Who Benefits from Remote Schooling? Self-selection and Match Effects

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Motivation

- School choice expansions are hypothesized to lead to improvements in student-school match quality

    → Families can more efficiently sort into schools that suit their students' needs (Hoxby 2003)

Motivation

- School choice expansions are hypothesized to lead to improvements in student-school match quality
- Match effects are theoretically important but evidence is thin
  - → Do parents know their match quality? Perhaps not, due to lack of information (Abdulkadiroglu et al. 2020; Clark, Martorell, and Wiswall 2022)
  - → Sorting on match quality? Limited evidence (Bruhn 2020; Campos and Kearns 2023)
  - → Horizontal differentiation is important in some settings (Bau 2021; Gilraine, Petronijevic, and Singleton 2021)

Motivation

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- The pandemic provides a unique context to study sorting and match effects
  - → Families compelled to switch to remote learning options
  - → Families learn about their match quality with respect to remote learning

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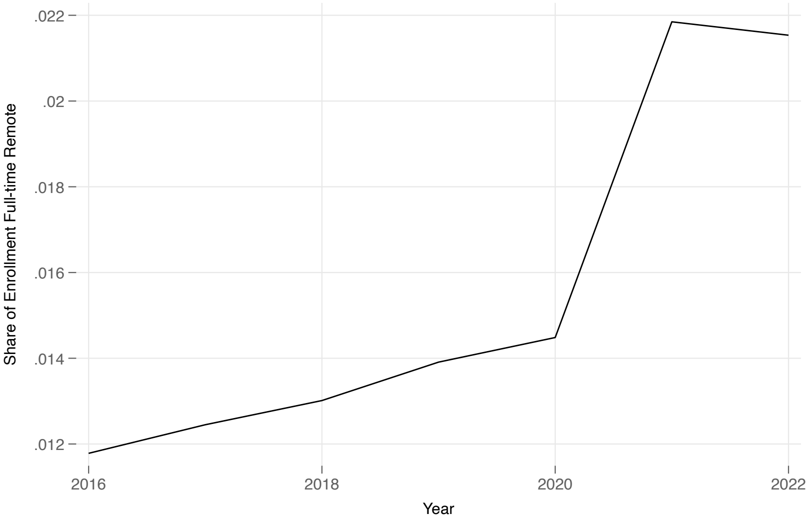
- Match effects are theoretically important but evidence is thin
- The pandemic provides a unique context to study sorting and match effects
  - → Families compelled to switch to remote learning options
  - → Families learn about their match quality with respect to remote learning
- Post-pandemic demand for remote learning is common across numerous cities
  - → Pandemic changed enrollment patterns (Dee and Murphy 2021; Musaddiq et al. 2022; Dee 2023)
  - → A host of explanations for why families may prefer remote learning (Bacher-Hicks et al. 2022)
  - → Common Core data reveals sizable increase in students enrolling in exclusively virtual schools

Motivation: Trends in Remote Learning (Common Core)

Definition of Remote School: All instruction offered by the school is virtual.



Motivation: In the Press

REMOTE LEARNING TEACHING & CLASSROOM CURRICULUM AND INSTRUCTION

Sticking around: Most big districts will offer virtual learning this fall, a sign of pandemic's effect

By Kalyn Belsha and Matt Barnum | Jun 6, 2022, 7:00am EDT

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LAUSD Virtual Academy: Pathway to the Future

Welcome to Los Angeles Unified's Virtual Academy! While the Los Angeles Unified School District (LAUSD) believes in-person learning is generally best for most students, some families may want or need other options. LAUSD is excited to announce new Virtual Academy Schools for the 2022 - 2023 school year. The online academies will explore and expand independent study in a broader way using technology and promoting creativity.

This paper

- Leverage the pandemic as a shock to families' awareness of their remote learning match quality
- Focus on Los Angeles where families were allowed to self-select into remote options in 2021-2022
- Collect novel survey data containing rich information about families' preferences for remote learning
  - → Build on existing working using conjoint experiments (Mas and Pallais 2017; Wiswall and Zafar 2018)
  - → Innovation: Link experimental preference estimates to potential outcome model to identify treatment effects
- Use experimental preference estimates to assess Roy-style selection into remote learning in the post-pandemic landscape
- **Open questions we focus on:**
  1. What are families' preferences for remote learning? Heterogeneity?
  2. What are the selection patterns into remote learning and how does that affect outcomes?

Preview of Results

Survey Evidence:

1. The typical family in Los Angeles dislikes remote learning
   - → Need to be compensated with a 40 percentage point higher school proficiency rate to be indifferent between remote and in-person learning
2. Roughly 25% of families anticipate demanding remote options in the future
3. Roughly 20% of families perceived their kids perform better in remote relative to in-person

Treatment Effects and Heterogeneity:

4. Use experimental preference estimates to construct propensity scores summarizing selection into remote
   - → Preferences predict actual choices
   - → Balance lagged achievement conditional on implied propensity score
5. Remote ATT: -0.11σ (SE: 0.028) for reading and -0.13σ (SE: 0.027) for math
6. Positive remote effects for families with large estimated tastes for remote learning; evidence of Roy-style selection

Related Literature

Match Effects

- Egalite et al. 2015, Arciadocono et al. 2016, Arciadocono and Lovenheim 2016, Bruhn 2019, Abdulkadiroğlu et al. 2020, Dillon and Smith 2020, Mountjoy and Hickman 2020, Angrist et al. 2021, Bau 2021, Bleemer 2021, Otero et al. 2021, Aucejo et al. 2022, Campos and Kearns 2022
- **Contribution:** Evidence of parents sorting children into schools that is consistent with theory

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Remote Learning

- Bueno 2020, Kofoed et al. 2021, Goldhaber et al. 2022, Jack et al. 2022, Singh et al. 2022
- **Contribution:** Study heterogeneity in remote learning effects in a post-pandemic landscape and implications for educational inequality and efficiency

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Using choice models to estimate treatment effects

- Heckman 1979, Heckman et al. 2006, Abdulkadiroğlu et al. 2020, Mas and Pallais 2017, Wiswall and Zafar 2018
- **Contribution:** Import insights from conjoint experiments to program evaluation framework

Roadmap

1. Setting: Remote learning during the pandemic and post-pandemic
2. Survey evidence
   → Eliciting Preferences and Estimation
   → Evidence
3. Conceptual Framework
   → Potential outcome model
   → Map conjoint experiment to treatment effects
   → Treatment Effects and Heterogeneity
4. Concluding Thoughts

Remote Schooling in Los Angeles

- LAUSD announced *two* week closure on March 13, 2020
- The 2019-2020 academic year finishes entirely remote
  - → 150,000 computer shortage
  - → 20% of families without computer or laptop and 16% without access to internet ▸ USC Annenberg Report
- 83% of LAUSD teachers voted to start the 2020-2021 year virtually
- LAUSD was criticized for staying virtual longer than neighboring districts
- LAUSD stayed remote until April 2021
  - → 30% of elementary school students return when schools reopen
  - → 12% of middle school students return
  - → 7% of high school students return

“Post-Pandemic” Remote Schooling in Los Angeles

- California mandates schools to offer a remote option for the 2021-2022 academic year
- LAUSD creates a virtual City of Angels school to accommodate families choosing remote
- 4.7% of students enroll in the remote option ▸ Evidence by grade
- LAUSD opens six virtual academies for 2022-2023 academic year
- Other large districts also expanding remote offerings ▸ Other Districts

Data

LAUSD Student Data 2019-2022

- Demographics
- Addresses
- Achievement

Novel Survey Data

- $\sim$3,400 survey responses
  - $\rightarrow$ Highly selected sample
  - $\rightarrow$ We model preference heterogeneity parametrically in extrapolation
  - $\rightarrow$ Extrapolation produces estimates that are forecast unbiased
- Link survey data with administrative data

The Survey

Goals:

- Collect descriptive facts about families' experiences during Covid remote era
- Collect descriptive facts about anticipated demand for remote learning
- Experimentally estimate preferences for remote learning

Issues in practice:

- Survey responses may not reflect real choices
  - → Our experimental estimates are consistent with estimates using actual choices
- Low survey response rates introduce selection bias (Dutz et al. 2021)
  - → Strong covariate support allows us to account for preference heterogeneity parametrically

Eliciting Preferences

- Well-developed literature using conjoint survey instruments to experimentally identify preferences (Mas and Pallais 2017; Wiswall and Zafar 2018; Aucejo, French, and Zafar 2022)
- Respondents presented with sequence of hypothetical choices randomly varying product attributes
- Experimental manipulation of attributes credibly identifies preferences
- We elicit preferences for three important school attributes
  - → Travel time
  - → Academic Quality
  - → Learning modality (in-person and remote)

Eliciting Preferences

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.

Eliciting Preferences

Type of Instruction	Fully Remote	In Person	Fully Remote
Percent of students meeting state academic standards	20	60	30
Travel time to school (minutes)	Zero	15	Zero
Best	○	○	○
Worst	○	○	○

Back Next

Eliciting Preferences

Type of Instruction	In Person	In Person	Fully Remote
Percent of students meeting state academic standards	10	50	70
Travel time to school (minutes)	60	15	Zero
Best	○	○	○
Worst	○	○	○

Back Next

Preference Estimation

Indirect utility of school j for respondent i at hypothetical choice k is

$$U_{ikj} = \underbrace{\omega_Q Q_j + \omega_R Remote_j + \omega_d d_{ij}}_{V_{ijk}} + \varepsilon_{ikj}$$

- Q_j : Academic quality of hypothetical school j
- $Remote_j$: Remote learning indicator
- d_{ij}: travel time to hypothetical school j
- ε_{ikj}: iid logit shock

Preference Estimation

Indirect utility of school j for respondent i at hypothetical choice k is

$$U_{ikj} = \underbrace{\omega_Q Q_j + \omega_R Remote_j + \omega_d d_{ij}}_{V_{ijk}} + \varepsilon_{ikj}$$

- We collect a rank-ordered list $R_{ik} = (R_{1k}, R_{2k}, R_{3k})$ in each hypothetical scenario, with top-ranked option satisfying

$$R_{1ik} = \underset{j \in \mathcal{J}_k}{\operatorname{argmax}} \, U_{ikj}$$

  and the following options satisfy

$$R_{irk} = \underset{j \in \mathcal{J}_k \setminus \{R_{imk} : m < r\}}{\operatorname{argmax}} U_{ikj} \quad r > 1, \quad k = 1, \cdots, 10$$

Preference Estimation

Indirect utility of school j for respondent i at hypothetical choice k is

$$U_{ikj} = \underbrace{\omega_Q Q_j + \omega_R Remote_j + \omega_d d_{ij}}_{V_{ijk}} + \varepsilon_{ikj}$$

- Logit assumption implies that the likelihood function for a given individual i and hypothetical scenario k is

$$\mathcal{L}(R_{ik}|Q_j, Remote_j, d_{ij}, X_i) = \frac{\exp(V_{iR_{i1k}})}{\sum_{m\in\{R_{i1k},R_{i2k},R_{i3k}\}} \exp(V_{im})} \frac{\exp(V_{iR_{i2k}})}{\sum_{m\in\{R_{i2k},R_{i3k}\}} \exp(V_{im})}$$

Survey Evidence

	All Students	Survey Respondents	Conjoint Respondents
Lagged ELA	0	.18	.46
	(1)	(1.05)	(1.05)
Lagged Math	.01	.17	.44
	(1)	(1.01)	(1.02)
Female	.48	.48	.49
	(.5)	(.5)	(.5)
Special Education	.12	.1	.09
	(.32)	(.3)	(.29)
URM	.8	.76	.65
	(.4)	(.43)	(.48)
N	225,696	3,447	1,148

Descriptive Survey Evidence

Survey Evidence

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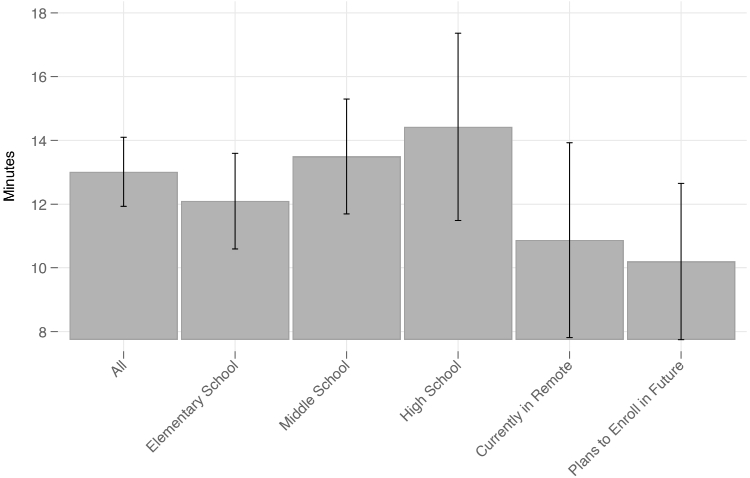
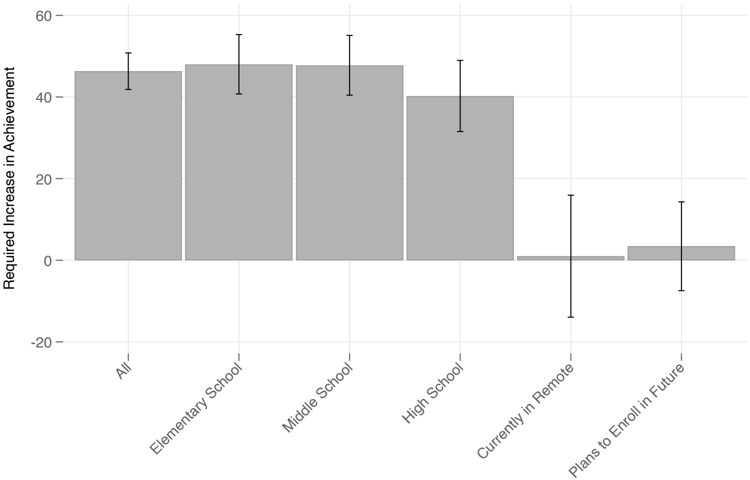
Descriptive Survey Evidence

Survey Evidence: Families value academic quality



Survey Evidence: Families dislike remote learning



Taking Stock of Results and Next Steps

Survey Evidence

- 23% of respondents are likely to choose remote learning options in the future
- 20% of respondents believe their students excelled in remote relative to in-person
- Families tend to value academic quality and dislike remote learning

Next Steps

- Pivot to causal remote learning effects
- Use propensity scores implied by choice model to selection correct estimates
- Do families with a higher proclivity for remote learning have larger treatment effects?

Empirical Framework

$$Y_i = \alpha + X_i'\gamma + \beta D_i + u_i,$$

- Y_i: 2022 math or ELA achievement
- D_i: Remote learning indicator
- X_i: Baseline covariates, including lagged achievement

Issues:

- Selection into remote is not random
- Preferences likely correlated with potential outcomes

We construct propensity scores using the conjoint experiment

The indirect utility of family i enrolling in the remote option relative to their neighborhood school is

$$U_i = \underbrace{\omega_R + \omega_Q Q_{j(i)} - \omega_d d_{j(i)}}_{v_i} + \varepsilon_i$$

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The indirect utility of family i enrolling in the remote option relative to their neighborhood school is

$$U_i = \underbrace{\omega_{Rc(X_i)} + \omega_{Qc(X_i)} Q_{j(i)} - \omega_{dc(X_i)} d_{j(i)}}_{v_i} + \varepsilon_i$$

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- Allow for heterogeneous tastes for quality, remote, and travel time
- Heterogeneity in terms of baseline covariates $c(X_i)$ which depend on grade, gender, baseline achievement, and URM status
- $Q_{j(i)}$: remote achievement relative to neighborhood school $j(i)$
- $d_{j(i)}$: travel time to neighborhood school $j(i)$

We construct propensity scores using the conjoint experiment

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$$U_i = \underbrace{\omega_{Rc(X_i)} + \omega_{Qc(X_i)} Q_{j(i)} - \omega_{dc(X_i)} d_{j(i)}}_{v_i} + \varepsilon_i$$

- Conjoint experiment identifies $(\omega_{Qc}, \omega_{Rc}, \omega_{dc})$
- We observe families' neighborhood school $Q_{j(i)}$ and $d_{j(i)}$
- With estimates of $(\omega_{Qc}, \omega_{Rc}, \omega_{dc})$ and $Q_{j(i)}$ and $d_{j(i)}$, we can construct individual-level propensity scores of choosing remote relative to the neighborhood school for the entire sample:

$$P(v_i) = \frac{\exp(\omega_{Rc(X_i)} + \omega_{Qc(X_i)} Q_{j(i)} - \omega_{dc(X_i)} d_{j(i)})}{1 + \exp(\omega_{Rc(X_i)} + \omega_{Qc(X_i)} Q_{j(i)} - \omega_{dc(X_i)} d_{j(i)})}$$

Propensity scores are forecast unbiased and predict actual enrollment

- Concern: Survey respondents are not representative
  - → We estimate preferences separately by covariate cell
  - → There is common support among respondents and non-respondents ▸ Evidence
- Concern: Extrapolation to the entire sample
  - → Propensity scores are forecast unbiased ▸ Evidence
- Concern: Hypothetical choices do not reflect real choices
  - → Propensity scores predict real enrollment patterns ▸ Evidence

Identifying Assumptions

$$E[Y_i|X_i, D_i, P(v_i)] = \alpha_{c(X_i)} + \beta D_i + \theta P(v_i) + \psi P(v_i) \times D_i. \quad (1)$$

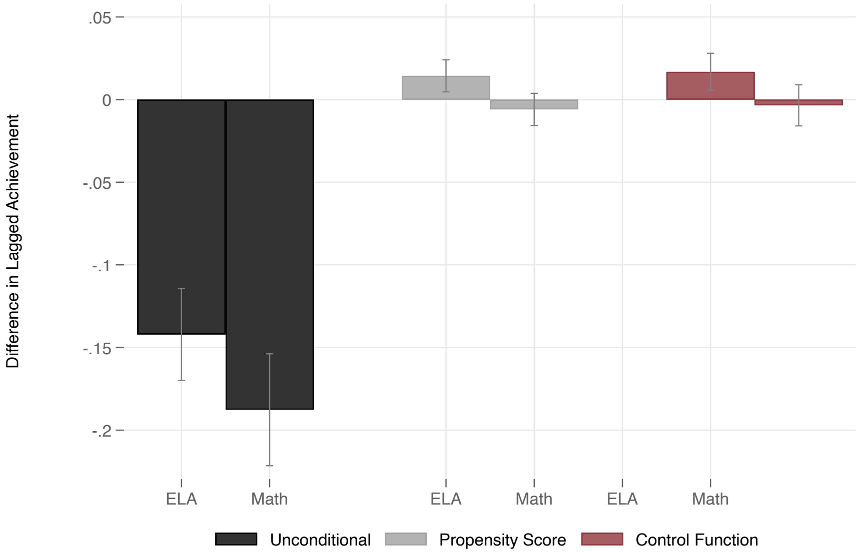
- θ governs selection on levels
- ψ governs selection on gains; match effects

Assumptions and implications

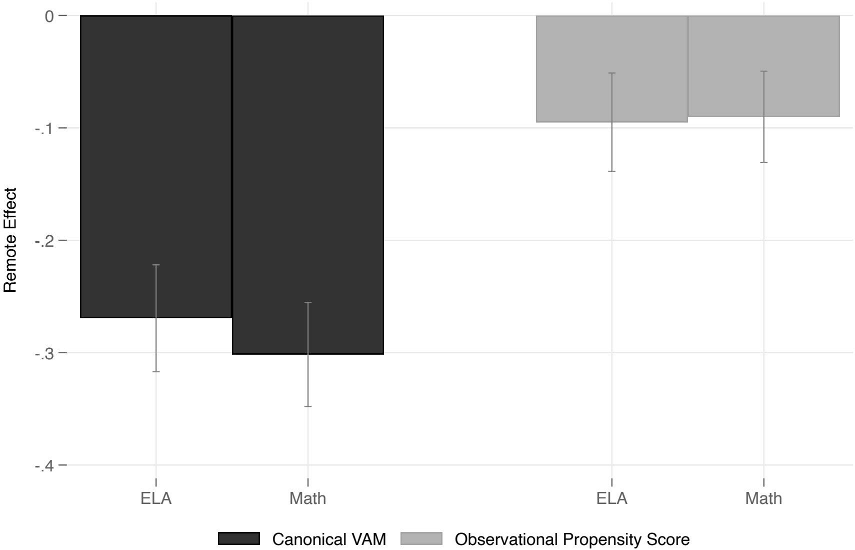
- Propensity score summarizes selection into remote
  - $\rightarrow$ Also try a related control function approach (Abdulkadiroglu et al. 2020) ▸ Evidence
- Linear treatment effect heterogeneity
  - $\rightarrow$ Assumption relaxed as a robustness check
- Testable Implication:

$$E[X_i|D_i = 1, P(v_i)] - E[X_i|D_i = 0, P(v_i)] = 0$$

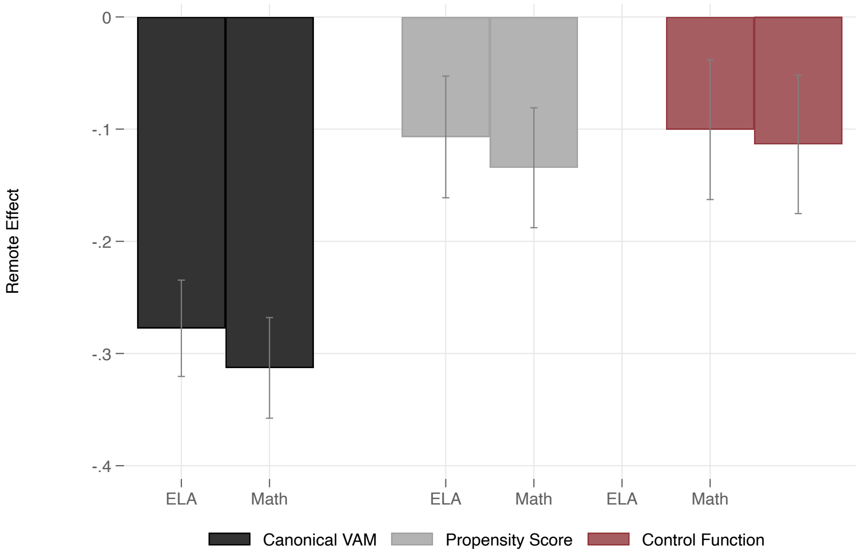
Propensity score mostly balances lagged achievement



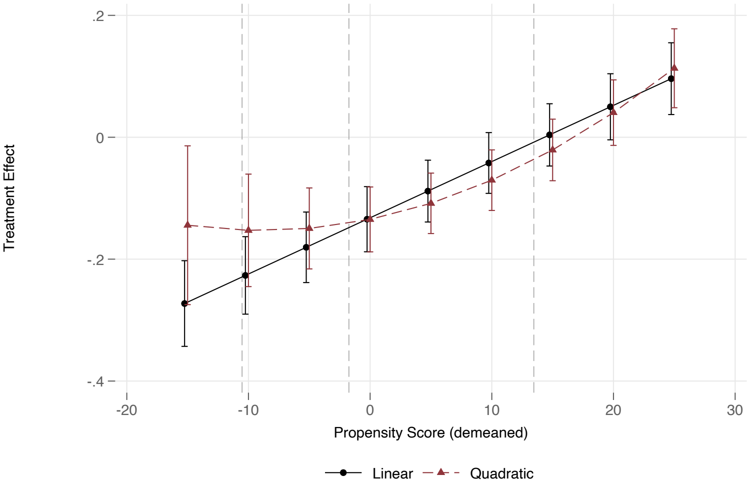
Observational propensity score does not balanced lagged achievement



Treatment Effects



Heterogeneity



Concluding Thoughts

Background

- There is an apparent sustained increase in demand for remote learning in the K-12 sector
- Families self-selecting into remote in the "post-pandemic" landscape arguably have improved signals of their remote match quality

Findings

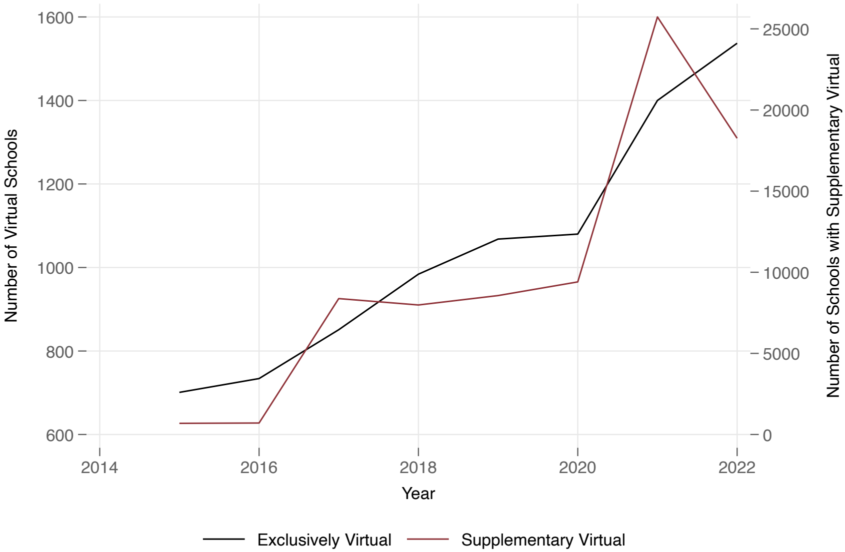
- The typical LAUSD family dislikes remote learning; families have heterogeneous preferences
- We find evidence of sorting on match quality, despite negative average remote learning effects

Future Research

- For what reasons do some families benefit? Bullying? Own-pace learning?
- Similar patterns in other districts?
- Formalize the link between conjoint experiments and program evaluation frameworks

Thank you!

Trends in Virtual Learning (Common Core)



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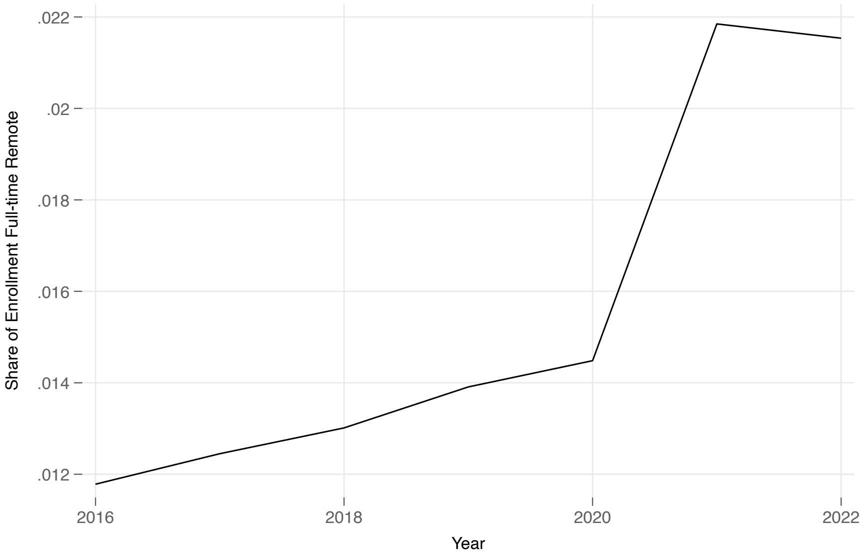
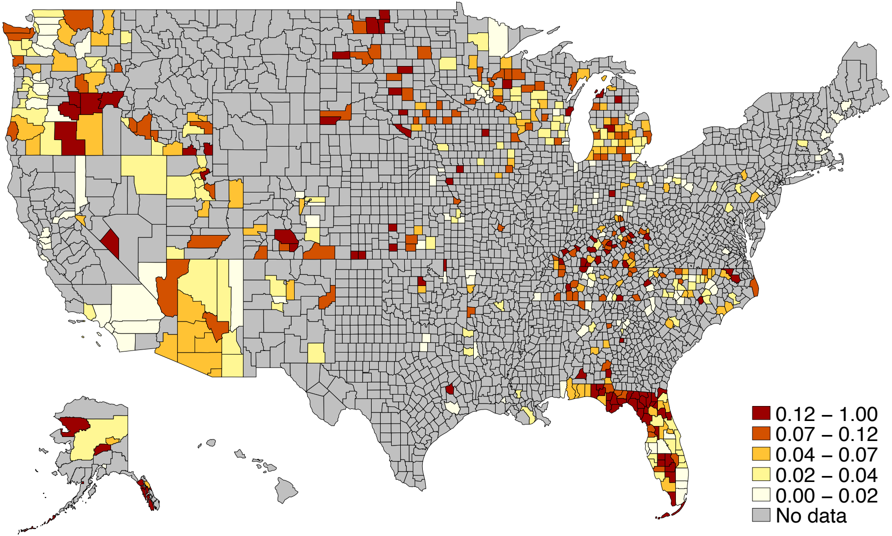
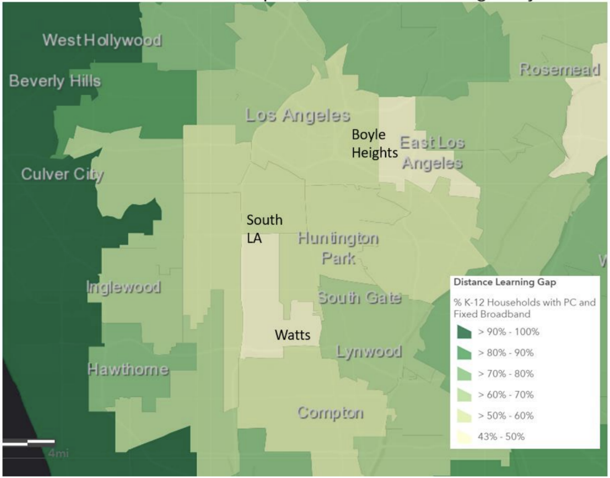


Remote Learning Market Shares by County



Distance Learning Gap

Internet and Device Adoption, from USC Annenberg Analysis



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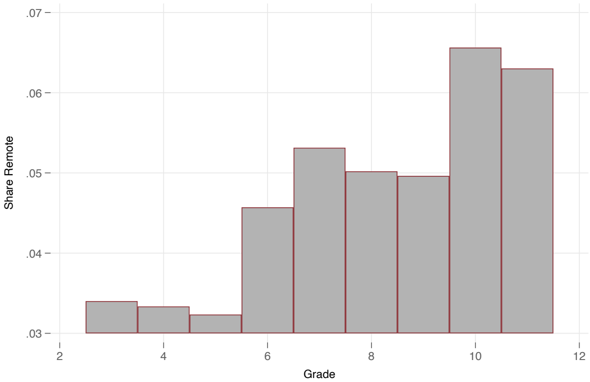
Remote Shares by Grade



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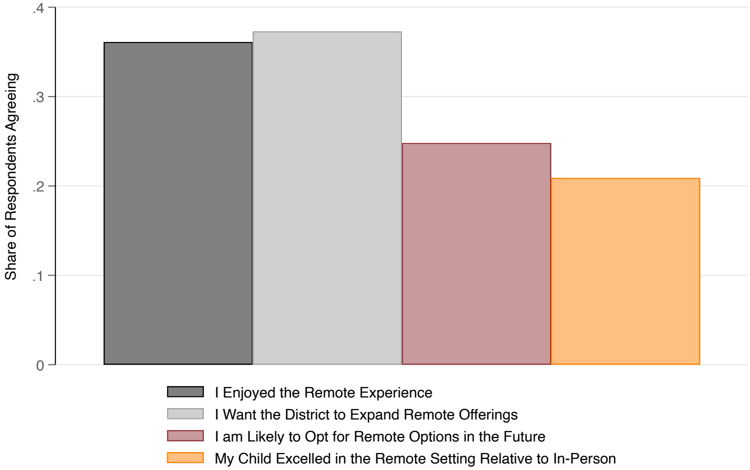
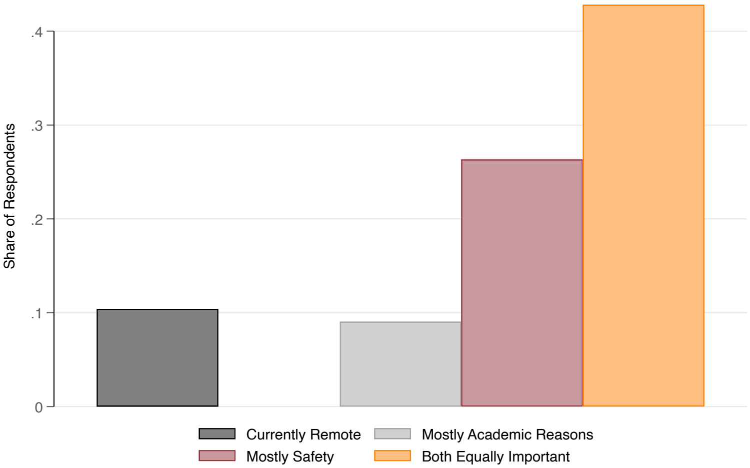
Survey Evidence: The Remote Experience in the Past and the Future



Survey Evidence: Reasons for remaining in remote



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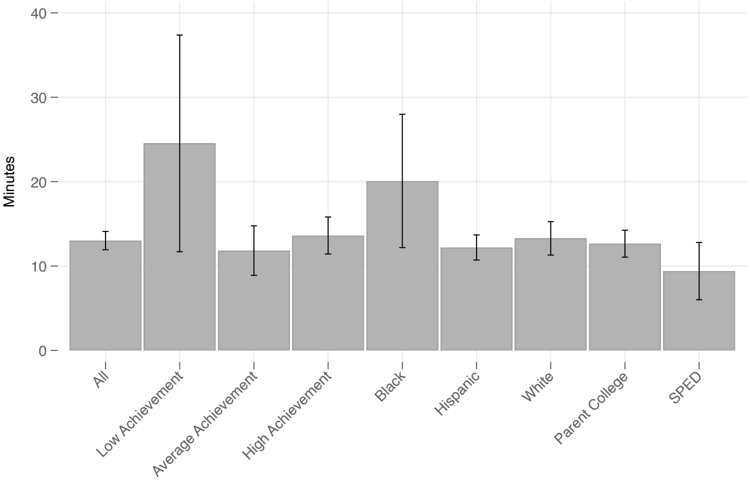
Survey Evidence: Heterogeneous valuation of academic quality



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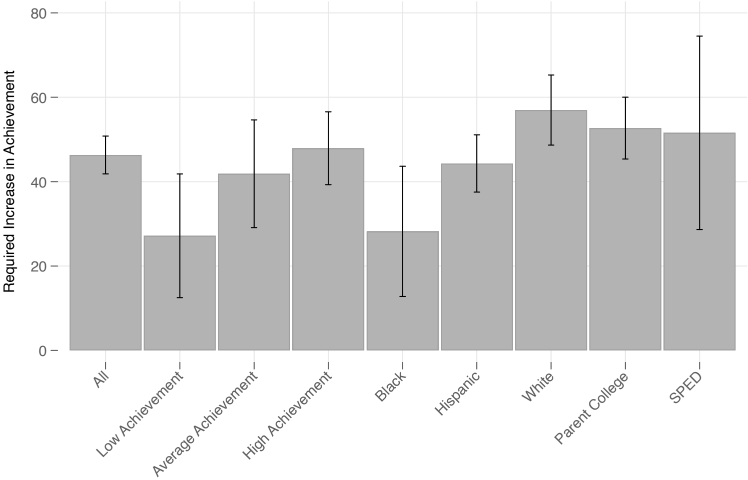
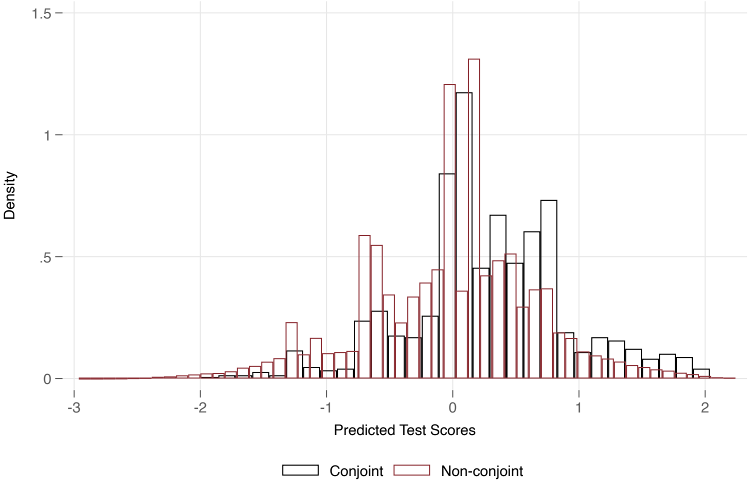


Common Support



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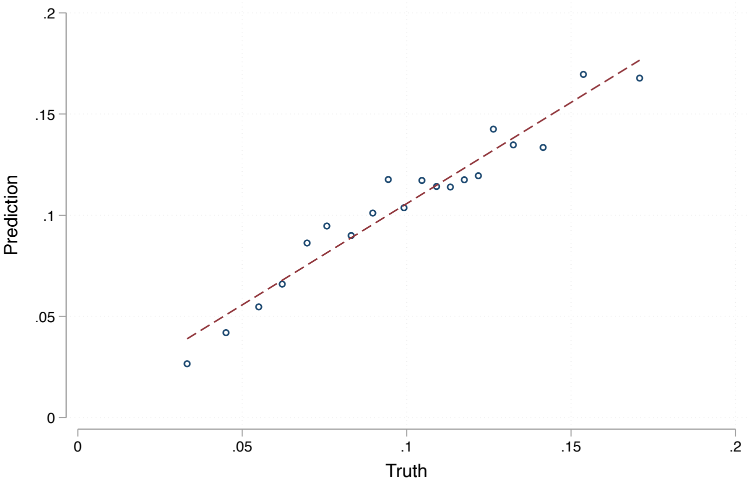
Propensity scores are forecast unbiased



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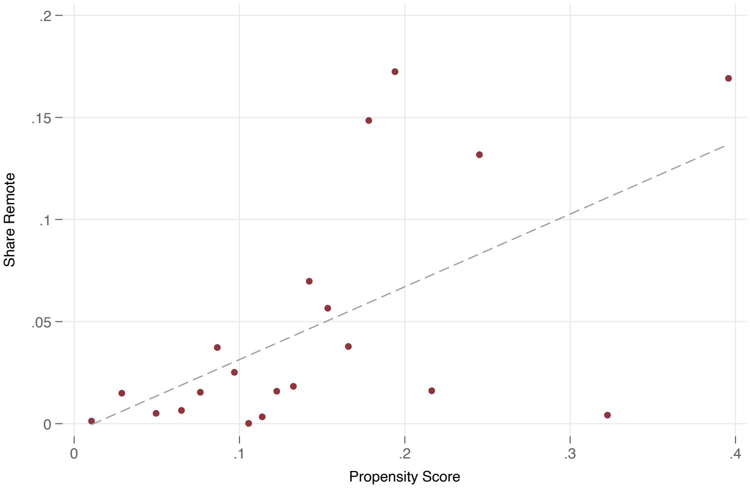
Propensity scores predict actual choices



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Identifying Assumptions for Control Function Approach

$$E[Y_i|X_i, D_i, P(v_i)] = \alpha + X_i'\gamma + \beta D_i + \theta\lambda(v_i, X_i) + \psi\lambda(v_i, X_i) \times D_i. \tag{2}$$

- θ governs selection on levels
- ψ governs selection on gains; match effects

Assumptions and implications

- Omitted variable bias entirely due to *unobserved* preference heterogeneity
- Testable Implication:

$$E[X_i|D_i = 1, \lambda(v_i, X_i)] - E[X_i|D_i = 0, \lambda(v_i, X_i)] = 0$$

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References I

Abdulkadiroğlu, Atila et al. (2020). "Do parents value school effectiveness?" *American Economic Review* 110.5, pp. 1502–39.

Agarwal, Nikhil and Paulo Somaini (2020). "Revealed preference analysis of school choice models". *Annual Review of Economics* 12, pp. 471–501.

Ainsworth, Robert et al. (2020). *Information, preferences, and household demand for school value added*. Tech. rep. National Bureau of Economic Research.

Allende, Claudia (2019). "Competition under social interactions and the design of education policies". *Job Market Paper*.

Arcidiacono, Peter et al. (2016). *College attrition and the dynamics of information revelation*. Tech. rep. National Bureau of Economic Research.

Armstrong-Mensah, Elizabeth et al. (2020). "COVID-19 and distance learning: Effects on Georgia State University school of public health students". *Frontiers in public health*, p. 547.

References II

Aucejo, Esteban M et al. (2020). "The impact of COVID-19 on student experiences and expectations: Evidence from a survey". *Journal of public economics* 191, p. 104271.

Bacher-Hicks, Andrew et al. (2022). "The COVID-19 pandemic disrupted both school bullying and cyberbullying". *American Economic Review: Insights* 4.3, pp. 353–70.

Bau, Natalie (2022). "Estimating an equilibrium model of horizontal competition in education". *Journal of Political Economy* 130.7, pp. 000–000.

Beuermann, Diether W et al. (June 2022). "What is a Good School, and Can Parents Tell? Evidence on the Multidimensionality of School Output". *The Review of Economic Studies*.

Bleemer, Zachary (2021). "Top percent policies and the return to postsecondary selectivity". *Research & Occasional Paper Series: CSHE* 1.

— (2022). "Affirmative action, mismatch, and economic mobility after California's Proposition 209". *The Quarterly Journal of Economics* 137.1, pp. 115–160.

Bruhn, Jesse (2019). "The consequences of sorting for understanding school quality".

References III

Bueno, Carycruz (2020). “Bricks and Mortar vs. Computers and Modems: The Impacts of Enrollment in K-12 Virtual Schools. EdWorkingPaper No. 20-250.”. *Annenberg Institute for School Reform at Brown University*.

Burgess, Simon et al. (2015). “What parents want: School preferences and school choice”. *The Economic Journal* 125.587, pp. 1262–1289.

Campos, Christopher (2023). “Social Interactions and Preferences for Schools: Experimental Evidence from Los Angeles”. *Available at SSRN 4352040*.

Campos, Christopher and Caitlin Kearns (2022). “The Impact of Neighborhood School Choice: Evidence from Los Angeles’ Zones of Choice”. *Available at SSRN 3830628*.

Cullen, Julie Berry, Brian A Jacob, and Steven D Levitt (2005). “The impact of school choice on student outcomes: an analysis of the Chicago Public Schools”. *Journal of Public Economics* 89.5-6, pp. 729–760.

Dale, Stacy Berg and Alan B Krueger (2002). “Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables”. *The Quarterly Journal of Economics* 117.4, pp. 1491–1527.

References IV

Dillon, Eleanor Wiske and Jeffrey Andrew Smith (2020). “The consequences of academic match between students and colleges”. *Journal of Human Resources* 55.3, pp. 767–808.

Dubin, Jeffrey A and Daniel L McFadden (1984). “An econometric analysis of residential electric appliance holdings and consumption”. *Econometrica: Journal of the Econometric Society*, pp. 345–362.

Einav, Liran, Amy Finkelstein, and Neale Mahoney (2022). “Producing Health: Measuring Value Added of Nursing Homes”.

Fack, Gabrielle, Julien Grenet, and Yinghua He (2019). “Beyond truth-telling: Preference estimation with centralized school choice and college admissions”. *American Economic Review* 109.4, pp. 1486–1529.

Goldhaber, Dan et al. (2022). *The consequences of remote and hybrid instruction during the pandemic*. Tech. rep. National Bureau of Economic Research.

Heckman, James J (1979). “Sample selection bias as a specification error”. *Econometrica: Journal of the econometric society*, pp. 153–161.

References V

Heckman, James J, Sergio Urzua, and Edward Vytlacil (2006). "Understanding instrumental variables in models with essential heterogeneity". *The review of economics and statistics* 88.3, pp. 389–432.

Hoxby, Caroline Minter (2003). "School choice and school competition: Evidence from the United States".

Jack, Rebecca et al. (2022). "Pandemic schooling mode and student test scores: evidence from US school districts". *American Economic Review: Insights*.

Kline, Patrick and Christopher R Walters (2016). "Evaluating public programs with close substitutes: The case of Head Start". *The Quarterly Journal of Economics* 131.4, pp. 1795–1848.

Koedel, Cory and Jonah E Rockoff (2015). "Value-added modeling: A review". *Economics of Education Review* 47, pp. 180–195.

Larroucau, Tomás and Ignacio Rios (2020). *Dynamic college admissions and the determinants of students' college retention*.

Mas, Alexandre and Amanda Pallais (2017). "Valuing alternative work arrangements". *American Economic Review* 107.12, pp. 3722–59.

References VI

Moshary, Sarah, Bradley Shapiro, and Sara Drango (2022). "Preferences for Firearms and Their Implications for Regulation". *University of Chicago, Becker Friedman Institute for Economics Working Paper* 115.

Mountjoy, Jack and Brent Hickman (2020). "The returns to college (s): Estimating value-added and match effects in higher education". *University of Chicago, Becker Friedman Institute for Economics Working Paper* 8.

Musaddiq, Tareena et al. (2022). "The Pandemic's effect on demand for public schools, homeschooling, and private schools". *Journal of Public Economics* 212, p. 104710.

Neilson, Christopher (2021). *Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students*. Tech. rep. Princeton University. Economics Department.

Otero, Sebastián, Nano Barahona, and Cauê Dobbin (2021). *Affirmative action in centralized college admission systems: Evidence from Brazil*. Tech. rep. Working paper.

Rosembaum, PR and DB Rubin (1983). "The central role of propensity scores in estimating dose-response functions". *Biometrika* 70.1, pp. 41–55.

References VII

Roy, Andrew Donald (1951). "Some thoughts on the distribution of earnings". *Oxford economic papers* 3.2, pp. 135–146.

Singh, Abhijeet, Mauricio Romero, and Karthik Muralidharan (2022). *COVID-19 Learning loss and recovery: Panel data evidence from India*. Tech. rep. National Bureau of Economic Research.

Wiswall, Matthew and Basit Zafar (2018). "Preference for the workplace, investment in human capital, and gender". *The Quarterly Journal of Economics* 133.1, pp. 457–507.