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

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NBER Spring Education Meeting May 2023

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)

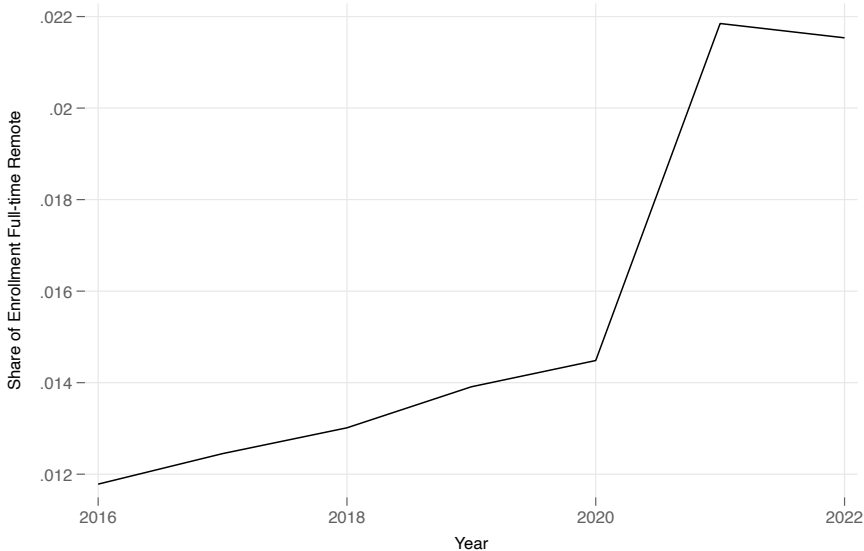
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- The pandemic provides a unique context to study sorting and match effects
  - → Families compelled to switch to remote learning options
  - → Families learn about their match quality with respect to remote learning

Motivation

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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)
  - → Yet, we know very little about families' preferences for virtual learning

Motivation: Trends in Virtual Learning (Common Core)



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 school with 40% higher proficiency rate to be indifferent between remote and in-person learning
2. Roughly 35% of families perceived their kids perform better in remote relative to in-person
3. Roughly 25% of families anticipate demanding remote options in the future

Treatment Effects and Heterogeneity:

4. Propensity score implied by choice model balances lagged achievement
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

Roadmap

1. Remote learning during the pandemic and post-pandemic
2. Survey evidence
   - → Data and framework
   - → Eliciting Preferences and Estimation
   - → Evidence
3. Conceptual Framework
   - → Potential outcome model
   - → Map conjoint experiment to treatment effects
4. Treatment Effects and Heterogeneity
   - → Selection on levels vs. selection on gains
5. Discussion

Remote Learning 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 Learning 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 Administrative Student Data 2019-2022

- Demographics
- Addresses
- Achievement

Novel Survey Data

- ∼3,400 survey responses
- 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
  - → Distance
  - → 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	In Person	In Person	In Person
Percent of students meeting state academic standards	10	80	40
Travel time to school (minutes)	75	60	30
Best	○	○	○
Worst	○	○	○

Back Next

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}: distance 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

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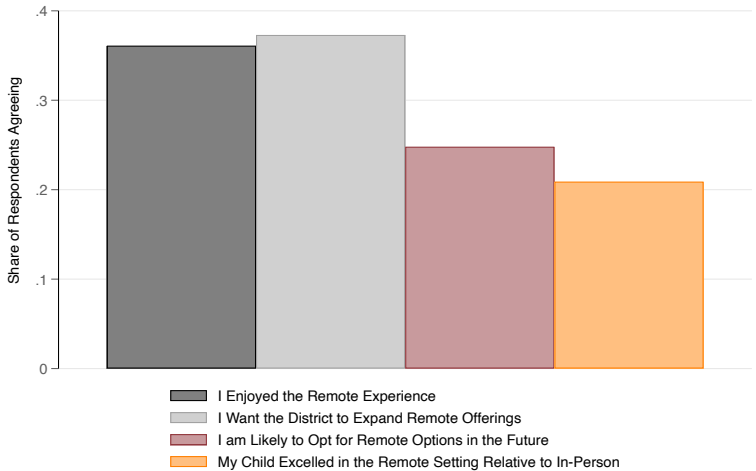
- Logit assumption implies that the likelihood function for a given individual i and hypothetical scenario k is

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

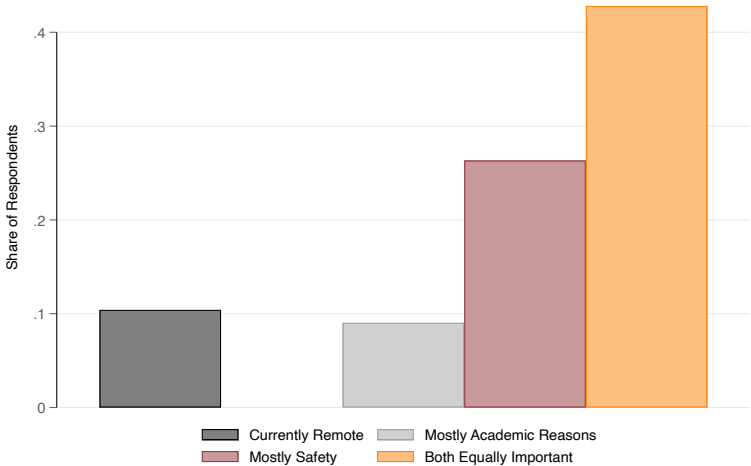
Survey Evidence: Who Responded?

	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

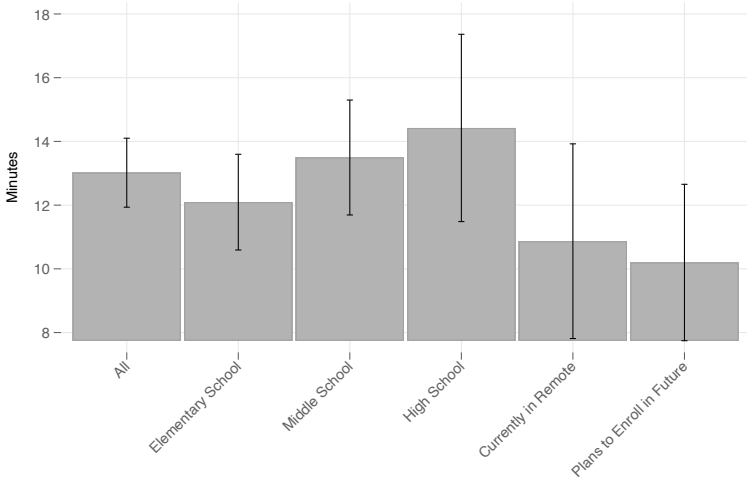
Survey Evidence: The Remote Experience in the Past and the Future



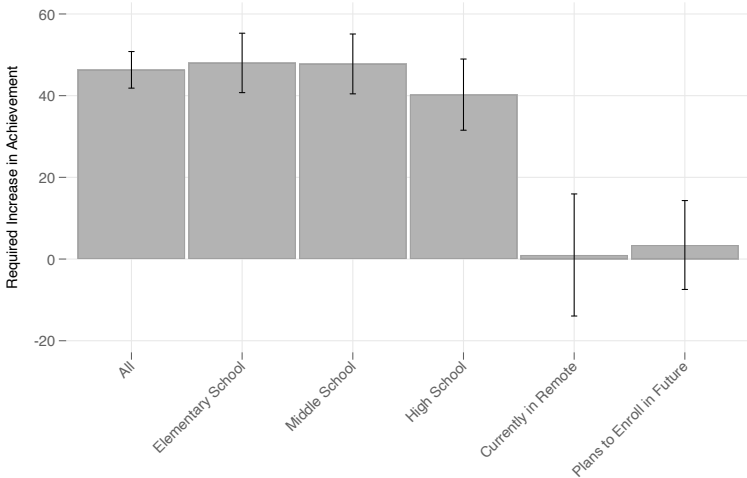
Survey Evidence: Reasons for remaining in remote



Survey Evidence: Families value academic quality



Survey Evidence: Families dislike remote learning



Taking Stock of Results and Next Steps

Survey Evidence

- 35% of respondents want expanded remote offerings
- 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

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

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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 $j(i)$

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- Conjoint experiment identifies $(\omega_{Qc}, \omega_{Rc}, \omega_{dc})$
- We observe families' neighborhood school Q_j and d_{ij}
- With estimates of $(\omega_{Qc}, \omega_{Rc}, \omega_{dc})$ and Q_j and d_{ij}, 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

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

Identifying Assumptions

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

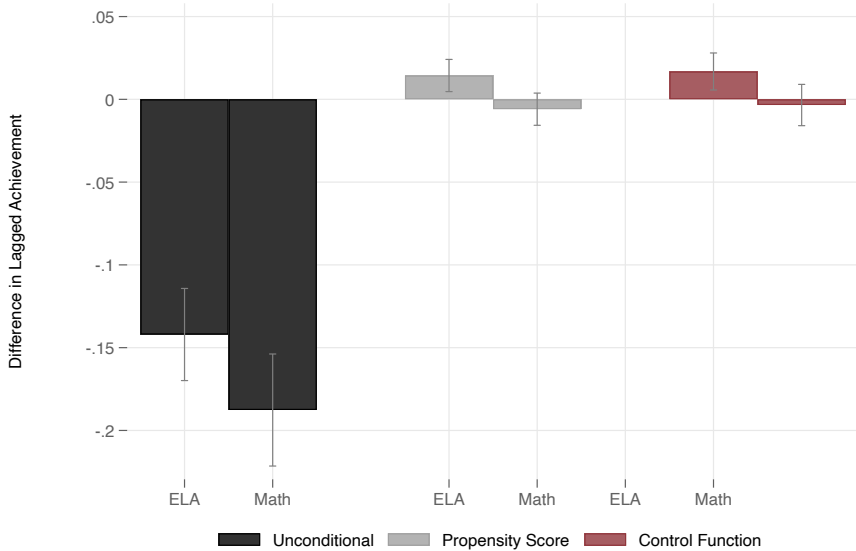
- θ governs selection on levels
- ψ governs selection on gains; match effects

Assumptions and implications

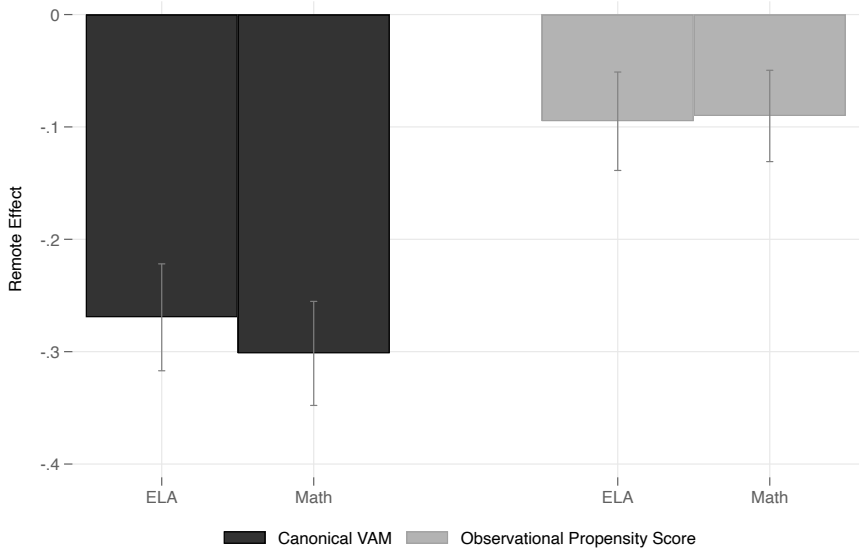
- Omitted variable bias entirely due to preference heterogeneity
- Rosenbaum and Rubin (1983)-like approach
  - → Also try a related control function approach (Abdulkadiroglu et al. 2020) ▸ Evidence
- Testable Implication:

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

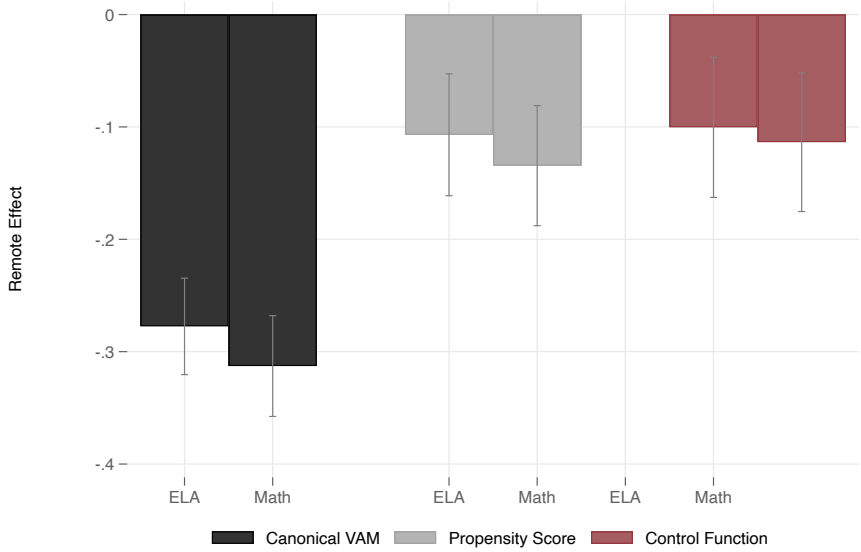
Propensity score mostly balances lagged achievement



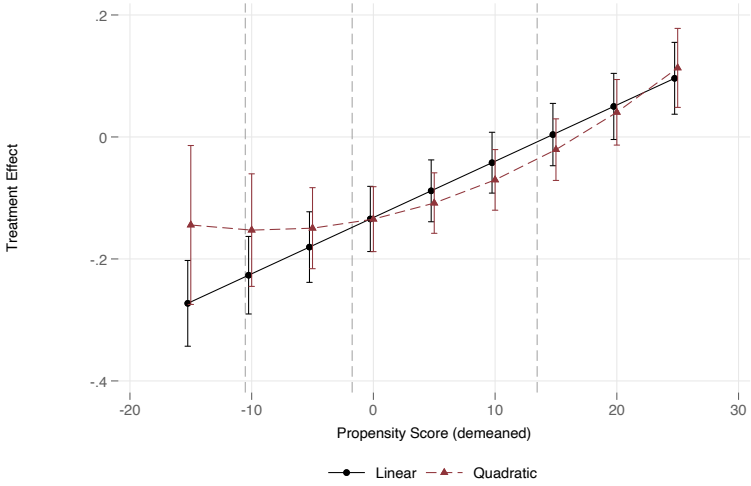
Observational propensity score does not balanced lagged achievement



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 in the “post-pandemic” landscape arguably better know their match quality

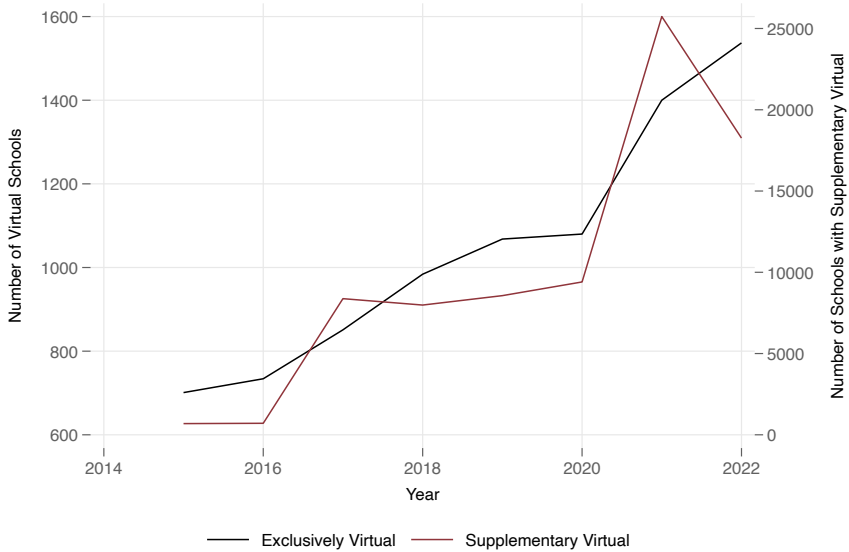
Findings

- The typical LAUSD family dislikes remote learning
- Families have heterogeneous preferences for remote learning
- Negative average remote learning effects but we find evidence of sorting on match quality

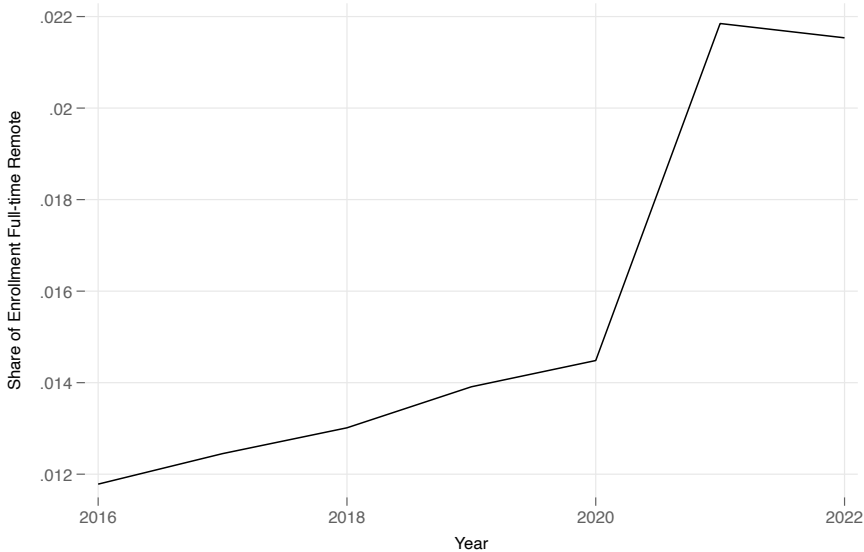
Future Research

- Similar patterns in other districts?
- For what reasons do some families benefit? Bullying? Own-pace learning?

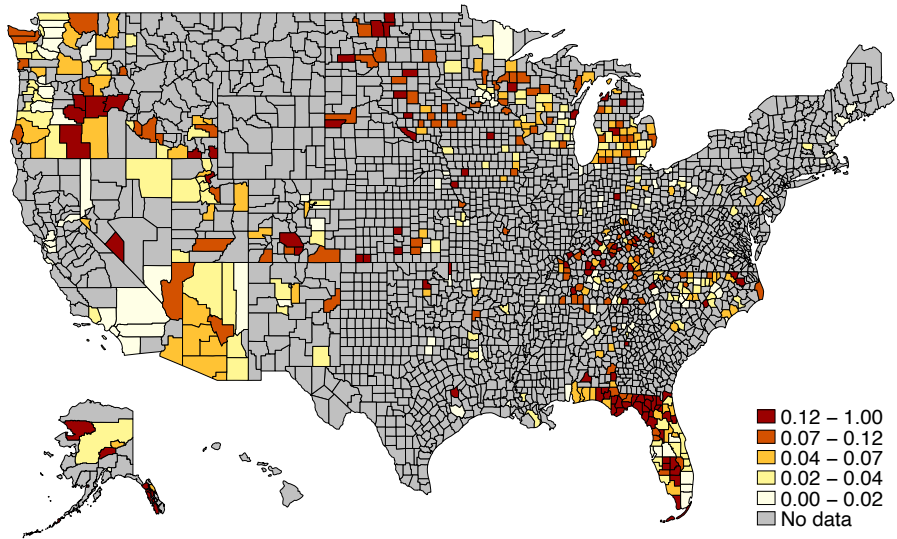
Trends in Virtual Learning (Common Core)



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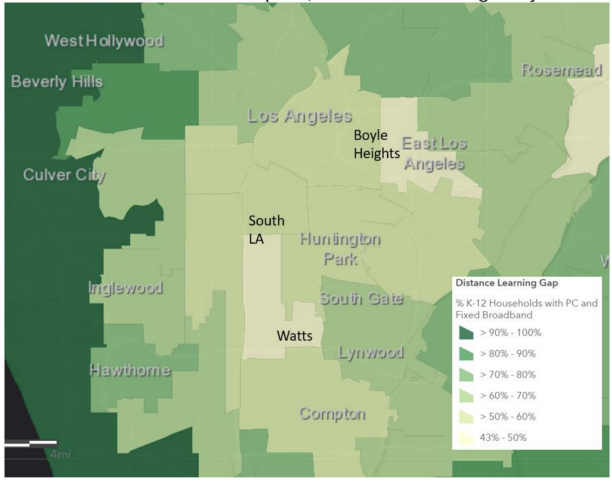


Remote Learning Market Shares by County



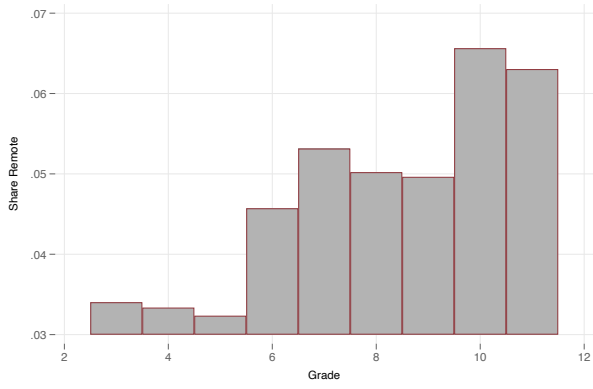
Distance Learning Gap

Internet and Device Adoption, from USC Annenberg Analysis



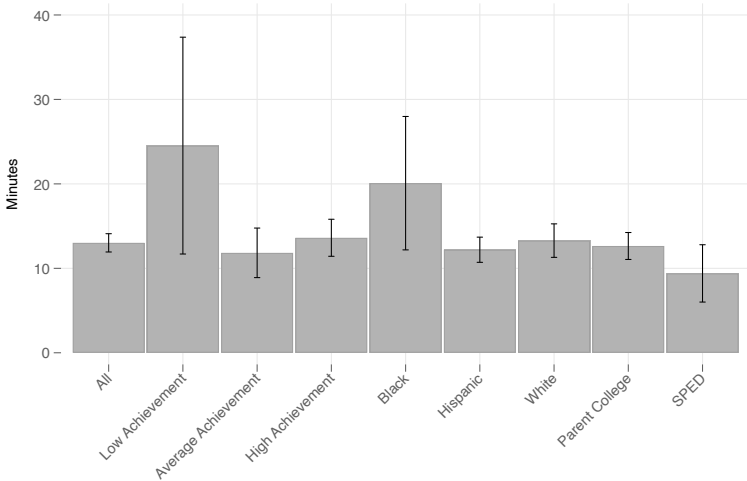
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Remote Shares by Grade

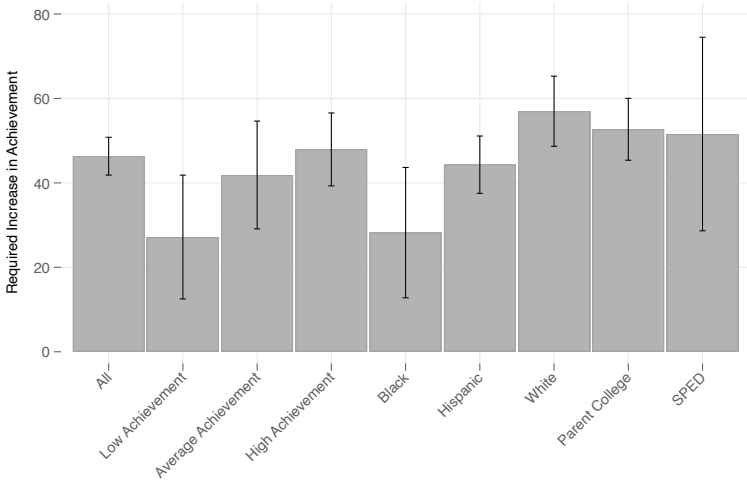


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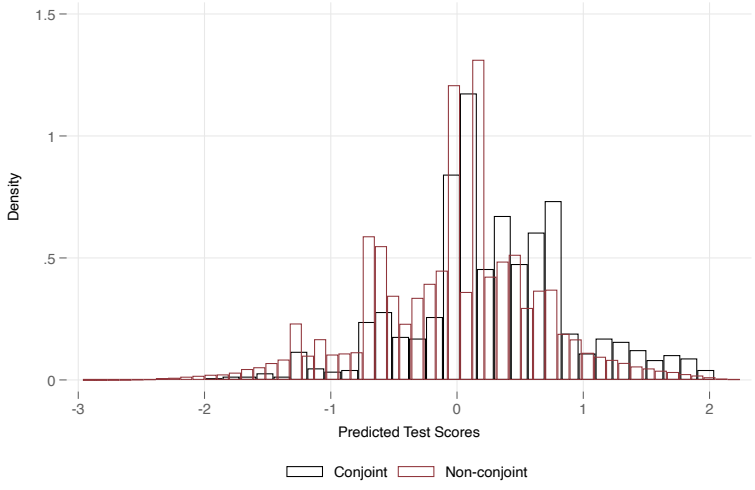
Survey Evidence: Heterogeneous valuation of academic quality



Survey Evidence: Families dislike remote learning

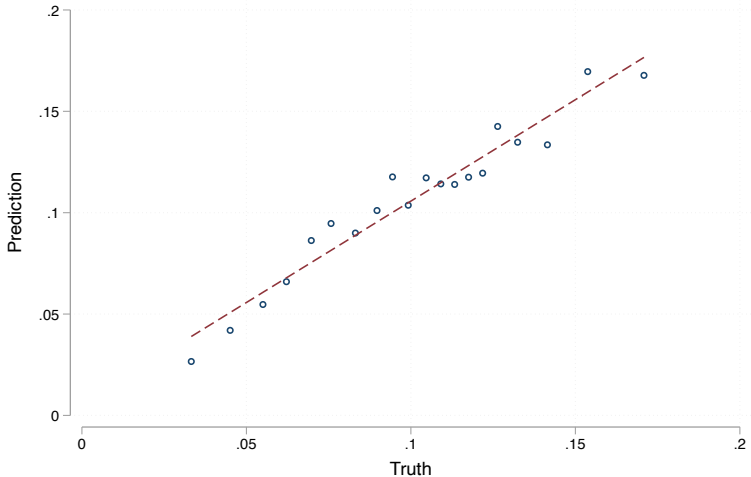


Common Support



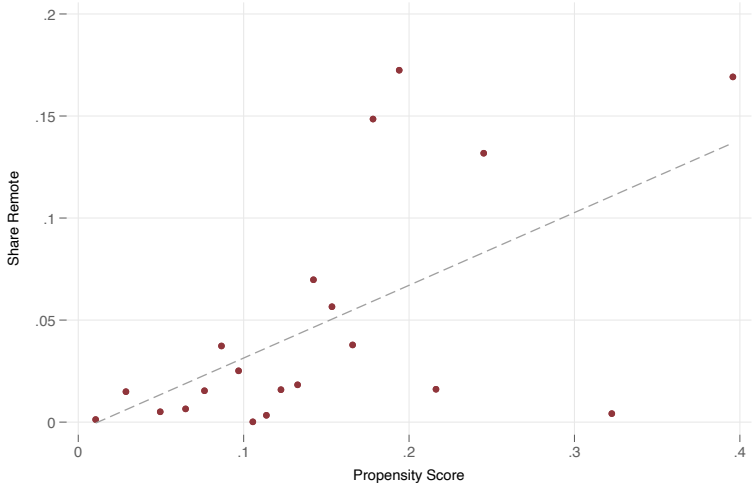
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Propensity scores are forecast unbiased



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Propensity scores predict actual choices



Go Back

Identifying Assumptions for Control Function Approach

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

- 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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