Centralized Admission Systems and School Segregation: Evidence from a National Reform*

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Abstract

This paper investigates whether the adoption of a centralized school admission system can alter within-school socio-economic diversity. We assess the importance of two factors: residential segregation and outside options. In theory, both have the potential to increase school segregation under centralized systems. We provide evidence confirming this premise. We take advantage of the largest school-admission reform implemented to date: Chile's SAS, which in 2016 replaced the country's decentralized system with a Deferred Acceptance algorithm. We exploit its sequential introduction across regions to quantify its heterogeneous impact on segregation. The empirical analysis is carried out using administrative data and a Difference-in-Difference strategy. SAS increased within-school segregation in areas with high levels of pre-existing residential segregation. School districts with higher provision of private education experienced an uptick in school segregation as well. The migration of high-SES students to private schools emerges as a driver.

Keywords: Education, Segregation, Mechanism Design.

JEL classification: I20, I24, I28.

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1 Introduction

All over the world, governments are increasingly adopting centralized school admission systems to coordinate students' assignment to schools. Currently, different versions of these mechanisms have been implemented in Belgium, England, France, Finland, Ghana, Holland, Hungary, South Korea, Spain, and the United States (Abdulkadiroğlu et al., 2005b, 2011, 2017; Calsamiglia and Güell, 2018). Also, pilot programs have been initiated recently in Brazil, Ecuador, and Peru. The arguments in favor of centralized over decentralized systems work mainly through two avenues. First, they eliminate supply-side selection, allowing equal access to higher quality schools for all (Abdulkadiroğlu and Sönmez, 2003; Pathak et al., 2011). Second, centralized systems should reduce the cost and effort of collecting information and applying to every school separately (Whitehurst and Whitfield, 2013).

In practice, centralized admission mechanisms are also used as policy tools aimed at promoting diversity within educational systems.[1] There are often priorities for low SES students at the randomization stage under these algorithms. For instance, New York and Boston have made substantial reforms in recent years to give minority groups higher chances to attend better schools to ensure greater equity in the public system. However, a more efficient and welfare-enhancing theoretical allocation might not lead to less segregated schools. As Calsamiglia et al. (2020) suggests, residential segregation has the potential to propel the opposite result. By examining a mechanism design problem embedded in a city model of centralized public school choice, these authors show that a trade off between travel cost and school quality in parent's preferences can, in theory, increase segregation levels under centralized admission systems.

Heterogeneity in outside options can also lead to a similar phenomenon as access to private schools gives an edge to families who can afford them (Baum-Snow and Lutz, 2011; Reber, 2005). This since students from wealthier families can be strategic in their rankings by only applying to the best public schools, opting out to private providers if they are not assigned to those schools (Calsamiglia et al., 2020). Akbarpour et al. (2018) discuss how this can increase segregation under manipulable assignment mechanisms (e.g. the Boston mechanism). These two conceptual channels, namely residential segregation and outside options, motivates our analysis.

This paper studies Chile's large-scale adoption of a centralized allocation algorithm and assesses the potential channels through which it can affect school segregation. The Chilean government

[1] School desegregation policies in the United States have resulted in better educational outcomes for minority groups as reflected by higher academic achievement, lower drop out rates, and higher graduation percentages (Guryan, 2004; Hanushek et al., 2009; Johnson, 2011). Additionally, effective desegregation has improved health and labor market outcomes (Ashenfelter et al., 2006). Other researchers have shown comparable results on segregation for OECD countries (Vandenberge, 2006; Baysu and de Valk, 2012). This body of evidence is relevant even for developing countries as one of the impending challenges for them has been the increasing levels of stratification in school (Epple et al., 2017).

introduced a Deferred Acceptance (DA) mechanism in 2016 as the central component of a major education reform aimed at promoting social inclusion and reducing school segregation. The new school admission protocol (SAS) was undertaken between 2017 and 2019, and it came to replace the country's widely studied decentralized system (Epple et al., 2017; Hsieh and Urquiola, 2006; Mizala and Romaguera, 2000). We exploit the sequential introduction of the reform across regions to quantify its impact on segregation using a Difference-in-Difference strategy. We analyze data from the universe of Chilean students during the period 2015-2019. The main analysis focuses on ninth-graders (approximately 250,000 individuals each year) as for this group we observe socio-economic background information and standardized test scores. Importantly, related research has shown that segregation at this level (high school) is more pronounced than in primary education (Torche, 2005).

Following the literature, the empirical analysis uses the unevenness of schools' socioeconomic distribution relative to the community (school district) as the outcome of interest (Allen et al., 2015; Napierala and Denton, 2017). In particular, we construct a dissimilarity indicator based on the share of students within a district that would have to be reassigned across schools to achieve an even distribution of students of different socioeconomic status (Duncan and Duncan, 1955). The socioeconomic status is defined using detailed information on family background characteristics. We take advantage of Chile's comprehensive road network and its rich geospatial data to construct a measure of residential segregation. For this, we calculate the travel times of student's place of residence to essential amenities (e.g., schools, hospitals and policy stations) in their neighborhoods (Massey et al., 1987).

We do not find a statistically significant impact of SAS on average school segregation. However, this finding masks considerable and systematic heterogeneity across local school districts (municipalities), which we empirically link to existing local outside options and residential segregation. In brief, we find that the DA mechanism increased (decreased) within-school segregation of students from low socio-economic (SES) backgrounds in areas with high (low) levels of existing residential segregation. When it comes to role of outside options, we find that school districts with higher pre-reform market shares of private schools report an increase in segregation relative to districts with a smaller percentage of private schools. Moreover, our evidence suggests this result is mainly driven by the migration of high SES families from public and voucher to private schools after the policy is in place.

In perspective, our analysis unravels a complex association between centralized admission systems and changes in school segregation, particularly in areas characterized by sharp variation in neighborhood quality and schooling structure. Thus, this paper provides new and robust empirical evidence on the interplay between the allocations due to parental strategic behavior and DA. Consistent with recent theoretical developments, we show that under Chile's SAS parental preferences and market forces can induce strategic behavior among families, which can increase segregation in the public school system under a DA mechanism (relative to the decentralized alternative). These settings and landscapes can be found in developed and developing countries.Overall, our findings alert about the potential unintended consequences of centralized systems and suggest venues to secure the efficacy of public school choice (Hastings et al., 2009).

The paper is organized as follows. Section 2 describes the key features of Chile's new centralized school admission system. Section 3 describes our data, while Section 4 presents our identification strategy. In Sections 5 we present our main findings and robustness checks. Section 6 concludes.

2 Background

In the early 1980s, Chile's military regime undertook a structural reform of the educational system. It involved a decentralization of the public school system by transferring the administration of local school districts from the central government to municipalities. A nationwide flat per-student voucher was established, paid directly to schools, and parents were allowed to freely choose their children's school. The school market was opened to new entrants and, as a result, three types of schools were established: (a) public schools, managed by local municipalities and financed by vouchers; (b) private-voucher schools, privately managed but financed by vouchers and; (c) private non-voucher schools, in which the private sector provides both funding and administration. We refer to private voucher and private non-voucher schools as voucher and private schools for the rest of the paper.

The reform has led to a massive entry of voucher and private schools into the market and, as a result, enrollment in public schools declined substantially. In 1993, voucher schools were allowed to charge out-of-pocket tuition to families, with a corresponding (and progressive) reduction of the state voucher according to the amount of tuition charged. Public schools could also charge add-on fees, but only at the secondary level and if all parents agreed.[2] Consequently, the Chilean education setting emerged into a system with multiple private providers, with for-profit and not for profit schools, with and without receiving public vouchers, and with and without parental co-payment. By 2015, out of the 3.5 million total students in the system, 36% attended public schools, 55% voucher schools, and 9% attended private schools.

One of the criticisms of the voucher system is that it led to higher socioeconomic stratification, with attendance to different school types depending greatly on family socioeconomic characteristics (Valenzuela et al., 2014; Hsieh and Urquiola, 2006). The student admission process was highly unregulated until 2008, and most voucher and private schools selected students based on parents'

[2]By 2014, the average fee was US $30.23 in voucher schools and US $4 in public schools (in nominal terms).

interviews, entry exams, and required proof of income. (Contreras et al., 2010; OECD, 2010). In addition, not only parents could have been discouraged from applying to top schools because of the out-of-pocket tuition and the selection processes, but there is also evidence that parents from low-income parents reacted less strongly to school quality when choosing a school (Carnoy and McEwan, 2003; Gallego and Hernando, 2010). This resulted in an overwhelming majority of low SES students in public schools, which is the principal reason for increased stratification.

Given the significance of school segregation for short- as well as long- term student outcomes, in 2008, the Chilean Congress passed the Law 20,248 of *Subvención Escolar Preferencial* (SEP), which established a targeted voucher that provided schools with an additional voucher for every priority student that they enroll. This policy aimed to address the existing segregation by socioeconomic status in the Chilean educational system and to improve educational outcomes for disadvantaged students (Sánchez, 2018; Kutscher, 2020).

In a new attempt to promote inclusion, in May of 2015 the Congress passed the Inclusion Act (*Ley de Inclusión Escolar*, N. 20.845). The new legislation set the expectations high as its text demonstrates "... [this Act] will allow us to make decisive progress in ending the high school segregation that characterizes our current system".

The Inclusion Act included three broad provisions. First, the country's decentralized admission model would be replaced by a centralized school admission system. This is the policy change examined in this paper. Second, by annually increasing the value of the vouchers from 2016 and on, the reform sought to eliminate the student co-payment system allowed in public and voucher schools since 1993. Third, starting in 2018, only not-for-profit schools could receive vouchers. The last two components of the reform were implemented nationally and without regional considerations. On the contrary, the centralized system was implemented sequentially across regions in a process that would take several years. This distinctive features enables our identification strategy.

2.1 The Centralized School Admission System (SAS)

As stated above, one of the foundations of the Inclusion Act was the regulation of the school admission system for public as well as voucher schools receiving state support. Nevertheless, admissions to private schools continued to be decentralized. This implies that a student must participate in SAS if he/she seeks admission into public and/or voucher schools.

Deferred Acceptance algorithm with multiple tie breaking was used for student assignments under this new mandate. This algorithm was first proposed by Gale and Shapley (1962) and modified later by Abdulkadiroğlu and Sönmez (2003).[3] It eliminated supply-side choice for state

[3] For evidence from Boston, New York, Denver see Abdulkadiroğlu et al. (2005b,a, 2009, 2011, 2017). For

sponsored schools. Therefore, since 2016, families are required to apply to public and voucher schools through a centralized web application platform.

The centralized web platform provides information about the schools' educational project, its facilities, extra-curricular activities, and other features. The algorithm allows for special priorities such as i) applicants that have a sibling enrolled in the school; ii) applicants classified as priority students, up to the minimum of 15% per level; iii) the children of school officials; and iv) former students of the school who had left for various reasons except for expulsion. Families indicate these priorities in their web applications. In this way, the new system intends to allocate every student to the highest plausible preference conditional on the priorities and vacancies at schools. If there are fewer applications than vacancies at a school, there is no requirement for the multiple tie-breaking rules. On the contrary, if the number of applications exceeds the number of vacancies, the tie-breaking rule kicks in.

In practice, the algorithm involves two stages. All the applicants are allowed to participate in the regular stage, which starts in August of each year. Once it ends (October), students are informed about the schools they will be attending during the next school year (next March). At that point, each student has the right to turn down the assigned school, in which case he/she can submit a new list of preferences during the complementary stage (November). Individuals who did not participate in the regular stage can submit preferences as well. The algorithm is launched again but only for the set of vacant seats. The complementary stage concludes in December. Students are assigned to the closest participating school if the process fails to assign a student to any of the preferred choices. Since private schools do not participate in DA, parents could switch to those providers if they are not satisfied with the DA assignment either in the regular or complementary stage.

The implementation of SAS has been gradual, which is critical for our identification strategy. The reform began in 2016 in Magallanes region, in 2017 it continued in the regions of Tarapacá, Coquimbo, O'Higgins, and Los Lagos, in 2018 included Arica and Parinacota, Antofagasta, Atacama, Valparaíso, Maule, Biobío, Araucanía, Los Ríos, and Aysén. Finally, in 2019 it was introduced in the Metropolitana Region (Santiago).[4]

3 Data and key variables

Our primary source of information comes from the student-level administrative files reported under Chile's SAS system. These documents contain detailed application data for all students who submitted their preferences to enroll in primary (pre-k to 8th grade) and secondary (9th to

Charlotte see Hastings et al. (2009), Barcelona see Calsamiglia and Güell (2018), and Beijing see He et al. (2012).

[4] Table A1 in the Web Appendix shows the number of schools that participated in each region.

12th grade) schools.

Figure 1 illustrates the differences in program participation by grade. The number of participants in the new policy has been largest for the first year of primary school (pre-K) and the first year of secondary school (ninth grade) relative to the other grades. The participation is high for pre-K since it is mandatory for parents seeking admission into public and voucher schools to apply through SAS. For ninth-graders, a notable percentage of students use SAS because some of them are forced to switch schools as their primary schools do not offer secondary education and others participate as they wanted to get themselves enrolled in a different institution. Table 1 provides details on the participation of students and schools for 2016, 2017, and 2018. On average, 46% of eighth-graders participated in SAS for ninth grade admissions in 2016 in the region where SAS was implemented. This increased to 51% in 2017 and 52% in 2018.

We focus our study on the ninth graders primarily because of data limitations. The dissimilarity index construction requires background information on a student's socioeconomic status, which we gather by matching students to their previous records from administrative sources. We use data from the Education Quality Measurement System (*Sistema de Medición de Calidad de la Educación* or SIMCE). It contains detailed individual-level information, including mother's education, father's education, and household income. Chile's SIMCE is generally administered twice during the students' educational history, either in second, fourth, sixth, eighth, or tenth grade. Therefore, despite its richness, no background information for students seeking admission in pre-k is available. In addition, there is evidence suggesting that the increase in school-segregation levels is more pronounced in secondary than in primary education (Torche, 2005). Hence, studying ninth-grade students is more appealing as they face higher levels of segregation. Thus, we focus on the entire universe of ninth graders in 2015, 2016, 2017, 2018, and 2019 in Chile and examine the school preferences and decisions of approximately 250,000 individuals per year.

We complement the student-level data with multiple sources of longitudinal information. We gather pre- and post-reform student-level enrollment information from the administrative records, containing student's residential and school locations, and school characteristics. Critical for this paper, these files can be linked to official information collected under the new admission system.[5]

Since our main empirical analysis is carried out at the school district level, from these data sets we construct a panel of 327 municipalities (out of a total of 345) over five years for an overall sample size of 1646 observations. For only 18 municipalities (all small and rural) student-level information from SIMCE files was not available.

[5]To obtain the background information on students, we match every ninth-grade cohort to the previous SIMCE available, either sixth or eighth depending on the cohort. This process was carried out in collaboration with the Ministry of Education of Chile and produced a sucesful match for approximately 80% of the students. See Table A2.

3.1 School segregation measures

Any measure of school segregation is constructed relative to a specific geographical area. In this paper, we use the school district, defined by the municipality, as the unit of analysis.[6] Multiple reasons explain this decision. First, as Table 2 suggests, a local district can be conceptualized as a proxy for a school market as 78% of students in Chile choose a school within this area (the corresponding figure for ninth graders is 66%). Importantly, we do not observe any notable difference in this fraction pre and post the inception of SAS, which suggests most of the parents were choosing among schools within their municipality both before and after the reform. Second, by examining school segregation across municipalities, we can capture significant within-region heterogeneity, hidden under broader definitions of local schooling markets. Third, this is the most commonly used definition of school markets in related work in Chile and other countries (Hsieh and Urquiola, 2006). This helps us to compare the implications of the current policy change with segregation related research on earlier policies of the government and other geographies.

After setting our unit of analysis, we proceed to combine the information from the sources listed above. This process results in a panel of 346 municipalities covering the period 2015-19. For each municipality and year, we construct the Duncan index for school segregation, which measures the percentage of students belonging to low socioeconomic status who have to be reallocated across schools for equal representation of students from all socioeconomic backgrounds within the district. Formally, we follow Duncan and Duncan (1955) and compute:

$$y_{ct} = \frac{1}{2}\sum_{j=1}^{n_{ct}} \left| \frac{P_j}{P} - \frac{NP_j}{NP} \right|,$$

where c and t correspond to municipality and year, respectively, whereas P_j (NP_j) is the number of students reporting low (non-low) socioeconomic status in school $j \in \{1, 2, ..., n_{ct}\}$ with n_{ct} denoting the number of schools in municipality c in year t. N and NP represent the total number of poor and non-poor students for the municipality.

We use the Duncan index for our main analysis as it is the most commonly used segregation index. However, we acknowledge that it suffers from various limitations. First, it does not always satisfy the transfers principle. Second, we can compare the disparity of only two groups in this index. Third, Duncan index does not account for the segregation resulting from randomness (Winship, 1978; Carrington and Troske, 1997; Hellerstein and Neumark, 2008; Söderström and Uusitalo, 2010; Allen et al., 2015). Fourth, it cannot be decomposed. Thus, to confirm the

[6]Although the funding for public education comes from the central government, local authorities (majors) are responsible for the management of public schools. Contrary to the school districts in the United States, students in Chile can attend public schools outside their local school districts. The robustness of our findings to this complexity is discussed in Section 5.3.

robustness of our findings, we complement our primary analysis using an alternative measure of segregation in Section 5.3.

As for the definition of socioeconomic status, we classify students who have mothers without a high school degree as low SES. This dimension has been identified as a crucial socioeconomic marker (McLanahan, 2004). Figure 2 displays the resulting Duncan index for Chile's fifteen regions for 2017 and 2019, documenting significant variation.[7] To put this in context, Jenkins et al. (2008) argue that school segregation in OECD countries during the last decade varied between [0.2,0.5] with countries such as Belgium, Germany, and Hungary being at the upper end of the spectrum, while Nordic countries reported lower levels than others in this group. Similarly, Reardon and Yun (2001) demonstrate that dissimilarity index estimates on racial lines varied between [0.38,0.46] for 323 Metropolitan Statistical Areas in the United States. For Chile, Valenzuela et al. (2014) report segregation levels varying between 0.4 and 0.6 for the period 1999 and 2008. According to our estimations, in 2019, the Duncan index ranges between 0.3 and 0.5 for the fifteen regions in Chile.

In addition, we intend to capture heterogeneous effects of SAS. We focus on two dimensions highlighted in the literature. Specifically, we exploit heterogeneous effects based on a residential segregation and the outside option value.

3.2 Residential segregation

As in other developing countries, geographical segregation is a widespread phenomenon in Chile (Garreton et al., 2020). This inherent constraint might limit the integration of students from different socioeconomic background within an educational community even under centralized admission systems. Intuitively, if low income families are more likely to list poor quality nearby schools in SAS, residential segregation could translate into higher levels of segregation in schools. In this paper we explore this hypothesis.

Several regions in the country, particularly the most populated ones, present concentration of individuals from different socio-economic strata in specific pockets. Figure 3 illustrates this fact for Chile's third largest region, Biobio, as it depicts its spatial segregation by income levels. Panels (A) and (B) show that spatial density contours are not overlapping: while high income families (A) are spatially more concentrated in the south west and the east, low income families (B) have higher densities in the north and central parts of the region.

To capture residential segregation within our framework, we build an index of commuting time to amenities such as hospitals and police stations. This strategy is consistent with the evidence from urban economics suggesting that neighborhood quality is a function of access to

[7] Chile created the sixteenth region Nuble, formerly part of Biobio in 2018. We merge Nuble with Biobio for our analysis. The Metropolitana Region (Santiago) initiated the policy in 2019, and the new student enrollment through the policy will be reflected in 2020 enrollment files

health care, police stations, and good quality schools (Cheshire and Sheppard, 2004; McKenzie, 2013). As a result, residents of advantaged and disadvantaged areas are exposed to very different bundles of amenities, unfolding inequalities that may be more deleterious than those of income inequality (Diamond, 2016). Figure 4 exemplifies the point that access to hospitals varies across municipalities in Chile.

We take advantage of the geospatial student-level data and the comprehensive road network of Chile for the construction of the index. We define an amenity as accessible if the driving time is within an hour for a student and compute the travel time for every student amenity pair within municipalities.[8] Given that the empirical analysis is done at the local level, we construct:

$$\text{Residential Segregation}_c = \sqrt{\frac{\sum_{i=1}^{N_c}(A_{ic} - \bar{A}_c)^2}{N_c - 1}},$$

where A_{ic} denotes the number of amenities within an hour of travel time for student i in municipality c, $\bar{A}_c$ is the average of this measure for the municipality, and N_c denotes the number of ninth graders in municipality c. The index then captures the variation (standard deviation) in access to amenities within a municipality. We generate it for the universe of ninth graders in 2018.[9]

The existing residential segregation can translate into higher segregation in schools if parents have a preference for nearby schools. Figure 5 presents evidence suggesting the prevalence of such preferences in Chile. It displays the distribution of travel times for ninth-grade participants in 2018 and confirms the affinity of parents towards shorter travel times. Figure 6 explores this further as, after taking into account the road network of Chile and real time traffic, it shows that the density of enrolled students (red) is much higher closer to the school relative to those who live far away from this school. The density of non-enrolled students consistently increases as students move further away from this school. In addition, there is direct evidence in Chile that parents are sensitive to travel costs and that the burden of these costs decrease with student income. In this same setting, Nath (2020) shows that high income families are more likely to list high score schools than low income families, and are less sensitive to travel distance to good quality schools.

Under these conditions, differential socio-economic ranking behavior could translate into under-representation of low income families in good schools. As Calsamiglia et al. (2020) argues, the trade off between travel cost and school quality in parent's optimization problem can, in theory,

[8] To avoid the endogeneity of travel time to schools with respect to the policy change, we exclude schools from the list of amenities.

[9] In collaboration with the Ministry of Education of Chile, we use geocoded information for the universe of ninth-grade cohort in Chile in 2018 (246,937 individuals) to generate precise measures of student's travel duration to basic amenities. The Open Source Routing Machine API was used for this purpose. As Web Appendix B discusses, the travel time measure (or travel distance) provides a different and more accurate picture relative to the geodetic measures of distance employed in related research. Figures B1 and B2 illustrate why it is pertinent to examine distance to schools using the actual travel time.

increase segregation levels across schools even under deferred acceptance algorithm. Low SES students often value school academic quality less than high SES students, and usually, travel costs to school are more binding for the former than the latter group. In other words, disadvantaged students have their effective choice sets restricted, as they cannot easily afford travel costs (Laverde, 2020) Thus, parental preferences for shorter travel time to schools can affect reallocation under the new policy. This can be reinforced by the evidence from developing countries suggesting that high income families are better at understanding the centralized systems and make more informed choices (Luflade, 2017; Ajayi et al., 2020).

3.3 Outside options

The second dimension of heterogeneity motivating this paper is the variation in outside options. Since private schools do not participate in DA, parents can switch to private schools if they do not like the DA assignment. However, private schools are expensive and there might be income barriers to entry (entry exams, interviews to parents, etc.). Table 3 shows that only 8.8% of ninth grade students are enrolled in private institutions.

The local provision of education throughout Chile is highly heterogeneous, across and within regions and municipalities. To illustrate this point, Figure 7 displays the spatial distribution of school types in two large regions. Panel (A) shows that while private schools are more common in municipalities belonging to the north-eastern sector of Santiago, it is almost non-existent in the southern districts. Therefore, even though the participation of private schools in Chile's capital is 13.7% (close to the national average), its distribution among districts is far from being homogeneous. For Coquimbo, Panel (B) offers quite a different picture as the distributions of school types are appreciably more homogeneous. Figure 8 examines this further as it presents spatial density plots of the different types of schools for Concepcion, Chile's second-largest region. It documents very distinctive patterns: higher concentrations of public (panel B), voucher (C), and private (D) in certain areas. Thus, these differences shed light on an obvious point and well-known fact: schools are strategically located in the territory (Epple et al., 2017). Our empirical analysis exploits this.

However, private school supply itself does not translate into higher segregation if the assignment mechanism is strategy proof. Nonetheless, it can increase segregation if parents are behaving strategically (Calsamiglia et al., 2020). One of the cases in which DA fails strategy proofness is when there are positive application costs to schools (Fack et al., 2019; Kuersteiner et al., 2020). Those costs can be direct (e.g., application fees) or indirect (e.g., gathering information on school attributes or adding schools to the list). The existence of such costs lead to partial rank order lists.

In the Chilean DA system, we observe parents revealing a partial rank order list over the schools available to them. Table 4 depicts reduced form evidence on the factors determining the length of the Rank Order List (ROL). It confirms that the supply of private schools has a negative impact on the length of ROL relative to the total number of schools participating in DA. On the other hand, Table 5 depicts the results obtained from a regression of the fraction of DA participants on the fraction of private and voucher schools. We can conclude that school districts with a higher fraction of private schools received fewer applications in DA. This shows that private schools are a feasible substitute for voucher and public schools at least for some families and the presence of such schools not just impacts strategic behavior in DA for participants but also the participation in DA.

To quantify the extend to which individuals within a school districts could potentially opt out of the centralized system and attend an outside option, we first construct the Herfindahl index (HHI) of local school market concentration. Since this is a measure of the size of schools in relation to the local supply, we would expect it to capture the amount of competition within the district, including private providers, and potentially shape how SAS affects within-school diversity.

And to take further advantage of the complexities of the Chilean schooling system, we analyze the distribution of school types (public, voucher and private) in each district. Importantly, since the contemporaneous proportions could be correlated with the new policy, we use those from 2015 (i.e., pre-SAS). In this way, we assess whether the impact of SAS may differ across municipalities as a function of the pre-reform distribution of school types. In theory, municipalities with a higher relative representation of private schools should experience an increase in school segregation after SAS.

4 Empirical Strategy

Table 6 presents the summary statistics. The mean for the municipality Duncan index is 0.25, with a standard deviation of 0.19, which is larger than the variation observed across regions. Additionally, we observe significant variation in residential segregation and the local schooling systems across school districts.

We take advantage of the longitudinal dimension of our data as well as the gradual implementation of SAS to estimate its impact on school segregation. In particular, we follow a standard Difference-in-Difference strategy where the outcome variable is the Duncan index in municipality c, located in the region r, constructed at time t, y_{crt}. Thus, we estimate the following DD regression:

$$y_{crt} = \delta_0 \times D_{rt} + Z_{1cr}\beta + \gamma_r + \lambda_t + \epsilon_{crt}, \tag{1}$$

where D_{rt} is the treatment variable, which takes a value of one if the program is implemented in the region r in year t, and zero otherwise. Since the Chilean government stepped up the new program gradually across regions, we add region fixed effects (γ_r) to account for time-invariant heterogeneity at that level. Moreover, to account for any aggregate variation in segregation over time, we control for year fixed effects (λ_t). The covariates Z_{1cr} comprise of the pre-SAS measures of local schooling structure such as the fraction of public, voucher and private schools, and the fraction of rural schools in the municipality. ϵ_{crt} is the error term. Throughout our analysis, we cluster the standard errors at the school district, as this accounts for serial correlation (Bertrand et al., 2004).The policy parameter of interest is δ_0.

The identification of δ_0 depends on the following assumptions (Athey and Imbens, 2018; Goodman-Bacon, 2018). First, the adoption date of the policy for every region in Chile should be random to existing levels of school segregation before the policy.[10] Second, there should not be any responses in anticipation of the treatment. This suggests that if region r has not adopted the policy, then the exact date at which it intends to adopt the policy should not affect the current outcomes. Third, school choices for students entering high school in a region in year t depends on SAS in year t and not on SAS's availability in previous years. Finally, we rely on the common trends assumption. We assess each of these assumptions in Section 5.

Under these assumptions, equation (1) secures the identification of the average effect of SAS for all school districts. To explore the heterogeneity in the effect of DA on segregation, below we extend expression (1) allowing for heterogeneous responses by residential segregation and the outside option value.

Residential segregation. School segregation could emerge as a result of residential segregation (Massey and Denton, 1985; Bonal et al., 2019). As a first step towards breaking down the source of school segregation, we document the association between school and our measure of residential segregation for Chile. We use access to hospitals and police stations as our primary measure of residential segregation (see Section 3.1 for details on the construction of this measure). The spatial location of essential amenities such as hospitals or police stations does not depend on the new policy[11] We examine the impact of SAS for regions with varying levels of residential segregation for ninth graders using the expression:

$$y_{crt} \quad = \delta_0 \times D_{rt} + \delta_1 \times D_{rt} \times \text{Residential Segregation}_c$$

[10]Table A3 in Web Appendix illustrates that the start date of the program was not correlated with the existing levels of school segregation in 2015.

[11]See Table A4 in Web Appendix for evidence suggesting no association between the new policy and the measure of residential segregation used in this paper. We also show below that there is no significant internal migration of students in response to the policy for targeting the schools of their choice.

$$+\delta_2 \times \text{Residential Segregation}_c + Z_{2cr}\beta + \gamma_r + \lambda_t + \epsilon_{crt}, \tag{2}$$

where residential segregation corresponds to the municipality level variation in access to amenities. From this expression, we explore the interplay of SAS and residential segregation using the interaction between the two variables. The coefficient of interest is δ_1. A positive δ_1 would imply that municipalities with higher residential segregation experienced an increase in school segregation due to the policy's implementation. The additional covariate Z_{2cr} is the measure of pre-SAS local schooling structure in municipality c in region r.

Although δ_1 informs about the heterogeneity in SAS impact by residential segregation, we are also interested in learning about the main effect of residential segregation on school segregation, which is captured by δ_2 (Graham, 2018). This since, as Figure 4 shows for Chile's two largest cities (Santiago and Concepción), there might exist extensive variation in the spatial location of amenities within metropolitan areas affecting the levels of school segregation. Furthermore, since Metropolitana did not have the new policy in place until 2019, from equation (2) we recover the effect of residential segregation in the absence of the new policy. Region and year fixed effects account for variation across municipalities within a region, warranting the identification of δ_2.

The outside option The new centralized student assignment system expanded school choices for Chilean families. However, under a schooling system characterized by heterogeneous quality and with private schools operating outside SAS, this might lead to complex changes in incentives and strategic behaviors (Gilraine et al., 2019; Hsieh and Urquiola, 2006). Therefore, we explore pre-reform variation in local school supply across districts as a source of identification of systematic differences in parental responses to SAS.

We approach the heterogeneity by local schooling structure in two ways. First, we take advantage of the heterogenous distribution of school types across Chile's school districts. In particular, we construct the local fraction of school types in 2015 and estimate:

$$\begin{aligned} y_{crt} &= \delta_0 \times D_{rt} + \delta_{1p} \times D_{rt} \times \text{Public}_c + \delta_{1v} \times D_{rt} \times \text{Voucher}_c \\ &+\delta_{2p} \times \text{Public}_c + \delta_{2v} \times \text{Voucher}_c + X_{crt}\beta + \gamma_r + \lambda_t + \epsilon_{crt}, \end{aligned} \tag{3}$$

where "Public_c" and "Voucher_c" correspond to the pre-reform percentages of public and voucher schools in the district c, respectively; and the coefficients of interest are consequently δ_{1p} and δ_{1v}. The baseline category for this specification is the percentage of private schools pre-reform. Notice that $\delta_{1p} < 0$ and $\delta_{1v} < 0$ would hint the plausibility that SAS enabled easier school switches for higher SES compared to low SES students as it could be easier for the former to overcome the constraints of school fees and transport costs. This unbalanced relocation would result in a disproportionate flight of non-poor students from public and voucher schools to private schools. Hence, municipalities with a higher fraction of private schools could witness an increase in school segregation due to SAS.

Secondly, we examine how market concentration affects school segregation. To this end, we include HHI and its interaction with SAS (D_{rt}) as additional controls in equation (1). Any influence of market concentration on school segregation would indicate that the market structure can explain some of the policy variations.

Equations (1), (2) and (3) use the binary treatment status of each region under SAS. However, the new policy's impact could vary depending on the number of schools that participated in the new system. In other words, a binary indicator of policy veils these participation differences across municipalities. To account for such variation, we construct a treatment intensity variable using the information on the number of schools that participated in SAS every year within each region. Specifically, we define $I_{rt} \in [0, 1]$ as the fraction of schools that participated in SAS in region r in period t. Thus, while the treatment dummy D_{rt} for region r is 1 if SAS was in place in year t, I_{rt} would be a continuous variable between [0,1]. Notice that a school participates if it has non zero vacancies for at least one school grade in year t, and the school accepts student applications for these vacancies. We complement our analysis with this intensity variable along with binary SAS dummy.

5 Main Results

We begin by exploring the overall impact of the new policy on school segregation. Table 7 presents the results for equation (1). The coefficient δ_0, which captures the average impact of the new policy (SAS dummy, D_{rt}), is small in magnitude (around -0.001) and statistically insignificant. The finding remains if we use treatment intensity (Intensity of SAS, I_{rt}) instead of the treatment dummy as the independent variable. The result is also robust to controlling for a rich set of other pre-SAS covariates.

Apart from SAS dummy (D_{rt}), it is interesting to examine the effect of other covariates on segregation reported under columns (3) and (4) of Table 7. We have decomposed the school market structure within a municipality into the pre-SAS fraction of public, voucher, and private schools and segregation can vary by school type (Figure 9). A higher fraction of public schools relative to private schools in a municipality drives down segregation. Additionally, voucher schools also affect segregation in the same negative direction, but the magnitude of the coefficient on the fraction of public schools is considerably higher than voucher schools. The primary reason behind this difference in coefficients is that although all public schools are free, some voucher schools might charge a small school fee. This small add on fee might act as a cost barrier for low SES students in voucher schools.[12]

The Difference-in-Difference parameter δ_0 identifies the average treatment effect across regions (Abadie, 2005). Consequently, it is plausible that the increased segregation in some regions is offsetting the decrease in other regions. Therefore, we examine the heterogeneous effects next.

5.1 Heterogeneous effects

The previous results document small estimates for δ_0 in equation (1). In this Section, we disentangle systematic differences in the impact of the policy by residential segregation due to travel costs and social segregation, which is related to the concentration of individuals from different socioeconomic strata in specific pockets within a district.

First, we report the estimated coefficients for equation (2). The coefficient of interest corresponds to the interaction of treatment dummy and variation in access to amenities (δ_1). Table 8 presents these results. The estimated value for δ_1 is positive (0.008) and statistically significant, suggesting that municipalities with higher variance in the access to these public goods experienced an increase in school segregation due to the policy. This finding of a positive association between residential segregation and school segregation has been observed in other geographies as well. Rivkin (1994) finds that schools remained segregated due to the persistent residential segregation in the United States and Boterman (2019) reveals that most of the variation in school segregation in Netherlands is explained by existing residential segregation levels.

We also observe that school segregation levels at baseline (without the policy) are consistently higher in more segregated municipalities. This is consistent with the evidence for the United States, showing that the disadvantaged groups face higher constraints in accessing better quality neighborhoods. For instance, the clustering of minorities in specific neighborhoods often results in them having access to public schools overpopulated with minority students. In other words,

[12] As described in Section 2, the Inclusion Act included two additional provisions. Despite being implemented nationwide, they could threaten our identification strategy. However, official statistics suggest that restricting access to public subsidies to only not-for-profit voucher schools had a small impact on the industrial organization of the sector as less than 2% of the voucher schools in 2015 turned into private schools by 2018. On the other hand, the evidence presented in Web Appendix C suggests the absence of an interaction between the provision aimed at eliminating the co-payment and the sequential application of SAS. First, Figure C1 confirms that there was a decline in the number of voucher schools with co-payment immediately after the Inclusion Act went into effect in 2016. But the decline emerged early on across all regions and it stabilized post-2016. Consequently, the reduction in the number of schools with co-payment does not correlate with the year at which SAS was introduced in each region. Figure C2 repeats the analysis but for the evolution of average fees (co-payment levels) within school districts. As expected, there was an overall decline in school fees among voucher schools during this period, but there is no clear association with SAS. Table C1 confirms this result. It presents the estimated parameters of equation (1) but using average fees as the outcome of interest. Finally, Table C2 shows that the findings displayed in Table 7 are robust to restricting the sample to school districts where the fraction of voucher schools with co-payment is 0, less than 10% or less than 60%. Thus, the overall impact of SAS does not seem to be connected to or mediated by policy changes affecting co-payment.

the higher concentration of minorities in certain neighborhoods results in higher levels of school segregation in those areas (Massey et al., 1987).[13] All in all, income-based residential clustering can translate into higher segregation in school if families prefer to send their children to nearby schools, which is exactly the case in our context, as we showed in section 3.2.

We now turn to the empirical analysis of outside options proxied by the presence of private school providers. If high-income families respond by switching to private schools, then the centralized admission system does not necessarily reduce school segregation (Calsamiglia et al., 2020). Such switches will be more prevalent in municipalities with a higher fraction of private schools. We first present results supporting this hypothesis.

Table 9 reports the results from equation (3). Column (1) explores potential underlying factors driving this result. We interact the fraction of students attending each type of school within a municipality in 2015 with the policy dummy which is our variable of interest. The reference category is the fraction attending private schools. We report negative and significant interaction coefficients γ_{1p} and γ_{1v}, indicating that municipalities that had a higher fraction of public/voucher schools than private schools experienced a decrease in segregation due to the policy. We replicate the analysis in column (2) but with the fraction of each school type rather than the fraction of students attending different school types within a municipality. In this case, we conclude that municipalities with a higher fraction of private schools in 2015 became more segregated due to the new admission system. The third column reports the results on market concentration (HHI index), suggesting that municipalities with higher existing levels of market concentration experienced an increase in Duncan index due to the policy.

Additionally, the findings in Table 9 show that the pre-existing schooling structure also impacts the levels of school segregation without the new policy (baseline). The main effects for a higher fraction of public and voucher schools are consistently positive and significant across all specifications. The factors driving these heterogeneous effects requires us to explore the response of high versus low SES families to the new policy.

Switches to private schools. We also investigate whether differential responses by household characteristics can explain why SAS pushed segregation upwards in regions with a high market concentration of private schools. School choice literature has shown that parents care about the SES make-up of the school when choosing schools.[14] Such parental affinity could have resulted

[13] For the main analysis, we use the data on access to hospitals. Results using policy stations as amenities are reported in Table A5 in the Web Appendix. The findings are robust to different types of amenities.

[14] For instance, Hastings et al. (2009) exhibit that parents value the school's racial composition when reporting their top three school choices. An analysis of parental preferences under centralized allocation in Paris also reveals parental inclination to send their children to schools that had a higher representation of students belonging to the same SES (Fack et al., 2019). Baum-Snow and Lutz (2011) highlight the importance of investigating heterogeneous responses across racial groups for exposing some of the unintended consequences of the desegregation laws in the

in high-income families switching their children from public/voucher schools to private schools if they do not like the final allocation.

To this end, we first construct the fraction of students switching from public/voucher to private schools between eighth and ninth grade for consecutive cohorts from 2015 to 2019. We anticipate that municipalities which had a higher fraction of private will make this transition easier. Additionally, we intend to understand what kind of families are more likely to make this transition. The outcome variable for this regression is the proportion of families that switched from public/voucher to private schools. We capture if these switches were more accessible for high-income parents in districts with a higher representation of private schools using a triple interaction between SAS dummy, the fraction of high SES families, and the presence of private schools in 2015. A positive coefficient on this triple interaction indicates that high SES students responded to the policy by moving to private schools from public/voucher schools.

Table 10 presents this result. The coefficient on the triple interaction on SAS dummy, private school dummy in 2015, and fraction of high SES mothers within a municipality is positive and statistically significant. This finding indicates that higher SES families responded to the new policy by switching to private schools. Consequently, we observe an increase in segregation in municipalities with a higher fraction of private schools in 2015.

This examination helps us unmask a critical underlying mechanism that is driving the mixed effects of the new policy on school segregation in Chile. High SES parents seem to have anticipated an increase in the representation of low SES students due to the policy. Consequently, they responded by switching to expensive private schools. Hence, we depict that these pre-existing variations on the supply and price of different types of schools matter across municipalities.

5.2 Threats to identification

In what follows, we perform a series of tests examining the common pre-trends assumption. Additionally, we examine the plausibility of any agent responses in anticipation of the policy. Such responses could make difficult to disentangle the changes in segregation due to SAS.

A critical characteristic of DA implementation in Chile was that it was scaled up gradually across regions. We have a panel of school districts from 2015 to 2019. By 2016 students in only one small region had participated in DA, and by 2017 implementation happened in four additional regions. Consequently, for the majority of regions (10 out of 15), we observe multiple years of pre-treatment data. We perform diverse robustness and placebo tests to alleviate any concerns on the violation of common trends assumption in this generalized Differences-in-Differences set-up

1960s and 1970s in the United States (out-migration of minority students cannot invalidate the hypothesis that whites used private schools to avoid desegregation in the south).

with variation in treatment timing.

The first identification assumption for the parameter of interest is that we expect to observe parallel trends in baseline outcomes denoted by $Y_{crt}^{baseline}$ across all groups. In other words, it implies that all groups should have followed a parallel trend in school segregation in the absence of treatment. The year and region-specific effects could explain these constant gaps in segregation across groups.

Since SAS's adoption was staggered over time, standard parallel trends visualization will not suffice as regions are switching their treatment status over time. We tackle this issue by providing formal tests to support the parallel trend assumption for our context with multiple regions and treatment time variation. First, we check for differences in pre-trends using the leads and lags test. Any evidence of significant coefficients for the lead treatment indicators is a threat to the parallel trend assumption.

Here we include the treatment indicator for m periods before the actual implementation of policy at $t = 0$ and q years after the implementation of policy for the lags and leads test. Figure 10 summarizes the result of this analysis. The coefficient for the lead term is not statistically different from zero. In other words, any policy change in the future does not affect the prevailing school segregation.

Next, we follow the region-specific trend test from Angrist and Pischke (2008) to provide further evidence to aid our assumption on pre-trends. We estimate equation (4) which includes region-specific trend variables:

$$y_{crt} = \gamma_r + \lambda_t + \sum_{j=-m}^{q} \delta_j \times D_{rt+j} + e_{crt}. \tag{4}$$

Table 11 presents these results. The comparison of its columns (1) and (2) in Panel (A) reveals that the inclusion of these additional variables does not alter the coefficient on the treatment dummy.

Third, we present an additional test for the pre-trends assumption using random assignment into treatment. We allocate the 15 regions into treatment using a random number generator for the implementation date of the treatment. In Table 12 shows that we do not find significant results for the overall effect as well as the heterogeneous effect.

Lastly, given the sequential implementation of the policy, we can visualize a modified version of the parallel trend assumption. We can split the regions into groups based on their year of treatment and then compare the early, late intervention and non-treated groups. The critical thing to note is that early and late treatment groups change their treatment status at different points between 2016 and 2019. This is the crucial point of divergence from a standard Differences-in-Difference set-up where all entities in the treatment group are treated at the same time. In our context, Metropolitana region is not treated till the end of 2018, and consequently, it serves as a control for all other treated regions in every period. Figure 11 depicts the parallel trend assumption using regions treated in 2018 and 2019 and the untreated group. This conclusion, combined with the other results, alleviates any concerns on the violation of equal pre-trends assumption.

In Section 4, we pointed out that identification of δ_0 requires the policy adoption date to be random, and rules out any strategic responses by the parents in anticipation of the policy. The algorithm takes into account residential proximity to school if it fails to allocate a student to any of the listed preferences. We want to provide evidence against any plausibility of parents relocating to different neighborhoods for a better school outcome before the policy implementation.

We take advantage of the student addresses for the complete universe of ninth graders for this analysis. We compare student addresses between 2017 and 2018 for nine regions. SAS was in place in these nine regions in 2018. Consequently, a high fraction of internal migration within these regions will be a threat to the identification strategy. We calculated the fraction of eighth-grade students who did not change their residence between 2017 and 2018. We compared these fractions with the average for the prior years to identify any threats to the identification strategy.

Figure 12 suggests that migration is very limited in these regions. Moreover, we do not observe any pattern of abruptly higher migration between 2017 and 2018. The fractions of families who do not change their residences in 2018 are comparable to the numbers computed for 2017. Most of these averages are well above 95% of the total population of students. Therefore, we conclude that parents are not responding to the policy announcement by changing their addresses.

A final concern is the potential correlation between the policy adoption date and the existing levels of school segregation in a region. Table A3 in Web Appendix addresses this issue. It displays the results from a linear regression of year of implementation on pre-SAS segregation. The evidence indicates no statistical association between the two variables.

5.3 Robustness Checks

Alternative definitions of socioeconomic status. We have used mother's education to define low and high SES students for the central part of our analysis. However, the SIMCE files also report father's education and a family income index. We replicate our main results using these alternative proxies for student SES.

Panel (A) of Table 13 mimics the analysis of Table 7 but using father's education to define the Duncan Index (as before a high school degree separates low and high SES groups). We reach the same conclusion. Overall, SAS does not affect segregation, and this result is not affected by the inclusion of covariates.

We repeat the analysis using the household income index. These results are displayed in panel (B) of Table 13. We categorize all students whose household income is less than 100,000 Chilean pesos as low SES and others with higher income as high SES. Again, we get no overall effect of SAS on segregation across all the specifications. These two exercises confirm the robustnesses of our findings.

Urban vs. rural areas. Urban and rural areas are likely to have different composition of school types. Public schools have a better reach in terms of geography and affordability than their private counterparts. Consequently, rural areas have a much higher fraction of public schools than urban areas.

To ensure that some of these rural-urban differences do not drive the principal conclusions, we replicate the central results solely for municipalities with urban schools. These results are reported in Table 14. We again get marginally positive estimates of the policy parameter δ_0, where the estimate is statistically insignificant across all specifications.

Provinces as school districts. From the analysis of Table 2, we conclude that around two-thirds of the students choose a high school in the same municipality as their residence. Since we compute the dissimilarity index at the municipality level, we implicitly assume that students are mostly choosing schools within the same municipality of residence. Alternatively, it implies that schools are catering to the students in the same municipality as their location. However, this assumption is not valid for one-third of the sample. Consequently, we proceed to confirm that our results are robust to the definition of the relevant market. To this end, we re-evaluate our main findings but this time using provinces, legally defined as a set of municipalities, as school districts. Panel (B) in Table 2 shows that 90% of ninth graders attend schools in the same province as their province of residence.

Table 15 displays the estimated impact of SAS on school segregation using this approach (there are a total of 54 provinces, so we get 270 observations for five years of data). This aggregate-level regression suggests qualitatively similar results to what we observed for the municipality level analysis. The policy parameter for the overall sample is marginally negative. However, the policy effect is not statistically significant.

Overall, we find that the differences in the definition of the schooling market, computation of Duncan index based on other socioeconomic indicators, and rural-urban differences do not make any substantial changes to the results. However, one concern that we did not address through the above checks is whether the results are robust to alternative socioeconomic disparity measures. We address this issue next.

Alternative segregation measure. Using the Duncan index as the primary outcome variable makes our analysis easy to interpret for policy recommendations and comparable to existing studies in the literature. However, as discussed above, Duncan index has some shortcomings. In this Section, we introduce and discuss an alternative measure of segregation (M index) as it overcomes some of the Duncan index's limitations and helps us ensure that our key results are robust to a different measure.

The Mutual Information index (M index) was first introduced by Theil (1971) and developed in Frankel and Volij (2011). M index is based on the concept of diversity. In our school segregation setting, it compares the representation of students from different socioeconomic backgrounds in schools with the overall levels of diversity in a region.

We first introduce the required notation. Let r denote a specific region (there are fifteen regions in Chile). For sake of simplicity, we assume the existence of S schools in every region. Of course, the empirical analysis relaxes this assumption allowing the number of schools (and municipalities) to differ across regions. Every student belongs to either a low or high SES group. Let N be the number of students residing in region r. For the sake of notation clarity, we omit the subindex r. Let N_1 and N_2 be the number of low SES students and high SES students, respectively ($N = N_1 + N_2$). Thus, the M index for school segregation is defined as:

$$M = \frac{N_1}{N} \ln\left(\frac{N}{N_1}\right) + \frac{N_2}{N} \ln\left(\frac{N}{N_2}\right) - \sum_{j=1}^{S} \frac{n_j}{N} \left[\frac{n_j^1}{n_j} \ln\left(\frac{n_j}{n_j^1}\right) + \frac{n_j^2}{n_j} \ln\left(\frac{n_j}{n_j^2}\right)\right],$$

where n_j is the fraction of students in school $j \in \{1, ..., S\}$. n_j^1, n_j^2 denote the number of low and high SES students in school j, respectively.

One interesting feature of this index is that it can be decomposed into between and within components, i.e., $M = I_b + I_w$. The first component I_b measures the extent of segregation across municipalities in a region, while the second component, I_w, measures the within municipality school segregation.

Note that the within component measures the extent of school segregation in a municipality, which is comparable to the Duncan index analyzed so far in the paper. We first replicate our key findings using the within component of the M index. Columns (1) and (2) in Table 16 provide results for equation (2) and (3), respectively. We confirm that the increase in school segregation happened in municipalities with more residential segregation and with a higher fraction of private schools in 2015. This ensures that our results are robust to this other measure of segregation.

In addition, we can use the M index to understand the source of variation helping us identify the policy implications. Panel (A) in Figure 13 shows the decomposition of the M index of school segregation into within and between municipality components for 2019. The graph suggests that the within component is the primary source of school segregation across regions. The M index varied between [0.07,0.14] across regions in 2019, and the extent of variation in the within component was [0.06,0.11]. On the other hand, the magnitude of between component variation was much lower ([0.00,0.04]).

Finally, Figure 13 also illustrates that there is substantial heterogeneity across regions in Chile. For example, in Magallanes, which was the first region that adopted the new policy in 2016, the M index showed a slight drop between 2016 and 2017, but it has sharply risen since then. The rise in within component pushed up the M index and the between component decreased between 2017 and 2019. Another compelling case is Los Rios (panel (C)), which adopted the program in 2018. In this region, the M index declined marginally between 2018 and 2019, and most of this decline came through the within component. Some of this drop was undone by the slight uptick in the between component. Such variation is also seen for other regions such as Valparaiso (Panel (D)).

6 Conclusion

In 2016 Chile adopted a Deferred Acceptance algorithm (SAS) to optimize the complex assignment of students to public and voucher schools. We contribute to the literature by shedding light on the impact of this new centralized school admission system on school segregation.

Despite the fact the Chilean government aimed this policy at advancing the representation of low SES students across schools, our findings do not suggest an overall improvement in the evenness of the student background distribution. We confirm this using multiple indicators. Interestingly, our results do indicate heterogeneous effects by levels of pre-existing residential segregation and local school supply. In particular, we document that school districts that had high (low) residential segregation experienced an increase (decline) in school stratification post the implementation of the new system. Beyond residential segregation, we find regions with a pre-SAS higher fraction of private schools have also seen an uptick in segregation due to SAS. These findings highlight the relevance of spatial distribution of schools across local districts as they might strategically locate to target specific groups.

We also provide evidence on a potential mechanism explaining our findings. If high SES parents anticipated a more integrated school as a result of SAS, heterogeneous preferences for school socioeconomic composition could have led to strategic responses, with some families switching to private schools. We present evidence supporting these transitions. Indeed, higher SES families responded to the new policy by out-migrating from public and voucher schools. SAS's unintended consequence explains why school districts that had a lower pre-SAS proportion of public or voucher schools witnessed more of this transition to private schools.

We conclude that the ultimate impact of centralized school admission systems depends on how the parents choose schools, which in turn depends on their location, and pre-existing characteristics of their neighborhoods. Any policy prescription that aims to improve the extent of diversity within schools requires taking into account the school district's features for desired results.

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Table 1: Student and school participation in SAS, national average

Year	All Students	All Schools	Ninth-grade students (%)
	(1)	(2)	(3)
2016	3436	63	46.2
2017	76821	2172	51.2
2018	274990	6421	52.4

Notes: Column (1) and (2) in panel A provide total number of students and schools that participated in SAS across all grades. Column (3) corresponds to the percentage of ninth-grade students participating in SAS. SAS implementation was sequential, therefore, every subsequent year, new regions were added.

Table 2: Percentage of students choosing schools in their municipality/province of residence, national level

Year	Students attending school in municipality/province of residence (N^*)	Total number of students (N)	% ($\frac{N^*}{N}$)
	(1)	(2)	(3)
	A. **Municipality (School district)**		
All students			
2015	2772746	3548845	78.1
2016	2758348	3550949	77.7
2017	2750364	3558394	77.3
2018	2759966	3582448	77.0
2019	2774174	3611057	76.8
Ninth graders			
2015	182643	265093	68.9
2016	176889	259037	68.3
2017	174451	255400	68.3
2018	167782	246937	67.9
2019	166001	246115	67.4
	B. **Province**		
All students			
2015	3289121	3548845	92.7
2016	3278951	3550949	92.3
2017	3273885	3558394	92.0
2018	3286719	3582448	91.8
2019	3301120	3611057	91.4
Ninth graders			
2015	242349	265093	91.4
2016	235396	259037	90.9
2017	230838	255400	90.4
2018	222144	246937	90.0
2019	219723	246115	89.3

Note: We match the resident municipality of each student with the municipality of their school using the enrollment files (panel A). Similarly, matching of student residential province and school province is done in panel B. Column (3) displays the percentage of students attending school in their municipality/province of residence.

Table 3: Composition and distribution of high school types at the national level

Variable	Number of schools	Percentage of schools/students
	A. **Supply of schools, by type**	
Public	915	30.9
Voucher	1614	54.5
Private	433	14.6
Total	2962	100
	B. **Student enrollment, by school type**	
Public	100793	40.8
Voucher	124295	50.3
Private	21849	8.8
Total	246937	100

Note: The sample for this table consists of all schools offering high school education and all ninth-grade students enrolled in high school in 2018.

Table 4: Rank Ordered List (ROL) and Private school supply

VARIABLES	Dependent Variable: Ratio of ROL and total school supply in SAS (1)
% enrollment in Private Schools	0.003
	[0.059]
Mother's Education	0.004***
	[0.001]
% enrollment in Private Schools×Mother's Education	-0.017***
	[0.005]
Constant	0.079***
	[0.006]
Observations	14,926
R-squared	0.008

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table uses the data at the student level seeking admission in ninth grade for five regions that participated in SAS in 2017. The table presents the results obtained from the following regression:

$$y_{ic} = \beta_0 + \beta_1 \text{Private supply}_c + \beta_2 \text{Mother's Education}_i + \beta_3 \text{Mother's Education}_i \times \text{Private Supply}_c + \eta_{ic},$$

where the outcome variable is the ratio of ROL of student i to total school supply in DA in municipality c (this includes public and voucher schools). This equation illustrates the relationship between ROL and private school supply. The coefficient on the interaction term suggests that once we condition on student SES (Mother's Education), higher private school supply is negatively associated with the ratio of ROL to total schools in DA.

Table 5: Participation in SAS and Private school supply

VARIABLES	Dependent Variable: % Participated in SAS (1)
Private	-0.529*
	[0.288]
Voucher	-0.077
	[0.067]
Constant	0.580***
	[0.029]
Observations	86
R-squared	0.066
Covariates	y

Note: *** p<0.01, ** p<0.05, * p<0.1. This table uses municipality-level data for five regions that participated in SAS in 2017. We regress the fraction of DA participants in each municipality on the fractions of private and voucher schools. The reference dummy is fraction of public schools. Thus, the table presents the estimates obtained from the following regression:

$$y_c = \beta_0 + \beta_1 \text{Private supply}_c + \beta_2 \text{Voucher supply}_c + \eta_{ic},$$

where the outcome variable of interest is the fraction of students participating in DA in municipality c. The sample was constructed using the information from ninth graders in 2018. $\beta_1 < 0$ (also statistically significant) provides reduced form evidence that the presence of private schools reduces the participation in DA. In other words, municipalities that had a higher supply of private schools relative to baseline category of public schools had fewer families participating in DA.

Table 6: Descriptive Statistics

Variables	N	Mean	Std. dev.	Min.	Max.
School segregation in municipality (Duncan index)	1,646	0.25	0.19	0.00	0.82
SAS dummy (D_{rt})	1,646	0.22	0.42	0.00	1.00
Intensity of SAS (I_{rt})	1,646	0.19	0.36	0.00	0.96
Residential segregation (access to amenities)	1,623	2.29	5.54	0.00	55.25
% of enrollment in public schools in municipality pre-SAS	1,646	0.60	0.26	0.05	1.00
% of enrollment in voucher schools in municipality pre-SAS	1,646	0.37	0.24	0.00	0.95
% of enrollment in private schools in municipality pre-SAS	1,646	0.03	0.10	0.00	0.81
% of public schools in municipality pre-SAS	1,646	0.61	0.26	0.06	1.00
% of voucher schools in municipality pre-SAS	1,646	0.37	0.24	0.00	0.94
% of private schools in municipality pre-SAS	1,646	0.03	0.09	0.00	0.79
Herfindahl Index pre-SAS	1,646	0.15	0.16	0.01	1.00

Notes: The sample size in our analysis corresponds to 327 municipalities that have Duncan index for all 5 years. Since Chile has 345 municipalities, for only 18 there is missing student-level information in SIMCE files preventing the construction of the Duncan index for one or more years. Hence, we have 1646 observations for the Duncan index panel. When it comes to residential segregation, we lose 23 observations due to missing travel duration data to the amenities. The missing travel data is due to the quality of geocoding of student addresses in some of the rural municipalities where the HERE geocoding API was not able to locate student addresses. The Duncan index measures school segregation at the level of the municipality. SAS dummy takes a value 1 if SAS was implemented in region r in year t and 0 otherwise. Intensity of SAS $\in [0, 1]$ depends on the fraction of schools in region r that participated in SAS in year t. Pre-SAS corresponds to the year 2015. Percentage (%) of enrollment in public (voucher) pre-SAS corresponds to the fraction of students attending a public (voucher) school in each municipality in 2015. Percentage (%) supply of public (voucher) pre-SAS corresponds to the proportion of public (voucher) schools in each municipality in 2015.

Table 7: The impact of SAS on School Segregation
Difference-in-Difference estimates

	Dependent Variable: Duncan index			
VARIABLES	(1)	(2)	(3)	(4)
SAS dummy (D_{rt})	-0.001	-0.000		
	[0.006]	[0.006]		
% enrollment in public pre-SAS		-1.051***		-1.051***
		[0.073]		[0.073]
% enrollment in voucher pre-SAS		-0.564***		-0.564***
		[0.079]		[0.079]
Intensity of SAS (I_{rt})			-0.001	-0.000
			[0.007]	[0.007]
Constant	0.109*	1.033***	0.109*	1.033***
	[0.064]	[0.082]	[0.064]	[0.082]
Observations	1,646	1,646	1,646	1,646
R-squared	0.141	0.603	0.141	0.603
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	y	n	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. Column (1) and (2) use SAS dummy as the treatment variable, while column (3) and (4) use intensity as treatment variable.

Table 8: The impact of SAS on School Segregation: The role of Residential Segregation
Difference-in-Difference estimates

	Dependent Variable: Duncan index	
VARIABLES	(1)	(2)
SAS dummy (D_{rt})	-0.012	-0.013
	[0.008]	[0.008]
Residential Segregation	0.002*	0.002***
	[0.001]	[0.001]
SAS dummy (D_{rt}) $\times$ Residential Segregation	0.008*	0.008*
	[0.004]	[0.004]
Constant	1.039***	1.046***
	[0.083]	[0.080]
Observations	1,623	1,623
R-squared	0.598	0.612
Region FE	y	y
Year FE	y	y
Covariates	y	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In specification (1) we also control for the pre-SAS percentage of students enrolled in public and voucher schools. In specification (2) we add pre-SAS fraction of students in rural schools.

Table 9: The impact of SAS on School Segregation: The role of Outside Options
Difference-in-Difference estimates

	Dependent Variable: Duncan index		
VARIABLES	(1)	(2)	(3)
SAS dummy (D_{rt})	0.372***	0.610**	-0.015
	[0.137]	[0.255]	[0.010]
% of enrollment in public pre-SAS	-1.053***		
	[0.072]		
SAS dummy (D_{rt})× % of enrollment in public pre-SAS	-0.373***		
	[0.136]		
% of enrollment in voucher pre-SAS	-0.557***		
	[0.077]		
SAS dummy (D_{rt})× % of enrollment in voucher pre-SAS	-0.389***		
	[0.148]		
Herfindahl index			-0.744***
			[0.066]
SAS dummy (D_{rt}) ×Herfindahl index			0.080*
			[0.042]
% of public schools pre-SAS		-1.029***	
		[0.087]	
SAS dummy (D_{rt})×% of public schools pre-SAS		-0.601**	
		[0.253]	
% of voucher schools pre-SAS		-0.569***	
		[0.092]	
SAS dummy (D_{rt}) × % of voucher schools pre-SAS		-0.656**	
		[0.274]	
Constant	1.082***	1.077***	0.367***
	[0.071]	[0.086]	[0.012]
Observations	1,623	1,623	1,623
R-squared	0.599	0.501	0.403
Region FE	y	y	y
Year FE	y	y	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In all specifications residential segregation is also included as an additional covariate. Column (1): Percentage (%) of enrollment in public (voucher) pre-SAS corresponds to the fraction of students attending a public (voucher) school in each municipality in 2015. Column (2): Percentage (%) supply of public (voucher) pre-SAS corresponds to the proportion of public (voucher) schools in each municipality in 2015.

Table 10: Students switching from public/voucher to private schools as a response to SAS
Difference-in-Difference estimates

VARIABLES	Dependent Variable: % of switchers
SAS dummy (D_{rt})	0.004**
	[0.002]
Educ mother >= 12	0.010***
	[0.003]
SAS dummy (D_{rt})$\times$ [Educ mother >= 12]	-0.004
	[0.004]
Private dummy (pre-SAS)	-0.009**
	[0.004]
Private dummy (pre-SAS) $\times$[Mother educ. >= 12]	0.015**
	[0.006]
SAS dummy (D_{rt}) $\times$Private dummy (pre-SAS)	-0.041*
	[0.025]
SAS dummy (D_{rt}) $\times$Private dummy (pre-SAS)$\times$ [Educ mother >= 12]	0.068*
	[0.038]
Constant	-0.004**
	[0.002]
Observations	**1,712**
R-squared	0.179
Region FE	y
Year FE	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. The outcome variable used here (transition) is the fraction of students that switched from public/voucher to private school in a municipality. Private dummy pre-SAS takes a value 1 for municipalities which had at least one private school previous to the reform, and 0 otherwise. Educ mother dummy takes a value 1 if student's mother has a high school degree, and 0 otherwise.

Table 11: Test for pre-trends with region specific trend variables

	Duncan index	
VARIABLES	(1)	(2)
SAS dummy (D_{rt})	-0.001	-0.001
	[0.006]	[0.007]
Constant	1.020***	1.011***
	[0.095]	[0.096]
Observations	1,646	1,646
R-squared	0.535	0.536
Region FE	y	y
Year FE	y	y
Set of covariates	y	y
State specific trend	n	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In panel (A) we perform the formal test for parallel trends using state specific trend variable.

Table 12: Test for pre-trends: Random assignment into treatment

	Duncan index			
VARIABLES	(1)	(2)	(3)	(4)
SAS dummy (D_{rt})	-0.002		-0.008	0.087
	[0.006]		[0.007]	[0.081]
% of enrollment in public pre-SAS				-1.001***
				[0.087]
SAS dummy (D_{rt})× % of enrollment in public pre-SAS				-0.100
				[0.080]
% of enrollment in voucher pre-SAS				-0.571***
				[0.094]
SAS dummy (D_{rt})× % of enrollment in voucher pre-SAS				-0.070
				[0.090]
Residential Segregation			-0.005**	
			[0.002]	
SAS dummy (D_{rt})×Residential Segregation			0.003	
			[0.002]	
Intensity of SAS I_{rt}		-0.001		
		[0.007]		
Constant	0.111*	0.109*	0.135*	0.991***
	[0.064]	[0.064]	[0.073]	[0.092]
Observations	1,646	1,646	1,623	1,646
R-squared	0.141	0.141	0.156	0.506
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	y	y	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. For this test we randomly allocate regions into treatment using a random generator with replacement.

Table 13: Alternative socioeconomic backgrounds when defining the Duncan Index
Father's education and family income
Difference-in-Difference estimates

	Duncan index			
VARIABLES	(1)	(2)	(3)	(4)
A: **Father's education**				
SAS dummy (D_{rt})	0.000		0.001	
	[0.006]		[0.006]	
Intensity of SAS (I_{rt})		0.001		0.002
		[0.007]		[0.007]
Constant	0.096	0.096	1.072***	1.072***
	[0.060]	[0.060]	[0.085]	[0.085]
Observations	1,646	1,646	1,646	1,646
R-squared	0.133	0.133	0.609	0.609
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	n	y	y
B: **Household Income Index**				
SAS dummy (D_{rt})	-0.004		-0.004	
	[0.011]		[0.010]	
Intensity of SAS (I_{rt})		-0.004		-0.003
		[0.012]		[0.012]
Constant	0.115***	0.115***	0.930***	0.930***
	[0.005]	[0.005]	[0.064]	[0.064]
Observations	1,646	1,646	1,646	1,646
R-squared	0.182	0.182	0.561	0.561
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	n	y	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In panel (A) we use father's education to construct the Duncan index, while in panel (B) it is computed using household income. In columns (1) and (3) we employ SAS dummy as the treatment variable, and in columns (2) and (4) we use intensity of SAS. Columns (3) and (4) also include additional covariates such as the pre-SAS fraction of public, voucher and private schools in a municipality.

Table 14: The impact of SAS on School Segregation
Sample of school districts with urban schools only
Difference-in-Difference estimates

	Duncan index			
VARIABLES	(1)	(2)	(3)	(4)
SAS dummy (D_{rt})	0.003		0.004	
	[0.010]		[0.012]	
Intensity of SAS (I_{rt})		0.006		0.006
		[0.014]		[0.014]
Constant	0.407***	0.407***	1.167***	1.167***
	[0.005]	[0.046]	[0.087]	[0.087]
Observations	224	224	224	224
R-squared	0.304	0.304	0.778	0.778
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	n	y	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In columns (1) and (3) we employ SAS dummy as the treatment variable, and in columns (2) and (4) we use intensity of SAS. Columns (3) and (4) also include additional covariates such as the pre-SAS fraction of public, voucher and private schools in a municipality.

Table 15: The impact of SAS on School Segregation using Province as School District
Difference-in-Difference estimates

VARIABLES	(1) SAS Dummy	(2) SAS Intensity
SAS dummy (D_{rt})	-0.006	
	[0.006]	
SAS treatment intensity (I_{rt})		-0.007
		[0.006]
Constant	0.288***	0.288***
	[0.108]	[0.108]
Observations	269	269
R-squared	0.348	0.348
Region FE	y	y
Year FE	y	y

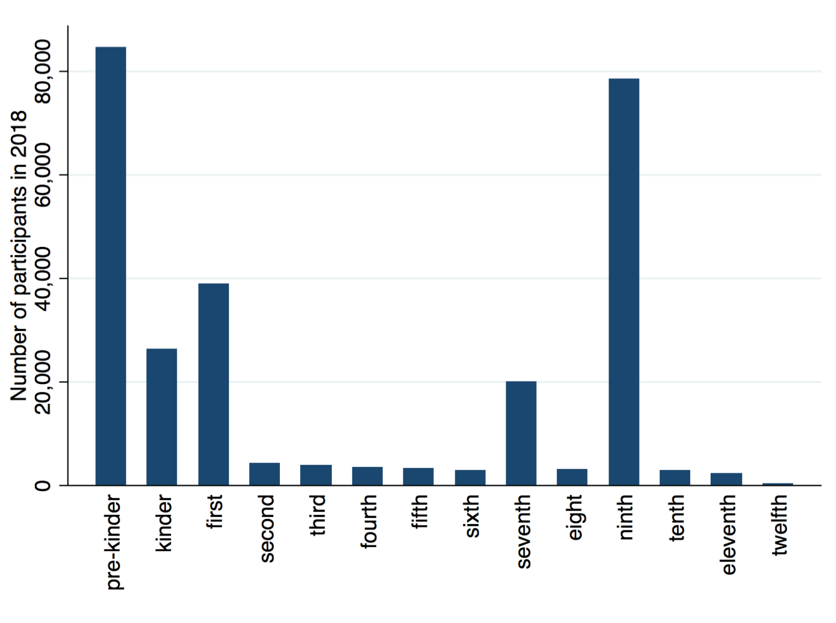
Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors in square brackets. As the Duncan index for this robustness check is constructed at the province level instead of municipality, standard errors are clustered at province. In column (1) we employ SAS dummy as the treatment variable, and in column (2) we use intensity of SAS.

Table 16: Alternative definition of School Segregation: The M index (within component)
Difference-in-Difference estimates

VARIABLES	(1)	(2)
SAS dummy (D_{rt})	-0.007*	0.251***
	[0.004]	[0.068]
% of enrollment in public pre-SAS		-0.206***
		[0.054]
SAS dummy (D_{rt})×% of enrollment in public pre-SAS		-0.248***
		[0.068]
% of enrollment in voucher pre-SAS		-0.078
		[0.059]
SAS dummy (D_{rt})×% of enrollment in voucher pre-SAS		-0.261***
		[0.072]
Residential segregation	-0.001	
	[0.001]	
SAS dummy (D_{rt})×Residential segregation	0.002***	
	[0.001]	
Constant	0.030**	0.210***
	[0.015]	[0.055]
Observations	1,623	1,646
R-squared	0.094	0.433
Region FE	y	y
Year FE	y	y
Covariates	n	n

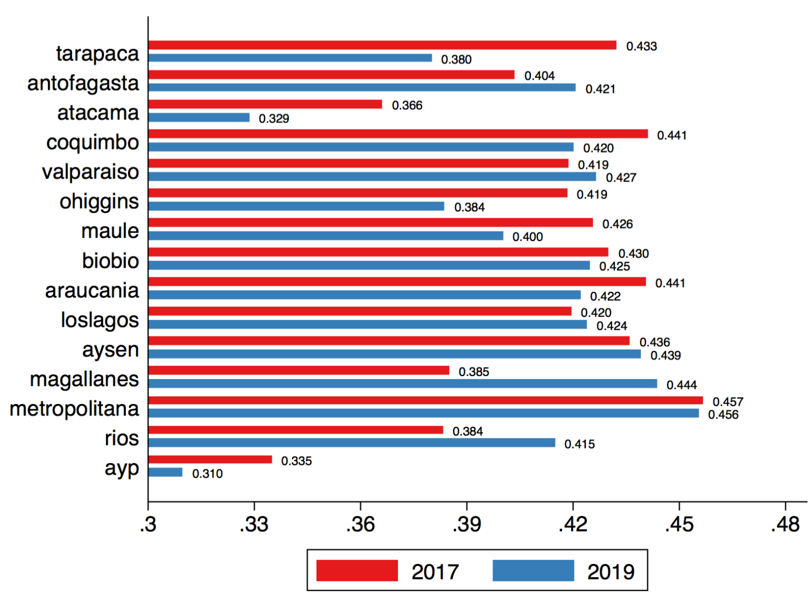
Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In column (1) we perform the heterogeneous effect using residential segregation. In column (2) we do the same using the local pre-SAS school structure.

Figure 1: Number of Students participating in SAS across grades (2018)



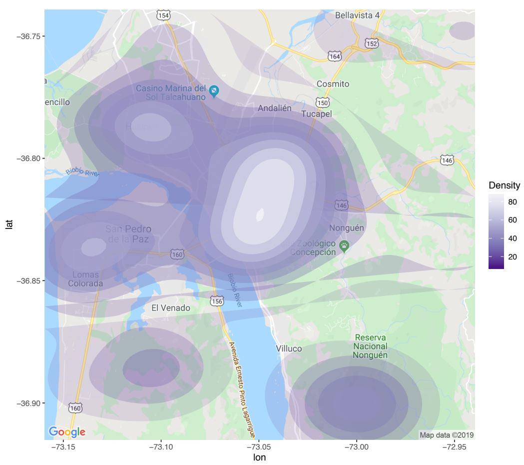
Notes: By 2018, all regions in Chile except Metropolitana had the new policy for school admission process. We observe that most participants apply to pre-k and ninth grade admissions.

Figure 2: Duncan index: 2017 versus 2019
By region

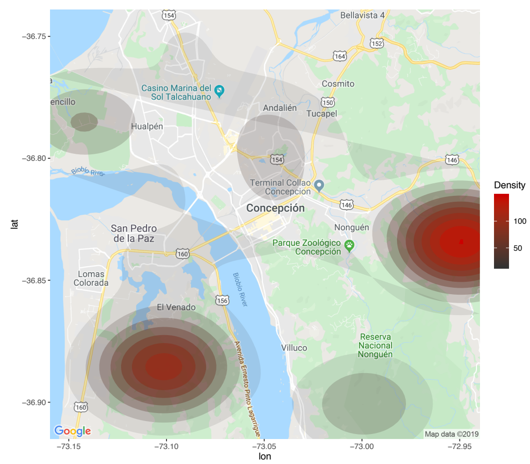


Notes: The only region that had the new policy implemented in 2017 was Magallanes. The new system was implemented in all other regions by 2018, except Metropolitana.

Figure 3: Spatial density plots of low and high SES students
The Biobio region



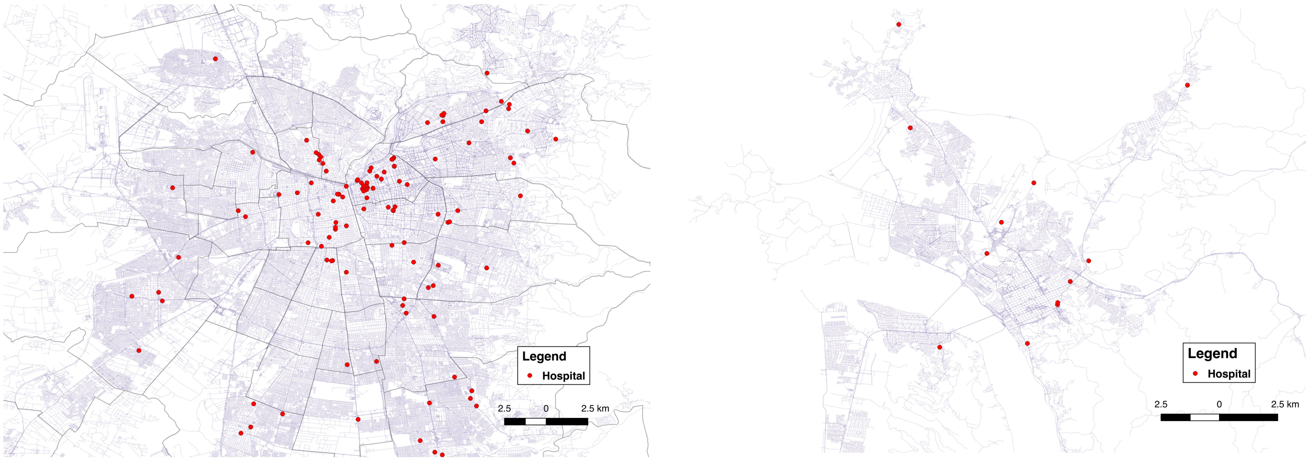
A. Students from low income families



B. Students from high income families

Notes: We plot the contour densities for low and high income students in Biobio region. The concentration can be seen using the color gradient for the densities shown with each graph. For instance, high income families have higher concentration in east and south west as the contour color gradient is red which corresponds to high density according to the color gradient (see density color gradient in panel (B)). According to the color gradient for low income families, they have high concentration in the north and central part of Biobio.

Figure 4: Spatial distribution of hospitals in Chile's two largest provinces

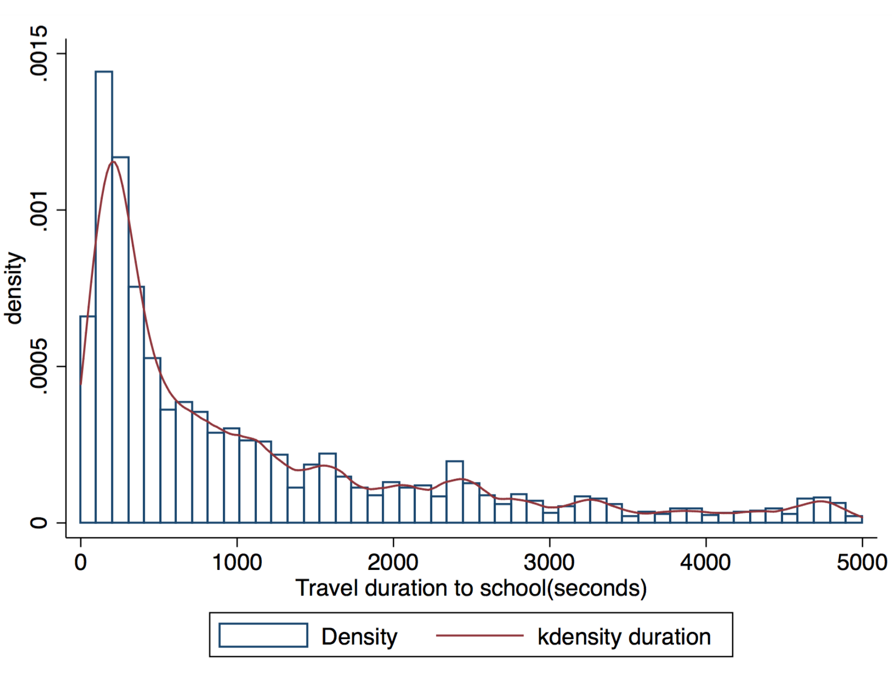


A. Santiago

B. Concepcion

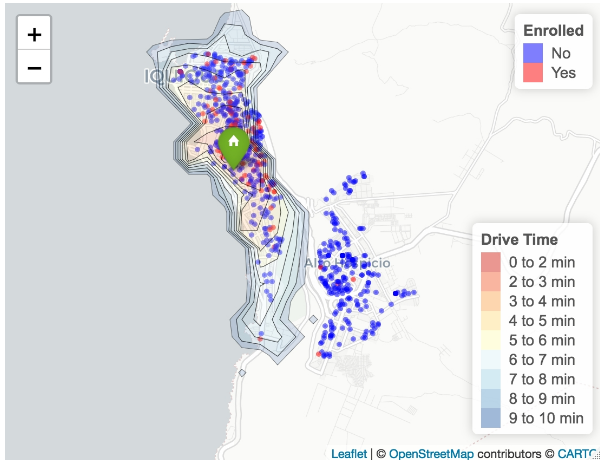
Notes: Panel (A) displays the spatial distribution of hospitals in Santiago province (in Metropolitana region). Panel (B) does it for Concepcion province (in Biobio region).

Figure 5: Travel time to school for ninth graders in 2018



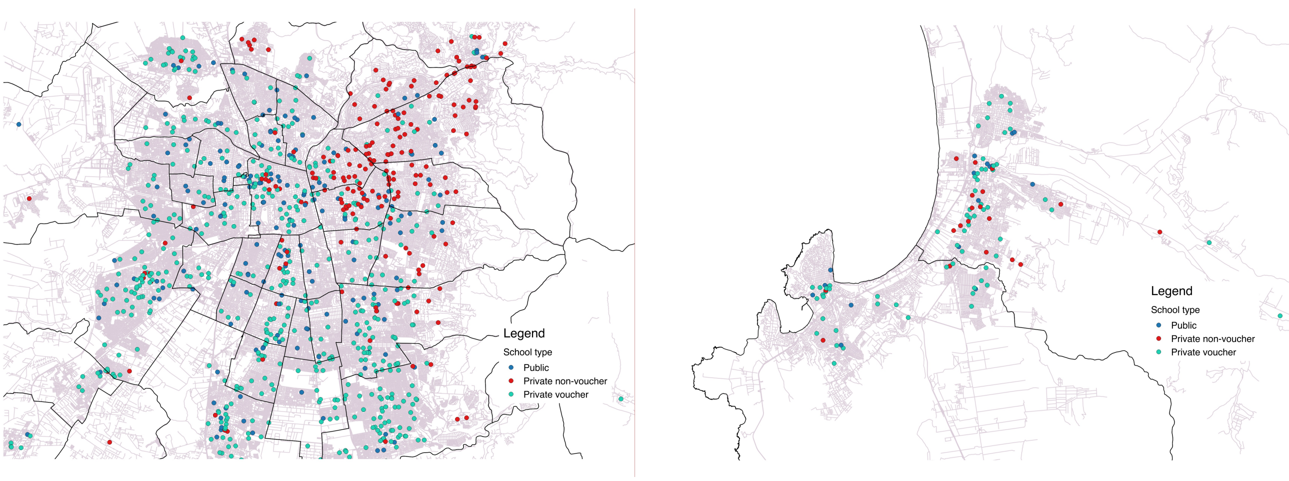
Notes: We display the travel time by car for ninth-grade students in 2018. This travel time computation was done using OSRM API.

Figure 6: Enrollment and travel time to school
The Tarapaca Region



Notes: We use the sample of students who participated in SAS for ninth grade admissions in 2017 and they were assigned new schools in 2018 in Tarapaca for illustration. The green marker indicates a large school but the average SIMCE score is below the mean SIMCE score for this school.

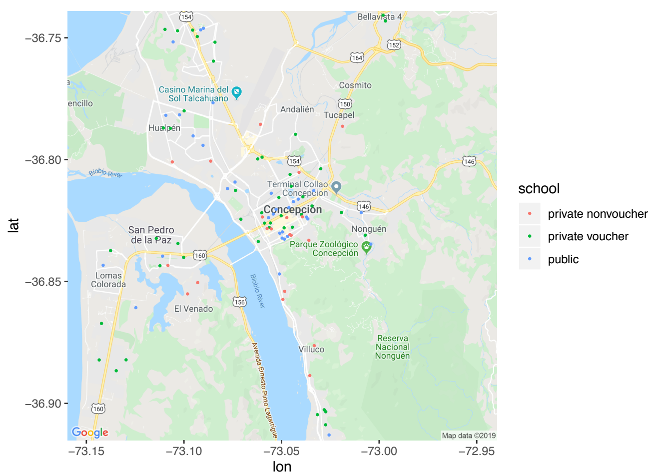
Figure 7: Spatial distribution of school types in the Metropolitana (Santiago) and Coquimbo regions



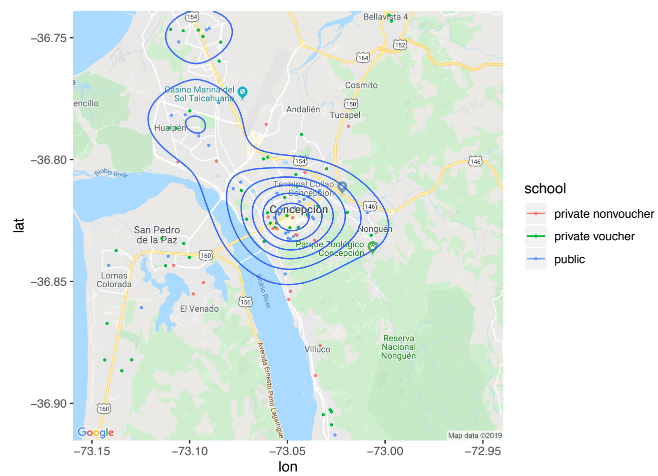
A. Metropolitana B. Coquimbo

Notes: The plots show the spatial distribution of public, voucher and private schools for different municipalities in Metropolitana and Coquimbo regions, respectively.

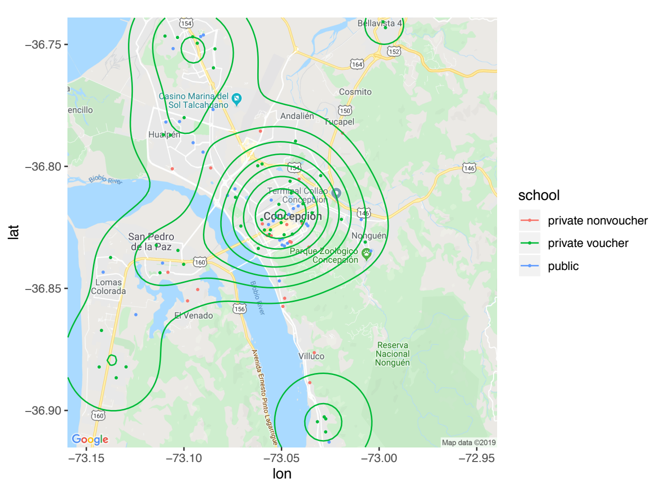
Figure 8: Spatial density plots of schools in the Biobio region by school types



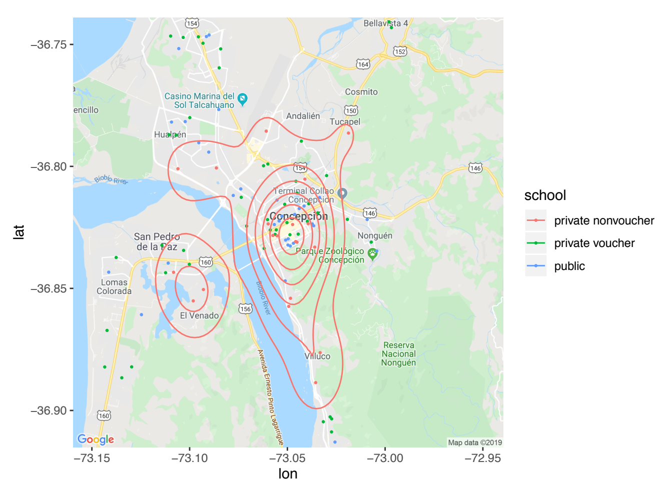
A. All schools



B. Public schools



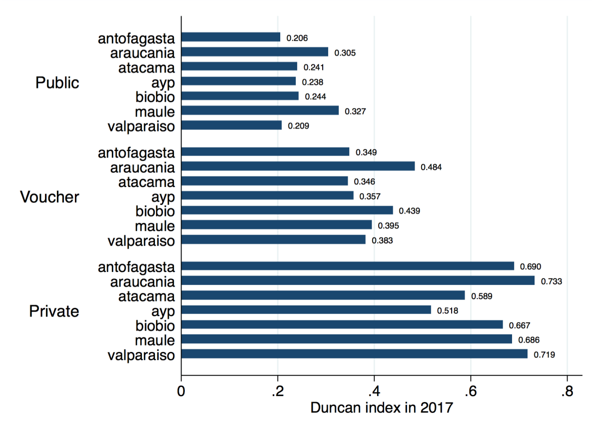
C. Voucher schools



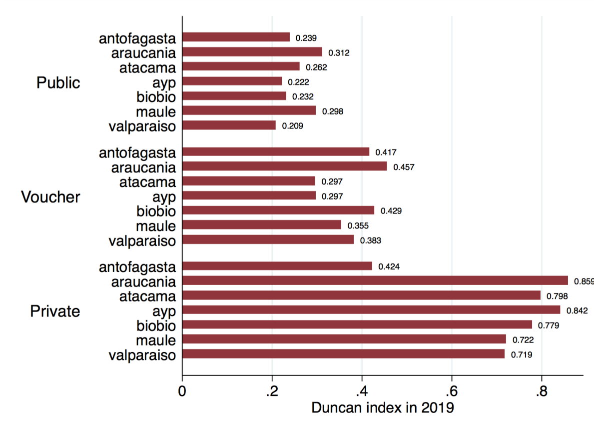
D. Private schools

Notes: Figure displays contour plots for spatial density of different school types. We observe that voucher schools are more evenly spread as compared to public and private schools in Biobio region.

Figure 9: Differences in segregation by school type: 2017 vs. 2019 by region



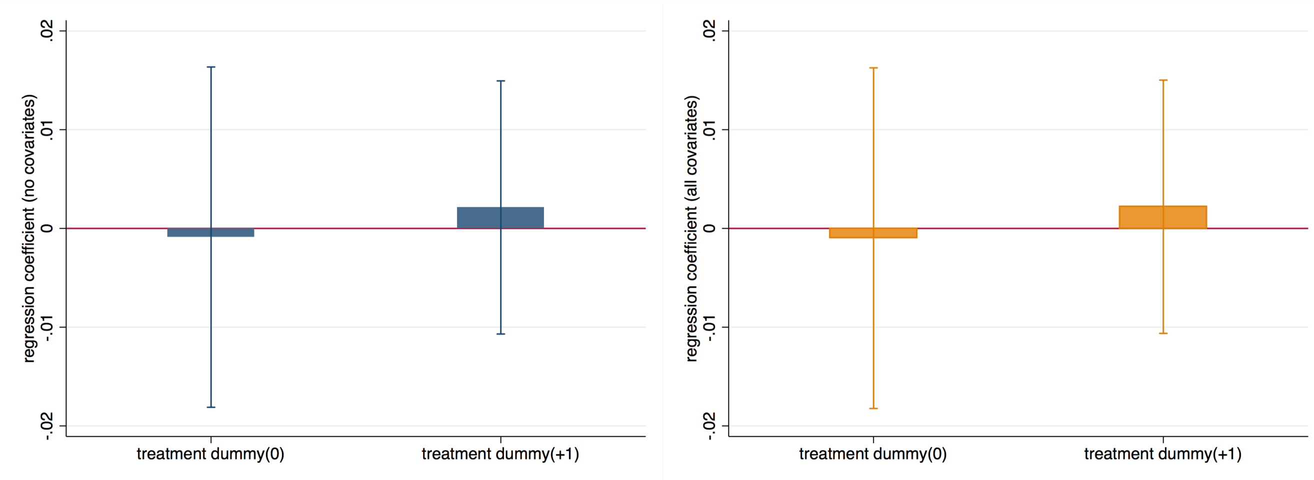
A. 2017



B. 2019

Notes: We consider differences in the Duncan index by three types of school-public, voucher, and private. Segregation is more pronounced in the private schools than in the public/voucher schools.

Figure 10: Leads and lags analysis for parallel trends



A. Model 1: No covariates

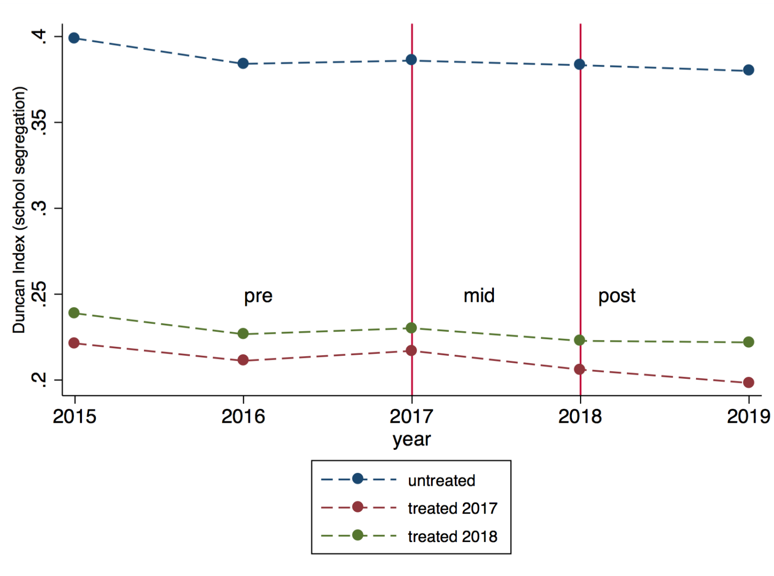
B. Model 2: With covariates

Notes: Figure displays the leads and lags test for parallel trends assumption. The list of control variables for the second specification in panel (B) includes the pre-SAS fraction of public, voucher, private schools and rural schools. The figure presents the estimates (vertical bars) and associated confidence intervals (vertical lines) obtained from the following regression:

$$y_{crt} = \delta_{01} \times D_{rt} + \delta_{02} \times D_{rt+1} + Z_{1cr}\beta + \gamma_r + \lambda_t + \epsilon_{crt} \tag{5}$$

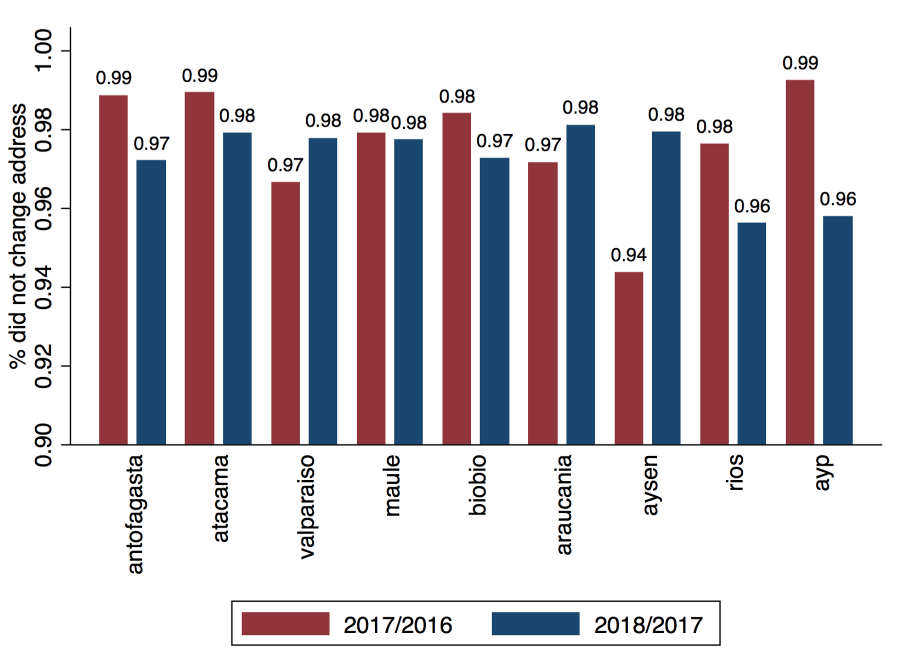
Here, y_{crt} corresponds to the Duncan index in municipality c in year t. We include the lead of the treatment dummy D_{rt+1}. Future policy should not impact the Duncan index in year t. We find δ_{02} to be statistically insignificant in our test.

Figure 11: Parallel trends with treatment time variation



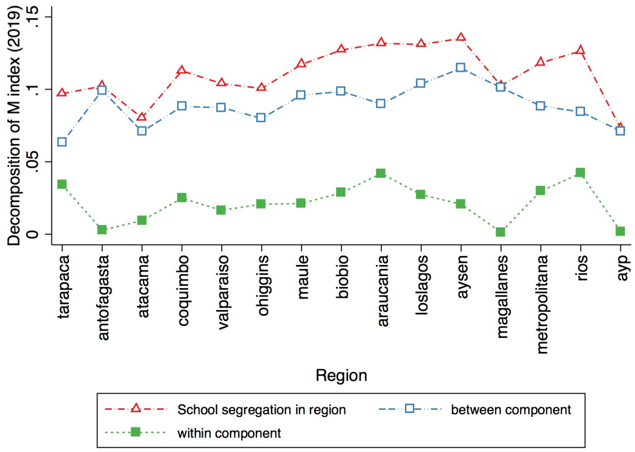
Notes: This is the visualization of the modified parallel trends assumption due to sequential implementation of SAS. For the purpose of this exercise the regions were divided into early (2017), late (2018) and control groups. We plot the average Duncan index for these groups and examine trends in the Duncan index before the policy was implemented. However, since the control group is varying overtime due to staggered implementation of SAS, we need to perform formal tests of pre-trends. We perform formal tests for pre-trends and provide details in section 5.2.

Figure 12: Change in residential addresses in response to introduction of SAS, by region

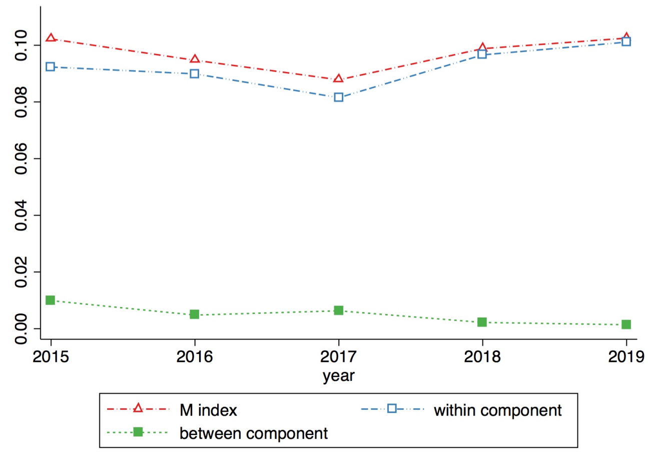


Notes: This figure illustrates that there were no systematic changes in residential addresses pre and post the introduction of SAS. We perform this analysis for regions in which SAS was implemented in 2017 and was effective in 2018. We display the fraction of students that did not change address between 2016 and 2017 (maroon vertical bars) and compute the same fraction for 2017 and 2018 (blue vertical bars). A comparison of these two fractions display that there are no substantial variations in the families changing addresses before and after the introduction of the policy.

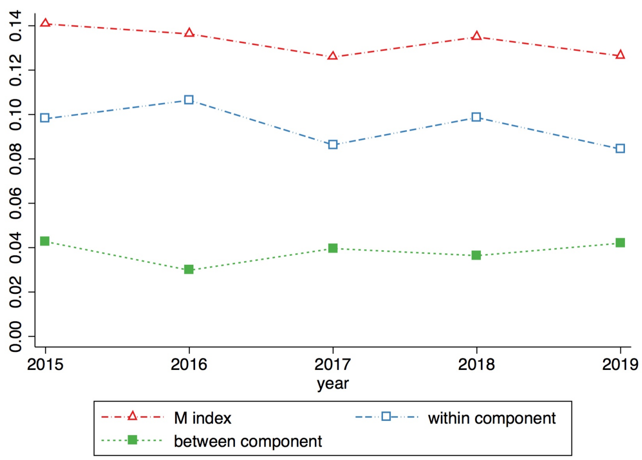
Figure 13: Decomposition of M information index into within and between components



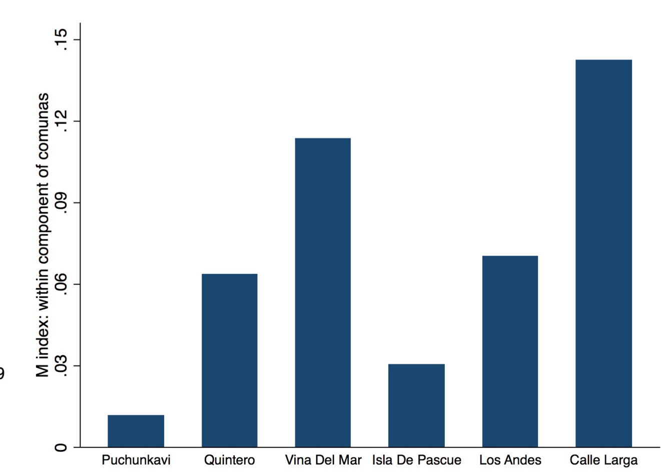
A. 2019 by Region



B. 2015-19: Magallanes



C. 2015-19: Los Rios



D. Within component: Valparaiso

Notes: Figure displays the decomposition of the M index into within and between components. For this exercise we use SIMCE and enrollment data for 2015, 2016, 2017, 2018 and 2019 for this analysis.