ECONOMICS

Working Paper Series

No. 5-2024

Impact of school closures on academic performance: Evidence from Chile

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Abstract: This paper studies the effect of school closures on students' test scores in the Chilean educational market, which was a relatively easy-to-free and exit market. With a school exit rate varying from 1% to 2%, thousands of students are forced to reallocate at the end of every academic year. I use a nationwide, standardised test applied to the same cohort three times during their primary and middle years to analyse the impact of these closures on their math and reading performance. Using value-added models, the estimations show no effects on average on both subjects for girls and boys. However, there are heterogeneous results by type of closing school, with no impact in public schools but negative in voucher and private ones. In addition, consistent with the previous literature, the results show an immediate negative impact the first year after the closure but null or even positive outcomes in the medium term. Results also suggest that students moving to schools with better performance than the closing one can see a boost in their scores.

JEL Codes: I210, I280

Keywords: planned school closures, student learning, test scores

Impact of school closures on academic performance: Evidence from Chile

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February, 2024

Work in Progress

Abstract This paper studies the effect of school closures on students' test scores in the Chilean educational market, which was a relatively easy-to-free and exit market. With a school exit rate varying from 1% to 2%, thousands of students are forced to reallocate at the end of every academic year. I use a nationwide, standardised test applied to the same cohort three times during their primary and middle years to analyse the impact of these closures on their math and reading performance. Using value-added models, the estimations show no effects on average on both subjects for girls and boys. However, there are heterogeneous results by type of closing school, with no impact in public schools but negative in voucher and private ones. In addition, consistent with the previous literature, the results show an immediate negative impact the first year after the closure but null or even positive outcomes in the medium term. Results also suggest that students moving to schools with better performance than the closing one can see a boost in their scores.

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1 Introduction

School closures are used as a policy measure to increase student outcomes by closing schools and relocating those students to other schools (with better results) to improve their academic performance. For instance, according to Engberg (2012), 70 urban districts in half of the states in the USA experienced a school closure in the 2000-2010 period. The states of Illinois, Ohio, and Michigan have experienced closures in the last decades, and countries such as Sweden and the Netherlands have used the same measures. In Latin America and the Caribbean, a few reports document the impact of shutting small rural schools on their surrounding communities in Ecuador (Tuaza Castro, 2016; Espinoza Freire and León Gonzalez, 2022), and Mexico (Galván Mora and Espinosa Gerónimo, 2017).

A growing body of the literature focuses on addressing the effects this measure has on the academic or attainment performance of the students using standardised tests, grades, or indicators like dropout, retention, or absenteeism. The discussion is centred on whether shutting down a (low-performing) school and forcing students to move to other alternatives translates into better outcomes, or at least not to their detriment.

So far, the evidence is mixed since some papers have shown positive, significant effects (Brummet, 2014; Kemple, 2016), while in some cases, the impact is negative or null (De la Torre and Gwynne, 2009; Engberg, 2012). Many factors have been included in the analysis, such as the student's gender, the performance of the closing and receiving school, and the educational context, although most of the papers initially focused on the USA due to data availability and the frequency of the school closures.

In this paper, I look at how planned closures (regardless of source) affect students' performance in Chile. This country had a liberalised educational market, allowing for relatively free opening and closing of private and voucher schools up to 2015. Until now, previous research has found a negative impact on two attainment indicators in this country, absenteeism and dropout (Grau et al., 2018), but there is no evaluation of academic achievement. I generated a panel of students who took a nationwide standardised test three times during their primary and middle years to measure the effects of school closings on their performance.

The results show that, on average, students do not see an increment or decrease in their scores when controlling for their previous achievements. I also see no difference between boys and girls. However, this outcome is heterogeneous depending on the type of (management) schools, where students in voucher or private schools experience a negative impact compared with the no-effect found on their peers at public schools. Besides, estimations show an immediate negative effect and some null or positive effects after two years or more, suggesting a catch-up effect. Another source of variation explored here is the difference in performance of the closing and receiving schools, showing that students moving to higher-performance institutions can see a boost in their scores.

The purpose of this paper is to help close the gap between the effects of school closure on academic achievement in developing or emerging countries by taking advantage of a highly liberalised educational market that has allowed for relatively free entry and exit of schools. This is done alongside the implementation of nationwide tests for primary and middle school students taken to the same students more than once.

I add to the current literature in different ways: By using a value-added model to address the effects of planned school closures on the student's academic performance, I contribute to the discussion on the direction and magnitude of the effects. In addition, I explore the heterogeneity of the results by student's gender, closing school's management type, closing school's area (urban/rural) time from the closing, and cohort affected. These exercises aim to disentangle which factors and under which context we see different results. Finally, I test a possible mechanism: The difference in performance between the closing and the receiving school.

The rest of the paper is organised as follows: Section 2 reviews the previous literature and discusses its results. Section 3 explains the Chilean educational system and context. Section 4 provides an overview of the data used for this paper. Section 5 explains the theoretical model and empirical approach. Section 6 explains the main results, while Section 7 explores heterogeneity and potential mechanisms. Section 8 presents the conclusion.

2 Literature review

There is ample literature documenting why schools close. As pointed out by Egelund and Laustsen (2006), in international educational journals, there were more than 100 references related to school closure, with most of them addressing the effects of individual school closures on their communities instead of the generalised impact of the measure. Until now, the literature has pointed out a few main reasons behind planned closures (i.e., unrelated to unforeseen conditions like health pandemics or natural disasters).

The first one is a decline in the schooling-age population. For reasons such as low birth rates (Egelund and Laustsen, 2006), de-enrolment of students due to the school's weak academic performance (Hanushek et al., 2004; Witte and Van Klaveren, 2014), an increase in school competition due to the introduction of new participants such as charter schools, or a combination of all of these, have caused some schools to struggle to enrol enough students, leading to closures, mergers, conversions, or other measures.

A second reason is financial strain due to insufficient funds, mismanagement, or inefficiencies. According to Churchill and Carrington (2000), the government of the city of Victoria, in Australia, closed 230 schools between 1992 and 1994 due to budgetary reasons (Churchill and Carrington, 2000), affecting students in these institutions. Ong and Witte (2014) analysed the closure of three primary schools in the Netherlands due to administrative mismanagement and poor assessment and how it affected student trajectories. Beuchert et al. (2018) researched the impact on academic scores of school consolidation in Denmark as a response to the idea that larger schools are more efficient financially.

Finally, a third reason is chronic student underperformance. Several papers have focused on or included closures related to low performance in high-stakes examinations or based on reports by educational directorates (Kirshner et al., 2010; Brummet, 2014; De la Torre and Gwynne, 2009; Engberg, 2012; Steinberg and MacDonald, 2019). Han et al. (2017) identified 1,522 closed low-performing schools between 2006 and 2013 in 26 states in the USA. For instance, Carlson and Lavertu (2016) analysed the shutting down of charter schools that did not meet the academic standard requirements in Ohio, forcing their exit.

The literature analysing school closures' effects on achievement is relatively new but burgeoning, with most papers published in the last decade. Many of them assess how forcing these students to look for new schools or reallocating them to new ones affected their academic achievement or attainment, with outcomes such as academic scores, GPA, dropout, retention, and graduation. Early work used propensity score matching techniques to generate control groups to isolate the disruption effect from other confounders (see, for instance, De la Torre and Gwynne (2009)). However, later papers, especially in the USA, have used repeated cross-sectional or panel data, tracking students' enrolment decisions and performance for up to a decade (For example, Billger and Beck (2021) used rich panel data to analyse the determinants of school closures, and Kirshner et al. (2010) traced students and their performance for five years).

Evidence from previous empirical work has shown mixed results. There is a set of studies that have found positive effects on student achievement or performance (Bross et al., 2016; Brummet, 2014; Witte and Van Klaveren, 2014; Carlson and Lavertu, 2016; Kemple, 2016), while others have found null or negative effects (De la Torre and Gwynne, 2009; Engberg, 2012; Kirshner et al., 2010; Özek et al., 2012; Larsen, 2020)

Early work was conducted by De la Torre and Gwynne (2009). In this policy paper, the authors estimated the impact of schools closing in Chicago between 2001 and 2006. Using annual standardised tests for students aged eight and older before and after a closure, and a subset of similar schools as a comparison group, the authors estimated the differences between the predicted and actual performance of pupils who attended closed schools.

Results show that most of the displaced students enrolled in academically weak schools; the most significant negative impact on reading and math occurred the year before the closing (when schools announced their decision to shut down); and students who faced closures in their earlier years had caught up with their pairs when they reached high school. However, the learning outcomes depended on the characteristics of the receiving school.

Engberg (2012) evaluated the impact of school closures in a mid-size urban district on student test scores and absenteeism. Using an instrumental variables approach (the designated new school by the government), the authors estimated an initial spike of 13% in absenteeism that became non-significant in the second year. Results also showed that students displaced by school closures could experience adverse effects on test scores and attendance. Still, these effects could be minimised when students move to higher-performing schools.

Using a similar approach, Özek et al. (2012) analysed the closing of 32 schools in the District of Columbia, USA, and found that the student's performance dropped between 0.1 to 0.2 standard deviations in the near term but rebounded in the following periods and became indistinguishable. And they found no evidence of increased mobility in affected students (unlike Engberg (2012)).

Larsen (2020) analysed the impact of school closures on two sets of outcomes: Achievement (GPA, attendance, discipline, and test scores) and attainment outcomes (high school graduation and college attendance) in the district of Milwaukee, USA. The author found that students facing a disruption had a GPA of 4.4% lower, an attendance rate of 2.7 percentage points lower, an 11% reduction in the on-time graduation rate, and an 8.4% decrease in the college attendance rate.

The literature is more scarce in other countries, given the lower likelihood of schools closing. Witte and Van Klaveren (2014) analysed the effects of closing primary schools on students' outcomes in the Netherlands. The authors found no impact on test scores, but it did affect the tracking decision into higher secondary school, where children who were displaced earlier were more recommended to more difficult education tracks. Although, similar to Özek et al. (2012), the effect faded out after a couple of years in the receiving high school.

There is some evidence in Chile as well. According to Grau et al. (2015), between 1994 and 2012, the number of schools closed in Chile was 2,151, yielding an average annual exit of 113 schools per year and a yearly destruction rate of 1.10 per cent.

Using those results as a starting point, Grau et al. (2018) studied the impact of school closures on two indicators: Dropout and grade retention. The authors used data from 2002 to 2011 to evaluate the effects on retention in fifth grade and dropout in grades 9 to 11. For dropout (measured as not being enrolled in two consecutive years), they used a Propensity Score Matching approach (matching by GPA, age, and gender) with students one year older in the same school that closed. For grade retention, since it also depends on the receiving school, the authors proposed an instrument that assesses the decrease in students' total population in the school's municipality. Results showed that facing a closure increased the probability of dropping out of high school between 49% and 68%. At the same time, it also raised the likelihood of retention in fifth grade between 3.9 and 4.4 percentage points.

The growing body of literature finds that students moving to better-performance schools increase their performance and lower their absenteeism and dropout rates. However, this is not always the case since displaced students also enrol in similar or academically weaker schools than their previous ones. However, a negative but temporary effect during the students' first years in their new schools could disappear after a couple of years.

3 Chilean educational context

The educational system in Chile comprises 12 years, from grades 1 to 12, all mandatory since 2003. The last year of preschool, *kinder*, is also mandatory since 2015, but not the previous levels. Grades 1 to 8 are considered primary education (*educación básica*), and grades 9 to 12 are middle/high school (*educación media*). The curriculum is standard until the last two years, when students choose between different tracks and specializations and the beginning of grade 11.

In 1981, Chile introduced a school reform, creating a highly liberalised educational market. In this market, three (management) types of schools emerged: Public or municipal schools that are run by the 345 municipal departments of education nationwide and receive a voucher per student enrolled; private-voucher schools that receive the same voucher per student but could also charge fees and are administered by private or independent entities; and private schools that are also independent and do not receive public funding. Neither of these schools has designated catchment areas, allowing students and their families to choose and apply to the schools freely and according to their preferences.

According to the Ministry of Education (2010), 8,685 public schools enrolled 39.3% of the student body in primary and secondary levels; voucher schools totalled 9,253 and 51.8% of the enrolment, and private schools matriculated 7.3% of the students in 1,320 schools in 2011. The rest corresponds to conjoint administrative corporations (these are similar to municipal schools and enrol 1.5% of the students in 92 schools, primarily vocational and highly tied to industry associations or firms)

In the same year, 64.9% of the schools that offered primary education offered from grade 1 to grade 8, 12.4% from grade 1 to grade 6, 1.6% offered only grades 7 and 8, and 21.1% had a different structure (including schools offering from grade 1 to grade 12). Until 2015, there were few barriers to entry, especially for vouchers or private schools. The creation of new schools was weakly regulated, and any independent administrator wanting to open a school could do so and shut it down, making this an easy-to-free and exit market.

In 2011, the *Agencia de la Educación* (Educational Agency) was created as part of the *Sistema de Aseguramiento de la Calidad de la Educación Escolar* (Quality Assurance System for School Education). The agency has three main goals, one of which is to assess and evaluate academic achievement according to the national curriculum. The agency has classified schools into four categories according to their performance since 2016. They also proposed a criteria to close schools depending on their performance, but as of 2019, no school has closed because of it. However, in said year, 36 schools were at risk of losing their licence due to their classification as 'insufficient performance'.

Unlike some countries like the United Kingdom or the United States, in Chile, students are not automatically allocated to schools according to their neighbourhoods, nor they have designated catchment areas. Therefore, after a closure is announced, it is up to the families and the students to find a vacancy in another school of their preference. Lastly, suppose the student has no spot in any school before the start of the academic year (March). In that case, the municipal education department will give the student a spot in any municipal school with the capacity to receive them, regardless if this is the closest to their home or if this one has the track (academic or vocational) of their preference.

Schools could also require students to take tests or their parents to present additional documentation (like a marriage certificate or the children's baptism proof). For instance, in 2011, 8.3% of public-school 4th graders who took a nationwide assessment test[1], 44.8% of voucher-school attendants, and 58.7% of private-school pupils had to take a test before enrolling in their current school (according to the data provided by the parents or the guardians in the supplementary form).

According to Decree 315, dated June 29, 2011, schools wanting to shut down permanently must notify the parents or guardians in a meeting before the school applies for the suspension, for which the deadline is June 30[2]. Those parents who couldn't attend have to be notified via a letter. Figure A1 in the appendix contains a letter (in Spanish) sent to the parents by a private school on June 23, 2023. In this letter, the school mentions the Decree and regulations of the closures, explains the motive, and states that the school will close after the end of the academic year (December 2023) and won't open next year. Besides, it advises parents and guardians to look for new institutions for their children.

[1]This is the SIMCE evaluation, which will be explained in more detail in the next section

[2]The academic year in Chile runs from March to December. Hence, schools apply before the end of June, are open until December, and do not reopen in March for students.

4 Data

4.1 Databases

I will focus on primary/middle schoolers (up to 8th grade) because, as explained in Section 3, many public schools offer from grade 1 to grade 8 in the same school (*escuela* or *colegio*), and from grades 9 to 12 in a different school (*liceo*). However, private or voucher schools usually offer from 1st to 12th grade in the same school (and sometimes even nursery school since age 3).

The *Sistema de Medición de la Calidad de la Educación* or *SIMCE* (Education Quality Measurement System) is a battery of standardised tests that measure certain subjects of the school curricula (such as Spanish, Mathematics, English, and Science) administered every year to fourth graders since 2005, and each other year for students in even grades. This setting created two cohorts that sat the SIMCE three times during their formative years. I will analyse the cohort that took the test in the fourth year in 2011, the sixth year in 2013, and the eighth year in 2015 and were tested in reading and math (the other cohort was only tested in reading in grades 2, 4, and 6 between 2012 and 2016. I include it as part of the robustness checks).

The databases used for this estimation are: (1) the three individual SIMCE databases of the cohort that was in fourth grade in 2011 and retook the test in sixth and eighth grade, including the parents' socioeconomic characteristics as they completed a questionnaire, (2) the list of schools open each year with their enrolment per level (primary and middle school), (3) the school's fourth-grade performance in the standardised evaluation (SIMCE) every year for the period 2010 to 2015, (4) the yearly individual enrolment of the students during the 2008-2016 period, and (5) the yearly municipal population by age.

The educational databases for the estimation come from the Ministry of Education. The individual databases are linked through a masked unique national identification number (*mrun*), and the schools by their identification number (*rbd*). The student datasets also contain socioeconomic and demographic characteristics, while the school's datasets contain enrolment, performance, demographic characteristics, and some administrative records about funding. About 80% of the student's parents or legal tutors completed the socioeconomic questionnaire. The municipal population database comes from the National Institute of Statistics (*INE*).

The choice of using SIMCE for these cohorts instead of high school GPA has two motives: The first one is that grades or marks heavily depend on the school's performance or quality. Therefore, students changing from one institution to another might receive different grades for similar efforts or results. The second reason is that there is a "GPA inflation effect" since schools have incentives to increase their students' GPAs. Even when this is more salient during high school (and more since the inclusion of the ranking index in 2012), the effect is present, and it is larger in private schools (Fajnzylber et al., 2019). Eyzaguirre (2021) analysed the differences between SIMCE growth and GPA and found a mismatch between those two indicators.

Since private schools in Chile do not have to inform their closure, I use the official school listings for each year between 2009 and 2015 to identify the schools that stopped offering their services and closed. I define a school closure as a school not opening for two consecutive years (some schools are missing for one period and appear with the same identification number the following year, so I assume it was a mistake or no student enrolled).

4.2 Data description

The database contains the students' performance in three subjects: Math, reading, and natural sciences. It also comes with an achievement classification: 'Basic', 'intermediate', or 'advanced'. Unfortunately, natural sciences were not evaluated in 6th grade (only in 4th and 8th grade), so this subject is not included in the analysis.

Figures 1 and 2 contain the histograms for the SIMCE scores by subject and year using the dataset as the Ministry of Education provided it. These scores are already standardised with a mean of 250 and a standard deviation of 50 (so they do not correspond to raw scores or the number of correct answers). Still, to compare my results with the previous literature, I normalise them to a mean of 0 and a standard deviation of 1 by year and subject.

[Figure 1 Here]

[Figure 2 Here]

Table 1 displays the summary statistics per year for math, while Table 2 does the same for the reading subject using the scores before normalisation. Between 205,000 and 220,000 students took the test every year, and the scores ranged from 106 to 398 (math) and 110 to 373 points (reading).

[Table 1 Here]

[Table 2 Here]

The panel with the three waves of the SIMCE evaluation contains 714,922 rows after removing 50,722 observations duplicated or with invalid identification numbers. Besides, there are 83,065 missing math scores and 84,113 missing reading scores[3]. Moreover, 66,394 observations have both subjects' scores missing.

In total, there are 289,037 unique students in the panel observed at least once. Of them, 188,557 students are observed in each wave (65.24%), 48,771 are observed twice, and 51,709 are seen once, as shown in Table 3. Nevertheless, not every student observed twice can be included in the analysis because if the student took the SIMCE in 2011 and 2015, the missing SIMCE in 2013 wouldn't be included.

[Table 3 Here]

Students who are not observed in every SIMCE examination can be attributed to several factors: Dropping out of school in between the grades (either permanent or temporary), being retained one or more grades, being absent on the day of the evaluation, taking the test in a school that is too small to present results individually, or it could be a problem

[3] The database contains a reason for not having a score. The two most common correspond to integrated students or students who don't speak Spanish; the other is the student's absence. Some scores are missing due to security concerns (usually when the schools are too small to avoid identifying students individually).

with the student's national identification number.

Table 4 contains the student's and parent's demographic characteristics according to the year of the SIMCE implementation. Around 51% of the test-takers are male, around 41% study at public schools, 51% at voucher schools, and 8% at private schools. The most common educational level for parents is incomplete high school (around 30% of the data, although there are between 14% and 26% of missing values for mothers and between 17% and 29% unknowns for fathers).

[Table 4 Here]

Three questions of interest were only included in 2011: If the student lived and studied in the same municipality (and 88% did), if the family belonged to any of the indigenous groups (12%), and if Spanish was the student's second language (only 1%).

4.3 Limitations

A limitation of this dataset is that I only observe students every other year while they could face closures yearly. This means that in between each SIMCE cycle, students could have been forced to reallocate twice. It also means that I could see the effects of the closure the year immediately after or two years after, but not both. Also, it might be the case that the student reallocated has transferred to a new school the year after the closure, for reasons unrelated to a school closure.

Another source of limitations is that there is no official listing of schools shutting down, so I base the closure on the disappearance of a school ID for more than two years. However, some mergers and consolidations could lead to a school receiving a new *rbd* that would flag the old one as a closure.

5 Empirical strategy

5.1 Value-added model

The basis of the value-added model was early modelled by Boardman and Murnane (1979), and it consists of a cumulative structural model of children's achievement. Following the notion by Todd and Wolpin (2003), and Todd and Wolpin (2007), although without specifying the household, the general functional form is the following:

$$T_{it} = T_t[F_i(t), S_i(t), X_i(t), \mu_{i0}, \epsilon_{it}] \tag{1}$$

Where T_{it} is an indicator of achievement or performance for child i at the end of the academic year t. F_i, S_i, and X_i are the family, school and individual input measurements up until year t, respectively. μ_{i0} is a time-invariant individual child endowment (or initial ability), and ϵ_{it} is a time-varying error term.

Assuming that the function components are additively separable and non-age varying (at least over the years used in the model), we could decompound the cumulative effects, expressing current outcomes as a function of contemporaneous and previous inputs.

$$\begin{aligned} T_{it} = {} & \alpha_1 F_{it} + \alpha_2 F_{(i(t-1))} + ... + \alpha_t F_{i1} + \beta_1 S_{it} + \beta_2 S_{i(t-1)} + ... \\ & + \beta_t S_{i1} + \gamma_1 X_{it} + \gamma_2 X_{i(t-1)} + ... + \gamma_t X_{i(t-1)} + ... + \phi_t \mu_i 0 + \epsilon_{it} \end{aligned} \tag{2}$$

This specification is the cumulative effects model since it includes the terms from the initial period up to time t.

The non-age varying assumption means that the impact of any input on the outcomes is the same regardless of the age when it was introduced, but the effect varies due to the time between its application and the time of the achievement. The term μ_{i0} remains untouched by this assumption, and the parameter ϕ_t will capture the initial endowment's varying effects at the individual's different ages.

Equation 2 presents an estimation challenge since it would require extensive tracking of every input at every period, and lagged terms would be highly correlated with current terms, adding only marginal new information. Besides, the endowment component is usually non-observable, and even proxy measures are difficult to find in the databases.

If we assume a geometric decay of previous inputs that is the same for all prior inputs, we have $\alpha_t = \lambda\alpha_{(t-1)}; \beta_t = \lambda\beta_{(t-1)}; \gamma_t = \lambda\gamma_{(t-1)}$, where $0 \leq \lambda \leq 1$.

Then the equation becomes

$$\begin{aligned} T_{it} = {} & \alpha_1 F_{it} + \lambda_1 F_{i(t-1)} + ... + \lambda^{(t-1)}\alpha_1 F_{i1} + \beta_1 S_{it} + \alpha\beta_1 S_{i(t-1)} + ... \\ & + \lambda^{(t-1)}\beta_1 S_{i1} + \gamma_1 X_{it} + \lambda\gamma_1 X_{i(t-1)} + ... + \lambda^{(t-1)}\gamma_1 X_{i(t-1)} + ... + \phi_t \mu_{i0} + \epsilon_{it} \end{aligned} \tag{3}$$

The concept of the declining impact (or decay) of the effect of the inputs over time is well documented in the literature for a few decades. For instance, the impact of the Head Start program, as well as two other model programmes related to early childhood education (preschool) in the USA, had an immediate positive effect on cognitive and social outputs, but that impact declined during the first years of public school (Haskins, 1989).

Subtracting $\lambda T_{i(t-1)}$ from both sides of equation (3), we have

$$T_{it} = \lambda T_{i(t-1)} + \alpha_1 F_{it} + \beta_1 S_{it} + \gamma_1 X_{it} + (\phi_t - \lambda\phi_{(t-1)})\mu_{i0} + \epsilon_{it} - \lambda\epsilon_{i(t-1)} \tag{4}$$

Finally, if the effect of initial endowment on achievement varies at a constant rate, the equation becomes

$$T_{it} = \lambda T_{i(t-1)} + \alpha_1 F_{it} + \beta_1 S_{it} + \gamma_1 X_{it} + \nu_i + \eta_i \tag{5}$$

Where $\nu_i = \phi\mu_{i0}$ and $\eta_i = \epsilon_{it} - \lambda\epsilon_{i(t-1)}$.

Equation 5 is the valued added model with a lagged score (VAM). It relates an achievement outcome to contemporaneous school and family input measures and the inclusion of a lagged (baseline) achievement measure. This lagged component is assumed to be sufficient to capture two unobservable components of the model: The child's initial endowment and the previous inputs (family, school, and student).

However, since the value of the parameter λ can be fixed at two extremes (zero and one), this is not the only specification of value-added models in common use. Assuming immediate decay or $\lambda = 0$, the effects of the inputs fade entirely from one period to another. On the other hand, if $\lambda = 1$, the assumption is that prior inputs are perfectly persistent on current outcomes.

The main VAM specification used in this paper is the following:

$$T_{itg} = \lambda T_{i(t-1)g} + \alpha_1 F_{it} + \beta_1 S_{it} + \gamma_1 X_{it} + \nu_i + \eta_i + \delta_1 C_{it} \tag{6}$$

Where T_{itg} is the test score of the student i in year t in subject g. And where C_{it} is a dummy variable that takes the value of 1 if the student i faced a school closure in the previous two years ($t-1$ or $t-2$) and takes the value of 0 otherwise. δ_1 is the parameter of interest since it captures the effects of a school closure. For instance, a student taking the SIMCE in 2015 would have $C_{i2015} = 1$ if their school closed while this student was enrolled in 2013, 2014, or both.

This specification does not include student or school's fixed effects. Chetty et al. (2014) showed that a lagged VAM like the one described above produces teacher value-added estimates with very little bias (2.6% and insignificant). Kane et al. (2013) and Kane and Staiger (2008) also show that specifications without the school's and student's fixed effects perform well. Therefore, I decided not to include this set of fixed effects[4].

Including the lagged score indicates that this model is estimated using a dynamic OLS, or DOLS. There are two sources of bias in this specification: It relies on the assumption that the previous lagged score is a sufficient proxy for the unobserved child endowment (or

[4]However, for a robustness check, I run the baseline model for math and reading, including school fixed effects in appendix A10. The estimates are very similar to the baseline models; thus, conclusions remain the same.

ability) as an assumption for the identification of the closure effects on performance. In addition, including the lagged test scores may introduce a measurement bias (Kane, 2017).

Two of the main criticisms of the value-added model are bias and stability, as pointed out in Koedel et al. (2015). These caveats do not apply here because the main motive of the paper is not to assess teachers (or schools) and use that as criteria to evaluate them but to retrieve the policy effect (as discussed in Todd and Wolpin (2003)) that arises from forcing students to relocate. The objective of this paper is not to estimate the individual's or school's fixed effects using a value-added framework but to assess the average treatment effect of closing schools and disrupting students' trajectories on their academic achievement.

As pointed out in Koedel et al. (2015), including demographic and socioeconomic controls depends on the richness of the prior-achievement controls in the model. Since this is a short panel where students have at most two previous test scores, I decided to run the main specifications with and without sociodemographic variables to see the change in the estimations. Another consideration for this decision is that since this paper does not aim to capture the value added by the teachers or the school but the policy implications, using all the available information about the school and the student's environment pursues that objective.

The controls typically available in the district and state administrative datasets include student's socioeconomic variables (race, gender, free/reduced-price lunch status), and personal and family educational status (first language, special-education status, mobility status, parental educational achievement, or some subset therein) (Koedel et al., 2015). As explained above, I estimate the VAM model with and without a subset of variables related to educational achievement and investment that characterise the student (such as gender), their family (mother and father's education, family income), and their school (type, and urban or rural area). The pupil and institution variables come from administrative records, while the family information comes from a questionnaire sent to the guardians. Thus, the income (classified in twelve brackets) and parents' education levels are self-reported. I transform the income brackets into a dummy variable, 'low income', which takes the value of one if the income is less than 300,000 Chilean Pesos[5].

6 Results

6.1 School closures

Each year, between 8,500 and 9,000 schools offer some grades of *educación básica* (grades 1 to 8) in Chile, with a decreasing trend. Some 100 to 200 schools close yearly, and around 100 offer their services for the first time. The exit rate fluctuates between 1% and 2% per year, as seen in Table 5, which is consistent with what was found by Grau et al. (2015).

[Table 5 Here]

Given that planned school closures are not random, there might be differences in the student body, staff, and performance between schools closing and those that remain open. Table 6 compares schools that closed against those that remained open yearly from 2009 to 2014. The ones shutting down had lower SIMCE scores in math and reading, lower enrolment in primary or middle levels, and had experienced a slightly higher reduction in student population in their municipalities in the last years. These two points refer to two of the three reasons mentioned in the literature about why schools close: Low performance and population decline. Unfortunately, I cannot see if there is financial mismanagement.

[Table 6 Here]

Between each SIMCE test, students had two opportunities where their schools could have closed. For instance, between 2011 and 2013, students could have been reallocated by the end of 2011 or 2012, which would be reflected in 2013. Table 7 shows the number of closures students faced in the two years before each SIMCE evaluation. In total, more than 4,800 students faced closures between 2009 and 2014. However, 1,4124 of these reallocations happened before the 2011 SIMCE assessment and thus are not used in the estimation.

[Table 7 Here]

[5]As a reference, the Minimum Monthly Wage (Gross) was 192,000 Chilean Pesos as of July 1st, 2011

Following the previous literature, one of the main questions, after students move to a new educational institution, is to see if they enrolled in an academically stronger school.

Tables 8 and 9 show where students enrolled after the closure of their institutions in terms of the school's performance (measured as 4th-grade SIMCE score): Rows contain their previous school's quartile, and the columns have their current school's quartile in the same subject (math or reading). For instance, 245 of the 744 (33%) students who were in a school that performed in the lowest quartile in math and closed are now in another institution in the same performing group. Regarding math, 293 of the 811 (36%) remained in the same lowest-performing group.

Out of the 3,447 students who faced at least one closure between the 2011 and 2015 evaluations, 382 are enrolled in a school without a math quartile classification[6]. Regarding reading, 383 pupils do not have their current quartile classification.

[Table 8 Here]

[Table 9 Here]

Given Chile's educational system, another question is related to the different types of schools in the market. Table 10 shows the same exercise regarding funding(management), reflecting that most students continued in the same type of school they were enrolled in before the closure, which is unsurprising. In total, 778 of 953 (82%) remained in municipal schools, 1,024 of 1,568 (65%) remained in voucher schools (and 32% moved to public ones), and 167 of 238 (70%) enrolled in another private school.

[Table 10 Here]

6.2 Baseline model

In tables 11 and 12, I present the results of the value-added models under the three model specifications explained in Section 5 (perfect decay, perfect persistence, or unrestricted persistence) using equation 6. The coefficient of interest is the 1[Closed school] binary

[6] Examples of this are schools that offer grades seven and upward and do not offer grade four

variable. The results vary significantly depending on the constraint of the term λ (the student's lagged score).

[Table 11 Here]

In the first two columns of table 11, the impact on math scores significantly increases after a school closure between 0.06 and 0.07 standard deviations when assuming perfect persistence. Columns three and four show that when perfect decay is assumed, the coefficients are negative and significant, decreasing between -0.26 and -0.23 standard deviations in the student's scores. Finally, the last two columns contain the main specification, allowing the coefficient of the previous test score to be estimated without restriction. We observe that the closed school's coefficient takes a value of 0.00 or -0.01, depending on whether other covariables are included.

Including the covariates does not change the estimations drastically between any of the paired estimations, suggesting that these estimations are robust to their inclusion. Interestingly, all of them are significant in column six, showing that these are highly associated with academic achievement. The total number of observations included in the estimation is around 350,000, which is the number of students with two consecutive math scores.

Table 12 contains the results of equation 6 for the standardised reading scores. A similar pattern is found. In the first two columns, the coefficients of interest are positive and significant, with coefficients of 0.04 and 0.05 standard deviations. Thus, students whose schools closed and had to reallocate increased their academic achievement when perfect persistence was assumed. However, the estimations are negative and significant under perfect decay, ranging between -0.20 and -0.17 standard deviations. In the last two columns, where there is no constraint on the coefficient of previous scores, we see negative results of -0.03 standard deviations (and significant) and -0.03 but slightly significant when covariates are included. Previous scores account for around 60-70% of current scores in both estimations. The coefficients in columns five and six are larger than those found for the math subject.

I check if some covariates are 'cancelling each other out', so I run a small exercise in Table

A1 in the appendix, in which I include the variables one by one and observe the change in the school closure's coefficient on the standardised math scores. This does not seem to be the case, supporting the idea that including covariates does not modify the estimations.

[Table 12 Here]

In Table A2, I run estimations for another cohort of students tested three times: In 2nd grade in 2012, in 4th grade in 2014, and in 6th grade in 2016. Unfortunately, second graders were only assessed in reading, not in math. Results show a significant negative impact of between -0.04 and -0.05 standard deviations in reading scores, which is slightly higher but still aligned with the effects on the reading performance of the main cohort (a significant decrease of 0.03 standard deviations).

As a robustness check, in Appendix A3, I estimate the preferred VAM using only students observed in the three SIMCE evaluations to explore if the results are affected but those students who did not sit every evaluation due to retention, dropping out, or absence. Of the total number of students, 188.557 (65%) were present three times. I only estimated using the unrestricted model for the parameter λ, with and without covariates, and for both subjects. I find no significance in math, in line with the baseline results in tables 11, and similar results in reading (0.02 standard deviations), but unlike Table 12, these are not statistically significant.

As explained in Section 5.1, there are two additional variables worth including in the estimation: The first is related to parental inputs, given the concern that the school's closure would change the parent's behaviour or effort, and the second is a proxy for the child's endowment or ability.

On parent's inputs, there is no information on the time or any other indicator they put on their kid's education (common questions included in other datasets refer to time dedicated to helping them with homework, reading to them in the evenings, spending time with them in other academic activities like going to the museum, or how much they value their children's schooling). The closest variables available are how often parents attend school meetings and whether they participate in extracurricular activities like sports matches or bake sales[7]. Hence, I decided not to include these proxies.

It would be ideal for controlling for the child's initial endowment, as stated in the theoretical derivation of the model. However, the database does not contain any information on the student's ability (and the closest proxy would be a question in the parent's questionnaire about the highest schooling level they think their child would achieve). Table A4 in the appendix shows the parents' answers (the most common level of education expected is a university degree), while table A5 contains estimations including this variable. Results remain virtually the same, suggesting that the model captures the child's endowment through the previous score.

Using off-subjects' test scores as part of the estimation was introduced by Ehlert et al. (2016) and used by Steinberg and MacDonald (2019). It includes the lagged value of both the same-subject and off-subject[8]. The result of this exercise is in Table A6 in the appendix, where we see the regressing of math scores on previous reading scores, with a significant estimate of 0.52, which reduces to 0.11 when including the previous math score, but it is still significant. This relates to the predicted value explained by (Ehlert et al., 2016) by showing that lagged reading scores are still a good predictor of current math scores, capturing many common factors. In the case of regressing reading or previous math scores, the estimate is 0.57 (and significant), also showing to be a good predictor when the other subject's score is unavailable. This is unsurprising since there is a high correlation between current reading and math scores and other combinations, as shown in Table A7 in the same section.

[7]Only the alternative cohort has a question about how much they read to their children in one of the questionnaires.

[8]In these two papers, if the off-subject lagged value is missing, the value is set to zero, a dummy variable is used indicating the presence of the missing test score, and an interaction term between the dummy variable and the contemporaneous same-subject is introduced. This manipulation allows to "upweight the predictive value of the same subject lagged score when the off-subject lagged score is unavailable" (Ehlert et al., 2016, p. 8). I use a different approach.

7 Heterogeneity and potential mechanisms

Using the baseline estimations as a starting point, I explore whether the results are heterogeneous by some variables related to educational achievement: school (management) type, student gender, and area (rural/urban).

In Table 13, I run the preferred VAM specification per type of school that closed (public, voucher, and private) to consider that the decision to shut a school is taken at different levels for schools that receive public funding against private ones. Also, the student's (and family's) profiles might change drastically from one type of school to another.

The first three columns correspond to math scores' estimations. The first one is for students who were in public schools that closed. The coefficient shows an increase of 0.04 standard deviations (although only slightly significant). The effect is negative and significant for students enrolled in voucher schools, with a decrease of 0.04 standard deviations (sd). Lastly, for students in private schools, the impact is even larger: a decrease of 0.15 sd.

Columns four to six show the estimations for reading scores, and these follow the same pattern. Students in public schools saw an increase in their scores of 0.01 standard deviations, which is not statistically significant. Their peers who were in voucher schools faced a significant decrease of 0.05 standard deviations. And finally, students in private schools saw the most significant effect: A decrease of 0.12 standard deviations in their scores.

[Table 13 Here]

Another possible source of heterogeneity is the student's gender. Table A8 in the appendix contains the baseline specification's results disaggregated by gender. The coefficients for mathematics (columns one and two) have a different direction for women than men, but both coefficients are small and statistically not significant. The coefficients for reading are both negative but not precisely estimated, making them both also insignificant.

I do the same by area (urban/rural) in Appendix A9, where I do not find drastically different results: Students coming from urban closing schools are affected negatively by

0.03 standard deviations in reading, while the other coefficients are insignificant.

Following the discussion in the literature, in Table 14, I look for heterogeneous effects based on the performance of the closing and receiving school. Instead of controlling for the difference in performance between these two institutions, I use an interaction term: The closed school's dummy × the difference in performance. And this difference is computed as the standardised SIMCE score (4th grade) of the student's actual school in the previous evaluation minus the standardised SIMCE scores (4th grade) of the student's previous school in the previous evaluation.

This variable captures the difference in school's performances (per subject), in 4th-grade scores (not necessarily the same grade the student is in). A positive value implies the students are now in a better-performing institution. And it is zero for those pupils who did not change schools. Interacting this term with the school closure variable, C_{it}, is to isolate the cases in which students moved to a different school, as some might have moved for other motives (and thus they would still have a difference in performance computed).

[Table 14 Here]

The positive coefficient for the interaction in the first column (math subject) indicates that moving after a closure to a school with a higher performance has a significant impact on the student's current mathematics performance. Column two shows something similar in reading, with a coefficient of 0.13.

Exploring another source of heterogeneity in the literature, in table 15, I replace the binary variable C_{it} with two dummies indicating if the school was shut down at the end of the last SIMCE assessment or the following year. This decomposition should shed some light on the difference between immediate and medium-term ones since the literature has shown that immediate effects are negative but could disappear in the medium or long term. The estimations show that having faced a closure the year right before a SIMCE evaluation has negative and significant effects both in reading and math (0.06 and 0.07 standard deviations), but a closure two years before has no impact on reading and a positive one in math (0.05 standard deviations), suggesting that after an initial drop, there are gains in numerical skills, unlike in reading, where there is a catch-up-only effect.

[Table 15 Here]

8 Conclusion

In this paper, I investigated the effects that school closures have had on the academic performance of students in primary or middle schooling in Chile, a country with a highly liberalised education market where between 1% and 2% of schools exit every year. The first outcome is that most displaced students did not end up in better-performing schools and mostly transferred to schools of the same funding-management type.

Secondly, using a less restrictive value-added model, the baseline model shows that, on average, students experienced no increase nor detriment in their achievement in both subjects. Previous scores explain between 65% and 75% of current scores, even when controlling for students' and parents' socioeconomic characteristics, suggesting the results are robust and not driven by any of these covariates.

Notably, when evaluating by type of management of the closing school, the outcomes are different: Students in municipal schools see no effect, students in voucher schools experience a negative (and significant result), while students in private schools see the most significant negative impact around 0.15 standard deviations in math scores, and 0.11 in reading. Another source of heterogeneity explored is the gender of students, showing no difference between female and male test-takers and the area of the school, with a slightly negative impact on the reading scores of students in urban settings.

Exploring the timing of the closures also provides interesting results. Estimations show that the immediate effect is negative, but the effect in two or more years can have positive or null effects depending on the subject and the number of years passed.

The difference in the closing and the receiving school performance is another source of heterogeneity since students moving to schools with better performance experience can see an increase in their scores, which is consistent with the previous literature.

This paper contributes to the growing literature on the academic effects of school closures on students' performance by analysing a highly liberalised country that allowed for almost free entry and exit of schools and exploiting the fact that a nationwide test is implemented consistently among primary and middle-year students. The agenda for future research includes investigating channels other than the one included here that help to explain these results and the spill-over effects on the students of the receiving schools, who might also experience a disruption or adjustment.

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9 Tables and Figures

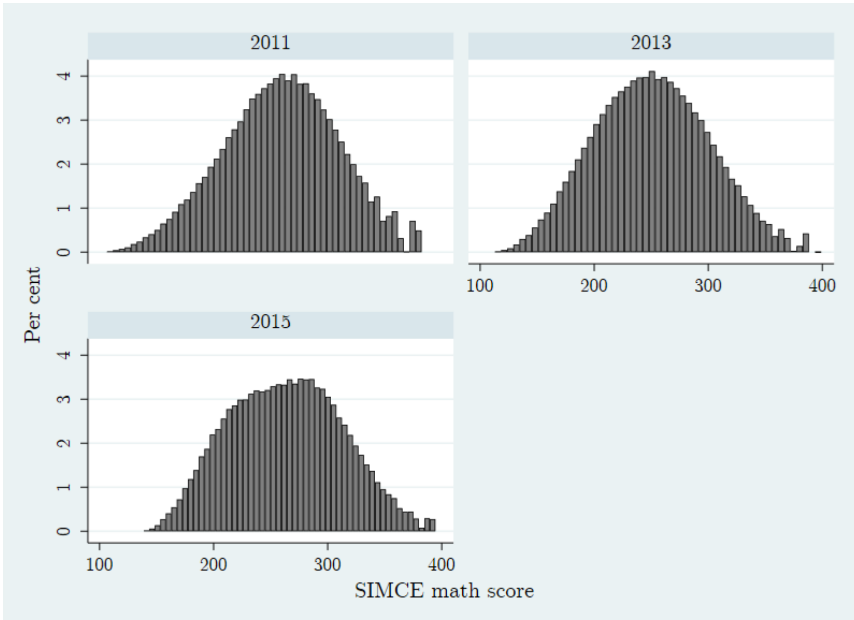

Figure 1: SIMCE math scores

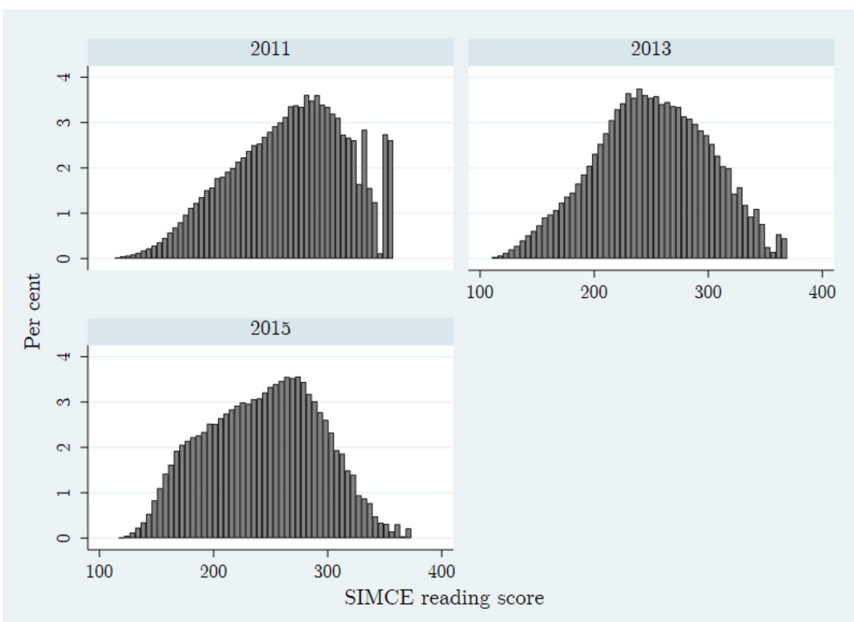

Figure 2: SIMCE reading scores

Table 1: Math SIMCE scores by year

	Mean	Standard Deviation	Minimum	Maximum	Observations
2011	259.11	50.58	106.51	382.25	210,936
2013	250.70	49.98	112.96	398.98	212,988
2015	263.39	49.30	138.82	394.39	207,933

Notes: There are 83,065 missing math scores.

Table 2: Reading SIMCE scores by year

	Mean	Standard Deviation	Minimum	Maximum	Observations
2011	267.00	50.37	113.28	357.41	211,159
2013	250.40	49.97	110.27	369.02	213,148
2015	243.72	49.97	116.65	373.16	206,502

Notes: There are 84,113 missing reading scores.

Table 3: Distribution of student's observations

	Freq.	Percent
1	51709	17.89
2	48771	16.87
3	188557	65.24
Total	289037	100

Notes: Around 65% of the students are present in the three evaluations.

Table 4: Summary of demographics

	2011		2013		2015	
	Mean	SD	Mean	SD	Mean	SD
1[Male student]	0.51	0.50	0.52	0.50	0.51	0.50
1[Public school]	0.41	0.49	0.41	0.49	0.42	0.49
1[Voucher school]	0.51	0.50	0.52	0.50	0.50	0.50
1[Private school]	0.07	0.26	0.07	0.26	0.08	0.27
1[Rural school]	0.12	0.34	0.11	0.32	0.09	0.29
1[Mother: primary or less]	0.20	0.40	0.17	0.38	0.17	0.38
1[Mother: incomplete high school]	0.30	0.46	0.26	0.44	0.27	0.44
1[Mother: complete high school]	0.12	0.32	0.10	0.30	0.10	0.30
1[Mother: higher education]	0.24	0.43	0.21	0.40	0.22	0.42
1[Mother: missing education]	0.14	0.35	0.26	0.44	0.23	0.42
1[Father: primary or less]	0.19	0.39	0.17	0.38	0.18	0.38
1[Father: incomplete high school]	0.30	0.46	0.26	0.44	0.26	0.44
1[Father: complete high school]	0.10	0.30	0.08	0.28	0.09	0.28
1[Father: higher education]	0.24	0.43	0.20	0.40	0.21	0.41
1[Father: missing education]	0.17	0.38	0.29	0.45	0.27	0.44
1[Non-low income]	0.35	0.48	0.35	0.48	0.44	0.50
1[Low income]	0.51	0.50	0.39	0.49	0.33	0.47
1[Income missing]	0.14	0.35	0.26	0.44	0.23	0.42
1[Same municipality]	0.88	0.33	.	.	.	.
1[Indigenous minority]	0.11	0.32	.	.	.	.
1[Spanish is second language]	0.01	0.12	.	.	.	.
Observations	714922					

Notes: Low income is a binary variable for families earning 300,000 Chilean Pesos monthly or less. Same municipality is equal to one if the student lives and goes to school in the same municipality. Same municipality, Indigenous minority, and Spanish as second language were only included in the 2011 form.

Table 5: Closed and new schools by year

	No. Schools	New	Closed	New(%)	Closed(%)
2009	8860	147	122	1.66	1.38
2010	8813	75	205	0.85	2.33
2011	8711	103	165	1.18	1.89
2012	8685	139	180	1.60	2.07
2013	8585	80	163	0.93	1.90
2014	8505	83	123	0.98	1.45

Notes: Schools offering some grades from 1 to 8

Table 6: Comparison of schools remained open and closing schools

	Year					
	2009	2010	2011	2012	2013	2014
Status						
Open						
Number of nonmissing values						
School ID	8738	8608	8546	8505	8422	8382
Mean						
Standardised school's 4th grade math score	0.00	0.01	0.01	0.00	0.00	0.00
Standardised school's 4th grade reading score	0.00	0.00	0.01	0.00	0.00	0.00
Enrolment in grades 1 to 8	237.01	235.44	232.27	229.76	230.26	231.15
Change in 6 to 17 yo population since 2002	-0.12	-0.13	-0.15	-0.16	-0.17	-0.17
Closed						
Number of nonmissing values						
School ID	122	205	165	180	163	123
Mean						
Standardised school's 4th grade math score	-0.35	-0.64	-0.94	-0.44	-0.46	-0.53
Standardised school's 4th grade reading score	-0.38	-0.40	-0.65	-0.37	-0.42	-0.30
Enrolment in grades 1 to 8	60.98	28.52	42.21	59.26	49.85	46.06
Change in 6 to 17 yo population since 2002	-0.14	-0.16	-0.17	-0.18	-0.20	-0.20

Notes: Math and reading standardised scores are computed as the 4th-grade SIMCE average by school and year in the panel, then normalised with mean zero and standard deviation of one

Table 7: Student faced at least one closure in the two years prior

	At least one closure		
Year	No	Yes	Total
2011	236,259	1,412	237,671
2013	236,942	1,918	238,860
2015	232,042	1,529	233,571
Total	705,243	4,859	710,102

Notes: If the student faced one or two school closures in the last two years

Table 8: Previous and current math quartile

	Current math quartile				
Previous quartile	1	2	3	4	Total
1	245	256	170	73	744
2	124	219	230	88	661
3	91	108	158	159	516
4	17	107	59	191	374
Total	477	690	617	511	2,295

Notes: Quartile 1 is the lowest performing group. Quartiles are calculated using the school's 4th-year SIMCE average in 2011, 2013, and 2015 and the national school listing. Previous quartiles correspond to the school in the previous SIMCE examination. The 1,412 observations in with a previous closure in 2011 do not have a previous school, thus are not included in this table.

Table 9: Previous and current reading quartile

	Current reading quartile				
Previous quartile	1	2	3	4	Total
1	293	297	161	60	811
2	177	213	142	107	639
3	77	176	114	124	491
4	40	54	66	194	354
Total	587	740	483	485	2,295

Notes: Quartile 1 is the lowest performing group. Quartiles are calculated using the school's 4th-year SIMCE average in 2011, 2013, and 2015 and the national school listing. Previous quartiles correspond to the school in the previous SIMCE examination. The 1,412 observations in with a previous closure in 2011 do not have a previous school, thus are not included in this table.

Table 10: Previous and current school type

	Current school type			
Previous Type	Public	Voucher	Private	Total
Public	778	173	2	953
Voucher	497	1,024	47	1,568
Private	16	55	167	238
Total	1,291	1,252	216	2,759

Notes: Previous school type corresponds to the student's type of school in the previous SIMCE examination, two years ago. Only 2,759 students who faced a closure between 2011 and 2014 have a previous SIMCE observation with their school and type.

Table 11: Baseline model, std. math score

	(1)	(2)	(3)	(4)	(5)	(6)
1[Closed school]	0.06***	0.07***	-0.26***	-0.23***	-0.00	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Previous score	1.00	1.00	0.00	0.00	0.78***	0.73***
	(.)	(.)	(.)	(.)	(0.00)	(0.00)
1[Father: Primary schooling or less]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Father: Incomplete high school]		0.00		0.08***		0.03***
		(0.00)		(0.00)		(0.00)
1[Father: Complete high school]		0.02***		0.21***		0.07***
		(0.00)		(0.01)		(0.00)
1[Father: Higher education]		0.02***		0.32***		0.10***
		(0.00)		(0.01)		(0.00)
1[Father: Missing education]		-0.01*		0.10***		0.02***
		(0.01)		(0.01)		(0.00)
1[Mother: Primary schooling or less]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Mother: Incomplete high school]		0.00		0.13***		0.04***
		(0.00)		(0.00)		(0.00)
1[Mother: Complete high school]		0.01**		0.27***		0.08***
		(0.00)		(0.01)		(0.00)
1[Mother: Higher education]		0.01**		0.33***		0.10***
		(0.00)		(0.01)		(0.00)
1[Mother: Missing education]		-0.01		0.09***		0.02**
		(0.01)		(0.01)		(0.01)
1[Male student]		0.01***		0.10***		0.03***
		(0.00)		(0.00)		(0.00)
1[Non-low income]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Low income]		-0.01***		-0.11***		-0.04***
		(0.00)		(0.00)		(0.00)
1[Income missing]		-0.02**		-0.02*		-0.02**
		(0.01)		(0.01)		(0.01)
1[Voucher school]		0.11***		0.32***		0.17***
		(0.00)		(0.00)		(0.00)
1[Private school]		0.17***		0.95***		0.38***
		(0.00)		(0.01)		(0.00)
1[Rural school]		0.03***		0.01		0.02***
		(0.00)		(0.01)		(0.00)
Constant	-0.01***	-0.09***	0.08***	-0.48***	0.01***	-0.20***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Observations	351434	351434	351434	351434	351434	351434

Notes: The dependent variable is the student's standardised score in math. The first two columns have the λ parameter fixed to 1, in columns three and four is fixed to zero, and in columns five and six is estimated through the model. Estimates are significant at the *10%, **5%, and ***1% level.

Table 12: Baseline model, std. reading score

	(1)	(2)	(3)	(4)	(5)	(6)
1[Closed school]	0.04**	0.05***	-0.20***	-0.17***	-0.03**	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Previous score	1.00	1.00	0.00	0.00	0.70***	0.66***
	(.)	(.)	(.)	(.)	(0.00)	(0.00)
1[Father: Primary schooling or less]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Father: Incomplete high school]		0.00		0.09***		0.03***
		(0.00)		(0.01)		(0.00)
1[Father: Complete high school]		0.01***		0.18***		0.07***
		(0.01)		(0.01)		(0.01)
1[Father: Higher education]		0.01**		0.27***		0.10***
		(0.01)		(0.01)		(0.00)
1[Father: Missing education]		-0.01		0.10***		0.03***
		(0.01)		(0.01)		(0.01)
1[Mother: Primary schooling or less]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Mother: Incomplete high school]		-0.00		0.10***		0.03***
		(0.00)		(0.01)		(0.00)
1[Mother: Complete high school]		0.01		0.22***		0.08***
		(0.01)		(0.01)		(0.00)
1[Mother: Higher education]		-0.00		0.28***		0.09***
		(0.01)		(0.01)		(0.00)
1[Mother: Missing education]		-0.02*		0.05***		0.01
		(0.01)		(0.01)		(0.01)
1[Male student]		-0.02***		-0.21***		-0.08***
		(0.00)		(0.00)		(0.00)
1[Non-low income]		0.00		0.00		0.00
		(.)		(.)		(.)
1[Low income]		0.00		-0.06***		-0.02***
		(0.00)		(0.00)		(0.00)
1[Income missing]		-0.04***		-0.05***		-0.04***
		(0.01)		(0.01)		(0.01)
1[Voucher school]		0.03***		0.23***		0.10***
		(0.00)		(0.00)		(0.00)
1[Private school]		0.05***		0.62***		0.24***
		(0.01)		(0.01)		(0.01)
1[Rural school]		0.08***		0.17***		0.11***
		(0.00)		(0.01)		(0.00)
Constant	-0.01***	-0.03***	0.07***	-0.24***	0.01***	-0.10***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Observations	350569	350569	350569	350569	350569	350569

Notes: The dependent variable is the student's standardised score in reading. The first two columns have the λ parameter fixed to 1, in columns three and four is fixed to zero, and in columns five and six is estimated through the model. Estimates are significant at the *10%, **5%, and ***1% level.

Table 13: Results by management type of school

	(1)	(2)	(3)	(4)	(5)	(6)
	Std. math			Std. reading		
	Municipal	Voucher	Private	Municipal	Voucher	Private
1[Closed school]	0.04*	-0.04**	-0.15***	0.01	-0.05**	-0.12**
	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.05)
Previous math Score	0.71***	0.74***	0.71***			
	(0.00)	(0.00)	(0.00)			
Previous reading score				0.66***	0.67***	0.66***
				(0.00)	(0.00)	(0.01)
Observations	132100	190658	28676	132820	189352	28397
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the standardised math score in columns one to three, and the standardised reading score in columns four to six. Columns one and four correspond to municipal closing schools, two and five for voucher schools, and four and six for private schools. Covariates are the same included in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

Table 14: Difference in performance between closing and receiving school

	(1) Std. math score	(2) Std. reading score
1[Closed school]	-0.14***	-0.05
	(0.04)	(0.06)
1[Closed school] x Difference in math	0.09**	
	(0.04)	
Previous math score	0.73***	
	(0.00)	
1[Closed school] x Difference in reading		0.13**
		(0.06)
Previous reading score		0.66***
		(0.00)
Observations	334227	333464
Covariates	Yes	Yes

Notes: The dependent variable is the standardised math score in column one, and the standardised reading score in column two. The difference in performance is computed as the performance of the actual school in the previous 4th-grade SIMCE - the performance of the previous school in the previous 4th-grade SIMCE. Covariates are the same included in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

Table 15: Time of closure

	(1) Std. math score	(2) Std. reading score
Closure two years before	0.05^{**}	0.02
	(0.02)	(0.02)
Closure one year before	-0.06^{***}	-0.07^{***}
	(0.02)	(0.02)
Std. previous math score	0.73^{***}	
	(0.00)	
Std. previous reading score		0.66^{***}
		(0.00)
Observations	351504	350639
Covariates	Yes	Yes

Notes: The dependent variable is the standardised math score in columns one and three, and the standardised reading score in columns two and four. Covariates are the same included in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

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A Appendix

SEK
PACÍFICO
COLEGIO INTERNACIONAL
INTERNATIONAL SCHOOL
SER MEJORES

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Martes 13 de junio de 2023

Estimados padres de familia:

Como es de su conocimiento, durante los últimos meses el colegio ha padecido una persistente inestabilidad respecto a lo que consideramos debe ser el normal desempeño de la actividad educativa.

Esto nos ha obligado a plantearnos si realmente es posible continuar con nuestro compromiso educativo con ustedes y sus hijos, de acuerdo con los niveles de dedicación, vocación y entrega con los que nuestro colegio está comprometido desde su fundación.

Consideramos que el derecho a la educación es un derecho fundamental y prioritario, muy por encima de cualquier otro, cada día de clase que se pierde nunca se recupera, porque la vida lamentablemente no tiene "marcha atrás". No obstante, parece que la legislación muchas veces no tiene eso en cuenta.

Consideramos que nuestra Institución, con sus aciertos y errores, como toda obra humana, ha realizado un gran trabajo en los 28 años de existencia del colegio, primero en Viña del Mar y ahora en Concón. Hemos realizado importantes innovaciones educativas, construido edificios de vanguardia, implementado programas únicos de intercambios internacionales, entregado beneficios a nuestro personal muy por encima de lo que obliga la legislación vigente, y todo ello cumpliendo siempre con total seriedad y puntualidad con nuestras obligaciones como institución educativa.

A pesar de ello, la Dirección Regional del Trabajo de Viña del Mar, desconociendo los sólidos argumentos del colegio y la oferta presentada por nuestra parte, nos ha fijado un "piso de negociación" que no refleja las condiciones reales del centro, generándonos una situación de gran incertidumbre. El sindicato decidió acogerse a este piso impuesto, lo que nos obliga a asumirlo a pesar del aumento de costos y riesgos que esto implica. Esta situación nos impide seguir realizando nuestra labor con la tranquilidad y seguridad de futuro necesarias, y contraviene nuestra planificación económica que promueve la modernización y mantenimiento de nuestro alto estándar educativo.

Por dicho motivo, en cumplimiento del Decreto 315 de 29 de junio de 2011, hemos acordado concluir la actividad educativa de nuestro centro con fecha 31 de diciembre de este año, lo que ponemos en su conocimiento a los efectos oportunos y con la debida antelación para que dispongan del tiempo necesario para buscar un nuevo centro para sus hijos, entre los muchos colegios que existen en la zona.

Pueden tener la certeza de que tomar esta decisión nos produce una enorme tristeza, acrecentada por el hecho de intuir claramente que quienes han provocado esta situación no buscan el bien común; ni de los alumnos, ni de nuestra comunidad educativa.

Quedo a su disposición y les envió mi más atento saludo,

Dr. Jorge Segovia
Presidente de la Junta Directiva

Figure A1: Closure letter by a private school in 2023

Table A1: Covariates exercise, std. math score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1[Closed school]	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Previous score	0.78***	0.76***	0.75***	0.75***	0.75***	0.73***	0.73***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Father: Primary schooling or less]		0.00	0.00	0.00	0.00	0.00	0.00
		(.)	(.)	(.)	(.)	(.)	(.)
1[Father: Incomplete high school]		0.08***	0.04***	0.04***	0.04***	0.02***	0.03***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Father: Complete high school]		0.16***	0.10***	0.10***	0.09***	0.07***	0.07***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Father: Higher education]		0.29***	0.18***	0.18***	0.16***	0.10***	0.10***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Father: Missing education]		0.08***	0.04***	0.04***	0.04***	0.02***	0.02***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Mother: Primary schooling or less]			0.00	0.00	0.00	0.00	0.00
			(.)	(.)	(.)	(.)	(.)
1[Mother: Incomplete high school]			0.06***	0.06***	0.05***	0.04***	0.04***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Mother: Complete high school]			0.12***	0.12***	0.10***	0.08***	0.08***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Mother: Higher education]			0.18***	0.18***	0.15***	0.09***	0.10***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1[Mother: Missing education]			0.08***	0.08***	0.05***	0.02**	0.02**
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1[Male student]				0.03***	0.03***	0.04***	0.03***
				(0.00)	(0.00)	(0.00)	(0.00)
1[Non-low income]					0.00	0.00	0.00
					(.)	(.)	(.)
1[Low income]					-0.06***	-0.04***	-0.04***
					(0.00)	(0.00)	(0.00)
1[Income missing]					-0.01	-0.02**	-0.02**
					(0.01)	(0.01)	(0.01)
1[Voucher school]						0.16***	0.17***
						(0.00)	(0.00)
1[Private school]						0.38***	0.38***
						(0.00)	(0.00)
1[Rural school]							0.02***
							(0.00)
Constant	0.01***	-0.11***	-0.15***	-0.17***	-0.11***	-0.19***	-0.20***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	351434	351434	351434	351434	351434	351434	351434

Notes: The dependent variable is the student's standardised score in math. Estimates are significant at the *10%, **5%, and ***1% level.

Table A2: Baseline model, other cohort

	(1)	(2)
	Std. reading score	Std. reading score
1[Closed school]	-0.04***	-0.05***
	(0.02)	(0.02)
Previous score	0.71***	0.67***
	(0.00)	(0.00)
Observations	345296	345296
Covariates	No	Yes

Notes: The dependent variable is the student's standardised score in reading for the secondary cohort. Covariates included are the same as in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

Table A3: Restricted sample, std. math score

	(1)	(2)	(3)	(4)
	Std. Math	Std. Math	Std Reading Score	Std. reading Score
1[Closed school]	0.01	0.00	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)
Previous score	0.78***	0.73***		
	(0.00)	(0.00)		
Previous score			0.70***	0.66***
			(0.00)	(0.00)
Observations	322015	322015	321190	321190
Covariates	No	Yes	No	Yes

Notes: The dependent variable is the student's standardised score in math in the first two columns and the standardised scores in reading in the other two. The estimation only includes the students who were present in the three SIMCE evaluations (around 65% of the pupils). Covariates are the same included in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

Table A4: Student's expected highest level achieved

	Year			
Level	2011	2013	2015	Total
Incomplete high school	3,704	3,288	2,070	9,062
Complete vocational HS	24,980	18,802	14,901	58,683
Complete academic HS	5,014	4,287	3,516	12,817
Vocational or technical tertiary degree	28,500	30,600	32,465	91,565
University degree	107,481	93,241	91,578	292,300
Postgraduate studies	28,065	26,754	37,547	92,366
Total	197,744	176,972	182,077	556,793

Notes: Answered by the parent or guardians in the socioeconomic questionnaire. There are 158,129 missing values in this variable.

Table A5: Effects including expected educational level

	(1)	(2)	(3)	(4)
	Std. Math	Std. Math	Std Reading Score	Std Reading Score
1[Closed school]	-0.01	0.01	-0.03*	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)
Previous score	0.73***	0.71***		
	(0.00)	(0.00)		
1[Incomplete HS]		0.00		0.00
		(.)		(.)
1[Cpmplete vocational HS]		0.08***		0.07***
		(0.01)		(0.01)
1[Complete academic HS]		0.08***		0.08***
		(0.01)		(0.02)
1[Vocational or technical tertiary degree]		0.11***		0.11***
		(0.01)		(0.01)
1[University degree]		0.21***		0.22***
		(0.01)		(0.01)
1[Postgraduate studies]		0.32***		0.35***
		(0.01)		(0.01)
Previous score			0.66***	0.65***
			(0.00)	(0.00)
Observations	351434	293481	350569	292112
Covariates	No	Yes	No	Yes
Expected education	No	Yes	No	Yes

Notes: The dependent variable is the student's standardised score in math in the first two columns and the standardised scores in reading in the other two. Covariates are the same included in Table 11. Estimates are significant at the *10%, **5%, and ***1% level.

Table A6: Off-subject estimations

	(1) Std. math	(2) Std. math	(3) Std. reading	(4) Std. reading
1[Closed school]	-0.12***	-0.01	-0.00	0.01
	(0.02)	(0.01)	(0.02)	(0.02)
Std. previous reading	0.52***	0.11***		0.52***
	(0.00)	(0.00)		(0.00)
Std. previous math		0.66***	0.57***	0.23***
		(0.00)	(0.00)	(0.00)
Observations	351624	344898	350350	343884
Covariates	Yes	Yes	Yes	Yes

Notes: The dependent variable is the standardised math score in columns one and two, and the standardised reading score in columns three and four. Estimates are significant at the *10%, **5%, and ***1% level.

Table A7: Correlation between subjects

	Std. Math Score	Std. Reading Score	Std. Previous Math Score	Std. Previous Reading Score
Std. Math Score	1.00			
Std. Reading Score	0.63***	1.00		
Std. Previous Math Score	0.77***	0.59***	1.00	
Std. Previous Reading Score	0.58***	0.69***	0.66***	1.00

Notes: Estimates are significant at the *10%, **5%, and ***1% level.

Table A8: Results by gender

	(1) Male std. math	(2) Female std. math	(3) Male std. reading	(4) Female std. reading
1[Closed school]	-0.03	0.01	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Previous math score	0.72***	0.74***		
	(0.00)	(0.00)		
Previous reading score			0.66***	0.67***
			(0.00)	(0.00)
Observations	174737	176697	174603	175966
Covariates	Yes	Yes	Yes	Yes

Notes: Notes: The dependent variable is the standardised math score in columns one and two, and the standardised reading score in columns three and four. Columns one and three correspond to male students, and columns two and four to female students. Covariates are the same included in Table 11 except for student's gender. Estimates are significant at the *10%, **5%, and ***1% level.

Table A9: Results by area

	(1) Rural std. math	(2) Urban std. math	(3) Rural std. reading	(4) Urban std. reading
1[Closed school]	0.05	-0.01	0.05	-0.03**
	(0.05)	(0.01)	(0.05)	(0.02)
Previous math score	0.70***	0.73***		
	(0.00)	(0.00)		
Previous reading score			0.65***	0.66***
			(0.00)	(0.00)
Observations	31738	319696	32014	318555
Covariates	Yes	Yes	Yes	Yes

Notes: Notes: The dependent variable is the standardised math score in columns one and three, and the standardised reading score in columns two and four. Columns one and two correspond to rural closing schools, and columns three and four to urban closing schools. Covariates are the same included in Table 11 except for school's areas. There are 379 observations without area, and thus are excluded from the estimations. Estimates are significant at the *10%, **5%, and ***1% level.

Table A10: Baseline model with school fixed effects

	Std. Math score			Std. reading score		
1[Closed school]	-0.00	-0.01	0.02	-0.03**	-0.03*	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Previous score	0.78***	0.73***	0.67***			
	(0.00)	(0.00)	(0.00)			
Previous score				0.70***	0.66***	0.62***
				(0.00)	(0.00)	(0.00)
Observations	351434	351434	351434	350569	350569	350569
Covariates	No	Yes	Yes	No	Yes	Yes
School fixed effects	No	No	Yes	No	No	Yes

Notes: The dependent variable is the student's standardised score in math in the first three columns and the standardised score in reading columns three to six. Estimates are significant at the *10%, **5%, and ***1% level.