Did Pre-Pandemic Administrative Capacity Predict School Districts' Remote Learning Success?

An Empirical Analysis of COVID-Era Education Outcomes Across U.S. Districts

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Abstract

The COVID-19 pandemic forced an abrupt transition to remote learning in K-12 education, exposing wide disparities in districts' ability to sustain instruction. Much of the existing research highlights household-level inequities such as broadband access and parental support, but less is known about the institutional capacity of districts themselves. This study examines whether pre-pandemic administrative capacity, including digital infrastructure, budget transparency, and organizational planning, shaped districts' ability to adapt during the crisis. Using publicly available panel data from 2018 to 2022 and a difference-in-differences (DiD) regression design, this study tests whether districts with stronger pre-2020 capacity achieved higher levels of remote learning success, measured through engagement, instructional weeks, and related outcomes. Results show that districts with higher administrative capacity prior to the pandemic delivered more resilient instruction and mitigated participation losses, particularly in lower-income contexts. These findings suggest that building institutional capacity before a crisis can reduce educational inequality and strengthen preparedness for future disruptions.

Keywords: COVID-19, Remote learning, School districts, Administrative capacity, Digital infrastructure, Difference-in-differences, Educational inequality, Education policy

JEL Codes: I20, I28, H75

1. Introduction

The COVID-19 pandemic disrupted schooling across the United States, with more than 55 million students moving into remote or hybrid instruction almost overnight in spring 2020 (Education Recovery Scorecard, 2022; NCES, 2020). This sudden shift revealed stark inequalities in the ability of districts to sustain teaching and learning. While research has documented the role of household factors such as internet access, income, and parental involvement, less attention has been paid to the institutional features of school districts themselves and how they shaped the success of remote instruction.

This study addresses that gap by focusing on pre-pandemic administrative capacity, defined as the organizational ability of districts to plan, invest, and implement complex changes in instruction. Administrative capacity encompasses not only digital infrastructure, but also fiscal transparency, staffing, and strategic management practices that could support a rapid shift to remote education. The central question is whether districts with stronger administrative or digital capacity before 2020 experienced more successful remote learning during the pandemic.

The analysis uses a district-level panel dataset covering the years 2018 through 2022. Data includes enrollment and staffing information, district finances, equity and demographic indicators, administrative and spending patterns, broadband coverage and costs, and instructional modality outcomes during the pandemic. Combining these sources allows for the construction of indices of administrative capacity and digital infrastructure that reflect conditions before 2020, linked to COVID-era measures of instructional resilience. A difference-in-differences regression design is used to estimate how pre-pandemic capacity interacted with the pandemic shock to shape outcomes.

Findings show that administrative capacity was a consistent predictor of remote learning success. Districts with higher pre-pandemic readiness achieved stronger outcomes during 2020-21, measured through student engagement and the delivery of instructional weeks, and these effects were most pronounced in low-income districts. Digital infrastructure also played a role, though its effects were smaller and less robust. Importantly, placebo regressions using pre-pandemic outcomes show no spurious correlation, reinforcing a causal interpretation.

This study makes three contributions. First, it shifts attention from households to districts, highlighting institutional preparedness as a determinant of resilience. Second, it develops an index of administrative capacity using pre-2020 data on finances, staffing, and technology. Third, it provides policy-relevant evidence on which types of pre-crisis investments allowed districts to navigate the pandemic more effectively. Together, these contributions offer insights into strengthening the capacity of education systems to withstand future public health emergencies or other systemic disruptions.

The remainder of the paper proceeds as follows. Section 2 reviews existing literature on remote learning and district-level preparedness. Section 3 outlines the research question and hypotheses. Section 4 describes the data sources and methods. Section 5 presents the main results. Section 6 discusses implications for education policy. Section 7 notes limitations, and Section 8 concludes.

2. Literature Review

Research on remote learning during the COVID-19 pandemic has primarily concentrated on disparities at the household level, with particular emphasis on broadband access, income-based inequalities, and racial or geographic divides. Bacher-Hicks, Goodman, and Mulhern (2021), for example, used Google search trends to show that families in wealthier districts engaged more with online learning platforms, widening existing achievement gaps. Similarly, Kogan and Lavertu (2021) documented substantial learning losses on Ohio's third-grade state assessment, especially in districts that remained remote longer, underscoring the unequal consequences of modality decisions.

Other studies have examined the determinants of instructional modality choices. Hartney and Finger (2022) found that partisan politics and union strength were among the strongest predictors of whether districts reopened in person, highlighting how governance factors shaped reopening patterns. However, these studies focus on why districts chose remote or in-person modalities, not on whether they were adequately prepared to succeed once remote instruction was implemented.

A smaller strand of research has investigated district-level preparedness and response capacity. Miller and Pedersen (2024) analyzed indicators of district digital capacity, finding substantial heterogeneity in technology infrastructure and organizational readiness, with important implications for equity. Panaggio et al. (2024) advanced the measurement of instructional modalities by developing a hidden Markov model to integrate multiple trackers into district-week learning modality series, providing a more reliable empirical basis for evaluating instructional responses. At a broader level, Hill et al. (2022) synthesized evidence from 2021-22, concluding that achievement losses were both widespread and unequal, with disadvantaged districts experiencing the steepest setbacks.

The present study extends this literature by applying a difference-in-differences panel regression design that leverages pre-2020 variation in district administrative capacity, including financial transparency, digital readiness, and organizational planning, as a treatment variable. This approach enables a causal estimate of how institutional preparedness shaped remote learning success during the pandemic. While prior work has explored digital infrastructure and reopening decisions, no study to date has directly linked pre-pandemic administrative capacity to district-level instructional resilience under COVID-19 using a quasi-experimental framework. By addressing this gap, the analysis contributes new evidence to education policy and public administration literatures, identifying which organizational features most effectively buffered districts against systemic disruption.

3. Research Question and Hypotheses

This paper asks whether pre-pandemic administrative capacity predicted school districts' ability to deliver remote learning successfully during the COVID-19 pandemic. Administrative capacity is defined as a district's organizational readiness, including staffing ratios, financial transparency, and planning. Digital infrastructure, such as broadband speed and device availability, is considered a complementary form of capacity.

Three hypotheses guide the analysis. First, districts with higher pre-pandemic administrative capacity were better able to provide remote learning once schools closed in 2020 (H1). Second, stronger digital infrastructure also improved districts' ability to operate remotely (H2). Third, these benefits were especially pronounced in low-income districts, where institutional readiness was likely more important for sustaining instruction (H3).

4. Data and Methods

4.1 Data Description

This study assembles district-level panel data for 14 U.S. states (Arizona, California, Colorado, Florida, Georgia, Illinois, Minnesota, North Carolina, New York, Ohio, Pennsylvania, Texas, Virginia, and Washington) covering 2018-2022. This window provides a two-year pre-pandemic baseline (2018-2019), the pandemic treatment years (2020-2021), and one early-recovery year (2022).

The panel integrates multiple public sources. The Common Core of Data (CCD) from the National Center for Education Statistics provides both fiscal and non-fiscal district files, including enrollment counts, staffing, expenditures, and per-pupil spending. School-level spending and fiscal transparency are drawn from Edunomics Lab's NERD$ database (National Education Resource Database on Schools). Demographic, discipline, and technology access information is obtained from the U.S. Department of Education's Civil Rights Data Collection (CRDC), which supplies pre-pandemic outcomes used in placebo tests (e.g., suspensions, AP participation, special education enrollment). Broadband speed, cost, and connectivity coverage are captured using E-Rate program data via Connect K-12 and EducationSuperHighway. Finally, COVID-era instructional modality outcomes, including weekly district-level estimates of remote, hybrid, or in-person learning, are drawn from the School Learning Modalities datasets hosted on Data.gov, which combine Burbio, AEI Return-to-Learn, and additional trackers curated by the CDC School Data Team. All files are harmonized by NCES LEAID, state, and year to form a consistent district-year panel.

4.2 Feature Engineering

Several constructs are derived to ensure consistent measurement across districts and time. Administrative capacity is built as a pre-pandemic index combining administrative staffing intensity, fiscal transparency, and the share of resources devoted to technology and planning; it is anchored using 2018-2019 information to avoid post-treatment contamination. Digital infrastructure summarizes broadband readiness (speeds, coverage) and device availability per student from pre-2020 inputs. The primary outcome, remote learning success, is an index of instructional continuity in 2020-2021, capturing student engagement under remote/hybrid delivery and the realized capacity to sustain remote instruction.

Two alternative outcomes are constructed for robustness: the simple proportion of weeks remote, and an enrollment-weighted measure of remote/hybrid weeks to reflect exposure at scale. District size is controlled using the log of enrollment from the administrative spine. Poverty concentration is proxied with a Title I indicator. All measures are aligned at the district-year level, where pre-2019 enrollment is missing, state medians are used as a fallback to avoid dropping districts.

4.3 Empirical Strategy

The central question is whether pre-pandemic administrative or digital capacity predicted COVID-era remote learning success. The estimation follows a difference-in-differences (DiD) design based on pre-2020 capacity measured before treatment and outcomes observed during treatment years. Because remote-instruction outcomes are only observed from 2020 onward, the identifying variation comes from cross-district differences in pre-period capacity interacted with COVID-period indicators, with year fixed effects absorbing common time shocks across 2020-2021.

The baseline specification is:

$$Y_{it} = \alpha + \beta 1(AdminCap_i \ X \ Post_t) + \beta 2(DigInfra_i \ X \ Post_t) + \gamma \ ln(Enroll_i) + \mu_t + \varepsilon_{it}$$

where Y_{it} is the outcome for district *i* in year *t*; $Post_t$ indicates the COVID period (2020-2021); $AdminCap_i$ and $DigInfra_i$ are pre-2020 capacity measures; μ_t are year fixed effects; and ε_{it} is the error term capturing unobserved shocks at the district-year level; and standard errors are clustered at the district level (LEAID). This specification directly tests H1 (administrative capacity) and H2 (digital infrastructure). In practice, when only 2020-2021 outcomes are included, $Post_t$ is collinear with the year dummies and is dropped by the estimator; identification then relies on cross-sectional differences in baseline capacity within the post period, with common time shocks absorbed by μ_t.

To test H3 (equity), the model includes interactions with low-income status:

$$Y_{it} = \alpha + \beta 1(AdminCap_i\ X\ Post_t) + \beta 2(DigInfra_i\ X\ Post_t) + \beta 3(AdminCap_i\ X\ Post_t\ X\ LowInc_i) + \beta 4(DigInfra_i\ X\ Post_t\ X\ LowInc_i) + \gamma\ ln(Enroll_i) + \mu_t + \varepsilon_{it}$$

where $LowInc_i$ is a Title I indicator. As above, with only post-years available for the outcomes, the triple interactions are empirically equivalent to cross-district differences by baseline capacity that vary with poverty status, net of common time shocks.

4.4 Placebo Tests

To guard against spurious correlations with pre-existing district characteristics, placebo regressions are estimated using CRDC 2017-2018 outcomes as dependent variables (e.g., suspension/expulsion rates, AP participation, dual enrollment, special education shares). These outcomes predate COVID and should not be systematically related to the pre-2020 capacity measures if the main results are truly COVID-specific. The placebo specification is:

$$Y_i^{placebo} = \alpha + \delta 1\ AdminCap_i + \delta 2\ DigInfra_i + \gamma\ ln(Enroll_i) + \mu_s + \varepsilon_i$$

where $Y_i^{placebo}$ is a 2017-2018 CRDC outcome, μ_s are state fixed effects with standard errors cluster. ε_i is the idiosyncratic error term that captures unexplained variation in pre-pandemic outcomes after accounting for capacity measures and state fixed effects.

Thus, the baseline model estimates H1 and H2; the equity-interaction model estimates H3. The state-by-year fixed-effects models, subgroup splits, and alternative outcomes constitute robustness exercises for H1-H3. The CRDC placebo regressions validate that estimated capacity effects are not artifacts of pre-COVID associations.

4.5 Robustness Checks

Three classes of checks assess stability.

(i) State-by-year fixed effects: To absorb policy shocks that vary by state and year (e.g., reopening mandates, relief funding timing), models are re-estimated with μ_{st} in place of μ_t:

$$Y_{it} = \alpha + \beta 1(AdminCap_i\ X\ Post_t) + \beta 2(DigInfra_i\ X\ Post_t) + \gamma\ ln(Enroll_i) + \mu_{st} + \varepsilon_{it}$$

(ii) Subgroup analyses: Estimates are compared across urban vs. non-urban districts and Title I vs. non-Title I districts to assess heterogeneity consistent with H3.

(iii) Alternative outcomes: The main capacity effects are re-estimated using (a) the share of weeks remote and (b) enrollment-weighted remote/hybrid weeks to test sensitivity to outcome definitions.

5. Results

The main results support all three hypotheses. As shown in Table 1, the interaction between administrative capacity and the post-COVID period is positive and statistically significant (~0.27, $p < 0.01$). This indicates that districts with stronger pre-pandemic administrative systems, such as staffing and planning capacity, were better able to sustain remote learning success during 2020-21. By comparison, digital infrastructure also shows a positive effect (~0.07) but is smaller and only marginally significant ($p < 0.10$). This suggests that technology alone was not as strong a predictor of resilience without corresponding administrative readiness.

For H3, results highlight the equity dimension of capacity. Interactions between administrative capacity and low-income status are positive and highly significant (~0.17, $p < 0.001$). Digital infrastructure interacted with low-income status shows a similar positive and significant effect (~0.15, $p < 0.001$). As shown in Figure 1, these findings imply that both organizational and technological preparedness disproportionately benefited disadvantaged districts, reducing inequality in remote learning opportunities during the pandemic.

Alternative outcomes provide additional perspective. Administrative capacity exhibits small but positive effects on the proportion of weeks districts operated remotely (~0.02–0.03). However, enrollment-weighted outcomes are not significant, with confidence intervals crossing zero, as illustrated in Figure 2. This suggests that administrative capacity was more important for ensuring instructional quality and continuity, rather than for determining the overall scale of remote weeks.

To probe the validity of these findings, placebo tests were conducted using pre-pandemic outcomes from the 2017-18 Civil Rights Data Collection (CRDC). As reported in Table 2, administrative capacity and digital infrastructure show no significant associations with outcomes such as LEP share, IDEA enrollment, or Section 504 participation. One exception is a weak negative association between digital infrastructure and AP exam participation, which likely reflects structural differences in advanced course availability across districts rather than causal effects.

These results are reinforced by the placebo figures. Figure 3 shows that coefficients in linear probability models are close to zero across all outcomes, while Figure 4 presents odds ratios from quasi-binomial models that cluster around one. Together, these findings confirm that there were no systematic relationships between pre-pandemic capacity and unrelated outcomes, strengthening the interpretation that the main DiD results reflect COVID-era dynamics rather than pre-existing trends.

Robustness checks further confirm the stability of the results. Models with state-year fixed effects, shown in Table 3, yield nearly identical conclusions to year-only fixed effects, indicating that the positive association between administrative capacity and remote success is not driven by unobserved state-level shocks. Alternative outcome models in Table 4 show consistent positive effects of administrative capacity when defining remote success as the proportion of weeks remote, but no significant effects when weighting outcomes by enrollment size. This robustness is also visible in Figure 4, which demonstrates the divergence between simple percentage-point outcomes and weighted measures of student-weeks.

Subgroup analyses provide additional nuance. As shown in Table 5, the positive effect of administrative capacity is strongest in non-urban, and Title I districts. The subgroup coefficient plot in Figure 5 illustrates that these disadvantaged contexts derived the greatest benefits from pre-pandemic readiness, while non-Title I districts display effects close to zero. Urban subgroup estimates could not be reliably produced after applying strict state-year fixed effects, reflecting sparse variation.

Finally, combined specifications in Table 6 confirm that results are robust across alternative fixed-effect structures. Administrative capacity remains a consistent and significant predictor of remote learning success, while the effects of digital infrastructure are weaker and less stable. Overall, these robustness checks support the conclusion that the main results are not sensitive to modeling choices or sample definitions.

6. Discussion

The findings highlight the central role of administrative capacity in shaping educational resilience. While digital infrastructure is often emphasized, the analysis shows that organizational preparedness such as administrative staffing, fiscal transparency, and strategic planning was a more consistent predictor of remote learning success. This effect was particularly pronounced in low-income districts, suggesting that capacity investments can help mitigate inequality during crises. Digital infrastructure also mattered, though its effects were smaller and less consistent. Broadband and device access may have been necessary but not sufficient: without strong administrative systems, districts struggled to translate technological resources into effective instructional delivery. These results confirm Hypotheses 1 and 3, underscoring that organizational readiness mattered more consistently than digital capacity, and that disadvantaged districts benefited disproportionately from pre-pandemic preparedness.

7. Limitations

While the analysis provides robust evidence, a few boundaries of interpretation should be acknowledged. First, the instructional modality data cover only the 2020-21 academic year, not the subsequent recovery period. Second, although the difference-in-differences framework helps mitigate confounding, unobserved district-level shocks may still influence outcomes. Third, the indices of administrative capacity and digital infrastructure rely on proxy measures such as per-pupil spending shares, administrative staffing ratios, and broadband coverage that may not fully capture the multidimensional nature of district readiness. Finally, state-level variation in relief funding and reopening mandates could have shaped outcomes in ways not fully absorbed by the fixed-effects structure. These considerations highlight the need for caution in extending the findings beyond the specific time frame and measures analyzed.

8. Conclusion

This study provides evidence that pre-pandemic administrative capacity significantly influenced school districts' ability to adapt to COVID-19. Stronger organizational readiness predicted more successful remote instruction, particularly in low-income districts, while digital infrastructure played a secondary but complementary role. Placebo tests confirm that these associations were not present before the pandemic, lending credibility to a causal interpretation. The policy implication is that resilience is not only technological but also administrative. Investments in broadband and devices remain essential, but equally important are sustained commitments to planning, staffing, and transparency. Strengthening district administrative capacity is a key strategy for preparing schools to weather future crises whether pandemics, natural disasters, or other systemic disruptions and these lessons extend beyond COVID-19 to broader questions of education governance and equity.

To translate these insights into practice, policymakers should consider establishing funding formulas that earmark resources not only for technology purchases but also for administrative staffing, IT support, and strategic planning. Federal and state agencies could require districts to publish annual "readiness audits" that document digital infrastructure, emergency response plans, and budget transparency, creating accountability and shared learning across systems. Capacity-building grants should especially target Title I and rural districts, where the payoff of organizational readiness for equity is highest. Together, these steps would help ensure that resilience is institutionalized, rather than improvised, when the next disruption arrives.

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Appendix

Table 1: Difference-in-differences Estimates (Main Models)

Dependent variable: Remote Learning Outcomes (2020-21)

Variables	Remote Success (Admin)	Remote Success (Digital)	Admin × Post × Low-Inc	Digital × Post × Low-Inc
Admin Capacity (pre)	0.268*** (0.081)		0.197** (0.067)	
Digital Infrastructure (pre)		0.066* (0.032)		0.005 (0.030)
Admin Cap × Low-Income			0.174*** (0.031)	
Digital Infra × Low-Income				0.150*** (0.040)
Log Enrollment (pre)	-0.006 (0.010)	-0.002 (0.010)	-0.007 (0.010)	-0.003 (0.010)
Year FE	Yes	Yes	Yes	Yes
Clustered SE	District (LEAID)	District (LEAID)	District (LEAID)	District (LEAID)
Observations	87,710	87,710	87,710	87,710
R^2	0.297	0.235	0.303	0.237

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: **Placebo Estimates (CRDC 2017-18 Outcomes)**

Dependent variables: Discipline, AP, and Subgroup Enrollment Rates

Variables	Dual Enroll	AP Exam ≥1	LEP Share	IDEA Share	Sec. 504 Share
Admin Capacity (pre)	-0.763 (0.323)	0.135 (0.049)	0.122 (0.080)	-0.044 (0.051)	-0.231 (0.122)
Digital Infrastructure	-0.258 (0.189)	-1.03* (0.258)	0.182 (0.290)	0.021 (0.047)	-0.142 (0.104)
Log Enrollment (pre)	0.043 (0.227)	0.312 (0.131)	0.282 (0.127)	-0.014 (0.019)	-0.003 (0.073)
State FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	State	State	State	State	State
Observations	1,525	1,525	1,525	1,525	1,525

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Robustness: State-Year Fixed Effects (Main Models)

Dependent variable: Remote Success Index (2020-21)

Variables	Admin × Post (State×Year FE)	Digital × Post (State×Year FE)
Admin Capacity × Post	0.044* (0.018)	
Digital Infrastructure × Post		0.020 (0.022)
Log Enrollment (pre)	0.046*** (0.004)	0.048*** (0.004)
State-Year FE	Yes	Yes
Clustered SE	District (LEAID)	District (LEAID)
Observations	87,710	87,710
R^2	0.618	0.617

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Robustness: Alternative Outcome Definitions

Dependent variables: Remote % Only and Enrollment-Weighted Remote (2020-21)

Variables	Remote % Only (State×Year FE)	Enrollment-Weighted Remote (State×Year FE)
Admin Capacity × Post	0.024* (0.010)	-23,622.3 (21,165.8)
Log Enrollment (pre)	0.046*** (0.006)	84,004.8** (28,363.8)
State-Year FE	Yes	Yes
Clustered SE	District (LEAID)	District (LEAID)
Observations	87,710	87,710
R^2	0.566	0.327

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Robustness: Subgroup Models (State-Year FE)

Dependent variable: Remote Success Index (2020-21)

Variables	Urban	Non-Urban	Title I	Non-Title I
Admin Capacity × Post	-0.010 (0.032)	0.051* (0.023)	0.069** (0.026)	0.025* (0.012)
Log Enrollment (pre)	0.013* (0.007)	0.049*** (0.005)	0.047*** (0.007)	0.046*** (0.004)
State-Year FE	Yes	Yes	Yes	Yes
Clustered SE	District	District	District	District
Observations	23,941	63,769	37,952	49,758
R^2	0.716	0.591	0.504	0.629

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness: Combined specifications (Year FE vs State-Year FE)

Dependent variables: Remote Success Index, Remote % Only, and Enrollment-Weighted Remote (2020-21)

Variables	H1 (Year FE)	H2 (Year FE)	H1 (State×Year FE)	H2 (State×Year FE)	Remote % Only	Weighted Remote
Admin Capacity (pre)	0.268*** (0.081)					
Digital Infrastructure (pre)		0.066* (0.032)				
Admin Capacity × Post			0.044* (0.018)		0.024* (0.010)	-23,622.3 (21,165.8)
Digital Infra × Post				0.020 (0.022)		
Log Enrollment (pre)	-0.006 (0.010)	-0.002 (0.010)	0.046*** (0.004)	0.048*** (0.004)	0.046*** (0.006)	84,004.8** (28,363.8)
FE Structure	Year FE	Year FE	State-Year FE	State-Year FE	State-Year FE	State-Year FE
Clustered SE	District	District	District	District	District	District
Observations	87,710	87,710	87,710	87,710	87,710	87,710

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Main model coefficient plot (admin and digital); panels for alternative outcomes (remote-only vs weighted)

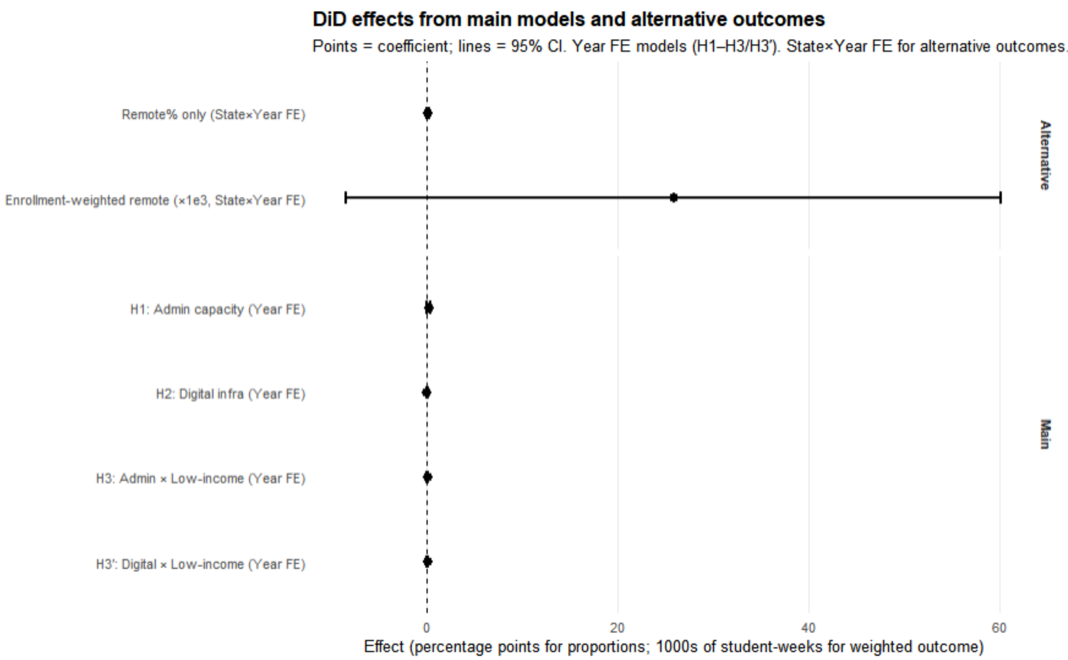

Figure 2: Placebo LPM coefficients (state FE)

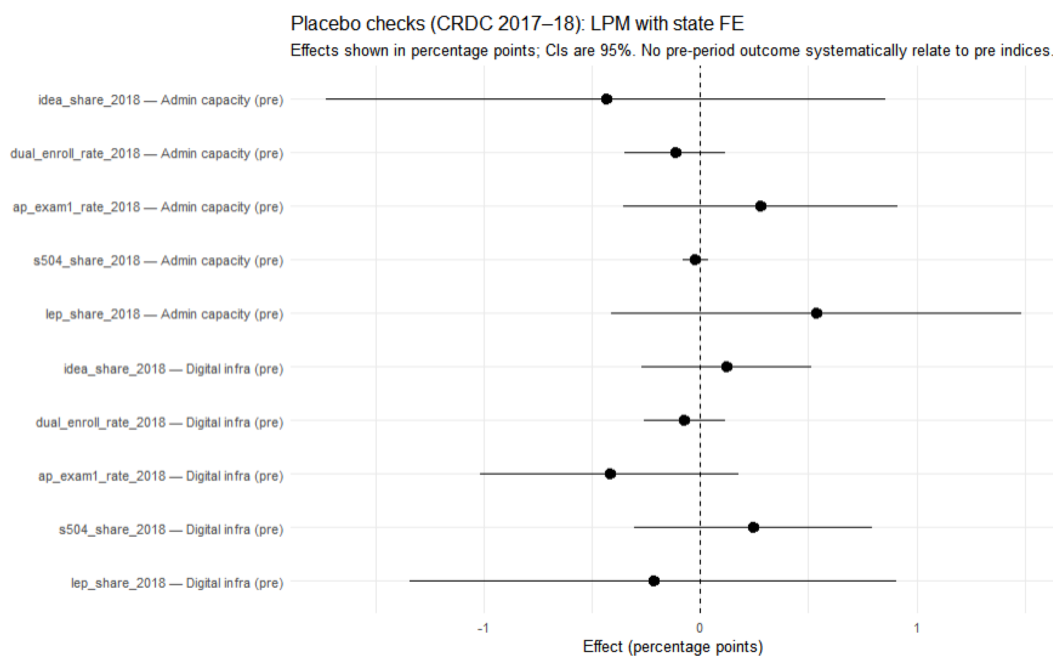

Figure 3: Placebo quasi-binomial odds ratios (enrollment-weighted)

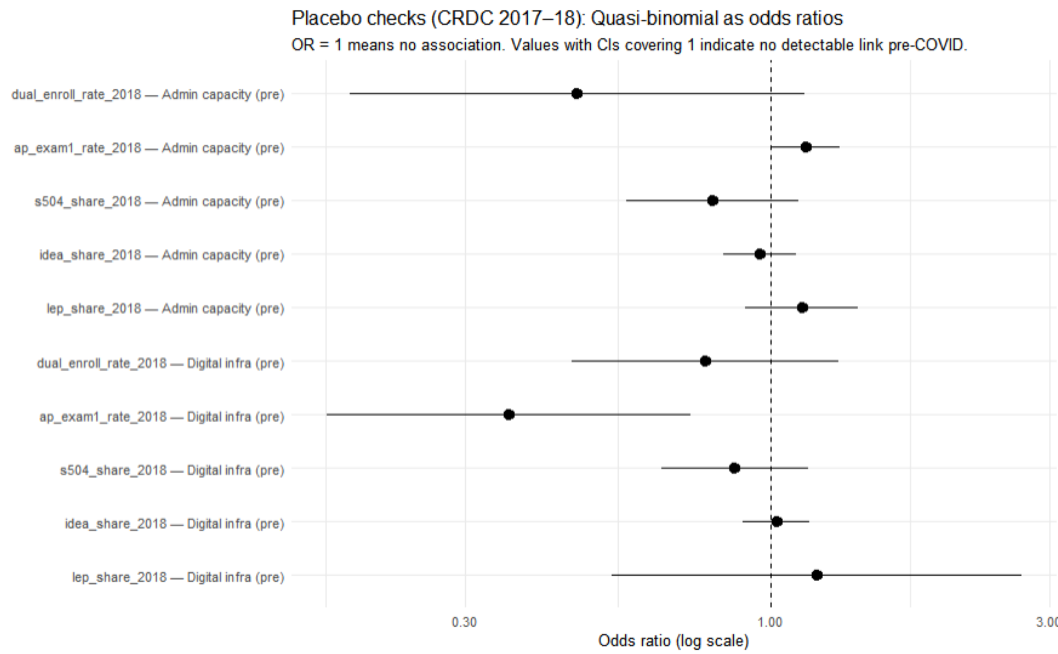

Figure 4: Robustness: Alternative outcomes (interpretation in percentage points vs thousands of student-weeks)

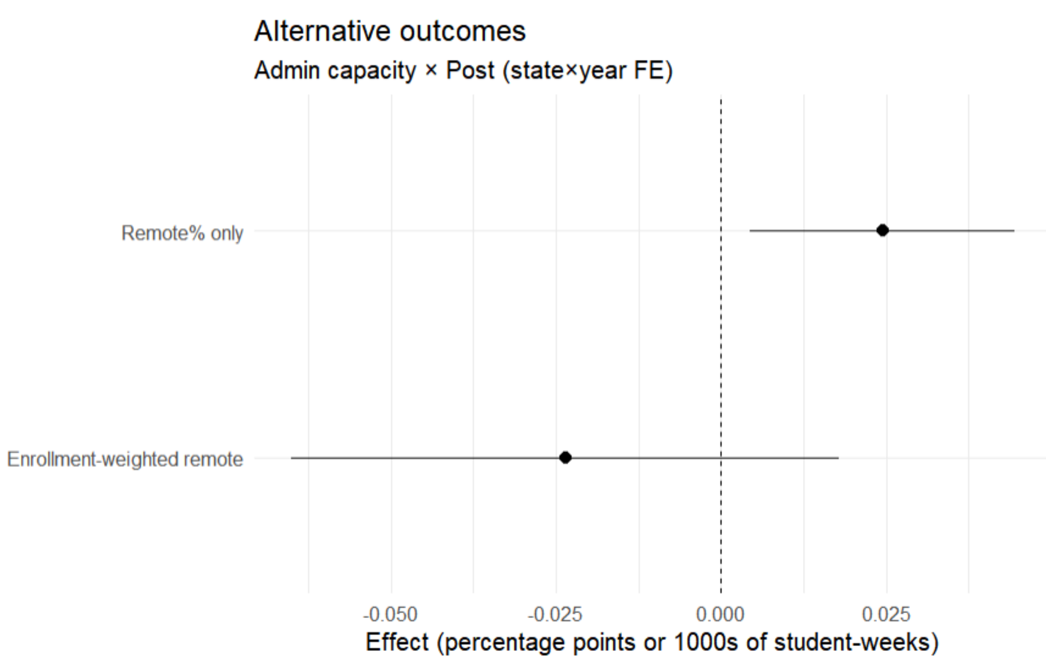

Figure 5: Robustness: Subgroup coefficient plot (Admin × Post under state×year FE)