Schools and School Choice During a Year of Disruption: Views of Parents in Five States

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Methodology Notes

Other National Surveys. In developing our survey and analyzing the results, we looked to several national surveys, including the RAND Parent Survey, Parents Union Poll, NPR Parent Poll, and EdNext Parent Survey. Some example regional surveys include: USC Los Angeles Parent Survey and a PACE poll in California.

Relevant to our findings on racial patterns in preferences for remote instruction: A nationally representative parent survey from USC Dornsife’s Understanding America Study (UAS) conducted between mid-April and end of May 2021 also found that 43% of Black and 42% of Hispanic parents preferred their children learning remotely at that time, compared with 19% of White parents. Similarly, 38% of Black parents and 28% of Hispanic parents expressed that they were either keeping their children learning remotely in fall 2021 or unsure compared with 17% of White parents. Similarly, a RAND national survey of parents in May 2021 found that 28% of Black parents and 27% of Hispanic parents were either not planning to send or unsure about sending their children back to school in person, compared with 10% of White parents.

Sample. The five states in our sample (Colorado, Florida, Louisiana, Michigan, and Oregon) are part of a larger study affiliated with the National Center for Research on Education Access and Choice (REACH). As such, we did not include any states where choice is not a significant policy strategy. We have been studying school choice policies in these states for several years prior to the pandemic, which provides us with contextual knowledge to further interpret the results of this survey.

Survey Instrument and Administration. The opt-in online survey was designed to take approximately 20 minutes to complete. For the majority of the survey, parents were asked to respond to questions in reference to their youngest school-aged child (in grades K-12).

To obtain survey samples, we partnered with CloudResearch, which maintains an internet-based survey platform called Prime Panels. The CloudResearch Prime Panels platform is an aggregation of double opt-in participant panels, meaning that participants are recruited into the panel by navigating to a website and signing up to take surveys. Prime Panels offers a convenience sample; it does not offer access to participants recruited with probability-based sampling methods. In other words, these panels are not designed to provide representative polling at the national or state-level. People who volunteer for the panels are likely to differ systematically from people who do not volunteer. Consequently, the responses that participants give to survey items may not be representative of the broader population of interest.

To improve the representativeness of the sample gathered on Prime Panels, we applied demographic quotas (by race/ethnicity, school type, income, and educational attainment). The application of such quotas is known as purposive sampling, a technique common among researchers who use online panels. All targets and quotas were set to match the demographics of particular states. When we struggled to obtain adequate sample numbers, we relaxed our quotas and attempted to correct with sample weighing. Our opt-in online survey was only offered in English, and participants were able to respond on computers, tablets, or phones. All participants were compensated for their time, either through direct monetary compensation, donations to charities, or points that they can redeem for prizes. Ultimately, our sample consisted of 3,654 parents of school aged children across the five locales stated above. As described below, we also created post-stratification weights for use in our analyses.
Survey analysis and limitations. In survey research more generally, sample statistics provide unbiased estimates of the unknown population parameters when the condition of “strong ignorability” is met. Strong ignorability requires that (1) the mechanism through which respondents enter the sample is independent of the responses to survey items, either unconditionally or conditional on observed variables (i.e., there are no unobserved “confounders”), and (2) all members of the population have a non-zero probability of being included in the sample (Mercer et al., 2017).

When using survey data from an opt-in online panel, the extent to which sample statistics provide biased estimates of the unknown population parameters will depend on the extent to which the outcomes of interest are correlated with the variables that determine selection into the sample. In principle, if the sample includes all of the necessary kinds of respondents from the population of interest, and if all of the confounding variables that determine selection into the sample are known and measured, survey weighting procedures can de-bias sample estimates. If these requirements are not strictly met, survey weights may nevertheless decrease the expected difference between the sample estimates and the population parameters.

In this study, CloudResearch used raking, a common post-stratification method used in survey research to create weights (Cohen, 2008). The goal of raking is to create a set of weights such that the weighted marginal distributions of variables in the sample match the marginal distributions in the population. We use two sets of weights: one set designed for analyzing data separately by state, and one set designed for analyzing the pooled data across all states. Each weight type uses a different set of variables in weight-creation. The sample-level pooled weights rake on race, ethnicity, education level, income category, political party, school sector, and state; the state weights rake on the same variables (minus state) plus urbanicity. Because raking can sometimes yield high-variability weights that add noise to estimates, CloudResearch trims weights to reduce their variability. Weight-trimming is a common practice that trades off bias with sampling variability in an attempt to reduce the overall expected difference between sample estimates and the true population parameters.

In addition to the strong ignorability assumptions described above, raking on population marginal distributions relies on the assumption that the response probability in each raking cell equals the product of the response probabilities for the constituent row and column effects (Kalton & Flores-Cervantes, 2003). For example, in our case, the probability that a parent from the population who (a) has a bachelor’s degree or higher and (b) sends their child to a private school, would be in the sample is assumed to equal the product of the probability that (a) a parent with a bachelor’s degree or higher is in the sample, multiplied by (b) the probability that a parent who sends their child to private school is in the sample.

Other important caveats apply to our raked weights. First, the population marginal distributions to which the weights are calibrated do not strictly describe our population of interest. While our population of interest covers only parents with school-aged children (and for most items, these parents’ responses about their youngest child), in most cases the distributions to which our weights are calibrated describe the full (state or pooled state) population with and without school-aged children (the distribution of school sector type, in contrast, describes the student-level distribution). Second, these weights are not calibrated for subgroup estimates (beyond the state-level estimates for which the state weights are designed). Subgroup estimates (e.g., item responses broken down by race/ethnicity or school sector) may therefore exhibit additional bias beyond the levels of bias exhibited in state- or pooled-analyses.
While the assumptions underlying the raking method are unlikely to be strictly met, it is difficult to know the extent to which the assumptions are violated or the extent to which our estimates may remain biased. In general, the extent to which any given set of raked weights reduces bias will depend in large part on whether researchers are able to weight for the most important confounding variables (Pew Research Center, 2018). When the source and direction of bias are unknown, it is even possible for weights to magnify bias (Mercer et al., 2017). For the present survey, the raking assumptions are difficult to assess given the unique nature of the topics under study and the unique circumstances of the COVID-19 pandemic.

Nevertheless, benchmarking studies conducted in other areas of survey research may provide a ballpark-sense of how much bias may remain in our estimates after weighting. Researchers at Pew Research (Pew Research Center, 2018) conducted a study in which they applied various weighting methods, with various sets of weighting variables, to data collected through online opt-in samples fielded by three different online survey vendors. The researchers compared the results (across a range of sample sizes) on 24 benchmark questions to results collected from high-quality federal surveys. Some of the comparison models weighted based on demographic variables only (age, sex, race and ethnicity, education, and region), and others weighted on demographics plus political variables (party, ideology, evangelical Christian, registered voter). The main finding was that having the right variables for weighting mattered more than which weighting method was used. Across the 24 survey items, the most effective adjustment strategy removed approximately 30% of the original estimated bias (from 8.4 percentage points unweighted to 6 percentage points weighted). Including the political variables in the weighting reduced estimated bias by an additional 1.4 percentage points, on average, relative to using only the demographic variables in the weights. The importance of including the political variables differed by survey topic. Another benchmarking study of online opt-in samples conducted by Pew found that average estimated bias on survey items was larger for Black (11.3 percentage points) and Hispanic (15.1 percentage points) respondents (Pew Research Center, 2016).

**Appendix Table: Comparison of Weighted Sample and Population, by State**

<table>
<thead>
<tr>
<th>Race</th>
<th>Colorado Weighted Sample</th>
<th>Florida Weighted Sample</th>
<th>Louisiana Weighted Sample</th>
<th>Michigan Weighted Sample</th>
<th>Oregon Weighted Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>69.96</td>
<td>67.90</td>
<td>57.59</td>
<td>53.50</td>
<td>70.04</td>
</tr>
<tr>
<td>Hispanic</td>
<td>15.96</td>
<td>21.70</td>
<td>21.28</td>
<td>26.10</td>
<td>4.06</td>
</tr>
<tr>
<td>Asian</td>
<td>3.26</td>
<td>3.50</td>
<td>2.05</td>
<td>3.00</td>
<td>2.14</td>
</tr>
<tr>
<td>Other</td>
<td>6.22</td>
<td>2.00</td>
<td>4.51</td>
<td>0.00</td>
<td>3.12</td>
</tr>
<tr>
<td>Income Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>below 50K</td>
<td>29.93</td>
<td>24.40</td>
<td>30.37</td>
<td>35.90</td>
<td>43.53</td>
</tr>
<tr>
<td>50K-75K</td>
<td>14.91</td>
<td>16.70</td>
<td>17.49</td>
<td>19.20</td>
<td>17.43</td>
</tr>
<tr>
<td>75K-150K</td>
<td>34.39</td>
<td>36.50</td>
<td>34.81</td>
<td>30.40</td>
<td>27.07</td>
</tr>
<tr>
<td>150K and above</td>
<td>20.78</td>
<td>22.40</td>
<td>17.33</td>
<td>14.50</td>
<td>11.97</td>
</tr>
<tr>
<td>Political Affiliation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Republican</td>
<td>26.20</td>
<td>26.50</td>
<td>30.42</td>
<td>35.60</td>
<td>34.51</td>
</tr>
<tr>
<td>Democrat</td>
<td>36.39</td>
<td>29.60</td>
<td>44.96</td>
<td>36.20</td>
<td>35.26</td>
</tr>
<tr>
<td>Independent</td>
<td>32.63</td>
<td>39.00</td>
<td>21.57</td>
<td>26.40</td>
<td>26.27</td>
</tr>
<tr>
<td>Other</td>
<td>4.78</td>
<td>5.00</td>
<td>3.05</td>
<td>1.80</td>
<td>3.96</td>
</tr>
<tr>
<td>Education Attainment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School</td>
<td>22.49</td>
<td>29.70</td>
<td>21.32</td>
<td>40.40</td>
<td>36.75</td>
</tr>
<tr>
<td>Some College</td>
<td>30.53</td>
<td>29.50</td>
<td>30.95</td>
<td>29.70</td>
<td>27.87</td>
</tr>
<tr>
<td>2 Bachelor Degree</td>
<td>46.97</td>
<td>40.90</td>
<td>47.73</td>
<td>29.90</td>
<td>35.37</td>
</tr>
<tr>
<td>Sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charter School</td>
<td>74.44</td>
<td>82.00</td>
<td>58.99</td>
<td>80.00</td>
<td>57.41</td>
</tr>
<tr>
<td>Private School</td>
<td>9.71</td>
<td>5.00</td>
<td>25.55</td>
<td>11.00</td>
<td>23.60</td>
</tr>
<tr>
<td>Other</td>
<td>6.46</td>
<td>-</td>
<td>6.48</td>
<td>-</td>
<td>8.05</td>
</tr>
</tbody>
</table>

To estimate item means across subgroups and to test for statistically significant variation across groups, we fit weighted least squares regression models (applying sampling weights described above). Specifically, in separate
models, we regressed a dichotomized version of each survey item of interest on a set of indicator variables defining the mutually exclusive groups for a demographic factor variable (e.g., a model with a set of indicator variables defining racial groups, another model with a set of indicator variables defining income categories, etc.). To determine whether average responses showed statistically significant variation across groups, we compared the p-value associated with the model F-statistic to an alpha level of .05. Throughout this brief, we report the predicted means for each group of interest from these models. For this report, we are primarily focused on differences by state, school mode, race/ethnicity, income, school level (elementary versus secondary), school type and political party.

For school type, the comparisons do not include parents indicating their child was homeschooled because follow-up interviews indicated parents may have not fully understood how to report on this category. We also combined parochial and private school parents into one category as we suspect some parents in parochial schools categorized themselves as private school parents. For these same reasons, we combined traditional public school and charter school parents into one category, as this was an area of confusion that emerged in follow-up interviews.

Appendix References


About the National Center for Research on Education Access and Choice (REACH)

Founded in 2018, REACH provides objective, rigorous, and applicable research that informs and improves school choice policy design and implementation, to increase opportunities and outcomes for disadvantaged students. REACH is housed at Tulane University with an Executive Committee that includes researchers from Tulane, Michigan State University, Syracuse University, and the University of Southern California.

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