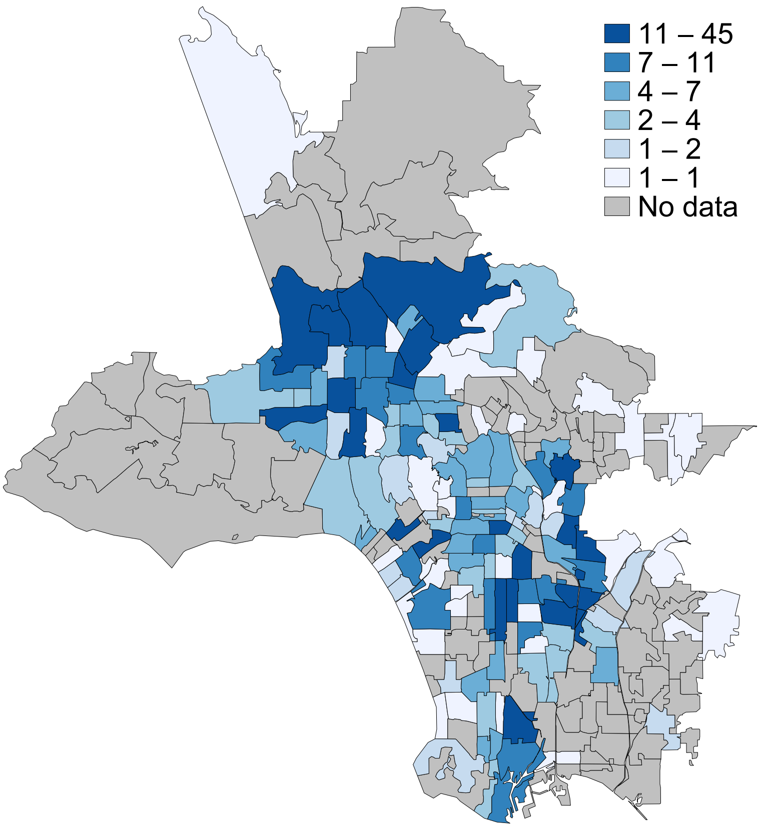
ONLINE APPENDIX

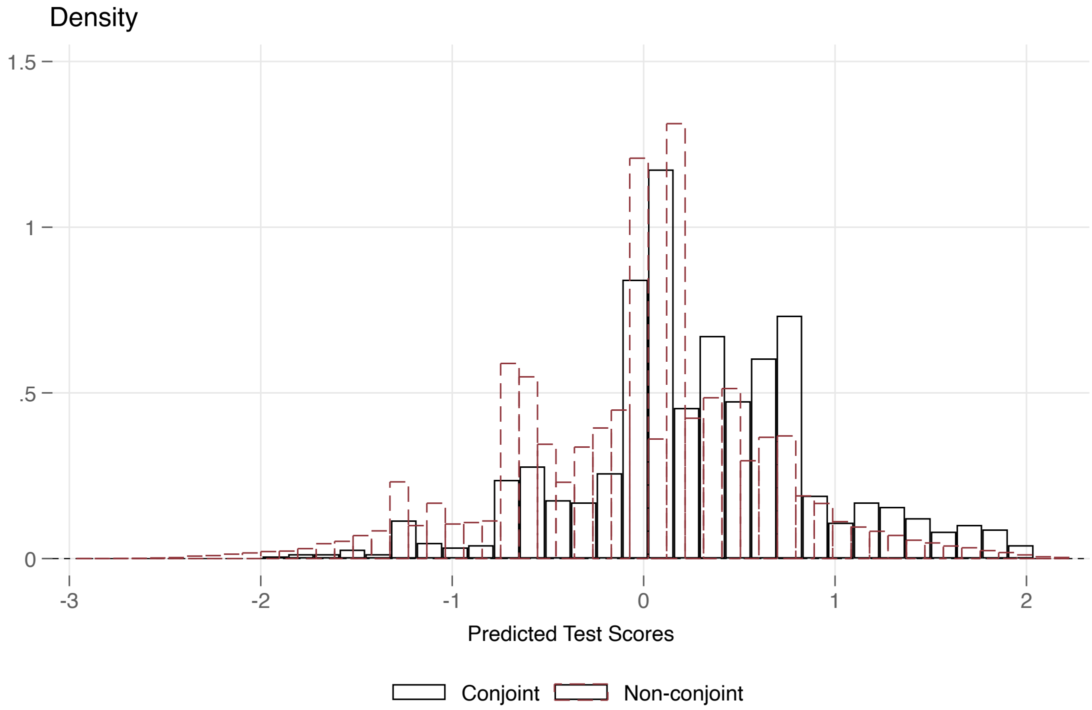
A Appendix Figures and Tables

Figure A.1: Spatial Distribution of Remote-Learning Survey Respondents



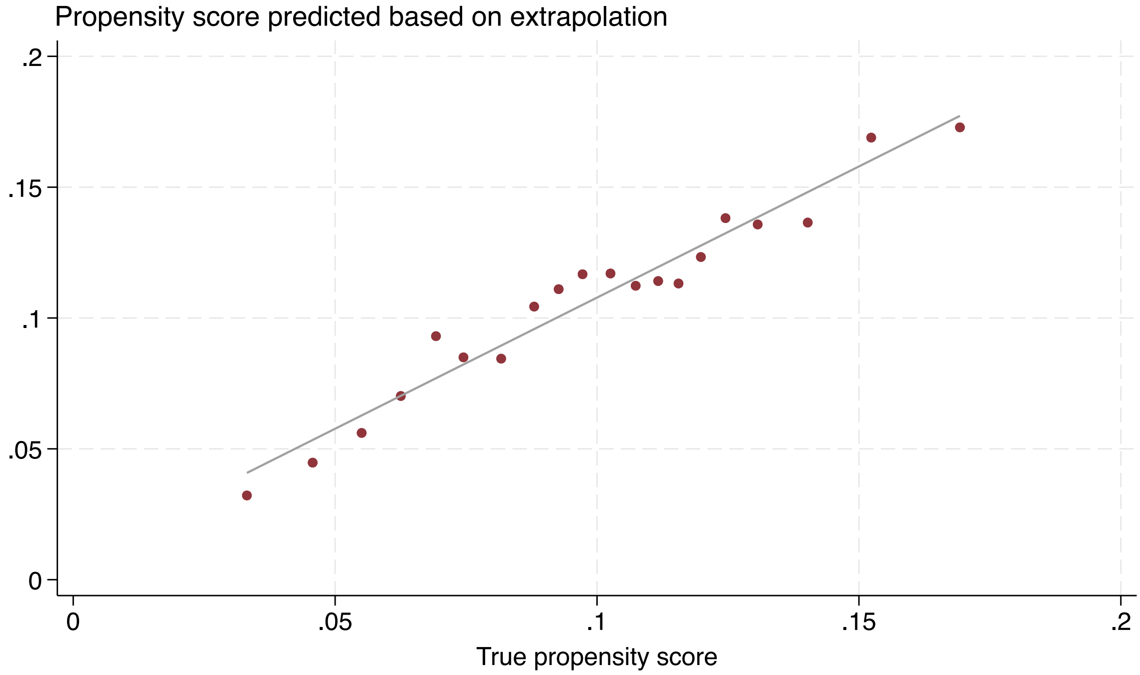
Notes: This figure is a map illustrating the spatial distribution of survey respondents. Each shaded polygon corresponds to a census tract and is shaded according to the number of remote-learning respondents residing in the census tract. Most of the gray areas in the figure are outside the purview of LAUSD.

Figure A.2: Distributions of an Index of Baseline Characteristics



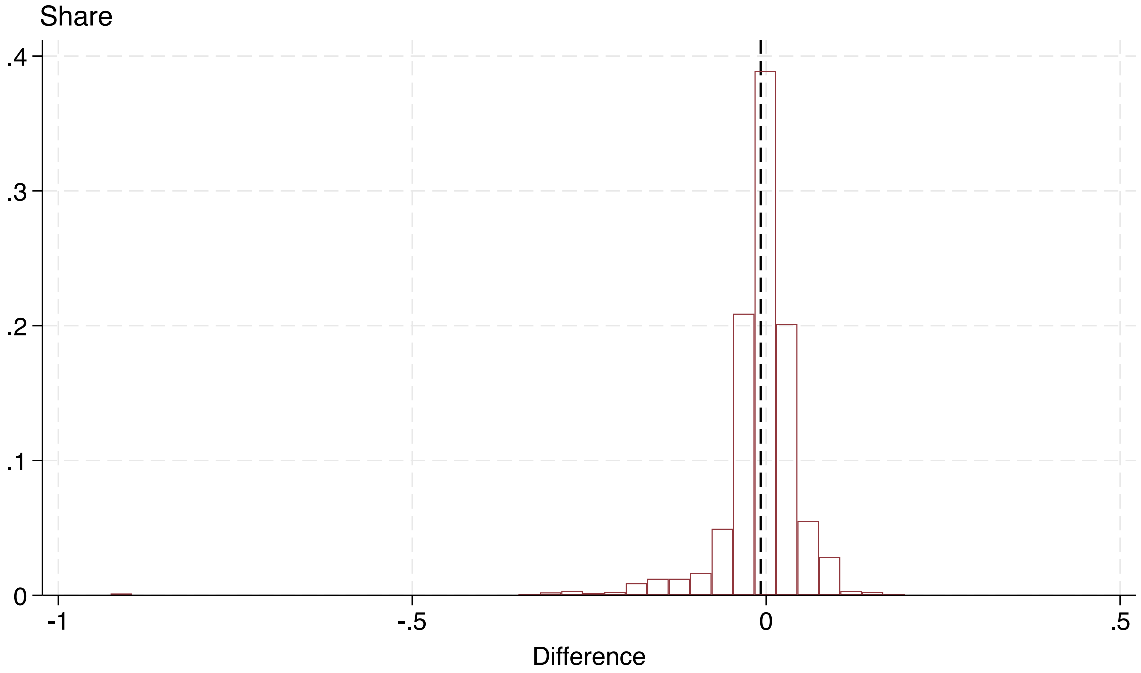
Notes: This figure reports the distribution of a summary index measure for the baseline covariates for students in the hypothetical choice and the general student samples. The summary index is constructed by regressing 2022 math test scores on an array of student characteristics including lagged (2019) achievement. The summary index corresponds to the predicted values from this regression. The histogram shows there is sufficient overlap between the hypothetical choice and the full LAUSD samples used in the empirical analysis.

Figure A.3: Correlation Between True Estimated Propensity and Extrapolated Propensity Scores



Notes: This figure compares two propensity scores that we construct to test the validity of our extrapolation approach. The two scores are estimated as follows. First, we create an estimation sample through stratified random sampling of one-third of the sample of hypothetical choice survey respondents. Our stratification ensures that the resulting estimation sample matches the average student's baseline characteristics. Using this estimation sample, we estimate preference parameters and construct propensity scores. Second, we return to the original survey hypothetical choice sample and use the residual set of respondents who were not included in the estimation sample. In this residual sample, we use our covariate cell approach to create a second set of preference estimates that we extrapolate to the estimation sample. The x-axis of the figure shows the "true" propensity scores that we estimate in the first step using the estimation sample. The y-axis of the figure shows the "predicted" propensity scores that we estimate for the estimation sample created by extrapolating the preference estimates from the residual sample.

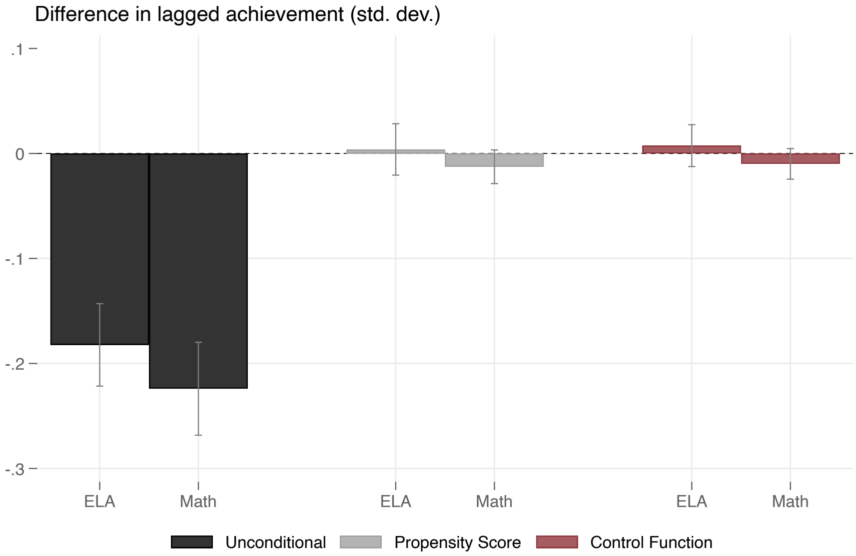
Figure A.4: Histogram of the Difference Between True Propensity and Extrapolated Propensity Scores



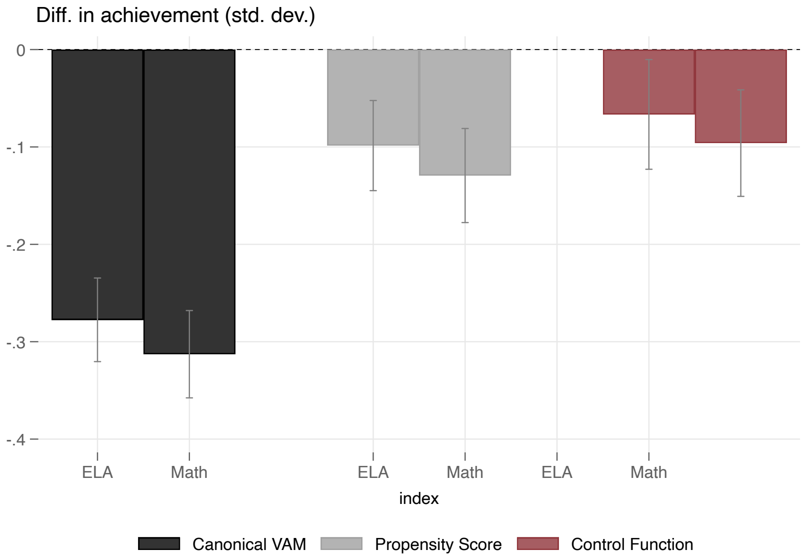
Notes: This figure reports a histogram of the difference between the extrapolated propensity score and the true propensity score for the estimation sample described in the notes to Appendix Figure A.3.

Figure A.5: Baseline Balance and the Average Effects of Remote Learning (Bootstrap Version)

(a) Student baseline characteristics

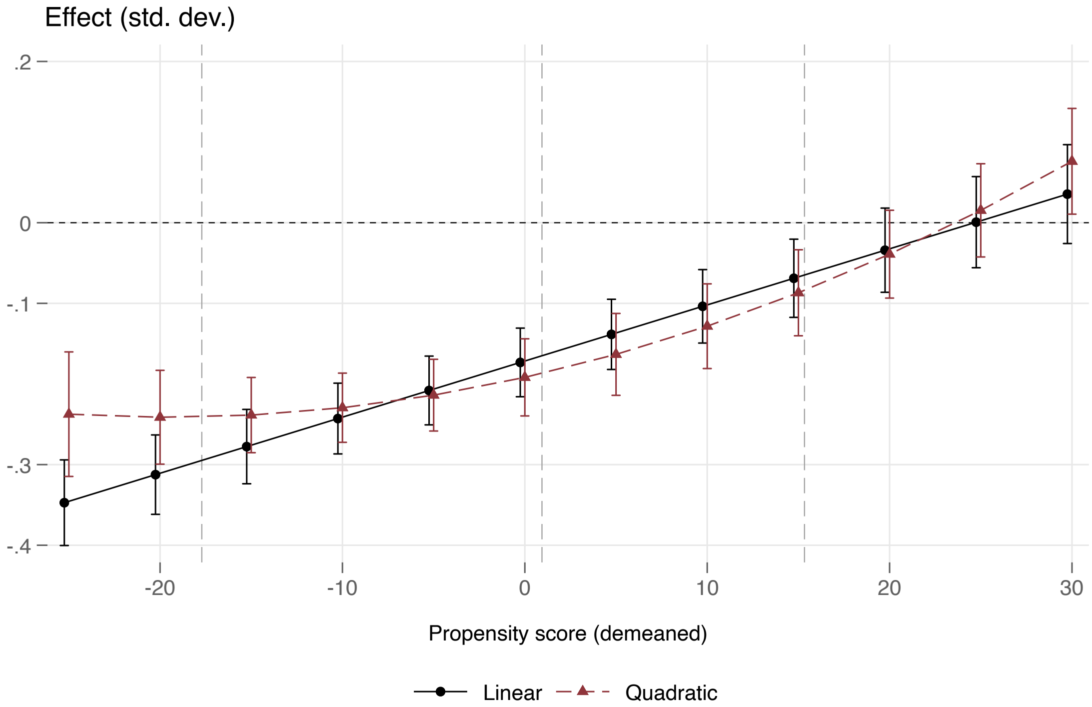


(b) Average effects on post-pandemic (2022) ELA and math achievement



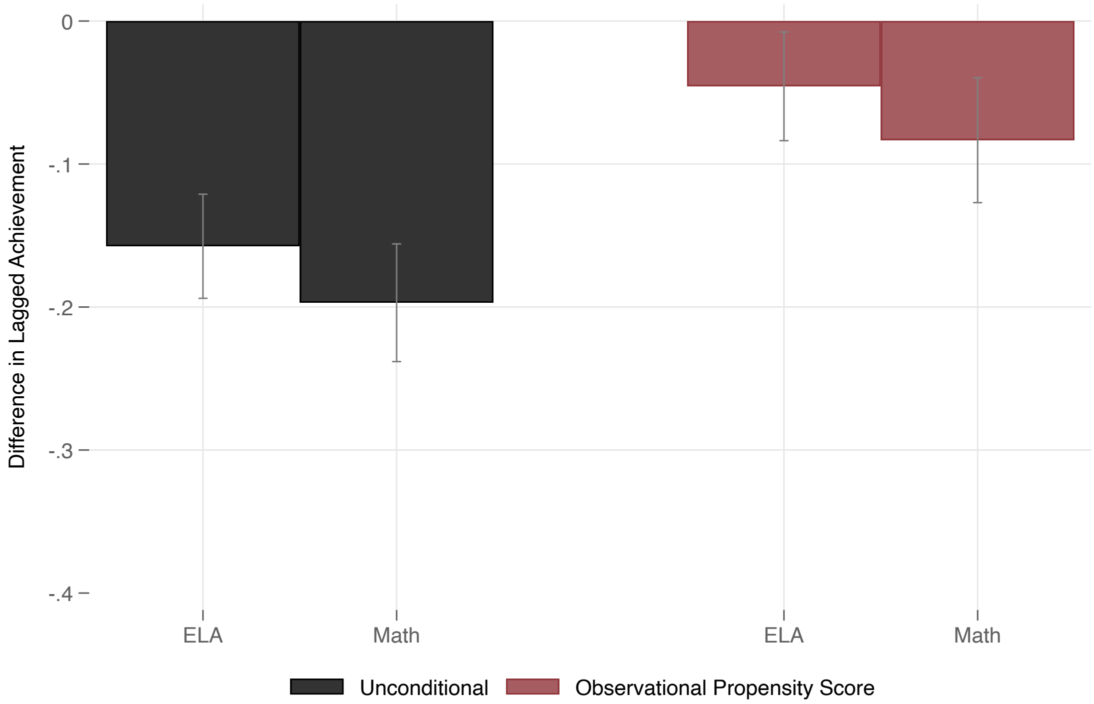
Notes: This figure reports estimates similar to those in Figure 3 but instead provides estimates and confidence intervals obtained through a bootstrapping procedure. To address estimation error in the propensity score estimation, we use a parametric bootstrap. We draw 250 sets utility weight estimates for each covariate from the joint normal distribution with the mean and variance-covariance matrix obtained in the initial estimation step. We then estimate the corresponding regressions 250 times. Finally, we report the mean parameter estimates and the 95 percent confidence region obtained in the bootstrapping procedure.

Figure A.6: Estimated Match Effects on Post-Pandemic Math Achievement (Bootstrap Version)



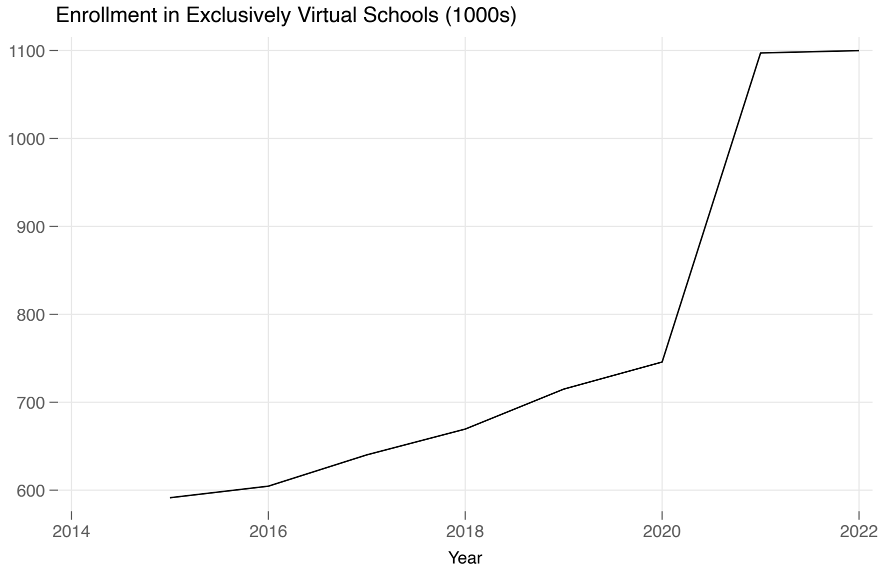
Notes: This figure reports estimates similar to those in Figure 4 but instead provides estimates and confidence intervals obtained through a bootstrapping procedure. To address estimation error in the propensity score estimation, we use the parametric bootstrap. We draw 250 sets utility weight estimates for each covariate from the joint normal distribution with the mean and variance-covariance matrix obtained in the initial estimation step. We then estimate the corresponding regressions and associated linear combination of the parameter estimates 250 times. Finally, we report the mean parameter estimates and the 95 percent confidence region obtained in the bootstrapping procedure.

Figure A.7: Balance Results Using Observational Logit Model



Notes: This figure reports the baseline balance of 2019 achievement (math and ELA) for both a conventional covariate-controlled and a propensity-controlled model derived from preferences estimated using observational data. The covariate-controlled model estimates correspond to regressions of 2019 achievement on remote indicators, baseline covariates, and grade indicators. The "Observational Propensity Score" estimates are derived from a model that augments the model with the implied propensity score from the observational data. Propensity scores are demeaned so that remote coefficients correspond to average differences.

Figure A.8: Enrollment Trends for Exclusively Virtual Schools (NCES)



Notes: This figure presents statistics on annual enrollment in exclusively virtual schools from the Common Core of Data, provided by the National Center for Education Statistics (NCES).

Table A.1: Respondent Descriptive Statistics

	(1)	(2)	(3)
	All Students	Survey Respondents	Hypothetical Choice Respondents
Lagged ELA	0.01	0.17	0.45
	(0.99)	(1.05)	(1.03)
Lagged Math	0.01	0.16	0.44
	(0.99)	(1.01)	(1.00)
Female	0.49	0.51	0.49
	(0.50)	(0.50)	(0.50)
Special Education	.13	.1	.07
	(0.34)	(0.3)	(0.26)
URM	0.82	0.77	0.68
	(0.38)	(0.42)	(0.47)
N	230,347	3,611	1,191

Notes: This table provides summary statistics for all LAUSD students and samples of survey respondents. Column 1 presents averages for every student in the relevant grades. We recruited a sample of survey respondents by randomly contacting 100,000 families through the LAUSD's internal communication system in April 2022. Column 2 reports averages for every family who completed at least one question on our survey. Column 3 reports averages for every student who completed the hypothetical choice experiment questions within the survey.

Table A.2: Summary Statistics for Preference Estimates

	(1) Mean	(2) SD	(3) P5	(4) P95
Academic Quality (ω_Q)	0.10	0.22	0.01	0.89
Remote (ω_R)	-5.06	13.03	-35.77	0.22
Travel Time (ω_d)	-0.07	0.17	-0.12	-0.01
(-ω_Q/ω_d)	1.53	1.20	0.48	3.81
(ω_r/ω_Q)	37.66	35.17	-6.91	74.23
Number of Cells		45		

Notes: This table reports summary statistics for preference parameters that were estimated separately for each covariate cell. Columns 1–4 report the mean, standard deviation, and the 5th percentile and 95th percentiles of the respective row variable, respectively. The last two rows report the willingness to travel for an extra percentage point in academic proficiency and the amount of compensation in achievement units necessary to make respondents choose the remote option. We omit two outlier observations in the statistics presented for the final row as they skew the mean and standard deviation.

Table A.3: Comparing Remote and In-Person Students

	(1)	(2)	(3)	(4)	(5)
	Remote in 2022	In Person in 2022	Mean Diff.	Mean Diff. Obs. *p*-score	Mean Diff. Exp. *p*-score
Lagged (2019) ELA Scores	-0.141	0.001	-0.142	-0.217	-0.078
			(0.016)	(0.017)	(0.075)
Lagged (2019) Math Scores	-0.185	0.002	-0.187	-0.254	-0.106
			(0.019)	(0.02)	(0.093)
Female	0.508	0.483	0.025	-0.039	0.001
			(0.017)	(0.015)	(0.049)
Special Education	0.151	0.141	0.01	-0.012	0.009
			(0.016)	(0.007)	(0.021)
URM	0.843	0.824	0.02	0.071	0.01
			(0.011)	(0.012)	(0.018)
# Students	12,902	257,877			

Notes: This table reports an analysis of baseline (pre-pandemic) student characteristics for students who selected remote and in-person learning options in the 2021–2022 academic year. Columns 1 and 2 report averages for remote and in-person students, respectively. Column 3 reports the corresponding difference in average characteristics based on Columns 1 and 2. Column 4 reports mean differences based on a regression that controls for an estimated propensity score based on an observational model. Specifically, the observational propensity score is estimated in a logit model predicting remote enrollment based on remote relative achievement, remote relative travel time, and baseline student characteristics. Column 5 reports mean differences based on a regression that controls for an estimated propensity score based on the experimental survey data. The difference in the estimates in Column 5 with those reported in Figure 3a is that estimates in Figure 3a further condition on cell strata. Column 5 demonstrates that conditioning on the propensity score alone is sufficient to eliminate baseline differences in achievement. Standard errors are reported in parentheses.

Table A.4: Effects of Remote Learning (Bootstrap Version)

	(1) Main Effect (β)	(2) Selection on Levels (θ)	(3) Selection on Gains (ψ)
(a) Baseline			
ELA	-0.097	-0.236	0.101
	(0.024)	(0.015)	(0.01)
Math	-0.128	-0.243	0.119
	(0.025)	(0.016)	(0.009)
(b) Non-linear pref.			
ELA	-0.142	-0.142	0.038
	(0.024)	(0.01)	(0.006)
Math	-0.163	-0.148	0.049
	(0.023)	(0.01)	(0.006)
(c) Non-linear dist.			
ELA	-0.159	-0.156	0.052
	(0.025)	(0.011)	(0.006)
Math	-0.177	-0.161	0.058
	(0.024)	(0.012)	(0.006)
(d) Non-linear pref. and dist.			
ELA	-0.152	-0.131	0.041
	(0.025)	(0.009)	(0.006)
Math	-0.17	-0.137	0.047
	(0.024)	(0.01)	(0.006)

Notes: This table reports estimates similar to those in Table 1 but instead provides estimates and standard errors obtained through a bootstrapping procedure. To account for estimation error in the propensity score estimation, we use a parametric bootstrap. We draw 250 sets utility weight estimates for each covariate from the joint normal distribution with the mean and variance-covariance matrix obtained in the initial estimation step. We then estimate the corresponding regressions and associated linear combination of the parameter estimates 250 times. Last, we report the mean parameter estimates and the standard errors (in parentheses) obtained in the bootstrapping procedure.

B Remote-Learning Survey Instrument

LAUSD Remote Learning Survey

(untitled)

1. Are you a mother, father, or guardian of a K-12 student? *

- Mother
- Father
- Guardian

2. In what grade is your oldest child currently enrolled? *

Kindergarten
1
2
3
4
5
6
7
8
9
10
11
12

3. Is your oldest child currently enrolled in a virtual schooling option?

- Yes
- No

4. Did you choose a remote option mostly for academic or safety (COVID) reasons? *

- Mostly academic reasons
- Mostly safety reasons
- Academics and safety were equally important

(untitled)

5. For the following, please tell us if you agree or disagree.*

	Agree	Disagree
My child excelled academically with the virtual experience compared to in-person instruction.	○	○
I would like the district to expand its virtual offerings in the future.	○	○
I am likely to opt for virtual schooling in the future.	○	○
I enjoyed the virtual schooling experience during the pandemic.	○	○

(untitled)

6. You will now see a sequence of scenarios, each with three school options that the school district could offer you in Fall 2022. For each set of three, indicate the one you prefer the most (Best) and the one you prefer the least (Worst).

Recall that a fully remote option is entirely virtual (100% remote) and traditional in-person instruction is 0% remote.

Travel time corresponds to the commute time in minutes from your home to the school. For traditional in-person instruction, students make the trip to school every day.

Assume pandemic-related safety issues are as they were in 2019 before COVID.

Besides the characteristics shown, assume that these schools are otherwise identical in terms of their academic instruction and quality.

There are no right or wrong answers to these questions. We only want to know which of the options you would most prefer.
*

Type of Instruction	In Person	In Person	In Person
Percent of students meeting state academic standards	50	30	90
Travel time to school (minutes)	15	30	45
Best	○	○	○
Worst	○	○	○

(untitled)

7. Do you think your choices will be similar in Fall 2023?*

- Yes
- No

(untitled)

8. Thank you for taking the time to answer these questions! We now ask that you let your student in grade 8 through 11 answer the remaining questions, so we can learn more about their experience with remote learning.

Will your child be answering the remaining questions? *

- Yes
- No

(untitled)

9. For the following, please tell us if you agree or disagree.*

	Agree	Disagree
I am likely to opt for virtual schooling in the future.		
I excelled academically with the virtual experience compared to in-person instruction.		
I would like the district to expand its virtual offerings in the future.		

(untitled)

10. You will now see a sequence of scenarios, each with three school options that the school district could offer you in Fall 2022. For each set of three, indicate the one you prefer the most (Best) and the one you prefer the least (Worst).

Recall that a fully remote option is entirely virtual (100% remote) and traditional in-person instruction is 0% remote.

Travel time corresponds to the commute time in minutes from your home to the school. For traditional in-person instruction, students make the trip to school every day.

Assume pandemic-related safety issues are as they were in 2019 before COVID.

Besides the characteristics shown, assume that these schools are otherwise identical in terms of their academic instruction and quality.

There are no right or wrong answers to these questions. We only want to know which of the options you would most prefer.

*

Type of Instruction	In Person	In Person	In Person
Percent of students meeting state academic standards	90	60	30
Travel time to school (minutes)	75	30	15
Best	○	○	○
Worst	○	○	○

(untitled)

11. Do you think your choices will be similar in Fall 2023? *

- Yes
- No

C Survey Responses and Covid Experience Heterogeneity

Although we asked survey respondents to remove the influence of Covid-related concerns from their stated choices, our preference estimates could still partly reflect residual COVID-19-related concerns. To assess this possibility, we generated new preference estimates by splitting the sample of choice survey respondents at the zip code level and generating geographic-specific estimates of willingness to pay measures. We correlate these zip-code-level preference estimates with measures from the COVID-19 Vulnerability and Recovery Index produced by Los Angeles County. For each area, the three index measures are intended to measure the risk, severity, and recovery need due to COVID-19.[15] In addition, we correlate the zip-code-level preferences with measures of local area case counts and deaths due to COVID-19.[16]

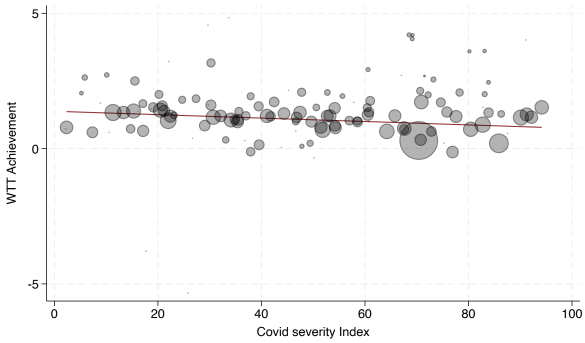
Appendix Figure C.1, Panels (a), (b), and (c) provide scatterplots of each zip code's estimated willingness to travel for academic quality and the three COVID-19 index measures. Each point's size is proportional to the number of respondents used to estimate preference parameters. To supplement these results, Panels (a) and (b) of Appendix Figure C.2 report similar plots for willingness to travel and measures of cases and deaths due to Covid. We report analogous results for estimated measures of preferences for remote schooling (i.e., the amount by which achievement would need to change to make a respondent indifferent between the remote and in-person options) in Appendix Figures C.3 and Figure C.4. Overall, there is little visual evidence of a systematic relationship between preference parameters and either the Covid-related index measures or health outcomes at the zip code level. This provides reassuring evidence against the possibility that Covid-related concerns influence respondent choices in our survey.

[15] These measures were defined as follows. The risk measure is based on American Community Survey data from the U.S. Census Bureau on the share of individuals without U.S. citizenship, the share of the population below 200 percent of the federal poverty line, the share of overcrowded housing units, and the share of essential workers. The severity index is based on asthma hospitalization rates, the share of the population below 200 percent of the federal poverty line, the share of seniors aged 75 and over in poverty, the share of the population who is uninsured, heart disease hospitalization rates, and diabetes hospitalization rates. The recovery need index is based on the share of single-parent households, gun injury rates, the share of the population below 200 percent of the federal poverty line, the share of essential workers, the unemployment rate, and the share of the population who is uninsured. The data used for these analyses were downloaded from https://geohub.lacity.org/datasets/lacounty::covid-19-vulnerability-and-recovery-index/about.

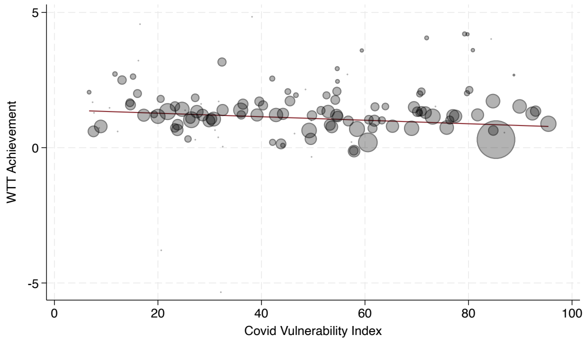
[16] The data used for these analyses were downloaded from http://publichealth.lacounty.gov/media/coronavirus/data.

Figure C.1: Preferences for Academic Quality and Covid Index Measures for Risk, Severity, and Recovery Need

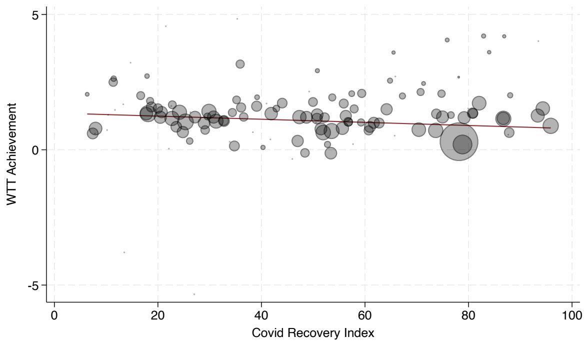
(a) Covid risk index



(b) Covid vulnerability index



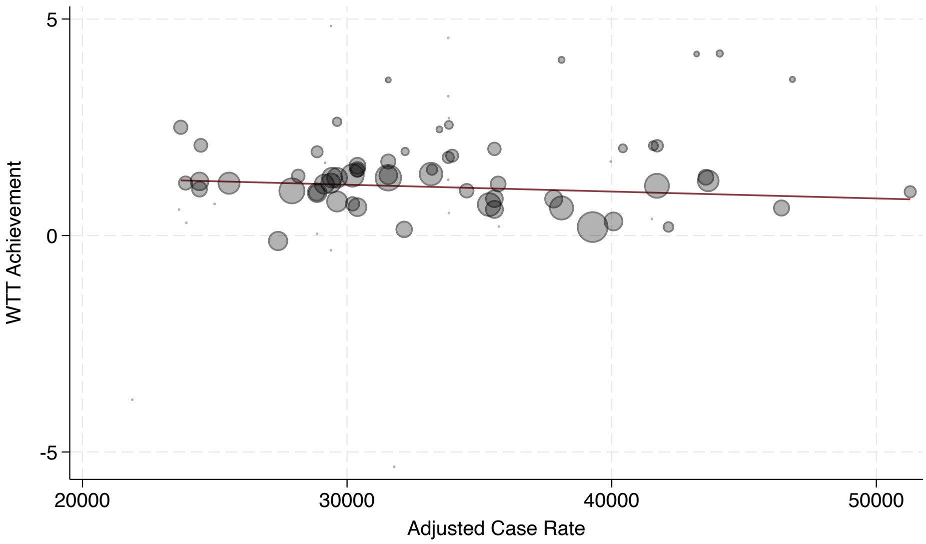
(c) Covid recovery need index



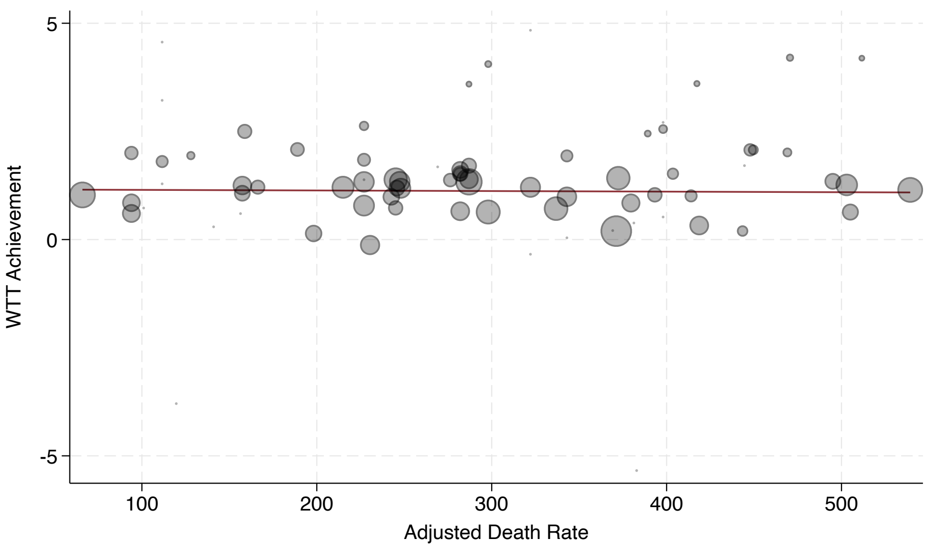
Notes: This figure presents scatterplots of zip-code-level mean willingness to travel for academic achievement (y-axis) and three measures from the COVID-19 Vulnerability and Recovery Index produced by Los Angeles County (x-axis). Panels (a), (b), and (c) present indices for the risk, severity, and recovery need due to COVID-19, respectively. Each point's size is proportional to the number of respondents used to estimate preference parameters.

Figure C.2: Preferences for Academic Quality and Covid-Related Health Outcomes

(a) Covid cases

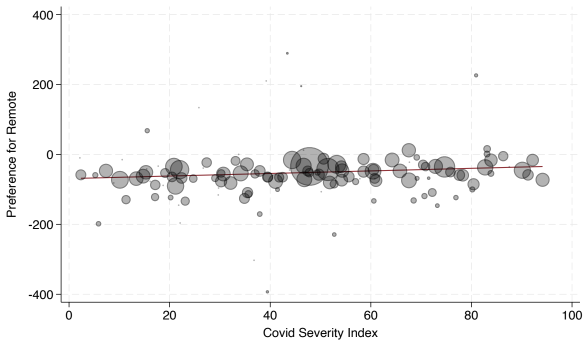


(b) Covid deaths



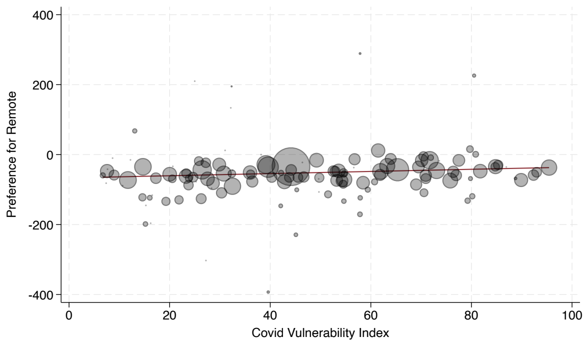
Notes: This figure presents scatterplots of zip-code-level mean willingness to travel for academic achievement (y-axis) and two measures of the severity of the COVID-19 pandemic on health outcomes in an area (x-axis). Panels (a) and (b) measure Covid health impact severity using case count and death measures, respectively. Each point's size is proportional to the number of respondents used to estimate preference parameters.

Figure C.3: Preferences for Remote Learning and Covid Index Measures for Risk, Severity, and Recovery Need

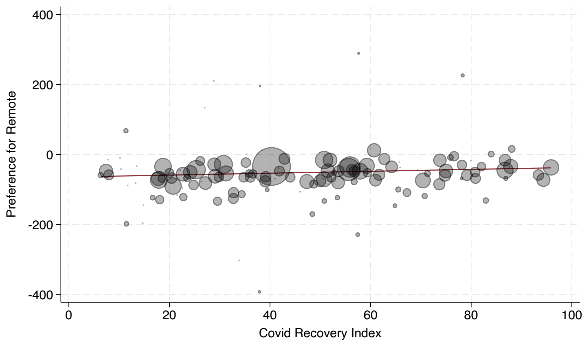


(a) Covid risk index

(b) Covid vulnerability index

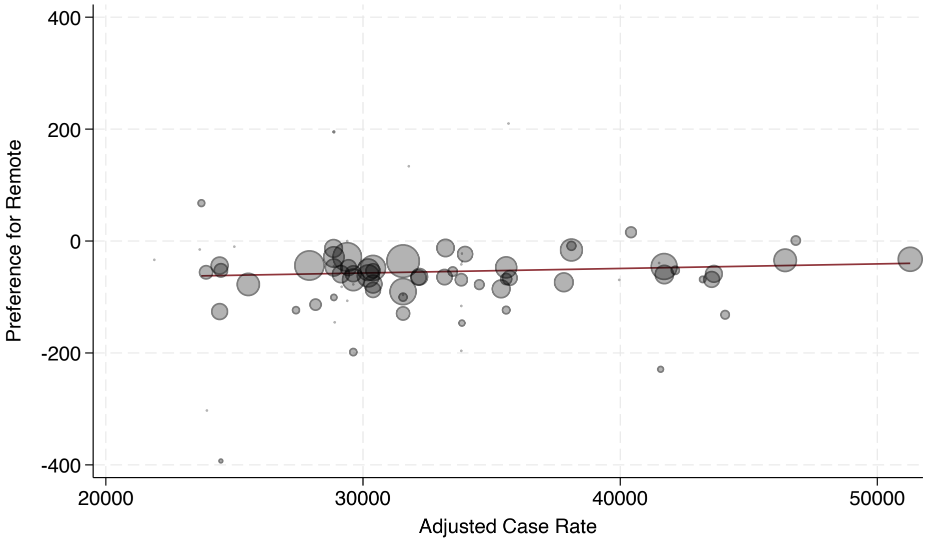


(c) Covid recovery need index

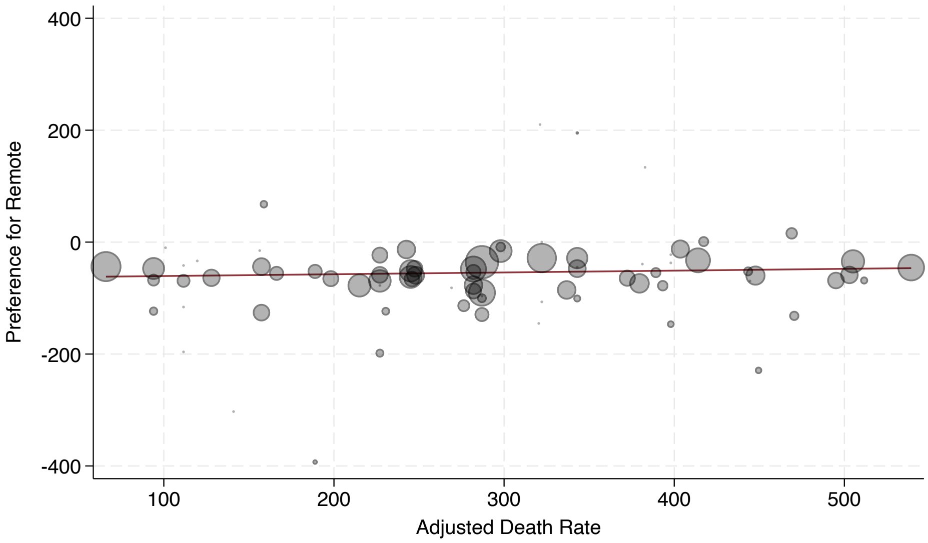


Notes: This figure presents scatterplots of zip-code-level measures of mean preferences for remote learning (y-axis) and three measures from the COVID-19 Vulnerability and Recovery Index produced by Los Angeles County (x-axis). Panels (a), (b), and (c) present indices for the risk, severity, and recovery need due to COVID-19, respectively. Preferences for remote learning are measured as the change in achievement needed to make a family indifferent between the remote and in-person schooling options. Each point's size is proportional to the number of respondents used to estimate preference parameters.

Figure C.4: Preferences for Remote and Covid-Related Health Outcomes



(a) Covid cases



(b) Covid deaths

Notes: This figure presents scatterplots of zip-code-level measures of mean preferences for remote learning (y-axis) and two measures of the severity of the COVID-19 pandemic on health outcomes in an area (x-axis). Preferences for remote learning are measured as the change in achievement needed to make a family indifferent between the remote and in-person schooling options. Panels (a) and (b) measure Covid health impact severity using case count and death measures, respectively. Each point's size is proportional to the number of respondents used to estimate preference parameters.