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Impact of the COVID-19 Pandemic on Thailand's Educational Inequality: Evidence from PISA Assessment in Mathematics

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Abstract

This study employs quantile regression to analyze the impact of COVID-19 on educational inequality in Thailand, utilizing the country's PISA mathematics scores from 2015, 2018, and 2022. It examines the determinants of student performance scores to reflect how the COVID-19 pandemic, which necessitated a shift from in-person to online learning, affected students at different performance levels. By doing so, it aims to elucidate the pandemic's influence on the learning gap among Thai students. The analysis reveals that socioeconomic status is a primary and persistent driver of low PISA mathematics achievement. The pandemic exacerbated pre-existing educational inequalities, primarily by widening the digital divide and disproportionately benefiting students with superior digital access. This intensified a persistent pattern of disparity tied to factors like school location and affiliation, which in turn necessitates targeted policy interventions to address these structural differences. Complementary Blinder-Oaxaca decomposition of outcome disparities between high- and low-achieving schools further confirms socio-economic status as a key driver of inequality and highlights the pandemic's role in widening digital divides. A considerable unexplained component suggests the potential influence of unmeasured heterogeneity, encompassing both inherently unquantifiable factors and the persistent effects of indirect discrimination as well as historical contexts.

Keywords: Education Inequality in Thailand, PISA Scores, Socioeconomic Status, Digital Divides

JEL Classification: I21, I24, I28, D63

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การเปลี่ยนแปลงของความเหลื่อมล้ำทางการศึกษาก่อนและหลังการระบาดของโควิด-19 ผ่านคะแนน PISA

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บทคัดย่อ

งานวิจัยนี้ใช้การวิเคราะห์การถดถอยเชิงควอนไทล์ (quantile regression) ศึกษาผลกระทบของการแพร่ระบาดโรคโควิด-19 และปัจจัยที่มีอิทธิพลต่อความเหลื่อมล้ำทางการศึกษาในประเทศไทย โดยอาศัยข้อมูลคะแนน PISA วิชาคณิตศาสตร์ในปี ค.ศ. 2015 2018 และ 2022 ผลการศึกษาพบว่าเศรษฐสถานะยังคงเป็นปัจจัยหลักที่ส่งผลให้คะแนน PISA วิชาคณิตศาสตร์อยู่ในระดับต่ำอย่างต่อเนื่อง นอกจากนี้การแพร่ระบาดยังได้ซ้ำเติมความเหลื่อมล้ำทางการศึกษาที่มีอยู่เดิม โดยเฉพาะการขยายช่องว่างทางดิจิทัล สถานการณ์นี้ยิ่งทำให้ความเหลื่อมล้ำที่เป็นผลสืบเนื่องมาจากปัจจัยด้านสถานที่ตั้งและสังกัดของโรงเรียนมีความรุนแรงมากขึ้น ซึ่งชี้ให้เห็นถึงความจำเป็นเร่งด่วนในการดำเนินนโยบายเชิงรุกแบบเจาะจงแก้ไขปัญหาความเหลื่อมล้ำเชิงโครงสร้างเหล่านี้ การวิเคราะห์ในส่วนของ Blinder-Oaxaca Decomposition ระหว่างกลุ่มโรงเรียนที่มีผลสัมฤทธิ์สูงและต่ำ เน้นย้ำว่าเศรษฐสถานะเป็นปัจจัยสำคัญของความเหลื่อมล้ำ และโรคระบาดเป็นปัจจัยสำคัญในการขยายช่องว่างทางดิจิทัล ทั้งนี้ ส่วนที่ไม่สามารถอธิบายได้ของตัวแปรสะท้อนถึงผลกระทบอันเป็นผลพวงมาจากปัจจัยเชิงคุณภาพนอกเหนือแบบจำลอง เช่น การเลือกปฏิบัติทางอ้อมและบริบทเชิงประวัติศาสตร์

คำสำคัญ: ความเหลื่อมล้ำทางการศึกษาไทย คะแนน PISA เศรษฐสถานะ ช่องว่างทางดิจิทัล
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1. Introduction

Human capital development through education is a well-established engine of economic progress, enabling countries to overcome poverty and the middle-income trap (Agenor, 2017). Empirical evidence suggests that educational attainment accounts for a significant portion (around 65%) of wage disparities, with family background explaining the remainder (Psacharopoulos, 2006). However, educational inequality remains a persistent challenge, particularly in developing economies. Thailand provides an interesting case study that could be relevant to developing countries. The government has prioritized education through initiatives like the 15-year free education program and the Student Loan Fund, and the 2023 national education budget is relatively substantial among the top five in government budget allocation by ministries (Figure 1). Nevertheless, a comparison with ASEAN neighbors reveals that Thailand's education expenditure as a percentage of GDP is lower than that of Malaysia, the Philippines, Indonesia, and Vietnam (World Bank, n.d.; Figure 2), raising questions about the intensity and the quality of investment relative to regional peers despite stated policy priorities.

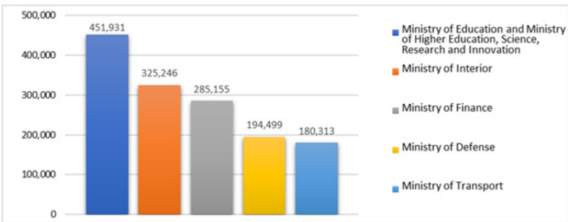

Figure 1. Government Budget Allocation Classified by Ministries, 2023 (Million Baht)

Source: National Statistical Office (2024)

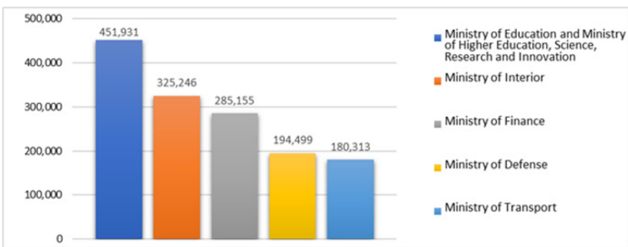

Figure 2. Education Budget (% of GDP)

Notes: Data represent ASEAN countries in 2022, with the following exceptions due to data availability: Brunei (2016), Indonesia (2021), Cambodia (2021), and Myanmar (2019).

Source: Data from World Bank (n.d.)

Thailand's educational landscape in 2021 presented a dichotomy. While a significant portion of the school-age population, 81.75%, was enrolled in formal education, approximately 10.89% participated in non-formal education. The average schooling attainment for the Thai population aged 15 years and over stood at 8.9 years in the same period (National Statistical Office, Department of Provincial Administration, and Ministry of Interior, 2023). However, despite this level of participation, concerns regarding educational quality persist. The national average on the Ordinary National Educational Test (O-NET) for grade 12 students in 2021 remained below 50 out of a possible 100 points across all subjects (Figure 3). Moreover, substantial regional disparities in educational outcomes were apparent, with students in Bangkok consistently outperforming those in other regions on the O-NET (National Institute of Educational Testing Service, 2021).

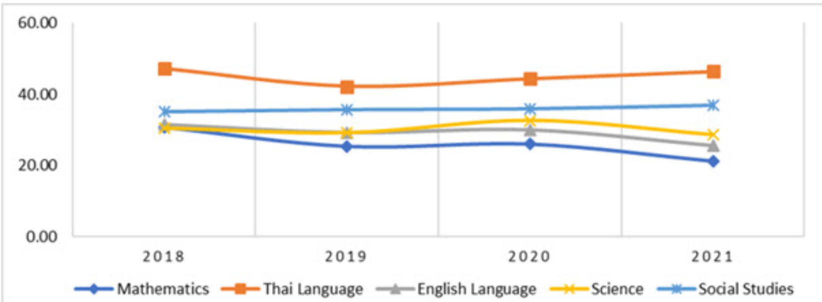

Figure 3. O-NET Test Scores of Grade 12, 2018-2021

Source: The National Institute of Educational Testing Service (Public Organization) (2021)

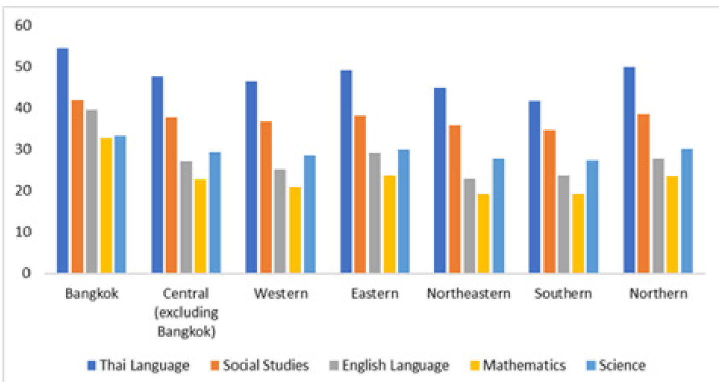

Figure 4. O-NET Test Scores of Grade 12, by Region, 2021

Source: National Institute of Educational Testing (Public Organization) (2021)

The Programme for International Student Assessment (PISA), a key indicator of educational quality administered by the Organisation for Economic Co-operation and Development (OECD) across three core subjects (reading, mathematics, and science), reveals a concerning trend for Thailand. The average PISA score of Thai students consistently falls below Level 2, which is the baseline proficiency indicating the ability to interpret and utilize basic information in familiar contexts, lags behind the OECD average. In typical circumstances, the mean examination score for Thailand is generally low. However, beneath this low average, significant disparities exist in student performance. These inter-student variations are attributable to several factors, including differences in the school's geographical location (urban versus rural), the socioeconomic status of the students' families, and the administrative affiliation of the school.

Notably, the PISA 2022 assessment, the first conducted post-COVID-19 pandemic and its widespread educational disruptions including school closures in Thailand, highlights significant disparities when students are disaggregated by school affiliation. Students attending science and demonstration schools demonstrate scores exceeding the OECD average, with a substantial proportion achieving Level 5-6 proficiency, as reported by the Institute for the Promotion of Teaching Science and Technology (IPST, 2024). Conversely, students from other school types generally score below the OECD average. The disparity in student examination scores between the aforementioned school affiliations has persisted over time.

It is crucial to note, however, that the sample coverage rate for Thailand in PISA 2022 was 72%, lower than the OECD average of 88%, suggesting that the exclusion of approximately one-quarter of Thai students likely underestimates the extent of the challenge. Examining trends across recent assessments (2015, 2018, and 2022) further reveals persistent within-country inequalities, with students in schools located in urban areas consistently outperforming their rural counterparts across all three PISA subjects. Moreover, significant disparities persist across various dimensions, including socioeconomic status, indicating substantial educational inequality within the country (IPST, 2024).

The selection of the PISA scores for this study is fully justified by its comprehensive and distinctive features. Firstly, PISA is specifically designed as a high-quality international assessment to measure and benchmark the performance of educational systems across participating nations. Secondly, the assessment's consistent administration every three years since 2000 provides a robust, reliable, and unique longitudinal dataset for analyzing trends over time. Thirdly, PISA's methodology involves collecting extensive contextual data on test-takers' backgrounds, learning environments, and other non-cognitive factors, which is crucial for identifying the specific variables that influence student outcomes. Finally, as a standardized international test, PISA allows for direct and meaningful global comparisons, which greatly enhances the utility of the data. This multidimensional scope supports a wider variety of in-depth analyses and research sub-questions. The resulting findings enable effective benchmarking against comparable countries and provide policymakers with actionable, empirically-grounded evidence to formulate targeted and effective developmental strategies.

This study aims to delve into the factors influencing PISA mathematics scores across different performance levels (high, medium, and low). Specifically, it seeks to identify the determinants of mathematics achievement for students at various quantiles of the score distribution. Additionally, the study investigates the differential impact of these factors on average mathematics scores before and after the COVID-19 pandemic. To achieve these aims, the study pursues two main objectives. The first objective is to analyze the effects of various factors on mathematics test scores at different points of the score distribution (quantiles) using Quantile Regression. The second objective is to compare the impact of the COVID-19 pandemic on average PISA mathematics test scores and to decompose the differences in scores between students in high-performing and low-performing school groups before and after the pandemic using the Blinder-Oaxaca decomposition method.

2. Literature Review

2.1 Factors Affecting Education Inequality

Education inequality in Thailand has been examined through various dimensions. Using the Gini coefficient, Prasartpornsirichoke and Takahashi (2013) found regional disparities, with Bangkok and its metropolitan area exhibiting the lowest inequality, while the northern region displayed higher levels. Similarly, Srisuchart (2016) noted that while the average years of schooling showed limited variation nationally, regional disaggregation revealed greater inequality in the northern region. Analysis of 2011 census data indicated that higher average household income is associated with decreased education inequality (Prasartpornsirichoke and Takahashi, 2013). This aligns with Thaweepreeda (2016), who, employing the Human

Opportunity Index (HOI), identified household income, family size, and residential area as significant determinants of access to education.

Studies utilizing PISA scores to analyze the drivers of educational inequality typically categorize influencing factors into school, family, student, and other characteristics. Regarding school factors, Ruangrat (2013), using Data Envelopment Analysis (DEA) and a Tobit model, found that increased teacher numbers, teaching resources, and school size positively impacted school efficiency, while greater dispersion in Maths and English scores had a negative effect. Pholphirul and Teimtad (2018) observed a trend of higher test scores for students in larger schools. Quantile regression analysis by Lounkaew (2013) indicated that school quality, the number of computers, and teaching media had a more pronounced effect on test scores for students in the bottom 30th percentile. Long-term positive impacts of increased teaching hours on test scores were identified by Blundell et al. (2022), and Barrera-Osorio et al. (2011) highlighted the role of teaching methods.

School location consistently emerges as a significant factor. Lounkeaw (2016) documented a performance gap between urban and rural students in the 2009 Thai PISA assessment, with Blinder-Oaxaca decomposition attributing the largest share of this gap to school quality, particularly for higher-achieving students. Chansompoth (2022) confirmed lower scores in rural schools in the 2018 PISA, noting a shift in the dominant school-related factors influencing score differences from school location and size (2009-2012) to quality-related factors like the student-to-teacher ratio (2015-2018). Rianngern (2022) similarly found that student-to-teacher ratio, internet-connected computers, school size, and location affected school production efficiency, with urban schools outperforming rural ones. International evidence from Colombia (Ramos et al., 2012) also showed lower PISA scores for rural students across subjects. Barrera-Osorio et al. (2011) identified school-related factors as drivers of score increases in Indonesia’s 2003 and 2006 PISA assessments.

Family factors also play a crucial role. Pholphirul and Teimtad (2018) found that students living with both parents tended to achieve higher scores, with parental education levels being influential. Chansompoth’s (2022) analysis of Thai PISA data (2009-2018) highlighted the increasing contribution of family quality factors, such as parents’ education, to educational inequality during the 2015-2018 period. Studies in developing countries suggest that socioeconomic status has a more substantial impact on educational outcomes than school-related factors. (Buchmann and Hannum, 2001), consistent with Liu's (2024) finding that family income affects academic accessibility. Conversely, research in the United States indicates that area and population factors, potentially reflecting socioeconomic disadvantages in rural areas, influence academic success. (Roscigno et al., 2006). Lathapipat (2010) found that spatial disadvantage negatively affected high school continuation rates in Thailand, with household income and parental education also being significant. Lounkeaw (2013) demonstrated the consistent significance of socioeconomic status on test scores across all student performance levels, a finding in line with Ramos et al. (2012) in the context of urban-rural PISA score differences in Colombia.

Student factors, such as gender, exhibit varying influences across countries. Munir & Winter-Ebmer (2018) found that males tended to outperform in mathematics, while females excelled in reading, particularly among lower-achieving students. In contrast, Barrera-Osorio et al. (2011) observed higher scores for female students in Indonesia.

Government policies also impact educational outcomes. Rianngern (2022) compared PISA scores (2006-2018) using Scholastic Frontier Analysis (SFA) to assess the impact of Thailand's 15-year free education policy on educational efficiency in urban and rural schools. The study found greater production efficiency in urban schools but a larger positive change in test scores in rural schools following the policy's implementation.

2.2 The Impact of the COVID-19 Pandemic on Educational Outcomes

The COVID-19 pandemic precipitated a global disruption across numerous sectors, with education experiencing particularly profound and multifaceted impacts on student learning. Beyond the immediate shift to remote instruction platform, the pandemic has exacerbated pre-existing educational inequalities. The rapid adoption of online learning modalities disproportionately affected students from lower socioeconomic backgrounds, who often lack consistent access to the necessary technological infrastructure (Hoofman & Secord, 2021). Even among students with technological access, Weerapan & Thinsandee (2021) highlight the potential for diminished learning outcomes due to the reduced human interaction inherent in online environments.

Empirical evidence from various contexts underscores the heterogeneous effects of the pandemic on student learning. Studies in developed countries indicate that pandemic-related disruptions, including school closures, contributed to increased dropout rates, particularly among students from rural areas facing infrastructural disadvantages (Tadesse & Muluye, 2020). Blundell et al. (2022) document a significant decline in learning hours in England during periods of school closure and online learning, with the adverse effects disproportionately concentrated among students from the poorest socioeconomic strata, raising concerns about long-term educational attainment.

Analysis of PISA test scores by Coryton (2024) reveals a concerning downward trend in educational performance across many countries since 2018. Coryton further notes that the resilience of students from high-income families, who often benefit from private tutoring, may mask the true extent of the pandemic's impact on the broader public education system. Interestingly, findings suggest that the effectiveness of online learning varies across countries, with evidence indicating a more pronounced negative impact in countries that previously exhibited higher reading test scores. This suggests that the transition to remote instruction may have differentially affected even seemingly high-performing education systems.

This body of literature collectively points to the significant and unequal consequences of the COVID-19 pandemic on educational outcomes, warranting further investigation into the long-term country-specific economic and social ramifications of these disruptions.

3. Theoretical Framework, Data and Methodology

3.1 Education Production Function

A production function serves as a technical representation delineating the relationship between inputs and outputs in the production process, with applicability across diverse economic sectors. Grounded in this fundamental concept, the education production function specifically investigates the relationship between educational inputs and outputs. Drawing upon human capital theory, as initially articulated by Hanushek (1979), this relationship can be formally expressed in equation (1).

$$A_{it} = f(B_i^{(t)}, P_i^{(t)}, S_i^{(t)}, I_i) \qquad (1)$$

In equation (1), A_{it} represents educational achievement of students i at time *t*, $B_i^{(t)}$ is a vector of a family factor of student i at time *t*, $P_i^{(t)}$ is a vector of a social factor of student i at time t, $S_i^{(t)}$ is a vector of a school factor of students i at time *t*, I_i is a vector of a talent factor of student i. However, educational achievement at time t is not only the result of input at time *t*, but also the result of inputs accumulated from the past, which can be represented equation (2).

$$A_{it} = f(B_i^{(t-t*)}, P_i^{(t-t*)}, S_i^{(t-t*)}, I_i, A_{it*}) \qquad (2)$$

In equation (2), *t* represents the time of the measurement period, and *t** represents a point in the past. Therefore, (*t* - *t**) represents the accumulated input from the past up to the measurement period. Modeling educational achievement A_{it} requires accounting for a multifaceted set of determinants. These include individual schooling inputs, as well as difficult-to-measure family $(B_i^{(t)})$, social $(P_i^{(t)})$, and school $(S_i^{(t)})$ factors. Empirical analyses often rely on proxies such as parental education and household wealth for family background and endowment, residential environment and peer influences for social context, and public educational budgets or measures of school staffing for school resources.

3.2 Data and Variables

This study leverages data from PISA, a triennial survey conducted by the OECD since its inception in 2000. The empirical analyses, using econometrics in Sections 3.3 and 3.4 model Thailand's PISA mathematics scores in 2015, 2018, and 2022 *(MATHi)* as a function of the independent variables and their hypothesized effects presented in Table 1.

Table 1. Independent Variables and Hypotheses on Dependent Variable, PISA Mathematics Scores

Independent variables	Description	Hypothesized effects on Dependent Variable
ESCS_Q	PISA's Economic and Social Status Index (Socioeconomic level) of Students, which is divided into 10 quantiles	(+) Students in higher socioeconomic level tend to have higher test scores.
DEVICE	Accessibility to electronic devices (including laptops and tablets), 0 = non-accessible, 1 = accessible	(+) An accessibility to electronic devices, smartphones and internet reflects the families educational resource tends to have positive effect on test score.
SMARTPH	Accessibility to smartphones for student i, 0 = non-accessible, 1 = accessible	
SCHLO	School location, 0 = rural, 1 = urban	(+) Students in urban areas tend to have higher score than those in rural areas.
SCHSIZE	School size, 0 = less than 119 students (small-size), 1 = 120-719 students (middle-size), 2 = 720-1,679 students (large-size), 3 = 1680 students or more (extra-large -size)	(+) Large schools tend to have more resources and students tend to have higher scores.
SCHTPYE	School type, 0 = private school, 1 = public school	(+) On average, at higher level of education, students in public schools tend to have higher scores than students in private schools.
SCHTRA	School affiliation, 0 = school with different affiliations other than 1, 2 or 3, 1 = private school, 2 = school under the Secondary Education Administration Bureau (SEAB), 3 = science and university-affiliated demonstration school	(+) Students in sciences and demonstration schools tend to have higher scores.
CLASSSIZE	Class size, 1 - 99	(+) The study hypothesizes heterogeneous effects of class size on student test scores in Thailand, contingent on the initial level of resources and existing class sizes. Given the observation that urban schools operate with larger classes while rural schools have smaller classes amidst teacher shortages, it is argued that increasing class size in resource-constrained rural schools may lead to gains in average test scores by alleviating inefficiencies in teacher allocation.
ST_RATIO	Student-to-teacher ratio, 1- 99	(-) Higher student-to-teacher ratio can lead to lower teaching quality, as it reduces students' access to teachers and the thoroughness of instruction in class. As a result, student test scores may decline.
GENDER	Gender, 0 = female, 1 = male	(+, -) Gender influences subject-specific test performance, with females performing better in reading and males performing better in science and mathematics.
AGE	Age	(+) Older students at the time of testing typically achieve higher scores, as age often corresponds with higher grade level.

3.3 Quantile Regression

To investigate the potentially heterogeneous relationships between determinants and educational outcomes, this study employs quantile regression (QR). Developed by Koenker and Bassett (1978) as an extension of median regression, QR enables the estimation of co-variate effects at various points of the conditional distribution, offering a more comprehensive analysis than traditional mean regression (MR). This is particularly relevant in contexts where the impact of independent variables may differ across the achievement spectrum. QR relaxes several key assumptions of MR, including distributional form and homoscedasticity, and is robust to outliers, making it appropriate for analyzing rich micro-data such as PISA. The PISA dataset for Thailand, with its substantial sample size (around 7,000-9,000 students per year) and broad range of performance, provides a suitable setting to examine a more comprehensive picture of educational quality. The analysis focuses on the 25th, 50th, and 75th quantiles (*q*) of the test score distribution, as specified in equation (3), to capture variations in the determinants of low, medium, and high achievement.

$$\begin{aligned} MATH_{i,q} = \beta_0 &+ \beta_1 ESCS\_Q_{i,q} + \beta_2 DEVICE_{i,q} + \beta_3 SMARTPH_{i,q} + \beta_4 SCHLO_{i,q} + \beta_5 SCHSIZE_{i,q} \\ &+ \beta_6 SCHTPYE_{i,q} + \beta_7 SCHTRA_{i,q} + \beta_8 CLASSSIZE_{i,q} + \beta_9 ST\_RATIO_{i,q} + \beta_{10} GENDER_{i,q} \\ &+ \beta_{11} AGE_{i,q} + u_i \end{aligned} \tag{3}$$

3.4 Blinder-Oaxaca Decomposition

The study further examines educational inequality in Thailand by employing the Blinder-Oaxaca Decomposition (BOD) (Jann, 2008) to analyze differences in educational outcomes between distinct school groups. BOD, a standard method for decomposing average outcome gaps into explained and unexplained components (Paweenawat & Liao, 2022), was initially developed to study wage disparities. Equation (4) categorizes schools in the three-year dataset into two groups: (1) the high-achieving (*h*) group (SCHTRA = 3) exceeding the national average in test scores and (2) the lower-achieving (*l*) group (SCHTRA= 0, 1, 2) falling below the national average. This allows us to identify the factors contributing to the observed educational gap between these school groups.

$$MATH_i = \begin{cases} \beta^{SCHSTRA\,l} x_i + \varepsilon_i^{SCHSTRA\,l} \\ \beta^{SCHSTRA\,h} x_i + \varepsilon_i^{SCHSTRA\,h} \end{cases} \tag{4}$$

In Equation (4), the outcome is modeled as a function of a vector of explanatory variables x_i, with associated coefficients β, and an error term ε_i. To understand the disparities in average outcomes, equation (5) presents the difference in mean outcomes.

The difference in mean outcomes between the high-performing and low-performing school strata can be expressed as in equation (5).

$$MATH^{SCHSTRA\,h} - MATH^{SCHSTRA\,l} = \beta^{SCHSTRA\,h}x^{SCHSTRA\,h} - \beta^{SCHSTRA\,l}x^{SCHSTRA\,l} \quad (5)$$

Building upon equation (5), equation (6) replaces the outcome variable with y and strategically decompose the right-hand side into three terms.

$$y^{SCHSTRA\,h} - y^{SCHSTRA\,l} = \Delta x\beta^{SCHSTRA\,l} + \Delta\beta x^{SCHSTRA\,l} + \Delta x\Delta\beta \quad (6)$$

In equation (6), $\Delta x = x^{SCHSTRA\,h} - x^{SCHSTRA\,l}$ represents the difference in mean endowments and $\Delta\beta = \beta^{SCHSTRA\,h} - \beta^{SCHSTRA\,l}$ represents the difference in estimated coefficients. The term $\Delta x\beta^{SCHSTRA\,l}$ represents the endowments effect (*E*), often referred to as the "explained effect". This component quantifies the portion of the outcome gap that can be attributed to differences in student endowments. Specifically, it estimates the change in the mean outcome that would result if students in low-performing schools had the same mean endowments as their counterparts in high-performing schools, holding the coefficients (β) at the level of the low-performing schools.

The sum of the remaining terms, $\Delta\beta x^{SCHSTRA\,l} + \Delta x\Delta\beta$, constitutes the "unexplained effect". The term $\Delta\beta x^{SCHSTRA\,l}$ represents the coefficients effect (*C*), reflecting the portion of the gap attributable to differences in the estimated returns to those endowments. The final term, is an $\Delta x\Delta\beta$, ction effect (*IE*), capturing the portion of the gap that arises from the interaction between differences in endowments and differences in coefficients. Further simplification, equation (6) boils down to equation (7).

$$y^{SCHSTRA\,h} - y^{SCHSTRA\,l} = E + C + IE \quad (7)$$

4. Result and Discussion

4.1 Descriptive statistics

The PISA test scores during 2000-2022 are shown in Figure 5. The Thai sub-samples in the analysis comprise 8,249, 8,633, and 8,495 observations for the years 2015, 2018, and 2022, respectively. The average age of students remained relatively stable across these periods, hovering around 15.7 years. Descriptive statistics reveal trends in key variables over time. The mean mathematics test score increased from 428.79 in 2015 to 438.37 in 2018, before experiencing a notable decline to 414.59 in 2022. Concurrently, the average highest parental school year exhibited a consistent upward trend, rising from 11.46 years in 2015 to 11.86 years in 2018 and further to 12.99 years in 2022.

Figure 5. PISA Thailand Test Scores, 2000-2022

Source: IPST (2024)

Regarding school-level resources, the average class size in Thailand demonstrated a gradual decrease over the observed period, moving from 37.07 students per class in 2015 to 35.36 in 2018 and subsequently to 33.99 in 2022. The student-to-teacher ratio, however, displayed more volatility, increasing from 19.10 in 2015 to 27.70 in 2018 before returning to 18.81 in 2022.

Beyond these aggregate trends, preliminary analysis indicates significant heterogeneity in student characteristics and outcomes. As detailed in Table 2, male students consistently exhibit lower mathematics test scores compared to their female counterparts. Furthermore, students in urban areas consistently outperform those in rural areas, with the urban-rural achievement gap widening following the onset of the COVID-19 pandemic (Table 3). While access to internet and smartphones was prevalent across the majority of students throughout the study period, access to other electronic devices, such as laptops and tablets, remained comparatively limited.

Table 2. Average Mathematics Score by Gender

Gender	2015	2018	2022
Female	429.70	445.50	417.34
Male	427.62	429.87	411.56

Source: Institute for the Promotion of Science and Technology Teaching (2022), processed by the authors

Table 3. Average Mathematics Score by School Location

School Location	2015	2018	2022
Rural	419.57	427.81	399.83
Urban	454.78	459.51	439.04

Source: Institute for the Promotion of Science and Technology Teaching (2022), processed by the authors

Leveraging the Programme for International Student Assessment (PISA) index of socioeconomic status (ESCS), categorized into deciles where 1 signifies the lowest and 10 the highest socioeconomic strata, the analysis reveals a positive correlation between students' socioeconomic background and their academic performance. Specifically, students from higher ESCS deciles consistently demonstrate superior test scores. Furthermore, examination of the pandemic's impact reveals a disproportionate decline in academic achievement among students from lower socioeconomic deciles across all assessed subjects, as illustrated in Figure 6.

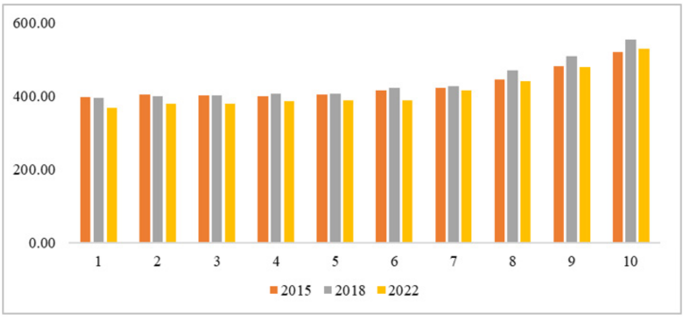

Figure 6. Average Score in Mathematics, classified by Socioeconomic Status (ECSC)

Source: IPST (2024), processed by the authors

Furthermore, as illustrated in Figure 7, a greater proportion of students from higher socioeconomic levels reside in urban areas. This trend extends to school affiliation, where high-achieving schools, such as science and demonstration affiliated institutions, are predominantly located in urban settings and enroll a larger proportion of students from higher socioeconomic backgrounds.

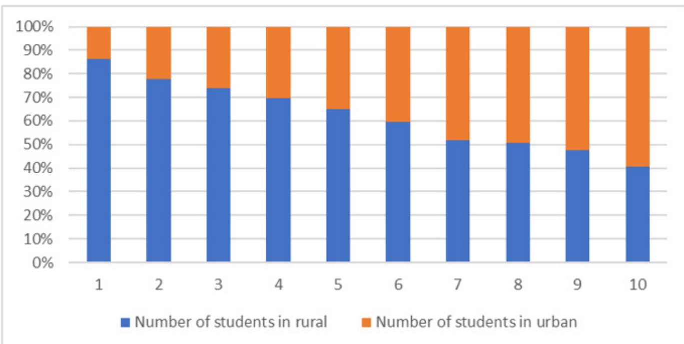

Figure 7. Proportion of Students in Urban and Rural Areas by a Socioeconomic Status, 2022

Source: IPST (2024), processed by the authors

To further examine potential multicollinearity in the reduced form, the study conducted a Variance Inflation Factor (VIF) analysis which confirmed that all VIF values were below the critical threshold of 4. When performing a robustness test on a model, a bootstrap resampling method was used on the dataset. The results show that the coefficients and significance levels remain unchanged. This confirms that the chosen model is appropriate and reliable.

4.2 Quantile Regression Estimates

Table 4 presents estimates from quantile regressions examining the determinants of mathematics test scores across the conditional distribution (25th, 50th, and 75th percentiles) for Thai students in 2015, 2018, and 2022. The coefficients on various socio-economic and school-level covariates are reported. The analysis focuses on the heterogeneous effects of these factors across the achievement distribution and the implications for educational inequality, particularly in light of the exogenous impact introduced by the COVID-19 pandemic in 2019. Figure 8 provides a histogram visualizing the intertemporal variation in the estimated coefficients for each explanatory variable influencing test scores. The figure captures the shifts across different quantiles in the consecutive assessment cycles: 2015, 2018, and 2022 (represented in sequential order).

Table 4. Quantile Regression Estimates for Q25, Q50 and Q75 in 2015, 2018 and 2022

	Quantile 25			Quantile 50			Quantile 75		
	2015	2018	2022	2015	2018	2022	2015	2018	2022
ESCS	6.04 *** (0.47)	8.34 *** (0.47)	4.71 *** (0.39)	7.26 *** (0.41)	10.60 *** (0.45)	6.75 *** (0.42)	8.24 *** (0.47)	11.31*** (0.47)	8.37 *** (0.46)
DEVICE	-6.41 ** (2.49)	-7.95 *** (2.51)	20.25 *** (2.00)	-6.65 *** (2.39)	-5.01 * (2.64)	29.88 *** (2.15)	-6.18 ** (2.43)	2.45 (2.96)	36.18 *** (2.54)
SMARTPH	26.44 *** (3.53)	35.36 *** (3.16)	21.75 *** (4.83)	24.23 *** (2.94)	36.43 *** (3.57)	21.11 *** (4.72)	23.99 *** (2.87)	33.43 *** (3.43)	22.89 *** (3.78)
SCHLO	9.21 *** (2.74)	16.46 *** (2.59)	12.12 *** (2.18)	7.81 *** (2.41)	11.78 *** (2.22)	19.12 *** (2.26)	11.05 *** (2.54)	7.10 ** (2.64)	17.35 *** (2.32)
SCHSIZE	6.19 *** (1.63)	1.43 (1.49)	3.55 *** (1.35)	6.43 *** (1.54)	-0.50 (1.50)	-0.62 (1.49)	6.65 *** (1.61)	-1.37 (1.52)	0.41 (1.38)
SCHTYPE	13.87 *** (3.74)	13.15 *** (3.15)	11.41 *** (2.24)	12.29 *** (3.41)	8.00 ** (3.77)	14.33 *** (2.28)	12.39 *** (3.57)	-5.80 * (3.74)	14.02 *** (2.52)
SCHTRA	23.2 *** (1.13)	27.60 *** (0.98)	18.32 *** (0.91)	27.8 *** (1.08)	31.14 *** (0.99)	26.38 *** (1.00)	29.33 *** (1.08)	35.25 *** (1.06)	31.67 *** (1.06)
CLASSSIZE	-0.19 * (0.10)	-0.69 *** (0.15)	0.36 ** (0.15)	-0.3 *** (0.11)	-1.17 *** (0.19)	-0.04 (0.16)	-0.49 *** (0.08)	-1.39 *** (0.15)	-0.83 *** (0.17)
ST_RATIO	-0.84 *** (0.14)	0.05 *** (0.01)	-0.93 *** (0.15)	-1 *** (0.11)	0.07 *** (0.02)	-0.63 *** (0.13)	-1.02 *** (0.10)	0.06 *** (0.01)	-0.65 *** (0.07)
GENDER	-0.27 (2.15)	-10.31 *** (2.06)	-7.19 *** (1.77)	2.43 (2.05)	-10.06 *** (2.08)	-2.32 (2.01)	8.4 *** (2.08)	-4.28 * (2.20)	3.53 * (2.09)
AGE	5.3 (3.42)	8.80 ** (3.86)	9.60 ** (3.14)	4.07 (3.55)	7.59 ** (3.44)	4.74 (3.13)	5.39 (3.70)	10.55 ** (3.53)	2.54 (3.46)
CONS	176.78 *** (53.87)	115.91 ** (61.75)	96.89 * (48.53)	234.86 *** (56.25)	191.80 *** (55.0)	197.96 *** (50.88)	254.16 *** (59.03)	204.16 *** (55.80)	277.90 *** (54.21)
Pseudo R-squared	0.13	0.17	0.14	0.18	0.23	0.21	0.23	0.29	0.32

Note: *** 0.01 significance level, ** 0.05 significance level, * 0.10 significance level

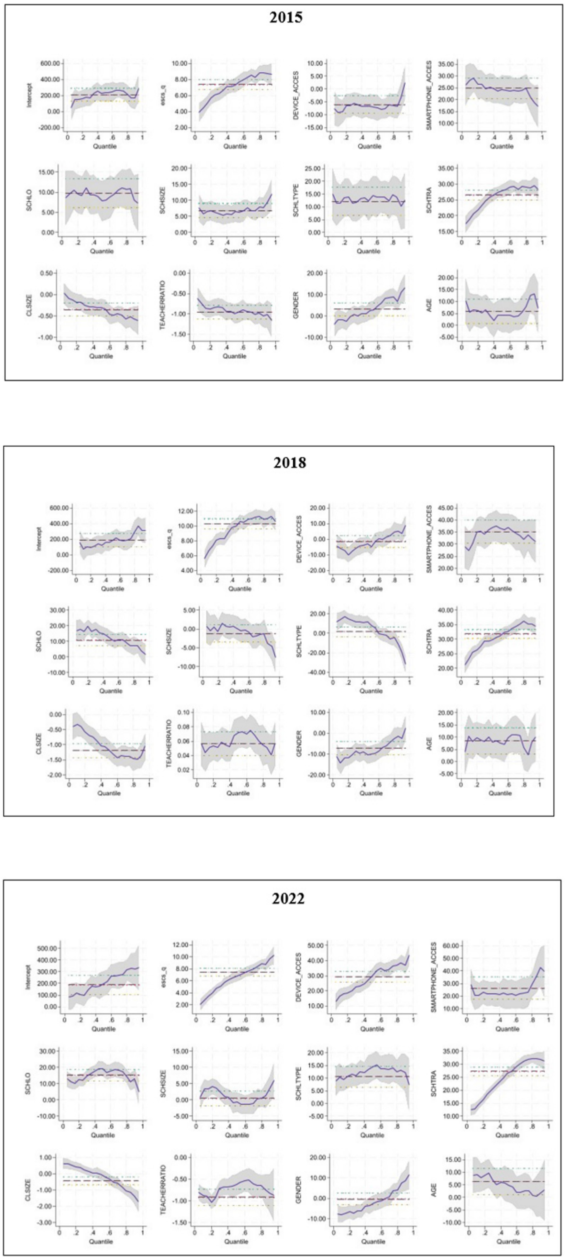

Figure 8. Histogram of coefficient estimates across different quantiles, 2015, 2018 and 2022

Source: IPST (2024), processed by the authors

The coefficient on socio-economic status exhibits a consistently positive and statistically significant relationship with mathematics test scores across all quantiles and time periods. These findings align with prior research, including the study by Lounkaew (2013) conducted in Thailand and the results from Ramos et al. (2012) in Colombia, all of which indicate that a student's family socioeconomic status is a significant factor influencing test performance. This underscores the persistent role of family background in educational attainment. Notably, the magnitude of this effect appears larger at the 75th percentile, suggesting a potential amplification of socio-economic advantages for higher-achieving students.

The coefficient on access to digital devices (e.g., computers, laptops) reveals a striking temporal evolution. Initially negative or statistically insignificant in 2015 and 2018, it becomes a highly significant and positive predictor across all quantiles by 2022, with the largest effect observed at the upper tail of the distribution. This transition likely reflects the increased salience of digital infrastructure for educational continuity during and after the pandemic-induced disruptions. It could be that technology has transitioned from a potential distraction or poorly integrated tool to an essential medium for learning during widespread remote education, necessitating digital fluency and focused academic use. The differential impact, favoring higher-achieving students, suggests a potential widening of the digital divide's influence on educational outcomes and an exacerbation of pre-existing inequalities. Access to smartphones also demonstrates a positive association with mathematics scores.

Regarding urbanicity of school location, students attending schools in urban areas consistently exhibit a statistically significant and positive performance differential across all quantiles and time periods. This result aligns with the previous study by Chansompoth, B. (2022), which also utilized Thai PISA scores and demonstrated that schools in rural regions reported lower average test scores than their counterparts in urban settings. Examining the lower tail of the conditional distribution in 2022 reveals a persistent urban-rural gap, indicating that the pandemic did not fundamentally reshape pre-existing spatial disparities in educational resources or student achievement at this margin. Conversely, the increasing coefficient observed across the upper quantiles suggests an exacerbation of these disparities at higher levels of the outcome distribution.

The effects of school size and school type display less systematic patterns across quantiles and time, indicating potentially complex interactions or non-linearities in their relationship with student achievement. These findings suggest the need for more comprehensive analyses that consider school-level heterogeneity and potential complementarities with other factors.

Attending schools with specific affiliations (e.g., private, science-focused) is generally associated with higher mathematics scores, particularly for students in the upper quantiles. The continued statistical significance of these coefficients in 2022 underscores the enduring impact of school affiliation on student performance.

The estimated coefficients for class size and student-teacher ratio are not consistently statistically significant across quantiles and time, and their signs vary. This suggests that the relationship between these resource allocation measures and student outcomes may be more context-dependent or mediated by other factors not fully captured in this specification.

The coefficient on gender fluctuates in sign and significance across years and quantiles, indicating a potentially complex and time-varying relationship with mathematics achievement that is not uniform across the performance distribution. As expected, age generally exhibits a positive and statistically significant correlation with mathematics scores, reflecting the accumulation of knowledge and cognitive development. The variations in the magnitude of the coefficient across quantiles may indicate differential learning trajectories.

The results of quantile regression offer suggestive evidence regarding the pandemic's impact on educational inequality. The heightened importance of digital access in 2022, particularly for higher-achieving students, implies that differential access to and effective utilization of digital resources may have widened the achievement gap. Furthermore, the continued significance of pre-existing disparities related to socio-economic status, school location, and school affiliation suggests that the pandemic may have exacerbated these vulnerabilities, as students with greater resources and more supportive environments were potentially better positioned to navigate the disruptions. The differential impact of digital access across the achievement distribution warrants further investigation into the mechanisms through which remote learning modalities affected students at different performance levels.

4.3 Blinder-Oaxaca Decomposition Estimates

The Blinder-Oaxaca decomposition provides a rigorous quantitative analysis of the educational inequality in mathematics scores between high-achieving and low-achieving schools in Thailand across three distinct time points: 2015, 2018, and 2022. The decomposition allows the study to partition the observed differences in mean math scores into two primary components: (1) the explained component and (2) the unexplained component

The explained component is the portion of the score differential that is attributed to differences in the average levels of observed characteristics (the independent variable) between the two school groups. It essentially indicates how much of the gap would be eliminated if low-achieving schools had the same average characteristics as high-achieving schools, using the returns to these characteristics observed in the high-achieving group as the baseline.

The unexplained component is the residual portion that represents the difference in math scores that cannot be accounted for by the disparities in the observed characteristics. It is often interpreted as the effect of differences in the "returns" or the coefficients associated with these characteristics between the two groups. This component can reflect a multitude of factors, including disparities in school quality not captured by the included variables, differences in the effectiveness of resource utilization, unobserved student or school characteristics, and potentially systemic inequalities or discrimination.

Table 5 Blinder Oaxaca Decomposition Estimates, by School Affiliation

	2015	2018	2022
Scores difference	109.94*** (2.18)	148.56*** (2.27)	143.77*** (2.50)
Separate elements			
Explained	52.67*** (1.59)	74.49*** (1.81)	75.8*** (1.74)
Unexplained	57.27*** (1.94)	74.07*** (2.11)	67.98*** (2.22)
Explained	**2015**	**2018**	**2022**
ESCS_Q	40.84*** (1.41)	53.81*** (1.56)	38.25*** (1.41)
DEVICE	-2.09*** (0.64)	0.91 (0.86)	18.63*** (0.95)
SMARTPH	2.65*** (0.31)	4.24*** (0.37)	0.85*** (0.15)
SCHLO	3.1*** (0.56)	2.1*** (0.35)	1.66*** (0.30)
SCHSIZE	-2.02*** (0.43)	-0.1 (0.52)	-0.41 (0.50)
SCHTYPE	3.92*** (0.32)	1.54*** (0.26)	2.69*** (0.32)
CLASSSIZE	0.3* (0.17)	11.44*** (0.98)	3.38*** (0.68)
ST_RATIO	5.63*** (0.76)	-0.46*** (1.67)	10.15*** (0.77)
GENDER	0.04 (0.04)	0.74*** (0.23)	0.14* (0.08)
AGE	0.29** (0.12)	0.27** (0.12)	0.46*** (0.15)

Note: *** 0.01 significance level, ** 0.05 significance level, * 0.10 significance level

Table 5 displays the Blinder-Oaxaca Decomposition estimates. The raw difference in average mathematics scores between high-achieving and low-achieving schools is statistically significant and substantial across all three years: 109.94 in 2015, 148.56 in 2018, and 143.77 in 2022. This highlights a persistent and considerable educational inequality in mathematics outcomes. The portion of the score difference attributable to the observed characteristics is 52.67 in 2015, 74.49 in 2018, and 75.8 in 2022. This indicates that a significant part of the educational gap can be explained by the differences in the levels of the included factors between the two school groups. The portion of the score difference that remains unexplained by the observed characteristics is 57.27 in 2015, 74.07 in 2018, and 67.98 in 2022. This substantial unexplained component suggests that factors beyond the measured variables play a crucial role in driving the educational inequality. These could include differences in pedagogical practices, school leadership, teacher quality aspects not captured by the student-to-teacher ratio, curriculum quality, peer effects, and potentially unobserved socio-economic or cultural factors.

The lower panel of the Table 5 breaks down the explained component by individual characteristics and their contribution to the score gap in each year. Socioeconomic status is consistently the largest contributor to the explained gap across all years. This underscores the persistent and powerful influence of socio-economic background on educational outcomes in Thailand. Disparities in socio-economic status between students attending high-achieving and low-achieving schools account for a substantial portion of the math score gap. The second largest contributor to the explained bap is device access. The impact of access to devices shows a dramatic shift. It has a negative and significant effect in 2015, becomes statistically insignificant in 2018, and then becomes a large and positive contributor in 2022. This likely reflects the increasing importance of digital resources in education over time, potentially exacerbated by the COVID-19 pandemic and the shift towards remote learning. By 2022, differential access to devices significantly favored high-achieving schools. The result is in line with the quantile regression estimate.

Several other factors also influence the math score gap. The impact of smartphone access has changed over time, being a significant advantage in 2015 and 2018. However, its effect decreased by 2022, suggesting that dedicated learning devices became more important. Urban schools consistently have a significant advantage over rural schools, highlighting a persistent urban-rural divide. School size has a negative and generally insignificant effect, indicating it is not a major factor. Attending a public school is consistently and significantly associated with a positive contribution to the gap, possibly due to a concentration of high-achieving students. Larger class sizes contributed positively and significantly to the gap in 2018 and marginally in 2015. The impact of the student-to-teacher ratio fluctuated, with a positive effect in 2015 and 2022 but a negative one in 2018, a dynamic that requires further investigation. Finally, being male and being older are both associated with a small but significant positive contribution to the math score gap across all years.

5. Conclusion

The quantile regression analysis in this study provides insights into the heterogeneous determinants of mathematics achievement in Thailand and how these relationships evolved around the COVID-19 pandemic. The findings underscore the persistent influence of socio-economic factors and the increasing importance of digital capital in shaping educational outcomes. The evidence suggests that the pandemic may have amplified certain dimensions of educational inequality. Future research should focus on identifying the causal mechanisms underlying these observed patterns, exploring the long-term consequences of the pandemic on educational trajectories, and evaluating policy interventions aimed at mitigating these disparities. Further investigation into the interaction effects between these covariates and the pandemic shock would also be a fruitful avenue for future work. The case of Thailand offers critical insights for the broader developing countries studies, highlighting the imperative to implement targeted interventions that effectively address educational inequalities stemming from socioeconomic background and digital access to ensure a more equitable and resilient education system.

This Blinder-Oaxaca decomposition provides compelling evidence of persistent and significant educational inequality in mathematics scores in Thailand. Socio-economic status and the urban-rural divide are consistently important factors. The analysis of the 2022 data suggests that the COVID-19 pandemic may have exacerbated inequalities related to digital access, further widening the explained portion of the achievement gap. However, a substantial portion of the inequality remains unexplained, necessitating further investigation into school-level and other unquantifiable factors. These findings have critical implications for policymakers in Thailand, highlighting the need for targeted interventions to address socio-economic disparities, bridge the digital divide, reduce urban-rural inequalities in educational resources, and improve the quality of education in low-achieving schools. The policy recommendations are further elaborated in Section 6.

6. Policy Recommendations

The findings and analysis lead to the several key policy and educational recommendations. First, the allocation of educational funding must prioritize equity and adequacy, specifically by considering the inherent differences among students. This differentiated approach is crucial for mitigating various dimensions of educational inequality. For instance, providing greater financial resources to disadvantaged or economically vulnerable student populations compared to their more affluent counterparts is necessary to address socioeconomic disparities. Similarly, schools in remote areas or those that are smaller in size should receive greater funding. This compensatory measure acknowledges their inability to leverage economies of scale as effectively as larger, urban schools, thereby reducing inequality linked to school location and size.

Second, educational funding mechanisms should emphasize decentralization. Granting greater authority to individual educational institutions and local-level agencies for planning and managing their budgets is essential. This flexibility allows schools to adapt expenditures to their unique local context and better respond to the actual needs of students, the community, and local resources. Furthermore, this approach promotes the meaningful participation of local stakeholders such as administrators, teachers, parents, and local government, in prioritizing budget expenditures.

Third, promoting the use of electronic devices and the internet in the learning process is critical for expanding access to information, knowledge, and learning resources. However, the integration of information technology tools in the classroom must be governed by clear pedagogical objectives and appropriate usage guidelines or regulations. This prevents excessive or non-essential use, which could negatively impact student concentration and disrupt the overall instructional process.

Fourth, the study’s findings indicate that school-level factors exert a greater influence on student test scores than do family-level factors. Consequently, the government must prioritize the development and enhancement of schools to ensure a consistent and high standard of instructional effectiveness across all geographical areas and affiliations. Key initiatives include the provision of a sufficient number of qualified teachers tailored to the specific needs of each school, alongside the establishment of appropriate class sizes. These measures will enable teachers to provide comprehensive supervision and personalized support to all students.

7. Limitations of the Study

The research findings provide a general indication of broad policy directions. Nevertheless, the assessment of educational achievement through the PISA scores is exclusively administered to students actively enrolled in the education system at the time of testing. Crucially, this methodology excludes students who have left the formal education system or are otherwise not enrolled. Consequently, utilizing PISA scores solely to measure changes in overall test performance or shifts in educational inequity may not fully reflect the true quality of the education system or the extent of educational disparity following the COVID-19 pandemic. This limitation arises because the methodology does not account for students who exited or were not within the education system during the pandemic. Therefore, a broader range of complementary data sources must be integrated to provide a more complete and accurate evaluation.

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