A Decade of Centralized School Choice Admission in Chile: Achievements and Challenges

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This paper reviews the first decade of Chile's Sistema de Admisión Escolar *(SAE), a national platform that replaced fragmented admissions with a coordinated assignment institution designed to reduce strategic incentives, cover public and private-subsidized schools, and ensure algorithmic transparency. Its staggered 2016–2019 rollout created a research-policy loop using administrative data, surveys, experiments, and quasi-experimental designs. The central lesson is that reducing strategic ranking incentives is necessary but not sufficient: families also need help forming realistic beliefs about admission chances and using that information to search and apply effectively. By 2025, 82.6% of applicants were assigned to one of their top three listed schools and 92.8% to a listed preference, but non-placement remained geographically concentrated. We synthesize evidence and add three contributions: replicated risk-warning regression-discontinuity estimates, linked records showing a large in-year aftermarket outside SAE's equity priorities, and an event study documenting improved* prioritario *representation at oversubscribed schools despite broader constraints from supply, residential stratification, and private-sector exit.*

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I. Introduction

Around the world, access to publicly funded education is rarely determined exclusively by who has more resources or by the price mechanism. Societies therefore need rules for rationing scarce seats: who has priority, how preferences should count, and how principles such as equal chances, sibling priority, or priority for vulnerable students should operate when demand exceeds supply. Those rules exist whether admissions are decentralized or centralized, but implementing them school by school makes equitable treatment and efficient coordination hard: families face fragmented information, schools process queues separately, and social priorities are difficult to apply consistently. Increasingly, countries implement rationing rules through coordinated choice and assignment systems (CCAS), digital platforms that collect preferences, coordinate supply and demand, process waitlists, and assign seats under common rules. A World Bank background review by Neilson (2024) covers admissions policies in 149 countries and finds that 60 percent have adopted some form of coordinated mechanism. Market-design theory predicts benefits from this kind of coordination, and empirical evidence from New York City and Ecuador finds large welfare gains from coordinating preferences and offers (Roth, 2012; Abdulkadiroğlu, Agarwal and Pathak, 2017; Elacqua et al., 2024).

Chile's *Sistema de Admisión Escolar* (SAE) was created to replace that kind of fragmented admissions regime. Introduced under the 2015 *Ley de Inclusión Escolar* and rolled out across regions between 2016 and 2019, with nationwide implementation consolidated by 2020, SAE centralized applications and assignments for primary and secondary education in the publicly funded sector. For the first time, families applied through a single national platform, schools were assigned under common legal priorities, and discretionary admissions practices were replaced by a transparent assignment mechanism. The reform was therefore not only a technical change in how seats were matched to students; it was a change in how access to publicly funded schooling was governed.

This paper reviews the first decade of SAE around four questions: what was implemented, how Chile learned while scaling, what happened after a decade, and what remains unfinished. The paper is therefore not primarily a new mechanism-design proposal or a single new estimate. It is a retrospective account of institution-building: Chile built a national assignment system using the best available evidence, used staggered implementation to make the system observable as it scaled, discovered important behavioral frictions through that process, and now faces a second-generation agenda about supply, the aftermarket, and governance of complex assignment rules.

Within this broader international movement, Chile is a useful case because the reform combined the empirical market-design lessons available by 2015 with unusually broad national coverage, public–private-subsidized coordination, and data infrastructure that made the system observable as it scaled. The Chilean experience therefore speaks both to countries adopting centralized assignment for the first time and to mature systems trying to move beyond the algorithm toward a smarter, more adaptive platform.

The first part of the story is what was implemented. SAE incorporated three pillars that were central to the best available evidence in 2015. First, it reduced strategic incentives across the full application design, not only through student-proposing Deferred Acceptance (DA), but also through unrestricted preference lists, a complementary round with little scope for withholding acceptable options, legally defined priorities, family-based tie-breaking, fallback guarantees, and sibling/family assignment rules (Gale and Shapley, 1962; Roth, 2008; Pathak, 2017; Kapor, Neilson and Zimmerman, 2020; Correa et al., 2019, 2022). The policy target was the payoff to sophisticated rule knowledge relative to straightforward participation: a system is less strategic when informed families gain less from gaming list length, rank order, rounds, or linked applications. Second, SAE coordinated the entire publicly funded school sector, including public and private-subsidized schools, under a single national platform and a common set of legally mandated priorities. Third, it made the system transparent: the algorithm, priorities, capacities, applications, and match outcomes became available for public scrutiny and research. In combination, these features made SAE a national assignment institution rather than simply a new application website.

The second part of the story is how Chile learned while scaling. Much about the reform was unknown ex ante. It was not obvious whether families would participate, understand the incentive properties of the design, submit long enough lists, trust a centralized process using common priorities and lotteries, or respond to different forms of information. Nor was it clear where local supply would become binding, how sibling and fallback rules would work in practice, or how the public would react to a national lottery-based assignment institution. Rolling the system out in legally controlled stages created a measurement window: researchers and policymakers could observe behavior as the platform expanded, identify frictions, test interventions, and feed evidence back into the next cycle. In this sense, SAE became not only an assignment mechanism but also a research-policy platform.

The main lesson from that measurement window is simple but important: reducing strategic ranking incentives solves truthful ranking, but it does not solve informed search. Families do not need to misrepresent their rank order under DA, but they still need to know which schools exist, what those schools offer, what they cost, and where admission is feasible. Across multiple studies, cohorts, and datasets, families systematically overestimated their admission chances, underestimated the quality and affordability of nearby options, and stopped searching earlier than a frictionless model would predict (Arteaga et al., 2022*a*;

Agte et al., 2024; Allende, Gallego and Neilson, 2019). These information gaps were larger among lower-SES families, making unequal information itself a source of structural inequality in access.

The policy response was to build an informational layer inside the application platform. Risk warnings, personalized feedback reports, the School Explorer (MIME), and WhatsApp notifications all share the same logic: the platform uses administrative data to forecast likely outcomes, identify safer or higher-value options, and show families relevant information at the moment they are making application decisions. The later digital in-year market, *Anótate en la Lista*, extended the same platform approach beyond the main round by making queues and vacancies visible at scale. The central claim of this retrospective is that the combination of a well-designed mechanism with an adaptive information layer helped convert SAE from a centralized assignment procedure into a system that could learn and improve over time.

What was known by 2015 was already substantial. Theory and practice had established that centralized assignment could improve welfare when preferences and capacities are coordinated, that strategy-proof designs such as student-proposing Deferred Acceptance reduce incentives to misrepresent rank order, and that replacing school-by-school admissions with a unified match could reduce administrative chaos and gaming on margins such as timing and multiple offers (Abdulkadiroğlu and Sönmez, 2003; Pathak, 2017; Kapor, Neilson and Zimmerman, 2020; Abdulkadiroğlu, Agarwal and Pathak, 2017). Separately, a growing body of evidence showed that school information could change choices and that information frictions could widen inequality in access (Hastings and Weinstein, 2008; Allende, Gallego and Neilson, 2019). Those lessons informed SAE's architecture, but they did not by themselves answer how they would combine at national scale inside a single platform.

What was not known ex ante in Chile—and what motivated much of the subsequent measurement—went beyond those general propositions. It remained unclear how families would participate in and trust a lottery-based national assignment institution; whether belief errors and short lists documented in smaller-scale or cross-sectional settings would bind equally in a nationwide rollout; how sibling rules, fallback guarantees, and complementary rounds would operate in practice; where local supply would become binding as demographics and school entry and exit evolved; and how quickly an informational layer could iterate relative to the legal core of priorities and tie-breaking.

The evidence reviewed in this paper shows how that learning process unfolded. Before SAE, mechanism-design evidence from settings such as New Haven, Boston, and New York emphasized the value of strategy-proof centralized assignment and the dangers of mechanisms that reward strategic behavior (Abdulkadiroğlu and Sönmez, 2003; Pathak, 2017; Kapor, Neilson and Zimmerman, 2020; Abdulkadiroğlu, Agarwal and Pathak, 2017). Evidence from school-information experiments showed that families' choices could change when they received clearer information about school quality and feasible alternatives (Hastings and Weinstein, 2008; Allende, Gallego and Neilson, 2019), and parallel evidence on undermatching and college-application interventions documented similar information-driven gaps in higher-stakes settings (Hoxby and Avery, 2013; Bettinger et al., 2012; Bergman et al., 2024). What the Chilean rollout added was a national platform on which these ideas could be tested repeatedly and at scale.

That body of evidence supports three broad findings. First, platform risk warnings changed application behavior: families added schools, reduced predicted non-placement risk, and were more likely to enroll in schools with higher measured value-added (Arteaga et al., 2022*a*). Second, school-attribute information and personalized reports changed families' search and application decisions, with effects that were especially relevant for lower-information households (Allende, Gallego and Neilson, 2019; Agte et al., 2024). Third, newer follow-up and companion evidence suggests that some of these individual-level gains may translate into longer-run and system-level outcomes: the warning intervention is linked to fourth-grade test-score gains in a companion working paper (Arteaga et al., 2026), and a separate event-study analysis finds that the share of *prioritario* students at oversubscribed schools converged toward the non-oversubscribed counterfactual by roughly 6 percentage points by year seven, closing about a third of the pre-SAE gap (Lepe, Muñoz-Ojeda and Neilson, 2026). These estimates are bounded, but they appear where the mechanism has room to act.

The third part of the story is what happened in the end. Operationally, SAE has produced assignment outcomes within the range of mature centralized systems and favorable relative to several city-level and developing-country benchmarks. In 2025, 82.6% of applicants were placed in one of their top three listed schools and 92.8% were placed in one of their listed preferences (Table 1). At the same time, the remaining 7.2% non-placement rate is unevenly distributed. It is geographically concentrated and closely connected to local scarcity, especially where school entry has slowed, voucher-sector exit has continued, or demographic growth and migration have outpaced available seats (Section II.G).

This is the main "what happened" qualification. SAE coordinates supply and demand more transparently, but it cannot create desirable seats in local markets where too few exist. After the Inclusion Law, new private-subsidized entry essentially stopped, net voucher-sector contraction continued, and some high-demand, high-value-added private-subsidized schools converted to the unsubsidized private sector. These descriptive supply patterns shape the platform's achievable outcomes: empty seats can coexist with acute scarcity in the schools and neighborhoods families most want. On segregation, the picture is similarly bounded. Aggregate effects are hard to identify cleanly and depend on the measure, but companion evidence indicates that at oversubscribed schools—where the mechanism has room to bind and where discretionary screening previously mattered most—access for *prioritario* students improved measurably. SAE therefore solved a major coordination and transparency problem, but it could not by itself expand desirable supply, prevent all exit from the regulated sector, or undo segregation outside the assignment mechanism's perimeter.

Beyond synthesizing this decade of evidence, the paper presents three new empirical contributions. First, it reports an out-of-sample replication of the QJE risk-warning regression discontinuity after that study's original observation window, covering SAE cycles from 2018 to 2023 and adding a linkage to fourth-grade SIMCE outcomes (Section IV). Second, it quantifies the school-choice aftermarket using linked SAE and within-year enrollment records, and documents the scale of the new digital in-year platform *Anótate en la Lista* (Section V). Third, it draws on a staggered difference-in-differences event study exploiting SAE's 2016–2019 regional rollout to document the convergence in *prioritario* composition at oversubscribed schools described above (Lepe, Muñoz-Ojeda and Neilson, 2026). Together, these contributions separate the established evidence from the new evidence added in this retrospective.

The final part of the story is what remains unfinished. The assignment mechanism cannot solve local scarcity on its own; supply constraints, school entry and exit, and the distribution of high-demand seats remain central policy problems. The aftermarket is now visible at scale, but its current first-come-first-served logic does not yet incorporate the equity priorities that govern the main round. And the system's information layer has evolved much faster than the core algorithm, priority hierarchy, tie-breaking rules, and capacity rules. Annual technical recommendations prepared for MINEDUC by ConsiliumBots and collaborators repeatedly proposed reforms on these margins, but many remain unimplemented (ConsiliumBots, 2024). Appendix Table C1 summarizes those recommendations and their adoption status. The next decade therefore requires not only better tools for families, but also better governance tools for citizens and policymakers: public-facing simulators, accessible documentation, and transparent evaluation of alternative rules so that debate over complex assignment algorithms can be informed rather than anecdotal.

The remainder of the paper is organized as follows. Section II describes the design, rollout, and evolution of SAE. Section III develops the behavioral frictions framework—search costs, biased beliefs about admission chances, and misperceptions of school attributes—and reviews the evidence from MIME and personalized school reports. Section IV presents the platform risk warnings and their effects, including the out-of-sample replication through 2023 and follow-up evidence on learning. Section V documents the aftermarket and the *Anótate en la Lista* reform. Section VI draws lessons and identifies open questions for the next decade.

II. Implementation Timeline and Design Evolution

This section documents the first two acts of the retrospective: the design choices (strategic-incentive reduction across the application design, unified public and private-subsidized coverage, data transparency), the staggered rollout that created the measurement window, and the pre-SAE baseline, satisfaction, market-dynamics, and segregation context needed to interpret what followed. The empirical consequences (the research–policy loop and the interventions it produced) are developed in Sections III–V.

A. Pre-SAE Admission Practices

Before the implementation of the current school assignment system, Chile operated under what was known as the traditional or decentralized admission system. For decades, families applied individually to as many schools as they wished, with each school setting its own admission rules, deadlines, and procedures. There was no unified platform or timeline, and families had to physically visit each school to submit applications, often during working hours and with limited and inconsistent information available. Each school also retained broad discretion in determining who to admit, making the process ambiguous and burdensome.

This decentralized structure was deeply shaped by reforms from the 1980s, when Chile underwent sweeping changes that decentralized education governance and introduced a large-scale voucher program. This led to the coexistence of three types of schools: public, private-subsidized (voucher), and private non-subsidized (Biblioteca del Congreso Nacional, 1980). While families were nominally free to apply to any school, in practice, access was shaped by socioeconomic status. Families had to navigate fragmented information systems, including unclear rules about fees, application procedures, and eligibility for various types of priority, such as those based on geography or siblings. This complexity reinforced existing inequalities and contributed to increasing school segregation, particularly in the 2000s (Valenzuela, Bellei and Ríos, 2013).

Attempts to regulate school admissions and curb discrimination began with a 2009 reform that introduced broad guidelines for admissions criteria (Biblioteca del Congreso Nacional, 2009). However, these rules left considerable discretion to schools, many of which continued to screen students based on academic or socioeconomic characteristics. Evidence shows that such practices persisted, undermining the goals of equity and fairness in access to quality education (Huerta Retamal, 2021).

In addition to equity concerns, the traditional system imposed significant logistical and financial costs on both families and schools. Aguilera et al. (2022) estimate that families incurred average costs of US$10 per child under the decentralized model, primarily for transportation and time spent traveling to and visiting schools. Schools also faced high administrative burdens, spending about US$13.60 per applicant on supplies, personnel, and admissions logistics. In contrast, under the centralized SAE system, these costs dropped dramatically, to US$2.81 for families and US$0.16 for schools, demonstrating substantial gains in cost efficiency (Aguilera et al., 2022). Coordinated, single-offer assignment has also been shown to reduce administrative placements and improve welfare in New York City's reform (Abdulkadiroğlu, Pathak and Roth, 2005; Abdulkadiroğlu, Agarwal and Pathak, 2017).

Moreover, the traditional system was rife with inefficiencies and credibility issues. The lack of standardization led to allegations of favoritism, lack of transparency, and even reports of informal payments to secure spots in desirable schools. These dynamics contributed to widespread dissatisfaction among families and undermined public trust in the admissions process (Aguilera et al., 2022).

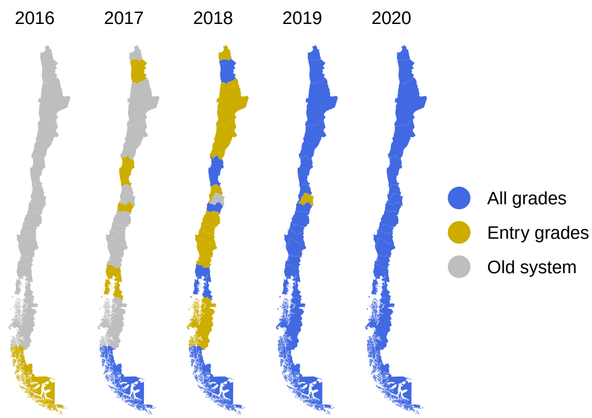
The introduction of SAE not only addressed these logistical and equity challenges but also enabled improved data collection, capacity planning, and monitoring, features entirely absent from the previous system. As Chile continues to refine its approach, understanding the failures of the prior system remains crucial for sustaining progress and resisting the return to more exclusionary practices.

B. Phased Rollout

The implementation of the Chilean centralized school assignment system followed a deliberately phased rollout strategy (see Figure 1), gradually expanding its geographic and institutional coverage over time. This progressive approach allowed the Ministry of Education (MINEDUC) and the engineering team to test, refine, and scale the system in stages, minimizing operational risks and enabling policy learning along the way. Importantly, the territorial staging was established by law: the transitory provisions of *Ley 20.845* authorized phased implementation through presidential *decretos con fuerza de ley* (DFLs), with DFL N°3 of 2015 designating Magallanes as the first region and subsequent DFLs specifying the regions incorporated in each later year (Ministerio de Educación de Chile, 2015). SAE was therefore designed from inception as a *national* system deployed through legally controlled staging, rather than a local pilot that later became policy through informal expansion.

The system was first piloted in 2016 in a single region (Magallanes), covering only entry-level grades. In 2017, it expanded to four additional regions and incorporated all grade levels within those territories. By 2018, the system covered 15 regions and over 6,400 schools, processing nearly 275,000 student applications. Full nationwide coverage was reached in 2019, when the Metropolitan Region (which includes Santiago, the capital of Chile) was incorporated, making Chile one of the few countries to implement a nationwide school choice mechanism for all grade levels from Pre-K to 12th grade.

Figure 1. SAE Staggered Implementation Design



Notes: Staggered rollout of Chile's SAE, 2016-2020. Gray indicates regions using the old system, yellow those covered only at entry grades, and blue regions where SAE applied to all grades. By 2020, the system was implemented nationwide.

Subsequent years saw continued high participation rates, with over 450,000 students assigned annually through SAE. The number of participating schools stabilized above 7,900, and student applications exceeded half a million in several years. This gradual scaling strategy proved essential in addressing implementation challenges, fine-tuning technical components (such as tie-breaking rules, sibling assignment, and quotas), and adapting the digital infrastructure to support growing system complexity.

C. *SAE Core Features*

Chile's SAE replaced a decentralized and often opaque admission process with a centralized and transparent platform. The reform was mandated by the 2015 Inclusion Law (*Ley de Inclusión Escolar*, *Ley 20.845*), which prohibits selective admissions in all publicly funded schools and requires that admissions "be carried out through a system that guarantees transparency, equity, and equality of opportunities" (Congreso Nacional de Chile, 2015).[1] Critically, the law goes beyond prohibiting selection: Art. 7° ter requires a Ministry-level review that ensures "the same student is not admitted to different schools... optimizing so that applicants are placed in their highest preference," language that anticipates a centrally coordinated matching system (Congreso Nacional de Chile, 2015). The operational details, including the definition of a *plataforma de registro* that

[1]In the original Spanish: "*Los procesos de admisión... se realizarán por medio de un sistema que garantice la transparencia, equidad e igualdad de oportunidades*" (*Ley 20.845*, Art. 7° ter, inserted in DFL N°2 of 1998).

records preferences, processes priorities, and communicates results, were later established by *Decreto Supremo N°152* of 2016 (Ministerio de Educación de Chile, 2016).[2] SAE thus guarantees equal access by standardizing procedures, eliminating discriminatory selection practices, and centralizing applications through a single online platform that covers all public and voucher schools.

SAE's first design pillar was not simply the use of the student-proposing Deferred Acceptance (DA) algorithm, inspired by Gale and Shapley (1962). It was a broader package intended to reduce the payoff to strategic behavior across the application window. DA makes truthful rank ordering a dominant strategy, but implementation details can reintroduce incentives to game the system if lists are capped, the choice menu is too coarse, first-preference rules are used, tie-breaking is opaque, or later rounds make it attractive to withhold acceptable schools. The Chilean design therefore combined DA with an unrestricted preference list, legally defined priority profiles, lotteries within priority profiles, option- and family-based lottery numbers, fallback guarantees, and family/sibling rules that were embedded directly in the mechanism (Pathak, 2017; Correa et al., 2019, 2022).

SAE also runs a *complementary* (second) round after the main match to fill residual vacancies. A recurring concern with two-round designs is that they can reintroduce strategic incentives in the first round: if families anticipate a meaningful second round, they may be tempted to withhold acceptable options from their main-round list in the hope of doing better later, undermining the incentive properties of the main match. The Chilean design addresses this by construction: the complementary round operates only on schools with leftover capacity after the main round and does not reassign students who already hold an offer, so there is little strategic gain from skipping a school in the first round in order to target it in the second. Combined with an unrestricted list length in the main round, this preserves truthful ranking as a weakly dominant strategy across the full application window, a feature of the mechanism that is formally described by the engineering team in Correa et al. (2019, 2022).

The second and third design pillars were coverage and transparency. SAE covers the full publicly funded sector, public and private-subsidized schools alike, under a single platform and a common priority structure. It also publishes clear rules, algorithmic documentation, and results, enabling public scrutiny and reproducibility. For the first time, comprehensive data on student demand, preferences, and school capacity became available to Chilean families and researchers, fostering more evidence-based educational planning (Agarwal and Somaini, 2018). The design thus significantly reduced the scope for arbitrary or opaque school choices and promoted procedural fairness.

Past literature has suggested that limiting the application list to a small number of schools prevents parents from reporting their true preferences, since admission

[2]The author participated in SAE design discussions with MINEDUC in 2014–2015 and worked with Gregory Elacqua during that reform-design period.

Table 1—SAE statistics

	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Panel A: Implementation – First Round										
Regions	1	5	15	16	16	16	16	16	16	16
Schools	63	2,172	6,421	8,064	8,014	7,979	7,941	7,893	7,843	7,760
Applicants	3,436	76,821	274,990	483,070	454,415	461,223	570,891	536,353	473,482	463,923
Panel B: Schools – First Round										
Subsidized	25.4%	32.3%	35.1%	40.4%	40.4%	40.4%	40.5%	40.5%	40.4%	40.4%
Urban	79.4%	45.3%	49.5%	58.9%	59.4%	59.6%	60%	60.3%	60.5%	60.9%
Pre-K	66.7%	49.9%	54%	58.1%	58.7%	59.1%	59.5%	59.9%	60.1%	60.2%
1st Grade	84.1%	87.6%	90.8%	90.1%	90.2%	90.2%	90.2%	90.2%	90.2%	90%
9th Grade	38.1%	22.8%	26.2%	31%	31.2%	31.4%	31.7%	32.1%	32.3%	32.9%
Panel C: Applicants – First Round										
1 application	0.8%	3.7%	4.7%	2.9%	3.5%	3.4%	3%	2.9%	3.3%	3.4%
2 applications	30.2%	26.2%	31%	32.9%	38.1%	37.7%	35.6%	33.8%	35.2%	36.6%
3 applications	30.8%	30.7%	30.7%	28.1%	26.9%	27.4%	27.3%	27.4%	25.4%	25.1%
4 or more applications	38.2%	39.4%	33.7%	36.1%	31.6%	31.4%	34%	35.8%	36.1%	34.9%
Urban†	98.8%	96.4%	93.7%	94.5%	93.8%	93.4%	93.1%	92.9%	93.1%	92.8%
Panel D: Assignment – First Round										
Assigned 1st Preference	59.1	59.3	59.0	52.4	55.1	54.5	47.7	48.5	52.4	52.3
Assigned Up to 3rd Preference	85.2	83.7	83.6	79.8	81.9	82.3	79.1	79.7	82.2	82.6
Assigned to Any Preference	91.2	91.3	91.1	89.6	90.6	91.5	91.2	91.9	92.7	92.8
Unassigned	0.0	8.7	8.9	10.4	9.4	8.5	8.8	8.1	7.3	7.2
Panel E: Non-filled vacancies – First Round										
All	31.6%	49%	56.5%	61%	65.5%	65.8%	63.5%	65.7%	68.1%	69.6%
Magallanes	31.6%	59.5%	63.1%	61.8%	64.6%	64.9%	63.5%	67.3%	71%	73.7%
Iquique	–	34.9%	50.8%	49.6%	48.8%	47.3%	44.7%	45%	49.4%	51.4%
Antofagasta	–	–	27.4%	45.4%	43.5%	47.1%	43.3%	44.7%	45.7%	46.5%
Concepción	–	–	48.4%	68.3%	70.3%	70.9%	70.4%	71.3%	73.3%	74.6%
Santiago	–	–	–	37.5%	57.9%	59.5%	57.2%	59.7%	62.7%	64.4%
Valparaíso	–	–	45.2%	63.5%	67.1%	66.2%	64.2%	66.8%	68.6%	70.3%
Panel F: Assignment - Complementary Round										
Assigned 1st Preference	83.4	83.4	46.6	65.3	72.4	72.3	67.6	72.3	78.9	77.9
Assigned Up to 3rd Preference	96.6	97.4	64.1	86.5	90.9	91.6	88.6	91.3	95.3	94.6
Assigned Any Preference	96.6	97.7	68.4	88.0	91.7	92.6	89.8	92.1	95.9	95.2
Assigned by Distance	3.4	2.3	27.9	10.4	6.7	6.1	7.8	5.4	3.3	3.7
Unassigned	0.0	0.0	3.6	1.6	1.6	1.3	2.4	2.5	0.8	1.1
Unassigned in first round, assigned in second round	51.9	46.5	41.7	49.4	52.7	67.5	58.2	56.7	62.1	62.9
Panel G: Applicant response – Main Round										
Accepts	–	–	53.8%	51.9%	56.5%	54.7%	49.2%	50.2%	52.8%	53.5%
Accepts and remains on waitlist	–	–	15.4%	13%	15.5%	15.4%	17.8%	18.3%	17.5%	21.2%
Rejects	–	–	7%	7.2%	5.8%	6.4%	8%	7.6%	6.8%	6.2%
No response	–	–	14.9%	17.5%	12.8%	15%	16.1%	15.8%	15.6%	11.9%
No assignment	–	–	8.9%	10.4%	9.4%	8.5%	8.8%	8.1%	7.3%	7.2%
Panel H: Applicant response – Post Waitlist										
Accepts	–	–	67.2%	59.3%	64.9%	66.8%	69.8%	71.3%	72.5%	76.2%
Rejects	–	–	0.9%	0.6%	0.4%	0.4%	0.6%	0.3%	0.3%	0.3%
No response	–	–	0.9%	2.1%	1%	1.5%	1.3%	1.8%	1.2%	0.7%
No assignment	–	–	30.9%	38%	33.7%	31.4%	28.3%	26.6%	26%	22.8%
Panel I: Enrollment										
Enrolled in SAE assignment	70.3	77.1	76.1	76.0	78.9	74.1	70.6	72.0	73.2	*
Percentage of new enrollments that got in via SAE assignment	0.3	6.5	22.4	39.4	47.0	36.3	37.3	38.5	37.3	*
Percentage of new enrollments that participated in SAE	0.4	8.5	29.7	53.2	61.0	50.1	54.4	54.5	51.6	*

Notes: Nationwide SAE statistics, 2016–2025. Panel A reports counts of regions, schools, and applicants. Panel B shows school-level shares (subsidized, urban, Pre-K, 1st grade, 9th grade). Panel C summarizes application-list length and share urban. Panel D reports first-round assignment outcomes. Panel E shows the share of non-filled vacancies, overall and by region. Panel F reports assignment outcomes in the complementary round. Panel G reports applicant responses in the main round. Panel H shows the same responses after the waitlist. Panel I reports enrollment outcomes. Cells marked “*” in Panel I require 2026 enrollment records, not yet available. The † in Panel C flags applicants classified as urban/rural by majority vote of the five closest schools.

chances come into play (Calsamiglia, Haeringer and Klijn, 2010). Consequently, the SAE platform does not limit the number of applications families can submit, encouraging truthful reporting of preferences. This does not mean that strategic concerns disappeared. Sibling applications, fallback rules, repeated applications, and the connection between the main round and the aftermarket can still create portfolio incentives that families may not understand well (Gazmuri et al., 2024; Rios et al., 2025). The core design lesson is that reducing strategic behavior requires attention to the whole application environment, not only the main matching algorithm.

Consistent with this concern, Table 1 reveals that many families continue to submit short preference lists. In 2025, 34.9% of applicants listed four or more schools, 25.1% listed three, 36.6% listed only two, and 3.4% listed just one, a pattern that has remained stable over time. These figures indicate that, despite unlimited lists, many families still submit short lists, often due to information gaps, overconfidence, or misunderstanding of the algorithm (Arteaga et al., 2022*a*). Short lists reduce match chances and blunt the practical benefits of the otherwise low-strategy design.

The system includes a legally mandated priority structure. Initially, the highest priority was granted to current students, followed by siblings of enrolled students, children of school staff, and former students. Additionally, specific quotas provided preferential access to high-performing students, socioeconomically disadvantaged students, and those with special educational needs. Currently, the algorithm no longer includes a quota for students with special needs, and schools are permitted to select fewer high-performing students each year. These priorities and quotas are directly embedded in the algorithm, ensuring complete alignment with policy objectives and law. Moreover, the system has proven effective in reducing the share of students who remain unassigned after the main round. As shown in Table 2, in 2025 only 5.4% of primary and 10.3% of secondary applicants in Chile were left unassigned (5.1% and 9.2%, respectively, in Santiago), figures that compare favorably with international experiences where initial non-assignment rates are often substantially higher — e.g., 25% for preschool in Boston (Laverde, 2024), 26% for secondary in Washington D.C. (My School DC, 2024), and 23% for secondary in Kenya (Ndonga, 2014). This relatively low level of non-assignment highlights that, despite the complexity of the priority structure, the centralized mechanism performs well in ensuring that most families secure a school seat in the first stage of the process.

D. Innovative Aspects

One of the most distinctive and pioneering features of the Chilean SAE system is the explicit incorporation of dynamic sibling priority into the school assignment process. Given that the Chilean education law does not include walk-zone

Table 2—Percentage of Students Unassigned Around the World

Country/City	% Unassigned	Level	Mechanism	Year	Sources
Chile	5.4%	Primary	DA	2025	Own estimations
Chile	10.3%	Secondary	DA	2025	Own estimations
Santiago, Chile	5.1%	Primary	DA	2025	Own estimations
Santiago, Chile	9.2%	Secondary	DA	2025	Own estimations
New York City	12.7%	Secondary	DA	2004-2005	Abdulkadiroğlu, Agarwal and Pathak (2017)
Cambridge, MA	10%	Preschool	IA	2004-2008	Agarwal and Somaini (2018)
New Orleans	15%	Primary	DA	2020-2021	NOLA Public Schools (2020)
Ghana	15%	Secondary	SD	2008	Ajayi and Sidibe (2020)
Madrid, Spain	5%	Primary	IA	2016	Gortázar, Mayor and Montalbán (2023)
Kenya	23%	Secondary	SD	2013	Ndonga (2014)
Boston	25%	Preschool	DA	2010-2013	Laverde (2024)
Washington D.C.	26%	Secondary	DA	2023	My School DC (2024)
Manta, Ecuador	21.6%	Preschool & Primary	DA	2021	Elacqua et al. (2024)
Copenhagen, Denmark	5.9%	Secondary	DA	2025	Børne- og Undervisningsministeriet (2025)
Mexico City, Mexico	13.3%	Secondary	SD	2025	Ortega-Hesles and Pariguana (2025)

Notes: This table summarizes reported or estimated rates of unassigned applicants across different centralized school choice systems. The Chilean estimate is based on own calculations using 2025 SAE administrative data. Other entries correspond to published estimates from the cited sources, which vary in year, education level, and definition of "unassigned." In most cases, the estimates reflect initial match outcomes before subsequent administrative placements. Mechanism abbreviations: *DA* = Deferred Acceptance (student-proposing), *IA* = Immediate Acceptance (Boston mechanism), *SD* = Serial Dictatorship by exam or merit score. Percentages might not be directly comparable across settings, since both institutional designs and reporting conventions differ.

preferences and that public school transportation is largely unavailable, assigning siblings to the same school significantly reduces the logistical and financial burden on families.

The SAE mechanism allows families to submit a "family application" expressing a preference for joint assignment across siblings (Correa et al., 2019, 2022). Because the algorithm runs a separate DA process for each grade level, from higher to lower, the older sibling is assigned first, based on their stated preferences and priority order. If matched, the younger sibling's application is dynamically adjusted in two ways: the older sibling's school is moved to the top of the younger sibling's list, and the younger sibling is granted sibling priority at that school. Siblings applying to the same grade also receive almost identical lottery numbers to preserve their relative ordering (Rios et al., 2025).

The current "family application" design simplifies the user interface, but in doing so it constrains how families can communicate their preferences. In effect, it asks families to express only a binary choice, link the children's applications or not, rather than to rank the joint outcomes ("tuples") that the assignment can actually produce: both children at school A, one at A and one at B, one assigned and the other unplaced, and so on. Recent work on the Chilean case documents two costs of this simplification. First, because families cannot directly communicate their preferences over portfolios, the algorithm must impute them, and the imputation does not always reflect what families would have chosen if asked; families learn that certain combinations of choices and the family-application toggle produce systematically better outcomes than others, which creates strategic incentives that the platform was designed to eliminate elsewhere (Gazmuri et al., 2024). Second, eliciting full preferences over assignment portfolios is genuinely hard—the number of relevant tuples grows quickly with the number of children and schools, and the cognitive burden of evaluating them is precisely the kind of friction that motivates the informational tools discussed in Section IV.

The design challenge is therefore not only *whether* to let families express tuple preferences, but *how* to do so in a way that families can understand and act on—a problem formally related to classic treatments of joint preferences (Nguyen and Vohra, 2018). Closely related theoretical work proposes contingent priority structures that allow dynamic sibling priority to flow in any direction, not only from older to younger siblings, and shows in simulation that such designs can substantially increase joint placement and reduce non-assignment among families with multiple applicants (Rios et al., 2025).

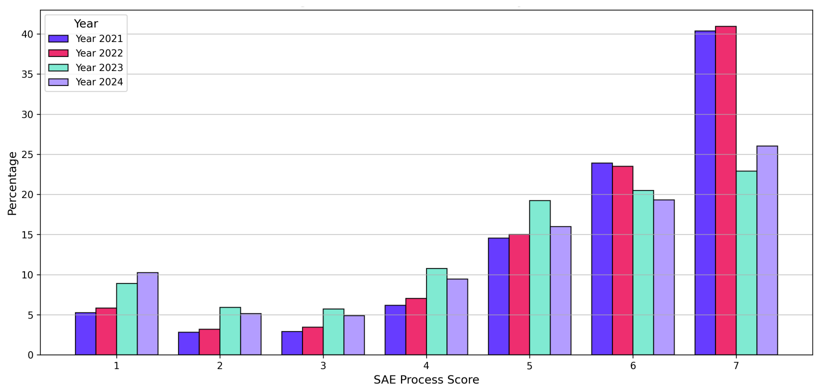
Beyond sibling assignment, the Chilean SAE introduced several other institutional innovations that distinguish it globally. Perhaps the most consequential is its *scope*: SAE applies uniformly to both public and private-subsidized (voucher) schools, covering the entire publicly funded sector under a single platform. This is globally unusual. Most well-known centralized systems cover only a subset of schools: New York City's match applies to public schools but not to charter or private schools that receive public funding; Boston's system similarly covers only the public sector; and many European systems carve out religious or privately managed schools. In Chile, by contrast, every school that receives a public voucher—whether managed by a municipality, by a local education service, or by a private operator—must participate in SAE and follow the same rules. The result is a single national platform that coordinates admissions across roughly 7,900 schools, from Pre-K through 12th grade, ensuring that procedural equity does not depend on school ownership. SAE also made comprehensive data on preferences, capacities, and match outcomes publicly available for the first time, enabling unprecedented transparency, public scrutiny, and policy-relevant research.

Finally, the system deliberately excluded residential proximity (neighborhood-based or distance-based) from the legally mandated priority and quota criteria. Among Latin American centralized systems—including Peru, Ecuador's Manta system, and the systems under development in Colombia—Chile is essentially the only one that does not use residential distance as a priority criterion. This decision reflects an explicit equity-oriented design choice: to decouple school access from residential location and reduce the reinforcing effects of spatial segregation on educational inequality.

Taken together, these innovations position Chile's SAE as a globally relevant model for combining centralized matching algorithms with equity-enhancing policy goals. While excluding distance priorities advances equity, it also raises commuting and coordination costs for some families; the dynamic sibling policy and transparent information tools were designed in part to mitigate these costs by facilitating co-assignment and enabling informed local search. They also show why incentive design is broader than the choice of DA: once applications are linked across children, fallback guarantees, repeated applications, and aftermarket options can create portfolio incentives that require their own diagnosis, simulations, and public rule design.

E. Public Satisfaction and Outcomes

Figure 2. Distribution of SAE Process Ratings by Year



Notes: Distribution of applicant ratings of the SAE application process, by year. Respondents rate the process on a 1–7 scale, with 1 indicating "very bad" and 7 "very good." Data come from an annual repeated cross-section with consistent question wording and sampling methods. Bars show the share of respondents in each rating bin.

In 2022, the SAE received an average satisfaction score of 5.6 on a 1-7 scale, indicating a high level of approval among users. This figure stands out when compared to other public institutions and services evaluated in the same year. For example, *Carabineros* (the national police) received an average rating of 4.4, while the Investigative Police (PDI) scored slightly higher at 4.6, according to the *Paz Ciudadana Index*. The judicial courts fared notably worse, with an average rating of just 3.0 (Fundación Paz Ciudadana, 2025).

To ensure comparability across years, these figures come from a repeated cross-section collected annually using consistent question wording and sampling methods. The satisfaction question asks respondents to rate the SAE application process on a 1-7 scale, with 1 indicating "very bad" and 7 "very good." Where sample sizes allow, satisfaction is moderately higher among higher-SES respondents and in regions with lower non-placement risk, suggesting perceptions track both information and local capacity constraints.

However, Figure 2 shows a recent decline in top ratings (6-7) in 2023-2024, with evaluations shifting toward the middle. Because question wording and methodology remained constant, this likely reflects growing dissatisfaction. Interviews and media narratives suggest two drivers: limited perceived control over admissions and misconceptions about "random tie-breaking," which some interpret as overriding preferences. These concerns have fueled declining confidence despite the system's technical stability and unchanged design. In response, the Ministry expanded communications (tutorials explaining DA, FAQs on priorities), strengthened helpline coverage, and introduced in-platform guidance (risk warnings and feedback reports) to improve understanding and reduce avoidable non-placement risk.

F. Justification and Evidence for SAE

Recent evidence from related centralized systems underscores the efficiency and fiscal benefits of digital assignment platforms. Aguilera et al. (2023) evaluate the implementation of a digital and centralized teacher assignment system in Ecuador and estimate net annual savings of over USD 17 million when transitioning from a decentralized model. These savings include reductions in administrative overhead, applicant search and transportation costs, and unfilled vacancies. Importantly, the reform also improved the quality of matches between teachers and schools, leading to measurable learning gains: better teacher placement under the centralized system increased student achievement by the equivalent of one-third of a school year, generating an additional annual benefit of over USD 12 million. A complementary result from smaller Latin American markets comes from Manta, Ecuador, where Elacqua et al. (2024) document sizable welfare gains from introducing coordinated school assignment.

Although the teacher-assignment evidence concerns a different market, the parallels to student assignment are direct: both reduce frictions, curtail discretion, and improve match quality via algorithmic, rule-based allocation. Translating Ecuador's magnitudes to the Chilean school context suggests analogous channels, lower administrative overhead, reduced applicant travel and search, and fewer unfilled seats, while acknowledging differences in market structure.

Before putting magnitudes on these channels, it is worth noting that the interventions themselves operate at very low cost. The risk-warning pop-up and MIME sit on existing SAE infrastructure, with the bulk of the investment going into one-time engineering and only modest marginal costs per applicant thereafter. This sets a low bar for the cost-benefit exercise: even a small benefit per applicant would compare favorably with the platform's running costs.

The evidence points to economically meaningful benefits, though the magnitudes should be read as an accounting exercise rather than a complete welfare calculation. Combining the platform-embedded warning with SAE's central match highlights three channels. First, the administrative-overhead savings quantified for analogous centralized platforms (Aguilera et al., 2022, 2023) translate to the Chilean context through reduced per-applicant time costs for families and schools, fewer in-person visits, and lower document-handling burden. Second, the warning produces a measurable reduction in non-placement and an improvement in the value-added of the school where compliers eventually enroll; if the follow-up SIMCE estimates are validated in future work, standard returns-to-learning calculations would imply potentially large gains relative to the platform's low marginal cost once the one-time engineering investment is amortized. Third, companion evidence points to distributional gains: a narrowing SES gap in assigned school quality from information interventions (Allende, Gallego and Neilson, 2019) and a roughly 6 pp narrowing of the *prioritario* composition gap at oversubscribed schools by year seven (about a third of the pre-SAE gap between excess-demand and non-excess-demand schools) (Lepe, Muñoz-Ojeda and Neilson, 2026).

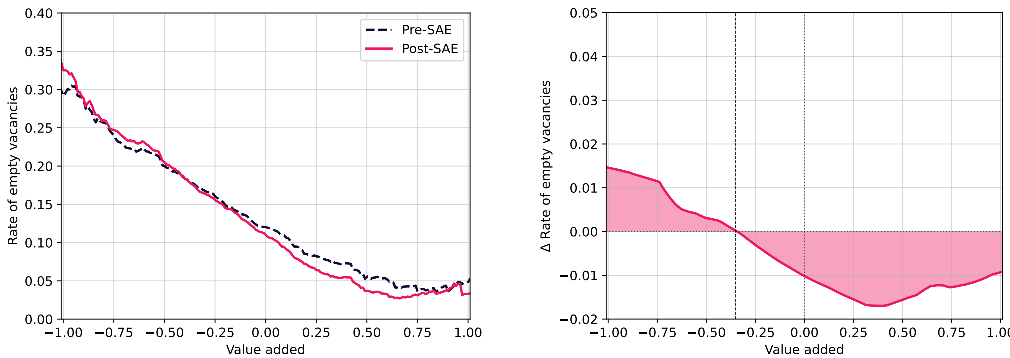
None of these three channels requires expanding school supply or raising per-pupil spending, which is what makes smart matching platforms promising relative to many education interventions in the cost-effectiveness literature: the potential benefits come from *reallocating* existing seats more efficiently and more equitably, at low marginal cost. A fuller welfare accounting, including equilibrium and supply-side responses, is still needed before making strong cost-effectiveness claims. A descriptive look at the data is consistent with this reallocation channel: Figure 3 shows that post-SAE vacancy rates fell weakly at mid-to-high value-added schools and rose modestly at the low end, a pattern one would expect if the centralized match is steering seats toward schools that can use them more productively.

A more detailed decomposition of the distributional gain is developed in the companion working paper Lepe, Muñoz-Ojeda and Neilson (2026). Consistent with the design intent of the 2015–2019 reforms (selection ban, copayment phase-out, and restriction on profit distribution), that paper finds evidence of within-sector segregation declines across multiple school- and comuna-level measures. At the same time, it documents a large supply-side response: an important share of subsidized schools exited to the unregulated fully private sector, attenuating the observed aggregate decline. The policy implication is that uniform assignment reforms may need to be paired with targeted retention or transition instruments for schools with high conversion risk, since endogenous private exit can offset part of the desired equity effects.

G. *Market Dynamics after the Inclusion Law*

The visible congestion at a small subset of schools that drives much of the public criticism of SAE is, in the main, a supply-side phenomenon, not a failure of the

Figure 3. Vacancy rates by school value-added



(a) Rate of empty vacancies

(b) Δ Rate of empty vacancies

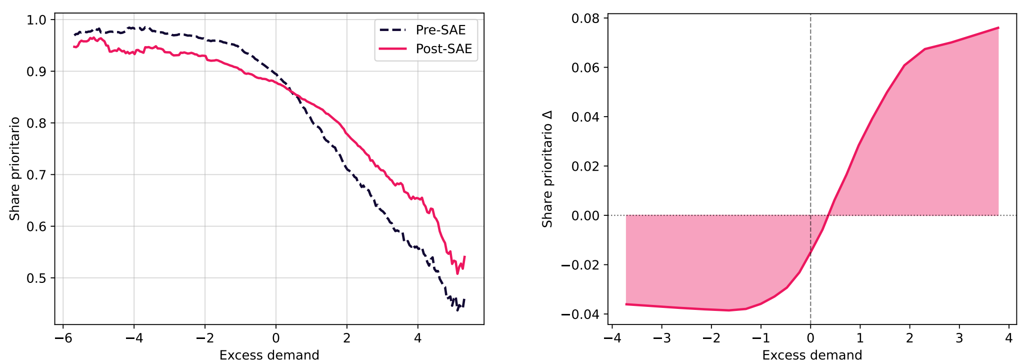
Notes: Sample restricted to public and voucher schools in the Metropolitan Region (934 schools). Panel (a) plots a non-parametric local-mean estimate of the rate of empty vacancies as a function of school value added in the pre-SAE (2019) and post-SAE (2020) periods, using a 0.75-wide moving window over value added and dropping bins with $\leq$ 10 schools. Panel (b) plots the corresponding post $-$ pre difference, smoothed with a 30%-span moving average. Post-SAE vacancy rates lie weakly below pre-SAE at mid-to-high value added and modestly above at the low end, a pattern consistent with fewer empty seats at higher-value-added schools. Interpretation is descriptive; estimates should not be read as causal effects. Data and value-added approach follow Aguilera et al. (2023).

assignment mechanism. Before turning to the effects of SAE on the composition of students at oversubscribed schools, it is important to document how the broader *supply* of school seats evolved over the decade following the *Ley de Inclusión*. SAE governs which students are assigned to which schools; it does not govern how many schools exist, how many seats they offer, or whether new schools open to absorb growing demand. Any assessment of what the platform has or has not achieved must therefore distinguish between changes driven by the assignment mechanism and changes driven by the evolving structure of the school market.

The *Ley de Inclusión* (Congreso Nacional de Chile, 2015) did not only reform admissions. It required all publicly funded schools to operate as non-profit entities, phased out family copayments (*financiamiento compartido*), and prohibited academic and socioeconomic selection. For the private-subsidized (voucher) sector, which at its peak enrolled roughly 57% of Chilean students, these provisions fundamentally altered the business model. Schools that had operated as for-profit enterprises were required to convert to non-profit status or exit the publicly funded system. Schools that had relied on copayment revenue faced a gradual elimination of that income stream. And schools that had used selective admissions to curate their student body lost that ability entirely.

The supply-side consequences are visible in Figure 5. Before the Inclusion

Figure 4. Share of prioritario students by school excess demand



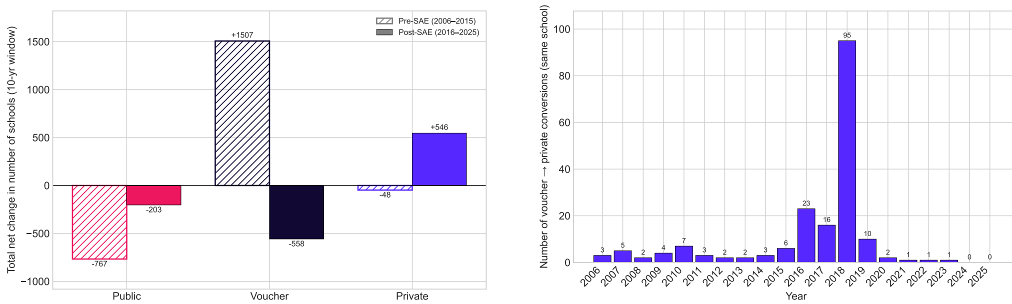
(a) Share prioritario (b) Δ Share prioritario

Notes: Sample of SAE-universe schools nationwide with non-zero applications (7,079 schools). Excess demand is measured at the school level as $\log_2$(apps/vacancies) at the school's first SAE process year, with positive (negative) values indicating excess demand (slack). Panel (a) plots a non-parametric local-mean estimate of the share of *prioritario* students per school in the pre-SAE (2013) and post-SAE (2023) periods, using a 0.75-wide moving window in $\log_2$ units. Panel (b) plots the corresponding post − pre difference, smoothed with a 30%-span moving average. Data and approach follow Lepe, Muñoz-Ojeda and Neilson (2026).

Law, Chile's school market was expanding: between 2006 and 2009, the voucher sector added a net 60–95 schools per year. After 2015, the pattern reverses. Net entry turns negative and stays negative through most of the subsequent decade. Between 2014 and 2023, the voucher sector lost roughly 80 more schools than it gained, a cumulative contraction that was not offset by entry in the public or private sectors. At the same time, exit of voucher schools continued at a pace similar to or slightly above pre-reform levels, while new entry essentially stopped.

The accumulated effect of this contraction is a measurable shift in the composition of Chile's school market, with the private (non-subsidized) sector — which operates entirely outside SAE — absorbing a growing share of enrolment. Figure D7 traces the private share of K–12 enrolment over 2010–2025 for Chile and each region. Nationally, the private share rose from 7.5% to 10.6% (+3.0 pp, +40% relative), with most of the gain concentrated in the post-SAE rollout years (2016–2018). The pattern is highly heterogeneous across regions: in Magallanes the private share climbed from 7.5% to 15.1% (+7.7 pp, +103%); in Coquimbo and Tarapacá it nearly tripled off lower bases (+5.5 pp / +168% and +2.6 pp / +114%, respectively); Biobío and Los Ríos grew by +68% and +73%; and the Metropolitan Region, which already had the largest private sector in the country, expanded from 12.0% to 16.2% (+4.2 pp, +35%). These shifts are uneven on the ground: in some markets the exit of even a few voucher schools

Figure 5. Supply-side response to the Inclusion Law: net school flows and voucher-to-private conversions



(a) Net change in number of schools by sector, 10-year windows pre vs post SAE

(b) Voucher-to-private conversions per year (same school)

Notes: Panel (a) reports the net change in the number of operating schools by sector over two 10-year windows: pre-SAE (2006–2015, hatched) and post-SAE (2016–2025, solid). Panel (b) reports same-school voucher-to-private conversions per year. Own calculations from the Mineduc *Directorio Oficial*.

creates acute scarcity, while in others excess capacity persists. Table 3 makes this explicit: outside the Metropolitan Region, the comunas with the lowest first-round matching rates (Pica, Zapallar, Concón, Algarrobo, and others) post Apps/Seat ratios above one and unassignment rates of 13–19%, well above the 7.4% non-Metropolitan benchmark. Their unassignment is driven primarily by a thin local supply of seats relative to demand, not by applicant behaviour.

The resulting problem is not only the national number of seats. It is a local and quality mismatch: many seats remain empty in some schools or markets while other neighborhoods have too few of the options families most want. The pre-reform voucher market gave private operators stronger incentives to enter where demand was growing; the post-Inclusion Law environment appears less able to generate that response automatically. That does not make local scarcity an algorithmic failure, but it does make supply-side adjustment central to the next generation of policy.

Appendix Figure D5 illustrates the geographic concentration of scarcity. The heatmaps show predicted non-placement risk by neighborhood for four urban markets, Iquique and Alto Hospicio, Valparaíso, Concepción, and Santiago. Non-placement is not uniformly distributed: it concentrates in fast-growing periurban areas and in neighborhoods where voucher school exit has reduced the local supply of seats. In Santiago, for example, risk is highest in the eastern periphery (Chicureo, La Florida, Puente Alto) and in municipalities where demographic growth has outpaced the supply of new schools.

Table 3 reports the ten comunas with the highest first-round unassignment rates in the 2024 SAE process (admission 2025), excluding the Metropolitan Region so that the table surfaces patterns outside the capital. The picture is consistent with the heatmaps: small fast-growing or peripheral comunas where local supply has not kept up (Pica, Zapallar, Concón, Algarrobo, Machalí), and larger regional capitals where mismatch between specific schools and applicants drives non-placement even when aggregate Apps/Seat is below one (Punta Arenas, Antofagasta, Puerto Varas, Ovalle, San Pedro de la Paz).

Table 3—Top 10 comunas by SAE first-round unassignment rate, excluding the Metropolitan Region (admission 2025)

Market	Applicants	Seats	Apps/Seat	Unassignment rate
Pica	573	395	1.45	18.5%
Zapallar	566	303	1.87	17.1%
Punta Arenas	3,552	7,555	0.47	15.0%
Puerto Varas	2,303	2,039	1.13	14.9%
Antofagasta	14,944	15,762	0.95	14.4%
Concón	1,383	1,462	0.95	14.4%
San Pedro De La Paz	4,950	5,490	0.90	13.7%
Machalí	1,877	1,967	0.95	13.4%
Algarrobo	1,066	618	1.72	13.3%
Ovalle	4,598	8,723	0.53	13.2%
All Chile (ex. Metropolitana)	306,599	766,047	0.40	7.4%

Notes: Markets are comunas, identified by the location of the school. The Metropolitan Region is excluded so that the table reflects unassignment patterns outside the capital. For each comuna M: *Applicants* is the number of unique applicants in the 2024 SAE regular round (admission 2025) who submitted at least one application to a school in M; *Seats* is the total *vacantes* offered by schools in M; *Apps/Seat* is the ratio of the two; and *Unassignment rate* is the share of those applicants who received no SAE assignment in the regular round (no *rbd admitido* in the public results file). Because applicants can apply to schools in more than one comuna, an individual is counted in every comuna where they applied, so per-comuna totals do not sum to the *All Chile (ex. Metropolitana)* reference row, which counts each applicant once across all non-Metropolitan comunas. No minimum-size filter is imposed. Own calculations from Mineduc public SAE files.

These market dynamics are not attributable to SAE. They are consequences of the broader regulatory transformation enacted by the Inclusion Law, the non-profit conversion requirement, copayment phase-out, and selection ban, together with demographic shifts that no assignment mechanism can absorb on its own. They do, however, shape what SAE can and cannot deliver, and they have shaped the public perception of the system. When local supply contracts and a well-functioning centralized match produces visible non-placement, media coverage frequently attributes the shortfall to "the algorithm" or "the lottery" rather than to the underlying supply problem. Disentangling the two is essential for an honest evaluation of the platform.

H. Evidence on SAE's Segregation Effects

Chilean schools entered the SAE era from an unusually segregated baseline. Valenzuela, Bellei and Ríos (2013) document that Chilean schools were among the most socioeconomically segregated in the OECD comparison, an equilibrium that the pre-reform market-oriented voucher system (with family copayments, for-profit school operation, and discretionary admissions) had reinforced for more than two decades.

Contreras, Sepúlveda and Bustos (2010) provide direct evidence of the underlying channel: using a 2005 SIMCE parent-survey module on school admission requirements, they show that academic and socioeconomic screening was a widespread practice in the private-subsidized sector, and that the 7–9% test-score advantage of schools using selection criteria was a sorting artifact rather than a quality effect. The *Ley de Inclusión* and SAE were explicitly designed to dismantle this screening channel, together with the copayment and for-profit features that sustained it.

Mechanism-design theory predicts that replacing discretionary selection with a lottery and vulnerable-student priorities should narrow the compositional gap precisely at the oversubscribed schools where screening previously bound (Pathak and Sönmez, 2013; Correa et al., 2022). But the same literature warns that centralized assignment alone is insufficient: when families hold biased beliefs about admission chances or about the quality of nearby schools, the resulting sorting can reproduce substantial segregation even under strategy-proof mechanisms (Calsamiglia, Martínez-Mora and Miralles, 2021; Allende, Gallego and Neilson, 2019; Agte et al., 2024; Allende et al., 2023). The predicted effect of SAE is therefore bounded: narrowing where the algorithm binds, with limited aggregate reach through residential sorting, the unregulated fully private sector, and the information frictions that shape which schools families consider in the first place.

The empirical evidence on SAE's segregation effects is broadly consistent with this bounded-reach prediction, and the apparent tension in the literature is easier to interpret once the measurement target is clarified. Identifying the aggregate segregation effect of the full reform package is difficult because the Inclusion Law changed selection, copayments, and profit status nationally, while SAE's assignment platform arrived through a staggered regional rollout. Kutscher, Nath and Urzúa (2023) evaluate the national reform and conclude that aggregate socioeconomic segregation did not fall and may have risen modestly after accounting for supply-side reallocation. Lepe, Muñoz-Ojeda and Neilson (2026), in a companion working paper that triangulates school-level, comuna-level, and national measures, find that the share of *prioritario* students at oversubscribed schools converged toward the non-oversubscribed counterfactual by roughly 6 percentage points by year seven—closing about a third of the pre-SAE gap ($\sim$17 pp in 2013) between excess-demand and non-excess-demand schools—and that comuna-level marginal-invariant indices (Duncan D and Theil H) declined by about 5–8% of baseline; they also document a simultaneous "escape-valve" exit of elite subsidized schools to the fully private-paid sector that offsets part of the aggregate gain. Huerta Retamal (2021) reach a broadly consistent reading in an earlier-window analysis. These studies are more complementary than competing: Kutscher, Nath and Urzúa (2023) measures the national aggregate, Lepe, Muñoz-Ojeda and Neilson (2026) decomposes the aggregate into a within-SAE-universe gain and a between-sector offset, and Huerta Retamal (2021) corroborates the early within-system signal.

Similar bounded-reach patterns appear in centralized-choice settings outside Chile: Campos and Kearns (2023) show that Los Angeles' *Zones of Choice* delivered measurable within-school quality gains without meaningfully reducing racial or socioeconomic segregation in the affected neighborhoods, because residential sorting continued to dominate the compositional margin; Idoux (2022) reaches a similar conclusion for New York City, where reform of selective-school admissions criteria moved school composition only modestly because the underlying preference and residential structure continued to bind.

The practical implication is that SAE appears to deliver a real but bounded equity gain at the margin where it operates. Residential stratification, the parallel unsubsidized private sector, and the elite-exit margin lie outside the perimeter the assignment mechanism can reach. As a result, access to high-value-added schools may improve in some local markets where the mechanism opens oversubscribed seats to priority students, while deteriorating or improving less in places where desirable subsidized supply exits the regulated sector. Closing those margins requires complementary policy instruments: expanded vulnerability quotas, investments in undersubscribed school quality, widening of the regulatory perimeter, retention or transition tools for high-demand subsidized schools, and the information interventions reviewed elsewhere in this paper.

This bounded-reach framing, of a mechanism operating where it has room to act inside a market whose broader structure continues to produce the patterns SAE was designed but not empowered to undo, is the interpretive frame I return to in Section VI.

III. Behavioral Frictions and Policy Responses

This section reports the third act of the retrospective: what a decade of measurement revealed about how families search and apply for schools. The central finding is that families do not behave as a frictionless model would predict, and that the biases they carry are unequally distributed across households—a source of information-driven structural inequality that complements the strategy-proof design of the mechanism rather than substituting for it.

A growing body of evidence shows that biased beliefs, limited search, and informational frictions distort high-stakes decisions in health, housing, and education, and that these frictions disproportionately affect lower-income populations.[3] I study these dynamics in the context of Chile's centralized school assignment system. While the system removes many structural barriers to school choice, families still face significant informational frictions (Agte et al., 2024). Using linked administrative application data, novel household surveys, and detailed search activity from a custom-designed "School Explorer" platform, the research shows that families systematically misperceive the local school market, consistent with evidence that improved information shifts school choices and outcomes, and that truthful ranking under strategy-proof mechanisms delivers welfare gains even with biased beliefs (Kapor, Neilson and Zimmerman, 2020).

Figure 6 summarizes the smart-platform model that connects these behavioral frictions to the policy responses reviewed in this section and the next. The platform guides families from registration through enrollment while using administrative data to surface search insights, personalized recommendations, and real-time feedback on predicted assignment risk.

A. *Conceptual Framework*

Arteaga et al. (2022*a*) formalize the first warning intervention as a portfolio-choice problem under Deferred Acceptance, and Agte et al. (2024) extend the same logic into a richer sequential-search model with subjective beliefs. The full structural model includes information states, search costs, and beliefs about unknown schools; the core intuition needed here is simpler. Under DA, truthful ranking is optimal conditional on the family's information, so the remaining decision is how large and how safe a portfolio of ranked schools to assemble.

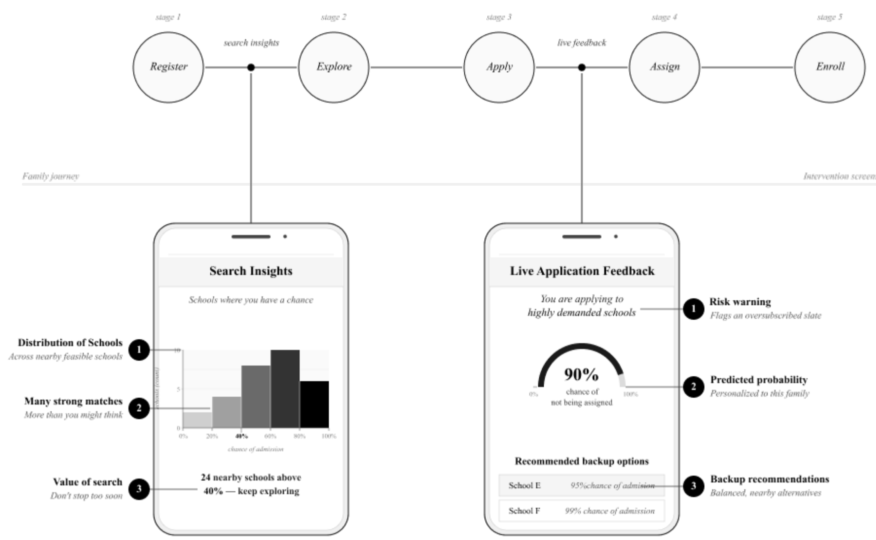
Let the family's current list be $\mathcal{C}_0 = \{1, \dots, N_0\}$, ordered by subjective utility $u_1 > \cdots > u_{N_0} > 0$ relative to non-placement. Let p_j denote the family's perceived probability of admission to school j, and $R_j = 1 - p_j$ its perceived rejection probability. The expected subjective value of the portfolio is

$$V(\mathcal{C}_0) = \sum_{j=1}^{N_0} p_j u_j \prod_{j'<j} R_{j'}. \tag{1}$$

The expression makes the portfolio nature of the application problem explicit: the value of each lower-ranked school is multiplied by the probability of being rejected by every school above it. Admission beliefs therefore affect not only whether a

[3] Examples include misperceptions about health insurance plan attributes (Abaluck and Gruber, 2011), biased beliefs about returns to schooling (Jensen, 2010), and the large effects of simplified school quality information on application behavior and student outcomes (Hastings and Weinstein, 2008).

Figure 6. The Smart Matching Platform: from registration to enrollment



Notes: The platform guides families through a five-stage sequence—Register, Explore, Apply, Assign, Enroll—with a virtual application assistant that provides real-time feedback on predicted match outcomes, personalized school recommendations, and risk warnings at each stage. This proactive informational layer is the defining feature of what this paper calls a *smart matching platform*.

particular school looks attractive, but also the marginal value of adding another school to the list.

Search continues when the expected gain from discovering one more school exceeds the search cost κ. If a new school s is drawn from the family's perceived distribution of available options, $F_{p,u}$, the one-step stopping rule is

$$U[\text{Search} \mid \mathcal{C}_0] = \iint \big(V(\mathcal{C}_0 \cup \{s\}) - V(\mathcal{C}_0)\big)\, dF_{p,u} > \kappa. \tag{2}$$

This is why beliefs matter even in a low-strategy mechanism. SAE's incentive design greatly reduces the payoff to reordering strategically, but it does not tell families which schools are feasible, which unknown schools are worth searching for, or whether the current list leaves them exposed to non-placement.

The first warning paper's key behavioral mechanism is biased optimism about admission chances. Let starred values denote true probabilities. If families underestimate rejection risk by a factor $a \in (0,1)$, so that $R_j = (1-a)R_j^*$, then perceived non-placement risk for the whole portfolio is

$$RISK_0 = \prod_{j=1}^{N_0} R_j = (1-a)^{N_0} RISK_0^*. \tag{3}$$

Because the bias compounds once per listed school, even modest optimism creates a large gap between perceived and true exposure. With $a = 0.3$ and a five-school list, perceived risk is only $(0.7)^5 \approx 17\%$ of the true value; a family whose application truly carries a 30% non-placement risk perceives a risk of about 5%. That gap shrinks the perceived return to adding another school, triggers the stopping rule too early, and generates short, top-heavy lists. The behavior can look like inattention or weak demand for quality, but in the model it is a rational portfolio decision made under biased beliefs.

The same portfolio logic organizes the broader search evidence. When families overvalue schools they already know or underestimate the quality, affordability, or feasibility of unknown nearby schools, $V(\mathcal{C}_0)$ looks too high and $F_{p,u}$ looks too poor, so the perceived gain from additional search falls below κ even when the true gain remains large. Risk warnings target the biased-probability channel in equation (3); MIME and personalized report cards target the beliefs about school attributes and the distribution of unknown options. The common lesson is that small corrections to beliefs can generate large application responses because they enter a multiplicative portfolio problem, not a one-school choice problem.

B. *Evidence on Biased Beliefs from MIME*

In collaboration with the Ministry of Education, my collaborators and I implemented a large-scale field experiment embedded within the national school application platform, designing and launching a new school search tool known as MIME. The tool provided families with personalized school recommendations based on proximity, academic quality, predicted admission chances, and net tuition cost. Appendix Figure D1 shows the MIME interface. The tool was made accessible to a randomly selected group of users during the application process, reaching over 3,100 families who formed the core of the analysis. In parallel, prior information interventions relied on a personalized "report card" (cartilla) summarizing nearby options; Appendix Figure D4 illustrates the format used in those treatments.

In parallel, a survey was conducted to measure parents' beliefs about the local school market. The survey asked parents to estimate how many schools were nearby and how many met basic quality, cost, and availability criteria. Several months before the application deadline, families were invited to use the "School Explorer." Parents were randomly assigned to: (i) personalized information on the distribution of school prices and quality within 2 km of the home, or (ii) the same plus a map highlighting low-price, high-quality schools. This design tests whether correcting beliefs changes search behavior.

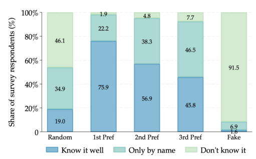
As panel (a) of Figure 7 shows, on average, parents know by name fewer than 50% of randomly sampled nearby schools and know well fewer than 20%. Even among listed preferences, knowledge declines sharply: 76.8% of families report knowing their first choice well, compared to 45.3% for their third ranked option.

Moreover, belief errors are widespread. Parents underestimate the number of high-quality or free schools within 2 km of their home by approximately five schools (panel (b) of Figure 7), reporting that only 55% of nearby schools are free when the actual figure is 86% (panel (c)). In addition, parents systematically mispredict placement probabilities, displaying both upward bias and "compression" in beliefs regarding admission chances (panel (d)).

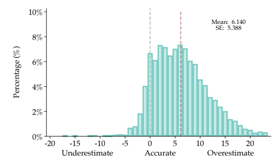
Furthermore, they tend to overestimate the quality of their intended top-choice school and overestimate tuition prices for known schools. These perception errors are not randomly distributed: high-SES parents have more accurate beliefs about quality and price, while low-SES parents are more prone to misperceptions but slightly more accurate about admission chances.

These biased beliefs, especially those about admission chances, reduce the perceived benefits of continued search, leading families to settle on a limited set of options (Agte et al., 2024). As a result, the theoretical benefits of the strategy-proof assignment mechanism are not fully realized: families acting on incorrect beliefs may misallocate applications and fail to find the best available

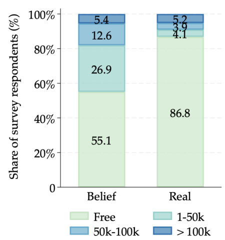
Figure 7. Key Behavioral Frictions Affecting School Choice



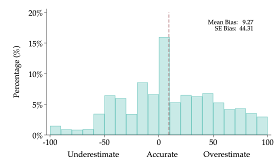
(a) Fact 1: Knowledge of nearby/chosen schools



(b) Fact 2: Underestimating quality supply



(c) Fact 3: Biased price beliefs (1st choice)



(d) Fact 4: Beliefs about admissions chances

Notes: Panel (a) shows reported knowledge of a random nearby school, the top three ranked schools, and a fake school. Panel (b) shows the bias in the beliefs of the number of highlight-worthy schools within 2km of the parent's home. Panel (c) shows the perceived (left) and actual (right) share of schools in each of the four school price categories. Panel (d) plots the baseline bias in perceived placement chances for the first-choice school, defined as perceived minus true probability.

matches. Appendix Figure D2 provides a visual timeline summarizing the mechanisms predicted by the model throughout the intervention.

The interventions demonstrate that the treatments increased perceived numbers of nearby highlight-worthy schools (by up to 23%), especially among high-SES households. High-SES parents in the first treatment arm reported knowing 38% more schools by name and were more likely to apply to higher value-added schools. Effects on low-SES families' search activity were positive but more modest at this early stage.

Agte et al. (2024) estimate the structural model described in Section III.A (with details in Appendix A) to quantify the welfare effects of different frictions. Holding search costs constant, correcting misperceptions about observable attributes of *known* schools (quality scores and prices) yields 45% of the welfare gains from a full-information benchmark and would close the SES gap in assigned school quality entirely.[4] Symmetrically, if misperceptions are left uncorrected, achieving comparable welfare gains through reduced search costs would require a 95% cost reduction. This underscores the complementarity between accurate beliefs and

[4]Providing correct perceptions and rational expectations would achieve 60% of the total welfare gains of a full-information zero-search-cost benchmark.

search technology.

Overall, the Chilean case illustrates that the theoretical benefits of centralized, strategy-proof school choice mechanisms can be undermined by biased beliefs and limited search, particularly among disadvantaged families. Evidence from the SAE platform shows that low-cost, scalable interventions—ranging from aggregate information displays to personalized risk warnings—can significantly improve search behavior, application quality, and match outcomes.

C. *Impact of Providing School Information*

Whether low-cost information tools could meaningfully change how families choose schools was an open question when SAE was being designed. Allende, Gallego and Neilson (2019) provided the first experimental answer for Chile. In an RCT targeting parents at public Pre-K centers (Integra network, ≈30% of public Pre-K enrollment), families received a short video emphasizing the returns to school quality together with a personalized "report card" listing nearby schools' test scores and tuition. Table 4 summarizes the results. Treated families chose schools with higher value-added, traveled slightly farther, and were more willing to pay above the voucher level—effects concentrated among families not yet enrolled at baseline. A five-year follow-up shows that these initial choices translated into statistically significant gains on standardized tests for the not-yet-enrolled subgroup, indicating that the intervention produced lasting improvements in learning outcomes.

A structural model of school choice and competition estimated alongside the RCT suggests that a national rollout would preserve roughly half the experimental effect after accounting for capacity constraints and supply-side responses (with quality improvements more than offsetting congestion), and would reduce the socioeconomic achievement gap (Allende, Gallego and Neilson, 2019). These findings provided the direct motivation for building personalized information tools into the SAE platform.

D. *Spillover and Congestion Effects at Scale*

A natural concern with information interventions is that individual-level gains may come at the cost of congestion: if many families simultaneously redirect applications toward the same high-quality schools, the net welfare effect could be smaller, or even negative, for untreated families. Allende et al. (2023) address this question directly with a multi-level RCT embedded in SAE.

The experiment randomized roughly 280,000 Pre-K applicants in Santiago at two levels: geographic clusters of families were assigned to treatment or control (with buffer zones to limit contamination), and within some clusters, individual

Table 4—Impact of Information Provision on School Choice Characteristics and Academic Outcomes

	Characteristics of Chosen Schools						Student Own Test Scores	
	Distance	Price > 0	Lang 2nd	Lang 4th	Math 4th	VA	Lang 4th	Math 4th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Treatment	0.1371**	0.0438	0.0108	0.0107	0.0147	0.0274	0.0601	0.0952*
	(0.0595)	(0.0354)	(0.0224)	(0.0275)	(0.0293)	(0.0273)	(0.0582)	(0.0540)
N obs.	1,378	1,775	1,758	1,752	1,752	1,752	1,586	1,586
Panel B: Already enrolled								
Treatment	-0.0843	0.0091	-0.0123	-0.0097	-0.0348	-0.0320	-0.0734	-0.0780
	(0.1234)	(0.0522)	(0.0430)	(0.0489)	(0.0570)	(0.0496)	(0.1164)	(0.0983)
N obs.	487	596	589	590	590	590	541	531
Panel C: Not enrolled								
Treatment	0.2390***	0.1198***	0.0591**	0.0377	0.0658*	0.0718**	0.1782**	0.1771**
	(0.0658)	(0.0399)	(0.0268)	(0.0323)	(0.0386)	(0.0345)	(0.0820)	(0.0691)
N obs.	780	975	967	961	961	962	863	870

Notes: This table reports treatment effects from Allende, Gallego, and Neilson (2019, 2021) on a range of outcomes related to school selection and student test scores. Panel A shows effects for the full sample, Panel B restricts to families already enrolled in the system, and Panel C to those not yet enrolled. The intervention increased the likelihood of choosing more distant and costly schools and improved subsequent test scores—especially among the not-enrolled subgroup. Standard errors are in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

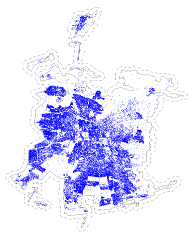
families were cross-randomized to allow estimation of both market-level and individual-level effects. Treated families received a personalized report card highlighting safer nearby schools; a parallel WhatsApp campaign reached 53,000 families in entry grades. Figure 8 illustrates the design.

Table 5 reports the individual-level IV estimates. Opening the report card raised the probability of changing the application by 17 pp, with the effect driven primarily by adding schools (+15 pp) and adding schools recommended by the report card (+12 pp). Non-assignment risk fell by 3.4 pp.

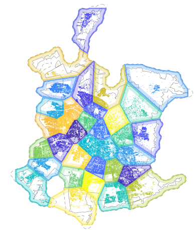
The more novel finding concerns equilibrium effects. Table 6 compares outcomes across treatment and control clusters, and the contrast with the individual-level results in Table 5 is what gives the experiment its leverage: while treated families improved their own assignment prospects, families in nearby untreated clusters experienced higher non-assignment risk. Congestion effects dominate spillovers, because treated families competed for the same limited capacity that would otherwise have absorbed untreated applicants.

The methodological implication is important. The authors show that a conventional small-scale RCT would have overstated the benefits of information provision by failing to capture these dynamics; simulation-based counterfactuals suggest that ignoring equilibrium effects leads to upwardly biased treatment effect estimates. For platform design, this points toward deploying information tools

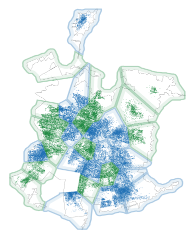
Figure 8. RCT Design Overview: From data gathering to randomization at the market and individual level



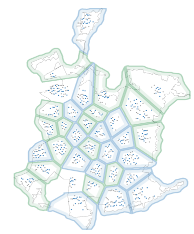
(a) Step 0: Information on all school applicants



(b) Step 1: Clustering of applicants into local markets



(c) Step 2: Market-level random assignment to treatment and control



(d) Step 3: Individual-level treatment within markets

Notes: This figure illustrates the experimental design used in the school choice RCT. Applicants were first mapped (Panel (a)) and clustered into geographically defined local markets using a density-based clustering algorithm (DBSCAN, Panel (b)). Markets were then randomly assigned to treatment or control, with buffer zones constructed to minimize spillovers across market boundaries (Panel (c)). Within selected markets, individual applicants were further randomized to treatment or control at a minimum distance of 0.5 km apart to allow for estimation of individual-level effects net of within-market spillovers (Panel (d)). Families in treatment groups received a personalized report card highlighting safer nearby schools.

broadly rather than narrowly, so that the gains are less likely to be redistributed through congestion.

The study shows that while personalized information can improve application behavior and outcomes, its large-scale deployment must consider congestion dynamics inherent in capacity-constrained assignment systems. Ignoring those dynamics may overstate the efficacy of interventions and inadvertently worsen outcomes for non-treated individuals.

IV. Unassignment Risk Warnings

Building on Section III, this section reports the platform-embedded tool that operationalized the discovery, the risk-warning pop-up, and reviews the evidence on application, enrollment, and follow-up learning outcomes, including an out-of-

Table 5—Individual Effects IV: Application behavior

	Change application (1)	Add school (2)	Add school from RC (3)	Delete school (4)	Δ Risk (5)
Open	0.171***	0.153***	0.122***	0.037***	-0.034***
	(0.024)	(0.023)	(0.019)	(0.010)	(0.006)
Observations	53,325	53,325	53,325	53,325	53,324
R-squared	-0.007	-0.007	-0.003	0.000	-0.001
Control mean	0.071	0.056	0.040	0.020	-0.006
C-D F statistic	1678	1678	1678	1678	1679
Market-Strata FE	YES	YES	YES	YES	YES
Individual-RC	YES	YES	YES	YES	YES

Notes: This table presents an instrumental variable (IV) analysis of the effect of opening the report card on application behavior, using WhatsApp assignment and cluster assignment as instruments. The table includes five dependent variables, reported in columns (1) to (5), respectively: an indicator of changing something in the application, an indicator of adding a school, an indicator of adding a school shown in the report card, an indicator of deleting a school, and the change in predicted non-placement risk (Δ Risk). Cluster-robust standard errors are reported in parentheses. The control mean reported is the mean of the dependent variable among students who received the control report card and did not open it.

sample RD replication through 2023 and a new linkage to fourth-grade SIMCE scores (Arteaga et al., 2026).

As Chile scaled SAE, policymakers encountered a persistent challenge: despite the platform's strategy-proof design and the removal of application limits, a significant number of families continued to submit overly short or risky preference

Table 6—Congestion Effects IV

	Change Application			Not Assigned		
	All	Cluster C	Cluster T	All	Cluster C	Cluster T
Open	0.167***	0.328***	0.141***	-0.043*	-0.200*	-0.011
	(0.025)	(0.113)	(0.022)	(0.026)	(0.112)	(0.022)
Observations	28,289	14,974	13,241	28,289	14,974	13,241
R-squared	-0.011	-0.016	-0.006	0.295	0.285	0.297
Control mean	0.070	0.071	0.052	0.160	0.161	0.141
C-D F statistic	1124	330	881	819	249	691
Market-Strata FE	YES	YES	YES	YES	YES	YES
Individual-RC	YES	YES	YES	YES	YES	YES

Notes: Standard errors are in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Estimates are instrumental-variable (IV) coefficients using cluster-level randomization as instruments. Market-strata fixed effects (FE) and individual report-card controls (RC) are included. The "Change Application" outcome indicates whether families modified their rank-order list, while "Not Assigned" reflects applicants left without an offer after the main round.

lists (see Appendix Figure D5). Motivated by survey evidence and theoretical work showing that families often hold overly optimistic beliefs about their placement chances and end their search prematurely (Agte et al., 2024; Arteaga et al., 2022*a*), the Ministry of Education introduced a novel policy tool: warnings issued when assignment chances are low. These pop-up messages, embedded within the online application platform, delivered real-time, personalized feedback on non-placement risk to families submitting high-risk applications. The goal was simple but powerful: prompt applicants to expand their preference lists and reduce the likelihood of remaining unassigned. Appendix Figure D3 shows how the warning interface evolved over successive cycles.

A. *Early Pilots (2016–2017)*

As part of this pilot, the Ministry tested an early version of behavioral "warning" nudges. These real-time messages provided feedback on the current application portfolio. The goal was to reduce non-placement risk by encouraging families to add more schools. The Ministry randomly assigned applicants into five groups: a control group that received no message and four groups that each received a different framing. These included prompts emphasizing that adding more schools increases admission chances, suggesting a broader range of school types, and highlighting the behavior of "Role model" applicants who successfully secured placements (Appendix Figure D3).

Table 7 reports the intent-to-treat estimates from this randomized controlled trial. The pooled estimate in column (1) indicates that receiving any nudge increased the likelihood of adding at least one new school by 1.5 percentage points relative to the control group. When focusing only on applicants facing a measurable risk of non-placement (column 2), the effect rises to 2.7 percentage points, suggesting that the intervention was more relevant and effective for higher-risk applicants.

The column-wise heterogeneity in Table 7 carries a practical signal for what should come next. The largest point estimates appear when restricting to applicants with any measurable non-placement risk (column 2, 2.7 percentage points versus 1.5 pp pooled) and in the "role-model" arm (column 5, 3.1 pp), while the more generic "add more schools" and "consider your range" variants produced smaller effects that are statistically indistinguishable from zero at conventional levels. The pattern is consistent with two ideas that shaped the subsequent design. First, message framing matters: a relatable, narrative-style prompt moved behavior meaningfully more than a bare instruction to lengthen one's list. Second, and more importantly, the behavioral lever has its clearest bite among families who actually face a non-trivial risk of non-placement, exactly the subpopulation that a well-calibrated, personalized warning could target directly.

Taken together, these patterns pointed toward a natural next question: would

Table 7—RCT Estimates of Behavioral Nudge Effects (2016 Pilot)

	Pooled (1)	**Risk > 0.01** (2)	**More schools** (3)	**Range** (4)	**Role model** (5)
Add any	0.015	0.027	0.006	0.008	0.031
	(0.009)	(0.018)	(0.012)	(0.012)	(0.013)
N treatment	1,402	479	463	455	484
N control	648	215	648	648	648

Notes: RCT effect estimates for behavioral nudge interventions conducted as part of the 2016 choice process. These interventions encouraged people to add schools to their lists but did not include information on non-placement risk. The sample is limited to the Magallanes region, which was the only region with centralized choice in 2016. Estimates are differences in the share of students adding any school to their baseline application between the treatment group and a control group that did not get any message. Columns (1) and (2) are pooled estimates of the treatments from columns (3)–(5). Column (2) limits the sample to applicants facing nonzero application risk.

a message personalized to an applicant's *own* non-placement risk outperform the generic, framing-based nudges piloted in 2016, and how should the risk threshold that triggers such a message be chosen? The 2016 pilot could not answer this, both because its sample was confined to a single region and because none of its arms conditioned on predicted risk. Answering it required a bigger, multi-region deployment with explicit variation in the risk threshold at which warnings fire, and that is the design adopted in 2017.

In 2017 the intervention scaled to five regions (2,175 schools, 76,821 applicants) and introduced a key refinement: three randomly assigned risk-threshold cutoffs (30%, 50%, 70%) for triggering warnings. Table 8 shows that warnings significantly reduced non-placement across all three thresholds, suggesting that even moderate-risk cutoffs can shift behavior toward safer strategies.

B. *New Evidence: Out-of-Sample RD Estimates, 2018–2023*

One of the main new empirical contributions of this paper is to examine whether the regression discontinuity (RD) effects of the non-placement risk warning documented in the QJE study by Arteaga et al. (2022*a*) replicate outside that study's original observation window. Applying the same design—running variable, cutoff, and outcome definitions—to each cycle from 2021 through 2023, I report year-by-year estimates for the full 2018–2023 window together with pooled six-year coefficients. The point is not to reproduce the original estimates on the original cohorts, but to test whether the effect persists *out-of-sample* in three nationwide cycles the original paper could not observe. The 2021–2023 point estimates are similar in magnitude to the 2018–2020 pooled coefficient, and the year-by-year pattern does not suggest meaningful drift. This makes the exercise an out-of-sample replication of a platform-embedded informational intervention at national scale.

Table 8—RD estimates of platform pop-up effects - 2017

Risky cutoff	(1)	(2)	(3)	(4)	(5)
	Pooled sample		Risky cutoff values		
		IV	0.3	0.5	0.7
Any modification	0.237		0.107	0.352	0.137
	(0.059)		(0.112)	(0.086)	(0.140)
Add any	0.192		0.024	0.321	0.132
	(0.056)		(0.101)	(0.084)	(0.135)
Schools Added	0.428	2.225	0.109	0.651	0.394
	(0.174)	(0.739)	(0.350)	(0.214)	(0.322)
Δ Risk	-0.060	-0.313	-0.003	-0.103	-0.046
	(0.024)	(0.099)	(0.039)	(0.038)	(0.051)
Placed to preference	0.120	0.624	-0.014	0.210	-0.003
	(0.058)	(0.314)	(0.098)	(0.077)	(0.155)
NL	671	671	187	354	130
NR	647	647	194	334	119

Notes: Local linear RD estimates of pop-up effects from warning pop-up on application platform in 2017 implementation. Unlike 2018-2020 implementation, the 2017 cutoff varied by city, taking values of either 0.3 (as in the 2018-2020 implementation), 0.5, or 0.7. Computed using triangular kernel with bandwidth 0.1. Heteroskedasticity-robust nearest neighbor variance estimator with minimum of 3 neighbors reported in parentheses; computed as in Calonico, Cattaneo and Titiunik (2014). We report estimates in the pooled sample and for each different risky cutoff definition. IV (column 2) shows the instrumental variable specifications, where the endogenous regressor is the add any school indicator. Columns 3 through 5 split the sample by value of the risk cutoff. NL and NR are sample counts to the left and right of the cutoff, respectively.

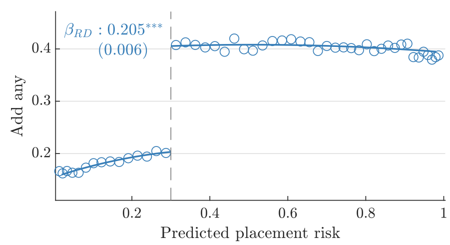
The section also incorporates outcome measures capturing longer-run academic impacts by linking application and enrollment records to standardized test scores from the SIMCE (*Sistema de Medición de la Calidad de la Educación*). Specifically, this document analyzes whether exposure to the platform warning is associated with changes in fourth-grade SIMCE mathematics and reading scores in the years following the intervention. I focus on this assessment because the intervention is especially relevant for entry-grade applicants, and fourth grade is the earliest level at which reliable, nationally standardized test data are consistently available. This addition is motivated by the original paper's findings that treated students were more likely to enroll in higher value-added schools, and that small improvements in enrollment outcomes translated into measurable gains in school quality metrics like teacher pay and peer composition.

The inclusion of effective ex-post SIMCE scores provides a complementary and policy-relevant lens through which to assess whether the intervention's enrollment effects are followed by measurable changes in learning outcomes. Whereas Arteaga et al. (2022*a*) report impacts on application behavior and characteristics of schools where students enroll, the student score-based outcomes help assess whether these shifts are visible in later academic performance.

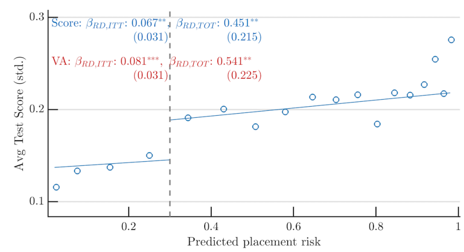
As shown in Figure 9, the estimated RD effects on fourth-grade standardized scores suggest positive academic effects. Scaling the reduced-form RD by the cohort-specific first-stage shift in enrolled-school value-added—i.e., recovering the effect on test scores per unit of new-school VA actually obtained—yields TOT estimates in the range of 0.1–0.5 SD on fourth-grade SIMCE mathematics across the 2018–2022 cohorts (excluding 2020). The cross-cohort spread appears related to variation in how much new-school VA the warning generated for compliers in each cycle: cohorts in which the warning shifted compliers into substantially higher-VA schools sit at the upper end of the range, those with smaller VA shifts at the lower end. The pattern is consistent with a mechanism in which warnings move marginal applicants into schools with higher measured value-added, and the realized score gains are of the same order as one would expect given several years of exposure before fourth-grade SIMCE. This interpretation is suggestive rather than definitive: peer effects, within-school selection, dynamic sorting, and general-equilibrium congestion are not separately identified here. Detailed estimates under different bandwidth selections are reported in Table B1. Moreover, Figure D6 suggests that sending personalized WhatsApp notifications shortly before the deadline can enhance applicants' responsiveness to the treatment.

These estimates raise a natural question: how could a platform pop-up, shown once before the deadline, be followed by fourth-grade test-score differences? The mechanism itself is laid out in Arteaga et al. (2022*a*): warnings prompt families to add schools to their preference list, expanding the portfolio and lowering non-placement risk (Table B1). The theoretical backbone is the multiplicative-optimism structure reviewed in Section III.A: equation (3) shows that perceived non-placement risk compounds exponentially in list length, so even a modest optimism parameter generates a large gap between perceived and true risk. A well-calibrated warning can help close that gap at the moment the list is being finalized, shifting the perceived return to search above the search cost.

Figure 9. Choice Behavior, Enrollment and Test score Outcomes in the Platform Pop-Up RDs (2018-2023 Pooled)



(a) Added at Least One School



(b) Average Test Score – 4th Grade SIMCE

Notes: This figure shows regression discontinuity (RD) estimates of the causal effects of the platform's non-placement risk pop-up on applicant behavior and enrollment outcomes. The vertical dashed line marks the eligibility cutoff for receiving the warning. Panel (a) presents the short-run application effect for cohorts 2018–2023 (the probability of adding at least one school to the preference list). Panel (b) links applicants to standardized test outcomes and plots impacts on the average fourth-grade SIMCE score (mathematics and reading) for the 2018–2022 cohorts excluding 2020, which is dropped due to COVID-related shocks that disrupted both the admissions cycle and SIMCE testing. Reported coefficients (β_{RD}) correspond to local linear estimates with robust standard errors in parentheses.

Because families near the risk threshold tend to have short lists concentrated on overdemanded schools, adding options mechanically shifts them toward schools where they are more likely to be admitted—and Arteaga et al. (2022*a*) show that these added schools tend to have higher value-added. Agte et al. (2024) offer a deeper account of why the response is so large: when search is costly and beliefs are biased, families arrive at the platform already under-searched, so a piece of information that corrects one belief updates their view of the entire landscape of options, triggering renewed search and reoptimization of the full portfolio.

The resulting causal chain runs through where a student applies, whether they are placed, and which school they ultimately attend. Given that Arteaga et al. (2022*a*) show that treated students enroll in schools with significantly higher value-added, the follow-up SIMCE pattern is consistent with the warning-induced shift in school VA explaining part of the later score gains, although other channels (peer effects, within-school selection, dynamic sorting, and general-equilibrium congestion) cannot be separately ruled out. This supports the interpretation that value-added measures capture meaningful differences in school effectiveness, while leaving room for complementary mechanisms.

It is also important to note that students who are not placed through the main centralized process are left to navigate the aftermarket, where only the vacancies that no other family preferred remain available. This can create a large gap in school quality between placed and unplaced students, amplifying the returns to even modest improvements in list composition. The RD estimates are local to the neighborhood of the risk threshold, where compliers are precisely those families whose behavior is most elastic to the warning—families who were close to expanding their lists but had not yet done so. For these marginal applicants, the combination of a better placement and actual enrollment in a higher value-added school can plausibly generate the observed test-score improvements. This also suggests that significant frictions in access persist in the aftermarket and that inertia may play an important role: once assigned through the centralized process, families are far more likely to follow through on enrollment.

Arteaga et al. (2026) study the long-run academic effects of the warning intervention in detail and report evidence that these gains extend beyond short-run enrollment measures. This extension is consistent with the original paper's conclusion that information frictions, particularly optimistic misperceptions about placement chances, constrain school choice even under strategy-proof mechanisms. Critically for the purposes of this retrospective, the pooled six-year estimates are backed by a year-by-year out-of-sample replication after the QJE study window: Figures D8 and D9 show that the RD on list expansion and on the change in predicted assignment risk is positive, statistically significant, and of similar magnitude not only in the 2018–2020 cycles studied in Arteaga et al. (2022*a*) but also in 2021, 2022, and 2023—three full cycles the original paper could not observe. The point estimates in the later years are stable: year-by-year the RD on "added at least one school" remains close to the pooled coefficient, and the RD on ΔRisk is consistently negative. The estimates show no evidence of attenuation as families become more familiar with the platform, which weighs against a simple novelty-effect explanation and is consistent with the structural interpretation in Agte et al. (2024): the warning is effective because it corrects a belief that families continue to hold even after repeated exposure to the system. Similar platform-based information interventions have shown comparable effects in Peru and Ecuador (Arteaga et al., 2022*b*). Taken together, the accumulating evidence suggests that addressing information frictions through low-cost, personalized feedback can improve placements and may generate measurable learning gains through improved matches.

As summarized in Table B1, the warning and feedback features substantially shift applications toward safer portfolios: adding at least one school rises by roughly 0.17, the number of schools added increases by about 0.30, and predicted assignment risk falls by about 0.03. These behavioral changes are associated with improved placement outcomes, higher subsequent enrollment, and the follow-up SIMCE effects documented above.

V. Aftermarket Design and Challenges

A second new empirical contribution of this paper is a systematic descriptive analysis of the SAE *aftermarket*: the set of placements, non-placements, rejected offers, and within-year transfers that determine where students actually sit once the school year has begun. The importance of the school-choice aftermarket for welfare was anticipated theoretically by Narita (2016), who developed the framework linking post-match reallocation to main-round incentives, and empirically by Arteaga (2024), who provides the most detailed prior treatment of rejected offers and within-year transfers in a centralized system. This section quantifies the scale and timing of this off-cycle flow in Chile using linked administrative records from SAE and the new digital in-year platform. The main descriptive fact is that student mobility after the main round is comparable in scale to the main round itself. In 2025, *Anótate en la Lista* processed 456,694 applicants, close to the 463,923 applicants who participated in the 2025 SAE main round (Table 1), so who ultimately sits in which school cannot be read off the main-round assignment alone. If the goal is to regulate *access* to schooling, the regulatory perimeter must therefore extend beyond the application window.

The regulatory framework for in-year admissions, the *Registro Público* during the *Periodo de Regularización de Matrícula*, predates both SAE and the *Ley de Inclusión*. Its original purpose was to limit discrimination: by requiring schools to maintain a public list and process applicants in order, the regulation aimed to prevent schools from selecting their preferred students above others. In practice, however, the rule was implemented through physical queues and paper lists at school doors. Compliance was nearly impossible to verify systematically, and schools could effectively discriminate by denying entry or skipping the list without consequence.[5] The predictable result was costly physical queues outside schools immediately after SAE—rationing-by-waiting in the sense of Barzel (1974), with the burden of allocation shifted onto families' time and stamina rather than the rule itself. Press coverage often portrayed these scenes as a problem with "SAE," but the mechanism producing them was the aftermarket rule, not the centralized assignment.

Beginning in 2024, the Ministry introduced a nationwide digital platform, *Anótate en la Lista* (AL), to implement the same *Registro Público* rules digitally. Families register interest online; the platform creates a transparent, time-stamped list for each school; schools retain authority to declare vacancies but cannot skip the next family in line and must record a reason when refusing to admit a student. Queues are public and auditable, and vacancy information is updated frequently. The digitalization changes two margins. First, it improves monitoring and transparency by making actions logged and auditable, which makes discriminatory gatekeeping harder to hide. Second, it lowers the transaction costs for families: no tents or repeated visits, and the ability to register at multiple schools simultaneously gives families more practical access to available options.

Table 9 provides a descriptive portrait of the platform's most recent cycle. In 2025, the second year of AL's operation, the platform processed over 1.7 million applications from 456,694 applicants—roughly comparable in scale to the main SAE round. On the demand side, applicants submitted an average of 3.73 applications each, and 77% received at least one offer, though only about 52% ultimately accepted one. On the supply side, 7,847 schools participated, making an average of 95 offers each, with an acceptance rate of approximately 75%. The average time from application to offer was about 41 days, though with substantial heterogeneity across schools. Notably, demand is highly concentrated: the top 10% of schools received 48% of all applications. These patterns show that in-year demand is large, that the platform intermediates a high volume of transactions, and that congestion at popular schools remains an important challenge even outside the main round.

It is important to note, however, that AL preserves the underlying first-come-first-served (FCFS) rule: in-year admissions involve no priorities and no coordination across schools. The main SAE round allocates seats according to legally mandated priorities—siblings, vulnerability quotas, and other criteria designed to promote equitable access—but none of these carry over into the aftermarket. A vulnerable student who missed the main deadline or who needs to transfer mid-year competes on the same chronological footing as any other family. FCFS has no mechanism to coordinate across queues, and to the extent that speed of registration correlates with digital access or schedule flexibility, it may

[5] Biblioteca del Congreso Nacional (2023).

Table 9—Descriptive Statistics *Anótate en la Lista* 2025

	Value
Panel A: Applications	
Number of applications	1,704,299
Number of applicants	456,694
Average applications per applicant	3.73
Fraction of applicants receiving at least one offer (%)	77.02
Average number of offers per applicant with at least one offer	1.86
Panel B: Admissions	
Average days: submit to offer	41.18
Average days: contact to response	7.11
Fraction of applicants with at least one accepted offer (%)	51.54
Fraction of applicants with at least one rejected offer (%)	19.79
Panel C: Supply side	
Average applications per school	248.95
Average offers made per school	95.47
Average acceptances per school	40.01
Average acceptance rate per school (%)	75.35
Schools with zero offers (%)	6.56
No-contact rate (%)	13.30
Average days: submit to offer (school mean)	34.16
Average days: contact to response (school mean)	6.12
Share of applications in top 10% of schools (%)	48.27

Notes: Descriptive statistics for the 2025 *Anótate en la Lista* process. Panel A reports application patterns (volumes, applications per applicant, offer receipt). Panel B shows admission dynamics (time from submission to offer and from contact to response, acceptance and rejection rates). Panel C summarizes school-level supply-side statistics (applications, offers, acceptances, no-contact rate, and demand concentration). The no-contact rate is the fraction of applications where a contact was attempted but the guardian was not reached. Waiting-list positions are determined by order of arrival. Own calculations from *Anótate en la Lista* 2025 administrative records.

disadvantage the same populations that the main-round priorities were designed to protect. The first year of AL's operation surfaced several design questions that remain to be studied systematically through the same iterative research-policy loop that guided the development of SAE's main round.

Strategic manipulation of seat availability was identified early on as a design concern and addressed through the system's fiscal architecture. Schools must report and justify their capacity well in advance of the SAE round, and the per-student voucher is not paid for seats above the approved total, leaving very limited scope for under-reporting vacancies. In practice, declared capacities are relatively stable across years—if anything, schools occasionally reduce seats. The more relevant strategic margin runs in the opposite direction: a school may declare *more* seats than it ultimately needs, observe the applicant pool assigned by SAE, and then adjust downward to stay within the approved level. This feature of the design helps convert the school's strategic problem into one with limited stakes, a point worth noting as other countries consider similar platforms.

Why this matters is evident in descriptive patterns that have not previously been central to evaluations of SAE. Even with strong main-round performance, a non-trivial share of applicants either receive no offer or later seek to move. In 2024, about half of applicants obtained their first choice, while roughly 34,000 students (7.3%) received no assignment; about 7% later rejected their assigned option and 16% did not respond (Tables 1, 2, 10). Off-cycle transfers are large: between December and March 2025 there were 533,148 moves; 33.2% occurred outside the SAE timeline, including 1.8% "better than SAE," 3.0% "worse than SAE," and 29.3% "not in SAE" (Table 11). Put differently, for a meaningful share of students, the seat allocated by the main round is *not* the seat they ultimately occupy—a gap between assignment and enrollment that the theoretical and empirical literature on school-choice aftermarkets had flagged as a first-order concern (Narita, 2016; Arteaga, 2024). These facts indicate that a transparent, low-friction aftermarket is a central, not peripheral, part of governing access.

Table 10—Applicants' responses to SAE 2024 assignment: Main Round

Response	Frequency	%
Panel A. Applicant response in main round		
Accepts assignment	249,997	52.80
Accepts assignment and remains on waitlist	82,965	17.52
Rejects assignment	32,400	6.84
No response	73,676	15.56
No assignment (Forced to waitlist)	34,444	7.27
Panel B. Applicant response post waitlist		
Accepts assignment	85,169	72.54
Rejects assignment	334	0.28
No response	1,420	1.21
No assignment	30,486	25.97

Notes: Panel A reports responses during the main round of the SAE 2024 process. Panel B shows responses after the waitlist assignment (prior to the complementary round). Results from the complementary round are not shown since all applicants are required to accept the assignment in that stage.

Dissatisfaction with the assigned school is one driver of aftermarket activity, especially in urban markets where demand concentrates. Preferences also evolve during the application cycle: some families reject their assignment (despite having listed the school), and others do not submit a response by the deadline. Late entry and unforeseen changes add pressure: migrants who missed the window, families who move, and students who repeat a grade often need rapid placement just before the school year begins.

Experiences elsewhere underscore that centralization alone does not eliminate post-assignment moves. In New York City, for example, 11.4% of students ultimately enrolled in a different public school than assigned and 6.4% exited the

Table 11—School transfers – December to March

	All			Pre-K			1st Grade			9th Grade		
	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025
Total transfers	616,163	570,519	533,148	94,884	88,879	81,423	72,106	62,491	61,171	131,272	128,789	127,384
Better than in SAE	2.4%	1.8%	1.8%	1.9%	1.2%	1.1%	2.1%	1.5%	1.3%	2.3%	1.6%	1.4%
Same as in SAE	64.2%	66.8%	65.9%	89.6%	90.7%	90.8%	64.6%	67.2%	67.5%	71.5%	73.5%	74.6%
Worse than in SAE	3.5%	3.2%	3%	1.7%	1.7%	1.8%	2.9%	3%	2.9%	2.4%	2.2%	2.4%
Not in SAE	30%	28.2%	29.3%	6.8%	6.4%	6.3%	30.4%	28.3%	28.4%	23.7%	22.7%	21.7%

Notes: The table summarizes student transfers during December–March for the 2023–2025 cycles. "Better than in SAE" indicates transfers to schools with higher estimated value-added than the SAE-assigned school; "Same as in SAE" corresponds to transfers into the same school assigned by SAE; "Worse than in SAE" reflects transfers to lower value-added schools; "Not in SAE" captures transfers into schools outside the centralized system (e.g., unsubsidized private schools and other establishments not covered by SAE). Figures are based on own calculations linking SAE administrative data to post-assignment enrollment records.

public sector; in Chilean higher education, broadening platform scope reduced rejected offers and dropout and increased graduation (Abdulkadiroğlu, Agarwal and Pathak, 2017; Kapor, Karnani and Neilson, 2024). Two design lessons follow. First, persistent aftermarket volume signals residual search and capacity frictions; making vacancy information more transparent and nudging longer preference lists in the main round may reduce ex-post reallocation (see Section IV). Second, formalizing rolling, priority-aware waitlists within the centralized platform, and expanding coverage to more private schools, could lower inequities and help allocate scarce seats transparently (Abdulkadiroğlu, Agarwal and Pathak, 2017; Kapor, Karnani and Neilson, 2024).

Prior to AL, schools often maintained informal lists and required in-person visits to check vacancies, practices that were inefficient, inequitable, and hard to monitor. The digital queue replaces physical lines with public, enforceable order; it makes discriminatory gatekeeping at the door more difficult and increases accountability for non-admission decisions. In short, who is offered a seat is now governed by a visible rule rather than by stamina, connections, or information rents.

If AL lowers transaction frictions at scale, several margins could move. One would expect a higher rate of within-year transfers among families who want to switch, with popular schools filling faster and staying full for more days of the year. A natural corollary is a possible rebalancing between the main match and the aftermarket for non-entry grades: some moves that would otherwise appear as new SAE applications in the next cycle may be resolved earlier through AL whenever capacity exists. Schools that historically carried vacancies late in the year may see a decline in "vacant-seat-days" as requests are processed through the public queue. In a setting where preferences evolve and families face shocks (moves, job changes, grade repetition), more continuous reallocation may raise allocative efficiency—students are more likely to sit in schools that fit updated constraints, and capacity is less likely to go idle.

Implementation details can also introduce inefficiencies. Independent queues across schools do not permit "trades," so mutually beneficial exchanges can remain blocked; a top-trading-cycles overlay in the spirit of Shapley and Scarf (1974) and Roth, S"onmez and Ünver (2004), applied dynamically as in Combe, Tercieux and Terrier (2022) and Pereyra (2013), could clear such cycles but would also create new strategic incentives early in the process.[6] Response-time rules that hold offers too long can freeze capacity, while deadlines that are too short can penalize families with less availability. Schools' discretion over when to declare a vacancy can create latency if under-reported, and allowing many simultaneous requests can generate temporary blocking if not rate-limited by design. These are design choices, not fixed constraints.

This is new territory. There is no off-the-shelf model to copy; progress will come from transparent documentation, small, well-designed tests, and cumulative learning, drawing on the same research-policy loop that guided the main platform. If policymakers aim to align in-year access with the normative priorities of the main round, a natural next step is to pilot ways to embed priorities year-round within AL while preserving its continuous, user-visible interface.

A broader lesson from this first year of AL concerns the pace of institutional change, and in particular the asymmetry between the speed at which the informational layer of SAE has iterated and the much slower evolution of the underlying algorithm and priority structure. I return to this asymmetry in Section VI, where I argue it is one of the recurring institutional themes of the decade.

VI. What a Decade of SAE Has Taught Us

This section returns to the organizing question of the paper: what was done, what was learned along the way, what happened after a decade, and what remains unfinished. The answer is not a simple success story or a simple cautionary tale. Chile built a best-practice national assignment institution; used staggered implementation to learn while scaling; discovered that reducing strategic ranking incentives does not by itself solve families' search problem; and ended the decade with strong average assignment outcomes, heterogeneous local congestion, evidence of bounded equity gains, and a new set of governance questions around supply, the aftermarket, and algorithmic reform.

A. What Was Built and How Chile Learned

The first lesson is institutional. SAE was not merely a website for collecting applications. It was a national assignment institution designed around the best

[6] Any trading overlay would require careful guardrails (consent windows, limits on simultaneous requests, short batch periods) to avoid strategic queueing and blocking.

available evidence in 2015 and organized around three pillars. First, it reduced strategic incentives across the application design: student-proposing DA removed rank-order manipulation incentives, unrestricted lists reduced incentives created by short choice menus, complementary-round rules limited incentives to hold back acceptable options, and legally defined priorities, family lottery numbers, fallback rules, and sibling/family assignment rules were embedded in the mechanism itself (Correa et al., 2019, 2022). Second, it coordinated the full publicly funded sector, including public and private-subsidized schools, under a single national platform. Third, it made the algorithm, capacities, applications, and match outcomes public enough for scrutiny, replication, and annual technical review. That combination, together with the deliberate decision not to use residential proximity as a priority criterion, made SAE a national assignment institution rather than a narrow algorithmic reform.

The second lesson is about implementation. Chile did not know, ex ante, how families would respond to a national low-strategy assignment system; whether lists would be long enough; how families would interpret risk; how sibling and fallback rules would operate in practice; or where local supply would become binding. The legally controlled staggered rollout therefore mattered not only for operational risk management but also for measurement. It created the window in which administrative data, surveys, randomized evaluations, and annual technical feedback could be combined into a research-policy loop. Without that design, many of the findings reviewed in this paper would have been much harder to detect and much less useful for policy iteration.

B. *What Was Learned*

The central intellectual lesson from that decade of measurement is that lowering the payoff to strategic ranking solves only part of the problem. Families do not need to misrepresent rank order under DA, but they still need to know which schools exist, what those schools offer, what they cost, and where admission is feasible. The first information lesson is therefore about option discovery: families need help learning about schools outside the network of relatives, friends, neighbors, and previously attended schools that normally structure search. Reducing search costs through accessible platform content, searchable maps, personalized school explorers, and simple report cards is not ancillary to the mechanism; it is part of making choice real.

The second information lesson is that aggregating options and reducing search costs are still only part of the story. Families may search too little even when information is readily available, because they overestimate their admission chances, underestimate the value of adding safer options, or fail to realize that the current list exposes them to non-placement. Agte et al. (2024) show why this matters: biased beliefs about admission chances and school attributes can make a rational family stop searching too early. Information about admission risk and information about school attributes are therefore complements rather than substitutes. Fixing attributes alone helps families search over a broader consideration set, but can leave them overestimating what they can reach; fixing chances alone can steer them toward safer lists, but leaves them searching over too narrow a set of known schools.

The policy implication is that the platform has to close both gaps proactively, because families do not know what they do not know. They cannot request information about schools they have never considered, and they cannot ask for a risk estimate they do not realize is theirs to ask for. The three lessons below make this unified takeaway operational and marshal the evidence behind each piece. They rest on the body of experimental, quasi-experimental, follow-up, and descriptive evidence summarized in Table 12: the risk-warning RDs, the MIME and personalized-report interventions, the long-run SIMCE estimates, and the staggered event study on segregation at oversubscribed schools.

Table 12—Summary of Causal and Quasi-Experimental Estimates

Intervention / Channel	**Design**	**Sample**	**Main Estimate**	**Source**
A. Platform Risk Warnings				
Add ≥ 1 school to list	RD at risk cutoff	SAE 2018–2020	+8.5 pp	Arteaga et al. (2022*a*)
Add ≥ 1 school (pooled replication)	RD at risk cutoff	SAE 2018–2023	+6–10 pp	Section IV
4th-grade SIMCE (math, TOT)	RD + long-run follow-up	SAE 2018–2022 (excl. 2020, COVID)	+0.1–0.5 SD across cohorts	Arteaga et al. (2026)
B. Information Interventions				
School value-added of chosen school	RCT (report card)	Pre-K families	+0.11 SD	Allende, Gallego and Neilson (2019)
5-year test scores (not enrolled)	RCT + follow-up	Pre-K families	+0.20 SD	Allende, Gallego and Neilson (2019)
Change application (add school)	Multi-level RCT (IV)	Pre-K Santiago	+15.3 pp	Allende et al. (2023)
Δ Non-assignment risk	Multi-level RCT (IV)	Pre-K Santiago	−3.4 pp	Allende et al. (2023)
C. Mechanism and Equity				
Prioritario share at oversubscribed schools	Staggered DiD event study	SAE 2016–2019 rollout	+6 pp by year 7 (∼1/3 of pre-SAE gap)	Lepe, Muñoz-Ojeda and Neilson (2026)

Notes: This table collects the main causal and quasi-experimental estimates discussed in the paper. “pp” = percentage points; “SD” = standard deviations. Panel A reports estimates from the platform-embedded risk warnings. Panel B collects results from information-provision experiments. Panel C reports the segregation event study. See the referenced sections and papers for full specifications, standard errors, and bandwidth choices.

First, families need help learning about options beyond their existing networks. A decade of evidence from SAE shows that making a centralized list of schools available is not the same as making the relevant option set usable. Families differ in what they know about nearby schools, how easily they can compare price and quality, and whether they discover schools outside the social networks that usually transmit school information (Allende, Gallego and Neilson, 2019; Agte et al., 2024). Search tools, maps, report cards, and plain-language platform content reduce these costs and can move applications toward schools that families would not otherwise have considered. The lesson is that centralized assignment platforms should be designed as search infrastructure, not only as submission infrastructure.

Second, low search costs are not enough: platforms also have to make admission chances salient. Even when the mechanism lowers incentives to game the rank order, truthful ranking does not tell families *what is achievable*. The decision of how many schools to rank, and which safer options to include, depends on beliefs about admission chances. Families who overestimate their chances at top choices submit short, risky lists and bear the cost of non-placement (Arteaga et al., 2022*a*; Agte et al., 2024). The interventions that worked in Chile share a common structure: the platform computes what is likely to happen under the family's current preference list—predicted placement, predicted non-placement risk, and nearby alternatives ranked by quality, price, and feasibility—and surfaces that information back to the family in real time, before the deadline. Risk warnings (Arteaga et al., 2022*a*, 2026), MIME, personalized feedback reports (Allende, Gallego and Neilson, 2019; Allende et al., 2023), and WhatsApp notifications are instances of the same idea. The general principle is that a centralized assignment platform should be a proactive forecasting and recommendation layer that helps families realize the benefits of continued search, not merely a low-cost catalog of options.

Third, these interventions can generate not only operational gains but evidence of learning and bounded equity gains. Early results from Chile documented behavioral improvements, more schools added, lower non-placement risk, and better enrollment outcomes (Arteaga et al., 2022*a*). New follow-up evidence suggests that these gains may transmit to student learning: TOT estimates of roughly 0.1–0.5 SD on fourth-grade SIMCE mathematics across the 2018–2022 cohorts (excluding 2020, dropped due to COVID-related shocks that disrupted both the admissions cycle and SIMCE testing) (Arteaga et al., 2026). This magnitude is economically meaningful for a light-touch, platform-embedded intervention, and it is consistent with the QJE finding that treated students enrolled in higher value-added schools.

On the equity side of the same lesson, a companion working paper (Lepe, Muñoz-Ojeda and Neilson, 2026) finds, in a staggered difference-in-differences event study exploiting SAE's 2016–2019 regional rollout, that the share of *prioritario* students at oversubscribed schools converged toward the non-oversubscribed counterfactual by roughly 6 percentage points by year seven after SAE's arrival—about a third of the pre-SAE gap ($\sim$17 pp in 2013) between excess-demand and non-excess-demand schools. This effect concentrates at oversubscribed schools—precisely the schools where, under the pre-SAE decentralized regime, discretionary screening could most easily exclude vulnerable families. That is where a centralized mechanism with vulnerable-student priority and random tie-breaking should have the greatest bite, and it is one empirical signature that the mechanism is doing equity work at the margin where it can bind. The practical implication is that the benefits of a smart matching platform are not only procedural (fairness, transparency, matched seats) but may also show up in measurable student learning and in reduced segregation at the schools where the mechanism has room to act.

Below these three lessons sits a set of more granular operational takeaways that emerged from a decade of iteration and are useful for platforms built on this model. Because pre-application guidance improves list quality and reduces non-assignment, outreach should extend beyond the standard SAE channels: information should reach families connected to pre-primary systems (JUNJI/Integra) earlier in the cycle, and nearby options should be foregrounded for students with permanent special needs and for those looking at technical-professional specialties (Hastings and Weinstein, 2008; Arteaga et al., 2022*a*). Families applying for more than one child need tools that make joint outcomes salient: estimated probabilities under joint versus separate applications, and, more ambitiously, the ability to rank assignment portfolios directly rather than relying on a single family-application toggle, building on the NRMP-couples literature for operationalizing tuple preferences (Nguyen and Vohra, 2018; Gazmuri et al., 2024). Relatedly, the legal definitions of "sibling" and "child" that determine these priorities should be broadened to match the household structures used by the Ministry of Social Development, so that non-traditional families are not mechanically excluded from priorities they would qualify for under a more inclusive definition of the household.

One example of this second-generation innovation agenda was the 2023–2024 sibling-application diagnostic project. Using administrative records, a review of the platform interface, simulations, and questions from the SAE satisfaction surveys, the project asked whether guardians applying for more than one child understood the "family application" option, how they valued joint assignment relative to school quality and rank, and what they believed would happen under joint versus separate applications (Gazmuri et al., 2024). The logic mirrors the broader smart-platform lesson: a binary toggle is too thin an interface for a multi-child portfolio problem. Stronger coupling can raise the probability that siblings are assigned together, which many families value, but it can also pull a younger sibling into the older sibling's fallback or assured-enrollment school rather than into a more preferred feasible option. The report's simulations make the tradeoff concrete: disabling family application for siblings with the same assured-enrollment school could benefit many families by avoiding unwanted fallback co-assignment, while still risking harm for families who used the rule to keep children together. The design implication is not simply to turn sibling coupling on or off, but to make joint and separate assignment probabilities visible, explain fallback consequences before submission, and test rule changes before changing the core algorithm.

Non-assignment warnings should be available to more families and calibrated in tiers so that guidance scales with exposure to risk (Arteaga et al., 2022*a*). Because distance enters the complementary-round fallback and the platform's school recommendations, registration should include a verified-address flow with a documented pathway to register a future address when moves are pending. The interface should allow applicants to explicitly disable features that, in their circumstances, appear to reduce expected welfare—particularly the fallback (*matrícula asegurada*) and the forced coupling of sibling applications when the older sibling is anchored at the origin school. And where scarcity is acute, narrowly capped extraordinary seats could be deployed in a data-guided manner to reduce non-assignment and raise top-rank placements without compromising transparency (Bobbio et al., 2023), including limited rule-based adjustments to co-assign same-grade siblings split at cutoffs and, more broadly, allowing dynamic sibling priority to flow in either direction rather than only from older to younger siblings (Rios et al., 2025).

These recommendations come from what worked. The retrospective is incomplete without what did not. Not every intervention the team tested moved the needle: several early message variants trialed alongside the risk warning produced small, statistically insignificant effects on list length and placement, and were retired in favor of the concrete, probability-based language that eventually became the platform default (Arteaga et al., 2022*a*). Some features that looked attractive on paper proved awkward in practice: the default *matrícula asegurada* fallback and the forced coupling of sibling applications appear to reduce expected welfare for a non-trivial minority of families, and only after several cycles was the interface modified to let applicants opt out.

The aftermarket is the clearest case of a problem that was harder to see before it was brought onto the platform. For most of the decade, in-year reallocation was treated as residual, something the *Registro Público* would discipline from outside the platform, and it was not until *Anótate en la Lista* launched in 2024 that the scale of off-cycle mobility (several hundred thousand moves per year) became fully visible. In hindsight, a priority-aware continuous queue should have been on the research agenda much earlier.

The most persistent bottleneck, however, was institutional rather than technical. The same annual policy memoranda that produced the tiered risk-warning interface (adopted in 2023 after five cycles) and the fallback and sibling-coupling opt-outs (adopted as interface modifications while the underlying defaults remained unchanged) have also repeatedly recommended changes at the rule level: broader legal definitions of "sibling" and "child," dynamic sibling priority that can flow from younger to older siblings (Rios et al., 2025), co-assignment of same-grade siblings split at cutoffs, narrowly capped extraordinary seats for acute scarcity, and periodic public review of the priority hierarchy and tie-breaking rules. Most of these have not been adopted. Appendix Table C1, based on annual ConsiliumBots policy memoranda prepared for MINEDUC (ConsiliumBots, 2024), makes the asymmetry explicit: items that live in the informational layer move; items that would touch the allocation rule, the priority hierarchy, or the tie-breaking logic largely do not. I treat this as one of the main institutional patterns of the decade, and it frames the priorities discussed below.

C. Aggregate Outcomes of the Research–Policy Loop

The final accounting is mixed in the way one should expect from an assignment mechanism operating inside a real school market. On the operational side, access to ranked options is within the range of mature centralized systems and favorable relative to several city-level and developing-country benchmarks: in 2025, 82.6% of applicants were placed in one of their top three listed schools and 92.8% in one of their listed preferences. But the 7.2% non-placement rate is not evenly distributed. It is concentrated in local markets where demand has grown, school entry has slowed, voucher-sector exit has continued, or demographic growth and migration have outpaced available seats. SAE can coordinate the seats that exist; it cannot create desirable supply where the local market has too little of it.

This distinction matters for interpreting what happened. The same reform package that created SAE also required publicly funded schools to operate as non-profit entities, phased out copayments, and eliminated selection. In the decade that followed, new private-subsidized school entry essentially stopped, the voucher sector contracted in net terms, and some schools converted into the unsubsidized private sector. These descriptive patterns are not evidence that the assignment mechanism caused supply contraction, but they do shape what the mechanism can deliver. The result is a local mismatch: some schools and markets have empty seats while others have too few seats in the options families most want. Improving access therefore requires not only better assignment and information tools, but also supply-side policy that can retain, create, or improve desirable seats where scarcity is binding.

Two aggregate-level patterns suggest that the individual-level gains documented through the risk-warning RDs and the MIME and report-card RCTs do not simply vanish into zero-sum reallocation; they are visible in system-level descriptive and quasi-experimental patterns, although the evidence is deliberately narrower than a full causal accounting of the reform package.

First, post-SAE vacancy rates shifted away from higher-value-added schools and toward lower-value-added ones (Figure 3 in Section II.F). This is consistent with the centralized match, aided by warnings and attribute-information tools, steering families toward schools that produce more learning per seat: seats at better schools fill, seats at weaker schools open up, and capacity planning can respond over time. The pattern is descriptive rather than causal—the vacancy-by-VA shift is contemporaneous with the broader supply-side contraction documented in Section II.G—but it is consistent with the micro-level RD and RCT estimates.

Second, at the oversubscribed schools where the assignment mechanism has room to bind—the schools where pre-SAE discretionary screening could most easily exclude vulnerable families—the share of *prioritario* students converged toward the non-oversubscribed counterfactual by roughly 6 percentage points by year seven (Lepe, Muñoz-Ojeda and Neilson, 2026). This is one empirical signature that a centralized mechanism with vulnerable-student priority and random tie-breaking is doing equity work where the rule can bind. The effect is bounded: residential stratification, the unsubsidized private sector, and the observed elite-exit margin sit outside the perimeter the mechanism can reach. But within that perimeter (the subset of schools where screening previously bound), the composition gap narrowed.

Taken together, these two patterns are system-level implications of the research–policy loop. The individual-level improvement in enrollment quality is consistent with a measurable reallocation of seats toward higher-value-added schools; the individual-level equity mechanism is consistent with a measurable composition shift at precisely the schools where the algorithm has room to act. Both effects are bounded. Overall segregation is difficult to identify cleanly and changes little on some measures because residential stratification, the unsubsidized private sector, and the observed exit of high-demand private-subsidized schools from the regulated sector sit outside the mechanism's direct perimeter. But within that perimeter—especially at oversubscribed schools where admissions discretion previously mattered most—access for priority students improved measurably. This is the central distributional lesson: SAE increased access at the margin where allocation rules bind, while access to high-value-added schools can still rise or fall locally depending on the supply of desirable regulated seats.

D. *What the Next Decade Has to Fix*

These lessons are the main answers a decade of research has produced. They sit alongside a further task: to carry forward several strands of unfinished institutional design that are better thought of as intertwined than as a checklist. The first is the algorithmic-stasis asymmetry noted above. Risk warnings, MIME, personalized feedback, and platform redesign have all advanced through a continuous research-policy loop, while the algorithm itself, the priority hierarchy (siblings, staff children, vulnerability quotas), tie-breaking rules, sibling-coupling logic, capacity adjustments, and aftermarket priorities have changed little since the national rollout.

This is itself a finding worth documenting. Governments appear to find it far easier to add tools that help families navigate the system as it exists than to change the rules by which the system allocates scarce seats. Why this is the case, what it implies for the political economy of mechanism reform more generally, and how to design legitimate channels for proposing and evaluating algorithmic changes remain unresolved. A natural starting point is an explicit governance process: transparent and accessible documentation of the assignment logic and priorities, periodic expert and civil-society review of alternative formulations, scoped pilots with ex-ante evaluation criteria and ex-post public reporting, and public-facing simulators that allow non-specialists to see the distributional consequences of alternative rules before they are adopted (Pathak and Sönmez, 2013; Dur et al., 2018; Pathak, 2017; Correa et al., 2022; ConsiliumBots, 2024).

The aftermarket is the second strand, raising governance challenges parallel to the algorithmic ones. *Anótate en la Lista* formalized in-year admissions for the first time, but it preserves a first-come-first-served rule that does not carry over the priorities used in the main round. A vulnerable student who needs to transfer mid-year competes on the same chronological footing as any other family, and there is no mechanism for coordinating mutually beneficial trades across school queues.

The agenda ahead includes how priorities should be embedded in the aftermarket without creating new strategic incentives or losing the speed and transparency that make a continuous queue useful; whether a top-trading-cycles overlay can clear blocked exchanges across schools without inviting strategic queueing; how mid-year arrivals (migrants, families relocating, students repeating a grade) should be treated when their options are systematically worse than those of families who participated in the main round; and how research access to the data generated by the new platform should be governed so that the same iterative learning loop that built the main round can be turned on the aftermarket. The first year of operation has surfaced these issues in concrete form; I hope to study them systematically as the system matures.

Public debate over how scarce seats are allocated is the third strand, and in many ways it runs through the first two. Decisions about priorities, distance weights, sibling rules, and capacity adjustments involve real trade-offs between competing notions of fairness, efficiency, and access, and these trade-offs are difficult for non-specialists to see. In their absence, public debate about SAE has tended to default to anecdotes, ideological framings, and proposals to return to the previous decentralized system, proposals that, if adopted, would risk discarding many of the coordination and transparency gains documented in this paper.

The same research-policy loop that produced the warning tools should now be turned toward building the democratic infrastructure that the next decade will require: public-facing simulators that let families, schools, and civil society explore the consequences of alternative allocation rules in their own neighborhood; accessible documentation that translates the algorithm into language a non-specialist can engage with; visualizations of distributional consequences that show, in advance, who would gain and who would lose from a proposed change. Such tools serve two purposes simultaneously: they help policymakers anticipate the political and distributional consequences of reform, reducing the risk of backlash, and they give citizens the means to participate in the debate on substantive rather than purely rhetorical terms. Without them, the asymmetry between rapid informational innovation and algorithmic stasis is likely to persist.

These strands are tightly connected. Algorithmic reform is politically difficult in part because the public lacks the tools to evaluate alternatives; the aftermarket is harder to govern well without the same kind of continuous research-policy loop that built the main round; and informed public debate is harder without the documentation and simulators that algorithmic governance would also require. The same logic that justified investing in smart platforms for families now justifies investing in smart tools for the citizens, scholars, and policymakers who govern the system.

A cross-cutting challenge is segregation. As Section II.G documents and Lepe, Muñoz-Ojeda and Neilson (2026) quantify in detail, the evidence is more nuanced than either side of the public debate tends to allow. Companion evidence indicates that SAE reduced segregation at oversubscribed schools, with the share of *prioritario* students converging toward the non-oversubscribed counterfactual by roughly 6 percentage points by year seven after arrival, closing about a third of the pre-SAE gap between excess-demand and non-excess-demand schools, but it cannot undo the residential stratification, the parallel unsubsidized private sector, or the supply-side contraction documented in the market dynamics section, all of which operate outside its perimeter. SAE appears to deliver a real but bounded equity gain at the point of admission. Further reductions in segregation will require complementary policies, expanded vulnerability quotas, investments in undersubscribed school quality, information interventions, and a widening of the regulatory perimeter, and SAE's transparency provides the data infrastructure to design and evaluate them.

The Chilean experience suggests that the full promise of a centralized assignment system, as a fair, efficient, and trusted institution, depends on four things in sequence: a deliberately good design that reduces strategic incentives across the whole application process, a staggered rollout that creates room for measurement, a continuous research–policy loop that identifies and addresses information frictions inside the platform, and a governance layer that allows the same iterative treatment to be extended to the algorithm, the aftermarket, supply policy, and the public debate over priorities. Chile has made substantial progress on the first three. The fourth is the work of the next decade.

VII. Conclusion

The first decade of Chile's *Sistema de Admisión Escolar* offers a rare view of a national assignment institution being designed, scaled, measured, and revised in real time. The reform replaced fragmented school-by-school admissions with a coordinated platform covering the publicly funded sector, using rules intended to reduce strategic incentives and make the allocation of scarce seats transparent. This paper has reviewed that decade as an institutional learning process: what Chile built, what the staggered rollout made possible to learn, what families and schools actually did, and which problems remain beyond the reach of the mechanism as currently designed.

The first conclusion is that the core design mattered. SAE was more than the adoption of Deferred Acceptance. It combined a low-strategy assignment rule with unrestricted preference lists, legally defined priorities, lottery-based tie-breaking, sibling and family rules, fallback provisions, national public/private-subsidized coverage, and public documentation of the algorithm and data. These features reduced many of the strategic and discretionary margins that characterized the pre-SAE system. They also created the data infrastructure needed for replication, public scrutiny, and evaluation. That institutional foundation is why the Chilean case travels: it shows what can be learned when school assignment is moved from decentralized discretion to a transparent national platform.

The second conclusion is that implementation design mattered almost as much as mechanism design. SAE's staggered rollout was not only an operational transition; it created a measurement window. Administrative data, surveys, randomized interventions, quasi-experimental variation, and annual technical recommendations could be connected to the choices families made inside the platform. That research-policy loop revealed the central behavioral lesson of the decade: reducing strategic ranking incentives is necessary but not sufficient. Families still need to discover schools, compare quality and cost, understand admission chances, and realize when their current list exposes them to non-placement risk. A centralized assignment mechanism only delivers its promise if families can use it well.

The evidence reviewed in the paper points to a consistent pattern. Platform-embedded warnings, school explorers, personalized reports, and follow-up messages changed application behavior by making the consequences of a family's current list visible before the deadline. Families added options, reduced predicted non-placement risk, and in several studies moved toward schools with higher measured value-added. New follow-up evidence is consistent with some of those gains translating into later learning, while companion evidence suggests that access for *prioritario* students improved at oversubscribed schools, where the allocation rule actually binds. These findings should be read with the evidence hierarchy in mind: some estimates come from published experimental and quasi-experimental work, while others are new or companion working-paper evidence.

Taken together, however, they support a practical conclusion: information and forecasting tools are not accessories to centralized assignment systems; they are part of the mechanism's effective design.

The third conclusion is that SAE's aggregate outcomes are strong but bounded. By 2025, 82.6% of applicants were assigned to one of their top three listed schools and 92.8% to a listed preference, placing Chile within the range of mature centralized systems. Yet the remaining 7.2% non-placement rate is geographically concentrated, and the average hides local markets where desired seats are scarce. The assignment mechanism can coordinate demand and supply, but it cannot create desirable seats where local supply is insufficient. The decade therefore exposed a supply-side agenda: flat or declining private-subsidized entry, demographic growth and migration in particular areas, conversion of some desirable, high-value-added private-subsidized schools to the unsubsidized private sector, and the coexistence of empty seats in some places with acute shortages in others. Improving access in the next decade will require assignment policy and supply policy to be treated together.

The fourth conclusion concerns equity. SAE appears to have improved access at the margin where the mechanism has power: oversubscribed schools where discretionary screening previously mattered most. The evidence on aggregate segregation is more cautious, because residential sorting, the unsubsidized private sector, and school entry and exit operate outside the assignment algorithm. A centralized mechanism with transparent priorities can change who gets scarce regulated seats, but it cannot by itself undo residential stratification, expand high-quality supply, or prevent exit from the regulated sector. The right reading is therefore neither triumphalist nor dismissive: SAE delivered measurable equity gains where allocation rules bind, while leaving deeper segregation and quality-access problems for complementary policy.

The unfinished agenda follows directly from these limits. The user-facing information layer has evolved much faster than the allocation rule, priority hierarchy, tie-breaking rules, sibling logic, capacity rules, and fallback design. There are many technically feasible algorithmic adjustments still to evaluate, from priority and tie-breaking rules to sibling, fallback, and capacity provisions. There are also policy improvements to make in the aftermarket: *Anótate en la Lista* has made in-year demand visible at scale, but its first-come-first-served logic still sits largely outside the equity priorities of the main round. Finally, communication with families remains a policy margin in its own right. Families need clearer, timely, and personalized explanations of risk, options, sibling trade-offs, fallback consequences, and aftermarket rules. Algorithmic governance also remains underdeveloped: citizens, policymakers, and researchers need public-facing tools to understand how alternative rules would change access before those rules are debated or adopted. The next generation of smart matching platforms should therefore include tools for families, policy improvements for the aftermarket, and tools for democratic deliberation over complex assignment rules.

The overall message is that Chile's experience is best understood as institution plus learning. Chile made substantial progress on the first three tasks of institutional reform: building a transparent national assignment system, learning while scaling it, and using the platform to identify and reduce information frictions. The next task is to extend the same iterative discipline to the margins that have changed more slowly: algorithm and priority adjustments, supply, the aftermarket, communication with families, and public governance of the assignment rules. The Chilean experience shows that centralized assignment can make school access fairer, more transparent, and more empirically governable. It also shows that the mechanism is only one part of the institution. What matters over time is whether the system can keep learning from its own operation and whether that learning can be translated into rules, tools, policy adjustments, and supply responses that families can trust.

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Sequential Search Model with Subjective Beliefs

This appendix records the notation behind the model sketch in Section III.A, drawing on Arteaga et al. (2022*a*) and Agte et al. (2024). Throughout, plain symbols denote subjective (family-perceived) values and a star marks true values. A family is endowed with a consideration set $\mathcal{C}_0 = \{1, \ldots, N_0\}$ ordered by utility $u_1 > \cdots > u_{N_0} > 0$ (relative to non-placement). For each school j the family has subjective admission probability p_j and rejection probability $R_j = 1 - p_j$; true values are p_j^*, R_j^*.

Portfolio value.. — Under DA, expected portfolio value is

$$V(\mathcal{C}_0) = \sum_{j=1}^{N_0} p_j u_j \prod_{j'<j} R_{j'}. \tag{A1}$$

Optimal stopping.. — The family pays search cost κ per new school s drawn from $F_{p,u}$. Search continues while

$$U[\text{Search} \mid \mathcal{C}_0] = \iint \big(V(\mathcal{C}_0 \cup \{s\}) - V(\mathcal{C}_0)\big)\, dF_{p,u} > \kappa. \tag{A2}$$

Multiplicative optimism.. — Biased beliefs are captured by $R_j = (1-a)R_j^*$ for $a \in (0,1)$:

$$R_j = (1-a)\, R_j^*, \qquad RISK_0 = (1-a)^{N_0}\, RISK_0^*. \tag{A3}$$

Because $(1-a)$ compounds once per school, even $a = 0.3$ with $N_0 = 5$ yields perceived risk at 17% of the true level.

Attribute misperceptions.. — When families overvalue known schools ($u_j \geq u_j^*$) or underestimate the outside distribution, the perceived return to search is deflated:

$$V(\mathcal{C}_0) \geq V^*(\mathcal{C}_0), \qquad U[\text{Search} \mid \mathcal{C}_0] \leq U^*[\text{Search} \mid \mathcal{C}_0]. \tag{A4}$$

Both channels—optimism about chances and overvaluation of known options—push the perceived marginal benefit of search below κ, generating premature stopping. Platform warnings correct the first channel; information tools such as MIME correct the second.

Bandwidth Sensitivity for Platform Pop-Up RD Estimates

Table B1—Platform Pop-Up RD Estimates of Main Outcomes with Alternate Bandwidths (4th grade, 2018–2022 excl. 2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth	Full	+-0.2	+-0.1	rdbwselect				
	Estimate	Estimate	Estimate	Estimate	BW left	BW right	N left	N right
A. Balance								
Economically Vulnerable	-0.009	-0.019	-0.036	-0.045	0.09	0.09	4,373	4,274
	(0.016)	(0.015)	(0.022)	(0.023)				
Rural	0.003	0.004	0.002	0.002	0.10	0.10	4,919	4,829
	(0.004)	(0.004)	(0.005)	(0.005)				
Predicted Math Score	0.005	0.009	0.008	0.008	0.14	0.14	6,996	7,029
	(0.007)	(0.007)	(0.010)	(0.008)				
Predicted Reading Score	0.004	0.010	0.012	0.011	0.11	0.11	5,573	5,507
	(0.006)	(0.006)	(0.008)	(0.008)				
Predicted Average Score	0.005	0.009	0.010	0.009	0.13	0.13	6,265	6,268
	(0.006)	(0.006)	(0.008)	(0.007)				
B. Choice Behavior								
Any modification	0.163	0.154	0.142	0.142	0.10	0.10	4,987	4,905
	(0.014)	(0.014)	(0.020)	(0.020)				
Add any	0.170	0.166	0.155	0.155	0.10	0.10	4,822	4,736
	(0.013)	(0.013)	(0.019)	(0.019)				
Schools Added	0.296	0.287	0.256	0.269	0.13	0.13	6,294	6,314
	(0.040)	(0.038)	(0.058)	(0.050)				
Δ Risk	-0.031	-0.034	-0.033	-0.033	0.11	0.11	5,111	5,073
	(0.005)	(0.005)	(0.007)	(0.007)				
C. Choice Outcome								
Placed to preference	0.031	0.050	0.056	0.051	0.14	0.14	6,667	6,727
	(0.015)	(0.015)	(0.021)	(0.018)				
Enrolled in placed	0.014	0.037	0.040	0.039	0.13	0.13	6,347	6,387
	(0.015)	(0.015)	(0.022)	(0.019)				
Enrolled in placed|placed	-0.009	0.008	0.003	0.009	0.13	0.13	3,945	3,762
	(0.019)	(0.019)	(0.027)	(0.024)				
Years enrolled at placed school	-0.039	-0.036	-0.060	-0.040	0.13	0.13	6,063	6,040
	(0.060)	(0.059)	(0.085)	(0.074)				
D. Test Scores and Value Added (4th Grade)								
Avg Score	0.070	0.067	0.120	0.139	0.07	0.07	2,589	2,604
	(0.031)	(0.031)	(0.044)	(0.054)				
Math Score	0.081	0.072	0.125	0.145	0.07	0.07	2,471	2,473
	(0.032)	(0.032)	(0.046)	(0.057)				
Reading Score	0.066	0.073	0.118	0.117	0.09	0.09	3,318	3,283
	(0.036)	(0.035)	(0.051)	(0.054)				
VA Avg at enrollment	0.049	0.081	0.080	0.088	0.12	0.12	4,954	4,858
	(0.022)	(0.031)	(0.044)	(0.041)				
VA Math at enrollment	0.050	0.085	0.098	0.100	0.12	0.12	5,182	5,130
	(0.024)	(0.034)	(0.048)	(0.044)				
VA Reading at enrollment	0.048	0.078	0.063	0.075	0.12	0.12	4,913	4,827
	(0.025)	(0.036)	(0.051)	(0.047)				
N left	17,407	10,378	4,893					
N right	55,713	10,056	4,797					

Notes: 4th grade sample, application years 2018–2022 excluding 2020, which is dropped due to COVID-related shocks that disrupted both the admissions cycle and SIMCE testing. RD estimates using triangular kernel with different bandwidths. "Full" uses 2nd order polynomial, "+-0.2", "+-0.1" and rdbwselect use 1st order (local linear) for test scores and 2nd order for VA. Heteroskedasticity-robust nearest neighbor variance estimator with minimum of 3 neighbors reported in parentheses; computed as in Calonico, Cattaneo and Titiunik (2014).

Annual Algorithmic-Reform Recommendations and Adoption Status

Section VI argues that one of the central observations of the decade is the asymmetry between the speed at which the user-facing informational layer of SAE has iterated and the near-complete inertia of the underlying algorithm and priority structure. Table C1 substantiates that observation by enumerating recurring technical recommendations submitted in annual ConsiliumBots policy memoranda prepared for MINEDUC (ConsiliumBots, 2024). The recommendations are organized by domain (algorithm and priority structure; user-facing tools; aftermarket; governance), with adoption status and the documented technical or regulatory pathway. The pattern is what the asymmetry claim predicts: items confined to the user-facing informational layer (warning interface, opt-out flows) have largely been adopted, while items that would change the underlying allocation rule, priority hierarchy, or tie-breaking logic have not.

Table C1—Annual ConsiliumBots technical recommendations on SAE algorithm, priorities, and aftermarket

First raised	Domain	Recommendation	Status	Stated reason / pathway
A. Algorithm and priority structure				
2018–2024	Priority definitions	Broaden legal definitions of "sibling" and "child" to match the household structures used by the Ministry of Social Development, so non-traditional families are not mechanically excluded from priorities they would qualify for under a more inclusive definition.	Not adopted	Requires regulatory amendment; no formal MINEDUC response.
2019–2024	Sibling priority	Allow dynamic sibling priority to flow in either direction (younger → older as well as older → younger), rather than anchoring strictly on the older sibling (Rios et al., 2025).	Not adopted	Algorithm change; flagged as out of scope of the original DA implementation.
2020–2024	Sibling priority	Co-assign same-grade siblings split at cutoffs through a narrow rule-based adjustment.	Not adopted	Algorithm change; preserved current tie-breaking logic.
2019–2024	Tie-breaking and priorities	Periodic public review of the priority hierarchy (siblings, distance, vulnerability quotas) and tie-breaking rules, with scoped pilots and ex-post reporting.	Not adopted	No formal review process established.
2021–2024	Capacity and seats	Deploy narrowly capped extraordinary seats in a data-guided manner to reduce non-assignment and raise top-rank placements without compromising transparency (Bobbio et al., 2023).	Not adopted	Capacity governed by separate fiscal channel (per-student voucher).
B. User-facing tools and platform interface				
2018	Risk warnings	Tiered, calibrated non-placement warnings at multiple risk thresholds (rather than a single cutoff) so guidance scales with exposure (Arteaga et al., 2022*a*).	Adopted (2023)	Implemented as multi-tier warning interface (Figure D3).

Continued on next page

Table C1—Annual ConsiliumBots technical recommendations, continued

First raised	**Domain**	**Recommendation**	**Status**	**Stated reason / pathway**
2018–2020	Fallback (*matrícula asegurada*)	Allow applicants to explicitly disable the default fallback when, in their circumstances, it reduces expected welfare.	Partially adopted (interface)	Opt-out path added after several cycles; default unchanged.
2019–2021	Sibling coupling at application	Allow applicants to explicitly disable forced coupling of sibling applications, particularly when the older sibling is anchored at the origin school.	Partially adopted (interface)	Opt-out path added; default coupling unchanged.
2020–2024	Multi-child applications	Provide tools that make joint outcomes salient: estimated probabilities under joint vs. separate applications, and the ability to rank assignment portfolios directly (Nguyen and Vohra, 2018; Gazmuri et al., 2024).	Not adopted	Requires algorithm and interface changes; under technical review.
2020–2024	Pre-application outreach	Extend outreach beyond standard SAE channels: information should reach families connected to pre-primary systems (JUNJI/Integra) earlier in the cycle.	Partially adopted	Limited inter-institutional pilots; no system-wide integration.
2020–2024	Address registration	Verified-address flow with documented pathway to register a future address when moves are pending.	Not adopted	Requires data integration with civil registry.
C. Aftermarket (Anótate en la Lista)				
2024	In-year priorities	Embed main-round priorities (siblings, vulnerability) into the aftermarket queue so equity does not stop at the application deadline.	Not adopted	Preserves FCFS rule from *Registro Público*; under technical review.
2024	Trade overlay	Pilot a top-trading-cycles overlay on AL to clear blocked exchanges across school queues, with consent windows and short batch periods to limit strategic queueing.	Not adopted	New territory; no implementation pathway agreed.

Continued on next page

Table C1—Annual ConsiliumBots technical recommendations, continued

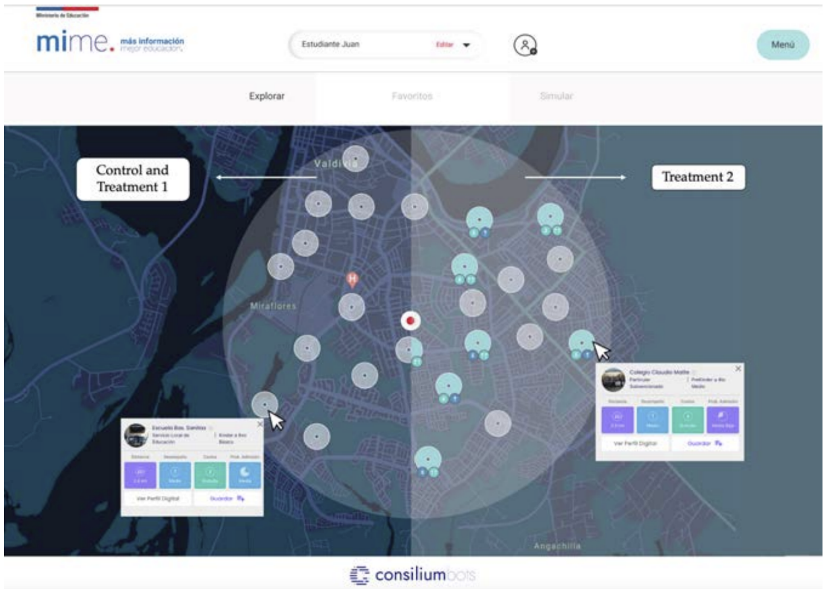
First raised	**Domain**	**Recommendation**	**Status**	**Stated reason / pathway**
2024	Mid-year arrivals	Differentiated treatment for mid-year arrivals (migrants, families relocating, students repeating a grade) whose options are systematically worse than main-round applicants'.	Not adopted	Requires regulatory clarification of in-year rights.
D. Governance and democratic infrastructure				
2022–2024	Transparency	Publish accessible documentation of the assignment logic, priorities, and tie-breaking rules in language a non-specialist can engage with (Pathak, 2017; Correa et al., 2022).	Not adopted	Partial technical documentation exists; no public-facing version.
2022–2024	Public simulators	Public-facing simulators that let families, schools, and civil society explore the consequences of alternative allocation rules in their own neighborhood.	Not adopted	No development pathway established.

Notes: This table summarizes recurring technical recommendations on the SAE algorithm, priority structure, platform interface, and aftermarket design raised in annual ConsiliumBots policy memoranda prepared for MINEDUC (ConsiliumBots, 2024). Items are grouped by domain. The "First raised" column reports the first cycle in which the recommendation was formally proposed and the most recent cycle in which it was repeated. "Adopted" indicates implementation in the production platform; "Partially adopted (interface)" indicates that an opt-out or interface modification was implemented while the underlying default rule remained unchanged; "Not adopted" indicates no implementation. The "Stated reason / pathway" column summarizes the response (where one is documented) or the technical/regulatory category that has prevented adoption. The pattern across rows is the central observation of Section VI: changes confined to the user-facing informational layer have largely been adopted, while changes to the underlying allocation rule, priority structure, or tie-breaking logic have not.

Additional Figures

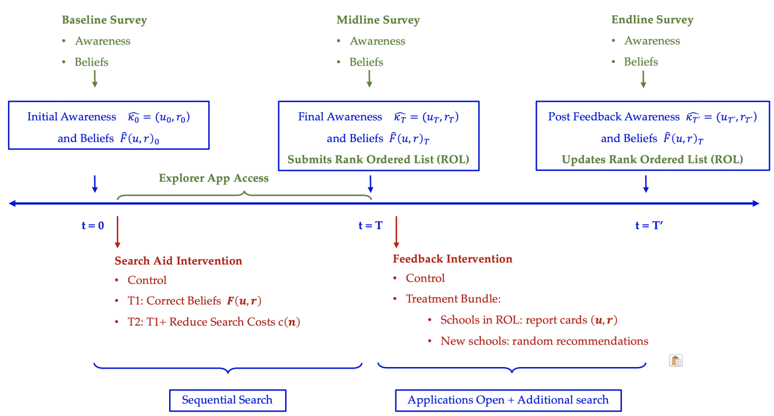
D1. Platform Interface Examples

Figure D1. School Explorer and Treatments



Notes: Image of the School Explorer interface used in the MIME intervention (Agte et al., 2024). Participating families receive personalized information on nearby schools, including the distribution of prices and quality within approximately 2 km of the home. Treatment arms vary in what is shown on top of this baseline information: (i) the distributional summary only, and (ii) the distributional summary plus a map highlighting nearby low-price, high-quality options.

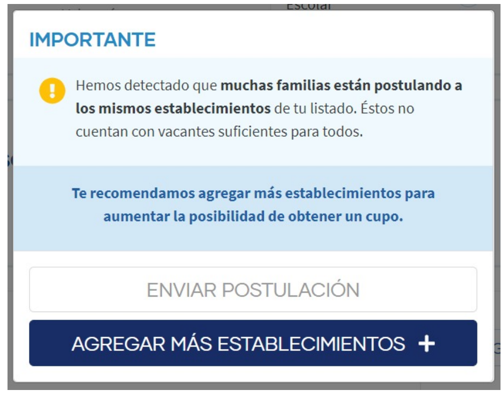
Figure D2. Timeline of Model Mechanisms and Interventions



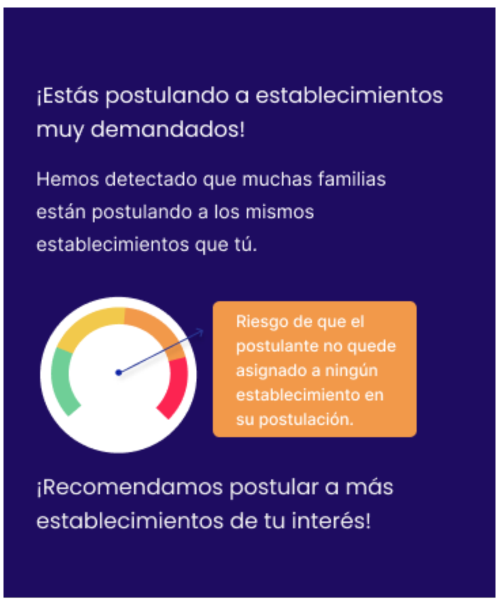
Notes: Schematic timeline summarizing beliefs, search, platform information, and application adjustments across the intervention window.

Figure D3. Platform Warning Pop-Ups Implemented Across Different Years

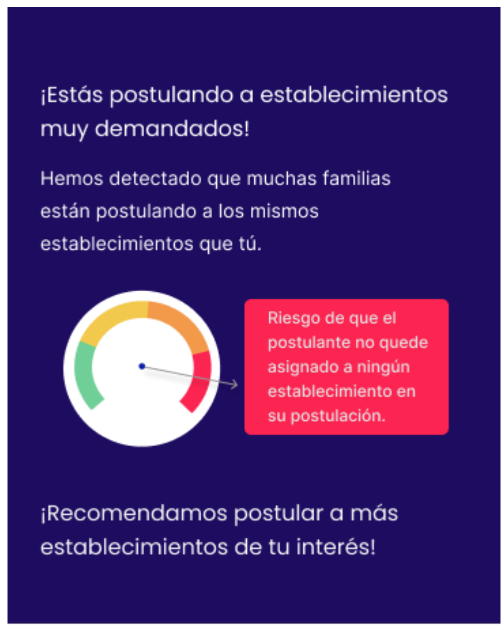
(a) 2018



(b) 2020



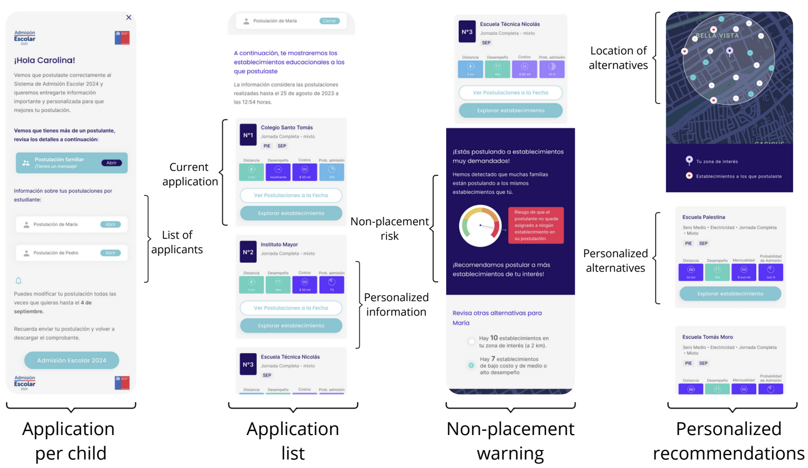
(c) 2023 moderate risk



(d) 2023 high risk

Notes: Screenshots of the platform's non-placement risk warnings implemented in 2018 and 2020 (top row), and the 2023 variants at moderate and high risk levels (bottom row). Layout and wording evolved to improve salience and clarity.

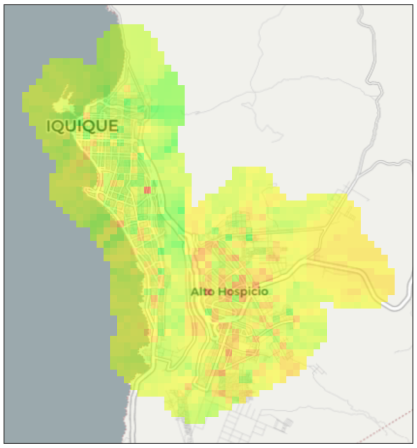
Figure D4. Current Warning and Feedback Report



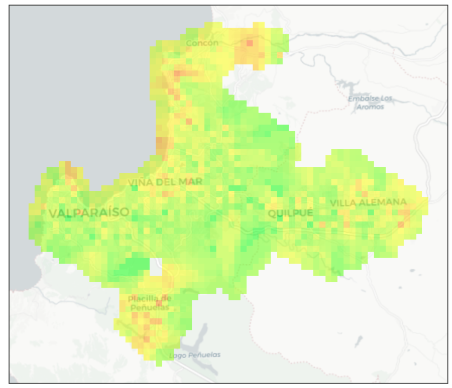
Notes: The current interface combines a risk warning with a summary of each listed school's price, quality, and predicted admission chances, along with suggestions to add safer alternatives.

D2. Local Non-Placement Risk

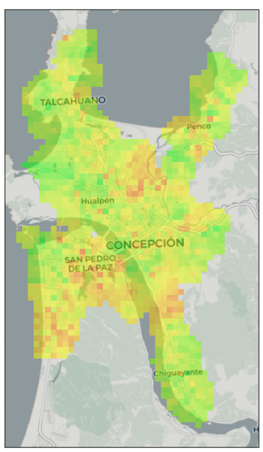
Figure D5. Distribution of non-placement risk probability across major cities



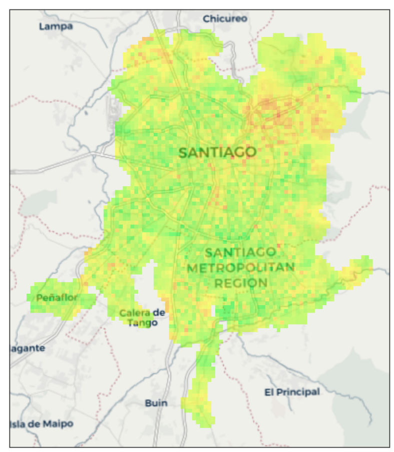
(a) Iquique & Alto Hospicio



(b) Valparaíso



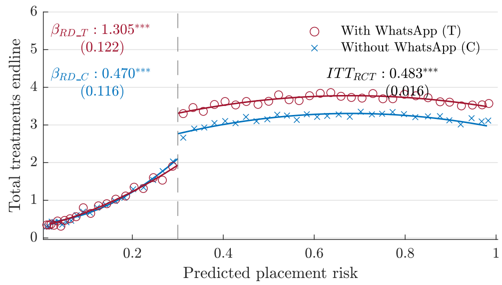
(c) Concepción



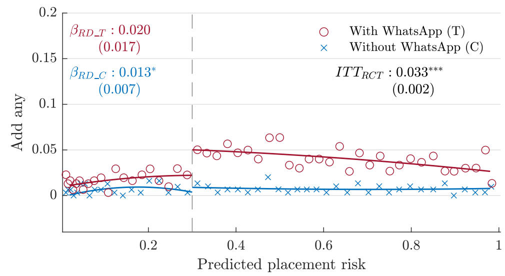
(d) Santiago

Notes: This figure shows the distribution of predicted non-placement probabilities across applicants in selected Chilean cities under the 2023 SAE admissions cycle. Probabilities are estimated following Arteaga et al. (2022*a*), which models the likelihood that a student remains unassigned given their submitted preference list and local school capacities.

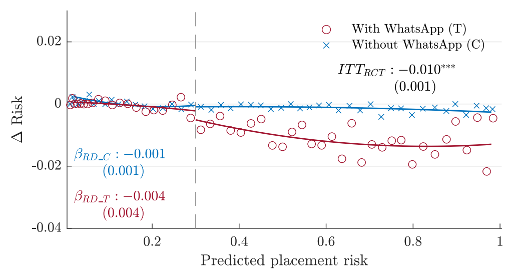
Figure D6. WhatsApp Pop-Up RD Estimates (2018-2020 pooled)



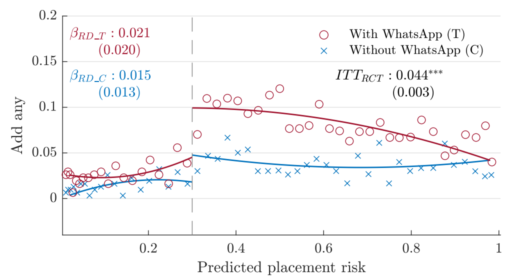
(a) Count of Feedback Messages Received



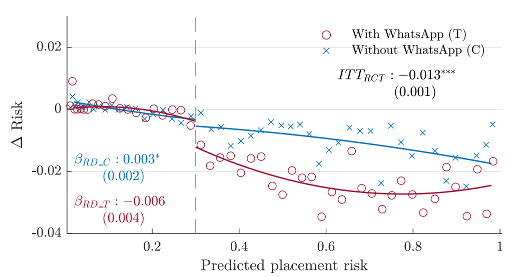
(b) Add at Least One School – 44 Hours



(c) Change in Risk – 44 Hours



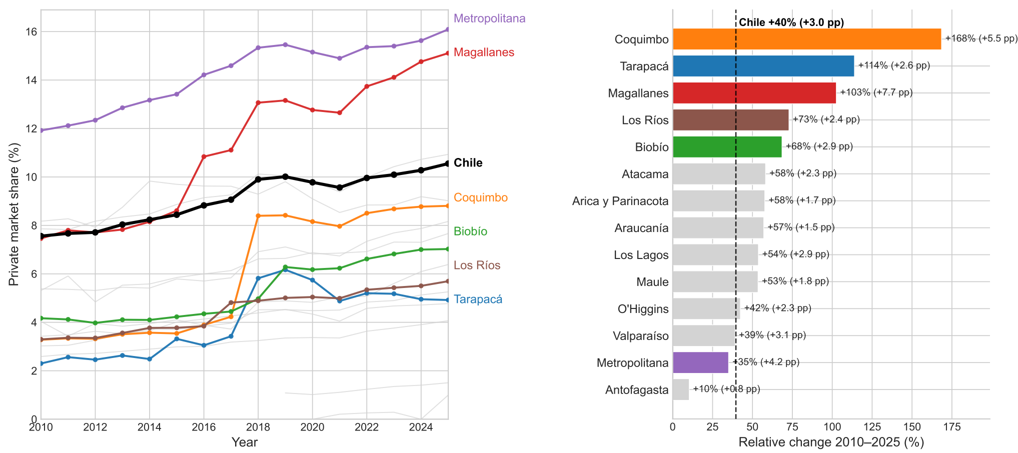
(d) Add at Least One School – Endline



(e) Change in Risk – Endline

Notes: Binned means and global fits of outcomes by predicted placement risk in the RCT sample. Solid lines show quadratic fits. Figures compare RCT treatment and control groups relative to the cutoff. "With WhatsApp" applicants receive a WhatsApp warning above the cutoff (0.3) and a generic message if below; "Without WhatsApp" receive no warning. Reported β_{RD} coefficients are local linear RD estimates with a ±0.1 bandwidth. Reported ITT_{RCT} values correspond to the experimental treatment effect for above-cutoff applicants.

Figure D7. Private market share of K–12 enrolment, Chile and regions, 2010–2025

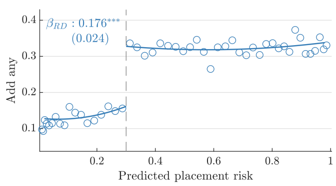


(a) Trends, Chile and regions

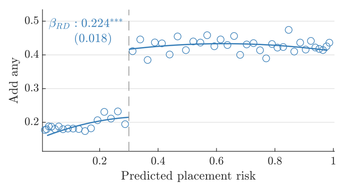
(b) Relative change 2010–2025, by region

Notes: Annual share of total K–12 enrolment attending private (non-subsidized) schools, computed as the ratio of students enrolled in P. Pagado schools to all enrolled students in each year. Panel (a) plots the time series for Chile (thick black line) and the regions, highlighting the five regions with the largest *relative* change in private share over 2010–2025 plus the Metropolitan Region; the remaining regions are shown in grey for reference. Panel (b) ranks all regions by their relative change in private share between 2010 and 2025, with each bar reporting the relative change (Δ% over the 2010 base) and, in parentheses, the change in percentage points; the dashed vertical line marks the Chile-wide change. Own calculations from administrative enrollment records (*Matrícula Básica*, 2010–2025).

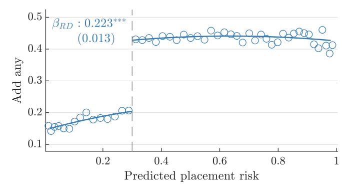
Figure D8. Added at Least One School — Year-by-Year RD Estimates (2018–2023)



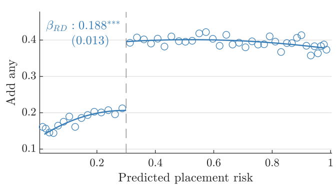
(a) 2018



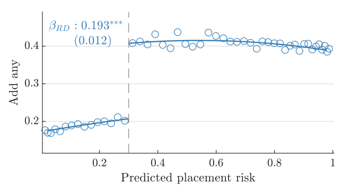
(b) 2019



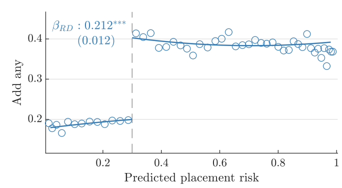
(c) 2020



(d) 2021



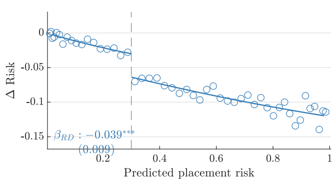
(e) 2022



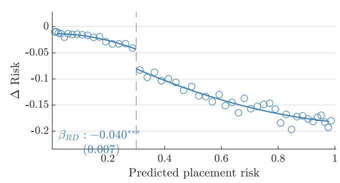
(f) 2023

Notes: Each panel shows the regression discontinuity estimate of the platform pop-up warning on the probability of adding at least one school to the preference list for a given SAE cycle. The vertical dashed line marks the eligibility cutoff for receiving the warning. Reported coefficients (β_{RD}) correspond to local linear estimates with robust standard errors in parentheses. See Figure 9(a) for the pooled estimate across all years.

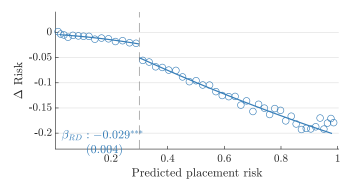
Figure D9. Change in Assignment Risk (Δ Risk) — Year-by-Year RD Estimates (2018–2023)



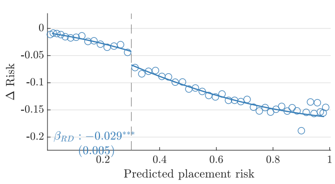
(a) 2018



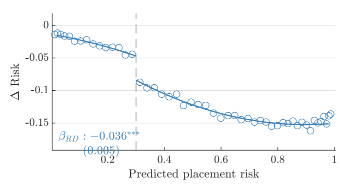
(b) 2019



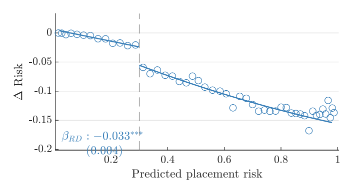
(c) 2020



(d) 2021



(e) 2022



(f) 2023

Notes: Each panel shows the regression discontinuity estimate of the platform pop-up warning on the change in predicted assignment risk (Δ Risk) for a given SAE cycle. The vertical dashed line marks the eligibility cutoff for receiving the warning. Reported coefficients (β_{RD}) correspond to local linear estimates with robust standard errors in parentheses.