 (4th, 8th, and 10th), and 2018 (4th, 6th, and 10th). Table 7 shows the effects on cognitive outcomes. In Columns (1) and (4) I exploit the cross-sectional variation for bench-marking purposes, comparing students in different schools facing different turnover levels. After a 1% increase in the proportion of students in the grade level that are new, Math and Reading scores fall by 0.02 SD and 0.015 SD, respectively. As described before, part of this effect might be driven by the fact that new students are not randomly enrolled at different schools; in other words, the share of new students in schools might correlate with

unobserved determinants of non-switchers performance. To deal with this challenge, Columns (2) and (5) show the results exploiting the within school (between grades) variation in the percentage of new students, which rules out any influence of unobserved factors that impact tests scores at the school level (such as management practices or facilities). In this case, after a 1% increase in the proportion of switchers, tests scores fall by 0.001 SD and 0.002 SD in Math and Reading, respectively. The huge drop in the point estimates indeed suggests that the benchmark estimates might be contaminated by endogeneity; in particular, a big part of the negative externality that new students seem to inflict on non-switchers (seen also in Figure 13b) operates through the possibility that incoming students self-select into schools that do a poor job at increasing non-switchers tests scores. To put in perspective the magnitude of these effects, one should take into account the fact that the average and S.D. of % Influx are 7.7 and 6.9, respectively, in both tests; hence a 1 SD increase in the key explanatory variable induces a drop equivalent to 0.007 of a SD in Math and 0.015 of a SD in Reading. In other words, the influx of new students in the grade level, on average, does not seem to be particularly harmful for non-mobile students' cognitive outcomes.

Table 7: The impact on non-switchers students' cognitive outcomes

	(1) Math	(2) Math	(3) Math	(4) Reading	(5) Reading	(6) Reading
% Inflow	-0.0140***	-0.00108***	-0.00176***	-0.0114***	-0.00206***	-0.00214***
	[0.000475]	[0.000216]	[0.000303]	[0.000367]	[0.000205]	[0.000281]
Obs	1692917	1692917	957615	1681935	1681935	946830
Clusters	8431	8431	8113	8430	8430	8118
Adj R2	.16	.32	.77	.1	.19	.700
Mob. Av.	8.92	8.92	8.30	8.91	8.91	8.300
Mob. SD.	7.55	7.55	7.14	7.55	7.55	7.14
Student F.E.	No	No	Yes	No	No	Yes
School F.E.	No	Yes	No	No	Yes	No
Year F.E.	No	Yes	Yes	No	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade.

Finally, as a robustness exercise, in columns (3) and (6) I show the results exploiting the within-student variation. This is, given that the calendar of tests scores evaluates a same individual twice (and up to three times during school-life), I observe a same student facing different levels of shares of new classmates, two years apart. On the brightside, this allows me to rule out the effect of time-invariant determinants of students' performance that could correlate with the share of new entrants. On the downside, in practice I lose many observations due to (likely non-random) missing values in lagged tests scores. For this specification to be biased, it should be the case that new students self select into new schools on the basis of non-switchers' performance evolution, a rather sophisticated way of selection. Columns (3) and (6) show the results of these specifications in Math and Reading, respectively. Relative to my preferred specifications comparing different students in the same school, point estimates increase (in absolute value) in math but slightly decrease in Reading. Repeating the exercise of translating these coefficients using the S.D. of % Influx, I find that per an increase equivalent to one SD of % Influx, non-switchers suffer a deterioration of 0.01 SD in Math and 0.013 SD in Reading, thus confirming the previous results.

Result 6: *Turnover moderately worsens non-switchers' non-cognitive outcomes*

Table 8 shows the estimates of Equation 6 using non-cognitive outcomes under my preferred specification exploiting the within school variation in the percentage of new students. I find that a 1% increase in the proportion of new students induces a fall in tests scores equivalent to 0.0020 SD in self-esteem, 0.0032 SD in school coexistence, 0.0023 SD in civic education, and 0.0007 SD in Healthy habits. Alternatively, a 1 SD increase in % Influx induces a reductions of 0.014 SD in self-esteem, 0.022 SD in school coexistence, 0.019 SD in civic education, and 0.005 SD in Healthy habits, respectively. These effects, while not big, are moderate enough to be meaningful so that in schools where turnover is particularly high can harm the non-cognitive outcomes of non-switchers. Also, something interesting to note is that the impact is more pronounced in outcomes that seek to capture dimensions related to the school environment such as school coexistence climate and participation and civic education (as opposed to more individually private ones, such as self-esteem and motivation, and the individual habits of healthy life).

Table 8: The impact on non-switchers' non-cognitive outcomes

	(1) Self-esteem	(2) Co-existence	(3) Civic education	(4) Healthy habits
% Inflow	-0.00181***	-0.00302***	-0.00253***	-0.000472*
	[0.000211]	[0.000282]	[0.000259]	[0.000262]
Obs	1683971	1624857	1679579	1626291
Clusters	8069	8017	8064	8024
Adj R2	.031	.167	.1	.079
Mob. Av.	8.93	8.86	8.92	8.88
Mob. SD.	7.53	7.48	7.53	7.5
School F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Result 7: *The negative effects on non-cognitive outcomes are compounded when the incoming share of new students are disadvantaged. Also, girls' are particularly hurt by the influx of new classmates.*

Next, I estimate four different specifications to explore the heterogeneity of the effects. First, I use the sub-sample of students whose lagged tests scores are below the average in each corresponding test. Second, I estimate using the sample of girls only. Third, using boys only. Fourth, I use the ratio of entrants that are new *and* disadvantaged to the total number of students in the grade level as key explanatory variable (also expressed as a number between 0 and 100), instead of the total share of new entrants.[24] Table 9 shows the results using the Reading tests scores. I find that, compared to the baseline coefficient

[24]The law defines disadvantaged (i.e., priority) students as those "who face socioeconomic obstacles to succeeding academically." The Ministry of Development identifies such students as those who meet at least one of three criteria. The first is enrollment in the Chile Solidario Social Protection System, Ethical Family Income (IEF) program or the Security and Opportunities System. These three initiatives are all means tested programs through which the Ministry of Development targets poverty alleviation resources. The second criterion is belonging to a household in the poorest third of the Social Registry of Households, a registry of the near universe of households in Chile. The third criterion is belonging to section A of the Public Health Insurance (Fonasa), which targets the poorest families in Chile by providing free access to health care

of -0.00219 (Column (5) of Table 7), the effects are similar across specifications with the exception to the one that uses the share of new entrants that are disadvantaged, in which case the effect is -0.0291.[25]

Table 9: The impact on non-switchers' Reading outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Inflow	-0.00200	-0.00218***	-0.00217***	
	[0.00171]	[0.000243]	[0.000248]	
% Inflow disadvantaged				-0.00288***
				[0.000281]
Obs	10992	851853	829522	1681935
Clusters	2290	7886	7908	8430
Adj R2	.12	.18	.18	.189
Mob. Av.	10.35	8.77	9.06	4
Mob. SD.	8.23	7.39	7.69	5.23
School F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Moving on to non-cognitive outcomes, Table 21 shows the heterogeneity analysis using the School coexistence tests scores, which are the most hurt by turnover in the baseline specification. I find that, compared to the baseline coefficient of -0.00327 (see Column (2) of Table 8), the effects are milder among students with baseline scores below average and boys, and stronger among girls. Also, the percentage of new entrants that are disadvantaged hurts particularly the school coexistence climate.[26]

Result 8: *Better (worse) outcomes of new students induce better (worse) effects on non-switchers cognitive and non-cognitive outcomes'.*

To explore the possibility that the composition of the incoming students might influence the effect of turnover, I estimate a specification of Equation 6 interacting the proportion of new students in the grade level with the average test scores of those new students. Figure 5 shows the marginal effects of % Influx, which now depends on the average tests scores of these new students. In Panel (a) I plot the effects on cognitive outcomes. The overall patterns are similar in Math and Reading; the better (worse) the outcomes of new entrants (in the vertical axis), the more positive (negative) is the effect on their peers (in the horizontal one). It is interesting to note that Reading tests scores seem to be more sensitive (although I can not reject that the effects are the same for high new-entrants tests scores) than Math tests, and that the effect is null as new entrants score around the average (zero). Panel (b) shows the results of

(almost 30% of Chilean workers are enrolled in FONASA A.) The set of these three criteria seeks to capture socioeconomic obstacles to school achievement.

[25] Table 19 in Appendix G shows the results on the Math tests scores; they are qualitatively equal.

[26] Tables 20, 22 and 23 in Appendix G shows the results on the other three non-cognitive tests scores; they are qualitatively equal.

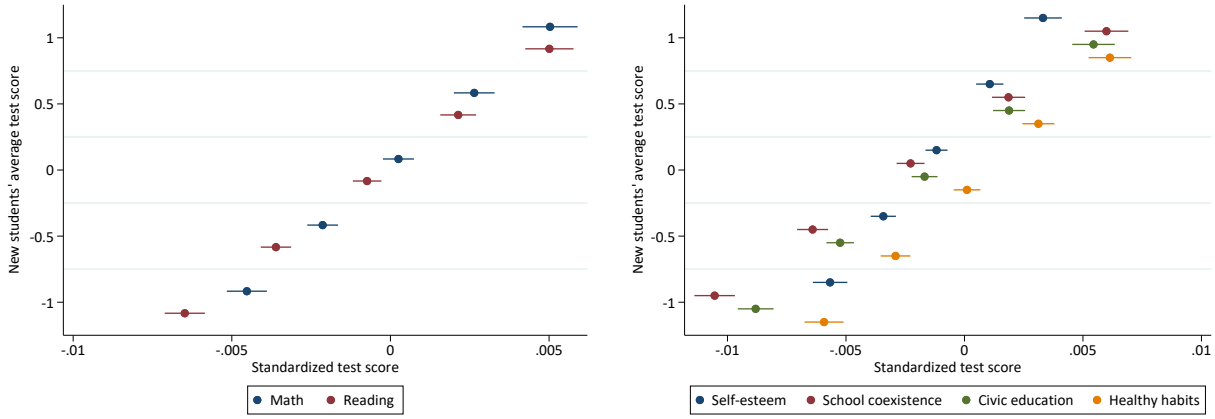
Table 10: The impact on non-switchers' School coexistence outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Inflow	-0.00857***	-0.00357***	-0.00309***	
	[0.00332]	[0.000334]	[0.000315]	
% Inflow disadvantaged				-0.00474***
				[0.000375]
Obs	6556	823008	801510	1624857
Clusters	1594	7515	7528	8017
Adj R2	.14	.17	.166	.167
Mob. Av.	9.93	8.72	9	3.98
Mob. SD.	7.83	7.33	7.62	5.18
School F.E.	Yes	Yes	Yes	Yes
Year_F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

the analogous exercise for non-cognitive outcomes. The patterns again are the same: the better (worse) the outcomes of new classmates, the more positive (negative) will be their effects on the non-cognitive outcomes of non-switchers. In this case, school coexistence suffers the most (and significantly different from the other outcomes) from the influx of new students with poor tests scores on this dimension.

Figure 5: Marginal effects of % Influx



(a) Cognitive outcomes

(b) Non-cognitive outcomes

Note: Marginal effects from regressions using a specification of Equation 6 including an interaction between % Influx and the average tests scores of new students, lagged scores and school fixed effects. 95% confidence intervals shown. Horizontal axes show the marginal effects on non-switchers.

6 Understanding the causes

Up to this point, I have documented that families are non-reactive to competitor schools' changes in academic and non-academic quality, that the effects of voluntarily switching schools are weakly positive, and that the externalities of the influx of new students on non-switchers are weakly negative. In this section, I use two complementary approaches to document that the reason why families do not switch schools more often is the presence of inertia in their preferences. This is, once they choose a school, they get "locked in" and their choice becomes persistent regardless of the availability of better alternatives. First, I describe the procedure to estimate a demand for heterogeneous schools in the presence of switching costs and the argument to identify its coefficients. Then, I detail a survey used to characterize families' preferences for schools in a direct way, further disentangle the content of switching costs, and to infer their "willingness to switch" schools.

A Demand for schools with switching costs

I assume every period t, family i chooses a school j that maximizes their flow utility, which depends on schools' price (p_{jt}), measures of schools' academic (q^a_{jt}) and non academic (q^{na}_{jt}) qualities, a measure of the socioeconomic background of peers (captured by the percentage of students in the school that are disadvantaged, % Dis), and a purely idiosyncratic taste shock ε_{ijt}, which is assumed to be identically and independently distributed as extreme value type I. In a friction-less world families should react to changes in the attributes of schools, potentially switching every period. To accommodate the fact that this is nor true in practice, I include a switching cost (η) that induces disutility and prevents them from switching. I assume that families have heterogeneous valuation for different attributes of schools; thus, the indirect utility for family i when choosing school j in year t is:

$$u_{ijt} = \beta^p p_{jt} + \beta^a q^a_{jt} + \beta^{na} q^{na}_{jt} + \beta^{dis} \%\text{ Dis}_{jt} - \eta \mathbb{I}\{s_{it-1} \neq j\} + \varepsilon_{ijt}. \tag{7}$$

$\mathbb{I}\{s_{it-1} \neq j\}$ is an indicator at the student level that equals one if the student chooses a school j different from s_{it-1}, the one where he or she was enrolled during the previous period. It activates the switching cost η, which induces a disutility from choosing a school different from the current one thus inducing persistence in households choices. I allow for two different sources: a search cost and a fixed cost (i.e., $\eta = \eta^s + \eta^f$). The former represents the pecuniary and non-pecuniary costs of collecting information about multiple alternative schools (average tests scores, vacancies, educational project, etc.) and filling paperwork when the application process is decentralized. The latter represents all other factors that "lock in" students in their current schools, such as the presence of specific teachers, friends, or the learning environment.

The role of preferences inertia has been studied before –for instance– in Marketing, where consumers exhibit brand loyalty in everyday products (Osborne, 2011), in markets for health insurances, where insured workers remain indefinetly in dominated plans even though better alternatives are available (Handel (2013), Heiss et al. (2021)), and in plans for retirement funds, where workers do not react to changes in the returns to funds (Luco, 2019). This literature has shown how the persistence of agents choices turns demands for goods captive, in turn growing firms' market power. In schooling, this could lead to decreased efforts of schools in providing quality, or fiercer competition in entry-level grades (i.e., 1st or 8th grades) such that students get "locked in" in early years.

Implicit in Equation 7 is the assumption that families are myopic; they choose schools every period without taking into account the expected evolution paths of the attributes they value. This assumption

only becomes problematic if parents are able to predict that evolution; for instance, if they anticipate changes in schools' average tests scores. If that was the case, switching costs would be overestimated as parents would remain in their status quo schools waiting for these changes to realize. I defend this assumption resting in the logic of school choice systems, which essential premise is that families are free to choose –and switch– schools every year according to their preferences.

Identification

The traditional challenge in identifying switching costs is that they are difficult to separate from unobserved heterogeneity in preferences for attributes; both changes in preferences and in switching costs produce observably equivalent impacts on choices. To overcome this problem, I adapt the identification strategy used in Handel (2013) and Luco (2019) to my school choice context.

In particular, different Chilean students face different switching costs depending on two dimensions. The first dimension is whether or not they have to actively choose a school; this one generates two groups of students. The first group is composed by those entering the system for the first time (i.e., rising 1st grade students) and those transitioning to a grade level which their status-quo school does not offer (most of them in 8th grade due to the common 1st to 8th grade configuration in Chile); I call them active students. The second group is composed by students already enrolled in the system who can remain in their status-quo by default (e.g., students in 4th grade); I call them passive students. The second dimension is whether or not they are subject to the CSCS, which in turn depends on the grade the student is seeking to enroll and the administrative region in which the school is located (see Section 2 and Figure 11 for an explanation of the system's gradual implementation). The intersection of these two dimensions generates four types of students: passive students exposed to the CSCS; passive students not exposed to the CSCS; active students exposed to the CSCS; and active students not exposed to the CSCS.

Passive students both exposed and not exposed to the CSCS can avoid both the search and fixed costs by remaining in their status quo schools. Active students exposed to the CSCS can avoid only the search cost, as the CSCS eliminated the hassle of having to collect information on different alternative schools, but not the cost of –for instance– abandoning a community to which students are used to. If decisions costs are high enough, passive students subject to the CSCS will remain in their status quo schools. Thus, comparing the choices of this group with those of active students subject to the CSCS identifies fixed costs. On the other hand, active students not exposed to the CSCS incur both costs when (forcedly) switching schools. Thus, the comparison of the choices of this group and active students exposed to the CSCS identifies search costs. Table 24 in Appendix F depicts a 2x2 matrix of the types of students and the costs they incur representing my identification strategy.

Finally, the argument to identify preferences for schools' attributes is analogous to the one made in the switching costs literature when researchers look at the choices of individuals that do not have a "default" option (and, hence, are forced to make an active choice). In this context, those individuals are: (i) the students seeking to enroll in 1st grade (specifically, the subset of them coming from kindergarten in a nursery school that, by definition, does not offer first grade) plus, (ii) the subset of students in 6th grade whose schools do not offer 7th grade due to schools' grade configurations, plus (iii) the subset of students in 8th grade whose schools do not offer 9th grade for the same reason. Since for them switching costs are unavoidable, they should not affect their decisions and so their choices truthfully reveal preferences for attributes.

Assessing the validity of the identification argument

For the identification argument to be valid, the four groups of students should be similar in observed characteristics, so that differences in choices could only be explained by the different costs they face and not by differences in the composition of the four groups and their preferences. To lend credibility to this argument, Table 11 reports means and standard deviations of a set of demographic characteristics of the students in each of the four groups. I observe no differences in the share of students that are female, in their marks, attendance and the proportion of them that attend to a rural school. Average age is slightly greater among active students as most of them correspond to rising 8th grade students whose schools do not offer 9th grade. Also, the share of students that are disadvantaged is lower among passive students, particularly those subject to the CSCS.

Table 11: Demographics among different students types

	Active				**Passive**			
	CSCS		Non-CSCS		CSCS		Non-CSCS	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female	0.50	0.50	0.52	0.50	0.49	0.50	0.50	0.50
Age	14.26	0.78	14.17	0.77	12.13	2.57	11.31	3.39
Marks	5.45	0.76	5.54	0.64	5.84	0.60	5.91	0.59
Attendance	91.65	10.10	93.30	8.06	91.92	7.63	93.28	7.15
Rural school	0.01	0.11	0.01	0.11	0.02	0.15	0.04	0.21
Disadvantaged student	0.65	0.48	0.63	0.48	0.54	0.50	0.60	0.49

Note: Note: Means and S.D. of the individuals included in the estimation sample, according to whether they are treated by the CSCS or not and whether they are active or passive.

Estimation

Estimating the valuation for attributes in Equation 7 requires the observation of students' school choices, their alternatives, and the schools' attributes. In the case of students exposed to the CSCS seeking to switch schools, and those entering the school system for the first time their alternatives are given by the schools they rank when submitting their rank-ordered list of preferences through the CSCS. Given the fact that they are allowed to rank as many schools as they wish, they have no incentives to strategize and so their rankings should truthfully reveal their preferences (Haeringer and Klijn, 2009). In the case of students that do not seek to switch nor are exposed to the CSCS, I do not observe their rank-ordered lists, so I am forced to make stronger assumptions. First, I assume that if they do not seek to switch in administrative regions where the CSCS is in place, then they prefer their status quo school to their alternative choices. Second, I assume that their choice sets are given by the schools located within k kilometers around their status quo schools, where k is the average distance of the status quo school and the rest of the schools in the choice sets of students seeking to switch.[27] To make the choices of students seeking to switch comparable to those of students not seeking to switch schools, I am forced to drop the information contained in the rankings of preferences of students exposed to the CSCS; I replace all the ranked alternatives with a zero except for the first one (i.e., the chosen one).

[27] A better approximation would be to use a radius around families' houses. Unfortunately, those coordinates are only available in the data through the CSCS. In the Appendix I show how sensitive my results are to different radii.

Under the assumption that taste shocks ε_{it} are i.i.d. extreme value type I, the probability that family i chooses alternative j in year t is given by

$$P_{ijt} = \frac{\exp\left(\beta^p p_{jt} + \beta^a q^a_{jt} + \beta^{na} q^{na}_{jt} + \beta^{dis}\% \text{ Dis}_{jt} - \eta \mathbb{I}\{s_{it-1} \neq j\}\right)}{\sum_k \exp\left(\beta^p p_{jt} + \beta^a q^a_{jt} + \beta^{na} q^{na}_{jt} + \beta^{dis}\% \text{ Dis}_{jt} - \eta \mathbb{I}\{s_{it-1} \neq j\}\right)}$$

The maximum likelihood estimator $\hat{\theta} = \{\hat{\beta}^p, \hat{\beta}^a, \hat{\beta}^{na}, \hat{\beta}^{dis}, \hat{\eta}^d, \hat{\eta}^e, \}$ is given by:

$$\hat{\theta} = \arg\max_{\theta \in \Theta} \sum_i \sum_k \sum_t \log\left(P_{ikt}\right) \mathbf{1}\left[d_{it} = k\right] \tag{8}$$

To benchmark my estimates of taste coefficients (and in particular how could they departure from an estimation including distance to school, only available for students subject to the CSCS), I use the rank-ordered lists of preferences submitted by the subset of active students. These data contain richer information as students rank higher alternatives they value the most (something that I miss when replace by zeros the dominated alternatives). Each of these students submits a list R_i of $l(i)$ elements (schools). The school ranked first on a student's list is $R_{i1} = \text{argmax}_{j \in \mathbb{J}} u_{ijt}$, while subsequent ranks satisfy $R_{ik} = \max_{j \in \mathbb{J} \ \{R_{im}: m<k\}} u_{ijt}, \ k > 1$, where u_{ijt} corresponds to Equation 7. Assuming that, conditional on observed attributes of schools, the unobserved taste ε_{ijt} is distributed extreme value type I, I can infer tastes for attributes using a rank-ordered multinomial logit model (Hausman and Ruud (1987)), which conditional likelihood of the rank list R_i is:

$$L(R_i|\mathbf{x}_{ijt}) = \Pi_{k=1}^{l(i)} \frac{\exp(u_{ijt})}{\sum_{j \in \mathbb{J} \ \{R_{im}: m<k\}} \exp(u_{ijt})}. \tag{9}$$

Estimating 9 by maximum likelihood produces loading parameters for each of the attributes of schools. I estimate this equation for active students only. Given that under the D.A. algorithm it is always optimal to reveal truthfully preferences for schools and that I use only active students' choices, the estimated coefficients capture tastes for attributes clean of inertia.

Demand estimation results

Result 9: *Parents value academic and non-academic quality of schools, and they don't distaste a disadvantaged student body composition nor out-of-pocket fees*

Table 12 shows the estimates of the parameters in Equation 7. Column (1) uses the full sample, composed of students of grades 1st through 12th, observed in years 2017-2019. I find that students value schools' average Math tests scores, and the non-cognitive test score measuring Habits of healthy life.The coefficient on schools' price turns out to be of the "wrong" sign (positive) which might reflect the fact that schools that charge out-of-pocket fees tend to be regarded as of greater quality than those that do not (most of them public) and, hence, preferred by parents. I find that parents don't dislike schools which student body has a high share of disadvantaged students (which finds support in the randomized survey). Columns (2) and (3) re-estimate this demand for disadvantaged and female students, respectively. Most notoriously, I find that parents of disadvantaged students have a weaker preference for Math tests scores, weaker taste for schools with disadvantaged students and their preferences for co-payments are not different from those in the full sample. The preferences for female students appear to have a greater taste for non-cognitive outcomes than those of males.

Result 10: *Preferences inertia is a key deterrent of school mobility*

Table 12: Estimated parameters of the Demand

	All students	Disadvantaged	Female
	(1)	(2)	(3)
Fixed Cost	-8.17***	-7.77***	-8.14***
	[0.00]	[0.00]	[0.00]
Information Cost	-0.22***	-0.17***	-0.14***
	[0.02]	[0.02]	[0.02]
Copayment	0.03***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]
Math	0.96***	0.51***	0.96***
	[0.00]	[0.00]	[0.00]
Healthy habits	0.15***	0.06***	0.19***
	[0.00]	[0.00]	[0.01]
% Disadvantaged	4.05***	3.60***	4.05***
	[0.00]	[0.00]	[0.01]
N	59014581.00	26519230.00	29774888.00

Note: Estimates of the parameters in Equation 7. Columns (1) uses the full sample, composed of students in grades 1st through 12th, observed in years 2017-2019. Column (2) restricts the sample to disadvantaged students only, which correspond approximately to those in the 30% poorest households (see the text for details). Column (3) uses the sample of female students. Observations are at the student-alternative-year level, where alternative refers to the schools in the choice set. Standard errors shown in brackets.

Both search and fixed costs deter families from seeking a new school, according to Table 12, but the former is significantly smaller than the latter. Admittedly, though, the latter is capturing a large set of components of inertia, a concern that I tackle in the next section with the survey results. To better characterize the meaning of the search cost, one can divide it's point estimate by the coefficient of the other attributes. Doing so, one can state that the search cost is equivalent to 0.22σ of Math tests scores (or 1.46σ in Healthy Habits score), which equals broadly to moving from the median school to one in the 60^{th} percentile of the schools-average tests scores distribution. Furthermore, disadvantaged students face a search cost equivalent to 0.3σ in the Math test score, implying that inertia stemming from search costs is much higher among this group of students. For women though, search costs are a bit smaller than those in the overall population. All in all, these results prove that parents have strong preferences for their status-quo schools. At the same time, given the sign and magnitude of search costs, these results provide support for policies that enrich the information environment, such as the introduction of the CSCS.[28]

Unpacking the sources of inertia: Survey of parents

The revealed preferences approach outlined in the previous section infers what families value from their choices; I do not observe directly their preferences for attributes. While these are potentially representative

[28]Table 26 in the Appendix shows the results of estimating the model with the sample of actives students including distance to school, which is only observed for students applying through the CSCS. Column (2) provides the most direct comparison (as it also uses a Conditional Logit); it shows that when including distance, all coefficients retain its sign, but the magnitudes are somewhat smaller than those in the main specification, which does not include distance, but does include switching costs.

of families' real-life choices, they might be contaminated by also real-life constraints. In this sense, stated preferences –this is, directly observing preferences for attributes in a vacuum, free of constraints– might reveal different valuations for attributes that complement my estimates of families' preferences. At the same time, even if the identification argument in the demand estimation is valid (and I can separate switching costs from unobserved heterogeneity in preferences) the content of switching costs (and in particular of η^f, the fixed cost) is still a bundle of multiple dimensions that I can not elucidate with the administrative data only. To deal with these two limitations and make progress in understanding the role of inertia in families' school preferences I conduct a survey to parents of primary-school students with three goals: (i) disentangle switching costs in its many possible sources of inertia; (ii) benchmark my revealed preferences estimates with stated preferences ones, by asking directly to parents what attributes they value the most in a hypothetical setting, and (iii) quantify switching costs in an alternative way through an incentive-compatible sequential mechanism to measure directly parent's willingness to switch schools (Becker et al., 1964).

I select the five most populous municipalities in the capital city of Santiago (Santiago, La Florida, Pudahuel, Peñalolén and Maipú). Then, in each municipality I stratify schools by administrative dependency; I select them randomly seeking to preserve the proportion of administrative dependency in each municipality (Traditional Public schools versus Private Voucher schools) and contact their principals to ask permission to reach out parents of students to conduct a short in-person interview. After gaining permission, surveyors approached parents randomly at the entrance of schools. If the person approached was in charge of a student between grades 1 through 8th, the questionnaire was applied. If not, the person was replaced by another until reaching the target sample size of 500. It should be noted that at the moment of conducting the data in 2023, all students in Chile enter their schools through the CSCS, so there is no way of exploiting this source of variation that I use in the demand estimation.

I seek to disentangle switching costs by asking parents of non-switchers for the reasons to not switch schools; I present them a closed list of possible reasons and ask them to answer whether or not each of those influenced their decision. Additionally, after hearing the full list, I request them to mention the most important one if they had to choose only one. Given that I can identify the school each student attends to, I can also focus on the reasons being cited by parents who have different outside options (for instance a neighboring school with better average tests scores) and thus explore how answers depend on them. I include a list of 16 possible answers that can be grouped among (i) specific relationships, (ii) search costs, (iii) traditional attributes such as academic quality and peers characteristics, (iv) school and neighborhood safety, and (v) non-academic attributes (e.g., infrastructure)[29].

At the same time, I use the survey to benchmark my revealed preferences estimates by directly asking parents what attributes they value the most. In particular, to parents of non-switchers, I present them the hypothetical case that their school closed at the end of the school year and ask them to tell how important a list of attributes are for choosing a new school. By presenting parents this scenario I seek to recover truthfully taste parameters, clean of inertia in their preferences. For parents of switchers (those who at the time of the survey were enrolled in a school different from the one they were during the previous year) I just present them the attributes and ask them how important they were to make their decision to switch. Possible answers for both groups of parents included "not important", "somewhat important", "important" and "very important". These answers complement my revealed preferences estimates; while stated preferences have been criticized because parents may feel compelled to give socially desirable responses and not require them to make the type of tradeoffs present in real choices (Jacob and Lefgren, 2007), if constraints contaminate their preferences, then revealed preferences inform more these constraints

[29] See the complete list in the questionnaire in Appendix E

than attributes per-se.[30]

Finally, I use the survey to quantify switching costs in a complementary way to the one of the demand estimation, by using the Becker–DeGroot–Marschak method (Becker et al., 1964). I present parents a hypothetical scenario in which there is a different school right next to the one the student is currently enrolled in (so it is at the same distance from home and parents' work) with similar classmates and teachers, and the same price (if applicable, in the case of those attending private-voucher schools). Then, I ask "Would you change your student if, by doing so, their overall grades increased by two tenths (for example, from 6.2 to 6.4)?". If parents said yes, the surveyor would record the answer and moved on to the next question; if parents said no, then they would ask "how about four tenths?" and the procedure will continue until ten tenths. The last possibility is "I would not change the student under any of these circumstances", which I record as "infinity". This question, and in particular they way of posing it, aims to infer how much academic improvement students should gain for parents to be willing to switch schools.[31] Additionally, I conduct similar questions to conclude whether parents would be willing to switch in case their children improved their non-academic outcomes; doing so is difficult as there is no obvious scale to communicate such improvements so I just include "yes" or "no" alternatives for two of the outcomes that are measured in the standardized tests scores (self-esteem and healthy habits). Finally, I include a similar question offering increasing amounts of money as a share of the minimum wage (0.4, 0.6, 0.8, 1).

Survey results

Table 13 shows the descriptive statistics of the sample, splitting it by mobility status. 14.8% of the students sampled are enrolled in schools different from the one enrolled during the previous school year, which is a bit higher than what I observe in the administrative data (see Figure 1). I sampled more boys than girls, but these shares are balanced across mobility status. Among switchers, 50% (49%) of fathers (mothers) have an education level equal or lower than primary education; 47% (51%) of fathers (mothers) have a secondary education diploma or higher. Among non-switchers the education levels for both fathers and mothers are skewed to the left. This is consistent with the fact that disadvantaged status is more prevalent among non-switchers. Finally, the proportion of students in Traditional Public and Private Voucher schools is similar between the two groups, although heavily skewed towards P.V. schools than in the universe of Chilean students, where the proportion is closer to half and half.

Result 12: *Parents mention distance to school, academic quality, educational project and friendships as main reasons to remain in their status quo schools*

I ask parents of non-switchers for the reasons to not switch schools. This gives me the opportunity to uncover attributes that I can not observe in the administrative data. I offer them a closed set of sixteen alternatives including closeness to work, neighborhood safety, and no bullying (see the full list in the questionnaire in Appendix E). Figure 6 I plot the reasons cited by parents, splitting the sample between students in schools with average Math tests scores below and above (the schools-level distribution) average. In both sub-samples distance to school, academic quality and the educational project account are the most important reasons to not switch.[32] Among high-performing schools (see Panel (b) academic quality is the reason cited by an absolute majority of parents.

[30] Note that this approach departs from that in papers that vary experimentally the attributes of hypothetical schools and observe how parents' choices change accordingly (Haderlein (2022), Hailey (2022), Clark et al. (2022)).

[31] The pilot of the survey revealed that parents are not very familiar with the standardized tests scores scale (SIMCE tests, which have a mean of 250 and S.D. of 50). Also, college entrance exams –even if the scale could be more familiar for some families (presumably the better off)– are not useful since college is far in time for most of students.

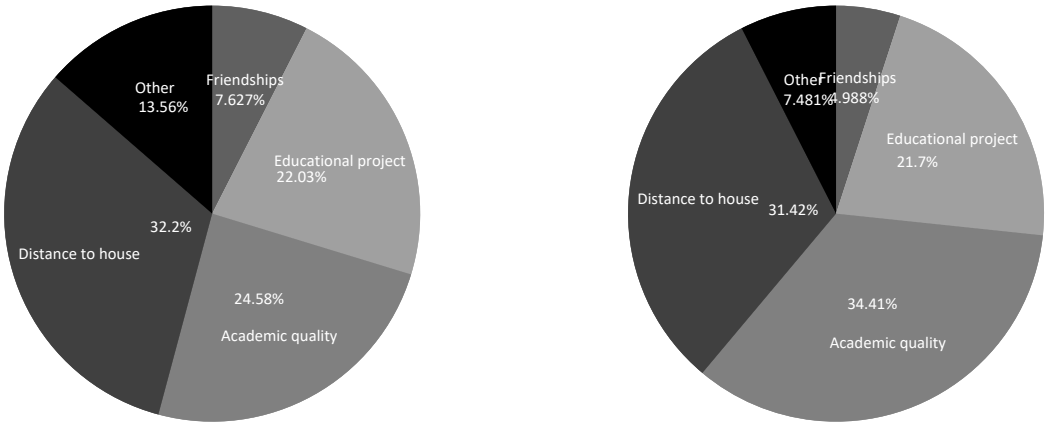
[32] Educational project is worded as: "Learning environment, educational project and values".

Table 13: Summary Statistics of surveyed students

	Switchers			Non-Switchers		
	N	Mean	S.D.	N	Mean	S.D.
Male	74	0.54	0.50	426	0.54	0.50
Female	74	0.43	0.50	426	0.44	0.50
Non-binary	74	0.01	0.12	426	0.00	0.05
Father: Primary	74	0.50	0.50	426	0.53	0.50
Father: Secondary	74	0.47	0.50	426	0.46	0.50
Mother: Primary	74	0.49	0.50	426	0.53	0.50
Mother: Secondary	74	0.51	0.50	426	0.47	0.50
Disadvantaged	74	0.66	0.48	426	0.70	0.46
TPS	74	0.18	0.38	426	0.20	0.40
P.V.	74	0.82	0.38	426	0.80	0.40

Note: Summary statistics of the students in the survey. Means correspond to the share of each row category, conditional on switcher status. PV: Private voucher school; TPS: Traditional Public School

Figure 6: What is the most important reason to remain in your current school?



(a) Below average schools (b) Above average schools

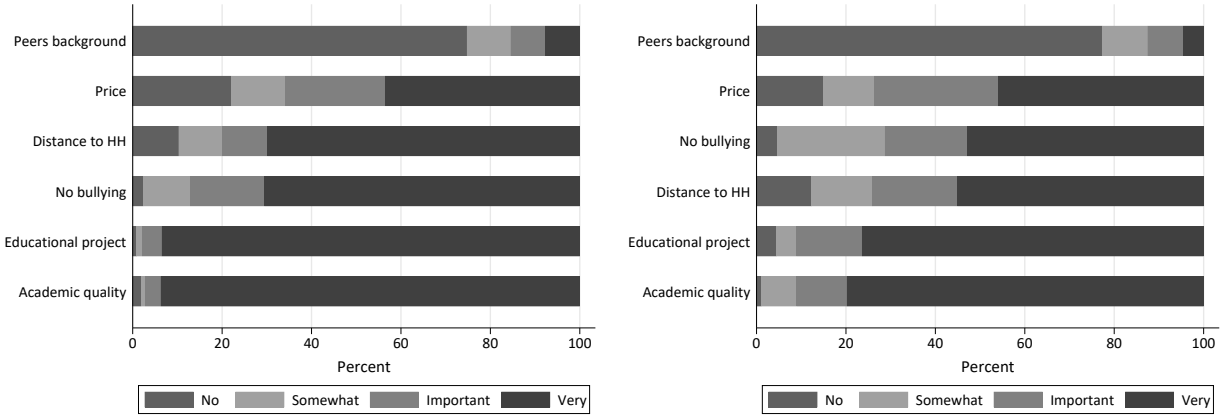
Note: The charts show the share of parents that mention each of the cited reasons as the most important one to remain in their current school. Panel (a) uses students in schools which average Math test score is below the national average. Panel (b) uses students in schools with Math test score above average

Result 13: *Faced with the actual and hypothetical scenario of choosing a new school, parents value academic quality, the educational project, an environment free of bullying, and distance to school. They do not distaste price nor student body background*

I compare the revealed preferences results from the demand estimates to stated preferences by directly asking parents what they seek in a school. This exercise allows me to account for a broader set of potential attributes that parents may value that are not observed in my dataset (and hardly observed in other similar administrative datasets). I split the sample between switchers and non-switchers. To the latter, I ask what attributes they sought for before moving to the school they are currently enrolled at. To the former, I ask them to think of an hypothetical scenario in which their school is going to close (a fairly common possibility in the Chilean school context), and they have to choose a new one. By doing so, I aim to isolate their answers from switching costs. I find that the reasons are similar in both cases; most importantly,

students value academic quality –which fits the revealed preference estimates– and most of them also agree that the "educational project" is important for them too –defined together with "values and the learning environment"– which I can not observe in the administrative data. In line with the demand estimates, parents say that the socioeconomic characteristics of classmates is not relevant for them to choose a school.

Figure 7: How important are the following attributes for you to choose a school?



(a) Hypothetical scenario: school is closing

(b) Answers among mobile students

Note: These graphs show the percentage of parents who judge each attribute according to different levels of importance. Only alternatives that are cited as "the most important one" (in a separate question) for more than 2% of parents surveyed are shown. Panel (a) uses parents of non-switchers facing the hypothetical scenario that their schools will close at the end of the year and they are being asked to tell how important is each attribute when seeking a new school. Panel (b) uses switchers and asks parents what attributes they sought after to switch to their current school. See Questionnaire in Appendix E for the exact questions' wording.

Result 14: *Most parents are only willing to switch schools if offered high hypothetical academic improvements or sums of money. Disadvantaged students are willing to switch at lower offers than regular students*

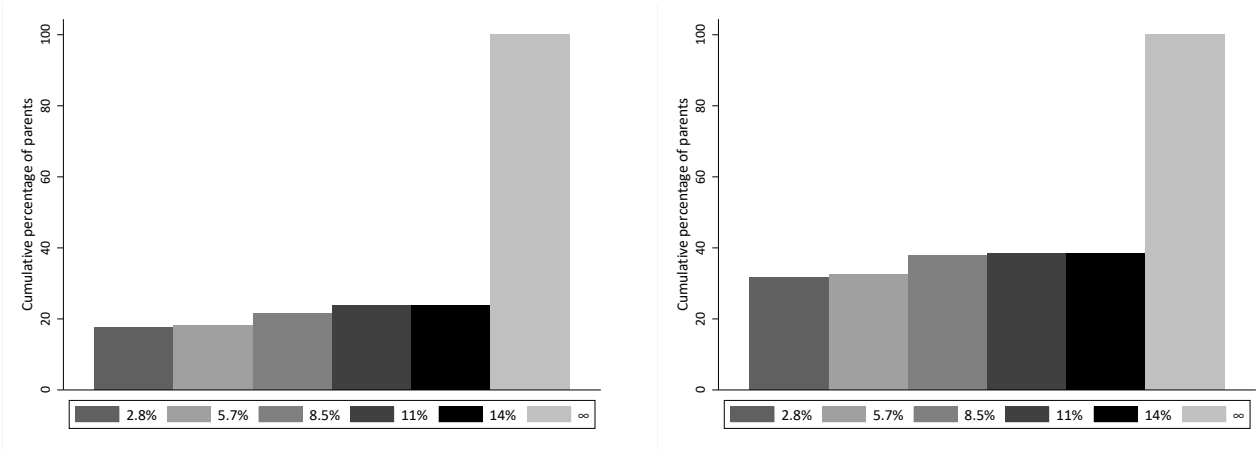
My final goal with the survey is to quantify switching costs in an alternative way. Figure 8 plots the cumulative distribution of "willingness to switch" measured in academic outcomes improvements. By construction, it increases monotonically in the offers made to parents and, importantly, it shows that parents are unwilling to switch unless they are offered an (theoretically) infinite increase in academic outcomes. Interestingly, though, the distribution for non-disadvantaged students (Panel (a)) dominates that of disadvantaged students (see Panel (b)). In other words, disadvantaged students are willing to accept lower academic improvement offers to switch schools.

I repeat the exercise using increasing lump-sum offers of money to recover a monetary quantification of switching costs. I re-express them as a percentage of the minimum wage and also split the sample between disadvantaged and non-disadvantaged students. In this case the distribution for the latter dominates that of disadvantaged students, meaning that disadvantaged students accept lower offers of money to switch schools. Also, the distribution of non-disadvantaged students is very flat, suggesting considerable "monetary" inertia in the preferences of this group.

Supply-side patterns

Result 15: *Schools facing a captive demand provide lower value-added than schools facing an active one*

Figure 8: "Would you switch your student if by doing so he(she) would improve their general grades by...?"

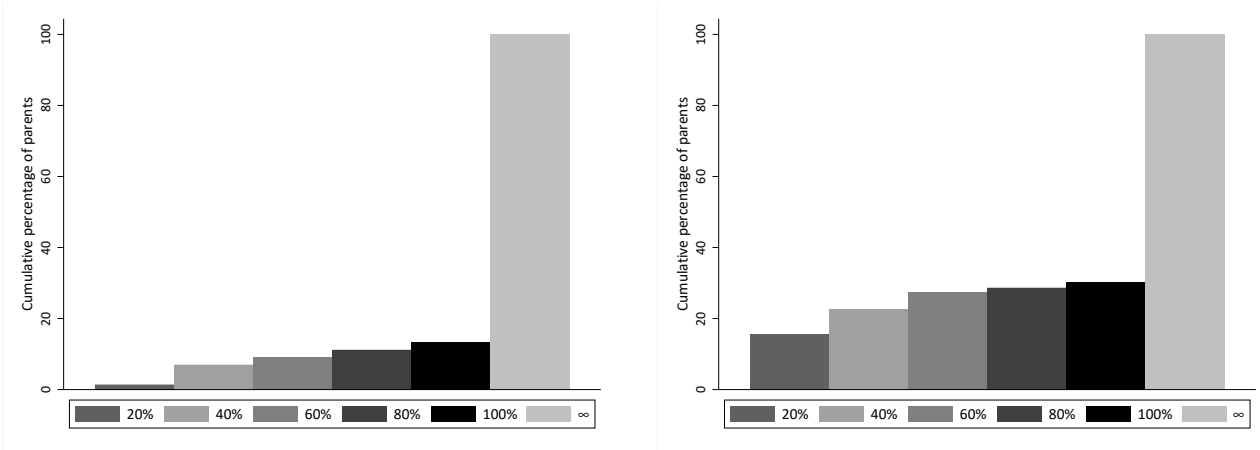


(a) Non-disadvantaged students

(b) Disadvantaged students

Note: Parents are given the following prompt: "Now I'm going to present you with a hypothetical scenario. Suppose there is a different school right next to the one your student is currently enrolled in (so it is the same distance from your home and work) with similar classmates and teachers, and the same price (if applicable)." Panels plot the cumulative distribution of affirmative answers to the different quantities offered after asking "Would you change your student if, by doing so, their overall grades increased by two tenths (for example, from 6.2 to 6.4)?"; "...four tenths?"; (...) "ten tenths?". The last alternative is "I would not change the student under any of these circumstances", which I interpret as being willing to switch only if offered an infinite improvement in academic outcomes. Note that parents are asked in terms of decimals in a scale from 1 to 7, which is the norm in Chile, which are transformed to percentage gains in the graph for ease of exposition.

Figure 9: "Would you switch your student if by doing so you would receive X% of a minimum wage...?"



(a) Non-disadvantaged students

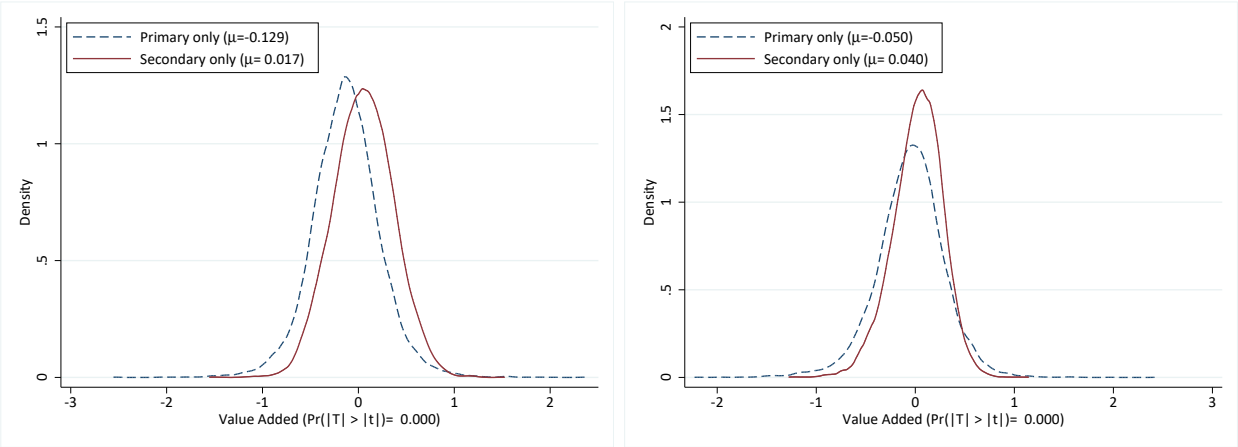
(b) Disadvantaged students

Note: Parents are given the following prompt: "Now I'm going to present you with a hypothetical scenario. Suppose there is a different school right next to the one your student is currently enrolled in (so it is the same distance from your home and work) with similar classmates and teachers, and the same price (if applicable)." Panels plot the cumulative distribution of affirmative answers to the different quantities offered after asking "Would you change your student if, by doing so, you received 20% of a minimum wage?"; "...40%?"; (...) "100%?". The last alternative is "I would not change the student under any of these circumstances", which I interpret as being willing to switch only if offered an infinite amount of money. Note that parents are asked in terms of increasing lump sum absolute offers of money, and are transformed to percentage of a minimum wage gains in the graph for ease of exposition.

The demand-side results suggest the presence of inertia in families' preferences for schools. In turn, this might translate into weaker incentives for schools to compete in improving students outcomes, given the demand is -to a great extent- captive. Without a model that accounted for this possibility explicitly it is difficult to test such channel. However, a clean test that can be performed in the Chilean context

is to explore if the value-added of schools facing captive and non-captive demands is different or not. In particular, schools with grade configurations 1st-8th grade do not have to attract rising 9th grade students by construction; schools with grade configurations 9th-12th must actively compete to attract 9th grade students. Given that -by the calendar of evaluations- I observe tests scores in 8th and 10th grade, I can compute value added of these two different kind of schools (Appendix B shows how I measure value-added) by controlling for a rich set of students' characteristics; doing so I and attribute any differences in value added to the starkly different incentives that schools face. Figure 10 shows the results for Math and Reading outcomes for both types of schools. I find that schools that offer Secondary only (9-12th) provide a higher value-added than schools that offer Primary only, suggesting that schools indeed react to the lack of strength of the demand.

Figure 10: School value-added by grade configuration



(a) Mathematics (b) Reading

Note: See Appendix for details on how value-added is calculated

7 Concluding remarks

Quality in school choice systems rests on the key premise that students choose wisely based on full information what the most suitable school for them is. The schools that succeed in providing the attributes that students and their families value gain enrollment, become competitive and remain in the market as long as they sustain the provision of the desired attributes. The schools that fail to provide these attributes suffer the loss of enrollment by students seeking better schools, which pushes failing schools to exit the market and pushes surviving schools to compete in attracting these switchers. This logic, however, might not hold if the consequences of switching schools are negative, to the point to deter students from doing so, or if the preferences of students for schools suffer inertia, making them non-reactive to changes in the economic environment that, in principle, should encourage them to switch.

This paper shows that in Chile, a country with a long tradition of school choice in which students can switch every year with no restrictions, the consequences of school mobility are, at least, non-harmful for the students that voluntarily switch and mildly negative for non-switchers that receive the influx of new classmates. Despite this, students tend to switch less than it would be expected according to the market environment, in which multiple alternatives are available. It shows that the introduction of a

CSCS alleviated part of the switching costs that can be associated with information frictions, but that the greatest fraction of the overall costs remain preventing students from switching.

From an academic point of view, this paper is relevant because the literature lacks a study on the consequences of voluntary and involuntary school mobility that deals rigorously with omitted variable bias and is able to explore not only the effects on cognitive but also non-cognitive outcomes; my paper closes this gap. Also, the growing literature on school choice has focused on static demands for school (see Ainsworth et al. (2022) or Beuermann et al. (2023)), disregarding the role that inertia in preferences might play, thus undermining a fuller understanding of the determinants of school choice. From a public policy perspective, answering these questions is crucial due to the ubiquitousness of school mobility in school systems around the world. Furthermore, given the growing popularity of room for school choice -in which demand side pressure is key to incentivize schools to provide quality- understanding the extent to which switching costs might curb parents' choices has implications for these systems' overall quality.

This study suffers from several limitations that future research could undertake. First, the consequences of voluntary switches are only measured after one year of switching. This is due to the fact that the CSCS that generates the natural experiment that allows me to estimate the effects was implemented in 2017, generating a window of data that stopped in 2019, due to the COVID-19 pandemic. In the future, one could replicate the analysis to understand whether looking at the effects two or three years after switching makes a difference. Second, this study is silent about the potential supply-side reactions of schools in the presence of inertia. Theoretical predictions indicate that schools quality should fall (price increases were forbidden starting in 2017, thus shutting off this margin) in response to schools' increased market power when the demand is captive (Dubé et al., 2009). Testing empirically this prediction is beyond the scope of this paper, but it is undoubtedly a promising avenue for future research.

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Appendix A: The chilean Deferred Acceptance algorithm

Families access an online platform containing all the relevant information on schools such as number of vacancies, educational project, internal school regulations, school hours, and co-payments (applicable in some private voucher schools).[33] They are allowed to apply to as many schools as they want and they are not constrained on the basis of location, religious beliefs nor socioeconomic status.[34] After families submit their rank-ordered list of preferences for schools, the system runs the Deferred Acceptance Mechanism algorithm, which aims to assign each student to their top preference provided that there are enough seats available (Abdulkadiroglu and Sönmez, 2003). If the number of applicants to a given school is lower than the number of available seats, all applicants are admitted, unless they can be reallocated in a more preferred school[35]. However, if the number of available seats is lower than the number of applicants, the system generates lists of students for each school taking into account three priority groups, quotas and a random number (drawn at the school level) to break ties. The algorithm runs in multiple consecutive iterations, each of which can be better understood by describing it in two stages.

In the first stage, the system generates lists of applicants ordered by the system's priorities, and within them by their random number, in the following order.[36] First, students with siblings already enrolled in the school. Second, disadvantaged students until the system's quota of 15% of disadvantaged enrollment is met. Third, students whose parents work at the school. Fourth, former students of the school. Fifth, the rest of the students with no priority status.[37] Importantly, a student will have as many random numbers as schools he or she applies to and will be placed in the same number of lists.

In the second stage of the process, students are assigned to schools using the ordered lists according to the number of available seats. Rejected students have their first choice erased and are assigned their second choice as a first one for the following iteration. In this next iteration new lists are generated with the schools that still have seats and including the students rejected in the first iteration and that declared as second choice a school that still has seats. Thus, the algorithm continues until there are no more rejected applications.

Once the algorithm allocates seats, the results are made public and families can either accept or reject the school they were assigned to. Families that refuse to accept their assigned school, that were not assigned (presumably because they applied to a few schools) or that did not apply can re-apply in a complementary process that has the same features as the regular one. Since the vast majority of seats are allocated in the regular process, I use data only from it.

[33] In strict terms, families apply not to a school but to a tuple of school, school hours and type of teaching. I refer to "school" hereafter for ease of exposition.

[34] Note that the unconstrained length of lists rules out potential strategic behavior of families at choosing schools. (Haeringer and Klijn, 2009)

[35] The number of available seats is calculated as the total number of seats for each grade, minus the number of students advancing towards that grade, minus the number of retained students.

[36] In a parallel stage, separated lists are generated for high achieving schools, early specialization schools, and special needs schools (PIE, but is acronymum in Spanish.) In the first case, a list is generated for the 30% of reserved seats for applicants from the top 20% of performance distribution in their previous school. For the other two cases, schools are free to use their own criteria to fill all their available seats. While I use these applications to replicate the admissions process (otherwise I would not be able to replicate the actual assignments), I drop students in these schools from our estimations.

[37] Note that –as opposed to several other centralized school assignment systems (for instance Mexico or Ghana)– distance to the school or previous academic performance are not considered in the algorithm.

Appendix B: Schools' Value Added

I follow the literature on Economics of Education (Deming, 2014) and estimate the following specification:

$$y_{isgt} = \alpha_s + \gamma_t + \lambda_{st} + \delta_g + y_{isgt-1} + \varepsilon_{isgt} \tag{10}$$

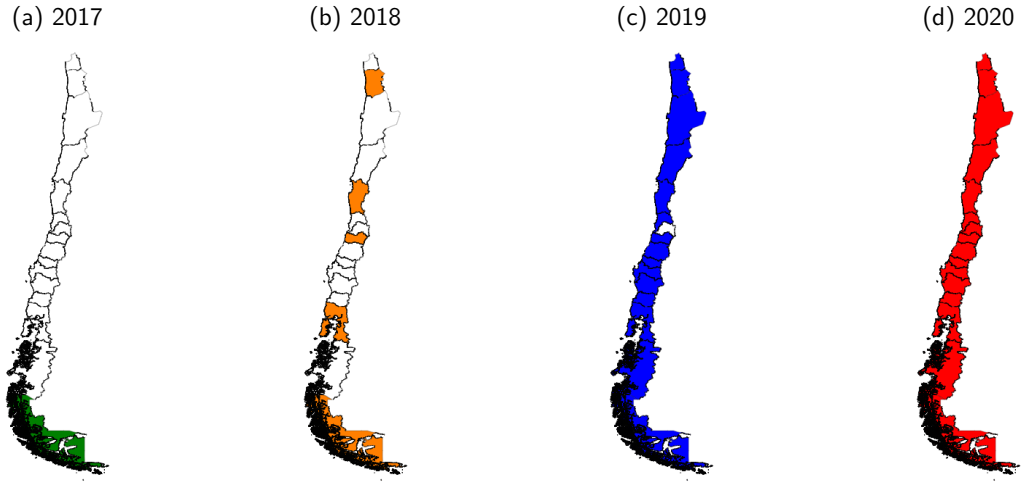
where y_{isgt} are either Math or Reading tests scores. α_s, γ_t, λ_{st} and δ_g are school, time, school-time, and grade fixed effects, respectively.

Then, I call λ_{st} school's s value added in year t. I use student level tests scores of 6th grades in 2014, 2015, 2016 and 2018 and their lagged tests scores from two years back. Also, I use 8th grades in 2017 and 2019 and their lagged tests scores from two years back.

Appendix C: Staggered implementation of the CSCS

The CSCS was first implemented in the southern Region of Punta Arenas in 2017 (i.e., parents applied for schools in around September of 2016) for grades 1st, 7th, and 9th. In 2018, it was implemented for all grades of Punta Arenas and, additionally 3 other regions were added, also starting with grades st, 7th, and 9th. The system was fully in place in 2020 after adding the most populous region of Santiago.

Figure 11: Roll-out of the centralized school schoice system



Note: Figures show different maps of Chile and its geographical regions. Colored regions indicate the CSCS is in place the corresponding year for grades 1, 7 and 9.

Appendix D: Calendar of evaluations

Table 14: Calendar of evaluations

Year	Grade										
2014	.	.	1	2*	3	4	5	6	7	8	.
2015	.	1	2*	3	4	5	6	7	8	9	10
2016	1	2	3	4	5	6	7	8	9	10	11
2017	2	3	4	5	6	7	8	9	10	11	12
2018	3	4	5	6	7	8	9	10	11	12	.
2019	4	5	6	7	8	9	10	11	12	.	.

Note: Grade-year combinations below the dashed line correspond to cohorts of students enrolled the corresponding year (hence applied the previous one through SAE). The first year of the CSCS en each region considers only pre-kinder, kinder, 1st, 7th and 9th grades. Light-green squares indicate that the exam was scheduled but not taken due to the 2019 protests.

Appendix E: Survey details

Sample Selection

In order to carry out a representative quantitative survey of subsidized public (municipal and dependent on Local Education Services) and private educational establishments in Chile, a field work is presented that considers surveys of parents of students between 1st and 8th grade of these dependencies in the most populous communes of the province of Santiago: Santiago, La Florida, Pudahuel, Peñalolén and Maipú.

I target a sample size of 500 observations (parents). These will be chosen randomly among the establishments that have basic education and more than 50 students enrolled by the year 2022 (according to the Ministry of Education), keeping the proportionality of the number of enrollments according to the type of establishment of each municipality.

	5 Municipalities	Sample
Private Voucher	151,185	404
Public	36,091	96
Total	187,276	500

Within each municipality/administrative dependence cell, I intend to sample one third of parents of 1st grade students, a third of parents of students between 2nd and 7th grade and a third of parents of students in 8th grade. 1st is specially targeted as this is the grade in which the vast majority of students enter the system while 8th is selected because many students switch either because their school do not offer 9th grade or because the "basic" cycle ends.

In order to recruit respondents, in the first place, coordination will be done directly with educational establishments to find out the possibility of attending a school activity in which to conduct face-to-face surveys and organize assistance with the withdrawal and delivery of students. For this, a sample of 5 schools per municipality was made (according to municipal, local service of education and private voucher) representative of the number of schools per commune according to their dependency. To choose the selected establishments, a random criterion was applied, both for the selected establishments and their replacement. The distribution of establishments by municipality is as follows:

		La Florida	Maipu	Panelolen	Pudahuel	Santiago	Total
Universe	Private Voucher	48	54	13	11	32	158
	Public	10	9	6	3	16	44
	Total	58	63	19	14	48	202
Sample	Private Voucher	6	7	1	1	4	19
	Public	1	1	1	1	2	6
	Total	7	8	2	2	6	25

Questionnaire

1. Which school is the student currently attending? – – –

2. Did the student attend the same school last year? Yes– No–

   If yes: Next, I will mention different reasons for staying in the same school. Please tell me if any of them influenced your decision or not (you can mention more than one):

   (a) Specific friendships the student wouldn't want to lose: Yes– No–

   (b) Learning environment, educational program, and values: Yes– No–

   (c) Specific teachers you wouldn't want to lose: Yes– No–

   (d) It's a hassle to look for better alternatives: Yes– No–

   (e) I don't know of any better alternatives: Yes– No–

   Remember, you need to tell me if any of the following reasons were important or not in your decision not to change schools:

   (f) I have another child in the same school: Yes– No–

   (g) Price: Yes– No–

   (h) Academic quality: Yes– No–

   (i) Proximity to home: Yes– No–

   (j) Proximity to work: Yes– No–

   (k) Socioeconomic status of classmates: Yes– No–

   Remember, you need to tell me if any of the following reasons were important or not in your decision not to change schools:

   (l) Safety of the neighborhood: Yes– No–

   (m) No cases of school bullying: Yes– No–

   (n) Extracurricular activities (sports, music workshops, theater, etc.): Yes– No–

   (o) Infrastructure: Yes– No–

   (p) If you had to choose only one (the most important one) for staying in the same school, which one would it be?: – – –

3. Suppose the school your student is currently enrolled in will close at the end of this year. Tell me how important each of the following attributes would be in choosing a new school, with possible responses being "not important, somewhat important, important, very important":

(a) Low price:
Not important– Somewhat important– Important– Very important–

(b) Good academic quality:
Not important– Somewhat important– Important– Very important–

(c) Proximity to home:
Not important– Somewhat important– Important– Very important–

(d) Proximity to work:
Not important– Somewhat important– Important– Very important–

(e) Learning environment, educational program, and values:
Not important– Somewhat important– Important– Very important–

(f) Good socioeconomic status of classmates:
Not important– Somewhat important– Important– Very important–

(g) Safety of the neighborhood:
Not important– Somewhat important– Important– Very important–

(h) No cases of school bullying:
Not important– Somewhat important– Important– Very important–

(i) Extracurricular activities (sports, music workshops, theater, etc.):
Not important– Somewhat important– Important– Very important–

(j) Infrastructure:
Not important– Somewhat important– Important– Very important–

(k) If you had to choose only one (the most important one) to choose a new school, which one would it be? – – –

If no:

4. Which school was your child in? – – –

5. How many schools did you consider in your search? – – –

   Tell me how important each of the following attributes was in choosing this school, where the possible answers are "not important, somewhat important, important, very important":

   (a) Low price:
   Not important– Somewhat important– Important– Very important–

   (b) Good academic quality:
   Not important– Somewhat important– Important– Very important–

   (c) Proximity to home:
   Not important– Somewhat important– Important– Very important–

   (d) Proximity to work:
   Not important– Somewhat important– Important– Very important–

   (e) Learning environment, educational program, and values:
   Not important– Somewhat important– Important– Very important–

   (f) Good socioeconomic status of classmates:
   Not important– Somewhat important– Important– Very important–

(g) Safety of the neighborhood:
Not important– Somewhat important– Important– Very important–

(h) No cases of school bullying:
Not important– Somewhat important– Important– Very important–

(i) Extracurricular activities (sports, music workshops, theater, etc.):
Not important– Somewhat important– Important– Very important–

(j) Infrastructure:
Not important– Somewhat important– Important– Very important–

(k) If you had to choose only one (the most important one) to choose a new school, which one would it be? – – –

To everyone: Now I'm going to present you with a hypothetical scenario. Suppose there is a different school right next to the one your student is currently enrolled in (so it is the same distance from your home and work) with similar classmates and teachers, and the same price (if applicable).

6. Would you change your student if, by doing so, their overall grades increased by two tenths (for example, from 6.2 to 6.4)?
   - ...four tenths? Yes– No–
   - ...six tenths? Yes– No–
   - ...eight tenths? Yes– No–
   - ...ten tenths? Yes– No–
   - I would not change the student under any of these circumstances
7. Would you change your student if it improved their self-esteem? Yes– No–
8. Would you change your student if it resulted in them adopting healthier habits (i.e., better nutrition, more active lifestyle, etc.)? Yes– No–

   Remember: You have to imagine that there is a different school right next to the one your student is currently enrolled in (so it is the same distance from your home and work) with similar classmates and teachers, and the same price (if applicable).
9. Would you change your student to this new school if, by doing so, you were given $88,000 just once?
   - $176,000? Yes– No–
   - $264,000? Yes– No–
   - $352,000? Yes– No–
   - $440,000? Yes– No– I would not change the student under any of these circumstances
10. Demographic characteristics
    (a) What is your child's age?
    (b) Gender?
    (c) How many siblings does the child have?

(d) What are their ages?

(e) What is the highest educational level achieved by the father?

(f) What is the highest educational level achieved by the mother?

(g) Are you enrolled in any of the following programs: Chile Solidario Social Protection System; Ingreso Ético Familiar; Seguridades y Oportunidades? Yes No I don't know

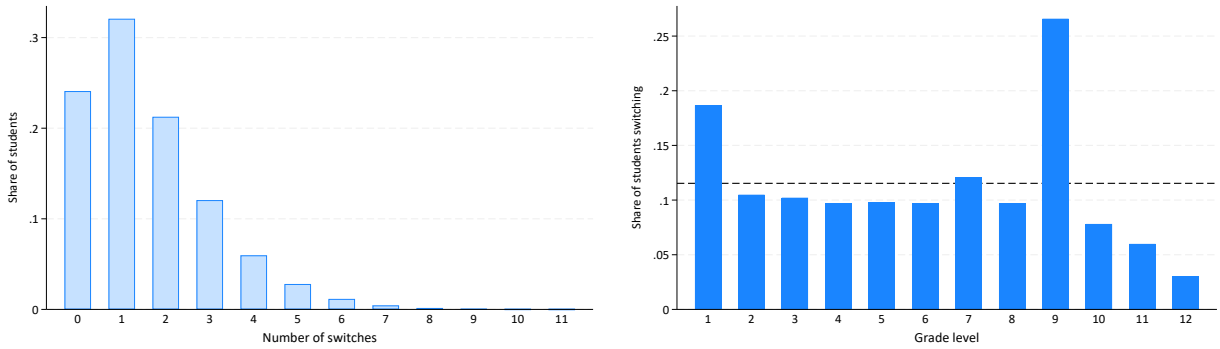
(h) Are you in the most vulnerable third according to your socioeconomic rating in the Social Registry of Households?

(i) Are you in Tramo A of the National Health Fund (FONASA)?

(j) Is the student disadvantaged ?

Appendix F: Additional tables and figures

Figure 12: Switching prevalence in Chile, using students in all schools regardless of grade configuration

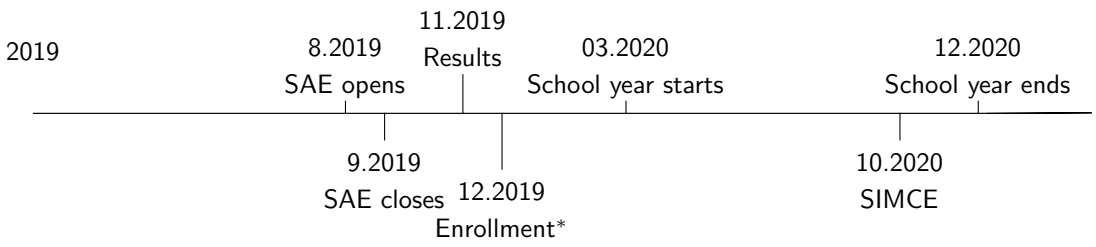


(a) Cumulative within cohort

(b) Flow

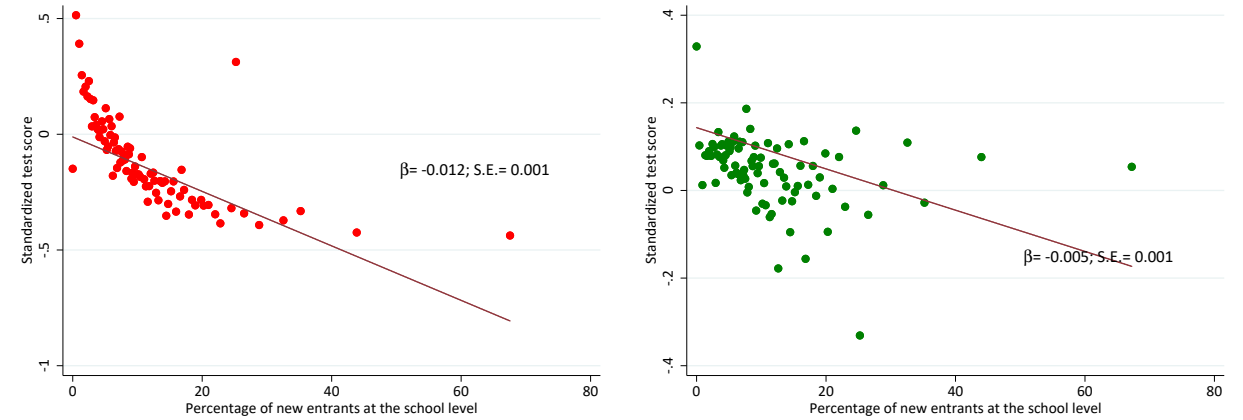
Note: Panel (a) follows the cohort of students that entered 1st grade in 2010 and graduated in 2021; it plots the share of students in the cohort (and in any school) that switched any given number of times in their school life. Panel (b) shows the share of students in each grade which school is different from the one enrolled the previous year. Each share is calculated as the average of switchers per grade over years 2010-2019. In both panels students in schools that offer any type of grade configurations.

Figure 14: School year and CSCS in Chile



Note: * Families enroll directly and physically at schools.

Figure 13: The observed relation between turnover, and reading and non-cognitive outcomes



(a) Reading (b) Participation and civic formation

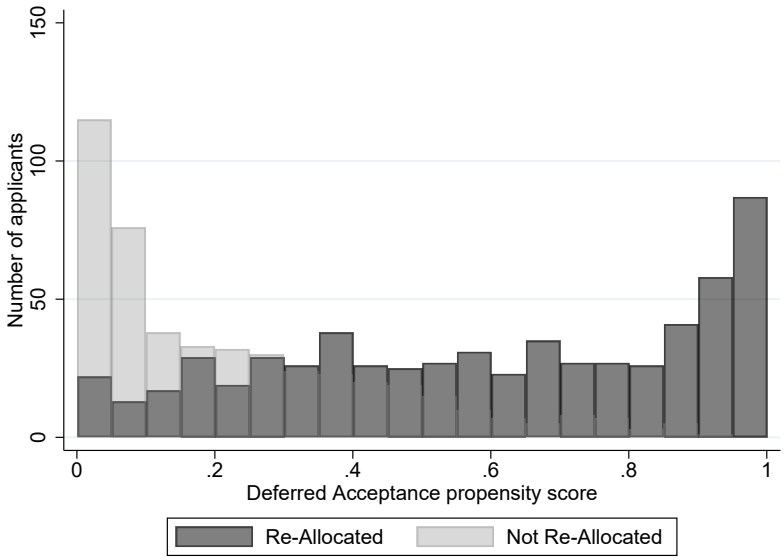
Note: Panels shows binscatter plots with the proportion of new entrants at the school level together with the standardized reading (Panel a) and Participation and civic formation (Panel b) test scores of 6th and 10th graders in 2018.

Table 15: Testing for differences in observed characteristics of re-allocated and non re-allocated students

	(1) Age	(2) Age	(3) Rural school	(4) Rural school	(5) Male	(6) Male
Re-allocated	0.240***	-0.0197	-0.0276*	-0.0121	-0.112***	-0.0499
	[0.0759]	[0.0948]	[0.0161]	[0.0176]	[0.0324]	[0.0392]
D.A.P.S.		0.721***		-0.0430		-0.173***
		[0.150]		[0.0273]		[0.0603]
Obs	946	946	946	946	946	946
Adj R2	.009	.035	.002	.003	.011	.019

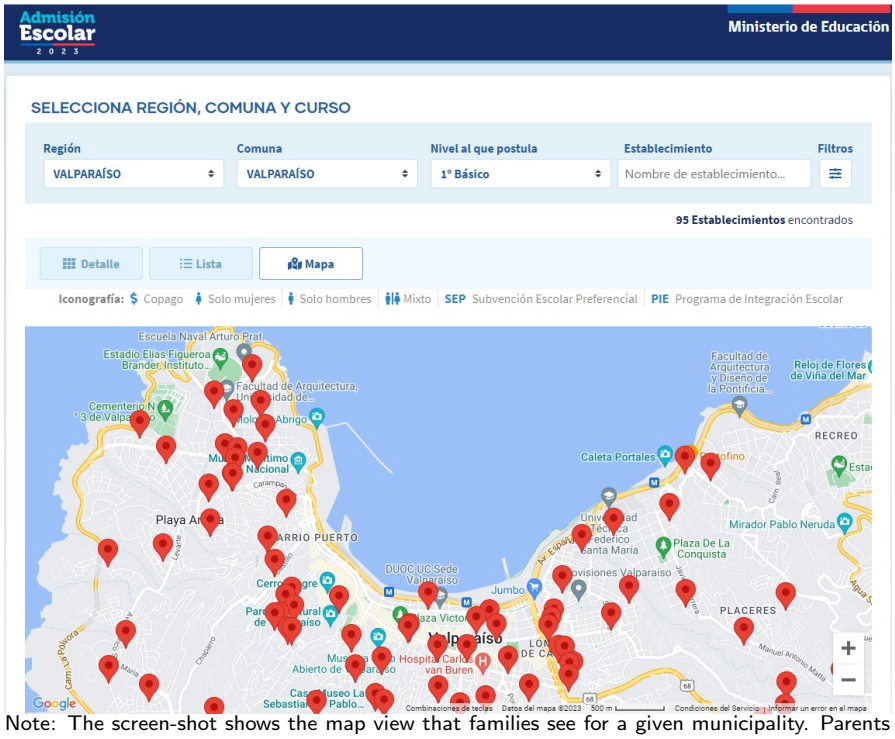
Note: Columns (1)-(3) report the results from regressions using the assignment indicator as dependent variable and the reported set of variables as covariates. Eicker–Huber–White standard errors in brackets.

Figure 15: DA Propensity Score, by Re-allocation Status



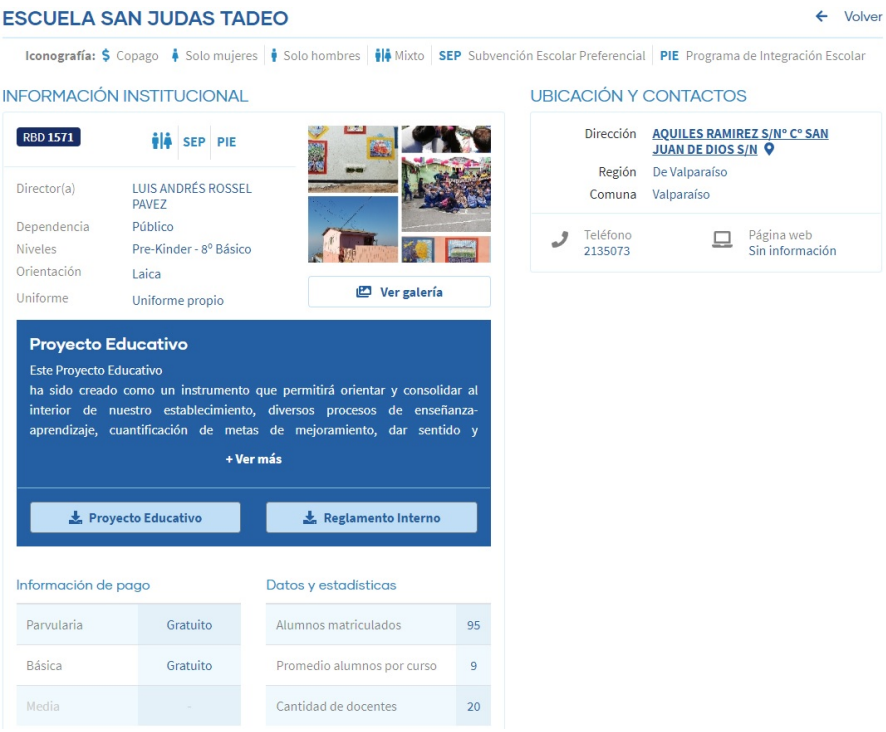
Note: This histogram depicts the distribution of the Deferred Acceptance Propensity Score for each student included in the sample. Students with a degenerate D.A.P.S. are excluded.

Figure 16: Shopping for schools in SAE



Note: The screen-shot shows the map view that families see for a given municipality. Parents can filter by grade to which they are applying to, and opt to visualize -instead of the map- a list of the schools and a detailed version of it.

Figure 17: Schools' information available to parents*



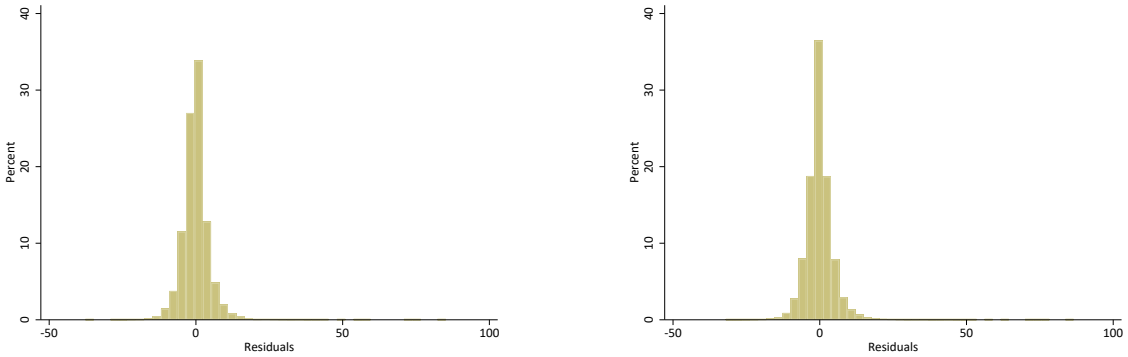
Note: After clicking in one particular school, the website display an array of information on the school's attributes. The screen-shot shows whether the school is gender-integrated or not, if it is enrolled in the SEP program (which gives the school extra resources for each disadvantaged students that enrolls), the administrative dependency, religious orientation, class size, number of teachers, and out-of-pocket fees. Also, parents can click on two links to pdf files describing the schools' educational project and its internal rules. * Although not shown in the screen-shot, parents can also see how many vacancies has the school and the schools-average tests scores.

Table 16: Assesing the validity of the school fixed effects approach

	(1)	(2)
Male	0.3366***	0.0516***
	(0.0445)	(0.0094)
Age	-0.3961***	-0.5752***
	(0.0171)	(0.0149)
Income=2	-0.4576***	-0.0087
	(0.0481)	(0.0126)
Income=3	-1.1396***	-0.0283*
	(0.0894)	(0.0167)
Income=4	-1.8118***	-0.0079
	(0.1307)	(0.0239)
Ethnicity	-0.0894	0.0472***
	(0.0647)	(0.0158)
School F.E.	No	Yes
Year F.E.	No	Yes
N	1682195	1681935

Note: estimates of regressions in which % Influx is the dependent variable. Standard errors clustered at the school level.

Figure 18: Identifying variation: Residuals of switchers share



(a) Math estimation

(b) Reading estimation

Note: These figures show the residuals of a regression with the percentage of switchers as the dependent variable, and covariates and school fixed effects as explanatory variables. Panel (a) uses the sample of the estimation for Math; Panel (b) uses the sample of of the estimation for Reading

Table 17: The impact on non-switchers' non-cognitive outcomes

	(1) Self-esteem	(2) Self-esteem	(3) Co-existence	(4) Co-existence
% Inflow	-0.00486***	-0.0163***	-0.0116***	-0.00973***
	[0.000243]	[0.000511]	[0.000408]	[0.000377]
Obs	1684273	1625156	1679883	1626598
Clusters	8371	8316	8368	8331
Adj R2	.004	.019	.011	.007
Mob. Av.	8.9	8.9	8.9	8.9
Mob. SD.	7.5	7.5	7.5	7.5
Student F.E.	No	No	No	No
School F.E.	No	No	No	No
Year F.E.	No	No	No	No

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, and an indicator variable for schools in rural areas. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade.

Table 18: The impact on non-switchers' non-cognitive outcomes

	(1) Self-esteem	(2) Self-esteem	(3) Co-existence	(4) Co-existence
% Inflow	0.000338	-0.00480***	-0.00378***	-0.00141***
	[0.000359]	[0.000473]	[0.000443]	[0.000437]
Obs	935503	874158	932868	879246
Clusters	7902	7809	7903	7817
Adj R2	.343	.393	.312	.328
Mob. Av.	8.4	8.3	8.4	8.3
Mob. SD.	7.1	7.10	7.10	7.10
Student F.E.	Yes	Yes	Yes	Yes
School F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and lagged test scores. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade.

Table 19: The impact on non-switchers' Math outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Influx	-0.00310**	-0.00106***	-0.00130***	
	[0.00150]	[0.000255]	[0.000248]	
% Influx disadvantaged				-0.00156***
				[0.000294]
Obs	11289	857600	834765	1692917
Clusters	2309	7891	7913	8431
Adj R2	.21	.32	.32	.321
Mob. Av.	10.28	8.77	9.07	4
Mob. SD.	8.02	7.4	7.69	5.23
School F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Table 20: The impact on non-switchers'self-esteem outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Inflow	-0.00406*	-0.00194***	-0.00186***	
	[0.00243]	[0.000270]	[0.000257]	
% Inflow disadvantaged				-0.00221***
				[0.000293]
Obs	9907	851778	831871	1683971
Clusters	2122	7572	7584	8069
Adj R2	.054	.034	.029	.031
Mob. Av.	9.75	8.77	9.08	4.03
Mob. SD.	7.83	7.37	7.68	5.23
School F.E.	Yes	Yes	Yes	Yes
Year_F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Table 21: The impact on non-switchers' school coexistence outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Inflow	-0.00857***	-0.00357***	-0.00309***	
	[0.00332]	[0.000334]	[0.000315]	
% Inflow disadvantaged				-0.00474***
				[0.000375]
Obs	6556	823008	801510	1624857
Clusters	1594	7515	7528	8017
Adj R2	.14	.17	.166	.167
Mob. Av.	9.93	8.72	9	3.98
Mob. SD.	7.83	7.33	7.62	5.18
School F.E.	Yes	Yes	Yes	Yes
Year_F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Table 22: The impact on non-switchers' healthy habits outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Influx	-0.00696***	-0.00289***	-0.00282***	
	[0.00269]	[0.000320]	[0.000289]	
% Inflow disadvantaged				-0.00508***
				[0.000340]
Obs	8040	850004	829257	1679579
Clusters	1849	7569	7585	8064
Adj R2	.102	.109	.099	.1
Mob. Av.	10.26	8.77	9.07	4.03
Mob. SD.	8.14	7.37	7.67	5.23
School F.E.	Yes	Yes	Yes	Yes
Year_F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Table 23: The impact on non-switchers' civic education outcomes

	(1) Below average	(2) Girls	(3) Boys	(4) Full sample
% Influx	-0.00489	-0.000534*	-0.000924***	
	[0.00339]	[0.000315]	[0.000301]	
% Inflow disadvantaged				-0.000616*
				[0.000345]
Obs	6167	824406	801556	1626291
Clusters	1552	7536	7529	8024
Adj R2	.093	.087	.079	.079
Mob. Av.	9.93	8.74	9.02	3.99
Mob. SD.	8.02	7.35	7.64	5.2
School F.E.	Yes	Yes	Yes	Yes
Year_F.E.	Yes	Yes	Yes	Yes

Note: Estimates of equation 6. Standard errors clustered at the school level in brackets. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample consists of students in 4th, 6th, 8th and 10th grade observed between 2014 and 2019. Covariates include students' age and gender, an indicator variable for schools in rural areas, and average test score of the school. % Influx corresponds to the percentage (measured as a number between 0 and 100) of students that are new in the corresponding grade. Appendix G provides details on the specific content of each non-cognitive test.

Table 24: Identification strategy: costs incurred by each group in their preferred alternative

	CSCS	Non-CSCS
Passive	0	0
Active	η^f	$\eta^f + \eta^s$

Note: If the fixed cost induces passive students to remain in their status quo schools, then the decision cost might be identified by comparing their choices to those of active students subject to the CSCS. The comparison of the choices between active students subject and non-subject to the CSCS identifies the search cost.

Table 25: Estimated parameters of the Demand

	All students			Disadvantaged students			Female students		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decision Cost	-7.04***	-7.06***	-7.05***	-6.58***	-6.58***	-6.58***	-7.00***	-7.02***	-7.02***
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Enrollment Cost	-1.12***	-1.08***	-1.09***	-1.39***	-1.36***	-1.37***	-1.07***	-1.03***	-1.04***
	[0.05]	[0.05]	[0.05]	[0.07]	[0.07]	[0.07]	[0.06]	[0.06]	[0.06]
Copayment	0.02***	0.03***	0.03***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Math	0.18***			0.13***			0.17***		
	[0.00]			[0.00]			[0.00]		
School coexistence	0.04***		0.04***	0.03***		0.03***	0.04***		0.04***
	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]
% Disadvantaged	-1.33***	-1.59***	-1.53***	-0.33***	-0.48***	-0.46***	-1.45***	-1.69***	-1.63***
	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Reading		0.10***	0.09***		0.07***	0.06***		0.11***	0.09***
		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]
Participation		0.04***			0.03***			0.04***	
		[0.00]			[0.00]			[0.00]	
N	12830042.00	12876556.00	12830042.00	5628856.00	5648564.00	5628856.00	6377230.00	6400414.00	6377230.00

Note: See the text for details.

Table 26: Robustness of the estimated parameters of the demand

	R.O.L.	Conditional Logit
	(1)	(2)
Copayment	0.001***	0.003***
	[0.00]	[0.00]
Math	0.280***	0.297***
	[0.01]	[0.01]
Healthy habits	0.049***	0.038**
	[0.01]	[0.01]
% Disadvantaged	-0.506***	0.459***
	[0.02]	[0.04]
Distance	-0.001***	-0.002***
	[0.00]	[0.00]
N	315484.000	315484.000

Note: Alternative estimates of Equation 7 using only the sample of active students treated by the CSCS. For this subset of the population, households' coordinates are observed through the CSCS, so the discrete choice model incorporates distance to school in the alternatives. Column (1) implements a Rank-Ordered Logit using the list of preferences submitted by students. Column (2) replaces with zeroes all the alternatives except for the most preferred and then estimates a Conditional Logit. Standard errors shown in brackets.

Appendix G: Non-cognitive outcomes

The four tests of non-cognitive outcomes measured by IDPS capture what is described below. After each description I show one example question, according to which respondents (either teachers, students or parents) have to state how much the agree with. Letters in parenthesis indicate whose answers are collected to calculate the non-cognitive test (s=students, p=parents, t=teachers).

1. **Self-esteem and school motivation (s):** captures the self perception and self valuation of students regarding their ability to learn and their perceptions and attitudes towards academic performance, challenges and frustration. For instance, when a student shows a high motivation towards learning, it is very likely that she has the conviction that, by working hard, she will be able to succeed, and that a good result will be something valuable and rewarding for her. Example question (students only): "I know I can get good grades"

2. **School coexistence climate (s,t,p):** considers perceptions and attitudes of students, teachers and parents regarding the respect, organization and safety of the school. In particular, it seeks to capture the existence of respectful treatment between community members, respect for diversity and no-discrimination; the existence of regulations that are clear, known and respected by everyone to resolve conflicts; and, the perceptions of parents, students and teachers regarding the degree of safety both psychological and physical and the existence of prevention mechanisms. Example questions: "Some student has been humiliated in front of his or her classmates" (teachers only); "For teachers, all students are equally important" (parents only)

3. **Participation and civic education (s,t,p):** captures students attitudes towards their schools, the perceptions of students and parents towards the extent to which the school promotes the participation and commitment of school members, and the students' perceptions on the promotion of democratic life. For instance, this includes student identification with their school and the pride they feel on belonging to it, the quality of the communication between parents and school authorities, and the extent to which schools promote the exchange of ideas and respect towards others' opinions. Example question (students only): " My opinion is taken into account by my classmates"

4. **Habits of healthy life (s):** assesses the self-reported attitudes and behaviors of students in relation to healthy living, and their perceptions about the degree to which the establishment promotes beneficial habits for health. It considers students' self-reported attitudes and behaviors toward eating, active living, sexuality, and tobacco, alcohol, and drug use. In addition, it considers their perceptions about the degree to which the establishment promotes healthy eating habits, physical activity, the prevention of risky behaviors, and the promotion of safety behaviors. self care and hygiene. Example question (students only): In the last month, how often have healthy foods been sold at your school?