The Bandwidth of Learning:

Digital Infrastructure, Test Scores, and the Pandemic Divide

The role of digital infrastructure in supporting education during the pandemic remains ambiguous, with studies attesting to both its capacity to mitigate learning disruptions and its potential to exacerbate existing inequalities. When infrastructure is widely available, there is evidence suggesting that digital tools can enhance resilience. Specifically, the OECD notes that schools with an existing online learning system were better able to transition into remote learning when the pandemic arrived, thereby limiting disruptions to education.[1] Similarly, UNESCO's Global Education Monitoring Report highlights cases where robust connectivity supported continuity of teaching, particularly in countries with strong integration of learning management systems.[2] However, UNESCO also warned that, in the midst of the pandemic, school closures risked reversing years of progress in mitigating educational inequality—with countries lacking digital infrastructure experiencing the most significant setbacks.[3] In countries with internet penetration below the global average–often low- or middle-income countries–the World Bank estimated that learning poverty (the inability of a 10-year-old to read or understand a simple text) increased significantly throughout the pandemic.[4] Even in developed economies, variations in students' access tended to influence learning outcomes. For example, the European Commission reported that disparities in broadband penetration among member states could lead to unequal opportunities for students, as variations in online learning participation occur.[5] Across the Atlantic, U.S. surveys conducted by the Pew Research Centre concluded that approximately one-third of lower-income households struggled to support their children's remote access due to insufficient digital access.[6] However, current literature has yet to identify whether these patterns are visible in standardised, cross-national measures of student achievement. Specifically, whether these patterns are consistent in both developing and developed economies. Also, existing studies have not concluded whether the pandemic altered the strength of the relationship between digital access and learning outcomes.

Leveraging student level data from the Programme for International Student Assessment (hereby PISA) in 2018 and 2022, in conjunction with data on mobile broadband coverage sourced from the International Telecommunication Union (hereby ITU), this paper evaluates whether mobile penetration, acting as a proxy for digital infrastructure, influences student achievement across mathematics, science, and reading, and whether this relationship intensified with the onset of the pandemic. A difference-in-difference methodology, accounting for country fixed effects, is employed to analyse over 730,000 students across fifty-five countries. This allows for the comparison of academic outcomes before and after the COVID-19 pandemic. The central research question is twofold: to what extent is digital infrastructure associated with student test performance across countries, and did the pandemic amplify its importance as countries transitioned to online learning due to lockdowns?

This paper is structured as follows: Section Two reviews existing research on digital infrastructure, learning outcomes, and the digital divide during the pandemic. Section Three outlines the empirical framework, describes the construction of variables, and details the PISA and ITU data sources. Section Four presents the regression results, while Section Five discusses the implications of the findings and addresses the limitations. Section Six concludes with a summary of the findings and directions for future research.

Literature Review

Digital Infrastructure and Learning Outcomes

Recent studies have reported mixed results regarding the role of digital infrastructure in education. Bulman and Fairlie identify widespread increases in computer and internet access, as well as their growing role in education, but conclude that information and communication technologies (hereby ICT) have ambiguous implications for learning outcomes.[7] Moreover, many studies have failed to identify consistent positive effects of digital integration and involvement. Escueta et al. demonstrate that the benefits of technology primarily emerge when it is integrated into structural learning, rather than when the technology and access are simply provided to the student.[8] Findings from school-level interventions bolster this argument: Comi et al. report that ICT investments, when combined with teacher training, can improve student outcomes in science and mathematics.[9] However, without pedagogical support, these investments yield negligible improvement or even negative results in some cases. Similarly, Hu et al. report that ICT investments, when combined with teacher training, can improve student outcomes in science and mathematics.[10] This suggests that digital technology does not serve as a substitute for traditional teaching methods, but instead amplifies the quality of teaching.

Reported in PISA 2018, the quality of school ICT infrastructure had a stronger association with student mathematics, science, and reading scores than teachers' (self-reported) readiness to use the technology.[11] Attending a school with an available online learning platform was correlated with higher reading performance, accounting for around 15 percent of the variance in performance between schools.

COVID-19 and the Intensified Digital Divide

The pandemic prompted an unprecedented volume of research on the role of digital infrastructure and education. Schleicher estimates that 1.6 billion students were affected by closures,[12] and OECD reports average mathematics scores declined by about 15 points between PISA 2018 and 2022.[13] At the micro level, Schachner et al. argue that providing network access in Chicago improved outcomes for high-achieving students, while reducing engagement for lower-achieving students.[14]

The majority of studies are either case-specific or aggregate, focusing on a specific school, city, or community, compared to those that focus exclusively on national averages. Relatively little research has examined whether improved infrastructure consistently mitigated pandemic-related declines by combining national digital infrastructure indicators with student-level performance data from different nations. This paper investigates this area by combining student data from PISA 2018 and PISA 2022 with mobile broadband coverage metrics from the International Telecommunication Union. It assesses the baseline impacts of infrastructure, as well as its function during COVID-19, in a large, internationally comparable sample.

Methodology and Data

Estimating Equations

To quantify the effect of digital infrastructure on student performance, this paper utilizes the following equation:

$$S_{c,i} = \beta_0 + \beta_1 I_{[2022]ic} + \beta_2 D_{ic} + \beta_3 (I_{[2022]ic} \times D_{ic}) + \beta_4 X_{ic} + \theta \underline{C}_{ic} + \varepsilon \quad (1)$$

where S_{ic} denotes the test score (mathematics, reading, or science) for a student i in the country c. D_{ic} is the student's residing country's digital infrastructure accounted for by the mobile network coverage at a given threshold–LTE/WiMAX. $I_{[2022]ic}$ is a dummy variable equal to 1 for observations from the PISA2022 dataset (after the COVID-19 pandemic) and 0 for PISA2018. The interaction term represents the interaction effect of digital infrastructure and COVID-19 on academic performance $I_{[2022]ic} \times D_{ic}$.

X_{ic} is a vector of student-level controlled variables, specifically gender, the highest parental education operationalised as the International Years of Schooling scale,[15] indicators for internet and computer availability at home, and the Economic, Social, and Cultural Status (ESCS) index. $\underline{C}_{ic}$ denotes country fixed effects, capturing time-invariant differences in education systems, culture, or unobserved infrastructure characteristics. ϵ is the error term of the model.

β_2 captures the impact of the level of digital infrastructure on test scores before the COVID-19 pandemic. The coefficient β_3 demonstrates whether this association strengthened or weakened in 2022, reflecting the extent to which reliance on digital tools during the pandemic altered the role of digital connectivity on learning outcomes.

Data

The data used in this study was obtained from the 2018 and 2022 Program for International Student Assessment and global network coverage data sourced from the International Telecommunications Union (ITU). PISA is an international, large-scale assessment administered every three years by the Organisation for Economic Co-operation and Development (OECD). PISA follows a two-stage stratified sampling design: schools are randomly selected within each participating country. Then, within each selected school, a random sample of approximately thirty-five students, aged between 15 years and 3 months and 16 years and 2 months, is chosen, regardless of their grade level. This ensures cross-country comparability based on age, bypassing potential differences in education systems.

PISA—the primary dataset—provides cross-nationally comparable data on the science, mathematics, and reading achievement results for students. It also provides further information on students' socioeconomic background, access to digital technology, sex, and other background control variables. Having the same questions and process, PISA 2018 and PISA 2022 provide insight into the magnitude and nature of the structural shift instigated by the COVID-19 pandemic.

Data from the ITU is used as a complementary source to provide a proxy for digital infrastructure, as the PISA studies did not collect data on country-level mobile network coverage. This dataset reports the proportion of the country's population covered by the various mobile technologies (i.e. 2G, 3G, LTE/WiMAX, 5G). This study focuses on LTE/WiMAX as the specific proxy for digital infrastructure because it is the minimum requirement for adequate video conferencing, streaming, and the majority of LMS systems.

While PISA 2018 and PISA 2022 encompass seventy-nine and eighty-one countries, respectively, and the ITU dataset provides mobile network data for nearly all UN member states, this study restricts its analysis to a subset of fifty-five countries to ensure consistent and complete data across the three sources. Specifically, countries were excluded if they lacked recent or reliable infrastructure data, did not participate in both PISA cycles, or were missing key student-level background variables.

The total number of students involved in the PISA 2018 and PISA 2022, restricting the student sample to the subset of fifty-five countries, is 733,207. Including only students with complete information across variables, the final sample sizes for PISA 2018 and 2022 are 395,957 and 337,250, respectively. This approach enables a consistent, policy-relevant comparison of how changes in national digital infrastructure interact with student outcomes across two critical time points: one preceding, and one following, the onset of the COVID-19 pandemic.

Table 1: Summary Statistics – PISA 2018

Statistic	Mean	St. Dev.	Min	Med.	Max
Gender (F=1, M=2)	1.50	0.50	1.00	1.00	2.00
Parent Education	13.51	2.88	3.00	14.50	16
Computer at Home	1.18	0.38	1.00	1.00	2.00
Internet at Home	1.08	0.28	1.00	1.00	2.00
Socioeconomic Index	-0.28	1.09	-7.75	-0.20	4.21
Number of Computers with Internet for students	87.97	149.21	0.00	48.00	3,938.00
Reading Score	458.92	106.09	54.67	458.19	887.69
Math Score	464.93	103.26	24.74	463.97	864.60
Science Score	463.80	101.41	58.74	461.18	879.29

Sample Size: 395,957

Table 2: Summary Statistics – PISA2022

Statistic	Mean	St. Dev.	Min	Med.	Max
Gender (F=1, M=2)	1.50	0.50	1.00	1.00	2.00
Parent Education	13.40	2.94	3.00	14.50	16.00
Computer at Home	1.20	0.40	1.00	1.00	2.00
Internet at Home	1.10	0.30	1.00	1.00	2.00
Socioeconomic Index	-0.34	1.12	-7.60	-0.27	4.21
Number of Computers with Internet for students	82.33	127.81	0.00	45.00	3,433.00
Reading Score	452.33	105.64	54.67	450.37	870.89
Math Score	457.36	102.49	24.74	455.57	863.08
Science Score	457.11	100.19	58.74	453.65	879.29

Sample Size: 337,250

Key Variables
Test Scores

The dependent variable in this study is student performance measured by PISA, which is subdivided into three academic disciplines: science, reading, and mathematics. In the PISA test, scoring is reported as plausible values (hereafter PVs) using *Item Response Theory*, rather than raw scores. For each subject, ten PVs ($m = 1, 2, \ldots 10$) are allocated for each student i in country c, thus denoted S_{ic}^{m}. These values are random estimates of each student's true score ϕ_{ic} , though unobserved in the PISA studies, and are based on:

i. the answers they gave to their subset of test questions (Y_{ic}^{obs})

ii. background information about the student, school, and country (Z_{ic})

$$S_{ic}^{m} \sim p(\phi_{ic} \mid Y_{ic}^{obs}, Z_{ic})$$

As each student only answers a subset of the test, the PVs extrapolate what they would have scored if they had taken the entire test.

In this study, however, only the first plausible value has been used (hence $m = 1$). This approach is adopted in applied research as a simplification, particularly when the primary focus is on cross-country or cross-year comparisons rather than particular estimates of within-country distributions. Using the first PV is not inherently invalid, as PVs are random draws from the same underlying distribution; each PV is an unbiased estimate of students' latent proficiency. Such an approach has been employed in prior studies, where only the first plausible value was used as a simplification for cross-country comparisons.[16]

Nevertheless, this choice does present an important limitation. By relying on a single PV rather than averaging across all ten PVs, the variance of student achievement may be underestimated. Furthermore, the standard errors of coefficient estimates may be distorted compared to those if Rubin's rules for multiple imputation were applied. Future studies should therefore consider incorporating all PVs, using established multiple-imputation techniques, to enhance the accuracy of both point estimates and uncertainty intervals.

Digital Infrastructure

The mobile network coverage within a given country is used as a proxy for the country's digital infrastructure, with 4G/WiMAX/LTE serving as a necessary threshold to support online learning. The ITU expresses this data as a percentage, representing the proportion of the population with access to WiMAX/LTE networks. Where multiple values are reported within the same year (e.g., mid-year and end-year), the annual average is used to minimise short-term fluctuations due to reporting schedules or seasonal variation in coverage expansion. For the purposes of descriptive analysis, a binary indicator was also created to capture whether a country meets a high-coverage threshold, defined as $D_{ic} \geq 0.99$—the median of the mobile network coverage across countries at the WiMAX/LTE level. This facilitates cross-country comparisons and the visualisation of countries passing or failing the digital infrastructure cutoff. The coverage measure was merged with the PISA dataset at the country–year level, such that all students i in country c in year t are assigned the same value of D_{ic}.

Control Variables

Several student- and school-level control variables are included in the analysis to account for background factors that may influence academic performance, including parents' highest level of education, gender, socioeconomic factors, computer and internet access at home, and the number of computers with internet available for students in school.

Gender is a dummy variable, denoting male or female, with values of 2 for male and 1 for female. Parental education is measured using PISA's *Index of Highest Parental Education (HISCED)*. Responses are first classified according to the International Standard Classification of Education (ISCED) categories and then converted to an equivalent number of years of education, taking into account country-specific school structures to maintain international comparability. Socioeconomic status is measured using PISA's index of ESCS, a standardised composite scale with an OECD mean of 0 and a standard deviation of 1 in the base year. These were all collected using PISA's student questionnaire.

Household access to technology is captured through two binary indicators: whether the student has a computer at home and whether they have access to the internet at home. While access to technology within the school environment is also accounted for.

Results

Table 3 presents the estimated coefficients for equation (1), obtained using OLS regression, which examines the relationship between digital infrastructure and academic performance before and after the COVID-19 pandemic. The models are estimated with country fixed effects to account for unobserved time-invariant heterogeneity across countries.

Table 3: OLS Coefficient Estimates

	Math (1)	Science (2)	Reading (3)	Math (4)	Science (5)	Reading (6)
Year (2022)	-3.2255 ***	-2.4618 ***	-2.9292 ***	-0.6300 **	-0.7721 ***	-0.8232 ***
Mobile Coverage	25.1332 ***	23.7141 ***	22.6280 ***	9.6685 ***	28.5944 ***	33.4916 ***
Mobile Coverage × Year (2022)	1.6301 ***	1.3856 ***	1.6650 ***	-0.5887	-0.5738	-0.6467
Intercept	546.8315 ***	550.3284 ***	602.0230 ***	542.2100 ***	526.924 ***	567.6218 ***
Computer at Home	-13.6036 ***	-11.2312 ***	-16.0794 ***	-11.8507 ***	-11.4026 ***	-12.9865 ***
Internet at Home	-12.3983 ***	-10.3911 ***	-16.6662 ***	-4.2824 ***	-5.0369 ***	-8.9864 ***
Socioeconomic Index	42.6354 ***	40.4645 ***	41.9484 ***	39.0549 ***	37.8235 ***	39.4424 ***
Country Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	733,207	733,207	733,207	733,207	733,207	733,207
Significance Levels				*p < 0.1; **p < 0.05; ***p < 0.01		

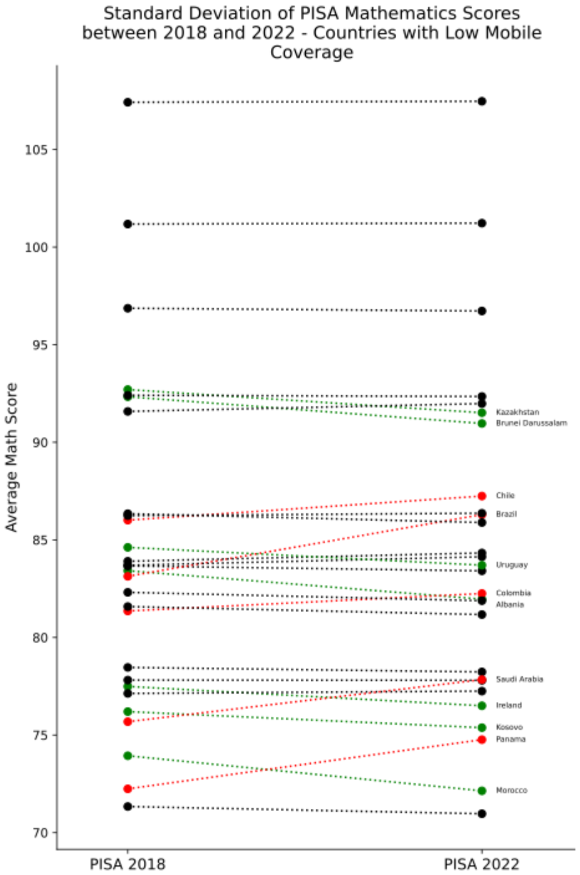
Evaluating the effect of mobile coverage (as a proxy for digital infrastructure) on academic outcomes, there is substantial evidence of performance differences: students in countries with mobile coverage (defined as 99 percent+ LTE/WiMAX coverage) are expected to score 25.1332, 23.7141, and 22.6280 points higher in mathematics, science, and reading, respectively. These effects are statistically significant at the 1 percent level of significance. The results shift with the inclusion of country fixed effects: the impact on mathematics decreases by more than half to 9.6685, while the estimated effect on reading increases to 33.4916; this change reflects the influence of unobserved country-specific factors. Overall, the estimates consistently indicate that digital infrastructure is positively associated with higher test scores.

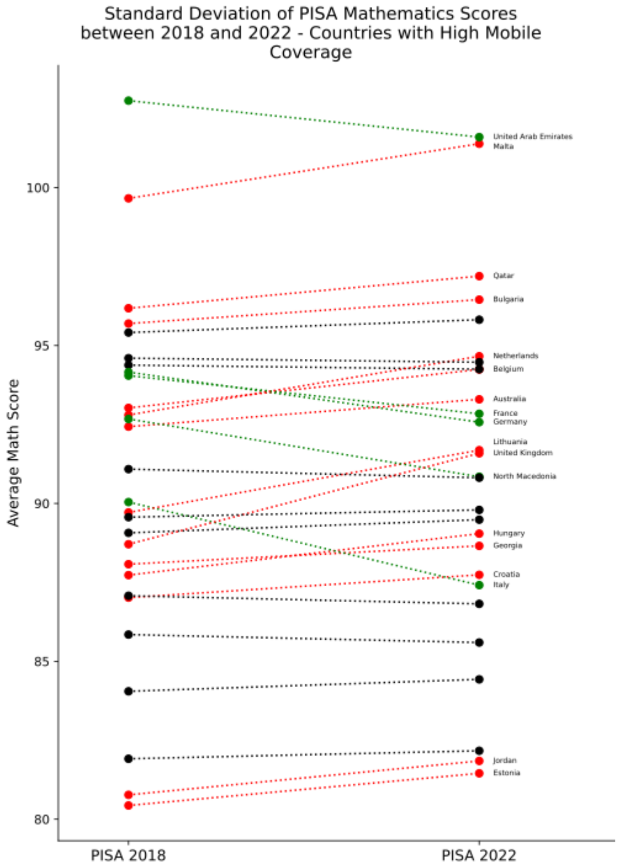
The 2022 indicator variable is negative for all three disciplines and statistically significant at the 1 percent level, except for mathematics with country fixed effects. Compared to 2018, academic performance in 2022 is estimated to be 3.2255, 2.4618, and 2.9292 points lower across mathematics, science, and reading, respectively. When country fixed effects are accounted for, the magnitude of the estimated decreases (–0.6300, –0.7721, and –0.8232); though, the effect remains negative. Hence, on average, test performance fell between 2018 and 2022, which is consistent with the disruptions associated with the COVID-19 pandemic.

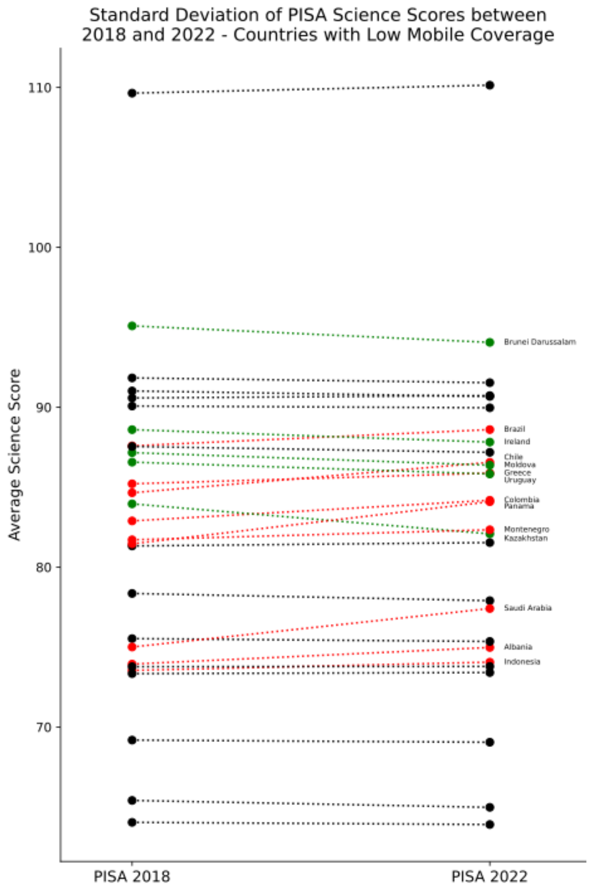
Notably, the interaction term between mobile coverage and the year 2022 is positive and statistically significant in the model without fixed effects (1.6301, 1.3856, and 1.6650 across mathematics, science, and reading, respectively), indicating that stronger digital infrastructure partially mitigated the observed performance decreases. However, when country fixed effects are accounted for, the interaction term becomes negative, though barely non-zero. Additionally, it is not significant at the 10 percent level, suggesting that variation within countries' mobile coverage had a limited role in offsetting pandemic-induced learning difficulties.

Control variables such as ‘Computer at Home,’ ‘Internet at Home,’ and ‘Socioeconomic Index’ are included in Table 3. Counterintuitively, the variables computer and internet at home were estimated with negative coefficients across all academic disciplines. This apparent negative association can be explained by the PISA coding: a student having internet/computer access at home was denoted as 1, while not having access was denotes as 2. Thus, the negative coefficient is a result of the PISA codebooks rather than a true negative correlation between computer and internet access and test scoring. Moreover, a one-unit increase in the socioeconomic status of a given student, on average, results in a score 39.0549, 37.8235, and 39.4424 points higher in mathematics, science, and reading, respectively, after accounting for country fixed effects.

Figures showcasing the standard deviation in test scores across the three disciplines are depicted below.


Standard Deviation of PISA Mathematics Scores between 2018 and 2022 - Countries with Low Mobile Coverage
Average Math Score
PISA 2018
PISA 2022
Kazakhstan
Brunei Darussalam
Chile
Brazil
Uruguay
Colombia
Albania
Saudi Arabia
Ireland
Kosovo
Panama
Morocco


Standard Deviation of PISA Mathematics Scores between 2018 and 2022 - Countries with High Mobile Coverage
Average Math Score
PISA 2018
PISA 2022
United Arab Emirates
Malta
Qatar
Bulgaria
Netherlands
Belgium
Australia
France
Germany
Lithuania
United Kingdom
North Macedonia
Hungary
Georgia
Croatia
Italy
Jordan
Estonia


Standard Deviation of PISA Science Scores between 2018 and 2022 - Countries with Low Mobile Coverage
Average Science Score
PISA 2018
PISA 2022
Brunei Darussalam
Brazil
Ireland
Chile
Moldova
Greece
Uruguay
Colombia
Panama
Montenegro
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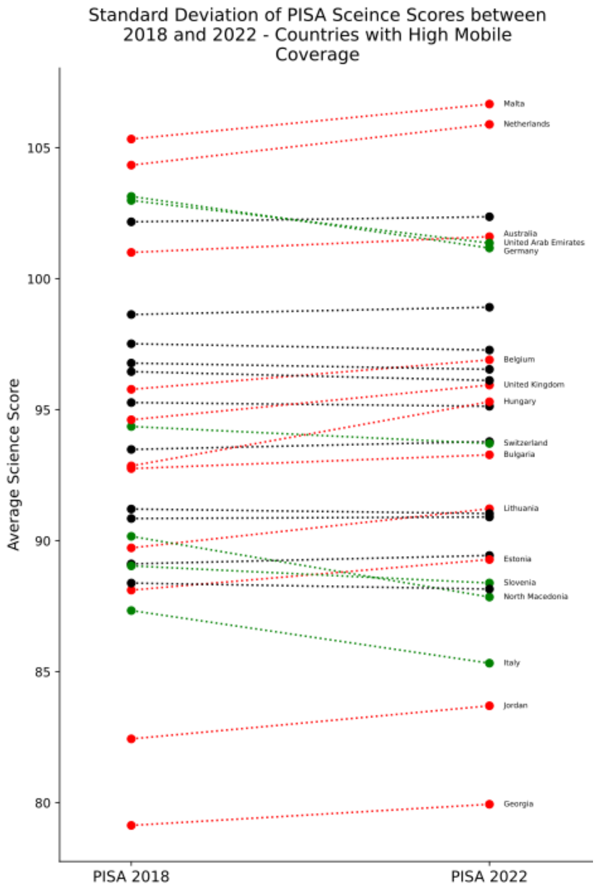
Saudi Arabia
Albania
Indonesia


Standard Deviation of PISA Sceince Scores between 2018 and 2022 - Countries with High Mobile Coverage
Average Science Score
PISA 2018
PISA 2022
Malta
Netherlands
Australia
United Arab Emirates
Germany
Belgium
United Kingdom
Hungary
Switzerland
Bulgaria
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Estonia
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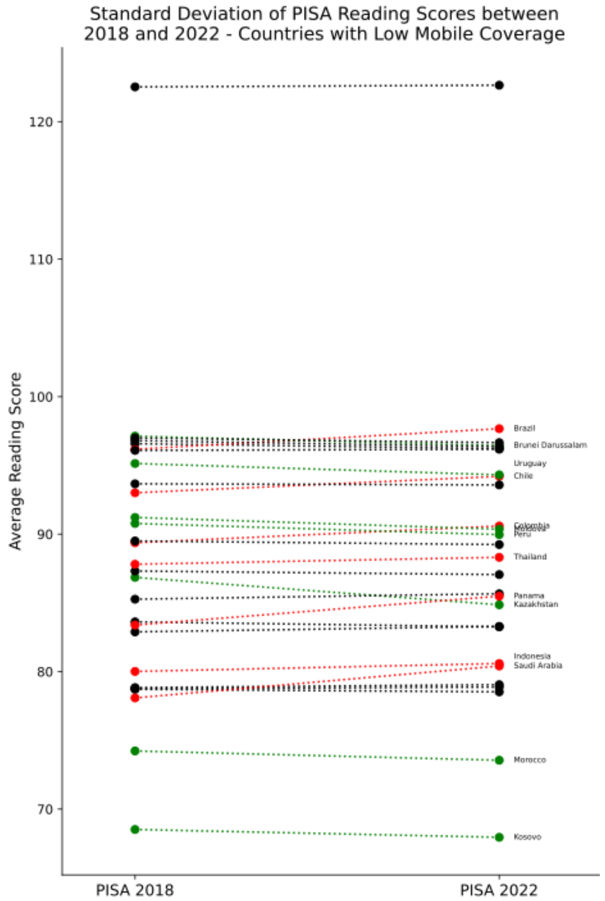
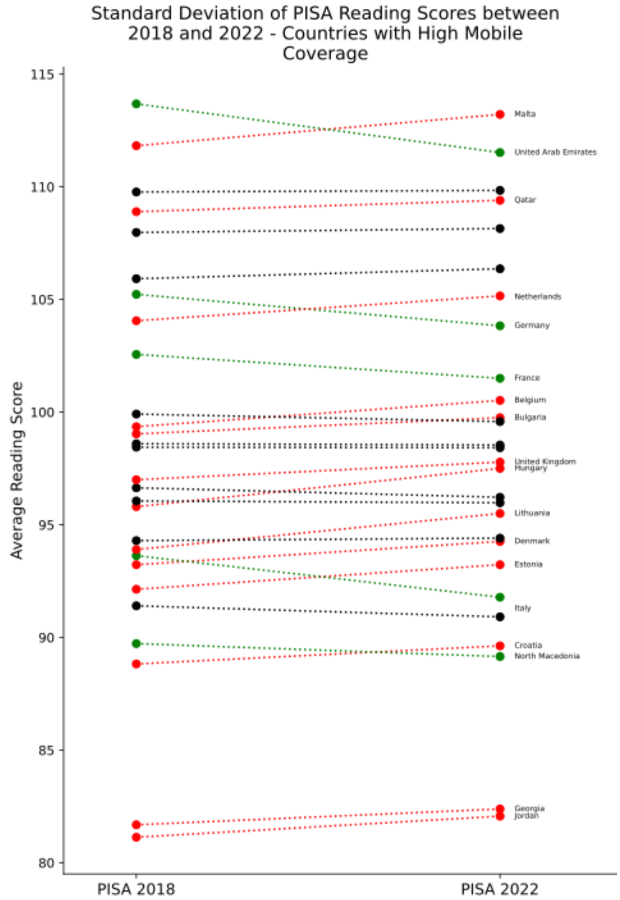
North Macedonia
Italy
Jordan
Georgia





The above graphs depict the standard deviation of test scores across the three disciplines in 2018 and 2022. Each academic discipline is subdivided into countries that have high mobile coverage (displayed on the right-hand side) and those with low coverage (on the left-hand side). Countries with high coverage have a higher standard deviation in test scores, indicative of higher inequality. Furthermore, the change in inequality appears more negative than positive (higher standard deviations in 2022 than in 2018), though the results are mixed. Some notable exceptions to this negative trend were Italy, the UAE, Germany, and North Macedonia, whose students had consistently lower standard deviations in test scores despite the pandemic. The range of standard deviations is also considerably higher in countries with high mobile coverage than in those with lower coverage; furthermore, the change in standard deviations is more negligible in countries with lower coverage. This pattern is more prevalent within reading scores than any other discipline.

In short, the standard deviation is higher and varies more in countries with high mobile coverage, while it is lower in countries with less coverage, indicating less variation.

Discussion

This study quantifies the extent to which digital infrastructure has a positive and significant effect on academic outcomes. The impact of digital infrastructure on academic outcomes varies once country fixed effects are considered, reflecting how mobile connectivity interacts with time-varying country variables such as education budgets and teacher digital training. Without country fixed effects, the mathematics score increase associated with improved digital connectivity is approximately 25; the estimate falls to ~9.5 after accounting for country fixed effects. In contrast, the estimated impact of mobile connectivity on reading scores increases from ~22.5 to ~33.5 after accounting for country fixed effects. This variation demonstrates the role of omitted variable bias: without fixed effects, time-invariant country-level factors correlated with both infrastructure and test outcomes, such as institutional quality and cultural emphasis on specific academic subjects, may inflate the estimated relationship. Another possible controlled variable to be incorporated in future studies is government funding within the education sector, as differences in fiscal commitment toward schooling are strongly correlated with both the rollout of digital infrastructure and student achievement.[17]

The measurement level of digital infrastructure is a key consideration. This study measures mobile network coverage at the country level but applies it to student-level outcomes. Country-level data enable cross-national comparisons but inevitably overlook within-country variation in access and quality of connectivity. For example, in a single country, almost all students in urban centres may have high-speed mobile connectivity, whereas those in rural or remote regions may have no access at all; the current classification method would, however, denote the whole country as being uniformly connected. Such aggregation distorts results by assigning national averages to students whose actual digital access differs. Future research could incorporate sub-national data on digital infrastructure or household-level mobile connectivity to capture the discrepancies of digital access across different student populations within a country.

Comparing PISA 2018 and 2022, represented by $I_{[2022]ic}$ and the interactive term $I_{[2022]ic} \times D_{ic}$, highlights how the COVID-19 pandemic (through lockdowns, distance learning, and school closures) altered the role of digital infrastructure in shaping academic outcomes. The pandemic functioned as an exogenous shock, forcing education systems worldwide to adopt online and hybrid modes of learning, institutionalising a reliance on digital tools. The negative coefficient $I_{[2022]ic} \times D_{ic}$ reflects the general decline in test performance across countries between 2018 and 2022. However, the positive and significant coefficient on the interaction term $I_{[2022]ic} \times D_{ic}$ indicates that students with access to digital infrastructure were able to mitigate the decline.

Expanding digital access through targeted policies, investments, and subsidies can help alleviate inequalities and enhance the resilience of education systems. This should be undertaken not only as a preventative measure against future exogenous shocks but also to improve academic outcomes, as this study showcases a positive correlation between mobile coverage and test performance, even before COVID-19.

It is difficult to hypothesise precise causes for the discrepancies across disciplines (mathematics, science, and reading) due to the variation in individual countries' fixed effects. However, a possible explanation is that mathematics, and science to a lesser extent, generally rely heavily on structured pedagogy, teacher guidance, and curriculum sequencing. This means that digital access alone may not result in higher academic performance. On the other hand, reading proficiency is often acquired through independent practice, and digital connectivity can expand this process. Previous studies support this interpretation: analyses of technology integration in classrooms have found that digital tools exert stronger effects on language acquisition and literacy than on mathematical reasoning, which depends more on teacher-guided instruction.[18]

Conclusion

In analysing the effect of digital infrastructures on test scores through an observational study, this paper establishes substantial evidence of a positive relationship between mobile coverage and improved test scores across mathematics, reading, and science. It also found an overall decrease in test scores from 2018 to 2022 and notably demonstrated that established digital infrastructure had a small effect in mitigating this decline.

The findings also highlight the nuanced way in which digital access interacts with different academic subjects since the positive effects of mobile connectivity were not uniform. This suggests that digital connectivity has various functions and effectiveness depending on the discipline. The most significant effect was on reading, with a 33.4916-point increase in test score when a student had 99 percent or greater mobile coverage. Mathematics was the smallest, with an estimated 9.6685-point increase in score. To understand the context of these increases, they represent a 5.9 percent and 1.8 percent increase in average score, respectively. The COVID-19 pandemic is treated as an exogenous shock in this study, resulting in school closures and a structural shift to online learning. When it occurred, resulting test scores from the PISA 2022 study, when compared to the PISA 2018 study, decreased across all three academic disciplines, though to a lesser extent when country fixed effects were accounted for. In terms of digital infrastructure mitigating the pandemic's effects, the results were mixed. The results, without country fixed effects, show a statistically significant and positive interaction between the pandemic and mobile coverage, indicating that having access to digital infrastructure partially mitigates some of the decline in test scores. Though when country fixed effects are considered, the statistical significance is relinquished, and the coefficients become both barely non-zero and negative.

This study is limited by its use of country-level infrastructure measures applied to individual students and by potential omitted variables such as government education spending, institutional quality, or teacher preparedness. These factors could influence learning outcomes and explain nuances in the varying effectiveness of digital infrastructure in particular subjects. Therefore, an investigation that combines individual or household-level measures of connectivity with expanded contextual data will better capture the heterogeneity of effects. Future studies could also examine how digital infrastructure influences educational pathways beyond test scores, including tertiary enrolment, skills acquisition, and the labour market.

ENDNOTES

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