Online Appendix for:

Social Interactions, Information, and Preferences for Schools: Experimental Evidence from Los Angeles

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A Data Appendix

A.1 School Experience Survey

The School Experience Survey (SES) is an annual survey administered by the Los Angeles Unified School District (LAUSD) every academic year since 2010. The survey is administered to parents, students, and staff. Response rates for students and staff are high, while response rates for parents vary substantially. For example, in the most recent academic year with available survey data, 2022-23, students had a 95% response rate, teachers had a 98% response rate, and parents had a 69% response rate. The survey has evolved over time, with questions entering and leaving the survey in some years, the formatting of questions also changing, and new categories being introduced over time. The analysis I conduct focuses on a somewhat stable part of the student survey that is less prone to changes, the sections I refer to as the core survey elements.

The core survey is organized into three categories, Academics, School Climate, and Social and Emotional Learning. The survey elements mirror data collected by Chicago Public Schools (CPS) studied by Jackson et al. (2020) and many other large urban school districts. Within the Academics category, there are subcategories related to Academic Focus, Cognitive Engagement, Future Orientation, and Technology, with the Technology subcategory being the most recent addition post-pandemic. The School Climate category consists of questions related to Safety, Expectations for Behavior, School Connectedness, and Bullying. The Social and Emotional Learning section contains questions related to Growth Mindset, Responsible Decision-Making, Self Awareness, Self-Efficacy, Self-management, and Student Social Awareness. The categorizations I reference are created by LAUSD.

In recent years, there has been growing emphasis on the importance of socio-emotional development and the potential ways teachers and schools affect these outcomes (Fricke et al., 2019, Jackson et al., 2020, Loeb et al., 2018). Jackson et al. (2020) finds that school impacts on socio-emotional measures in CPS, closely related to socio-emotional measures in the LAUSD SES, are predictive of long-run outcomes and suggestive evidence they are causal. I follow Jackson et al. (2020) in categorizing survey elements as their categorizations have closer associations to a large body of work across economics and psychology (Alan et al., 2019, Duckworth et al., 2007, Heckman and Rubinstein, 2001, Lindqvist and Vestman, 2011).

Using the wealth of data in the survey, I construct five indices that serve as outcomes in my analysis. The first four closely mirror the indices created by Jackson et al. (2020), including an interpersonal skills index, school connectedness index, academic effort index, and bullying index. The fifth is a happiness index which includes elements from the other four but is constructed to more closely isolate school satisfaction. I now report the questions related to each index.

Interpersonal Skills Index : This index consists of six questions. They include the following: During the past 30 days,

1. How often did you compliment others' accomplishments?

2. How well did you get along with students who are different from you?

3. When others disagreed with you, how respectful were you of their views?
4. How clearly were you able to describe your feelings?
5. How carefully did you listen to other people's points of view?

Please answer how often you did the following during the past 30 days,

6. I stayed calm even when others bothered or criticized me.

School Connectedness Index: This index consists of thirteen questions. They include the following: Do you strongly agree, agree, neither agree or disagree, somewhat disagree, or strongly disagree with the following statements:

1. I am happy to be at this school.
2. I fell like I am part of this school.
3. I feel close to people at this school.
4. The teachers at this school treat students fairly.
5. Teachers care if I am absent from school.
6. I feel accepted for who I am at this school.
7. Adults at this school treat all students with respect.
8. I feel safe in this school.
9. I feel safe in the neighborhood around this school.
10. Lesbian, gay, bisexual, transgender, and/or queer students at this school are accepted.
11. Teachers encourage students to make decisions.
12. There are lots of chances for students at my school to get involved in sports, clubs, or other school activities outside of class.
13. I participate in extra-curricular activities offered through my school, such as school clubs or organizations, musical groups, sports teams, student government, or any other activities.

Academic Effort Index: This index consists of ten questions. They include the following: During the past 30 days,

1. I came to class prepared.
2. I remembered and followed directions.
3. I got my work done right away instead of waiting until the last minute.
4. I paid attention even when there were distractions.

Do you strongly agree, agree, neither agree or disagree, somewhat disagree, or strongly disagree with the following statements:

5. School is important for achieving my future goals.
6. When learning new information, I try to put the ideas into my own words.
7. In my classes, I use evidence or collect data to come to my own conclusions.
8. In my classes, I work on projects or assignments with other students.
9. For my assignments, I explain my thinking in writing.
10. In my classes, I think about how to solve problems in new ways.

Bullying Index: This index consists of eight questions. They include the following: During the past 30 days,

1. How many times on school property have you had mean rumors or lies spread about you?
2. How many times on school property have you been teased about what your body looks like?
3. How many times on school property have you been made fun of because of your looks or the way you talk?
4. How many times on school property have you been pushed, shoved, slapped, hit, or kicked by someone who wasn't just kidding around?
5. How many times on school property have you had sexual jokes, comments, or gestures made at you?
6. How many times have other students from your school bullied you online?

Do you strongly agree, agree, neither agree or disagree, somewhat disagree, or strongly disagree with the following statements:

7. Kids at this school are kind to each other.
8. If I told a teacher or other adult at this school that another student was bullying me, he or she would try to help me.

A.2 School Experience Survey Descriptive Statistics

Table A.1: School Experience Survey AG-IA Correlates

	Univariate	Multivariate
	(1)	(2)
	Incoming Achievement (student σ)	
Bullying Index	1.50***	1.44***
	(0.26)	(0.35)
Connectedness Index	1.08***	0.62
	(0.34)	(0.64)
Effort Index	0.74***	0.07
	(0.24)	(0.57)
Interpersonal Index	0.46*	0.15
	(0.24)	(0.44)
	Achievement Growth (student σ)	
Bullying Index	1.09***	0.89***
	(0.11)	(0.15)
Connectedness Index	0.89***	1.12**
	(0.23)	(0.44)
Effort Index	0.56***	0.28
	(0.14)	(0.19)
Interpersonal Index	0.21	-0.57
	(0.18)	(0.35)
N	280	

Notes: This table reports school-level regression estimates of Incoming Achievement and Achievement Growth (in student standard deviation units) on standardized socio-emotional outcomes. Column 1 reports estimates from univariate regressions, while Column 2 reports estimates from multivariate regressions. Standard errors are robust and reported in parentheses.

A.3 Experimental Balance

Table A.2: Saturation School-Level Balance

	Control	Low - Control	High - Control
	(1)	(2)	(3)
ELA	-0.094	-0.051	-0.069
		(0.104)	(0.111)
Math	-0.108	-0.054	-0.076
		(0.096)	(0.103)
College	0.082	0.007	-0.012
		(0.024)	(0.028)
Migrants	0.086	-0.011	0.006
		(0.007)	(0.013)
Female	0.495	-0.016	-0.004
		(0.010)	(0.010)
Poverty	0.954	-0.024	0.026
		(0.035)	(0.029)
Special Education	0.115	0.015	0.021
		(0.008)	(0.010)
English Learner	0.158	0.014	0.032
		(0.016)	(0.019)
Black	0.051	-0.007	-0.012
		(0.013)	(0.015)
Hispanic	0.863	-0.011	0.013
		(0.043)	(0.033)
White	0.001	0.000	-0.001
		(0.001)	(0.000)
Number of Schools	41	32	31

Notes: This table reports estimates from school-level regressions of row variables on saturation-specific indicators and zone fixed effects. The schools are stacked across both years. Column 1 reports the control school means, and Columns 2 and 3 report low- and high-saturation school differentials. Robust standard errors are reported in parentheses.

Table A.3: Within-School Randomization Balance

	Control	Peer - Control	School - Control	Both - Control	P-value
	(1)	(2)	(3)	(4)	(5)
ELA Scores	-0.126	0.006	-0.015	-0.006	0.860
		(0.020)	(0.020)	(0.024)	
Math Scores	-0.124	0.013	-0.010	-0.018	0.607
		(0.017)	(0.016)	(0.019)	
Parents College	0.077	-0.001	-0.001	0.000	0.993
		(0.005)	(0.004)	(0.005)	
Migrant	0.034	0.006	-0.002	0.004	0.182
		(0.004)	(0.004)	(0.003)	
Female	0.485	-0.005	0.001	0.003	0.892
		(0.009)	(0.010)	(0.008)	
Poverty	0.938	0.001	0.000	-0.005	0.561
		(0.004)	(0.003)	(0.004)	
Special Education	0.138	-0.002	0.008	-0.002	0.597
		(0.006)	(0.007)	(0.006)	
English Learners	0.152	0.002	0.001	0.013	0.324
		(0.005)	(0.006)	(0.007)	
Black	0.031	0.002	-0.004	0.002	0.663
		(0.003)	(0.003)	(0.004)	
Hispanic	0.906	-0.004	0.003	-0.005	0.506
		(0.005)	(0.005)	(0.004)	
White	0.016	-0.002	0.000	0.001	0.802
		(0.002)	(0.002)	(0.002)	
Joint Test P-value		0.769	0.951	0.716	

Notes. Column 1 reports within-school control group means, and Columns 2–4 contain mean differences between treated and control group individuals. Column 5 contains p-values on a joint test of equality of means across groups for that given row. The p-values reported on the bottom of the table come from a column-wise test of no difference between the treated and control groups. Note that the population in this table is those assigned to non-pure control schools. Standard errors are clustered at the school level for all tests.

A.4 Treatment Letters

Figure A.1: Incoming Achievement Treatment Letter Example: Belmont Zone of Choice

We are providing information about schools within your Zone of Choice to ensure you have the best information available prior to your upcoming decision.

Belmont Zone of Choice

We determine the quality of a school based on students' average scores on state exams

Some schools have high scores because they attract high-achieving students. We can measure a school's ability to attract high-achieving students by measuring the average test scores of their incoming students—**Incoming Achievement**. The table below provides each school's district-wide ranking.

Incoming Achievement

Incoming achievement is the average test scores of school's incoming students at the time they enter school.

We hope you use this information when choosing the right school for your student.

School	Incoming Achievement*	Campus Location	Type of School
School Of Social Justice	37	Miguel Contreras LC	Pilot School
Science, Arts & Green Engineering	27	Belmont HS	Small Learning Community
Computer Science Academy	66	Edward R. Roybal LC	Small Learning Community
Academy Of Educational Empowerment: School of Medicine and Law	58	Edward R. Roybal LC	Small Learning Community
Visual Arts Academy	72	Ramon C. Cortines School for the Visual & Performing Arts	Small Learning Community
School Of Business & Tourism	31	Miguel Contreras LC	Pilot School
Los Angeles School Of Global Studies	19	Miguel Contreras LC	New Technology HS
Dance Academy	60	Ramon C. Cortines School for the Visual & Performing Arts	Small Learning Community
Music Academy	54	Ramon C. Cortines School for the Visual & Performing Arts	Small Learning Community
Academy of Social Work and Child Development: Spanish Dual Language Program	75	Edward R. Roybal LC	Small Learning Community
Los Angeles Academy Of Medical & Public Services	47	Belmont HS	Small Learning Community
Theater Academy	44	Ramon C. Cortines School for the Visual & Performing Arts	Small Learning Community
Academic Leadership Community School	42	Miguel Contreras LC	Small Learning Community
Business & Finance Academy	59	Edward R. Roybal LC	Small Learning Community
Multimedia Academy Of Film And Photography	19	Belmont HS	Small Learning Community

*Schools' Incoming Achievement are provided in percentiles. For example, if a school has a incoming achievement of 55, this means that the average test scores of its incoming students are better than 55 percent of other high schools in LAUSD.

Estamos proporcionando información sobre las escuelas dentro de su Zona de Opción, para asegurarnos de que tenga la mejor información disponible antes de su próxima decisión.

Zona de Opción Belmont

Determinamos la calidad de una escuela en función de los puntajes promedio de los estudiantes en los exámenes estatales

Algunas escuelas tienen puntuaciones altas porque atraen a estudiantes de alto rendimiento. Podemos medir la capacidad de una escuela para atraer estudiantes de alto rendimiento midiendo los puntajes promedio de las pruebas de sus estudiantes entrantes: **rendimiento entrante**. A continuación, proporcionamos la clasificación de cada escuela comparado a todas escuelas en el distrito.

Rendimiento Entrante

El rendimiento entrante de una escuela es el puntaje promedio de sus estudiantes cuando ingresan a la escuela.

Esperamos que utilice esta información al elegir la escuela adecuada para su estudiante.

Escuela	Rendimiento Entrante*	Ubicación del campus	Tipo de escuela
Escuela de Justicia Social	37	Miguel Contreras LC	Escuela Piloto
Escuela de Ciencia, Arte e Ingeniería Ecológica	27	Belmont HS	Comunidad Educativa Pequeña (SLC)
Academia de Ciencias de Computación	66	Edward R. Roybal LC	Comunidad Educativa Pequeña (SLC)
Academia de Empoderamiento Educativo: Escuela de Medicina y Leyes	58	Edward R. Roybal LC	Comunidad Educativa Pequeña (SLC)
Academia de Artes Visuales	72	Ramon C. Cortines School for the Visual & Performing Arts	Comunidad Educativa Pequeña (SLC)
Escuela de Negocios y Turismo	31	Miguel Contreras LC	Escuela Piloto
Preparatoria de Estudios Globales de Los Ángeles	19	Miguel Contreras LC	Escuela Secundaria de Tecnología
Academia de Danza	60	Ramon C. Cortines School for the Visual & Performing Arts	Comunidad Educativa Pequeña (SLC)
Academia de Música	54	Ramon C. Cortines School for the Visual & Performing Arts	Comunidad Educativa Pequeña (SLC)
Academia del Trabajo Social y Desarrollo Infantil: Programa de Lenguaje Dual en Español	75	Edward R. Roybal LC	Comunidad Educativa Pequeña (SLC)
Academia de Servicios Médicos y Públicos de Los Ángeles	47	Belmont HS	Comunidad Educativa Pequeña (SLC)
Academia de Teatro	44	Ramon C. Cortines School for the Visual & Performing Arts	Comunidad Educativa Pequeña (SLC)
Escuela Académica, Liderazgo y Comunidad	42	Miguel Contreras LC	Comunidad Educativa Pequeña (SLC)
Academia de Negocios y Finanzas	59	Edward R. Roybal LC	Comunidad Educativa Pequeña (SLC)
Academia Multimedia de Cine y Fotografía	19	Belmont HS	Comunidad Educativa Pequeña (SLC)

*El rendimiento entrante de las escuelas se proporcionan en percentiles. Por ejemplo, si una escuela tiene un rendimiento entrante de 55, esto significa que los puntajes promedio de las pruebas de sus estudiantes entrantes son mejores que el 55 porciento de otras escuelas secundarias en LAUSD.

Notes: The front page of the letter is in English, while the second page is in Spanish. The letters list all the relevant schools for the Zone of Choice that the feeder middle school feeds into. The letters provide a simple and short explanation about incoming achievement and achievement growth, along with a quick summary with some graphics that aid in understanding the differences. The letters included a QR code that linked to a treatment-specific video to further aid with interpreting the information.

Figure A.2: Achievement Growth Treatment Letter Example: South Gate Zone of Choice

We are providing information about schools within your Zone of Choice to ensure you have the best information available prior to your upcoming decision.

South Gate Zone of Choice

We determine the quality of a school based on students' average scores on state exams

Some schools have high average scores because their students experience larger learning gains—**achievement growth**. We can measure a school's ability improve test scores by measuring the growth of their students' test scores between entry into the school and some later date. We provide each school's district-wide ranking below and hope you use this information when choosing the right school for your student.

Achievement Growth

We measure a school's ability to improve test scores by measuring the growth of their students' test scores between entry into the school and eleventh grade.

We hope you use this information when choosing the right school for your student.

School	Achievement Growth*	Campus Location	Type of School
Media & Communications	77	South Gate HS	Small Learning Community
Law, Government & Public Service	80	South Gate HS	Small Learning Community
School Of Health Science & Environment	90	South East HS	Small Learning Community
Science, Technology, Engineering, Arts & Math (STEAM) High School	94	Legacy HS	Small School
Visual & Performing Arts (VAPA) High School	67	Legacy HS	Small School
School Of Business, Innovation & Leadership	95	South East HS	Small Learning Community
International Studies Learning Center	97	Legacy HS	Small School
School Of Justice & Law	99	South East HS	Small Learning Community
Math, Science & Engineering	83	South Gate HS	Small Learning Community
School Of Visual & Performing Arts	98	South East HS	Small Learning Community
Business & Technology	75	South Gate HS	Small Learning Community
Health Science & Medicine	80	South Gate HS	Small Learning Community

*Schools' Achievement Growth are provided in percentiles. For example, if achievement growth is 75, then the school's ability to improve test scores is better than 75 percent of high schools in LAUSD.

Estamos proporcionando información sobre las escuelas dentro de su Zona de Opción, para asegurarnos de que tenga la mejor información disponible antes de su próxima decisión.

Zona de Opción South Gate

Determinamos la calidad de una escuela en función de los puntajes promedio de los estudiantes en los exámenes estatales

Algunas escuelas tienen puntajes altos porque sus estudiantes experimentan mayores ganancias de aprendizaje: **crecimiento de logros**. Podemos medir la capacidad de una escuela para mejorar los puntajes de los exámenes midiendo el crecimiento de los puntajes de los exámenes de sus estudiantes entre el ingreso a la escuela y una fecha posterior. A continuación, proporcionamos la clasificación de cada escuela en todo el distrito.

Crecimiento de logros

Medimos la capacidad de una escuela para mejorar los puntajes de los exámenes midiendo el crecimiento de los puntajes de los exámenes de sus estudiantes entre el ingreso a la escuela y el onceavo grado.

Esperamos que utilice esta información al elegir la escuela adecuada para su estudiante.

Escuela	Crecimiento de logros*	Ubicación del campus	Tipo de escuela
Medios de Comunicación	77	South Gate HS	Comunidad Educativa Pequeña (SLC)
Ley, Gobierno y Servicio Público	80	South Gate HS	Comunidad Educativa Pequeña (SLC)
Escuela de Ciencia de Salud y del Medioambiente	90	South East HS	Comunidad Educativa Pequeña (SLC)
Preparatoria de Ciencia, Tecnología, Ingeniería, Artes y Matemáticas (STEAM)	94	Legacy HS	Escuela Pequeña
Preparatoria de Artes Visuales y Técnicas (VAPA)	67	Legacy HS	
Escuela de Negocio, Innovación y Liderazgo	95	South East HS	Comunidad Educativa Pequeña (SLC)
Centro de Aprendizaje de Estudios Internacionales	97	Legacy HS	Escuela Pequeña
Escuela de Justicia y Ley	99	South East HS	Comunidad Educativa Pequeña (SLC)
Matemáticas, Ciencia e Ingeniería	83	South Gate HS	Comunidad Educativa Pequeña (SLC)
Escuela de Artes Visuales y Escénicas	98	South East HS	Comunidad Educativa Pequeña (SLC)
Negocios y Tecnología	75	South Gate HS	Comunidad Educativa Pequeña (SLC)
Ciencia de Salud y Medicina	80	South Gate HS	Comunidad Educativa Pequeña (SLC)

*El crecimiento del logros de las escuelas se proporcionan en percentiles. Por ejemplo, si el crecimiento de legros es 75, la capacidad de la escuela para mejorar los puntajes de las pruebas es mejor que el 75 porciento de las escuelas secundarias del LAUSD.

Notes: The front page of the letter is in English, while the second page is in Spanish. The letters list all the relevant schools for the Zone of Choice that the feeder middle school feeds into. The letters provide a simple and short explanation about incoming achievement and achievement growth, along with a quick summary with some graphics that aid in understanding the differences. The letters included a QR code that linked to a treatment-specific video to further aid with interpreting the information.

B Peer and School Quality Estimation

In this section, we discuss the peer and school quality estimation. We consider a constant-effects value-added model (Angrist et al., 2017). In particular, potential outcomes are denoted as

$$Y_{ij} = \mu_j + a_i \tag{8}$$

where α_j is the mean potential outcome at school j and a_i is student ability. We denote school j enrollment indicators as D_{ij}, so that we can write the observed outcome Y_i as

$$Y_i = \mu_0 + \sum_j \beta_j D_{ij} + a_i.$$

We further assume that $a_i = \gamma' X_i + u_i$, where X_i is a vector of student baseline covariates including lagged test scores. With this assumption, the observed outcome is

$$Y_i = \mu_0 + \sum_j \beta_j D_{ij} + \gamma' X_i + u_i \tag{9}$$

which is the canonical causal value-added model considered in the literature (Campos and Kearns, 2024).

In estimation, however, a regression of observed outcomes on school indicators and the vector of student covariates is

$$Y_i = \alpha_0 + \sum_j \alpha_j D_{ij} + \theta' X_i + e_i$$

and e_i need not be uncorrelated with D_{ij}, and $\alpha_j \neq \beta_j$.

Although we estimate school quality using the standard selection on observables assumption, we leverage the lottery variation embedded in the Zones of Choice markets to assess for bias in the school quality estimates (Angrist et al., 2017). With forecast unbiased estimates, we then proceed to construct our measures of school and peer quality.

B.1 VAM Validation

We use the procedure outlined by Angrist et al. (2017) to test for bias in the VAM estimates. We can construct predictions using the value-added model we estimate, which we denote as $\widehat{Y}_i$. To test for bias, we treat $\widehat{Y}_i$ as an endogenous variable in a two-stage least squares framework using L lottery offer dummies $Z_{i\ell}$ that we collect across zones and cohorts:

$$Y_i = \xi + \phi \widehat{Y}_i + \sum_\ell \kappa_\ell Z_{i\ell} + \boldsymbol{X}_i' \delta + \varepsilon_i \tag{10}$$

$$\widehat{Y}_i = \psi + \sum_\ell \pi_\ell Z_{i\ell} + \boldsymbol{X}_i' \xi + e_i. \tag{11}$$

If lotteries shift VAM predictions in proportion to the shift of realized test scores Y_i, on average, then $\phi = 1$, which is a test of forecast bias (Chetty et al., 2014, Deming, 2014). The overidentifying restrictions further allow us to test whether this applies to each lottery and thus to test

the predictive validity of each lottery.

Table B.1 reports results for two value-added models. Column 1 reports results for a model that omits any additional covariates beyond school-by-year dummies; this is the uncontrolled model. As discussed in Deming et al. (2014), Chetty et al. (2014), and Angrist et al. (2017), models that do not adjust for lagged achievement tend to perform poorly in their average predictive validity. Indeed, we find the forecast coefficient to be 0.63, indicating that the uncontrolled model does not pass the first test. Column 2 reports estimates from a constant effects VAM specification and demonstrates that our VAM estimates are forecast unbiased and the overidentification tests provide reassuring evidence regarding the predictive validity of each VAM estimate. While the results in Table B.1 do not entirely rule out bias in OLS value-added estimates, they are reassuring.

Table B.1: Forecast Bias and Overidentification Tests

	(1) Uncontrolled	(2) Constant Effect
Forecast Coefficient	.63	1.111
	(.105)	(.134)
	[0]	[.41]
First-Stage F	277.507	37.016
Bias Tests:		
Forecast Bias (1 d.f.)	12.528	.683
	[0]	[.409]
Overidentification (180 d.f)	172.281	187.744
	[.647]	[.331]

Notes: This table reports the results of lottery-based tests for bias in estimates of school effectiveness. The sample is restricted to students in the baseline sample who applied to an oversubscribed school within a school choice zone. Column (1) measures school effectiveness as the school mean outcome, Column (2) uses time-invariant value-added estimates. The forecast coefficients and overidentification tests reported in Columns (1)–(2) come from two-stage least squares regressions of test scores on OLS-fitted values estimated separately, instrumenting OLS-fitted values with school-cohort-specific lottery offer indicators, controlling for baseline characteristics.

B.2 School and Peer Quality Measures

School average achievement follows from Equation 9

$$\bar{Y}_j = \alpha_j + \theta' \bar{X}_j$$

School quality is therefore defined as $\hat{\alpha}_j$ and peer quality is defined as $\hat{\theta}'\bar{X}_j$. We convert these measures to percentile ranks in terms of the LAUSD high school distribution. In particular,

$$Q_j^S = \text{int}\left(\frac{\text{rank}(\hat{\alpha}_j)}{J} \times 100\right) \tag{12}$$

$$Q_j^P = \text{int}\left(\frac{\text{rank}(\hat{\beta}'\bar{X}_j)}{J} \times 100\right) \tag{13}$$

where Q_j^S and Q_j^P are school and peer quality, respectively, measured in percentile ranks, rounded to the nearest integer.

B.3 Peer Effects

In this section, I briefly assess the potential influence of peer effects. The constant effects model does not explicitly model peer effects or the influence of the student body on school quality. An extreme case would have peer effects entirely mediate value-added estimates, so in this section, I explore that potential with observables.

A linear-in-means model would suggest school quality is

$$\alpha_j^* = \alpha_j + \delta\bar{X}_j.$$

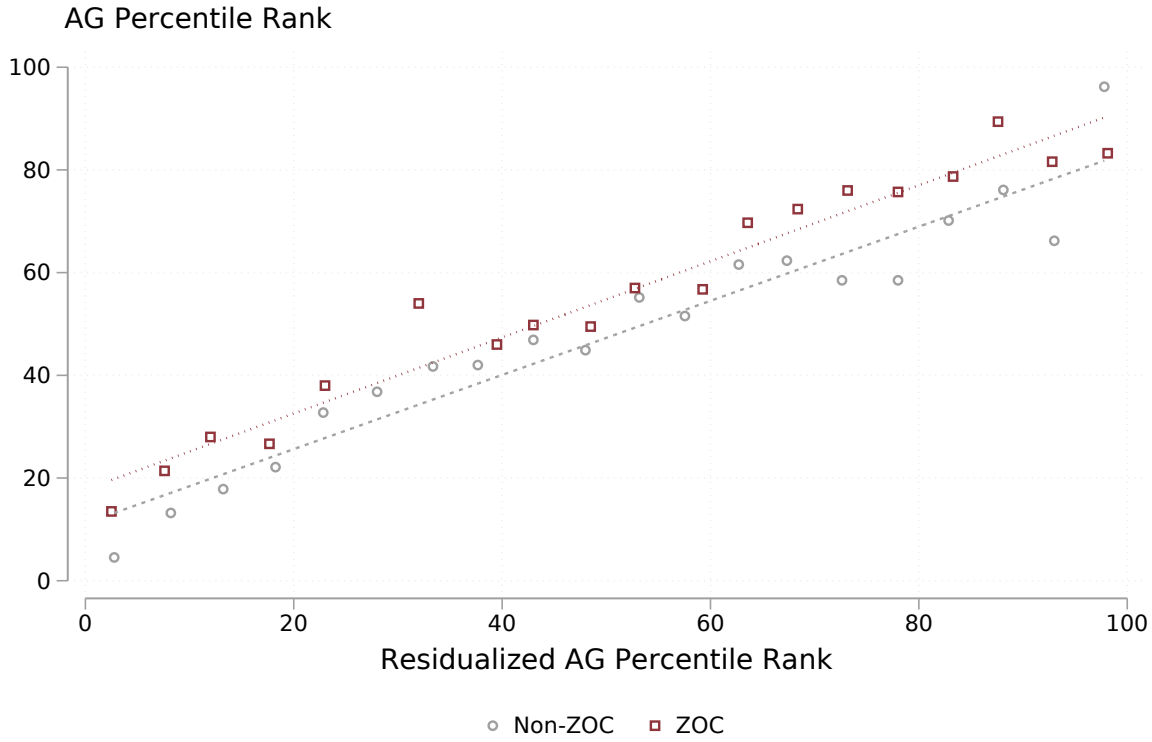
We can assess this possibility by relating estimated values of α_j^* to $\bar{X}_j$. Appendix Table B.2 demonstrates that estimated school quality is unrelated to essentially all of the observables in the data. In particular, lagged achievement is not a strong predictor of school quality both unconditionally and conditional on other observables. Evidence notwithstanding, one may still have chosen to regression adjust school quality estimates to remove the influence of student attributes. Appendix Figure B.1 shows that doing so produces minimal changes in the ordinal ranking of schools and, as a consequence, would have minimally affected the information contained in treatment letters. The evidence in this section suggests peer effects do not play a significant role in mediating school quality estimates.

Table B.2: Relationship between α_j and student observables

	(1)	(2)	(3)	(4)
	α_j	α_j	α_j	α_j
Poverty Share			0.4573	0.5344
			(0.3258)	(0.3552)
Black Share			-0.6247	-0.6173
			(0.3647)	(0.3850)
White Share			-0.5110	-0.4251
			(0.5157)	(0.5625)
College Share			0.4637	0.3071
			(0.9182)	(0.9399)
English Learner Share			-0.4083	-0.3489
			(0.3652)	(0.4032)
English at Home Share			0.1554	-0.0106
			(0.3367)	(0.3765)
Spanish at Home Share			0.2423	0.0917
			(0.2490)	(0.2906)
Special Education Share			0.2443	0.3085
			(0.4116)	(0.3992)
Female Share			0.0375	0.0584
			(0.1394)	(0.1366)
Migrant Share			0.2889	0.2122
			(0.3358)	(0.3625)
Lagged ELA Achievement	0.0531			0.0231
	(0.0472)			(0.0841)
School Enrollment		0.0003		0.0004
		(0.0004)		(0.0003)
R-squared	0.011	0.010	0.156	0.176

Notes: This table reports bivariate and multivariate relationships between estimated school quality and school-level observables. Column (1) reports the bivariate relationship between estimated school quality and school average achievement levels. Column (2) reports the bivariate relationship between school quality and school size. The following two columns report multivariate relationships between school quality and an array of school attributes. Robust standard errors are reported in parentheses.

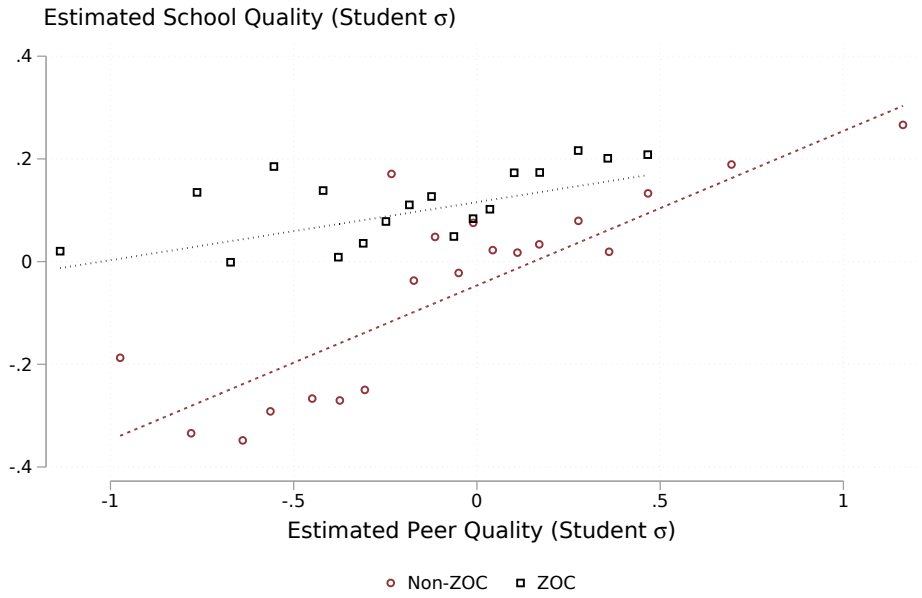
Figure B.1: Rank-rank Correlation Between Estimated School Quality and Regression-Adjusted School Quality



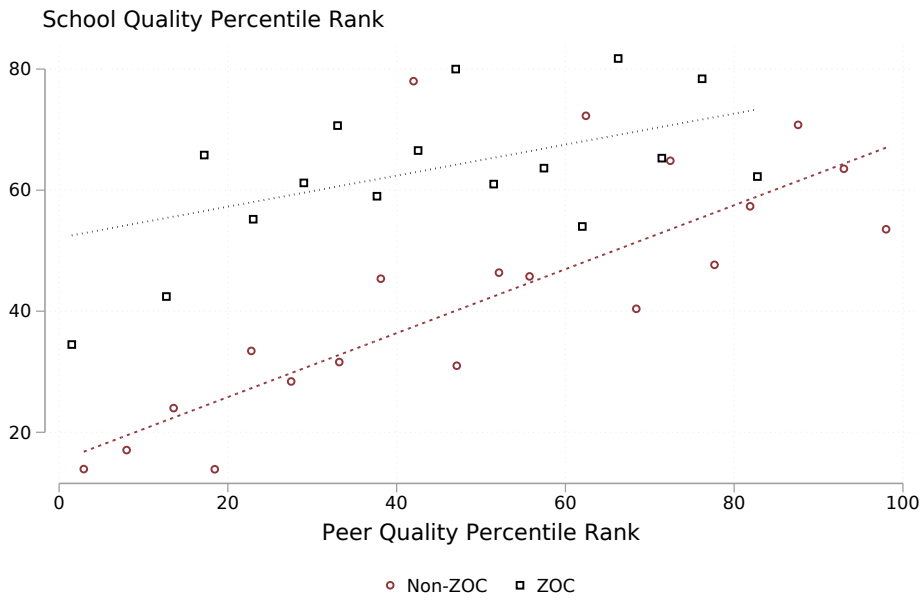
Notes: This figure reports the rank-rank relationship between estimated school quality used in the intervention and an alternative that regression adjusts for observable school-level attributes. The rank-rank relationship is reported separately for ZOC and non-ZOC schools; the differences are not statistically significant or meaningful.

B.4 Summary Statistics

Figure B.2: AG-IA Bivariate Relationship



(a) Student Standard Deviation Units



(b) Percentile Rank Units

Notes: This figure reports bivariate-binned scatter plots of the AG-IA relationship. Panel (a) reports the relationship of AG and IA in student standard deviation units. AG, also referred to as value-added, is demeaned with respect to the mean in the district, so it reflects the average treatment effect of enrolling in a given school. IA, also referred to as incoming achievement, is the fraction of test scores predicted by baseline covariates. Panel (b) reports the IA-AG relationship in terms of percentile ranks defined above.

C Additional Experiment Results

In this section, I report additional experimental evidence discussed in the main paper. To begin, I report disaggregated estimates for each experimental arm and evidence regarding other outcomes of interest. Heterogeneity results follow. I also report additional impacts on enrollment outcomes and the reduced form estimates implied by the structural model estimated in the paper. I conlcude with evidence discussed in the paper but with corresponding randomization-based inference.

C.1 Additional Evidence and Outcomes

The experiment's design contains eight treatment groups whose effects can be estimated using the following regression specification

$$\begin{aligned} Y_i = \alpha_z + & \underbrace{\beta_{Ph} T_i^P \times D_{s(i)}^h + \beta_{Sh} T_i^S \times D_{s(i)}^h + \beta_{Bh} T_i^B \times D_{s(i)}^h}_{High\ Saturation\ Effects} \\ & + \underbrace{\beta_{P\ell} T_i^P \times D_{s(i)}^\ell + \beta_{S\ell} T_i^S \times D_{s(i)}^\ell + \beta_{B\ell} T_i^B \times D_{s(i)}^\ell}_{Low\ Saturation\ Effects} \\ & + \underbrace{\beta_h C_i \times D_{s(i)}^h + \beta_\ell C_i \times D_{s(i)}^\ell}_{Spillover\ Effects} + u_i, \end{aligned} \tag{14}$$

where α_z is a zone fixed-effect (or randomization block), T_i^x are individual-level treatment x indicators for $x \in \{P, S, B\}$, $D_{s(i)}^x$ are school-level treatment indicators, and C_i are individual-level indicators for untreated parents. The specification contains a total of eight saturation-specific parameters of interest. β_{xh} and $\beta_{x\ell}$ are treatment $x \in \{P, S, B\}$ effects for high- and low-saturation groups, respectively, and β_h and β_ℓ are saturation-specific spillover effects. All parameters are identified with comparisons to families in pure control schools. This design is an multiple treatment extension of other work studying spillover effects across a variety of domains (Andrabi et al., 2020, Crépon et al., 2013). Standard errors are robust and clustered at the school level.

Appendix Table C.1 and Appendix Table C.2 report estimates for the 2019 and 2021 wave, respectively. Column 1 reports effects on most-preferred school AG, and Column 2 reports effects on most-preferred IA. Each column reports estimates for the eight parameters from the full specification. Effect sizes tend to be similar within saturation group. For example, I cannot reject that most preferred AG impacts are the same for those in the high-saturation treatment arm regardless of being directly treated or in the spillover group. The same is true for most-preferred IA. The evidence motivates the aggregation of the evidence reported throughout the paper.

C.1.1 Heterogeneity

Prior information interventions tend to find that relatively advantaged families and students are more responsive to information, exacerbating existing gaps that information interventions aim to address (Cohodes et al., 2022, Corcoran et al., 2018). In the ZOC setting, there is less

variation in socioeconomic status but there is variation in student's baseline achievement, so I focus on that.

Appendix Table C.3 summarizes the evidence. Panel A reports treatment effects on the most preferred incoming achievement for various groups of students categorized based on their baseline achievement levels. Although most estimates are not distinguishable from each other statistically, there is suggestive evidence that higher-achieving families are most responsive to incoming achievement information. It is also worth noting that higher-achieving families tend to apply to schools with higher achievement levels. This finding mirrors evidence in Corcoran et al. (2018) in that relatively advantaged families are more responsive to information treatments.

Panel B reports similar evidence for most-preferred achievement growth. To begin, I find that higher-achieving families in the control group rank better schools at the top of their list in terms of their achievement growth. Mirroring the evidence displayed in Figure 4, most impacts are detected among parents in high-saturation schools. In the first experimental wave, I find the most pronounced effects among low-achieving and moderately-low-achieving families, that is, students performing below district averages on standardized exams at baseline. In the second experimental wave, I find mostly similar effects across the various achievement groups. Throughout, however, differences are noisy and indistinguishable from statistical noise so they are suggestive at best. The evidence does suggest that the intervention reduced achievement-based differences in accessing higher-quality schools in the first experimental wave and kept it constant in the second experimental wave.

Table C.1: Baseline Experimental Effects 2019 Wave

	(1) AG	(2) IA
High Saturation Treatment		
Peer Quality	3.966	-5.222**
	(3.259)	(2.462)
School Quality	3.117	-5.317**
	(3.164)	(2.373)
Both	3.123	-4.991**
	(3.217)	(2.396)
Low Saturation Treatment		
Peer Quality	1.885	-5.294*
	(2.803)	(2.821)
School Quality	0.495	-4.719*
	(2.997)	(2.806)
Both	3.376	-5.213*
	(2.805)	(2.807)
Spillover Treatment		
High Saturation	2.322	-5.867**
	(2.843)	(2.444)
Low Saturation	1.519	-5.267*
	(2.814)	(2.839)
Pure Control Mean	65.739	45.749
R2	0.240	0.400
N	11,541	11,541

Notes: This table reports baseline experimental effects from the 2019 wave of the experiment. Estimates come from regressions of most-preferred AG (IA) on eight separate treatment indicators, including two saturation-specific spillover indicators, and three saturation-specific information-specific indicators. Column 1 reports estimates for a model with most-preferred AG as the outcome, and Column 2 reports estimates from a model with most-preferred IA as the outcome. Standard errors are robust and clustered at the school level.

Table C.2: Baseline Experimental Effects, 2021 Wave

	(1) AG	(2) IA
High Saturation Treatment		
Peer Quality	6.307	-3.007
	(4.156)	(2.160)
School Quality	7.816**	-2.659
	(3.717)	(2.370)
Both	7.241*	-3.852*
	(4.029)	(2.226)
Low Saturation Treatment		
Peer Quality	0.871	0.563
	(3.410)	(2.231)
School Quality	0.205	0.079
	(3.416)	(2.480)
Both	1.322	1.037
	(3.369)	(2.317)
Spillover Treatment		
High Saturation	5.910	-3.308*
	(4.090)	(1.949)
Low Saturation	0.787	0.171
	(3.313)	(2.274)
Pure Control Mean	66.914	51.647
R2	0.290	0.380
N	9,008	9,008

Notes: This table reports baseline experimental effects from the 2021 wave of the experiment. Estimates come from regressions of most-preferred AG (IA) on eight separate treatment indicators, including two saturation-specific spillover indicators, and three saturation-specific information-specific indicators. Column 1 reports estimates for a model with the most-preferred AG as the outcome, and Column 2 reports estimates from a model with most-preferred IA as the outcome. Standard errors are robust and clustered at the school level.

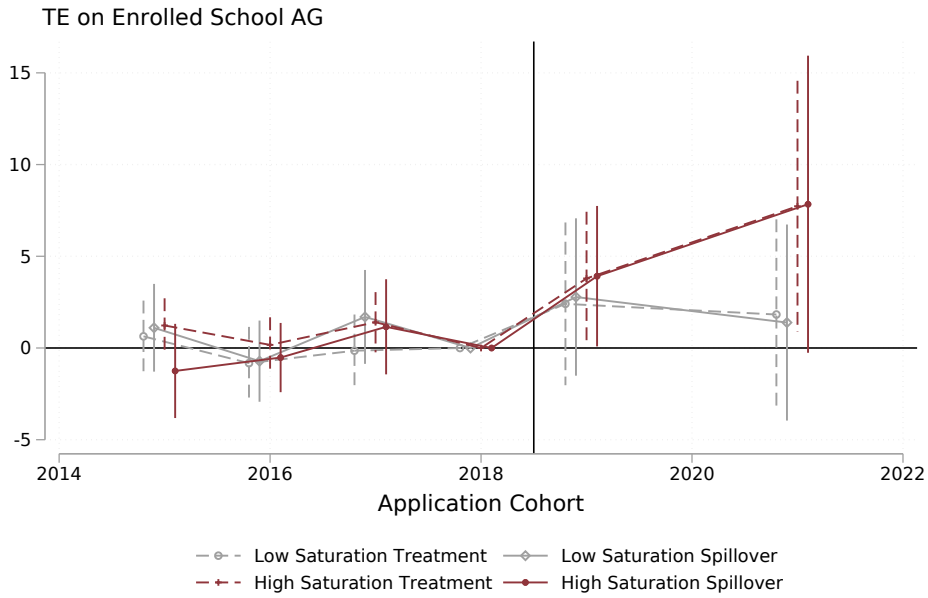
Table C.3: Heterogeneity Results

	(1) Pure Control Mean	(2) High Saturation 2019	(3) Low Saturation 2019	(4) High Saturation 2021	(5) Low Saturation 2021
		Panel A: Incoming Achievement Percentile			
Low Achievers	33.402	-1.785	-1.061	-2.673	1.099
		(1.421)	(1.527)	(2.261)	(1.729)
Moderate Low Achievers	36.428	-1.769	-0.071	-0.112	2.358
		(1.479)	(1.500)	(2.325)	(1.551)
Moderate High Achievers	37.352	-2.186	-1.704	0.060	4.787***
		(1.420)	(1.337)	(2.280)	(1.294)
High Achievers	40.900	-1.664	-1.996*	-1.635	3.616*
		(1.074)	(1.158)	(2.605)	(2.014)
		Panel B: Achievement Growth Percentile			
Low Achievers	63.966	5.293***	0.336	8.296*	-1.788
		(1.714)	(1.399)	(4.553)	(2.173)
Moderate Low Achievers	65.990	3.475**	1.906	7.587**	-1.068
		(1.707)	(1.487)	(3.559)	(2.953)
Moderate High Achievers	66.752	1.027	-0.730	5.615	-0.852
		(2.119)	(1.819)	(3.660)	(2.022)
High Achievers	67.700	2.755	-0.007	6.698**	1.886
		(1.737)	(1.446)	(3.219)	(2.371)

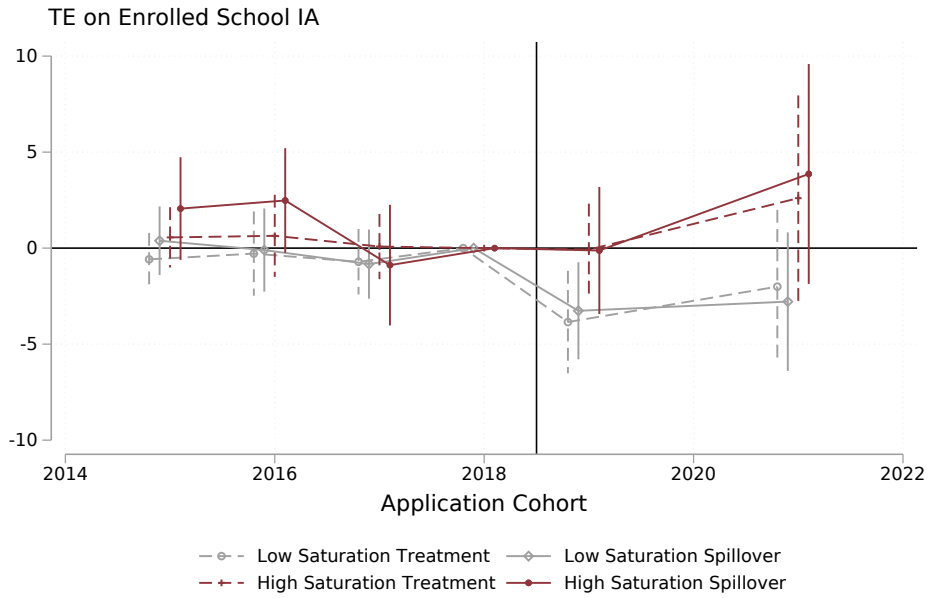
Notes: This table reports cluster-specific treatment and spillover effects on top-listed Incoming Achievement (in Panel A) and Achievement Growth (in Panel B) for various subgroups of students. The group Low Achievers corresponds to students whose baseline test scores are -0.5σ or below. Moderate Low Achievers are students whose baseline test scores are between -0.5σ and 0, while Moderate High Achievers are students whose baseline test scores are between 0 and 0.5σ. High Achievers are students whose baseline test scores are 0.5σ or greater. Each row corresponds to estimates from a separate regression conditioning on the group. As elsewhere in the paper, standard errors are robust and clustered at the school level and reported in parentheses.

C.1.2 Impacts on Enrollment

Figure C.1: Difference-in-Difference Estimates



(a) Impacts on Enrolled School Achievement Growth



(b) Impacts on Enrolled School Incoming Achievement

Notes: This figure reports difference-in-difference estimates from models considering four different school-level treatments. These estimates come from regressions of ninth-grade enrolled school attributes—either incoming achievement or achievement growth—on year and treatment group fixed effects along with treatment group indicators interacted with event-time indicators. All estimates are identified by comparisons with pure control schools. The omitted year is 2018, the year before the first wave of the intervention. Standard errors are robust and clustered at the school level.

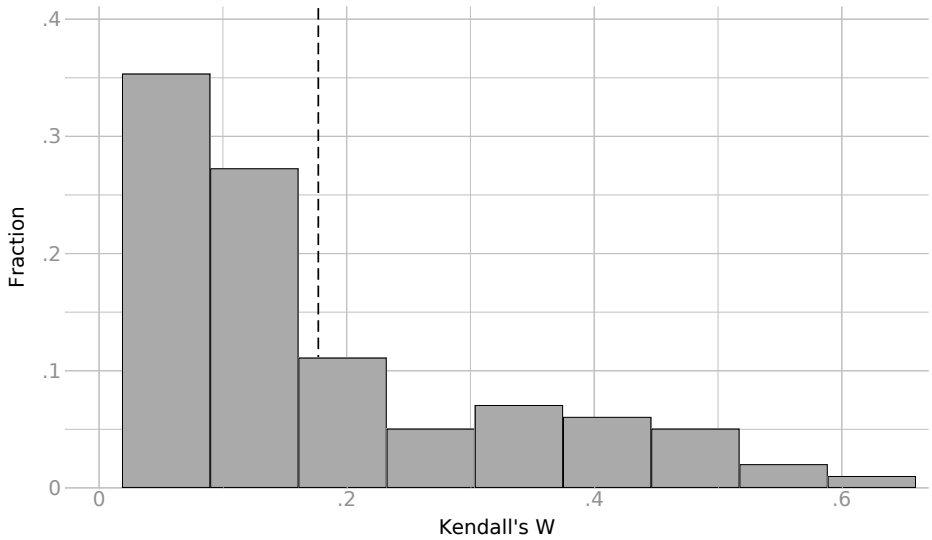
C.2 Evidence on the Lack of Parental Coordination Efforts

This section provides evidence suggesting that coordination among parents in ZOC markets is not widespread. To measure coordination or agreement in rank-ordered school lists, I estimate Kendall's W for each school (Kendall and Smith, 1939). A value of Kendall's W close to one indicates a high degree of similarity in parents' submitted rankings, while values closer to zero indicate little similarity.[23] This concordance measure allows me to assess the extent to which parents from each ZOC feeder school align their schooling decisions, with higher values indicating greater coordination or less variation in preferences.

Appendix Figure C.2 shows the distribution of concordance estimates across all feeder-year schools in the experiment. The average concordance level is low, at 0.18, and approximately 75% of schools have concordance values at or below 0.2. This indicates little coordination in the submitted rankings among parents across feeder schools.

Despite this, it is possible that the intervention increased coordination among parents. To explore this, Appendix Table C.4 reports the treatment effects on rank-ordered list concordance. Across both treatments, I find no substantial evidence that the information interventions significantly altered concordance levels. Even when adjusting for school size, the results remain consistent. Overall, the findings suggest that parental coordination efforts played a limited role in the ranking process.

Figure C.2: Rank-ordered list concordance across schools



Notes: This figure reports the distribution of school-level measures of rank-ordered list concordance as measured by Kendall's W. A value of zero is associated with no concordance and a value of one is associated with high concordance.

[23] Kendall's W is similar to the average value of Spearman's rank coefficient across all applicants for a given school (Kendall and Gibbons, 1990).

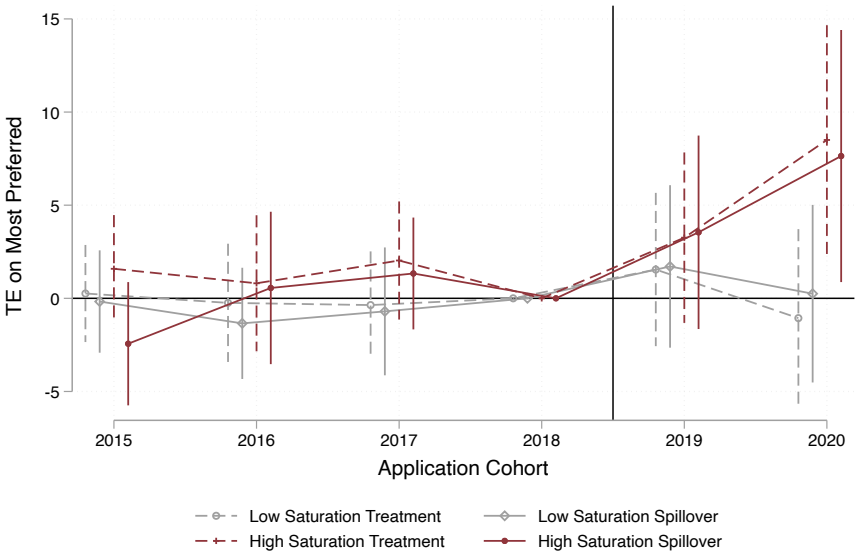
Table C.4: Changes in ranked-ordered list concordance

	(1)	(2)
Kendall's W	Kendall's W	
Treatment High	.01	.01
	(.04)	(.04)
Treatment Low	-.01	.01
	(.04)	(.04)
Control Mean	.18	
Weighted by Size	No	Yes

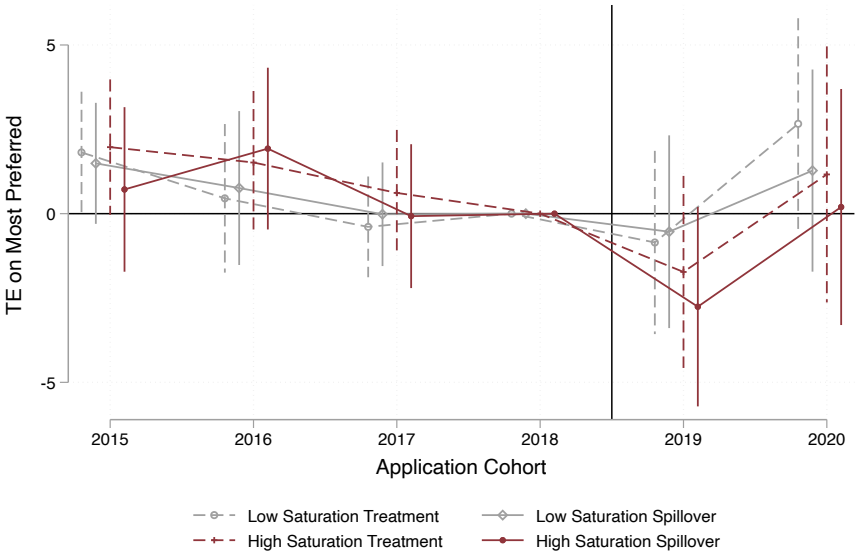
Notes: This table reports results from a regression of school-level estimates of Kendall's W measuring concordance of rank-ordered lists within each cluster (school) unit. A value of zero is associated with no concordance and a value of one is associated with high concordance. Column 1 reports differences between treated and untreated schools, and Column 2 reports similar differences but weighing each observation by the size of the unit. Standard errors are robust.

C.3 Reduced Form Estimates Implied by Structural Model

Figure C.3: Implied Reduced Form Estimates



(a) Impacts on Most-Preferred Achievement Growth

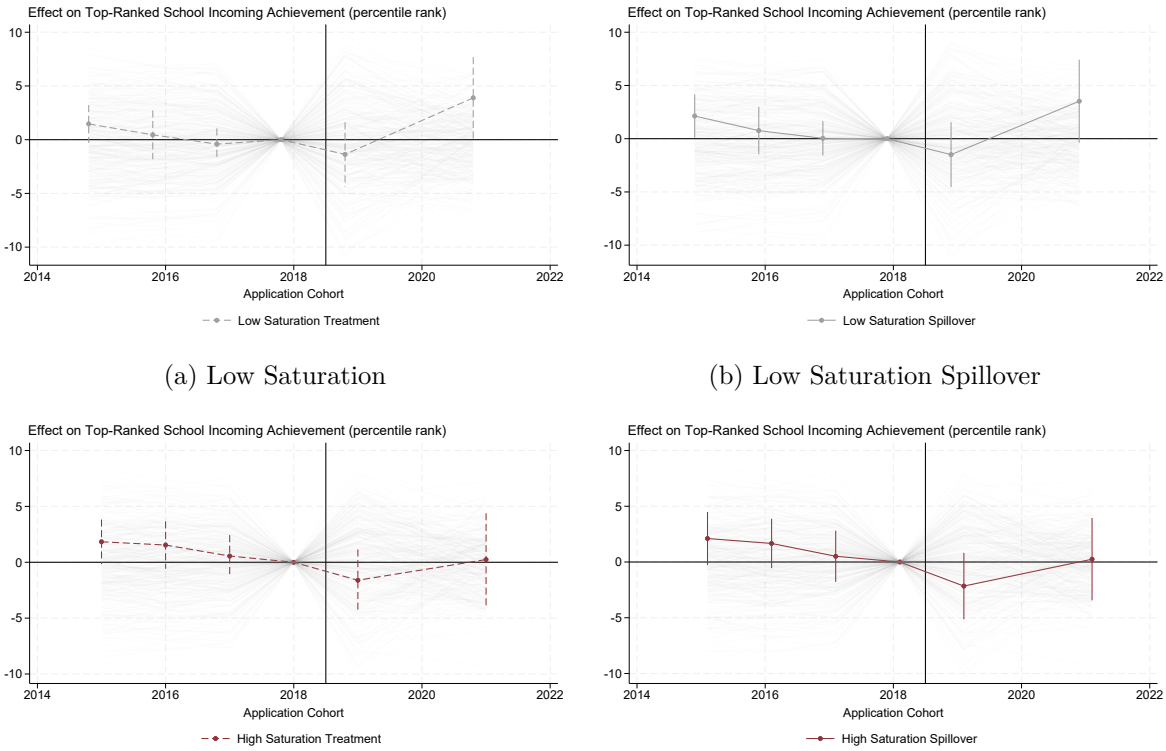


(b) Impacts on Most-Preferred Incoming Achievement

Notes: This figure reports difference-in-difference estimates from models considering four different school-level treatments. These estimates come from regressions of most-preferred school attributes—either incoming achievement or achievement growth—on year and treatment group fixed effects along with treatment group indicators interacted with event-time indicators. Most-preferred schools are the implied most-preferred school using the structural estimates. In practice, we take random draws of the unobserved preference heterogeneity for each option and add that to the estimated systematic component of utility for each option. We use these indirect utility estimates to construct new rank-ordered lists. All estimates are identified with comparisons between the treatment groups and pure control schools. The omitted year is 2018, the year before the first wave of the intervention. Estimates are robust and clustered at the school level with 95 percent confidence bands reported by bars.

C.4 Randomization Inference

Figure C.4: Impacts on Most-Preferred IA (with Randomization Inference)



(a) Low Saturation

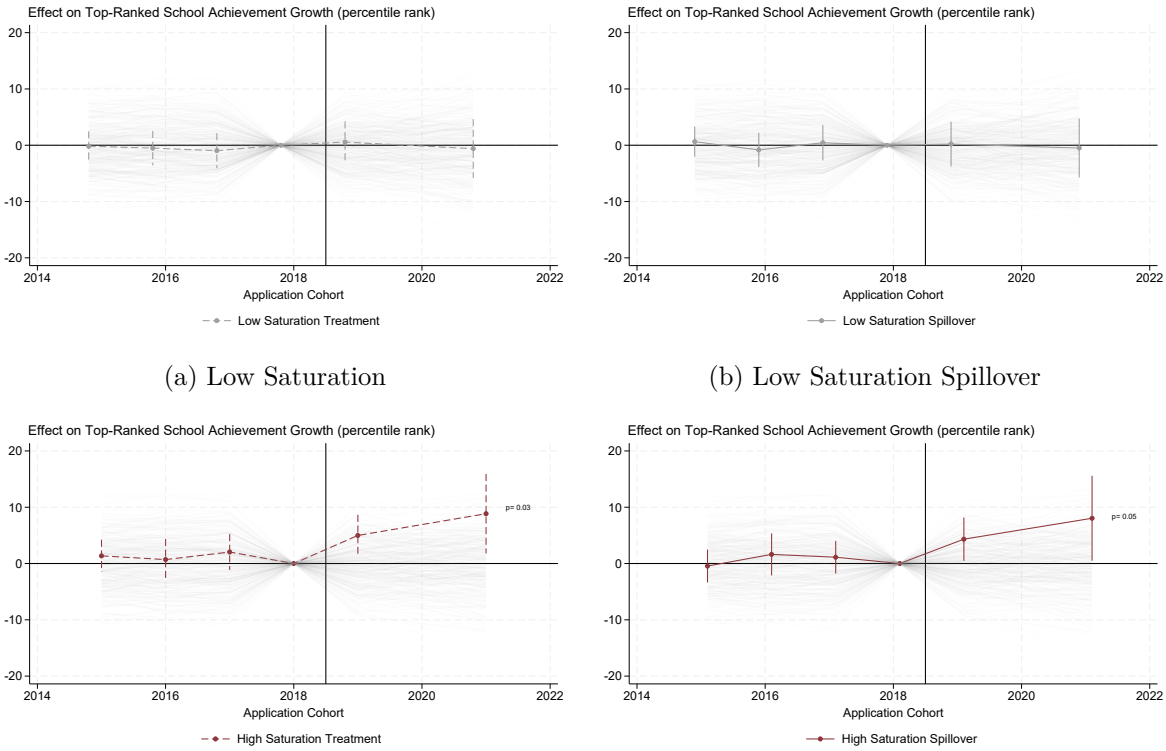
(b) Low Saturation Spillover

(c) High Saturation

(d) High Saturation Spillover

Notes: This figure reports difference-in-difference estimates from models considering four different school-level treatments. These estimates come from regressions of most-preferred school attributes—either incoming achievement or achievement growth—on year and treatment group fixed effects along with treatment group indicators interacted with event-time indicators. All estimates are identified by comparisons with pure control schools. The omitted year is 2018, the year before the first wave of the intervention. The shaded lines correspond to estimates under alternative treatment assignments and provide a visual perspective on the distribution of treatment effects under the sharp null of no treatment effect.

Figure C.5: Impacts on Most-Preferred AG (with Randomization Inference)



(a) Low Saturation

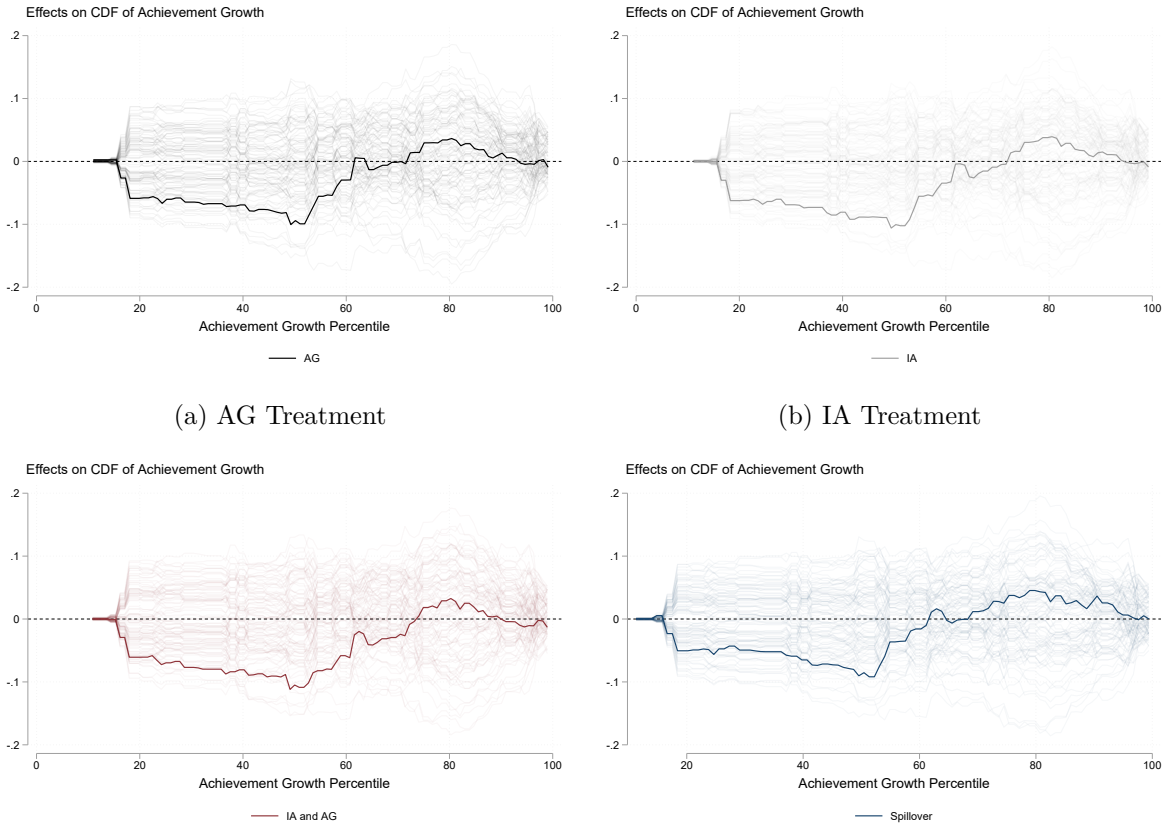
(b) Low Saturation Spillover

(c) High Saturation

(d) High Saturation Spillover

Notes: This figure reports difference-in-difference estimates from models considering four different school-level treatments. These estimates come from regressions of most-preferred school attributes—either incoming achievement or achievement growth—on year and treatment group fixed effects along with treatment group indicators interacted with event-time indicators. All estimates are identified by comparisons with pure control schools. The omitted year is 2018, the year before the first wave of the intervention. The shaded lines correspond to estimates under alternative treatment assignments and provide a visual perspective on the distribution of treatment effects under the sharp null of no treatment effect. Randomization inference-based p-values are reported for the 2021 cohort (labeled 2022 because of academic year 2021-2022).

Figure C.6: AG Distributional Estimates (with Randomization Inference)



(a) AG Treatment

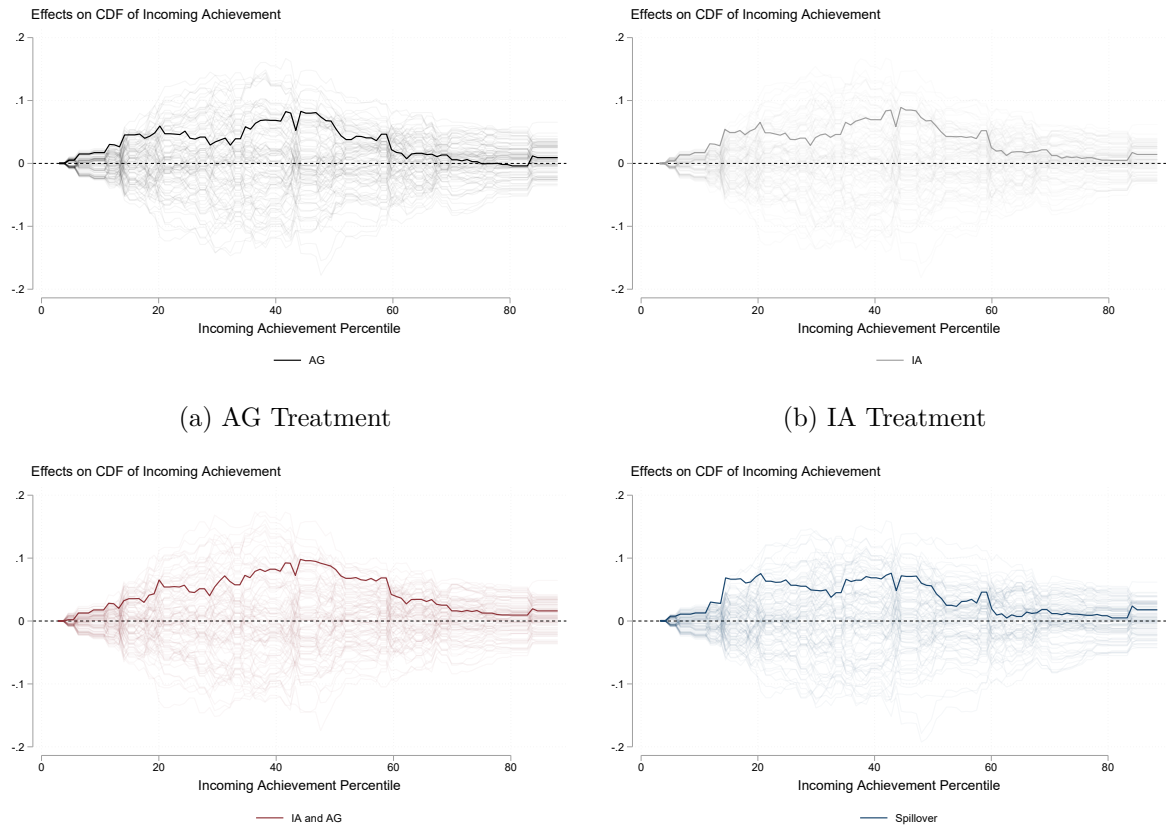
(b) IA Treatment

(c) AG and IA Treatment

(d) Spillover

Notes: This figure displays distribution regression estimates across the achievement growth distribution, mirroring estimates in the main body of the paper. The sample stacks experimental waves and includes experiment-year fixed effects along with student baseline controls included in other estimates throughout the paper. Panel (a) reports estimates among those in the AG-only treatment; Panel (b) reports estimates among those in the IA-only treatment; Panel (c) reports estimates among those in the IA and AG treatment; and Panel (d) reports estimates among those in the spillover group. The shaded lines correspond to estimates under alternative treatment assignments and provide visual perspective on the distribution of treatment effects under the sharp null of no treatment effect.

Figure C.7: IA Distributional Estimates (with Randomization Inference)



(a) AG Treatment

(b) IA Treatment

(c) AG and IA Treatment

(d) Spillover

Notes: This figure displays distribution regression estimates across the achievement growth distribution, mirroring estimates in the main body of the paper. The sample stacks experimental waves and includes experiment-year fixed effects along with student baseline controls included in other estimates throughout the paper. Panel (a) reports estimates among those in the AG-only treatment; Panel (b) reports estimates among those in the IA-only treatment; Panel (c) reports estimates among those in the IA and AG treatment; and Panel (d) reports estimates among those in the spillover group. The shaded lines correspond to estimates under alternative treatment assignments and provide visual perspective on the distribution of treatment effects under the sharp null of no treatment effect.

D Field Survey Details and Evidence

In this section, I report the survey instrument used in the paper and details about a pilot regarding messaging strategies. In Section D.3, I report additional survey evidence alluded to in the main paper.

The additional survey evidence is categorized into four topics. The first corresponds to the attributes of survey respondents (see Table D.2). The second is additional survey evidence not reported in the main paper (see Table D.3 and Figure D.1). The third corresponds to descriptive evidence about belief correlates, including both student-level attributes and researcher-generated measures of quality.

D.1 Survey Questions

The survey has a total of 10 questions and in piloting took roughly 5-8 minutes to complete. The questions are reported below.

Section A - The following questions are useful to help the district better communicate the program to families.

1. What is your relationship to the student?
    - Father
    - Mother
    - Grandparent
    - Guardian

2. Has anyone mentioned the Zones of choice to you before?
    - Yes
    - No

Section B - The following questions are to assess your planned participation in the application cycle and for us to learn what to emphasize in future years.

3. How many hours do you anticipate spending researching schools?
    - Less than 2 hours
    - 2-5 hours
    - 6-10 hours
    - 11-15 hours
    - More than 15 hours

4. Do you anticipate doing any of the following? (check all that apply)
    - Visit school fair
    - Watch school promotional videos
    - Online research
    - Talk to teachers
    - Talk to other parents
    - Consider your student's input

5. Rank the following school characteristics in terms of importance (1-7), where 1 is the most important

- Test score improvement
- Performance of other students
- Safety
- Reputation of teachers
- Distance from home
- Available sport offerings

6. How important are a school's students when choosing a school?

   - Not important
   - Somewhat important
   - Important
   - Very important

7. How important are a school's test scores when choosing a school?

   - Not important
   - Somewhat important
   - Important
   - Very important

8. Do you think schools that attract the highest performing students are also the most effective at facilitating test score growth?

   - Yes, definitely
   - Not necessarily

Section C - We are going to ask you questions about your preferences and beliefs about two important characteristics of schools. We determine the quality of a school based on students' average scores on state exams.

This measure has two parts you should consider: One (1) which measures the school's ability of attracting high scoring students, and the second (2) is the school's impact on test score growth.

- Incoming Achievement (IA): We can measure a school's ability to attract high-achieving students by measuring the average test scores of its incoming students.
- Achievement Growth (AG): Similarly, we can measure the school's ability to improve test scores using the growth of the same student's test scores between entry into the school and some later date.

9. For the next table, please give each school a rating between 0-10, 10-20, $\cdots$, 90-100 according to your beliefs about their ability in terms of (1) Incoming Achievement and (2) Achievement Growth.

10. Please rank the schools as if you were submitting the application today. Note there are K schools you can choose from, so rank your most preferred as 1 and the least preferred as K.

D.2 Pilot Details

Several months before the intervention, I piloted different messaging strategies on Amazon Mechanical Turk (mTurk). I provided respondents with brief descriptions of each quality measure and asked questions to assess two things: (i) whether they were paying attention and (ii) their level of understanding. To gauge attention, I presented hypothetical scenarios where respondents had to infer peer and school quality based on the available information. In these scenarios, either incoming achievement (IA) or achievement growth (AG) was held constant, and respondents had to distinguish between schools based on the other measure. To assess their understanding, I asked them to describe the difference between the two measures. Independent researchers then subjectively evaluated the responses.

To better reflect the demographic characteristics of ZOC families, I imposed a few restrictions on who could participate in the mTurk survey. Respondents had to be parents, under the age of 60, and have at most a high school diploma. However, there were too few Hispanic participants at the time to hold that attribute constant across respondents.

Table D.1 presents the results. Approximately 90% of participants were able to correctly infer IA and AG. Hispanic respondents had a slightly lower correct response rate, but the difference was not statistically significant. For the written responses, about 70% of participants demonstrated an understanding of the difference between IA and AG. Interestingly, Hispanic respondents provided correct written explanations at a slightly higher rate, though this difference was also not statistically significant. Overall, the pilot results suggest that the chosen terms for school and peer quality effectively convey the differences to parents, and the pedagogical videos should further enhance their understanding.

Table D.1: MTurk Piloting Results

	Non-Hispanic	Hispanic	Difference
	(1)	(2)	(3)
Incoming Achievement	0.926	0.833	-0.092
			(0.058)
Achievement Growth	0.946	0.917	-0.029
			(0.044)
Both	0.892	0.792	-0.101
			(0.064)
Understood	0.671	0.687	0.0163
			(0.078)
Time to Completion	290	320	30.1
			27.8
N	149	48	

Notes. Incoming achievement results come from a question holding achievement growth constant for two hypothetical schools and asking respondents which school had the highest incoming achievement. Achievement growth results similarly come from a question holding incoming achievement constant and asking respondents to infer hypothetical schools' achievement growth. Both corresponds to respondents who got both questions right. Understood presents results from a subjective evaluation of responses explaining the difference between achievement growth and incoming achievement. Time to completion corresponds to response times (in seconds)

D.3 Additional Survey Evidence

Table D.2: Survey Respondent Characteristics

	(1) No Survey	(2) Partial	(3) Complete
ELA Z-Score	-0.199	0.011	0.151***
		(0.032)	(0.025)
Math Z-Score	-0.187	0.010	0.162***
		(0.044)	(0.022)
Female	0.495	-0.011	-0.018**
		(0.013)	(0.009)
Migrant	0.002	0.002	0.000
		(0.002)	(0.001)
Poverty	0.901	0.004	-0.012
		(0.009)	(0.008)
Special Education	0.144	0.012	-0.008
		(0.010)	(0.008)
English Learner	0.179	0.009	-0.028***
		(0.009)	(0.008)
College	0.081	-0.010	0.023**
		(0.010)	(0.010)
Black	0.032	-0.010***	0.000
		(0.003)	(0.002)
Hispanic	0.911	-0.001	-0.017*
		(0.009)	(0.010)
White	0.016	0.001	0.001
		(0.003)	(0.002)
N	5,154	1,355	4,132

Notes: This table reports estimates from regressions of each row variable on indicators for survey completion status. Partial indicates that the respondent did not finish the survey, usually corresponding to missing beliefs information, and complete corresponds to respondents who completed the survey. The response rate is 51.5%, and the completion rate is 38%. Robust standard errors are reported in parentheses.

Table D.3: Survey Responses

Panel A: Anticipated Participation in the School Choice Process

Respondent Relationship	Father: 0.109	Mother: 0.866	Grandparent: 0.006	Legal Guardians: 0.019
Anticipated Research Hours	Less than 2 hours: 0.373	2-5 hours: 0.352	6-10 hours: 0.352	10+ hours: 0.156

	Yes	No
Have you heard of ZOC	0.340	0.660
Do you anticipate doing any of the following:		
Visit a school fair	0.470	0.530
Watch promotional videos	0.430	0.570
Talk to teachers	0.520	0.480
Talk to parents	0.470	0.530
Online research	0.640	0.360

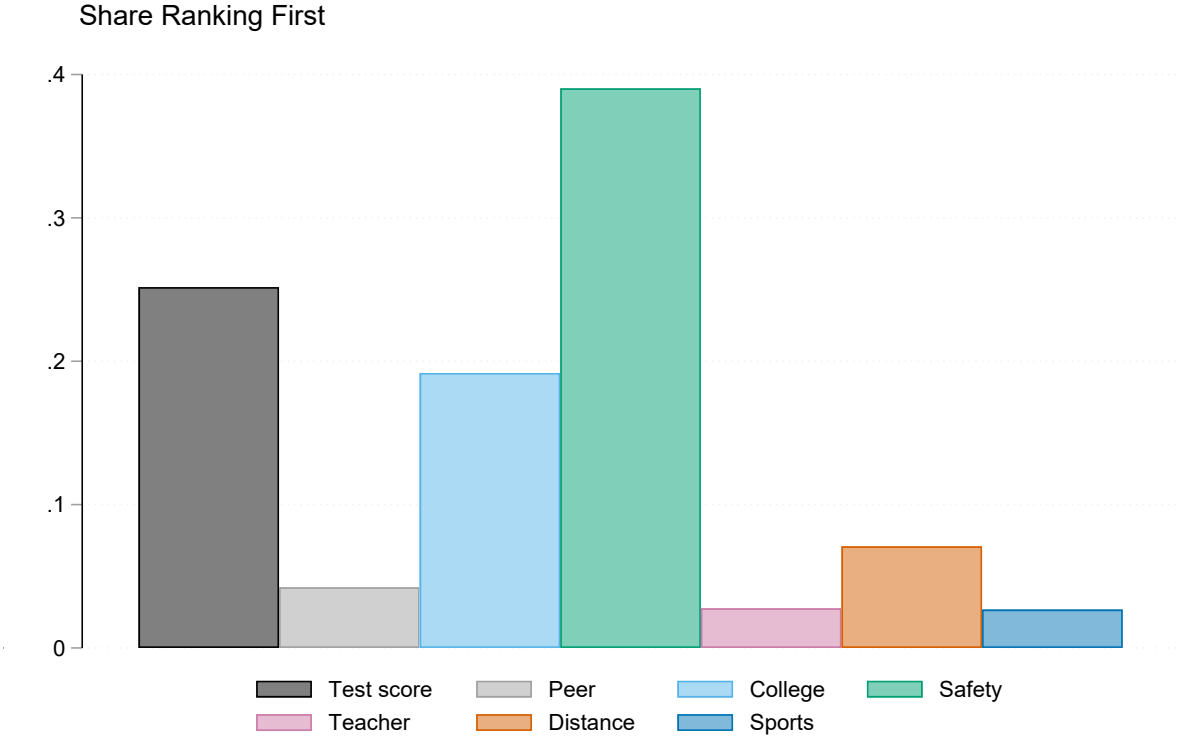
Panel B: Perception of school characteristics

	Not Important	Somewhat Important	Important	Very Important
Peer importance	0.080	0.224	0.326	0.370
Test score importance	0.013	0.079	0.369	0.539

Do you think that...	Yes, definitely	Not necessarily
Good Peers Imply High Growth?	0.320	0.680

Notes: This table reports a series of descriptive statistics from the baseline survey. The questions correspond to Section A and Section B of the baseline survey discussed in Appendix D.

Figure D.1: Stated Preferences over School Attributes



Notes: This figure reports survey item results from a question asking parents to rank various school attributes from most important (1) to least important (7). Each bar corresponds to the share of parents ranking the attribute first. The precise question is listed in Appendix Section D.

Table D.4: IA and AG Pessimism Correlation with Student Characteristics for Top-Ranked School

Bias Measure	IA		AG	
	Bivariate	Multivariate	Bivariate	Multivariate
Parent College	1.085 ***	0.627 ***	-0.009	0.126
	(0.179)	(0.197)	(0.197)	(0.220)
Hispanic	-0.883 ***	-0.243	0.844 ***	1.045 ***
	(0.178)	(0.196)	(0.258)	(0.288)
English Learner	-0.365 **	-0.146	-0.064	-0.247
	(0.152)	(0.167)	(0.189)	(0.210)
Special Education	0.202	0.354 *	0.202	0.211
	(0.157)	(0.171)	(0.182)	(0.201)
Black	0.723 **	0.499	-0.882 **	0.288
	(0.323)	(0.359)	(0.437)	(0.490)
White	0.924 **	0.279	-0.024	0.781
	(0.410)	(0.449)	(0.525)	(0.584)
Female	-0.091	-0.141	-0.094	-0.091
	(0.107)	(0.118)	(0.114)	(0.127)
Poverty	-1.708 ***	-1.572 ***	0.086	-0.154
	(0.171)	(0.190)	(0.197)	(0.220)
Math Z-Score	0.161 ***	-0.043	-0.040	-0.043
	(0.060)	(0.066)	(0.098)	(0.110)
ELA Z-Score	0.194 ***	0.158	-0.026	0.010
	(0.061)	(0.067)	(0.102)	(0.114)
Migrant	-1.265	-1.019	-1.484	-1.533
	(1.026)	(1.123)	(1.006)	(1.118)
Mean	-1.63		-0.52	
SD	3.07		3.36	

Notes: This table reports univariate and multivariate correlations between student-level IA and AG pessimism measures and student-level covariates. Column 1 and Column 2 consider IA pessimism and Column 3 and Column 4 consider AG pessimism. Odd-numbered columns consider bivariate regressions of the pessimism measure on the row variable, and even-numbered columns report estimates from the multivariate analog. Robust standard errors are reported in parentheses.

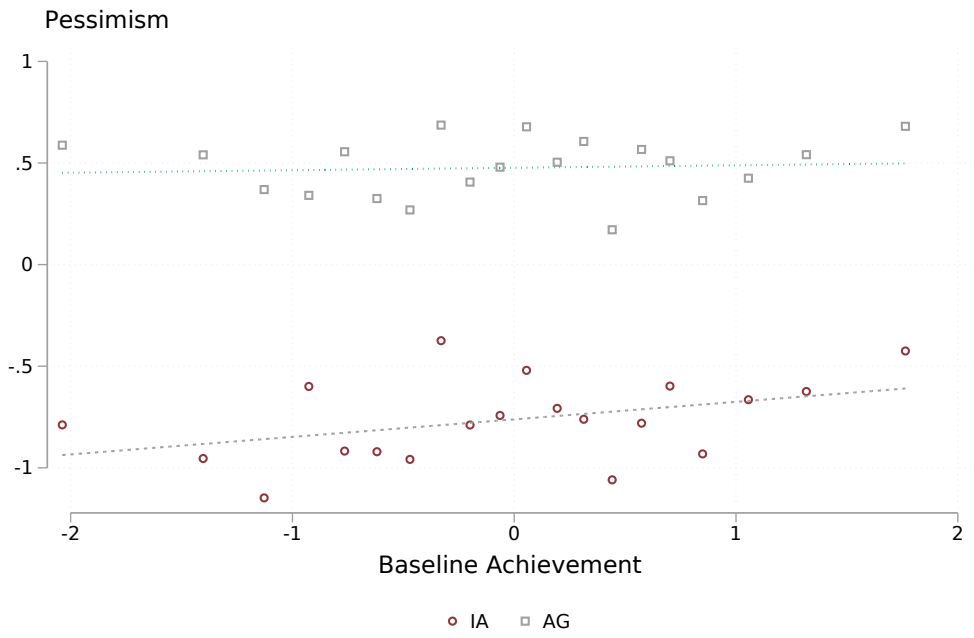
Table D.5: IA and AG Absolute Bias Correlation with Student Characteristics for Top-Ranked School

Bias Measure	IA		AG	
	Bivariate	Multivariate	Bivariate	Multivariate
Parent College	-0.678 ***	-0.586 ***	-0.035	0.033
	(0.113)	(0.127)	(0.126)	(0.142)
Hispanic	0.221 *	-0.046	-0.300 **	-0.303
	(0.113)	(0.127)	(0.165)	(0.185)
English Learner	0.319 ***	0.128	0.231 **	0.164
	(0.096)	(0.108)	(0.121)	(0.135)
Special Education	0.061	-0.108	0.236 **	0.075
	(0.099)	(0.111)	(0.116)	(0.129)
Black	-0.202	-0.400	0.549 **	0.183
	(0.204)	(0.232)	(0.279)	(0.316)
White	-0.061	0.307	0.385	0.128
	(0.260)	(0.290)	(0.336)	(0.376)
Female	-0.044	0.016	0.044	0.042
	(0.068)	(0.076)	(0.073)	(0.082)
Poverty	0.501 ***	0.275 **	-0.094	-0.169
	(0.109)	(0.123)	(0.126)	(0.142)
Math Z-Score	-0.151 ***	-0.031	-0.182 ***	-0.220 ***
	(0.038)	(0.043)	(0.063)	(0.071)
ELA Z-Score	-0.168 ***	-0.109 *	-0.119 ***	0.075
	(0.039)	(0.043)	(0.065)	(0.074)
Migrant	0.004	-0.099	0.045	-0.021
	(0.649)	(0.724)	(0.644)	(0.721)
Mean	2.88		2.62	
SD	1.94		2.17	

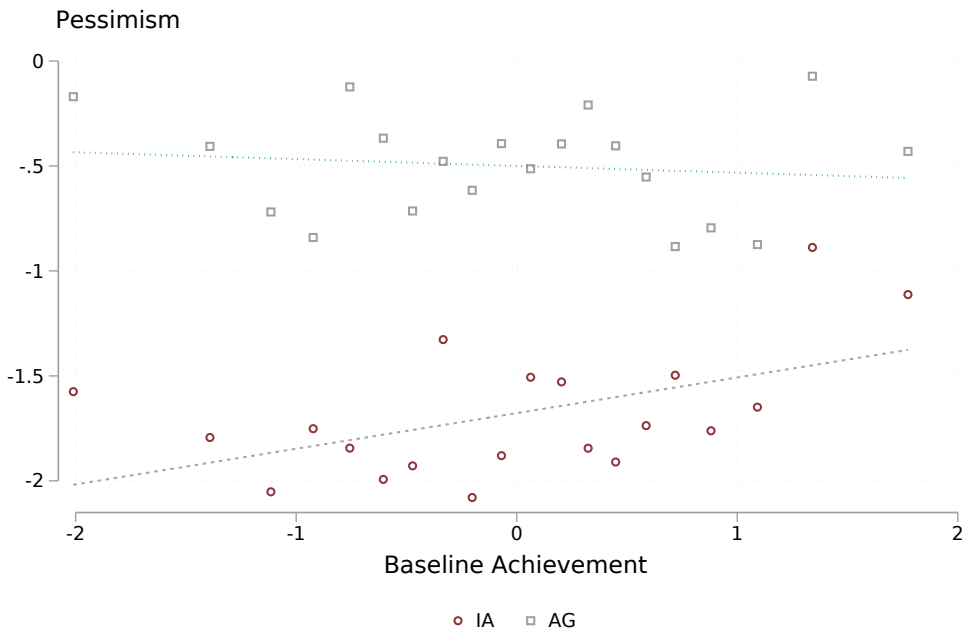
Notes: This table reports univariate and multivariate correlations between student-level IA and AG absolute bias measures and student-level covariates. Column 1 and Column 2 consider IA bias and Column 3 and Column 4 consider AG bias. Odd-numbered columns consider bivariate regressions of the pessimism measure on the row variable, and even-numbered columns report estimates from the multivariate analog. Robust standard errors are reported in parentheses.

Figure D.2: Pessimism-Achievement Relationship

(a) All Options on Rank-Ordered List



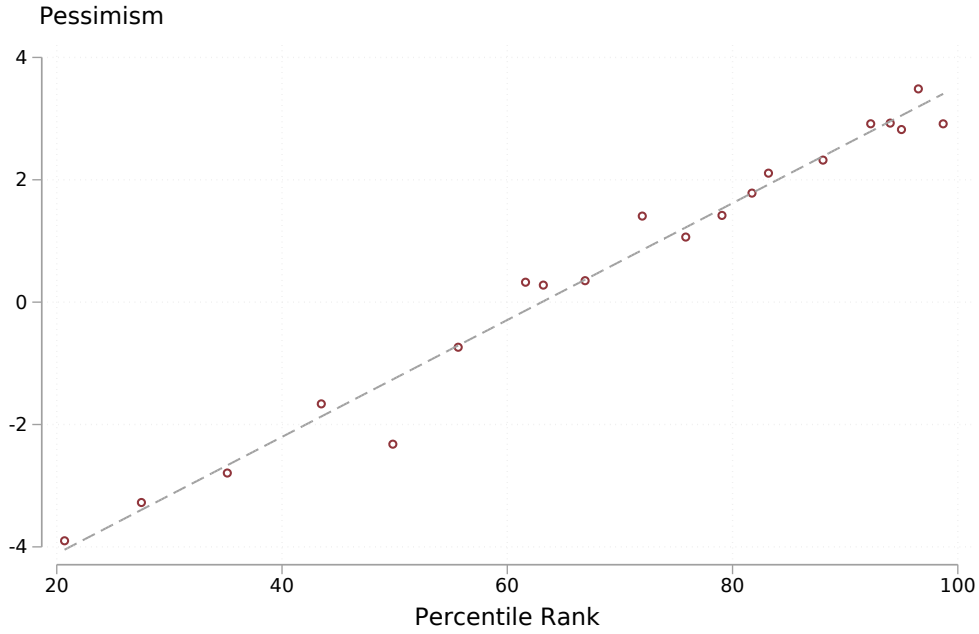
(b) Only Top-Ranked Option on Rank-Ordered List



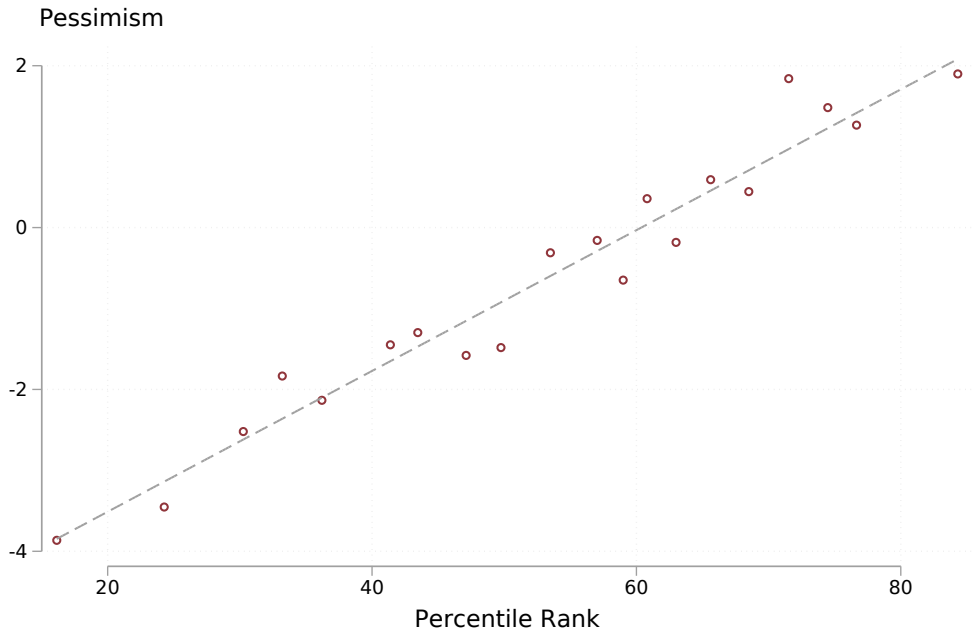
Notes: This figure reports bivariate-binned scatter plots of the pessimism-achievement relationship. Panel (a) reports the relationship across all options contained on the rank-ordered list, while Panel (b) reports the relationship only among the top-ranked option of applicants' rank-ordered lists.

Figure D.3: AG/IA Bias-Truth Relationship

(a) Achievement Growth



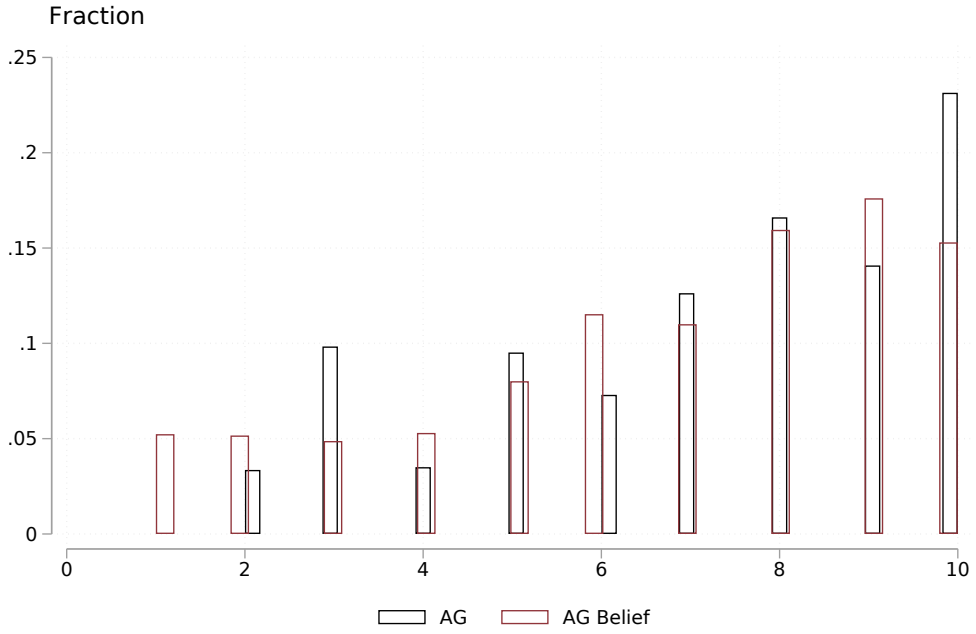
(b) Incoming Achievement



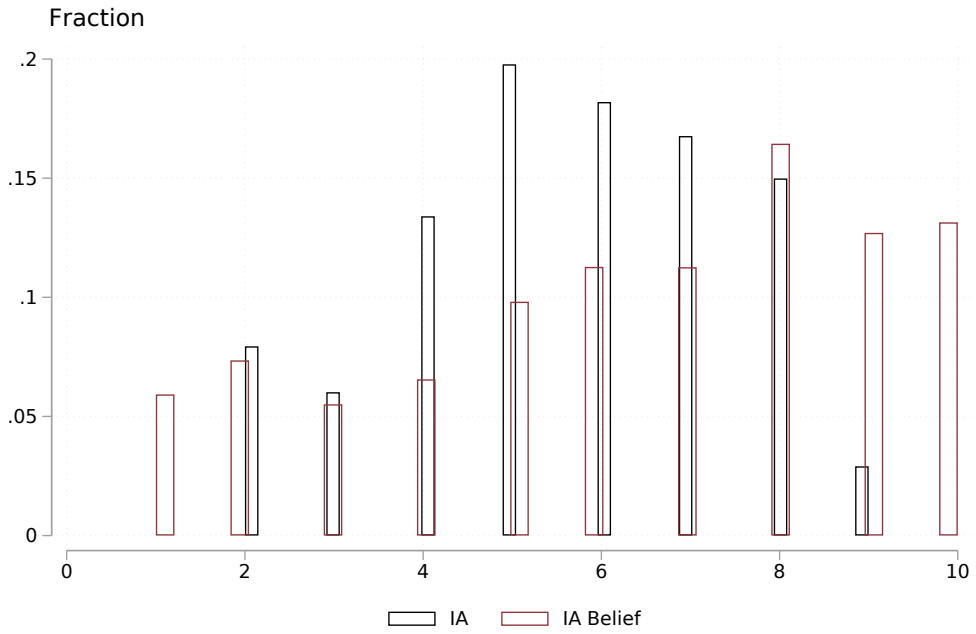
Notes: This figure reports bivariate-binned scatter plots of the pessimism-achievement relationship. Panel (a) reports the relationship across all options contained on the rank-ordered list, while Panel (b) reports the relationship only among the top-ranked option of applicants' rank-ordered lists.

Figure D.4: AG/IA Decile and AG/IA Belief Distribution

(a) Achievement Growth



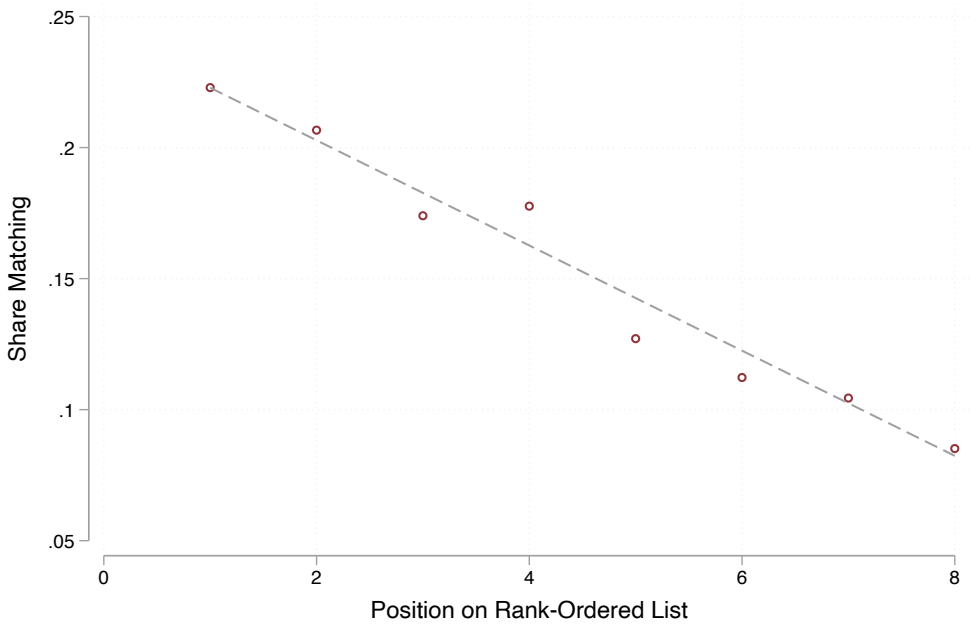
(b) Incoming Achievement



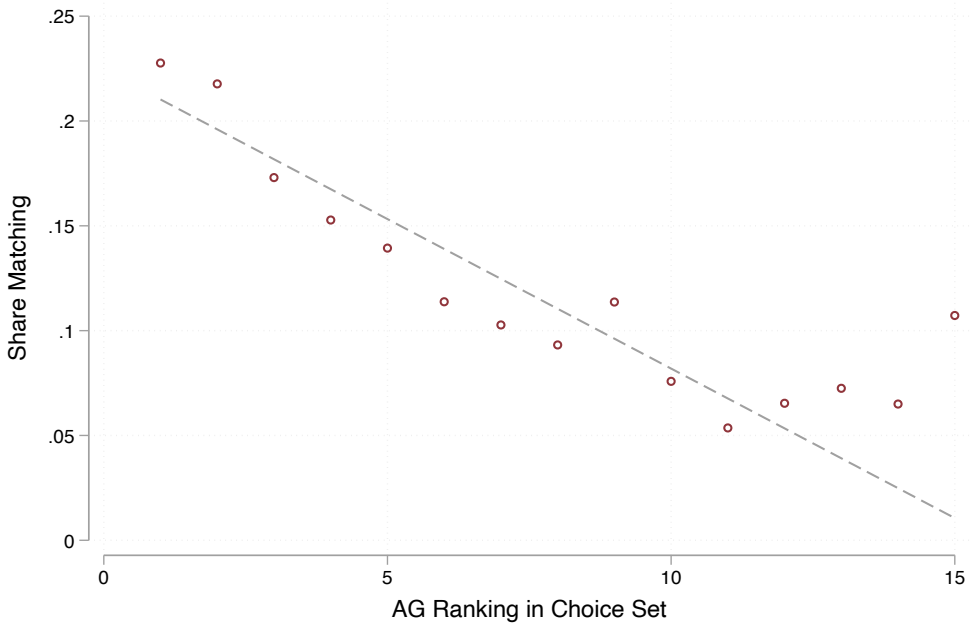
Notes: This figure reports option-specific distributions of AG (IA) deciles and AG (IA) beliefs. If applicants' decile beliefs were perfectly on target, then their belief distribution would perfectly overlap with the decile distribution.

Figure D.5: Choice Relevance of AG Biases

(a) By Position on the Rank-ordered List



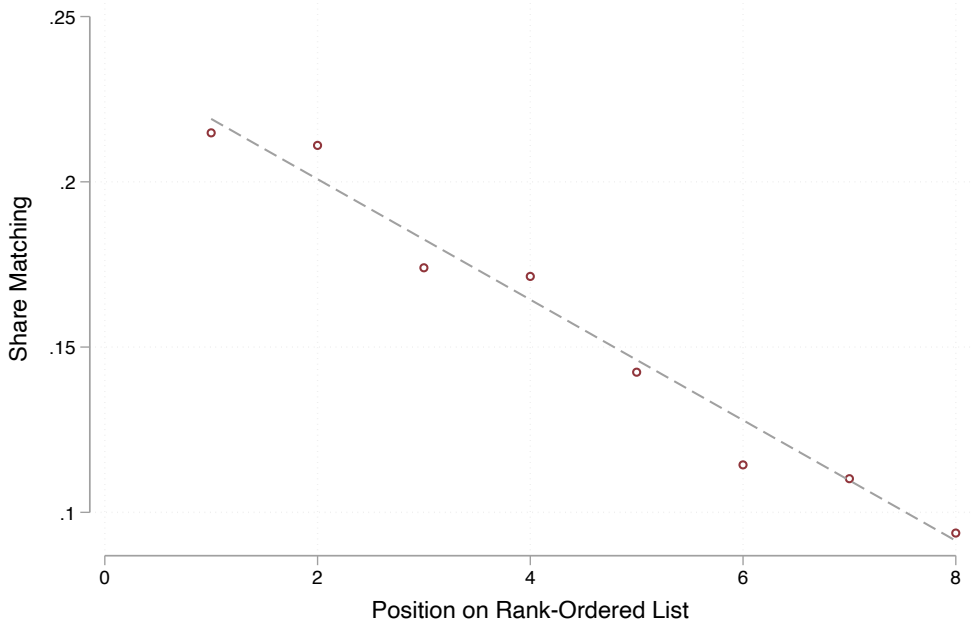
(b) By Option's Actual Ranking



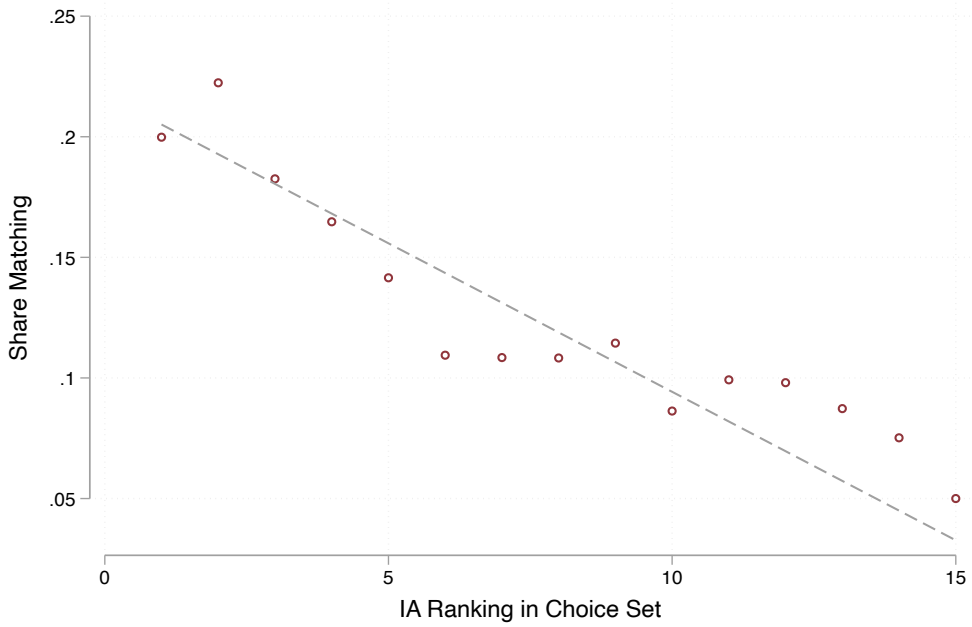
Notes: This figure reports the share of applicants whose ordinal AG belief ranking of schools matches the actual ordinal ranking of AG. Panel (a) reports that by position on the applicant's rank-ordered list and Panel (b) reports that by the actual ranking for that option.

Figure D.6: Choice Relevance of IA Biases

(a) By Position on the Rank-ordered List



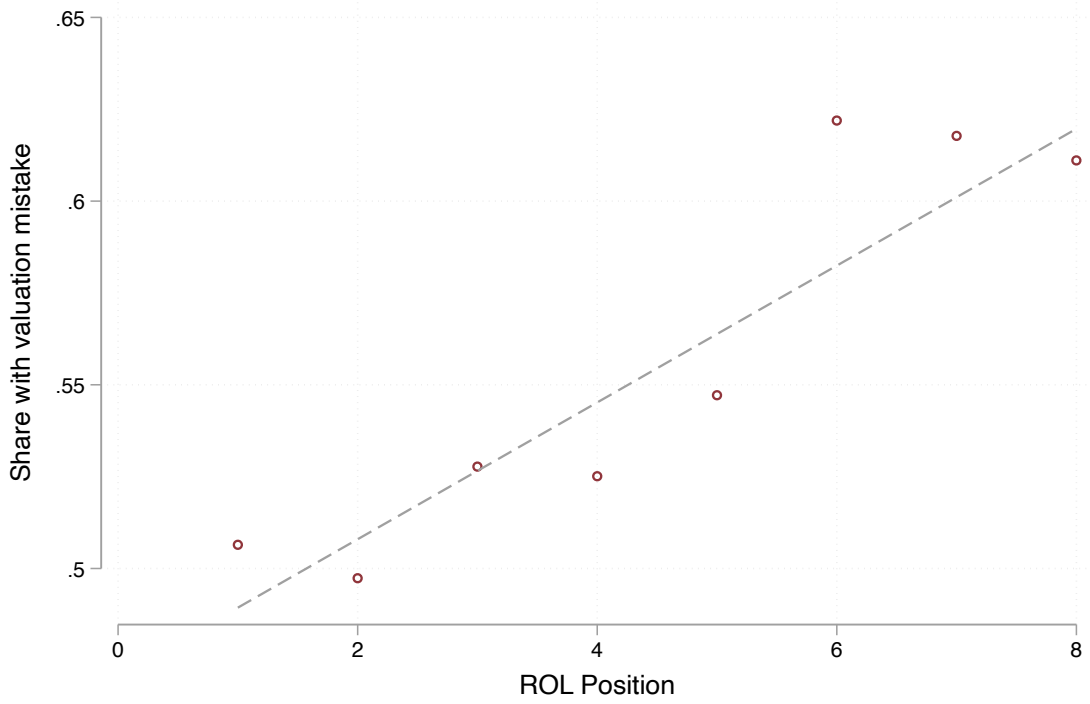
(b) By Option's Actual Ranking



Notes: This figure reports the share of applicants whose ordinal IA belief ranking of schools matches the actual ordinal ranking of IA. Panel (a) reports that by position on the applicant's rank-ordered list and Panel (b) reports that by the actual ranking for that option.

D.4 Application Mistakes

Figure D.7: Valuation-Induced Application Mistakes



Notes: This figure reports the share of applicant-level valuation-induced application mistakes across the rank-ordered list. To define a valuation mistake, I first estimate preferences for schools using elicited beliefs about IA and AG and distance to schooling options. With those preference estimates, I then predict the systematic component of utility using beliefs and researcher-generate quality separately. I then take random EVT1 draws to capture unobserved preference heterogeneity, and combined with estimated systematic components of utility, I generate new rank-ordered lists. If there is disagreement at a given position of the ROL, I define that as a valuation-induced application mistake. This figure reports the share of these across the rank-ordered list at baseline.

E Online Survey Details and Evidence

I complement the field experiment with an online survey administered on the Prolific platform. I survey parents with school-aged children to mirror the field experiment and provide additional details about social interactions in the school choice process, while also eliciting beliefs about peer and school quality after using pedagogical videos to teach parents about the concepts in a nationally representative sample. The survey is packed with information, but only a few are emphasized in the main body of the paper that I report in this section.

The goals of the online survey directly relate to the core questions of the field experiment. The survey, therefore, mirrors the field experiment in that respondents are provided with similar pedagogical videos to teach them about school and peer quality, then asked about their beliefs about each. Preferences are then experimentally identified, and a series of descriptive questions establish that social interactions are important to parents and then aim to understand why.

E.1 Measuring Beliefs and Biases

The Prolific sample contains parents from all parts of the United States and we do not have any information about the schools their children are enrolled in before they take the survey. To benchmark beliefs against an objective measure, we use information on GreatSchools.org. To measure beliefs, after showing parents pedagogical videos explaining peer and school quality, we ask them about their beliefs about their schools' decile rank across all other schools in their particular state; those are the measures of beliefs about school and peer quality. After that, we ask them to look up their school on GreatSchools.org and to enter the URL of the link, and then to report their school's Great Schools Summary, Test Score, Progress, and Equity rating. The Summary Rating is a weighted average of the subcomponents. Because we elicit their beliefs in terms of deciles and the Great Schools ratings are analogous to decile ranks, we use the Great Schools ratings as an objective benchmark. We also inspect responses to ensure the URL parents provide corresponds to actual schools in respondents' reported county and state.

E.2 Sample Summary Statistics and Beliefs

Appendix Table E.1 presents the demographic and regional characteristics of survey participants, along with information about their children's schools and their beliefs about school ratings. Compared to the most recent decennial census, the survey sample has a slightly lower proportion of Hispanic respondents and a higher proportion of Black respondents. Additionally, there is a slight underrepresentation of individuals with annual incomes below $100,000. In terms of regional representation, the sample closely mirrors Census statistics. Panel C shows the GreatSchools ratings of the schools attended by respondents' children. On average, respondents enroll their children in schools with a Summary rating in the sixth decile of the GreatSchools distribution. The GreatSchools Test Score rating, which corresponds to peer quality or incoming achievement, and the Progress rating, which reflects school quality or achievement growth, are also reported. Parents tend to be optimistic about both peer and school quality, though their optimism is more tempered for school quality. Interestingly, parents' beliefs about school quality are not significantly misaligned with the actual ratings.

Mirroring the field survey evidence, Appendix Figure E.1 shows that respondents on Prolific tend to overestimate peer and school quality if their schools' are below the median and underestimate if their schools are over the median. This pull-to-the-center effect, also appearing in the field survey evidence (see Appendix Figure D.3), is common in many studies. Appendix Figure E.2 reports the mean pessimism measures across all the states represented in the sample, showing there is substantial spatial heterogeneity.

E.3 Preferences

The respondents watched videos similar to the ones in the field experiment. After the videos and questions that allow us to gauge respondents' overall understanding of the content, we asked them about their preferences for school and peer quality. Appendix Figure E.3 reports the share of parents who report preferring school quality over peer quality, demonstrating that roughly 80 percent of parents report having a stronger preference for school quality. We also experimentally elicited their preferences for peer and school quality using a sequence of hypothetical choice trials. Appendix Figure E.4 reports experimental preference estimates for various subgroups, quantifying preferences in willingness to travel units. The typical parent in the sample is willing to travel an additional 5.5 minutes to enroll their child in a school with a one-unit higher GS Progress rating, a measure analogous to school quality. In contrast, the willingness to travel for peer quality is 28 percent lower. The findings that preferences tend to exhibit a stronger preference for school quality over peer quality after being informed about each mirrors the key findings in the main paper. In terms of heterogeneity, there is some heterogeneity with the most pronounced corresponding to URM families exhibiting larger willingness to travel for both peer and school quality. Across all groups we find that families have a stronger taste for school quality that is statistically and economically significant.

E.4 Social Interactions

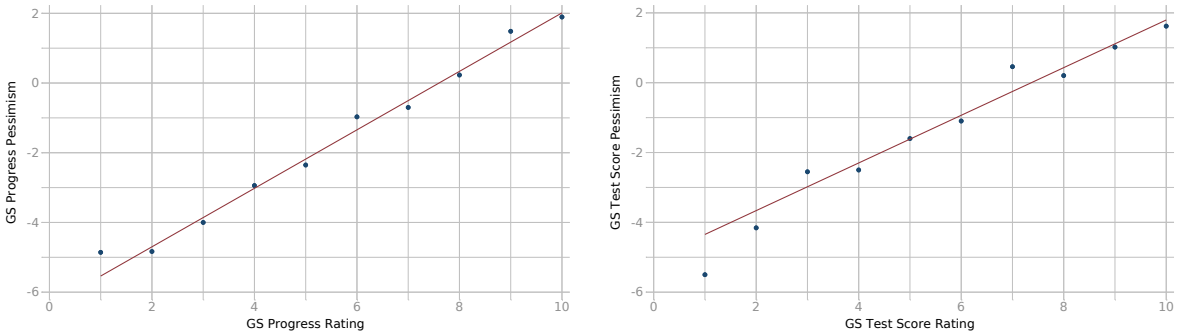
Parental interactions are common throughout the school choice process. To begin, Appendix Figure E.5 demonstrates that parents rely on other parents for information during the school choice process, with 73 percent of parents reporting that they talk to other parents for information about schools, coming in second to online research. Appendix Figure E.6 demonstrates that information shared by the district influences schooling decisions as much as information shared by other parents, and that most parents believe district-provided information is more likely to influence schooling decisions if discussed with other parents. To unpack why parents believe talking to other parents is important, Appendix Figure E.7 reports the reasons why parents rely on engagement with other parents. The overwhelming majority of parents rely on parental discussions because they think discussions with other parents make the information more credible and help them understand complex information. A minority of parents report talking to other parents to coordinate schooling decisions. In summary, the evidence reported in Appendix Figure E.5, Appendix Figure E.6, and Appendix Figure E.7 demonstrate that social interactions are important in the school choice process, and when it comes to how district-provided information affects choices, social interactions give information more credibility and help parents better understand and distill information.

Table E.1: Prolific Sample Descriptive Statistics

	Mean	Standard Deviation
	Panel A: Respondent Demographic Variables	
College Educated	0.58	0.49
White	0.66	0.47
Black	0.24	0.43
Hispanic	0.08	0.27
Asian	0.06	0.23
Lower Income	0.57	0.50
Higher Income	0.43	0.50
	Panel B: Respondent Census Regions	
Northeast Region	0.18	0.38
Midwest Region	0.20	0.40
South Region	0.42	0.49
West Region	0.19	0.39
	Panel C: Respondent Great School Ratings	
GS Summary Rating	5.99	2.23
GS Test Score Rating	6.42	2.50
GS Progress Rating	6.11	2.46
GS Equity Rating	5.27	2.50
	Panel D: Respondent Great School Rating Biases	
GS Progress Pessimism	-0.67	2.53
GS Test Score Pessimism	-1.26	2.69
N		1,000

Notes: This table reports summary statistics for the sample of Prolific respondents. A sample of parents with school-aged children was surveyed on Prolific with an aim to mirror the typical parent in the United States. Panel A reports demographic characteristics. Lower income is defined as someone self-reporting annual earning of less than $100,000, and Higher Income is the complement. Panel B reports the representation of different Census regions using respondents' self-reported state and county information. Panel C reports self-reported Great Schools ratings of schools respondents' children attend. To elicit Great School ratings, we asked respondents to search for their school on GreatSchools.org and report the URL. After that, we asked them to report the GS Summary Rating, Test Score Rating, Progress Rating, and Equity Rating. Panel D reports Great School rating pessimism measures. Before asking respondents to search for their school on GreatSchools.org, we asked them to rank the decile they believed their school belonged to with respect to the distribution of schools in their state. We asked them this question for both peer and school quality. Beliefs were elicited after they viewed pedagogical videos explaining the differences between peer and school quality.

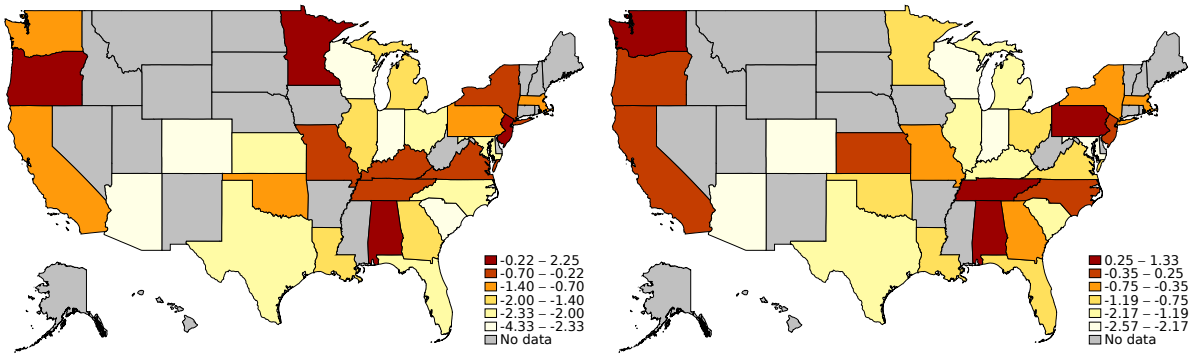
Figure E.1: GS Summary Ratings Biases



(a) School Quality (b) Peer Quality

Notes: This figure reports a binscatter relationship between respondents' elicited pessimism for both GS-based school and peer quality against objective GS-based school and peer quality. States with fewer than ten respondents are not included in the figures.

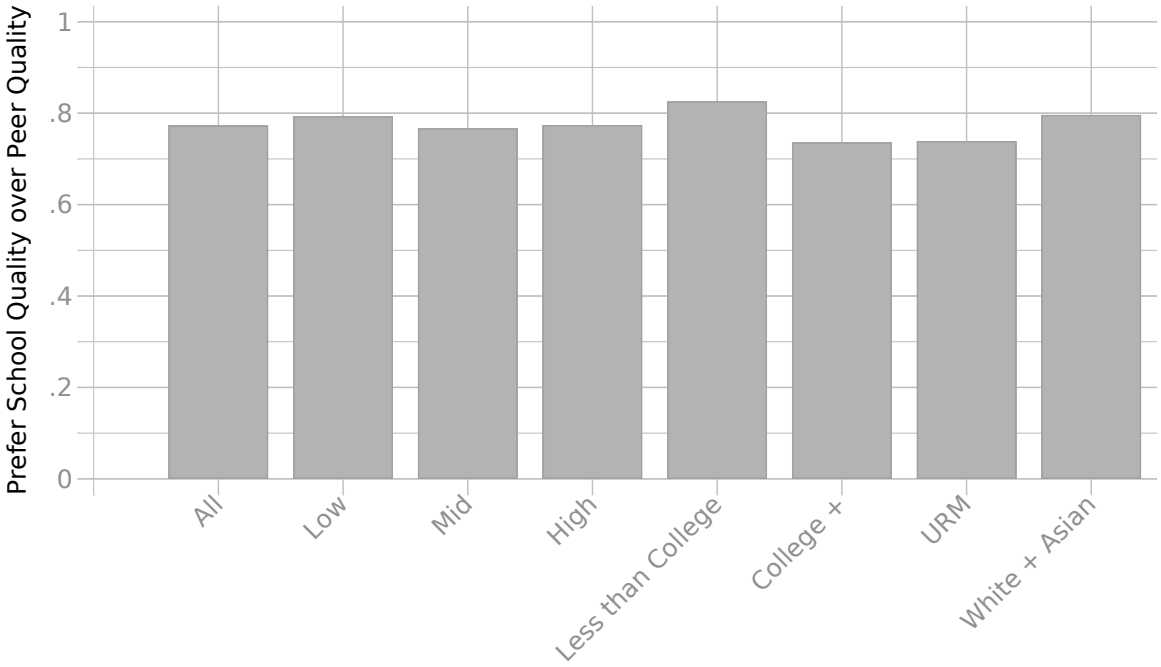
Figure E.2: Spatial Distribution of GS Summary Ratings Biases



(a) School Quality (b) Peer Quality

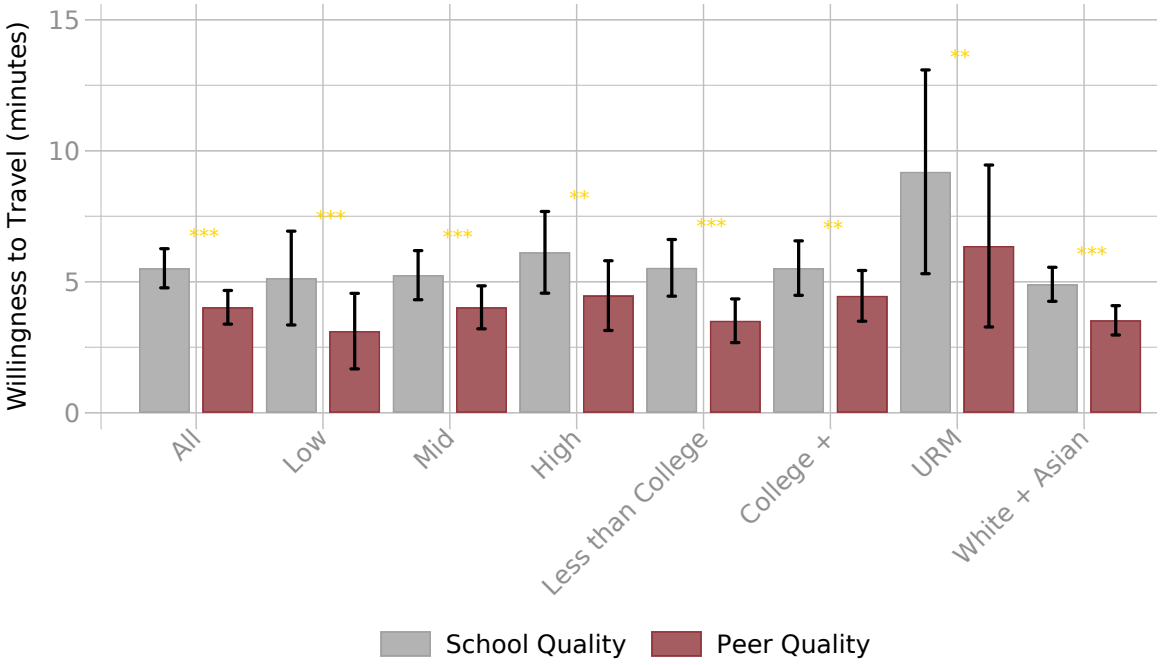
Notes: This figure reports a mean pessimism score of GS-based peer and school quality measures for each state represented in the sample. Statistics for states with fewer than ten respondents are not included in the figure.

Figure E.3: Share of Parents Preferring School Quality



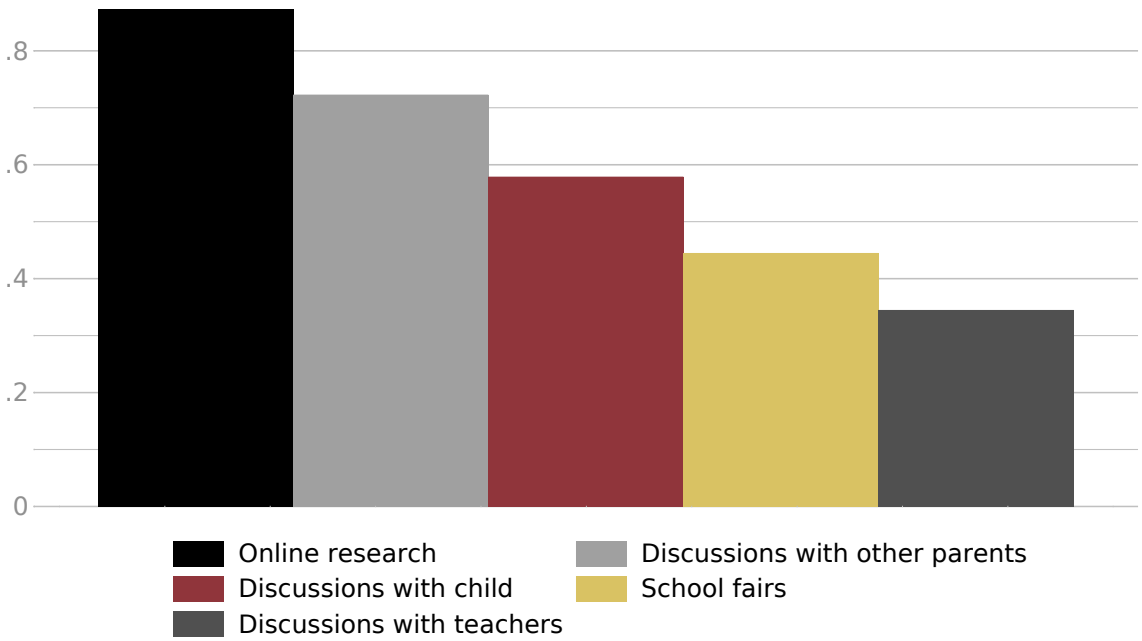
Notes: This figure reports the share of parents stating they prefer school quality over peer quality. The question is asked after the parents watch pedagogical videos explaining the difference between the two quality measures. Parents are asked to list an ordinal ranking over the two measures and the bars report the share of parents listing school quality as their most-preferred. The first bar reports the mean for the entire sample, the next three bars list the means for different groups with different GS Summary ratings, Less than College correspond to parents who report not having a four-year college degree, College + corresponds to parents stating they have at least a four-year college degree, URM corresponds to parents reporting they are Black or Hispanic, and the final bar corresponds to White and Asian parents.

Figure E.4: Experimental Preferences for School and Peer Quality



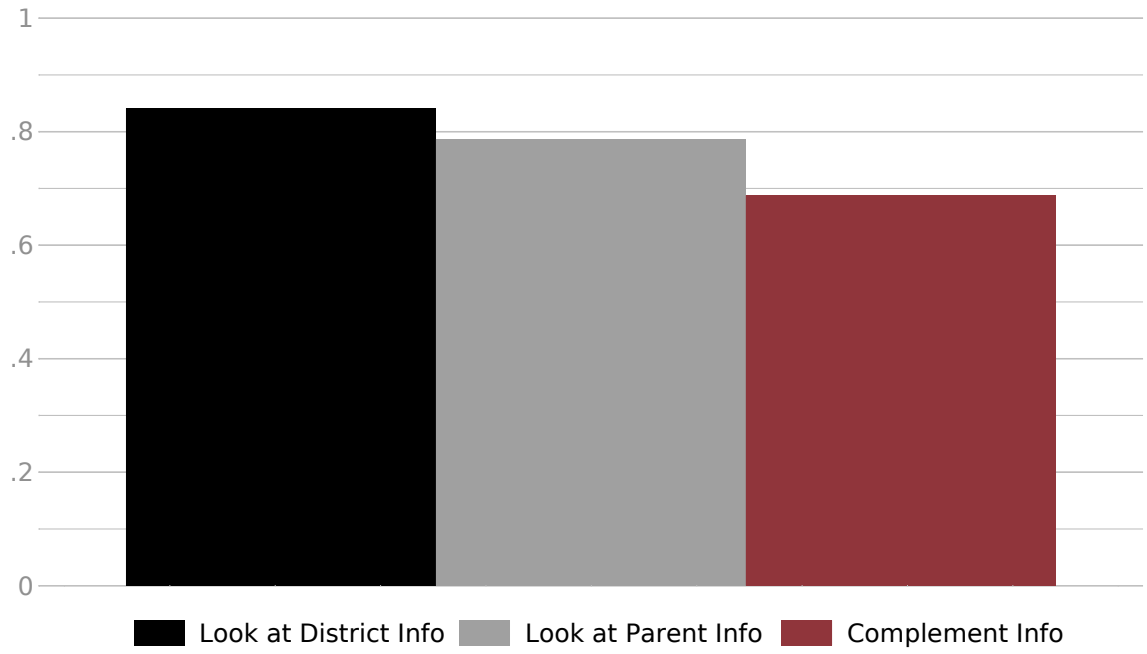
Notes: This figure reports experimental willingness to travel estimates for school and peer quality. Respondents are presented with hypothetical schools that vary in terms of travel time, school quality, and peer quality. Respondents report a ranking of the hypothetical schools. We assume logit preference shocks for each hypothetical scenario, and each respondent is presented with ten hypothetical scenarios. We aggregate across respondent-choice trials to estimate utility weights via maximum likelihood. Estimates reported in the figure correspond to the ratio of estimated utility weights on each attribute scaled by the estimate distance coefficient, so they correspond to marginal willingness to travel estimates. Standard errors are robust and clustered at the respondent level. Gray bars correspond to school quality willingness to travel estimates, while maroon bars correspond to peer quality willingness to travel estimates. The first group of bars report the WTT for the entire sample, the next three groups of bars list the WTT for different groups with different GS Summary ratings, less than College corresponds to parents who report not having a four-year college degree, College + corresponds to parents stating they have at least a four-year college degree, URM corresponds to parents reporting they are Black or Hispanic, and the final bar corresponds to White and Asian parents. 95 percent confidence intervals are reported. The stars above each pair of bars indicate statistical significance corresponding to rejections of tests of the null hypothesis that willingness to travel for peer and school quality are equal. One star corresponds to significance at the 10 percent level, two stars correspond to significance at the 5 percent level, and three stars correspond to significance at the one percent level.

Figure E.5: Sources of Information



Notes: This figure reports information on the share of activities parents report doing when researching schools. Parents may report doing various activities so they are not mutually exclusive. Online Research corresponds to any kind of research online, discussion with parents corresponds to parents reporting talking to other parents as a source of information, Discussions with child corresponds to parents asking for the opinion of their child, School fairs corresponds to parents reporting attending school fairs, and Discussion with teachers corresponds to parents talking to teachers about schooling options.

Figure E.6: Information that influences school choices

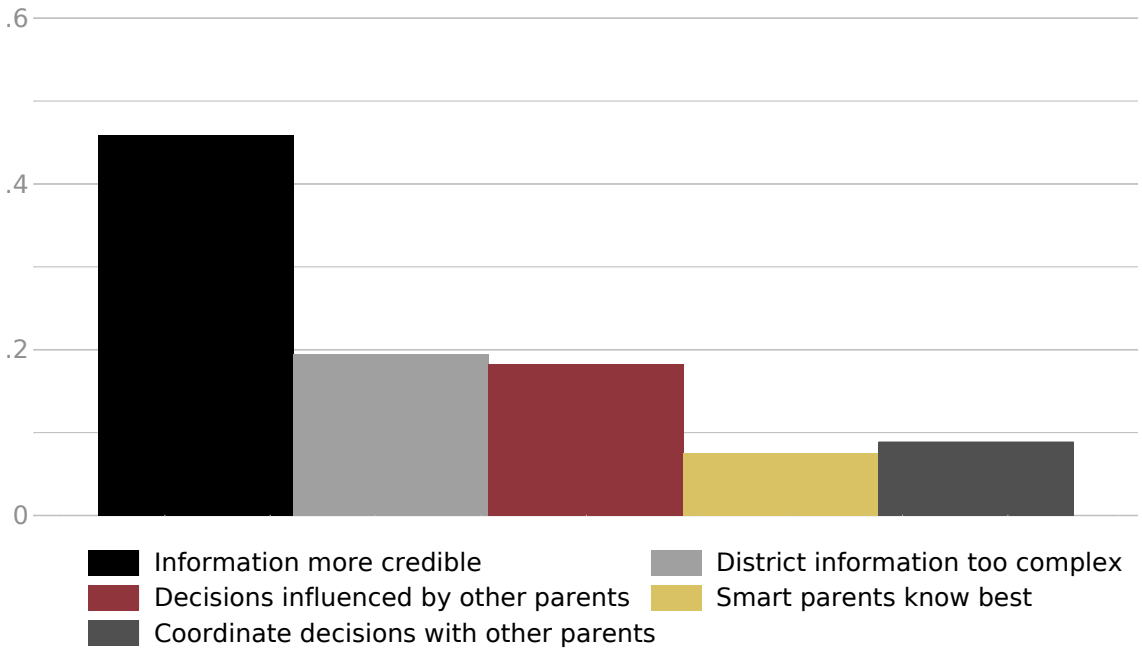


Notes: This figure reports the share of parents stating that they at least agree (or at least somewhat likely) with the following statements.

- Look at District Info: Suppose your school district sends you information about several schools' Incoming Achievement and Achievement Growth ratings. How likely is the information to influence your school choice?
- Look at Parent Info: Suppose a parent sends you information about several schools' Incoming Achievement and Achievement Growth ratings. How likely is the information to influence your school choice?
- Complement Info: It is more likely that district-provided Incoming Achievement and Achievement Growth information influences my school choices if other parents also engage with it and we discuss it together.

The questions were asked after parents watched pedagogical videos explaining the differences between Incoming Achievement and Achievement Growth.

Figure E.7: Reasons for social interactions



Notes: This figure reports the share of parents ranking the various categories as at least second most important. Parents were asked to rank the categories from most to least important. The categories are reasons for why other parents' discussions about district-provided information influence their school choices. The listed categories in the figure correspond to the following reasons:

- Information is more credible: The information is more credible after the discussion.
- District information too complex: The information is hard to understand.
- Decisions influenced by other parents: My decisions are influenced by the opinions of other parents.
- Smart parents know best: Knowledgable parents help me understand the information.
- Coordinate decisions with other parents: I coordinate with other parents about my schooling decisions.

F Decomposition Exercise Details

Canonical school choice models assume families have accurate information at the time they make decisions, yet a growing body of evidence suggests this assumption is far from true (Ainsworth et al., 2023, Andrabi et al., 2017, Arteaga et al., 2022, Hastings and Weinstein, 2008). Imperfect information will distort choices and introduce allocative inefficiencies and affect outcomes (Abaluck and Compiani, 2020, Ainsworth et al., 2023). In this section, I outline a school choice model that models the effects of information treatments in a setting with and without information frictions. The comparison of the settings allows for a natural decomposition of treatment effects that inform about the role of salience and information updating in contributing to the effects induced by information campaigns.

Families are indexed by $i \in \mathcal{I}$ and schooling options by $j \in \mathcal{J}$. The indirect utility of family i being assigned school j is

$$U_{ij} = \delta_j - \lambda d_{ij} + \varepsilon_{ij},$$

where δ_j captures mean utility of school j, d_{ij} measures the distance between household i and school j, and ε_{ij} is unobserved preference heterogeneity. I assume that mean utility is summarized by school and peer quality, Q_j^S and Q_j^P, respectively:

$$\delta_j = \gamma_P Q_j^P + \gamma_S Q_j^S.$$

The school district distributes information to a subset of families, randomizing the families who receive information and the information they receive (see Section 3 for intervention details). Let $\mathcal{I}_P$ and $\mathcal{I}_S$ be the set of families receiving peer quality and school quality information, respectively, and let $\mathcal{I}_B$ correspond to the families receiving information about both. The effects of the information campaign can be summarized by changes in the weights families assign to peer and school quality. In particular,

$$U_{ij} = \gamma_P Q_j^P + \gamma_S Q_j^S + \sum_{t \in \{P,S,B\}} (\beta_{Pt} Q_j^P + \beta_{St} Q_j^S) \times \mathbf{1}\{i \in \mathcal{I}_t\} - \lambda d_{ij} + \varepsilon_{ij}$$

where β_{St}, β_{Pt}, and β_{Bt} summarize the average change in weights treated families assign to the various quality measures. In a model without information frictions, any changes in the weights families place are due to changes in preferences or salience. This is analogous to the salience impacts driven by bottom-up attention discussed by Bordalo et al. (2013) and Bordalo et al. (2022).[24] In this framework, any change in preferences must be due to families making it more prominent in their decision-making after being reminded of the information.

In a model with information frictions, families make decisions using their beliefs about Q_j^P and Q_j^S. One way to model beliefs is to allow families to have idiosyncratic quality-specific biases, b_{Pi} and b_{Si}, that produce proportional deviations from Q_j^P and Q_j^S: $\tilde{Q}_{ji}^P = (1 + b_{Pi}) Q_j^p$

[24] Three salience mechanisms are discussed in Bordalo et al. (2022). The framework discussed above is most closely related to the prominence channel. The prominence channel indicates that an information intervention will make attributes related to the intervention more prominent in the decision maker's choice, causing a reorientation of their relative importance.

and $\tilde{Q}^S_{ji} = (1 + b_{Si})Q^S_j$. I assume b_{Pi} and b_{Si} are random with mean μ_P and μ_S, respectively.

In the absence of the information campaign, families' perceived indirect utility is

$$\tilde{U}_{ij} = \tilde{\gamma}_{Pi}Q^P_j + \tilde{\gamma}_{Si}Q^S_j - \lambda d_{ij} + \varepsilon_{ij} \tag{15}$$

where $\tilde{\gamma}_{Pi} = \gamma_P(1 + b_{Pi})$ and $\tilde{\gamma}_{Si} = \gamma_S(1 + b_{Si})$. Making decisions with beliefs distorts the effective weights families assign the various attributes. As in the case with perfect information, the information campaign induces salience effects but also affects belief biases, b_{Pi} and b_{Si}, and the combined effects are summarized by changes in the implicit weights families assigned to Q^P_j and Q^S_j:

$$\tilde{U}_{ij} = \tilde{\gamma}_{Pi}Q^P_j + \tilde{\gamma}_{Si}Q^S_j + \sum_{t\in\{P,S,B\}} (\beta_{Pt}Q^P_j + \beta_{St}Q^S_j) \times \mathbf{1}\{i \in \mathcal{I}_t\} - \lambda d_{ij} + \varepsilon_{ij}. \tag{16}$$

Because the implied change in average marginal willingness to travel is identified by comparing the choices of applicants across treatment groups that are making choices with and without information, we can decompose the impact.[25]

Conceptually, we can define potential outcomes with respect to the marginal willingness to travel for peer quality of individual i with treatment t, $MWTT_{iPt}$. In practice, only one outcome is observed for each individual, so the observed marginal willingness to travel for peer quality is

$$MWTT_{iP} = \sum_{t\in P,S,B,0} MWTT_{iPt}D_{it},$$

where $D_{it} = \mathbf{1}\{i \in \mathcal{I}_t\}$. The estimand of interest that summarizes the effects of receiving peer quality information is the observed average change in the marginal willingness to travel,

$$E[\Delta MWTT_{iP}] = E[MWTT_{iPP} - MWTT_{iP0}] \quad . \tag{17}$$

In a randomized intervention, this quantity is identified by comparing the implied $MWTT$ of treated and control applicants.[26] Through the lens of the model, the estimand is equal to

$$E[\Delta MWTT_{iPP}] = \frac{\beta_{PP} - \gamma_P\mu_P}{\lambda}. \tag{18}$$

The intervention's impacts nest both a change in preferences governed by the salience term present in the frictionless model and a term governed by imperfect information. The latter term pins down the portion of the change attributable to the mean baseline bias in the population. In the perfect information setting, we have $\mu_P = 0$ and the changes in willingness to travel are

[25]Implicit in this is a constant salience effect assumption, a perfect compliance assumption, and a similar variances of unobserved preference heterogeneity across treatment groups assumption. The compliance assumption assumes that treated individuals update perfectly, or in other words, their $b_{Pi} = 0$ or $b_{Si} = 0$. This would be implied by a model where families perceive zero noise in the signal of quality they receive. Even without this assumption, one can generate a range of estimates for a variety of compliance rates. Related to similar variances across treatment groups, the randomized assignment to groups makes this assumption plausible.

[26]There are a variety of estimation approaches that aid in identifying this change. Train (2009) argue that a simple logit can be used to approximate average tastes and average changes in tastes. Alternatively, one can estimate treatment group by school indirect mean utilities in willingness to travel units in a first step, and then estimate the relationship in a multivariate regression model in similar spirit to Abdulkadiroğlu et al. (2020), Bayer et al. (2007), Campos and Kearns (2024).

only due to salience. As alluded to above, with a randomized intervention, $E[\Delta MWTT_{iPP}]$ is estimated by comparing treated parents to control group parents, γ_P is identified by choices made among control group parents, and auxiliary survey data pins down the moment μ_P. The salience impact is, therefore,

$$\beta_{PP} = E[\Delta MWTT_{iP}] + \frac{\gamma_P \mu_P}{\lambda}.$$

The salience impact, β_{PP}, is attenuated or amplified depending on the direction of the bias at baseline. For example, if $\gamma_P \mu_P > 0$, then the estimated salience impact will, in general, be biased downward. The opposite is true if $\gamma_P \mu_P < 0$. The intuition for this follows from the fact that an information intervention nests two somewhat sequential steps, a debiasing step and a salience step. Appendix Figure F.1 provides some intuition.

Similar expressions can be derived for those receiving only the school quality treatment and those receiving both. One way hypothesize that receiving treatment about only one attribute may have information and salience effects on other attributes through a correlated beliefs channel. That is indeed the case but an additional assumptions related to the second moments of the belief distribution are necessary.

One way to model beliefs is to allow families to have idiosyncratic quality-specific biases, $\tilde{Q}_{Pji} = (1 + b_{Pi})X_{Pj}$ and $\tilde{Q}_{Sji} = (1 + b_{Si})Q_{Sj}$. I assume that beliefs are bivariate normal,

$$\begin{pmatrix} b_{Pi} \\ b_{Si} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_P \\ \mu_S \end{pmatrix}, \begin{pmatrix} \sigma_P^2 & \rho\sigma_P\sigma_S \\ \rho\sigma_P\sigma_S & \sigma_S^2 \end{pmatrix} \right),$$

with ρ governing the correlation of biases and σ_P and σ_S the respective standard deviations.

The willingness to travel for the attributes now depends on the different treatment statuses. The willingness to travel estimands are the following:

$$E[WTT_{iP0}] = \frac{\gamma_P(1 + \mu_P)}{\lambda} \tag{19}$$

$$E[WTT_{iPP}] \equiv E[WTT_{iPP}|b_{iP} = 0] = \frac{\gamma_P + \beta_{PP}}{\lambda} \tag{20}$$

$$E[WTT_{iPS}] \equiv E[WTT_{iPS}|b_{iS} = 0] = \frac{\gamma(1 + \mu_P - \rho\frac{\sigma_P}{\sigma_S}\mu_S)}{\lambda} + \frac{\beta_{PS}(1 + \mu_P - \rho\frac{\sigma_P}{\sigma_S})\mu_S}{\lambda} \tag{21}$$

$$E[WTT_{iPB}] \equiv E[WTT_{iPB}|b_{iP} = 0, b_{iS} = 0] = \frac{\gamma_P + \beta_{PB}}{\lambda}. \tag{22}$$

As before, the experimental assignment helps identify changes in willingness to travel induced by the information intervention. The results from the single attribute model translate to the multiple attribute model, but it is worth discussing how correlated beliefs about quality influence the effects of information about one attribute on preferences for other attributes. Continuing from the leading example above, individuals assigned treatment 2 may exhibit a change in their willingness to travel for attribute 1. The change in willingness to travel will nest several factors governed by the degree of imperfect information in the population. The change in the average

willingness to travel for this group is

$$E[\Delta WTT_{i12}] = \frac{\beta_{12}(1+\mu_1)}{\lambda} - \frac{(\gamma+\beta_{12})\rho\frac{\sigma_1}{\sigma_2}\mu_2}{\lambda}. \tag{23}$$

The expression is intuitive and has two countervailing forces. If the information about attribute 2 induces a salience effect for attribute 1 due to a reprioritization of the importance of each, this is captured by β_{12} which is amplified by the degree of bias in the population at baseline, μ_1. This effect is potentially offset by the correlated nature of beliefs. In particular, if beliefs are positively correlated and families overestimate school quality, then the second term offsets the amplification in the first term. Overall, the factors influencing the effects of one attribute on another depend on the presence of salience effects and the degree of imperfect information at baseline. In the case with perfect information, the average change in willingness to travel is only due to salience. In the core of the paper, I only report decomposition estimates for the primary effects of interest.

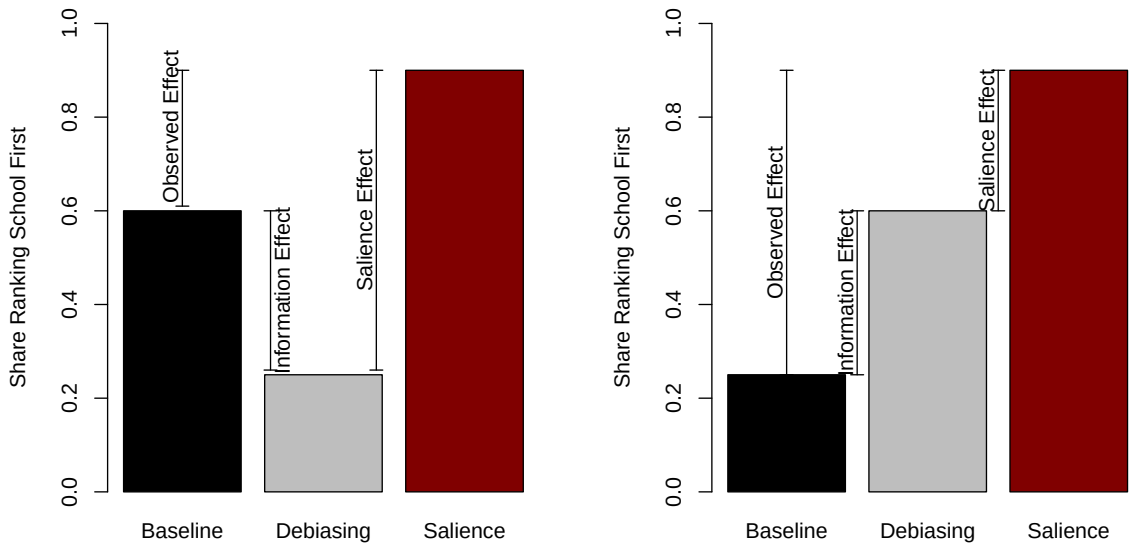
F.1 Intuition for Decomposition

I discuss a hypothesized scenario with one school, School A, and an outside option with families being informed about the relative quality of School A and families only care about one attribute. Appendix Figure F.1 provides intuition for the decomposition, considering cases where families overestimate or underestimate quality at baseline. In both cases, I assume families have a positive taste for the attribute.

In Panel (a), the case where $\gamma\mu > 0$, the debiasing step induces individuals to revise their beliefs downward, leading to a ceteris paribus decrease in their demand for X_j; this is the information effect. The act of providing the information makes families reprioritize the importance they assign X_j, what I refer to as salience, the effect from the second bar to the third bar. The estimand, however, recovers a quantity that subtracts the information effect from the salience effect, since we only observe the change from the first to the third bar.

Panel (b) provides a visual description of the case where families beliefs are biased downward (on average) at baseline. In this case, the information effect leads to a ceteris paribus increase in demand for School A as families revise their beliefs upward. The salience effect is also positive.

Figure F.1: Intuition for Decomposition



(a) With Positive Bias ($\gamma\mu > 0$)

(b) With Negative Bias ($\gamma\mu < 0$)

Notes: This figure reports two panels demonstrating factors contributing to treatment effects in information interventions. The figure relates to a hypothesized scenario with one school, School A, and an outside option with families being informed about the relative quality of School A. The black bars correspond to the share of families choosing school A before the intervention. The gray bar corresponds to the share of families choosing School A in a setting where they had perfect information. The maroon bar depicts the share of families choosing School A in a setting where an information intervention is used to debias their beliefs. Panel (a) reports a setting where families were initially biased upward in their beliefs about relative quality, and Panel (b) reports a setting where families are initially biased downward. In both cases there is a positive salience effect. Comparing the black to the gray bar pins down the information effect. The salience effect is identified by comparing the gray bar to the maroon bar. Empirical estimates identify the difference between the maroon and black bar, which nests both salience and information effects.

G Evidence on Strategic Behavior

The evidence documented throughout the paper demonstrates that the prevalence of information led to families placing substantially more weight on school effectiveness in their schooling decisions. However, both reduced-form and discrete choice perspectives are silent about the role of families' perceived changes in admissions chances at schools which is an additional channel contributing to changes in choices. The potential scope for strategic behavior introduces additional concerns. In this section, I provide distinct pieces of evidence to assuage these concerns and provide suggestive evidence that changes in admissions chances or strategic behavior play a minimal role in this setting.

I approach this in four ways. First, as discussed in the main body of the paper, I demonstrate that many families face no risk in applying as most admissions probabilities at their top-ranked program are degenerate. This is consistent with many discussions with ZOC administrators. In settings with degenerate risk, optimal portfolio models no longer apply and standard discrete choice models identify preferences. Second, I report static evidence regarding strategic behavior in the spirit of Abdulkadiroglu et al. (2006), demonstrating little evidence that families behave strategically as would be implied by simple descriptive tests. Third, I do not find evidence of changes in market-level strategic behavior that would be implied by changes in families' perceived admission chances. Last, I assess the robustness of my leading estimates to various assumptions that attenuate strategic considerations.

G.1 Admissions Probabilities

Appendix Table G.1 reports statistics on applicants' admission probabilities at their top-ranked program for each market. I simulate admissions probabilities by fixing the population of applicants and rerunning the match by redrawing lottery numbers. I do this 1000 times for each market and an applicant's admission probability is the mean across all iterations. I report the mean admission probability, the standard deviation, the share that are exactly equal to zero, and the share that are exactly equal to one.

Across all markets, the mean admission probability across applicants is 0.968 indicating most applicants in the experimental sample face no risk when applying. In fact, Column 4 shows that 73 percent of applicants face no risk, and four markets are entirely risk-free. This is partly a consequence of broader enrollment trends in urban school districts suffering from enrollment decline over the past two decades. LAUSD, in particular, has lost 46% of its enrollment from its peak in 2004.[27]

The prevalence of degenerate risk in ZOC markets opens the door for more straightforward discrete choice models to estimate preferences. Indeed, an applicant with rational expectations and no admission risk will treat the school choice problem as a typical discrete choice problem proposed in the paper. While the share of applicants without admission risk is high, some applicants do face risk. The large share of applicants without admission risk provides a sizable sample to assess the robustness of results to subsamples of applicants with and without

[27] In the 2003-2004 academic year, LAUSD had 746,000 Grade 1-12 students enrolled in the district. Enrollment is 406,000 in the 2022-2023 academic year.

admission risk. I return to this in a following subsection.

Table G.1: Admission Probability Statistics by Zone

	Mean	SD	Share Zero	Share One
Bell	0.885	0.318	0.000	0.713
Belmont	0.999	0.001	0.000	0.270
Boyle Heights	1.000	0.000	0.000	1.000
Carson	1.000	0.000	0.000	1.000
Eastside	0.876	0.330	0.124	0.876
Fremont	0.948	0.221	0.052	0.948
Hawkins	0.999	0.000	0.000	0.463
HuntingtonPark	0.999	0.000	0.000	0.394
Jefferson	1.000	0.000	0.000	1.000
Jordan	1.000	0.000	0.000	1.000
Narbonne	1.000	0.000	0.000	1.000
NorthEast	1.000	0.000	0.000	1.000
NorthValley	1.000	0.000	0.000	1.000
RFK	1.000	0.000	0.000	0.680
SouthGate	0.971	0.168	0.029	0.971
All Zones	0.968	0.176	0.019	0.734

Notes: This table reports summary statistics for simulated admissions probabilities of applicants' top-ranked option on their rank-ordered list. Each row corresponds to summary statistics of applicants in that market. For each market and iteration, I draw new lottery numbers for each applicant, assign them the same priority they had in the match, and reassign applicants to programs using the immediate acceptance mechanism. I do this 1000 times for each market. For each applicant, their simulated admission probability is their mean acceptance rate across all iterations. Each row reports summary statistics corresponding to applicants' simulated admission probabilities. Column (1) reports the mean across applicants, Column (2) reports the standard deviation, Column (3) reports the share of applicants with admission probability equal to zero, and Column (4) reports the share of applicants with admission probability equal to one.

G.2 Evidence on Strategic Behavior

The rules of the mechanism used for assignment are not salient to ZOC families. In fact, the mechanism is not a typical discussion point in the numerous information sessions ZOC administrators organize for parents. If anything, families are instructed to report truthfully and any mention of the benefits of strategic play is nonexistent. This is similar to school choice in Charlotte studied by Hastings et al. (2009) in that the rules of the mechanism are not salient to families.

A few additional facts make strategic play less of a concern in these markets. First, 66 percent of families have not heard of the program one month before applications are due (see Appendix Table D.3), suggesting strategic incentives are not a salient feature of the application process. Second, Campos and Kearns (2024) evaluates the ZOC policy and finds that demand estimation that accounts for strategic incentives yields estimates that are statistically similar to estimates that do not account for strategic incentives. Third, as documented in the preceding section, many families face no admission risk, attenuating the incentives to behave strategically. Evidence notwithstanding, I now provide additional empirical evidence suggesting strategic behavior is not an important feature of the choice process in ZOC markets.

An intuitive test for the presence of strategic behavior is to focus on the most demanded schools in each market and look for sharp drops in demand. As Abdulkadiroglu et al. (2006) point out, under an Immediate Acceptance mechanism it is a mistake to rank an overdemanded school second. Appendix Figure G.1 reports evidence for these intuitive tests. I restrict to the markets that contain evidence of potential strategic behavior.[28] For zones that have schools that meet this requirement, I then report the share of families that rank the given school at the top of their list and the share of families who rank it second.

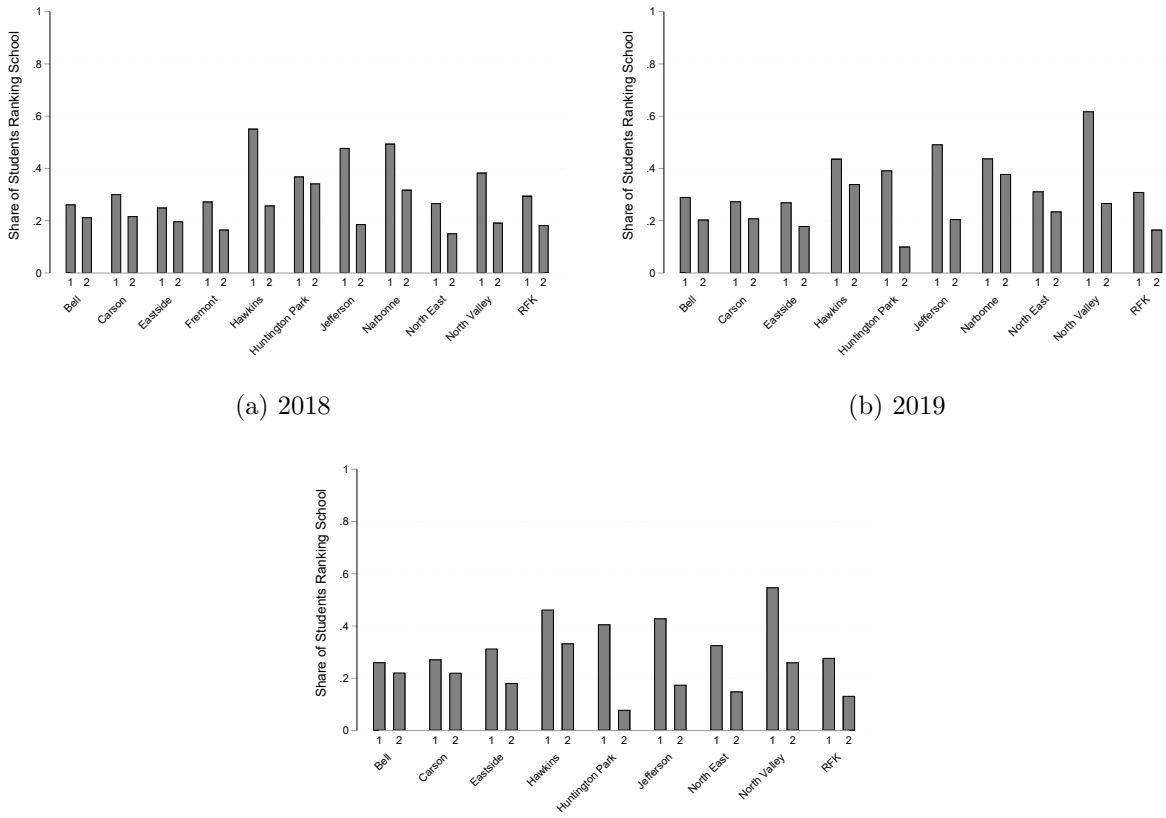
Panel (a), which focuses on the year before the intervention, does not reveal striking evidence of steep drops in demand. In fact, there is not a zone containing a school where most families rank it at the top of their ROL, an indication of substantial preference heterogeneity. Panel (b) reports the same for the 2019 cohort. The first difference between both panels is the increased representation of zones, a consequence of families changing their choices due to the prevalence of information. Except for the North Valley zone, where Humanitas Futures Academy experienced a sizable increase in demand from pre-intervention to post, all zones do not contain a school that most families rank at the top of their ROL.

Evidence of preference heterogeneity notwithstanding, three zones, Huntington Park (HP), Jefferson, and North Valley, stand out with relatively mild drops in demand. For example, in the case of Lyndon Elementary and Quincy Elementary in Abdulkadiroglu et al. (2006), the number of families ranking these schools at the top of their ROL was 5 to 6 times as many as the number of families ranking them second. The drops in demand in North Valley ZOC, for example, are nowhere near as high as the Quincy and Lyndon case. The patterns for Jefferson and North Valley also appear to be similar across all three years. That leaves Huntington Park as a candidate zone where the intervention may have induced mild strategic behavior. Overall, however, evidence of strategic behavior is not present in nearly all zones (or markets),

[28] A zone like Belmont is excluded as the number of families ranking the most popular school at the top of their ROL is roughly 10%, limiting the scope for a sharp drop in demand.

corroborating the anecdotal evidence that the rules of the mechanism are not salient to most parents.

Figure G.1: Reporting Behavior Before and After the Intervention



(a) 2018

(b) 2019

(c) 2021

Notes: This figure reports evidence about reporting behavior in the year before the first experimental wave, 2018, and in the first experimental wave, 2019. In each panel, we report reporting behavior in zones where the most-demanded school had at least 25 percent of families ranking it first. The first bar corresponds to the share of families ranking the given school as their most preferred, and the second bar corresponds to the share of families ranking the school second.

G.3 Robustness Exercises

The evidence in Appendix Figure G.1 motivates additional robustness exercises to assess how the potential strategic incentives of a small subset of families affect the conclusions of the primary findings. Given that an immediate acceptance mechanism has the strongest bite at the top of the rank-ordered list, one reasonable assessment is to probe the robustness of the results when excluding the top-ranked school. Second, we can assess the robustness of the results when excluding the markets where we found some indirect evidence of strategic behavior in Appendix Figure G.1. Last, we can focus on the subset of applicants who face no admission risk, and thus no strategic incentives under a rational expectations framework, to assess if strategic incentives affect the conclusions in the paper.

Appendix Table G.2 and Appendix Table G.3 report evidence regarding the first two tests, with Appendix Table G.2 focusing on models that consider information treatments and Ap-

pendix Table G.3 focusing on saturation-level treatments. The first two columns report evidence documented in the paper coming from the preferred estimates. Column (3) and Column (4) report estimates from a sample that excludes the top-ranked option in the estimation procedure. Column (5) and Column (6) report estimates that exclude the potentially concerning zones in Appendix Figure G.1. Across all specifications, the results are qualitatively similar and statistically identical to the baseline specification. This assuages concerns about the potential influence of strategic behavior driven by particular zones or regions of the rank-ordered list most prone to strategic behavior.

Appendix Table G.4 and Appendix Table G.5 compare baseline estimates to estimates from samples of applicants who face no admission risk. These analyses are restricted to the 2019 cohort because we do not observe capacities for 2021 and are unable to replicate the match.[29] Like the other evidence in this section, the baseline estimates are statistically identical to the estimates from applicants without admission risk. This suggests that the behavior of applicants for whom strategic incentives are largest is highly similar to those who face no strategic incentives. The assorted set of results in this section strongly suggest that strategic incentives are weak in ZOC markets and, as a consequence, do not find evidence that strategic behavior influences the primary findings in the paper.

[29] This can be requested if necessary for a revision.

Table G.2: Rank-ordered logit estimates (Information-specific model)

	WTT Estimates					
	Baseline		Excluding Top-Ranked		Excluding Zones	
	IA	AG	IA	AG	IA	AG
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment						
Untreated	0.392***	0.658***	0.594***	0.755***	0.483***	0.734***
	(0.093)	(0.078)	(0.116)	(0.095)	(0.101)	(0.087)
Information: IA	-0.972***	0.474	-1.150***	0.459	-1.164***	0.425
	(0.174)	(0.104)	(0.206)	(0.117)	(0.192)	(0.107)
Information: AG	-0.865	0.424***	-1.010	0.431***	-1.040	0.413***
	(0.171)	(0.101)	(0.200)	(0.114)	(0.186)	(0.106)
Information: Both	-0.815***	0.565***	-0.892***	0.471***	-0.977***	0.534***
	(0.154)	(0.100)	(0.176)	(0.108)	(0.168)	(0.103)
Spillover	-0.947***	0.336***	-1.139***	0.417***	-1.153***	0.320***
	(0.172)	(0.100)	(0.204)	(0.115)	(0.191)	(0.104)
Distance	-0.068***		-0.065***		-0.070***	
	(0.006)		(0.007)		(0.007)	

Notes: This table reports estimates from three separate random utility models. Each considers treatment effects on utility weights for IA and AG that vary by the information treatment that is either IA, AG, Both, or Spillover. The latter corresponds to indirectly treated parents in treated schools. The first two columns report estimates from the baseline model including all applicants and choices. The third and fourth columns consider all applicants but exclude their top-ranked choice. The fifth and sixth columns consider applicants not belonging to Huntington Park, Jefferson, and North Valley, zones flagged with weak evidence of strategic behavior. Estimates correspond to the average marginal willingness to travel except for the reported distance coefficient. Standard errors are robust and clustered at the school level and estimated via the delta method.

Table G.3: Rank-ordered logit estimates (Saturation-specific model)

	WTT Estimates					
	Baseline		Excluding Top-Ranked		Excluding Zones	
	IA	AG	IA	AG	IA	AG
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment						
Untreated	0.391***	0.656***	0.612***	0.757***	0.483***	0.733***
	(0.093)	(0.077)	(0.120)	(0.097)	(0.101)	(0.087)
Information: High	-0.977***	0.616***	-1.090***	0.424***	-1.103***	0.561***
	(0.154)	(0.095)	(0.185)	(0.098)	(0.168)	(0.097)
Information: Low	-0.743***	0.312***	-0.960***	0.467***	-0.981***	0.323***
	(0.147)	(0.088)	(0.182)	(0.109)	(0.166)	(0.093)
Spillover: High	-1.358***	0.642***	-1.544***	0.528**	-1.471***	0.598***
	(0.322)	(0.196)	(0.367)	(0.223)	(0.332)	(0.206)
Spillover: Low	-0.852***	0.255**	-1.083***	0.405***	-1.078***	0.248**
	(0.175)	(0.105)	(0.214)	(0.125)	(0.194)	(0.109)
Distance	-0.068***		-0.063		-0.070	
	(0.006)		(0.007)		(0.007)	

Notes: This table reports estimates from three separate random utility models. Each considers treatment effects on utility weights for IA and AG that vary by the saturation status of an applicant's middle school treatment and whether they directly received treatment or were part of the spillover group. The latter corresponds to indirectly treated parents in treated schools. The first two columns report estimates from the baseline model including all applicants and choices. The third and fourth columns consider all applicants but exclude their top-ranked choice. The fifth and sixth columns consider applicants not belonging to Huntington Park, Jefferson, and North Valley, zones flagged with weak evidence of strategic behavior. Estimates correspond to the average marginal willingness to travel except for the reported distance coefficient. Standard errors are robust and clustered at the school level and estimated via the delta method.

Table G.4: Rank-ordered logit estimates (Saturation-specific model): Baseline versus Sample Without Risk

	WTT Estimates			
	Baseline		No Risk	
	IA	AG	IA	AG
	(1)	(2)	(3)	(4)
Treatment				
Untreated	0.209	0.777***	-0.091	0.834***
	(0.157)	(0.142)	(0.173)	(0.164)
Information: High	-0.364	0.450***	-0.499*	0.476***
	(0.234)	(0.134)	(0.264)	(0.150)
Information: Low	-1.774***	0.429***	-1.616***	0.372**
	(0.354)	(0.142)	(0.373)	(0.151)
Spillover: High	-1.504**	0.479	-1.689**	0.490
	(0.630)	(0.291)	(0.700)	(0.322)
Spillover: Low	-2.246***	0.388**	-2.257***	0.355**
	(0.443)	(0.167)	(0.492)	(0.181)
Distance	-0.056***		-0.054	
	(0.009)		(0.009)	

Notes: This table reports estimates from two separate random utility models. The sample of applicants corresponds to the 2019 cohort of applicants, the cohort for which we can simulate admission risk. The first two columns report utility weight impacts on IA and AG in the baseline model. Treatment is allowed to vary by saturation status and whether an applicant is directly or indirectly treated. The third and fourth columns restrict to the sample of applicants without admission risk, meaning their admissions chances are equal to one at their top-ranked program. The problem reduces to a standard discrete choice program in this case. All estimates are average marginal willingness to travel estimates except for the distance coefficient. Standard errors are robust and clustered at the school level and estimated via the delta method.

Table G.5: Rank-ordered logit estimates (Information-specific model): Baseline versus Sample Without Risk

	WTT Estimates			
	Baseline		No Risk	
	IA	AG	IA	AG
	(1)	(2)	(3)	(4)
Treatment				
Untreated	0.209	0.776***	-0.092	0.838***
	(0.156)	(0.141)	(0.174)	(0.165)
Information: IA	-1.371***	0.539	-1.453***	0.594
	(0.341)	(0.162)	(0.389)	(0.185)
Information: AG	-1.141	0.371**	-1.047	0.336**
	(0.316)	(0.152)	(0.346)	(0.167)
Information: Both	-0.560**	0.415***	-0.606**	0.404***
	(0.259)	(0.142)	(0.289)	(0.156)
Spillover	-2.111***	0.404**	-2.161***	0.384**
	(0.418)	(0.157)	(0.473)	(0.172)
Distance	-0.056***		-0.054***	
	(0.009)		(0.009)	

Notes: This table reports estimates from two separate random utility models. The sample of applicants corresponds to the 2019 cohort of applicants, the cohort for which we can simulate admission risk. The first two columns report utility weight impacts on IA and AG in the baseline model. Treatment is allowed to vary by information treatment and whether or not individuals are indirectly or directly treated. The third and fourth column restrict to the sample of applicants without admission risk, meaning their admissions chances are equal to one at their top-ranked program. The problem reduces to a standard discrete choice program in this case. All estimates are average marginal willingness to travel estimates except for the distance coefficient. Standard errors are robust and clustered at the school level and estimated via the delta method.