

Evaluating Controlled Choice with a Decomposition Approach: Evidence from Washington, D.C.

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Abstract

Equity goals are increasingly embedded directly in school-assignment mechanisms ("controlled choice"), but evaluations of these reforms after implementation remain scarce. I evaluate Washington, D.C.'s Equitable Access (EA) reform to its deferred-acceptance lottery, which prioritizes economically disadvantaged ("at-risk") students at high-demand schools. Using administrative lottery and enrollment records, exact simulations of the assignment mechanism, I separate the effect of changing assignment rule from concurrent changes in capacity, applicant volume, and school ranking behavior with a Shapley decomposition. Between 2020 and 2023, the rule raised the share of all at-risk pre-kindergarten applicants matching to EA schools by 2.4 percentage points, a 30 percent increase. The rule had a larger effect than a contemporaneous 17 percent expansion in seats at these schools. Crowd-out of other applicants was modest and more than offset by capacity growth. The intervention itself was modest, as the rule did not bind at more than half of EA schools, and was concentrated at EA public charter schools. School ranking behavior was remarkably stable around implementation, with one possible exception. At-risk students who matched enrolled and persisted at rates similar to other applicants.

Key words: school choice; controlled choice; deferred acceptance; pre-kindergarten.

Introduction

Equitable access to high-quality schools is the promise of school choice: by decoupling school assignment from residential location, policymakers aim to reduce the inequities created by geographic zoning and residential sorting. As choice has gained policy traction, centralized assignment lotteries have been adopted across the United States, including in Boston, Chicago, Denver, New Orleans, New York City, San Francisco, and Washington, D.C. Students submit ranked school choices, and an algorithm assigns seats based on those rankings and each school's priorities and capacity. However, the promise of school choice remains unfulfilled. Families differ in the resources and information needed to navigate choice (Corcoran et al., 2018), and the expansion of choice has at times exacerbated segregation (Bifulco & Ladd, 2007; Monarrez et al., 2022). In response, policymakers have begun embedding equity goals directly into school-assignment mechanisms: a strategy known as controlled choice.

Evaluating changes to a school-assignment mechanism, such as controlled choice, poses an empirical challenge. First, the outcomes of interest, applicant-school matches, are equilibrium objects: one student's assignment depends on and affects the assignments of all others. Consequently, we cannot evaluate a rule change by comparing treated and untreated applicants or schools. Second, the education market equilibria reflect more than just assignment rules. The seats offered by schools, the number of applicants, and their choices may all shift alongside, or in response to, rule changes. These challenges make standard comparative approaches to identify counterfactuals, such as difference-in-differences, poorly suited to isolating the effect of a rule change. Structural models offer an alternative but rely on strong assumptions about latent utility, and their ex ante forecasts depend on predicting auxiliary inputs (Pathak and Shi, 2021). As a

result, despite a robust theoretical literature, ex post evaluations of implemented controlled choice reforms remain rare.

In this paper, I leverage the deterministic nature of an assignment algorithm to evaluate a controlled choice reform. With the assignment mechanism known, I can perfectly¹ replicate the realized outcomes of the lottery given the random tie-breaking numbers used, and three observed inputs: 1) the rank-order lists applicants submit, 2) school capacities, and 3) assignment rules. Varying these inputs lets me construct any counterfactual lottery, such as changing only the assignment rule while holding applicant school rankings and other inputs fixed. This can be calculated directly without specifying a random utility model, making strong assumptions about latent utility functions, or assuming preference stability.

Specifically, I calculate the probability of each applicant-school match (deferred acceptance propensity scores) for every combination of pre- and post-treatment inputs. These counterfactuals allow me to attribute each input's contribution to changes in equilibrium match probabilities between pre- and post-reform lotteries with a Shapley decomposition (Shorrocks, 2013). The resulting rule component is a causal, partial equilibrium effect of the assignment rule (holding rankings and capacities fixed), capturing crowd-out and spillovers.

The rank-order list component captures endogenous responses to the rule and other shifts in ranking behavior, such as responses to new schools. I test whether the distribution of ranked list types changed unusually around the reform relative to year-to-year variation. An unusual change may signal a shift in who participates or in how families rank schools in response to the rule, but it may also reflect other contemporaneous shocks. The test is most informative when no unusual

¹ My replication implements the full MSDC assignment mechanism, including dynamic sibling priority, pre-K guarantee preferences, and Equitable Access designated seats, which are modeled as separate “phantom” programs. Using the realized lottery numbers, rank-order lists, capacities, and priorities, it reproduces each applicant-school match in the lotteries from 2018 to 2024.

change appears: that suggests any shift in ranked list behavior in response to the rule was small relative to normal variation, unless offset by an unusual shock in the opposite direction.

Additionally, DA propensity scores support several policy-relevant extensions. They weight each applicant-school match, so I can decompose changes in match quality outcomes, such as first-choice matches. Further, DA propensity scores are commonly used in lottery-based causal designs (Abdulkadiroğlu et al., 2017). As the goal of a controlled choice policy is school access, I use such a design to test whether students prioritized by the policy are as likely as other applicants to enroll and stay at a targeted school after receiving a lottery offer.

Washington, D.C. provides a useful setting for applying this decomposition approach. The city introduced Equitable Access (EA) in 2022 with the goal of increasing access to high-demand schools for economically disadvantaged (“at-risk”²) students. By 2024, nearly 1 in 5 schools prioritized at-risk applicants, who constitute nearly half of all D.C. students, in at least one grade (predominantly in pre-kindergarten programs). Schools adopted EA in two forms: 1) EA Priority, which adds at-risk applicants as a new priority group within the DA algorithm, or 2) EA Designated Seats, which reserves a fixed number of seats for them. Implementation strength varied both across and within these categories, as schools differed in designated seats and priority order.

I use administrative records on every My School D.C. (MSDC) lottery from 2018 to 2024, linked to enrollment records, and focus on pre-kindergarten for three-year-olds (PK3), the grade with the most applicants and the heaviest EA targeting. My main comparison is 2020, the last pre-COVID lottery, against 2023, EA’s second year; other year pairs serve as robustness checks.

² At-risk is D.C.’s measure of economic disadvantage. In general, it is the same measure used for “direct certification” for federally subsidized free and reduced-price lunch. It includes families receiving SNAP or TANF, children in the foster system, children who are homeless, or high school students who are overage, or under-credited (D.C. Law 12-207; D.C. Official Code § 38-2901(2A))

To preview results, between 2020 and 2023, among at-risk applicants who applied to at least one EA school, the probability of matching to one rose from 22 to 37 percent. Six of those points came directly from the rule change, and most of the rest came from changes in system capacity and applicant volume. Shifts in school ranking behavior were not statistically significant overall. The rule reduced non-at-risk applicants' offer rate at EA schools by 3 points, but capacity and volume growth left them more likely to match to an EA school than in 2020. Across all at-risk applicants, the rule raised the share matching to EA schools by 2.4 percentage points, a 30 percent increase over the 8 percent baseline. This exceeded the effect of capacity changes (1.9 points), even though seats at EA schools grew 17 percent.

Despite this substantial increase, the intervention itself was modest: roughly 320 of the 6,292 PK3 seats were reserved for or prioritized at-risk students. The rule did not bind at over half of EA schools, which often reserved fewer seats than at-risk students already won or limited eligibility to in-boundary applicants. Its effect was instead concentrated at public charter schools, increasing at-risk applicants' probability of matching to EA priority schools by 215 percent and to designated-seat schools by 29 percent, relative to their respective baseline probabilities. Reach was also limited by who applies: only 40 percent of at-risk applicants ranked an EA school, compared with 74 percent of others.

Overall, the EA rule change increased at-risk applicants' probability of matching to their first-choice school by 1.5 percentage points and lowered it by the same amount for non-at-risk applicants. For context, contemporaneous capacity changes between 2020 and 2023 increased first-choice match rates by about 4.5 percentage points for both groups. Finally, the enrollment and persistence results indicate that after receiving a match, at-risk applicants are no less likely to accept and remain enrolled at EA schools than non-at-risk applicants.

In principle, this decomposition approach could evaluate any change to a deterministic, fully replicable assignment mechanism, such as controlled-choice policies Denver and Chicago are exploring. It also provides policymakers a more robust version of an approach planners already use.³ Under DA, propensity scores can be computed analytically, and because DA is strategy-proof, the decomposition can support analyses of welfare and match quality. Investigating those welfare changes, however, would require additional structure beyond the decomposition itself.

Background, Related Literature, and Policy Context

The Deferred-Acceptance Algorithm. In the canonical student-proposing deferred-acceptance (DA) algorithm, students apply sequentially to schools in order of preference, and schools tentatively match applicants up to capacity by priority group.⁴ The process repeats until no student wishes to make further proposals (Gale & Shapley, 1962; Abdulkadiroğlu & Sönmez, 2003). The DA algorithm produces a stable matching: no student–school pair would both prefer to be matched over their current assignments and is strategy-proof for students (Gale & Shapley, 1962; Roth, 1982; Abdulkadiroğlu & Sönmez, 2003). Truthfully ranking schools according to one’s actual preferences is a dominant strategy.

Controlled Choice Mechanisms. Theoretical work has explored multiple ways to embed equity goals directly into school-assignment mechanisms. Ehlers et al. (2014) provide a useful taxonomy: “hard-bound” and “soft-bound” rules. Hard-bound rules impose quotas that guarantee a minimum or maximum share of seats for particular student types, while soft-bound rules

³ Practitioners often re-run the lottery under alternative rules and compare the resulting assignments. However, this approach is fragile. Assignment outcomes are affected by the stochastic noise generated by random tie-breaking numbers. Consequently, comparing two single lottery runs will likely misrepresent the expected effect of the rule, regardless of whether the tie-breaking numbers are held fixed across runs.

⁴ Examples of common priority groups include if the applicant lives within a school-specific geographic boundary, or if the applicant has a sibling enrolled at the school. For tie-breaking, students are also sorted within priority groups by the random lottery number each student is assigned at the start of the lottery.

merely prioritize certain applicants without fixed targets. Hard rules can directly enforce equity goals but may sacrifice the stability of the deferred-acceptance (DA) mechanism, whereas soft rules preserve the DA properties but achieve equity only if demand is sufficiently responsive (Hafalir et al., 2013; Ehlers et al., 2014; Kurata et al., 2017).

Because soft-bound rules rely on applicant behavior, a key question is whether equity priorities themselves alter demand. Even when the mechanism remains strategy-proof, new priority structures may still shift families' preferences through two channels. First, prioritizing certain students at a school can signal quality or status, creating an information shock, which can shift behavior (Kapor et al., 2020). Second, changes in the expected composition of peers may alter demand, as parents exhibit strong preferences for school demographics (Hastings et al., 2006; Glazerman & Dotter, 2017). Both channels are plausible in D.C., as the central web portal used for school applications highlights school demographic details and school EA policies specifically, setting them apart from other priority groups.

Empirical evidence on the effectiveness of controlled-choice mechanisms remains scarce. Several U.S. districts—Chicago, Denver, New Orleans, Indianapolis, and Washington, D.C.—have adopted controlled choice mechanisms, but existing evaluations are largely internal policy analyses or descriptive (Coffin & Mason, 2024; DPS, 2018). A standard approach to evaluating changes to lottery systems is to re-run the lottery with the relevant policy change, as seen in DPS (2018) and MSDC reports. However, relying on one or two realizations of the lottery can produce fragile estimates. Additionally, these approaches do not characterize the variation in estimated effects arising from lottery randomness, nor do they quantify the effects of other concurrent changes.

The Institutional Context. My School D.C. (MSDC) is the unified application and lottery for D.C. Public Schools (DCPS) and public charter schools (PCS). It uses a student-proposing DA algorithm, assigns a unique lottery number to each applicant for tie-breaking, and includes several practical modifications. First, applicants may rank up to twelve schools.⁵ Second, the lottery employs dynamic priority groups that depend on tentative matches within the algorithm (whereas the standard model assumes static priorities).⁶ Third, in the pre-Kindergarten market, a few schools grant a “guarantee” preference to in-boundary applicants who submit early applications, allowing students to be matched even if doing so would exceed stated capacity.

DCPS and PCS differ in how they set priorities. DCPS establishes priority structures for its schools, which fall into two general types: neighborhood and citywide. Neighborhood schools offer in-boundary priority for zoned students, while citywide schools do not. PCS, by contrast, determines its own priorities subject to Public Charter School Board approval.

The lottery plays a central role in the pre-Kindergarten market. Nearly all public schools participate, with exceptions limited to alternative programs and one charter network that does not offer pre-K. Roughly 79% of eligible three- and 88% of four-year-olds in D.C. are enrolled in a publicly funded pre-K program (Friedman-Krauss et al., 2024), with the vast majority attending MSDC schools (Doromal et al., 2025). Although families can join waitlists after the main round, the lottery is the essential entry point to the city’s most in-demand programs.

Equitable Access. In late 2020, the Council of the District of Columbia passed the *Expanding Equitable Access to Schools Amendment Act of 2020* (D.C. Law 23-237), which

⁵ Truncated lists, common in school-choice systems, may invite strategic behavior (Calsamiglia et al., 2010). In D.C., this concern is minimal. According to publicly available MSDC lottery data, PK3 applicants who rank between 8 and 12 schools have roughly the same chance (95%) of matching to a school (MSDC, 2023).

⁶ Dynamic priorities for siblings break the theoretical guarantee of strategy-proofness, but meaningful manipulation is unlikely in practice as such mechanisms remain strategy-proof in large markets (Ríos et al., 2024).

authorized charter schools to prioritize “at-risk” students beginning in the 2022-23 school year. In response, the D.C. Public Charter School Board (PCSB) approved the *At-Risk Preference Approval and Monitoring Policy in May 2021*, establishing a process for charter schools to apply for Equitable Access (EA) status. DCPS, which sets its own priorities, adopted EA in parallel. One DCPS school, Stevens Early Learning Center, had piloted at-risk set-aside seats beginning with the 2020 lottery.

The first EA school cohort, approved in September 2021, included eleven charter local education agencies (sixteen PCS schools) and nine DCPS schools, representing roughly 10 percent of all public schools. Adoption expanded rapidly: in the 2024 lottery 43 schools (20 PCS and 23 DCPS) had an EA policy. Schools adopted EA in two forms: 1) an EA Priority, which adds a new priority group for at-risk students within the standard DA algorithm; or 2) EA Designated Seats, which reserves a fixed number of seats exclusively for at-risk students. The designated seats option proved far more popular: 19 of the initial 25 schools adopted EA designated seats, and as of the 2024 lottery, no subsequent adopters implemented EA priority.

Within the DA framework, an EA Priority serves as both a conventional soft-bound rule and a normal priority group in the algorithm. EA Designated Seats require a mechanical modification whereby the algorithm creates a “phantom” school to represent the reserved seats. Qualified students are treated as if they ranked the phantom EA program above the school with the EA seats. After the lottery, schools can hold unfilled reserved seats for at-risk applicants until they are filled, or at their discretion convert them to general seats. At-risk students effectively participate in two successive lotteries at the school: first competing against other at-risk students for a reserved seat, then competing alongside all other applicants for the school’s general seats.

Both EA variants affect access only if sufficient demand exists among at-risk applicants. Because qualified students are treated as ranking the phantom program first, reserved seats are filled before general seats, so at-risk applicants who would have won a general seat with their lottery number instead fill reserved seats. A reserve that is smaller than the number of seats at-risk applicants would win is unlikely to change assignments, since those applicants fill reserved seats before competing for general seats. Filling reserved seats first in this way makes the reserve a minimum guarantee rather than an addition to what at-risk applicants would win on their own. Filling them last would yield a larger effect for the same number of reserved seats, at the cost of greater crowd-out of non-at-risk applicants (Dur et al., 2018; Dur, Pathak, & Sönmez, 2020). An EA Priority likewise has no effect if higher-priority groups have already filled the available seats, or if the school is undersubscribed and admits every applicant regardless. Hence, whether either rule binds depends on the size and composition of each school’s applicant pool relative to its capacity.

By the taxonomy above, EA Designated Seats are a hard-bound rule: reserved seats are unavailable to non-at-risk students during the lottery, which can block a higher-priority non-at-risk applicant even when doing so displaces no at-risk student — the standard source of instability in quota-based mechanisms (Ehlers et al., 2014; Kurata et al., 2017). Within the lottery, however, the phantom-program design is still DA on an expanded set of programs and remains strategy-proof. A separate concern arises because reserved seats revert to the general pool only at the school’s discretion: this ex-post, non-mechanical step sits outside the deterministic algorithm and is the more direct threat to strategy-proofness. This threat raises the importance of checking if ranking behavior changed to an unusual degree after the introduction of the policy.

Data and Measures

This paper uses administrative data covering all MSDC lotteries from 2018 through 2024 combined with school enrollment records maintained by the D.C. Office of the State Superintendent of Education (OSSE). The lottery data contain applicant information covering the schools to which applicants apply, the rank order of those schools, family identifiers, assigned priority groups, lottery numbers, and geocoded home addresses at the census-block level. School records report the number of seats offered for each grade and the priority groups used in assignment. Enrollment records contain a unique student identifier and record each student's enrolled school and grade as of October 5th of each academic year from 2017-18 through 2024-25. I supplement the lottery and enrollment records with census-tract SNAP receipt shares and poverty measures from the American Community Survey linked to applicant addresses.⁷

For the decomposition analysis, I use all PK3 lottery applications between 2018 and 2024 for pairwise comparisons. The focus is PK3, as this grade consistently receives the most applications and was the primary target of the EA policy. I define EA schools as those that had an active EA policy in 2023 (2022 in a robustness exercise) and apply that definition across all years. For the complementary analysis on enrollment and persistence, I pool PK3 applicants to EA schools across the 2018 to 2023 lotteries restricted to applicants with non-degenerate match probabilities. The match probability restriction is to ensure a credible comparison between those who matched to an EA school in the lottery and those who did not. Specifically, I restrict the sample to EA school applicants with EA propensity scores (the probability of matching to any EA school) between 0.05 and 0.70 (**Figure 1**), where there is reasonable overlap between groups.

⁷ ACS data are used to characterize applicants whose at-risk status is not directly observed, as well as for robustness in 2SLS regressions concerning student persistence.

Using these data, I define an indicator variable $EverAtRisk_i$ that equals one if any observed application sharing a family identifier is flagged as at risk in either enrollment or lottery records. Because lottery files only record at-risk status for applicants to schools with an active EA policy, I recover missing values using fall enrollment records. Although unique student identifiers exist only for applicants who immediately enrolled, family identifiers link applications across years and lotteries. Each year, roughly 80 percent of applicants enroll immediately, revealing their at-risk status directly, while another 8 percent are inferred indirectly through the family identifier. The remaining 12 percent, whose status appears in neither source, are treated as non-at-risk. Non-enrolling applicants overwhelmingly come from advantaged neighborhoods,⁸ and virtually none are classified as at-risk by the lottery when their status is observed. Because $EverAtRisk_i$ is constructed the same way every year, it does not depend on whether a school had an EA policy, so changes in the lottery's own at-risk flag after the reform cannot be mistaken for policy effects.

To validate $EverAtRisk_i$, I compare it with the at-risk status recorded by the lottery for non-enrolling applicants to EA schools in 2022 and 2023, from whom the lottery observes status but enrollment records do not. The two measures agree for 93 percent of these non-enrolling EA school applicants. Of the 7 percent that disagree, 5 percentage points are at-risk applicants classified as non-at-risk and 2 points are the reverse. Because misses outnumber false flags, the measure slightly undercounts at-risk students among non-enrollers, which if anything understates differences between at-risk and non-at-risk applicants.

To measure persistence and enrollment outcomes, I define a series of indicator variables. $FallEnrolled_{it}$ equals 1 if applicant i is enrolled at an MSDC school in the following fall of

⁸ On average these applicants come from neighborhoods that are 11 percent SNAP eligible. For observed non-at-risk and at-risk applicants the shares are 12 and 26 percent, respectively.

lottery year t .⁹ $SchEnrolled_{ijt}$ equals 1 if applicant i receives a match and enrolls at school j . $PersistNext_{it}$ and $PersistSecond_{it}$ each equal 1 if applicant i is enrolled at an MSDC school one and two years after the lottery, respectively. Similarly, $SchPersistNext_{it}$ and $SchPersistSecond_{it}$ each equal 1 if applicant i is one or two years after the lottery in the same school they attended in the following fall, or in any MSDC school if that school's grades end before then. Because enrollment records end in fall 2024, one-year persistence is observed for lotteries through 2023 and two-year persistence for lotteries through 2022.

Decomposition Method

To estimate the effect of the EA policy on at-risk students' chances of matching to the targeted schools, I exploit the centralized lottery administered by MSDC. Because the agency's source code is not public, I reconstructed the city's DA assignment mechanism. My replication *perfectly* reproduced the official main-round lottery matches for every applicant, every year, and every grade, using the official lottery inputs.

For each applicant-school pair, I calculate the probability of a match: the DA propensity score. For tractability, I compute the propensity scores analytically from a single run of the lottery, following Abdulkadiroğlu et al. (2017). DA propensity scores are central to the analysis; they serve as the outcomes of interest in the decompositions and as key identifying covariates summarizing assignment probabilities in the enrollment and persistence models.

Mechanism-Based Decomposition of Access. I leverage the structure of the assignment mechanism itself and construct a series of counterfactual lotteries. I then use the counterfactual lotteries to decompose total changes in access between pre- and post-policy periods into changes

⁹ Students who enrolled but withdrew or switched schools prior to October 5th count as not enrolling.

from rules, capacities, applicant volume, and the distribution of rank-order list types using a Shapley decomposition.

Let the propensity scores be denoted $pscore_{ij}(L_l, V_v, C_c, R_r)$ for applicant i and school j . Propensity scores are equilibrium probabilities jointly determined by four inputs: the distribution of rank-order list types L_l , the number of applicants (applicant volume) V_v , all seats offered by schools (capacity) C_c , and the assignment rules of all schools R_r (such as designated seats or lottery priorities). I observe each input during a lottery year, such that $l, v, c, r \in \{2019: 2023\}$. I compute $pscore_{ij}(L_l, V_v, C_c, R_r)$ for each combination of observed inputs. Schools not open in the capacity year are assigned zero capacity, so applicants who rank them proceed to their next choice. EA rules carry over as a share of capacity: each school's designated seats are applied as its reserved share of seats, which reflect the assigned capacity input.

To separate applicant volume from the distribution of list types I partition applicants into cells w defined by Ward of residence, grade, and at-risk status. Within each cell, I hold the distribution of list types fixed and rescale the number of applicants to the target year. Let $I_w^{t'}$ and I_w^t be the set of applicants in cell w during baseline year t' and target year t , with counts $N_w^{t'}$ and N_w^t . For each cell w :

- If $N_w^t > N_w^{t'}$: I randomly resample with replacement $N_w^t - N_w^{t'}$ applicants from $I_w^{t'}$
- If $N_w^t < N_w^{t'}$: I randomly subsample N_w^t applicants from I_w^t
- If $N_w^t = N_w^{t'}$: retain all applicants as is.

This produces a synthetic pool of applicants $\hat{I}_w^{t' \rightarrow t}$ with the same distribution of list types in expectation, but with a new total mass. I construct the analogous synthetic pool in the inverse direction, rescaling target-year applicants to baseline counts, so that every combination of list

types and volume is defined. Because resampling occurs within cells, the relative frequency of ranked lists remains constant – holding L fixed while changing the total number of applicants.

Because the four inputs can interact nonlinearly and each component can be “turned on” in any order, I use a Shapley decomposition to assign unique, additive contributions to each component between two periods. In short, a component’s Shapley value is the average marginal contribution across all possible sequences (or paths) in which the components could be introduced. Let the expected propensity scores at school j for group g be

$$\rho_j^g(L_t, V_t, C_t, R_t) = E[\text{pscore}_{ij}(L_t, V_t, C_t, R_t) \mid \text{EverAtRisk}_i = g], \quad g \in \{0,1\}$$

The total change in expected propensity scores between periods t and t' is

$$\Delta_{t,t',g,j}^T = \rho_j^g(L_t, V_t, C_t, R_t) - \rho_j^g(L_{t'}, V_{t'}, C_{t'}, R_{t'}) = \phi_{t,t',g,j}^R + \phi_{t,t',g,j}^C + \phi_{t,t',g,j}^L + \phi_{t,t',g,j}^V$$

For any $S \subseteq \{L, V, C, R\}$, $\rho_j^g(S)$ means: components in S are evaluated at their post-values (t) and components not in S remain at the pre-values (t'). For example, $\rho_j^g(\emptyset) = \rho_j^g(L_{t'}, V_{t'}, C_{t'}, R_{t'})$ and $\rho_j^g(\{L, C\}) \equiv \rho_j^g(L_t, V_{t'}, C_t, R_{t'})$.

Shapley values for rules $\phi_{t,t',g,j}^R$, capacity $\phi_{t,t',g,j}^C$, rank-list behavior $\phi_{t,t',g,j}^L$ and applicant volume $\phi_{t,t',g,j}^V$ changes, are computed as the marginal change in ρ_j^g across all possible orderings of components:

$$\phi_{t,t',g,j}^x = \frac{1}{24} \sum_{S \subseteq \{R,C,L,V\} \setminus \{x\}} |S|! (4 - |S| - 1)! [\rho_j^g(S \cup \{x\}) - \rho_j^g(S)], \quad x \in \{R, C, L, V\}$$

To illustrate, for $x = R$: $S \in \{\emptyset, \{L\}, \{V\}, \{C\}, \{L, V\}, \{L, C\}, \{V, C\}, \{L, V, C\}\}$.

In practice, I assess the second year of implementation, $t = 2023$, against $t' = 2020$. I take 2020 as the baseline because it predates COVID-related disruptions (which began mid-March 2020, after the lottery closed) and reflects the most recent pre-policy demand conditions, and because its set of schools is the most similar to that of the post-policy years.

I calculate the decomposition for the schools as described above, and also calculate it for each EA school implementation type: 1) DCPS – Citywide, 2) DCPS – Neighborhood, 3) PCS – Designated, 4) PCS –Priority, and 5) Never Adopters. The procedure remains the same, but first I sum the propensity scores by type for each applicant, and then take the expected value for each school type rather than for school j . I report the decomposition for schools open from 2019 through 2023. All schools are included in the equilibrium calculation for propensity scores, but for interpretation purposes, newly opened schools are treated as a separate school type.

Decomposition, Precision, and Inference. To assess the stability of these decompositions, I implement a nonparametric bootstrap. There are two important sources of uncertainty that motivate this approach. First, there is stochastic variation from the analytic approach: the closed-form solution relies on a single realization of the lottery and is formally derived under large-market assumptions that may not hold in finite samples. Second, there is sampling variation in the applicant pool: the specific set of families that choose to participate in the lottery each year.

To address both sources, I stratify the applicant population into cells defined by D.C. Ward of residence, grade, at-risk status, and lottery year, thereby preserving the broad geographic and demographic composition. Within each cell, I resample applicants with replacement. Each bootstrap replication assigns new random lottery numbers to all applicants, reruns the assignment algorithm, recomputes the full set of propensity scores and decomposition values, and stores the resulting statistics. I perform 1,000 replications and report confidence intervals based on this empirical distribution.

Testing Ranking Behavior. The Shapley value for changes in the distribution of list types, $\phi_{t,t',g,j}^L$, provides a test of whether ranking behavior changed to an unusual degree between t and t' . If applicants in year t and t' are drawn from the same underlying distribution of submitted list

types, then in expectation $\phi_{t,t',g,j}^L = 0$. I calculate $\phi_{t,t',g,j}^L$ for varying t, t' pairs, which allows me to also compare the shift from pre to post policy against general year-to-year variability.

Match Quality. The Shapley decomposition framework can be extended to assess changes in match quality. Because propensity scores give the chance of each applicant-school match, they can be used to calculate expected match outcomes, and thus expected match quality. Let SQ denote some school quality for applicant i for matching to school j then the expected match quality (EMQ) under lottery configuration (L_l, V_v, C_c, R_r) will be

$$EMQ_i(L_l, V_v, C_c, R_r) = \sum_j p_{score_{ij}}(L_l, V_v, C_c, R_r) * SQ_{ij}.$$

By calculating the expected match quality for each lottery configuration, I can proceed as above and calculate the Shapley values for each lottery input. I consider two measures of match quality: matching to an applicant's first choice and not matching to any school.

Measuring Policy Strength. Whether EA binds depends on how many seats it targets relative to the seats at-risk applicants already win. For each school-grade j , I compare the share of seats targeted by the 2023 rule, D_j , with at-risk applicants' expected share of 2020 matches, s_j :

$$B_j = \frac{D_j}{s_j}.$$

Because reserved seats are filled first, a rule with $B_j \leq 1$ guarantees no more than at-risk applicants already receive and should not change assignments; $B_j > 1$ indicates a rule likely to bind. B_j uses only 2020 matches and 2023 rules, so it is fixed before the 2023 lottery. See appendix B for details on construction.

Decomposition Results

The descriptive patterns in the PK3 market underscore the need for a decomposition. As shown in **Table 1**, between 2020 and 2023 the total number of applicants fell 16 percent, from

5,678 to 4,747. This follows from the sharp decline around the onset of COVID.¹⁰ However, despite this large decline in applicants, the share who were at-risk remained remarkably stable around 40 percent. The lone exception was the first lottery that occurred during the pandemic in 2021, when it fell to 34 percent. The share of at-risk applicants who applied to at least one EA school rose only gradually, from 37 percent in 2020 to 40 percent in 2023, while the share for non-at-risk applicants stayed between 72 and 76 percent. Yet the share of at-risk applicants matching to an EA school barely moved before the policy, from 8 percent in 2020 to 9 percent in 2021, and then jumped to 13 percent in 2022 and 15 percent in 2023, when EA policies were active. Because applicant volume and capacity also changed over these years, that jump alone cannot be attributed to the rule.

As total applicants fell, there was mechanical upward pressure on match rates, since there was less competition overall. Additionally, as shown in **Table 2**, capacity was increasing at the same time, which also lessened competition for seats. Across the system, there were 6 percent more seats available in the lottery in 2023 than in 2020 (including the 4 EA schools excluded from Table 2 that opened after 2019). However, the seats expanded even more aggressively at the EA schools that offered PK3 seats: growing 17% from 870 to 1,019. Half of this growth occurred at the two schools with EA Priority. Thus, a simple pre/post comparison could not tell us how much of that change came from the rule itself rather than the capacity expansion or the shift in who applied.

Finally, it is worth noting the large differences in policy strength evident in **Table 2**. At the DCPS citywide schools, 22 percent of seats were reserved in 2023, well below the share at-risk applicants won in 2020. Because the reserved seats are filled first, the reserve acts as a minimum

¹⁰ The lottery for the 2020-21 school year (2020 in the table) occurred early in 2020, before the pandemic was declared.

guarantee, so it is unlikely to bind at most of these schools. While that is not the case for the DCPS neighborhood schools, these schools restricted EA eligibility to in-boundary students only. Thus, EA is almost certain to bind at these schools for that subset of students, but the rule effect for all at-risk students will be smaller because out-of-boundary at-risk students can also be crowded out. The PCS schools that had designated seats reserved a slightly smaller share than the DCPS schools – but they typically enrolled far fewer at-risk students before the policy, so the rule is more likely to bind. At the PCS EA priority schools, the rule almost certainly binds, as their other higher priority groups (e.g. children of staff, siblings already attending) are unlikely to fill all the seats.

Between 2020 and 2023, the chance that an at-risk applicant to an EA school matched to one rose sharply: from 22 to 37 percent (**Figure 2, Panel A**). Non-at-risk applicants also saw a small increase – about a third as large as for at-risk applicants – and now have a lower offer rate than at-risk applicants. Decomposing these changes shows that EA rules played the principal role in the increase for at-risk applicants (**Figure 2, Panel B**). The EA rules alone increased offer rates by 6.2 percentage points for at-risk applicants, the largest single component. Capacity growth added 4.9 points, while lower applicant volume added 2.9 points. Changes due to shifts in ranking behavior (1.0 points) were not statistically significant. For non-at-risk applicants, the rules led to crowd-out. Despite the overall rate increasing, the rules themselves reduced offer rates by 2.6 percentage points, which either lower applicant volume (4.4 points) or capacity growth (4.9 points) alone more than offset. Shifts in ranking behavior lowered their rate a further 1.5 points, significant at the 90% level.

In general, non-at-risk applicants were far more likely to apply to EA schools than at-risk applicants. For this reason, it is worth asking what the overall change in match probabilities was,

without conditioning on applying to an EA school. As shown in **Figure 2, Panel C**, the share of all at-risk applicants that matched to an EA school nearly doubled between 2020 and 2023: rising from 8.0 to 14.9 percent. The rule alone accounted for 2.4 percentage points of this increase, or a 30 percent increase over the 2020 level (**Figure 2, Panel D**). Non-at-risk applicants still faced crowd-out, as the rules decreased their share matching by 1.9 points, but they benefited about twice as much as at-risk applicants from changes in seats and applicant volume (7.0 versus 3.4 points). This reflects the fact that non-at-risk applicants were far more likely to apply to an EA school. Once again, changes in ranked-list behavior between these periods were the smallest component, but significant at the 90% confidence level for at-risk students.

Despite the large increase in overall offer rates to EA schools, most of these effects were concentrated in two specific types. **Figure 3 (point estimates in Appendix Table A2)** presents the four-way decomposition of the total change in match rates for each EA school type among all applicants (Appendix Figure A1 shows the same for applicants to each school type). For at-risk applicants, the rule component was statistically significant only at the charter schools that adopted the uncapped priority or had designated seats. The rule had a dramatic effect at the two PCS priority schools: it increased match rates by 1.33 percentage points from a baseline of just 0.62 percent, a 215 percent increase. For context, the capacity effect at these schools, where the number of seats more than doubled (from 62 to 140), was smaller (1.12 points). As for the designated seat PCS schools, the rule increased match rates by 1.0 percentage points, or a 29 percent increase over the base rate of 3.4 percent. The rule did not increase access to DCPS citywide or neighborhood schools. At-risk students' match rates to DCPS citywide schools barely changed between 2020 and 2023, and the 1.0-point rise at DCPS neighborhood schools (from 1.6 to 2.6 percent) came from demand and capacity rather than the rule

The rule's effect was concentrated at the PCS schools because that is largely where it bound. The rule can raise at-risk match rates at a school only if it targets a larger share of seats than at-risk applicants were already expected to win there. Appendix Figure A5 compares each EA school's 2023 targeted seat share with the at-risk share of its expected 2020 matches. Seven of the 20 schools set targets at or below that share, so the rule would be unlikely to bind there. These were mostly DCPS schools: the rule was not binding at five of the nine DCPS schools but at only two of the eleven PCS schools. **Figure 4** plots each school's rule effect for at-risk applicants against this ratio. At every school where the rule was not expected to be binding (the ratio less than 1), the effect was zero or negative. The large effects came from binding schools: about 12 and 18 percentage points at the two PCS priority schools, about 5 to 9 points at three PCS designated-seat schools, and about 5 points at a DCPS citywide school, which was also among the most binding. However, three DCPS neighborhood schools where the rule was expected to bind saw little or no effect, since they offered their designated seats only to at-risk applicants living within their boundaries.

In general, changes in school ranking behavior around the time of the policy had little effect on overall access to EA schools. However, at PCS designated-seat schools, the ranked-list component for at-risk applicants was both significant at the 99 percent level and large in magnitude, slightly larger than the rule effect (1.11 versus 0.98 percentage points; **Figure 3**). **Figure 5** compares this ranking component across EA school types, and for EA schools overall, for several pairs of years. For most EA school types, the component is largely stable and clustered around zero, both before and after the policy. Even the 2020 to 2021 comparison, which spans the COVID lottery, shows no shift in ranking behavior large enough to change access to any EA school type. The exception is the PCS designated-seat schools: the at-risk

component is near zero in both pre-policy comparisons but positive and significant, about 1.1 points, when comparing 2020 to both 2022 and 2023. This result also holds with 2019 as the base year (about 0.8 points; Appendix **Figure A3**). This consistent result suggests a real shift in how at-risk applicants ranked these schools, which affected their access to them. However, we cannot ascribe that change to the policy. It could also reflect other concurrent changes, such as new schools opening, changes in school leadership or location, or a host of other possibilities.

Match Quality. The rule modestly shifted first-choice matches from non-at-risk to at-risk applicants (**Figure 6**). It lowered non-at-risk applicants' chance of matching to their first choice by 1.5 percentage points, from a baseline of 46 percent, and raised at-risk applicants' chance by the same amount, from 77 percent. It also slightly lowered at-risk applicants' chance of not matching to any school, by 0.5 points from 6 percent, and raised it by 0.5 points for non-at-risk applicants, from 17 percent. These rule effects are small next to the other changes. First-choice match rates rose by about 5 points for both groups, mainly because of capacity growth and the drop in applicant volume, which more than offset shifts in ranked lists that lowered them by 3.2 points for non-at-risk and 4.6 points for at-risk applicants (See Appendix **Table A3** for point estimates).

Additional Robustness. The results are similar for PK4 applicants (Appendix Figure A2), although the rule effect is smaller – as there are fewer seats subjected to the EA rule. Between 2020 and 2023, the rule raised at-risk PK4 applicants' match rate to EA schools by 3.3 percentage points and lowered non-at-risk applicants' rate by 1.9 points, while capacity growth raised both. Unlike in PK3, shifts in ranked lists significantly lowered at-risk PK4 applicants' match rate, by 4.6 points, but this is driven by a single school that changed locations, and it disappears with 2019 as the base year. For PK3, using 2019 rather than 2020 as the base year

leaves the rule and ranked-list components largely unchanged (**Appendix Figure A3**). The exception is the ranked-list component for non-at-risk applicants to EA schools overall. This reflects a shift in non-at-risk applicants' ranking between 2019 and 2020, before the policy

The pattern also holds when the outcome is matching to any competitive school, EA or not, defined as a school-grade where applicants ranking it first faced at least a 25 percent chance of not matching there in 2020 (**Appendix Figure A4**). The rule raised at-risk applicants' chance of matching to a competitive school by 1.2 percentage points and lowered non-at-risk applicants' chance by 1.0 point, about half its effects on matching to an EA school (2.4 and 1.9 points), while capacity growth and the drop in applicant volume raised both groups' rates by more than the rule changed them.

Enrollment and Persistence

Design. DA propensity scores can also be applied to identify the causal effects of 1) receiving a match on actual enrollment, and 2) enrollment on later outcomes such as persistence. The key idea is that the lottery creates a series of randomized experiments in school assignments by using the random lottery number to resolve ties. As shown by Abdulkadiroğlu et al. (2017), conditional on DA propensity scores, assignment is random: students with the same score have the same chance of being matched to any given program.

The instrument is highly relevant. The lottery is the primary method for enrolling in high-demand schools. For PK3, there is no by-right school option, so families must apply to a school through the lottery or the post-lottery matching process. The exclusion restriction requires that an EA offer affects later enrollment only through enrollment at the matched school, which is plausible because an offer carries no obligation and no other benefit.

The first stage measures how much receiving a match (through random EA offers) translates into actual enrollment: the take-up of offers. Specifically, I estimate:

$$Y_{it} = a_0 + a_1 Z_{it} + a_2 (Z \times EverAtRisk)_{it} + a_3 EverAtRisk_{it} + \mu'(EApscore_{it} \times \gamma_t) + \gamma_t + v_{it}$$

This is estimated on applicant-level data for those who applied to an EA school. Y_{it} is either $FallEnrolled_{it}$ or $SchEnrolled_{it}$. As the sample is EA school applicants, $SchEnrolled_{it}$ equals 1 if the applicant enrolled in an EA school they matched to. $Z_{it} =$

$\max_{j \in \{EA\ Adopter\}} Matched_{ijt}$ indicates receipt of an EA match, and $EApscore_{it} =$

$\sum_{j \in \{EA\ Adopter\}} pscore_{itj}$ is the cumulative DA propensity of matching to an EA adopting program, and γ_t is application-year fixed effects.

The coefficient a_1 identifies the causal effect of being matched on enrollment, while a_2 captures heterogeneity for at-risk applicants. A significant a_2 would imply that at-risk applicants respond differently to EA offers, revealing differential take-up.

Enrollment is endogenous, as families differ in their propensity to accept offers. I therefore instrument for both $SchEnrolled$ and its interaction with at-risk status using Z and $Z \times EverAtRisk$. The predicted values are then used in the second stage:

$$Y_{it} = \beta_0 + \beta_1 \widehat{SchEnrolled}_{it} + \beta_2 \widehat{SchEnrolled \times EverAtRisk}_{it} + \beta_3 EverAtRisk_{it} + \mu'(EApscore_{it} \times \gamma_t) + \gamma_t + \epsilon_{it}$$

Here Y_{it} includes each of the outcomes: *PersistNext*, *PersistSecond*, *SchPersistNext* and *SchPersistSecond*. β_1 captures the local average treatment effect (LATE) of EA enrollment on persistence for non-at-risk applicants, while β_2 measures the differential effect for at-risk students. Standard errors are clustered at the family level to account for correlated enrollment decisions across siblings.

Although the DA propensity score ensures conditional randomness, I estimate alternative specifications including controls for the number of schools ranked, ward of residence, and neighborhood demographics (% Black, % SNAP). This is similar to Braga et al. (2024)’s specification, which also used propensity scores in the context of D.C. pre-kindergarten.

Results. An EA offer is a strong instrument for enrollment, with a first-stage F statistic above 1,000. Regardless of at-risk status, receiving an offer raised enrollment to an EA school by about 65 percentage points (**Table 3**). In other words, at-risk students were not less likely to accept an EA offer and enroll than non-at-risk students. An offer also raised enrollment in any MSDC school, by 17.7 percentage points for non-at-risk applicants and by 10.3 points for at-risk applicants. The smaller effect for at-risk applicants reflects their higher enrollment without an offer (78 versus 64 percent); adding the offer effect, their approximate enrollment rate with an offer is higher (88 versus 82 percent). Persistence follows the same pattern (**Table 4**). For non-at-risk students, enrolling at the matched EA school raised the chance of staying at the same school by about 40 percentage points, both the following year and two years later; for at-risk students the effect was 10 and 14 points smaller. But at-risk applicants without an offer were already more likely to stay at the same school: 54 versus 42 percent the following year and 44 versus 29 percent two years later. As a rough approximation, adding each group’s estimated effect to its no-offer rate suggests that at-risk and non-at-risk students who enrolled at an EA school stayed there at similar rates: about 83 and 82 percent the following year, and 69 and 68 percent two years later. Because the IV estimates apply to students whose enrollment was changed by the offer, these figures are approximate rather than directly estimated persistence rates. Adding the additional regression controls does not significantly change the results.

These results are largely robust when restricting the sample to 2022 and 2023. During these active policy years, we do not have to infer at-risk status as the lottery observes it for EA school applicants. The estimates in Appendix Tables A4 and A5 tell essentially the same story, although they are less precise and the at-risk gap in staying at the same school two years later, which rests on the 2022 lottery alone, is larger.

Discussion and Conclusion

This paper examines the impact of an equity-oriented school-choice reform on realized equity outcomes within a centralized deferred-acceptance market. The core methodological contribution is an exact replication of the assignment mechanism, which permits quantification of how much of the observed change in equitable access can be attributed to the assignment-rule change itself. Additionally, this approach provides a mechanism-based accounting of equilibrium changes due to capacity changes, as well as contemporaneous system-wide shifts in applicant volume and the distribution of ranked-choice lists. This approach is valuable because evaluating changes in equilibrium outcomes poses significant challenges to traditional comparative methods, as all units are, in effect, treated the same. Other methods, such as structural demand modeling, would require strong assumptions about utility. With the decomposition approach, we do not need to estimate a random utility model, assume how families perceive admission probabilities, or assume stable preferences. All that is required is a faithful replication of the assignment mechanism.

I find that between 2020 and 2023, among at-risk applicants who applied to an EA school, the EA rule raised the probability of matching to one by 6 percentage points over a baseline rate of 22 percent: an increase of 29 percent. In fact, at-risk applicants to these schools are now more likely to receive an offer from an EA school than non-at-risk applicants. However, at-risk

applicants are far less likely to apply to these schools. Despite this large effect, the intervention was more modest than it initially appeared. The rule effect did not raise at-risk match rates at more than half the schools, and the aggregate effect was largely driven by the PCS designated-seat and priority EA schools. It raised at-risk match rates only where it was binding, that is, where the share of seats exposed to it exceeded the school's pre-policy at-risk share. While the PCS and DCPS schools with designated seat policies set aside a similar share of seats for at-risk applicants, the DCPS schools tended to already serve more at-risk applicants or limited the preference to in-boundary at-risk applicants.

Crowd-out effects for non-at-risk applicants were real, concentrated, and offset by capacity changes. Overall, EA rules reduced the chance that non-at-risk applicants to EA schools would receive an offer by 3 percentage points, which was more than offset by the expanding capacity across the system. However, at PCS priority schools, the rule cut offer rates by about half (a 3.9 point decrease from a baseline of about 7), a dramatic reduction. But even here, capacity growth increased offer rates by more than twice this loss. The crowd-out at PCS designated seat EA schools was more muted but still significant. Since the policy was implemented, both priority schools have opted to weaken the EA preference. And as of the 2025 lottery, one of the original EA schools has opted to use designated seats instead.

With one exception, I find no evidence that between 2020 and 2023, ranking behavior changed to an unusual degree. For both at-risk and non-at-risk groups, differences in access attributable to changes in the distribution of rank-ordered lists between the pre- and post-policy periods fall well within historical variability. The contribution of ranking behavior was remarkably stable across all years: the estimated rank-list behavior component of the decomposition remained tightly clustered around zero between 2020 and subsequent years,

including during the COVID period. The one exception is at-risk applicants to PCS designated-seat schools, whose ranked-list component became positive and significant after the reform, about as large as the rule effect there. This does not mean that families did or did not respond to the policy. The decomposition does not separately identify policy-induced demand responses from other unrelated changes, such as changes in school desirability or the impact of COVID. However, given that an unusually large change did occur at PCS designated-seat schools, further work is warranted to explore if this was in response to the policy, or other concurrent changes. Future work would require a structural approach and demand modeling to separate effects.

From a policy planning perspective, this stability is consequential. Despite substantial year-to-year change in the market — most notably from COVID and separately from EA's own rollout — the distribution of submitted rank-order lists did not shift overall by more than the market's ordinary year-to-year variation. This is useful for a policymaker: it suggests match probabilities can be reasonably approximated from the mechanical effect of a proposed rule alone, using historical variation in submitted choices as a bound on how far off that projection could be. For policymakers conducting ex ante evaluations, historical changes in submitted rankings provide a useful benchmark for assessing how sensitive projected rule effects are to changes in applicant behavior.

Although the rule raised at-risk match rates at fewer than half of the EA schools, it had a significant impact on access for the at-risk population. The intervention itself was modest, with roughly 180 seats reserved for at-risk applicants and another 140 seats at the two schools with uncapped priority. Yet it raised the share of all at-risk applicants matching to an EA school by 2.4 percentage points, a 30 percent increase over the 2020 baseline of 8 percent. That gain was larger than the 1.9 points from capacity growth, even though EA schools added 17 percent more

seats. The rule's effects on match quality were smaller. It raised at-risk applicants' chance of matching to their first choice by 1.5 percentage points and lowered non-at-risk applicants' chance by the same amount. It also moved the chance of not matching at all by about half a point, down for at-risk applicants and up for non-at-risk applicants. These rule effects are small next to other changes in the market: capacity growth raised first-choice match rates by about 4.5 percentage points for both groups, while shifts in ranked lists lowered them by 3 to 5 points.

Concerns that at-risk students would fail to enroll or persist at EA schools are not supported by these results. Both at-risk and non-at-risk applicants were equally likely to accept an EA offer, and those who enrolled appear to have stayed at the same school at similar rates. Enrolling at an EA school raised the chance of staying in the same school the following year and two years later by about 40 percentage points for non-at-risk students and by 25 to 30 points for at-risk students. These effects, like the effect of an offer on enrolling in any MSDC school, are smaller for at-risk students, who were more likely to enroll and stay even without an offer. The persistence results matter because they show that the additional access created by EA translated into sustained enrollment rather than unused offers or short-lived placements that might have “blocked” other students. For students and families, staying in the same school provides continuity and signals satisfaction with the placement. For policy planners, persistence signals the policy’s success in nudging disadvantaged students into high-demand schools, since pre-kindergarten is the largest lottery entry point.

By exploiting the mechanism’s exact structure, this analysis provides a transparent template for evaluating similar policies in other choice settings. The decomposition is not specific to EA or deferred acceptance. And changes to the assignment mechanism need not be rule changes. To highlight the flexibility of this approach, suppose we are interested in the effects of changing

capacity to a single school. Similar to how I split observed applicant lists into applicant counts and the distribution of list types, I could split the capacity component into school subcomponents. Doing so would allow us to isolate the contribution of changing a single school's capacity, including closing it, on match rates of all other schools – as well as the impact on student match quality by any characteristic of interest. Ultimately, this paper provides an illustrative test case for the value and flexibility of this decomposition approach.

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Table 1: PK3 Applicant Characteristics by Year and At-Risk Status

	2018	2019	2020	2021	2022	2023
	(1)	(2)	(3)	(4)	(5)	(6)
Applicants	5,669	5,708	5,678	4,380	4,761	4,747
% EverAtRisk	40.4	39.1	39.2	34.3	38.7	39.3
Panel A. EverAtRisk						
Average # Schools Ranked	4.6	4.4	4.3	4.2	4.3	4.0
% Applied to EA School	34.9	34.3	36.9	37.6	38.4	40.3
% Matched	94.5	94.5	95.1	96.4	96.6	96.5
% Matched to EA School	6.4	7.8	8.4	9.1	13.3	14.6
Panel B. NeverAtRisk						
Average # Schools Ranked	6.6	6.5	6.7	7.0	6.5	6.3
% Applied to EA School	71.0	71.9	72.0	75.9	73.9	73.5
% Matched	80.9	81.4	83.4	90.1	85.8	89.7
% Matched to EA School	16.8	17.7	19.3	23.9	21.1	22.1

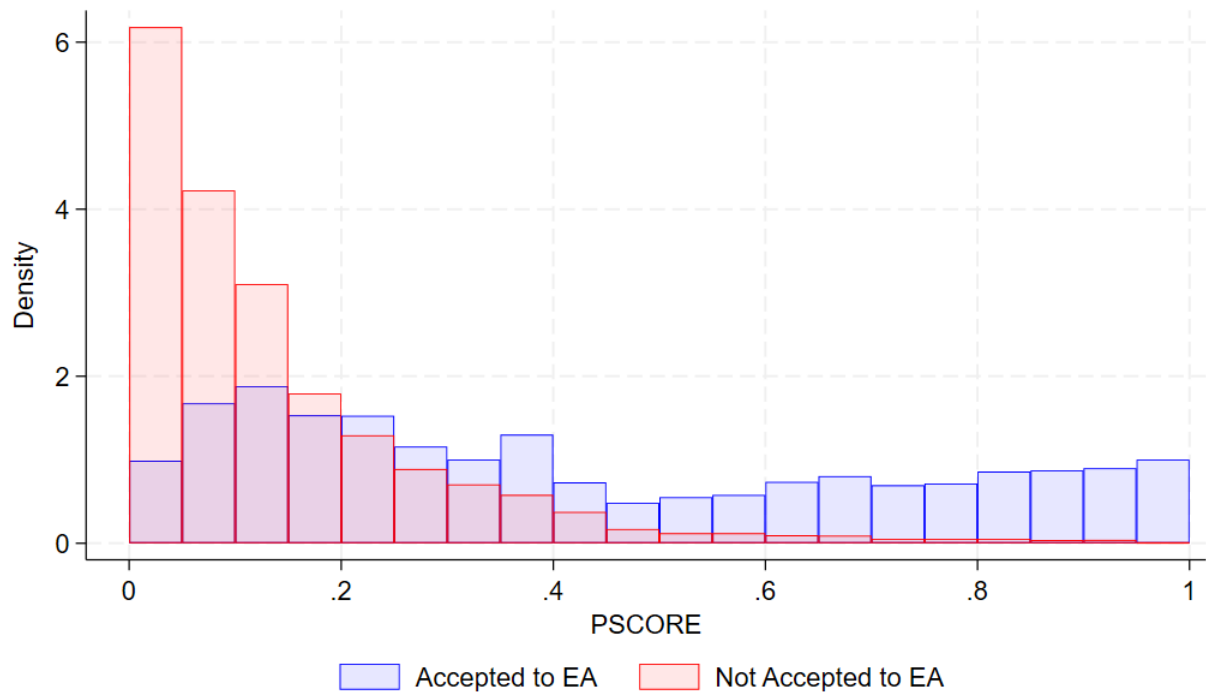
Note: Sample includes all PK3 lottery applicants. Percentages in Panels A and B are within each group. % Matched is the share matched to any school in the main round. EA schools are schools with an equitable access policy in 2023 that were open in 2020. EverAtRisk equals one if any observed member of the applicant's family was flagged at-risk in the lottery or enrollment records.

Table 2: PK3 School Characteristics by EA Implementation Type, 2020 and 2023

	DCPS Citywide		DCPS Neighborhood		PCS Seat		PCS Pref		EA Never Adopters	
	2020	2023	2020	2023	2020	2023	2020	2023	2020	2023
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Applications										
Total	1,806	1,655	1,543	1,339	4,923	3,406	961	1,094	22,169	16,272
% EverAtRisk	19.0	19.8	19.6	19.2	16.1	20.0	21.6	19.2	35.4	33.9
Seats										
Total	188	203	170	183	450	493	62	140	5,342	5,273
% EA Designated	0.0	21.7	0.0	23.5	0.0	19.7	0.0	0.0	0.0	0.0
Matches										
Total	172	155	170	168	450	448	62	140	4,013	3,079
% EverAtRisk	34.9	29.7	19.4	30.4	18.0	29.0	22.6	32.9	47.6	45.5
N (Schools)	4	4	5	5	9	9	2	2	123	121

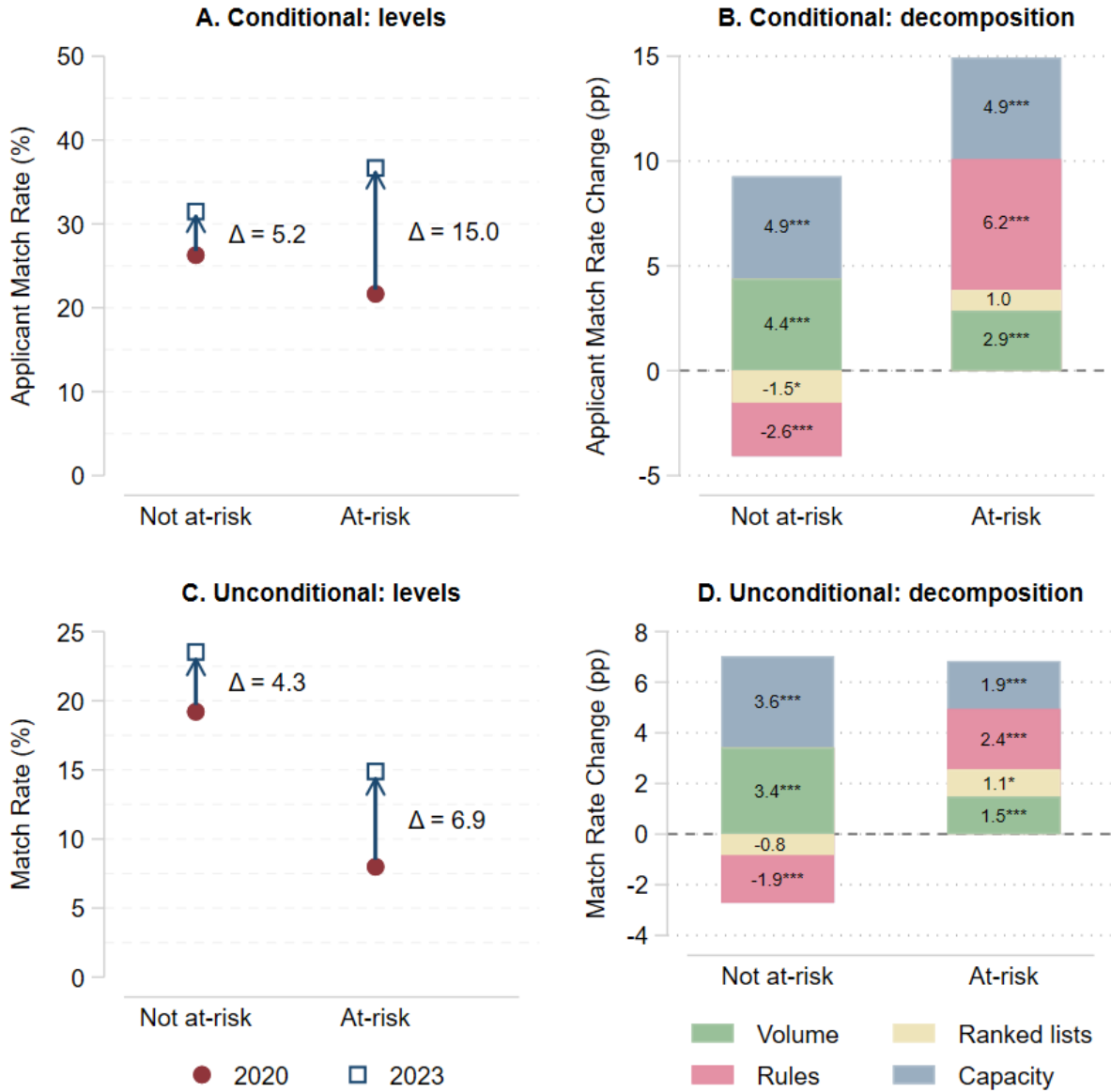
Note: Applications are applicant-school pairs from submitted rank-order lists. Seats and matches are from the main lottery round. % EA Designated is the share of seats reserved for at-risk applicants. PCS Priority schools give at-risk applicants priority instead of reserving seats. DCPS neighborhood schools reserve seats only for in-boundary at-risk applicants. EverAtRisk is defined as in Table 1. Four schools that opened after 2019 and offered EA priority in 2023 are excluded.

Figure 1. Distribution of EA Propensity Scores, by EA Match Status



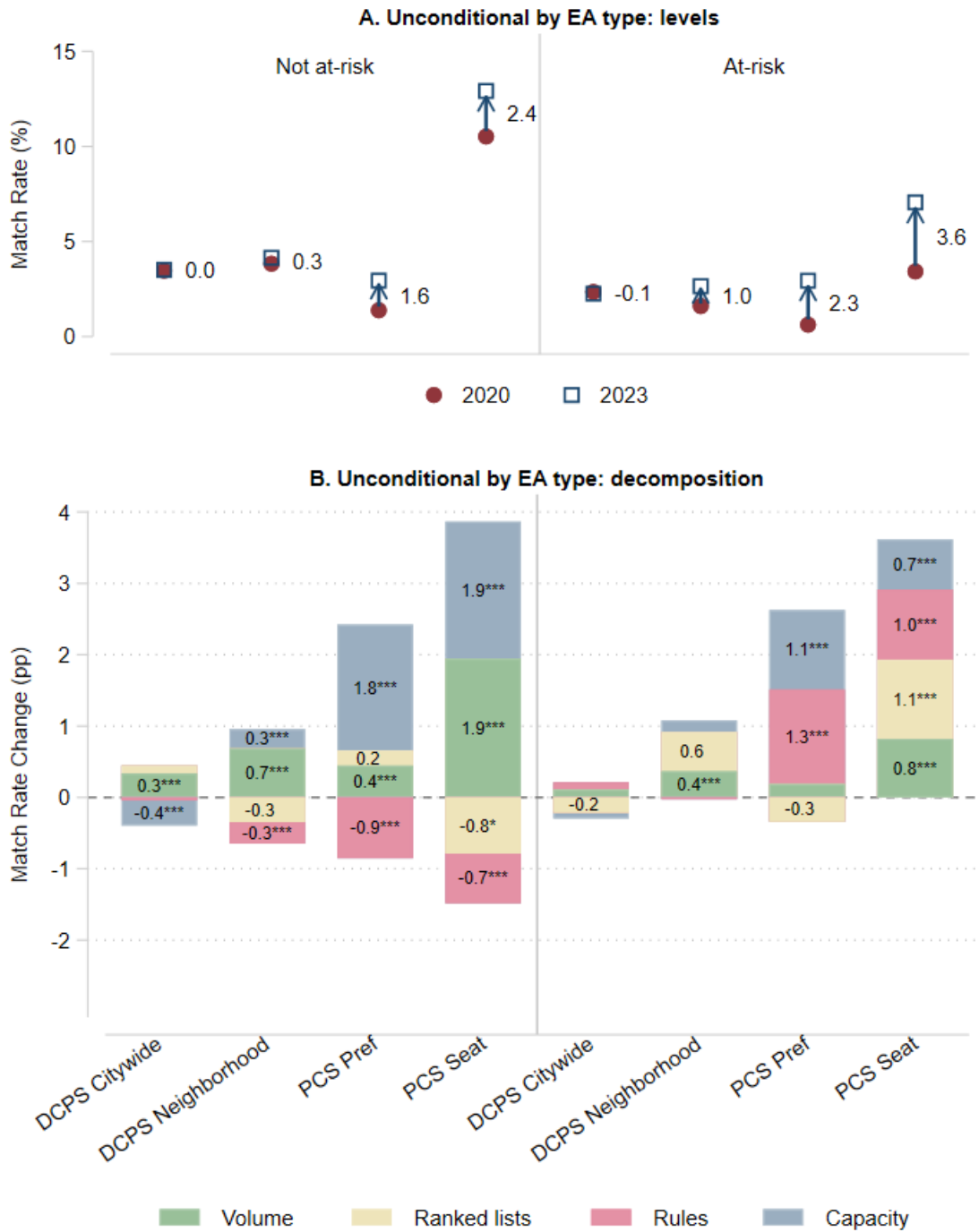
Note: Analytic sample includes PK3 applicants to EA schools in the 2018–2023 lotteries with EA DA propensity scores strictly between 0 and 1. The EA DA propensity score is the probability of matching to any EA school.

Figure 2: Decomposition of EA School Match Rate Changes, 2020–2023



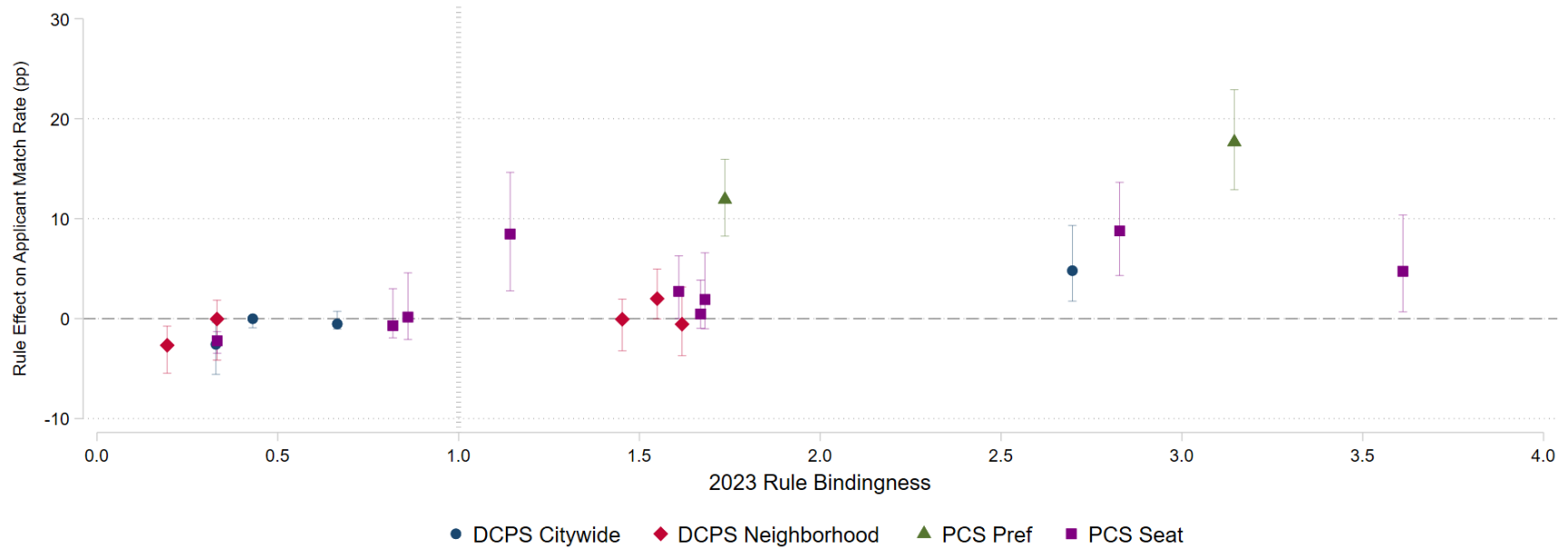
Note: Analytic sample includes PK3 applicants, 2020 to 2023. The match rate is the probability that an applicant is matched to an EA school in the lottery. Conditional rates are among EA school applicants, and unconditional rates are among all applicants. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure 3: Decomposition of Match Rate Changes by EA School Type, 2020–2023



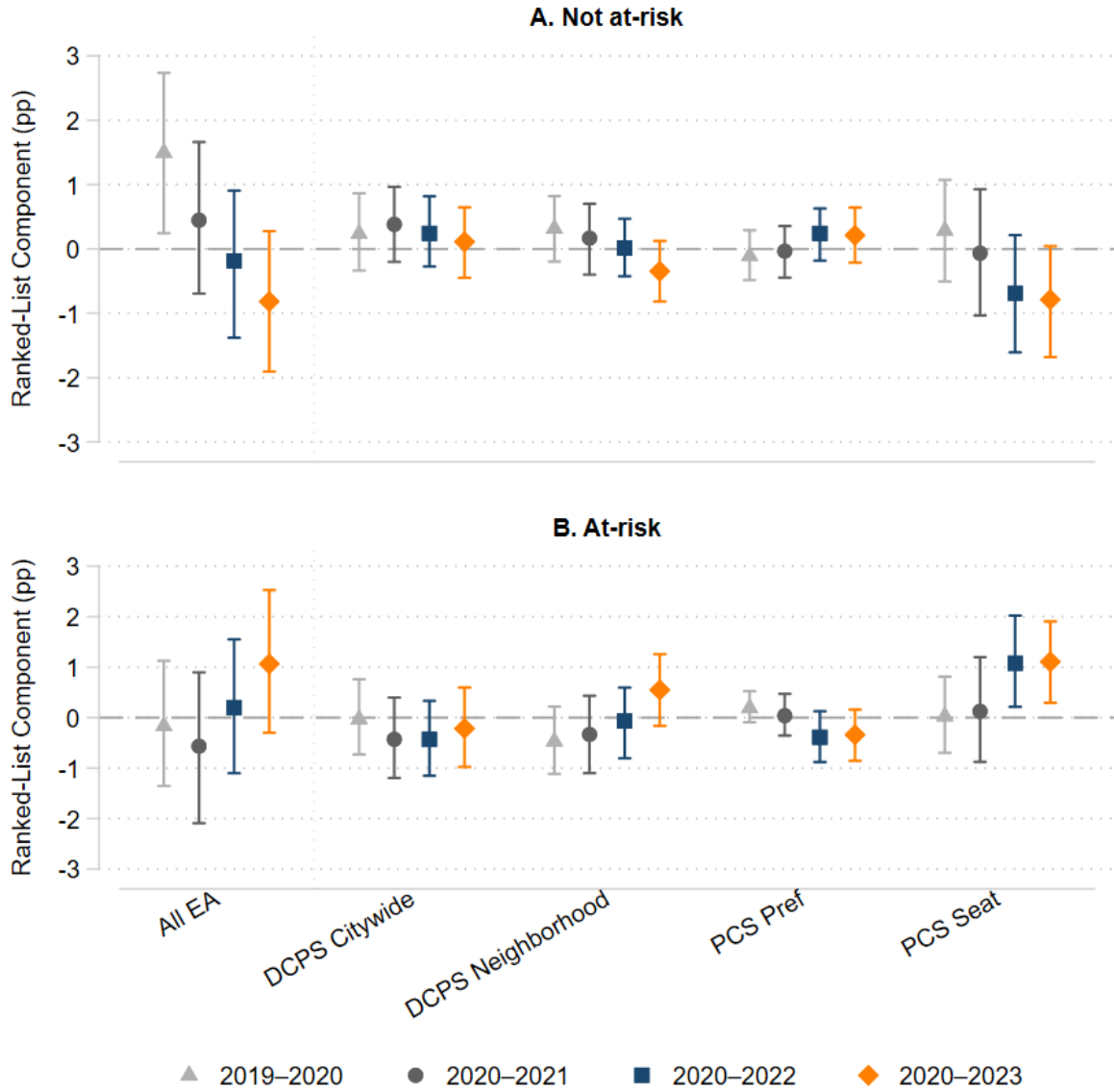
Note: Analytic sample includes all PK3 applicants, 2020 to 2023. The match rate is the probability that an applicant is matched to an EA school of the given type in the lottery. PCS Pref and PCS Seat are charter schools that use EA priority and designated EA seats, respectively. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure 4: Rule Effect by School and Rule Bindingness



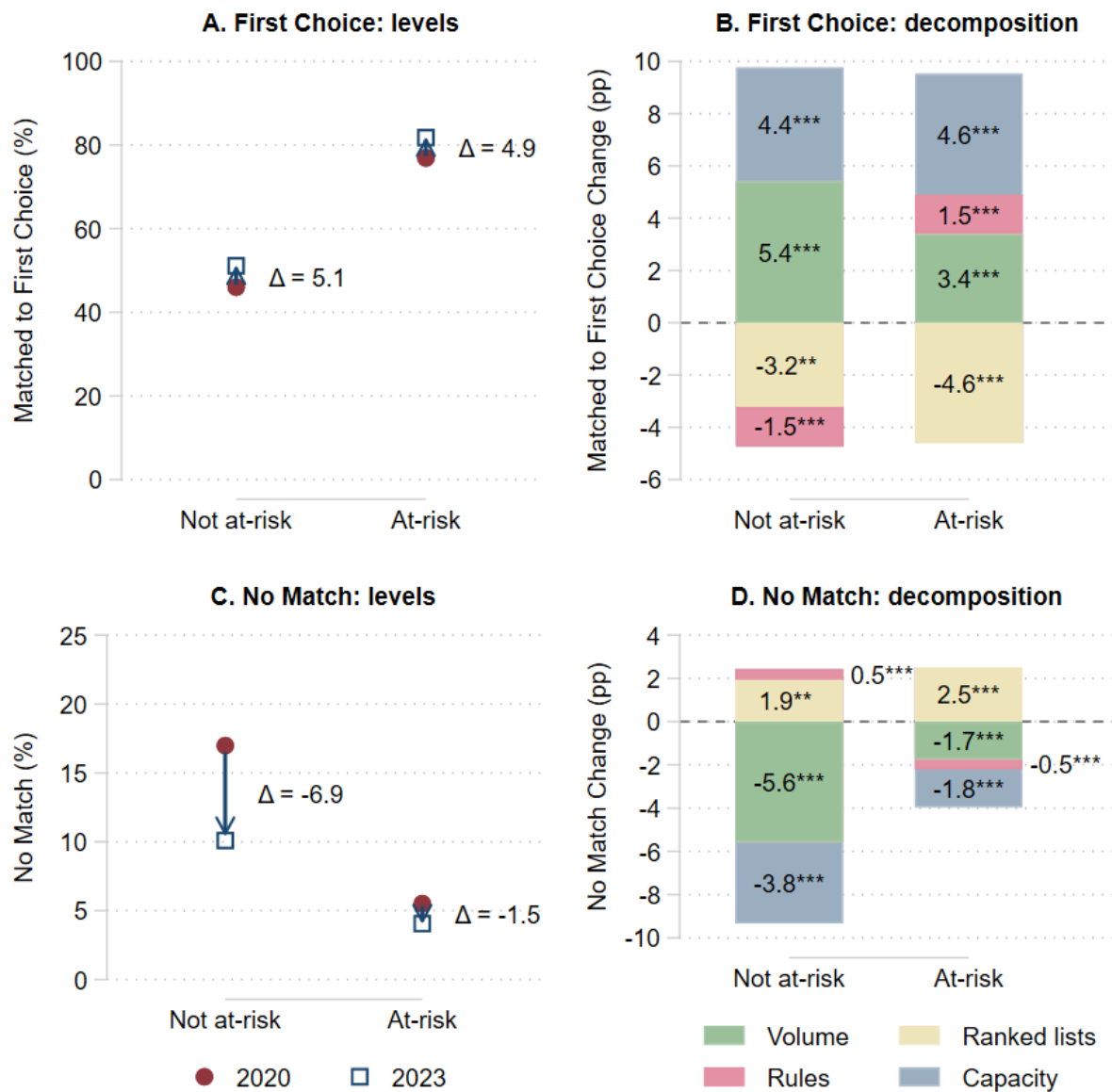
Note: Each point is one EA school. The vertical axis shows the Rules Shapley value for at-risk applicants to that school for the 2020 to 2023 change. Points are medians and bars are 95% percentile intervals across 1,000 bootstrap replications. Rule bindingness is the share of seats exposed to the EA rule in 2023 divided by the at-risk share of expected 2020 matches (Appendix B). Values above 1 mean the exposed share is larger than the school's pre-policy at-risk share.

Figure 5: Ranked-List Component by EA School Type and Period



Note: The figure shows the Ranked lists Shapley value from the four-way decomposition for each period comparison, in percentage points of the match rate. Points are medians and bars are 95% percentile intervals across 1,000 bootstrap replications. Analytic sample includes all PK3 applicants. The match rate is the unconditional probability that an applicant is matched to an EA school of the given type in the lottery.

Figure 6: Decomposition of First-choice and No-Match Rate Changes, 2020–2023



Note: Analytic sample includes all PK3 applicants. First choice is the probability of matching to the first-ranked school, and no match is the probability of not matching to any school. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Table 3: IV First Stage: Receiving EA Offer on Enrollment by Risk Status

	FallEnrolled		SchEnroll		SchEnroll x EverAtRisk	
	(1)	(2)	(3)	(4)	(5)	(6)
EAMatch	0.177*** (0.013)	0.170*** (0.012)	0.646*** (0.012)	0.651*** (0.012)	0.001 (0.001)	0.001 (0.001)
x EverAtRisk	-0.074** (0.027)	-0.062* (0.027)	0.003 (0.029)	-0.001 (0.029)	0.641*** (0.027)	0.641*** (0.027)
No-offer mean, at-risk	0.775	0.775				
No-offer mean, not at-risk	0.640	0.640				
Controls		X		X		X
R ²	0.04	0.09	0.56	0.56	0.63	0.63
N	6,565	6,443	6,565	6,443	6,565	6,443

Note: Standard errors clustered by family in parentheses. *EAMatch* equals one if the applicant received an offer to an EA school. *FallEnrolled* equals one if the applicant enrolled in any DCPS or PCS school in the lottery fall; *SchEnroll* equals one if the applicant enrolled in the EA school they matched to. *EverAtRisk* equals one if the family was flagged at-risk in any lottery or enrollment record. No-offer means are outcome means among applicants without an EA offer. All columns control for lottery year, the EA propensity score, their interaction, and *EverAtRisk*. Columns marked X add the number of applications and neighborhood shares of Black and SNAP-eligible families. Sample: PK3 applicants to EA schools in the 2018-2023 lotteries with EA propensity scores between 0.05 and 0.70.

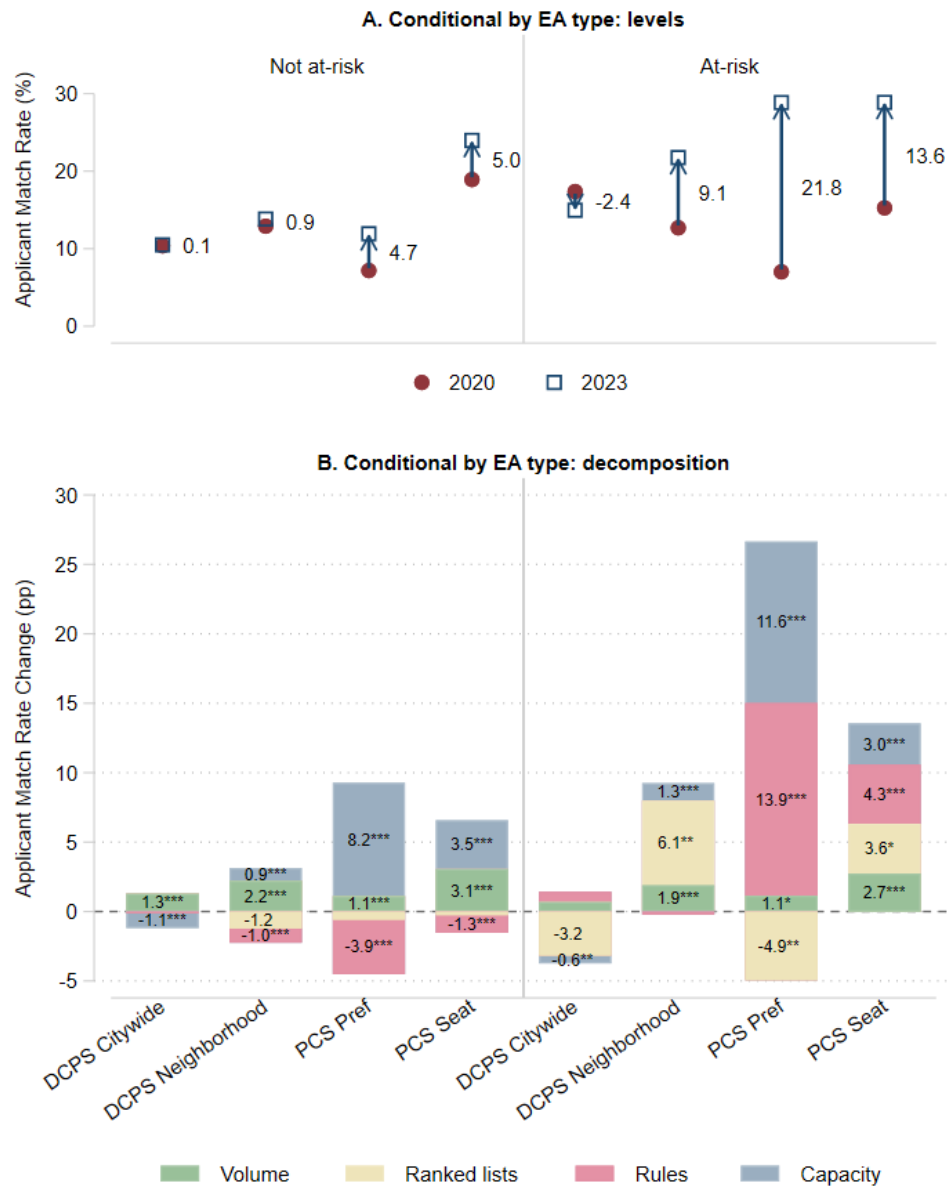
* p<0.05, ** p<0.01, *** p<0.001

Table 4: IV Second Stage Result: EA Enrollment Impact on System and School Persistence

	PersistNext		PersistSecond		SchPersistNext		SchPersistSecond	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EASchEnroll	0.259*** (0.020)	0.251*** (0.020)	0.238*** (0.024)	0.235*** (0.024)	0.395*** (0.021)	0.392*** (0.021)	0.390*** (0.025)	0.389*** (0.025)
x EverAtRisk	-0.074 (0.044)	-0.059 (0.045)	-0.098 (0.052)	-0.084 (0.053)	-0.101* (0.051)	-0.094 (0.051)	-0.139* (0.060)	-0.128* (0.060)
No-offer mean, at-risk	0.728	0.728	0.711	0.711	0.538	0.538	0.441	0.441
No-offer mean, not at-risk	0.578	0.578	0.512	0.512	0.423	0.423	0.294	0.294
Controls		X		X		X		X
First-stage F	1,681.24	1,469.77	1,171.34	1,204.60	1,681.24	1,469.77	1,171.34	1,204.60
R ²	0.09	0.13	0.08	0.12	0.10	0.12	0.09	0.10
N	6,565	6,443	5,414	5,308	6,565	6,443	5,414	5,308

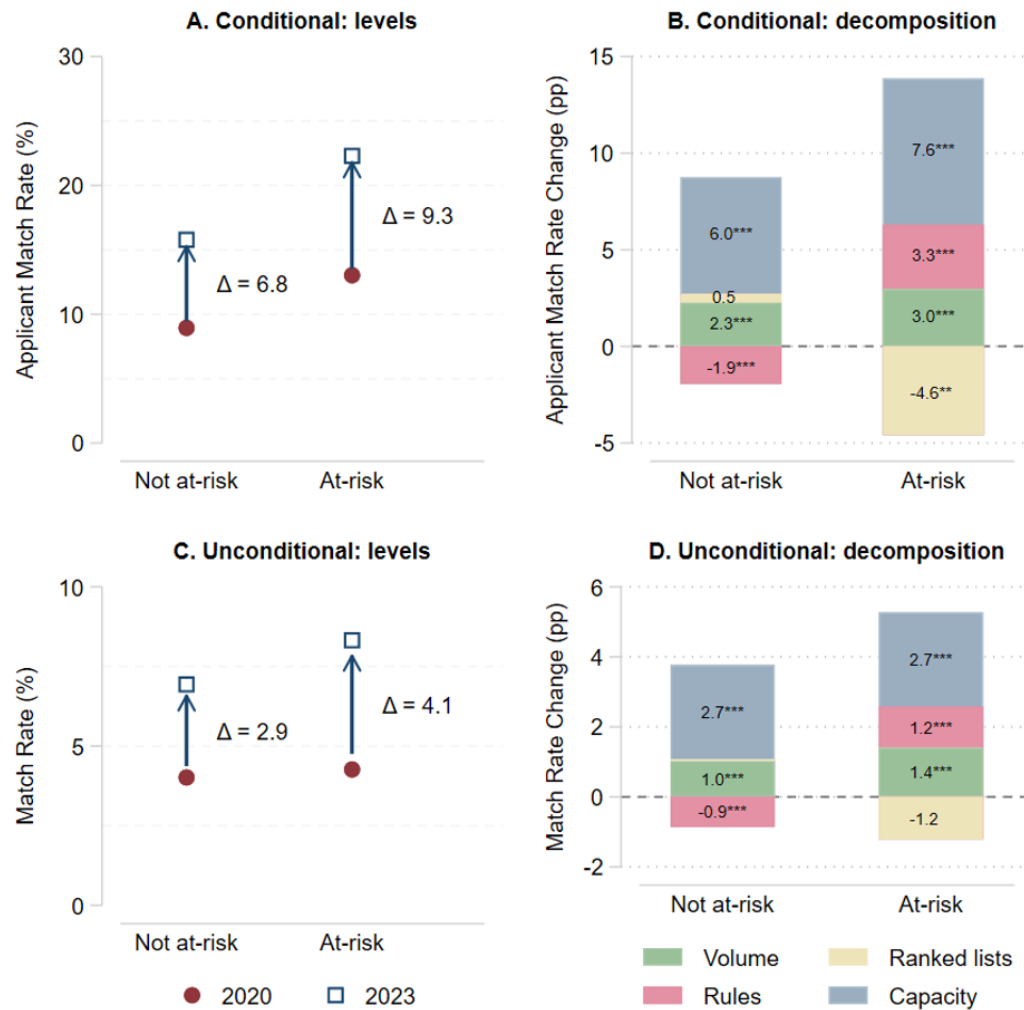
Note: Standard errors clustered by family in parentheses. *EASchEnroll* equals one if the applicant enrolled in the EA school they matched to. *EASchEnroll* and *EASchEnroll* x *EverAtRisk* are instrumented with *EAMatch* and *EAMatch* x *EverAtRisk*; first-stage F is the Kleibergen-Paap Wald F. *PersistNext* and *PersistSecond* equal one if the applicant is enrolled in any DCPS or PCS school one and two years after the lottery. *SchPersistNext* and *SchPersistSecond* equal one if the applicant is enrolled in the same school as in the lottery fall one and two years later, or in any school if that school ends before then. Observed enrollment runs through fall 2024, so *PersistSecond* and *SchPersistSecond* are unobserved for the 2023 lottery. All columns control for lottery year, the EA propensity score, their interaction, and *EverAtRisk*. Columns marked X add the number of applications and neighborhood shares of Black and SNAP-eligible families. Sample: PK3 applicants to EA schools in the 2018-2023 lotteries with EA propensity scores between 0.05 and 0.70. * p<0.05, ** p<0.01, *** p<0.001

Figure A1: Conditional Match Rate Changes by EA School Type, 2020–2023



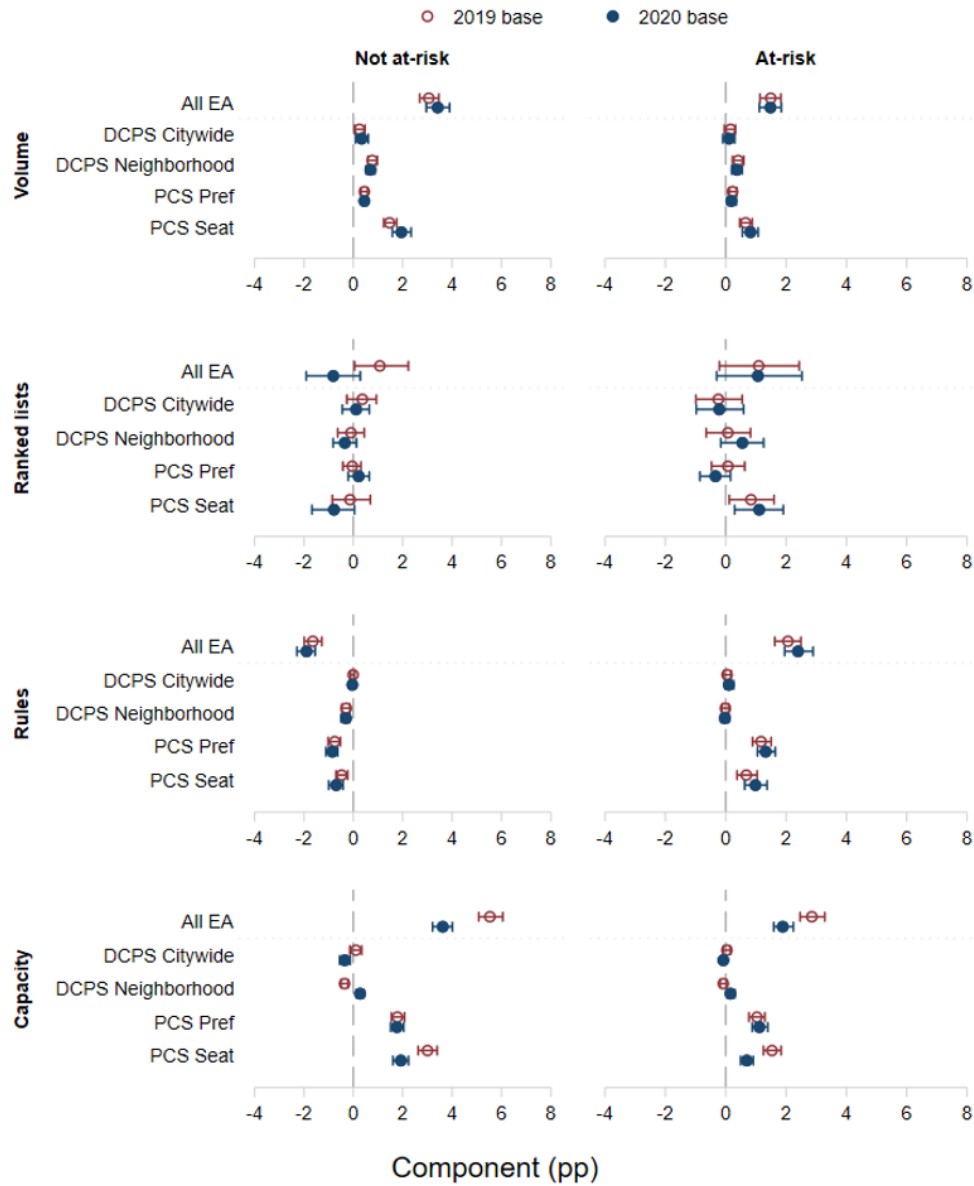
Note: Analytic sample includes PK3 applicants who ranked at least one school of the given type. The applicant match rate is the probability of matching to a school of that type in the lottery. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure A2: PK4 EA School Match Rates and Four-Way Decomposition, 2020–2023



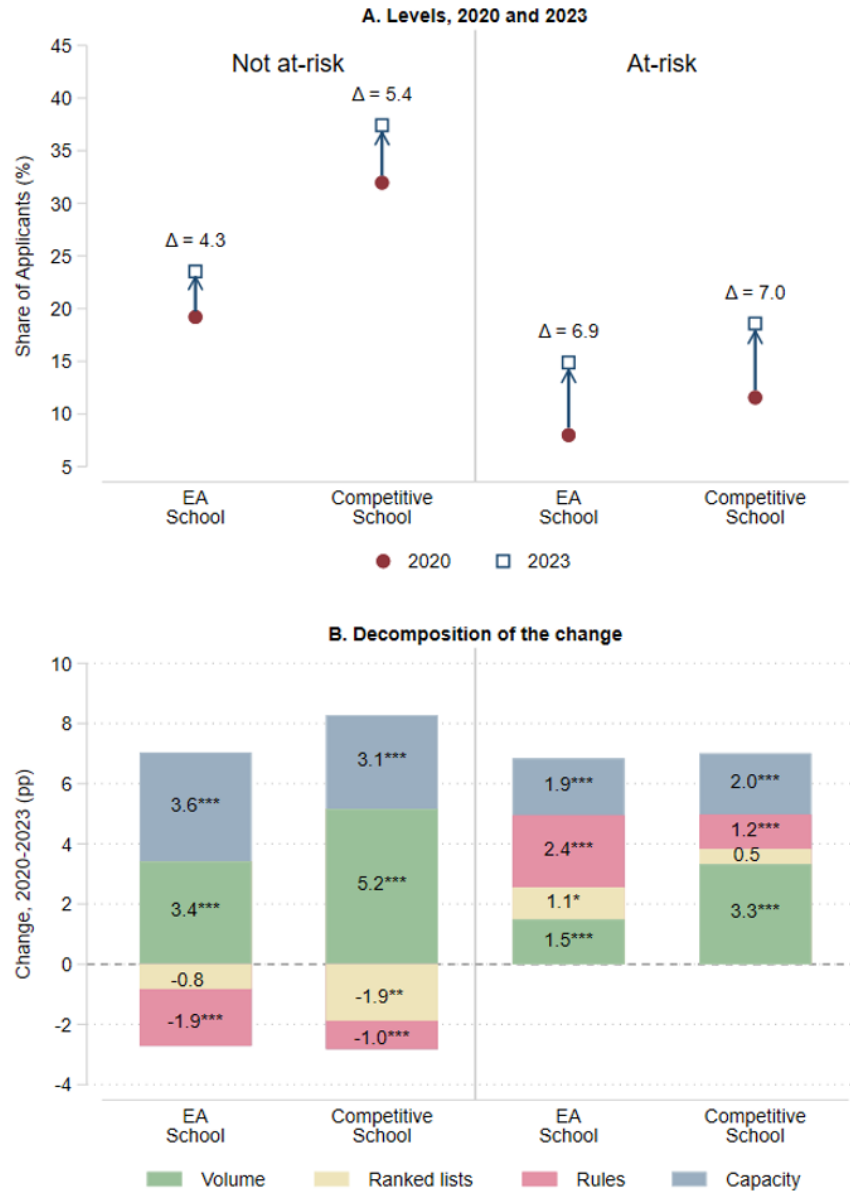
Note: Analytic sample includes PK4 applicants. The match rate is the probability that an applicant is matched to an EA school in the lottery. Conditional rates are among EA school applicants, and unconditional rates are among all applicants. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure A3: Decomposition Components by Baseline Year



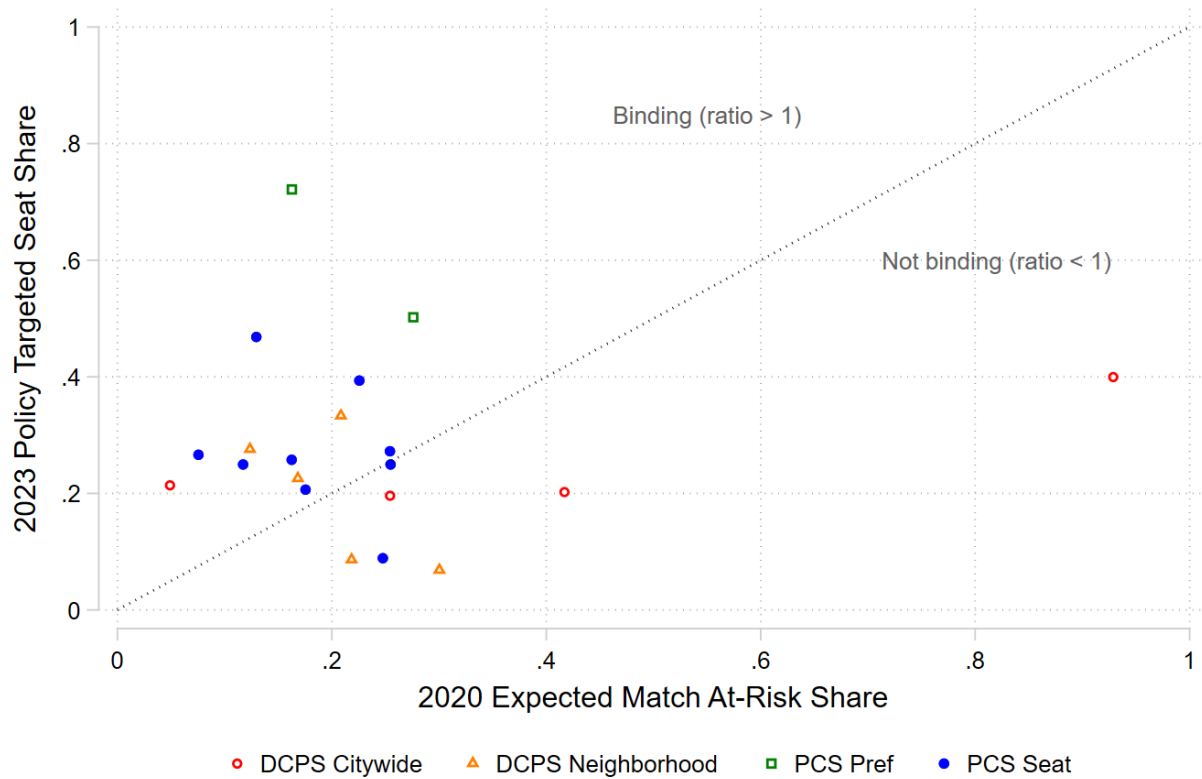
Note: Each panel shows one Shapley component of the change in the unconditional match rate from the baseline year to 2023, using 2019 (hollow) or 2020 (solid) as the baseline. Analytic sample includes all PK3 applicants. The match rate is the probability of matching to an EA school of the given type. Points are bootstrap medians, and bars are 95% percentile bootstrap confidence intervals.

Figure A4: Match Rate Changes at EA and Competitive Schools, 2020–2023



Note: Analytic sample includes all PK3 applicants. Panel A shows the share of applicants matched to an EA school or to a competitive school. Competitive schools are school-grades, EA or not, where applicants ranking them first faced at least a 25% expected chance of not matching there in 2020. Levels and components are bootstrap medians. Volume, Ranked lists, Rules, and Capacity are Shapley values. *, **, and *** denote significance at the 90%, 95%, and 99% levels.

Figure A5: EA Rule Bindingness by EA School



Note: Each point is one EA school. The horizontal axis is at-risk applicants' expected share of the school's PK3 matches in the 2020 lottery, computed from 2020 DA propensity scores. The vertical axis is the share of seats targeted by the school's 2023 EA rule, defined for each implementation type in Appendix B. The ratio of the two is rule bindingness. Above the dotted 45-degree line the ratio exceeds one, so the rule targets more seats than at-risk applicants were already expected to win and is likely to bind. Below the line, it targets no more than that and is unlikely to bind.

Table A1. Decomposition of EA School Match Rate Changes, 2020–2023

	Baseline (1)	Total (2)	Rules (3)	Ranked lists (4)	Volume (5)	Capacity (6)
Panel A. Not at-risk						
Applicant Match Rate	26.26 [25.08, 27.56]	5.19*** [3.27, 7.09]	−2.57*** [−3.09, −2.11]	−1.51* [−3.13, 0.11]	4.37*** [3.73, 5.03]	4.90*** [4.34, 5.43]
Match Rate	19.21 [18.38, 20.07]	4.32*** [2.96, 5.65]	−1.90*** [−2.28, −1.55]	−0.82 [−1.90, 0.27]	3.42*** [2.96, 3.90]	3.62*** [3.21, 4.01]
Panel B. At-risk						
Applicant Match Rate	21.66 [19.56, 23.99]	15.04*** [11.30, 18.91]	6.22*** [5.03, 7.56]	1.00 [−2.27, 4.52]	2.85*** [1.89, 3.78]	4.85*** [4.13, 5.73]
Match Rate	7.99 [7.17, 8.90]	6.89*** [5.32, 8.52]	2.40*** [1.96, 2.89]	1.07* [−0.26, 2.52]	1.48*** [1.12, 1.84]	1.89*** [1.60, 2.24]

Note: Estimates plotted in Figure 2. Analytic sample includes PK3 applicants. Applicant Match Rate is the probability of matching to an EA school among EA school applicants. Match Rate is the same probability among all applicants. Column 1 is the 2020 rate (%). Column 2 is the total change from 2020 to 2023, and columns 3 to 6 are its Shapley components (pp). Cells are medians across 1,000 bootstrap replications, with 95% percentile bootstrap confidence intervals in brackets. *, **, and *** denote significance at the 90%, 95%, and 99% levels. Components need not sum exactly to the total because each is a median.

Table A2. Decomposition of Match Rate Changes by EA School Type, 2020–2023

	Baseline (1)	Total (2)	Rules (3)	Ranked lists (4)	Volume (5)	Capacity (6)
Panel A. Not at-risk						
DCPS Citywide	3.47 [3.03, 3.91]	0.04 [−0.64, 0.76]	−0.04 [−0.17, 0.06]	0.11 [−0.44, 0.65]	0.33*** [0.09, 0.60]	−0.35*** [−0.55, −0.13]
DCPS Neighborhood	3.83 [3.49, 4.21]	0.31 [−0.23, 0.85]	−0.30*** [−0.48, −0.14]	−0.35 [−0.82, 0.12]	0.68*** [0.52, 0.87]	0.27*** [0.13, 0.42]
PCS Pref	1.38 [1.12, 1.68]	1.56*** [0.93, 2.28]	−0.85*** [−1.11, −0.64]	0.21 [−0.21, 0.64]	0.44*** [0.33, 0.58]	1.76*** [1.51, 2.04]
PCS Seat	10.52 [9.83, 11.25]	2.39*** [1.29, 3.38]	−0.70*** [−1.00, −0.42]	−0.79* [−1.68, 0.04]	1.94*** [1.58, 2.34]	1.92*** [1.61, 2.23]
Panel B. At-risk						
DCPS Citywide	2.35 [1.85, 2.88]	−0.09 [−0.81, 0.73]	0.10 [−0.02, 0.26]	−0.21 [−0.97, 0.59]	0.11 [−0.09, 0.30]	−0.08** [−0.16, −0.01]
DCPS Neighborhood	1.60 [1.15, 2.07]	1.04** [0.33, 1.77]	−0.03 [−0.16, 0.11]	0.55 [−0.16, 1.26]	0.37*** [0.20, 0.54]	0.16*** [0.05, 0.30]
PCS Pref	0.62 [0.42, 0.86]	2.31*** [1.46, 3.09]	1.33*** [1.05, 1.64]	−0.34 [−0.85, 0.16]	0.19*** [0.05, 0.34]	1.12*** [0.88, 1.39]
PCS Seat	3.42 [2.84, 4.00]	3.63*** [2.61, 4.61]	0.98*** [0.63, 1.37]	1.11*** [0.29, 1.90]	0.82*** [0.56, 1.07]	0.70*** [0.49, 0.91]

Note: Estimates plotted in Figure 3. Analytic sample includes all PK3 applicants. Each row is the probability of matching to an EA school of that type. Column 1 is the 2020 rate (%). Column 2 is the total change from 2020 to 2023, and columns 3 to 6 are its Shapley components (pp). Cells are medians across 1,000 bootstrap replications, with 95% percentile bootstrap confidence intervals in brackets. *, **, and *** denote significance at the 90%, 95%, and 99% levels. Components need not sum exactly to the total because each is a median.

Table A3. Decomposition of First-Choice and No-Match Rate Changes, 2020–2023

	Baseline (1)	Total (2)	Rules (3)	Ranked lists (4)	Volume (5)	Capacity (6)
Panel A. Not at-risk						
First Choice	46.01 [44.42, 47.43]	5.10*** [2.71, 7.64]	−1.52*** [−1.81, −1.23]	−3.21** [−5.44, −0.80]	5.41*** [4.81, 6.08]	4.36*** [3.88, 4.92]
No Match	16.98 [15.99, 18.09]	−6.89*** [−8.37, −5.39]	0.49*** [0.32, 0.67]	1.93** [0.51, 3.38]	−5.57*** [−6.08, −5.08]	−3.76*** [−4.15, −3.38]
Panel B. At-risk						
First Choice	76.91 [75.11, 78.83]	4.88*** [2.35, 7.55]	1.52*** [1.18, 1.88]	−4.61*** [−7.02, −2.07]	3.38*** [2.55, 4.16]	4.63*** [3.94, 5.37]
No Match	5.52 [4.66, 6.37]	−1.45** [−2.64, −0.27]	−0.46*** [−0.63, −0.28]	2.52*** [1.37, 3.63]	−1.74*** [−2.20, −1.27]	−1.76*** [−2.18, −1.37]

Note: Estimates plotted in Figure 6. Analytic sample includes all PK3 applicants. First Choice is the probability of matching to the first-ranked school, and No Match is the probability of not matching to any school. Column 1 is the 2020 rate (%). Column 2 is the total change from 2020 to 2023, and columns 3 to 6 are its Shapley components (pp). Cells are medians across 1,000 bootstrap replications, with 95% percentile bootstrap confidence intervals in brackets. *, **, and *** denote significance at the 90%, 95%, and 99% levels. Components need not sum exactly to the total because each is a median.

Table A4: IV First Stage: Receiving EA Offer on Enrollment by Risk Status, 2022-2023

	FallEnrolled		SchEnroll		SchEnroll x EverAtRisk	
	(1)	(2)	(3)	(4)	(5)	(6)
EAMatch	0.159*** (0.022)	0.150*** (0.021)	0.652*** (0.021)	0.659*** (0.021)	0.001 (0.002)	0.001 (0.002)
x EverAtRisk	-0.064 (0.048)	-0.073 (0.048)	-0.019 (0.050)	-0.024 (0.050)	0.616*** (0.046)	0.617*** (0.045)
No-offer mean, at-risk	0.801	0.801				
No-offer mean, not at-risk	0.660	0.660				
Controls		X		X		X
R ²	0.04	0.08	0.55	0.55	0.60	0.60
N	2,074	2,040	2,074	2,040	2,074	2,040

Note: Standard errors clustered by family in parentheses. *EAMatch* equals one if the applicant received an offer to an EA school. *FallEnrolled* equals one if the applicant enrolled in any DCPS or PCS school in the lottery fall; *SchEnroll* equals one if the applicant enrolled in the EA school they matched to. *EverAtRisk* equals one if the family was flagged at-risk in any lottery or enrollment record. No-offer means are outcome means among applicants without an EA offer. All columns control for lottery year, the EA propensity score, their interaction, and *EverAtRisk*. Columns marked X add the number of applications and neighborhood shares of Black and SNAP-eligible families. Sample: PK3 applicants to EA schools in the 2022-2023 lotteries with EA propensity scores between 0.05 and 0.70.
* p<0.05, ** p<0.01, *** p<0.001

Table A5: IV Second Stage Result: EA Enrollment Impact on System and School Persistence, 2022-2023

	PersistNext		PersistSecond		SchPersistNext		SchPersistSecond	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EASchEnroll	0.232*** (0.033)	0.215*** (0.033)	0.200*** (0.060)	0.187** (0.059)	0.358*** (0.036)	0.348*** (0.035)	0.432*** (0.062)	0.422*** (0.061)
x EverAtRisk	-0.066 (0.080)	-0.078 (0.081)	-0.148 (0.129)	-0.180 (0.130)	-0.114 (0.096)	-0.129 (0.097)	-0.358* (0.157)	-0.361* (0.157)
No-offer mean, at-risk	0.766	0.766	0.789	0.789	0.567	0.567	0.500	0.500
No-offer mean, not at-risk	0.618	0.618	0.560	0.560	0.461	0.461	0.291	0.291
Controls		X		X		X		X
First-stage F	92.90	93.74	46.96	46.45	92.90	93.74	46.96	46.45
R ²	0.08	0.12	0.08	0.12	0.10	0.12	0.10	0.13
N	2,074	2,040	923	905	2,074	2,040	923	905

Note: Standard errors clustered by family in parentheses. EASchEnroll equals one if the applicant enrolled in the EA school they matched to. EASchEnroll and EASchEnroll x EverAtRisk are instrumented with EAMatch and EAMatch x EverAtRisk; first-stage F is the Kleibergen-Paap Wald F. PersistNext and PersistSecond equal one if the applicant is enrolled in any DCPS or PCS school one and two years after the lottery. SchPersistNext and SchPersistSecond equal one if the applicant is in the same school as in the lottery fall one and two years later, or in any school if that school ends before then. Observed enrollment runs through fall 2024, so PersistSecond and SchPersistSecond are unobserved for the 2023 lottery. All columns control for lottery year, the EA propensity score, their interaction, and EverAtRisk. Columns marked X add the number of applications and neighborhood shares of Black and SNAP-eligible families. Sample: PK3 applicants to EA schools in the 2022-2023 lotteries with EA propensity scores between 0.05 and 0.70. * p<0.05, ** p<0.01, *** p<0.001

Appendix B: Constructing the Policy Strength Measure

Each school's general program and its EA designated-seat program are combined into one school-grade unit j . Let A_j and M_j be the expected at-risk and total matches in the 2020 lottery, the sums of 2020 DA propensity scores. Then $s_j = A_j/M_j$, and $D_j = E_j/K_j$, where the exposed seats E_j and capacity K_j depend on the implementation type:

- **Designated seats (DCPS citywide, PCS):** E_j is 2023 reserved seats; K_j is 2020 seats.
- **DCPS neighborhood:** Eligibility is limited to in-boundary at-risk applicants, so reserved seats raise at-risk access only by displacing non-at-risk out-of-boundary students. E_j is reserved seats times the non-at-risk share of expected 2020 out-of-boundary matches (one if there were none); K_j is 2020 seats.
- **PCS EA Priority:** $E_j = \max(0, M_j - H_j)$, where H_j is expected 2020 matches from priority groups ranked above EA; $K_j = M_j$.

Aggregates sum components before taking ratios: $B_G = (\sum_{j \in G} E_j / \sum_{j \in G} K_j) / (\sum_{j \in G} A_j / \sum_{j \in G} M_j)$.

Rationing. A school-grade is rationed if its expected 2020 first-choice denial rate, $r_j = 1 - (\text{expected matches among first-choice applicants}) / (\text{number of first-choice applicants})$, is at least 0.25. For DCPS neighborhood schools, r_j uses in-boundary first-choice applicants.