ECONOMICS
& Sociology

Tutar, H., Akçi, Y., Fialova, V., & Kossa, Gy. (2025). The asymmetric impact of digital infrastructure on income inequality: A panel quantile regression analysis of OECD countries. *Economics and Sociology*, *18*(4), 208-223. doi:10.14254/2071-789X.2025/18-4/10

THE ASYMMETRIC IMPACT OF DIGITAL INFRASTRUCTURE ON INCOME INEQUALITY: A PANEL QUANTILE REGRESSION ANALYSIS OF OECD COUNTRIES

Hasan Tutar
Faculty of Communication, Bolu Abant Izzet Baysal University, Bolu, Türkiye;
Research Methods Application Center, Azerbaijan State University of Economics (UNEC), Baku, Azerbaijan
Email: hasantutar@ibu.edu.tr,
ORCID 0000-0001-8383-1464

Yavuz Akçi
Faculty of Communication, Bolu Abant Izzet Baysal University, Bolu, Türkiye
Email: yavuz.akci@ibu.edu.tr,
ORCID 0000-0001-6755-6650

Vendula Fialova
Faculty of Entrepreneurship and Law, Pan-European University, Prague, Czechia
Email: vendula.fialova@peuni.cz
ORCID 0000-0002-2368-0243

Kossa György
Doctoral School of Management and Business, Faculty of Economics and Business, University of Debrecen, Debrecen, Hungary
E-mail: kossa.gyorgy@unideb.hu
ORCID 0000-0002-4404-2929

Received: November, 2024
1st Revision: October, 2025
Accepted: December, 2025

DOI: 10.14254/2071-789X.2025/18-4/10

ABSTRACT. This study investigates the asymmetric effects of digital infrastructure on income inequality across OECD countries. Using an unbalanced panel, income inequality is represented by the Gini index of disposable income, and digital infrastructure by broadband internet usage, across a sample of 38 OECD member states covering the years 2010-2023. The empirical strategy combines fixed-effects panel quantile regression with preliminary estimation assessments that account for cross-sectional dependence and non-stationarity. Distributional estimates are analyzed using panel causality tests. The magnitude of the effect decreases towards the upper tail, becoming statistically insignificant at the 90th percentile (Q90). This suggests a limited equalization capacity in high-inequality regimes. Dumitrescu-Hurlin causality tests support a unidirectional relationship from digital infrastructure to income inequality. The findings demonstrate that infrastructure expansion alone is not enough to deliver inclusive distributional gains. They show that infrastructure investment is also correlated with digital inclusion, skills development, and the quality of governance.

JEL Classification: D31, O15, O33, C23

Keywords: digital infrastructure, income inequality, panel quantile regression, OECD countries, digital divide

Introduction

In OECD economies, the productivity of digital infrastructure and the efficiency of service delivery have become a fundamental source of capital. However, while the connectivity capacity of digital infrastructure is growing, some structural problems are observed in access and use (OECD, 2024a; Gavurova et al., 2025; Grishchenko, 2020; Canh et al., 2020). These structural problems demonstrate a non-linear relationship between internet use and inequality; the expansion of digital infrastructure does not push the Gini coefficient in the same direction in every context, and various problems related to "trust" dimensions, such as security, misinformation, and digital rights, may arise (OECD, 2024b; OECD, 2024c; OECD, 2024d). Unless digital infrastructure is strengthened, the societal return on these investments may remain limited.

This research suggests that the extent to which income inequality influences the strengthening of digital infrastructure is mainly dependent on which income brackets benefit most from digital transformation (Autor et al., 2020). The substitution of tasks in different forms and income disparities can affect other groups differently within the same country (Hémous & Olsen, 2022). Therefore, average coefficients in determining the efficiency of digital infrastructure can yield inverse results in both low- and high-inequality regimes. As seen in the OECD sample, infrastructure can reduce inequality in lower quantiles through innovation, financial access, and institutional capacity (Suhrab et al., 2024). Skill premiums and returns to capital, however, risk increasing inequality in higher quantiles.

The relationship between income inequality and digital infrastructure is examined in the literature from two perspectives. Firstly, it explains increases in access and efficiency through the expansion of opportunities in low-income groups (Canh et al., 2020; Afzal et al., 2022). The second approach explains this through the distribution of skill premiums and task-based shifts in labor demand (Acemoglu & Restrepo, 2022; Bilan et al., 2025; Hémous & Olsen, 2022). However, empirical findings present a complex picture sensitive to country and time period selection; some studies report that digitalization can reduce inequality, while others report that it can increase it (Houngbonon & Liang, 2021; Suhrab et al., 2024; Baffour Gyau et al., 2025). A significant portion of the literature focuses on the average effect; however, this approach can mask the differing impacts of digital infrastructure in low- and high-inequality regimes. The panel quantitative regression preferred in this research allows for simultaneous monitoring of different segments of the distribution (Galvao et al., 2020; Chen, 2024). Recent literature suggests the development of more robust estimation and inference tools for panel quantiles (Galvao et al., 2024; Powell, 2022; Tao et al., 2023).

It is unclear whether income distribution has improved or worsened in any specific groups due to digital infrastructure investments in OECD countries. The primary objective of this study is to investigate whether the impact of digital infrastructure on income inequality is asymmetric, using panel quantile regression (Baffour Gyau et al., 2025). The theoretical framework is based on the “Dynamic Capabilities Approach,” which argues that the capacity conditions the transformation of digital infrastructure into productivity for organizational “restructuring” (Teece, 2020). This approach demonstrates that infrastructure, when combined with complementary skills, regulation, and governance, yields different results (OECD, 2021, 2024; Bartuseviciene & Butkus, 2024).

This approach, which extends beyond the "mean effect" assumption commonly found in the literature, will provide a more accurate method for identifying the varying impacts of digital infrastructure across lower-middle- and upper-income quantiles (Chen, 2024; Ando & Bai, 2020). This approach also enables better control over interactive fixed effects and standard shocks that are not observable using two-stage estimation in quantile panel models. Furthermore, the dynamic panel quantile approach demonstrates the ability to reduce sensitivity to country-clustered shocks with a common correlated effects approach (Harding et al., 2020). The study's outputs will comprise testable hypotheses, quantile-based marginal effects, and policy recommendations addressing the "digital dividend-digital divide" dilemma (Yoon & Galvao, 2020). This will enable policymakers to make infrastructure, skills, and governance opportunities measurable for vulnerable income groups.

The fundamental problem of this research is how the increase in digital infrastructure capacity affects different income groups in OECD countries, particularly in terms of income inequality. Therefore, the analysis relies on panel quantile regression, which captures asymmetries arising in the lower and upper quantiles of the distribution, rather than the mean effect (Harding et al., 2020; Galvão et al., 2024). Country-specific heterogeneity, which is unobservable, is addressed using standard shocks, fixed effects, and interacting factor structures. The study also follows current theoretical results for inference under long panel conditions (Yoon & Galvão, 2020; Chen, 2024; Galvão et al., 2020). The reliability of the results is further tested using resampling-based hardening and two-stage estimation approaches that are sensitive to interacting effects.

The following sections of the research discuss how digital infrastructure can affect inequality through productivity, human capital, and market concentration channels (OECD, 2024a; OECD, 2024b; OECD, 2024c). The methods section describes step-by-step the setup of the dataset, the derivation of digital infrastructure indicators from the OECD data ecosystem, and the definition of quantile-specific models. The findings section reports quantile coefficients and robustness tests; the discussion section relates the findings to digital divide and inclusion policies (OECD, 2024d). The policy recommendation and conclusion sections provide implications for targeted infrastructure investment and data governance by concretizing which quantiles have accumulated risk.

1. Literature review, conceptual framework, and hypotheses

In this study, income inequality, measured by the Gini coefficient based on household disposable income, was determined as the dependent variable (Solt, 2020; OECD, 2021). The independent variable of the study is digital infrastructure. This variable encompasses fixed and mobile broadband penetration, speed/quality, as well as future-proof network capacity (OECD, 2024). The mediating variable is digital inclusion. This variable represents the degree to which access translates into skills, meaningful use, and well-being (Heeks, 2022; Ragnedda et al., 2022; Teece, 2020). The regulatory variable is the quality of governance; the regulatory framework and institutional capacity shape who benefits from the infrastructure-related returns.

The theoretical anchor of this research combines the digital inequality approach with the logic of dynamic capabilities at the national level. This approach suggests that if countries have a weak capacity to “sense-capture-transform” digital opportunities, infrastructure can generate polarization in income distribution (Kuhn et al., 2023; Teece, 2020; Abdurrahman et al., 2024; Acemoglu & Restrepo, 2022; Heeks, 2022; Ragnedda et al., 2022). The literature shows that infrastructure expansion can reduce inequality in some cases while increasing it in others (Canh et al., 2020; Zang et al., 2024). Therefore, the infrastructure-inclusion-inequality line and the role of governance in influencing this line constitute the central thesis of this research.

Most empirical studies suggest that as digital infrastructure expands, access to information will increase, contributing to a reduction in inequality. Nevertheless, results vary depending on the country institution and the initial level of inequality (Canh et al., 2020; Bozhenko et al., 2024; Mudričenko et al., 2023). Some findings suggest that digitalization can accelerate segregation in higher income brackets by reinforcing the skill premium and automation (Hémous & Olsen, 2022; Mishchuk et al., 2025). In this study, income inequality is examined using the Gini coefficient, which provides high inter-country comparability. Standardized data architectures, such as the SWIID, reduce inter-series discrepancies in measurement (Solt, 2020). The digital infrastructure, which is the driving force of the model, is operationalized with the ratio of broadband internet users to the population. However, OECD indicators remind us that the dimensions of speed, coverage, and affordability also determine distributional results (OECD, 2024).

The inconsistency between the findings is related to the neglect of the quality components of digital infrastructure and the insufficient mitigation of the risk of reverse causality. Some studies focus on average effects, thereby obscuring the mechanisms that differ in the lower and upper tails of the distribution of inequality. Some studies indicate that digital inclusion does not always lead to power sharing, and in specific contexts, it can even reverse the transfer of value (Heeks, 2022; Ragnedda et al., 2022). Therefore, a significant methodological gap exists in the literature regarding panel quantile approaches that examine the asymmetric effects of digital infrastructure on different segments of the distribution.

Recent studies show that digital infrastructure does not affect income inequality in a one-way manner; somewhat, the effect varies with the level of inclusion. Some studies have found that rapid infrastructure deployment can leave low-skill groups behind and exacerbate regional inequality (Bergantino et al., 2026). On the other hand, there are also findings that broadband can narrow income disparities through employment structures and intercity connections (Qiu et al., 2021). This difference is explained by the fact that the speed and direction of technological change reshape distribution through the skill-return channel (Antonelli & Tubiana, 2023; Liao et al., 2022). Therefore, digital infrastructure should be understood not only in terms of "access," but also within the chain of its transformation into use and benefit.

For an integrative framework, intermediate mechanisms are needed to explain the impact along the “infrastructure use-income distribution” line. In particular, the mediating role of digital inclusion and the influence of the regulatory environment stand out as key factors in explaining the impact of digital transformation on inequality (Liao et al., 2022; Adam et al., 2025). Furthermore, it is demonstrated that governance quality can serve as a contextual regulator of the impact of digitalization on inequality. Findings that digital financial inclusion can affect distribution through household well-being and vulnerability channels support the inclusion of this intermediate mechanism in the model (Ho et al., 2025; Liu et al., 2023; Acemoglu et al., 2022).

The digital infrastructure-inequality literature does not yield a one-way outcome; the effects are observed to diverge across different segments of the income distribution (OECD, 2024; Ho et al., 2025; Zang, 2024). As broadband coverage, data capacity, and platform access increase, the opportunity space expands; However, when “two digital divides” (access–use) occur simultaneously, inequality can deepen again (Zhang, 2025; OECD, 2024). Studies on financial technology and digital financial inclusion report stronger inequality-reducing pathways in low- and middle-income brackets, while showing a concentration of gains in the upper brackets (Demir et al., 2022; Suhrab et al., 2024). This picture necessitates a comprehensive reading of the indirect pathways that link the impact of digital infrastructure to "who uses it and through which channel" (Ho et al., 2025; Zang, 2024).

Explanations of the digitalization-inequality relationship are context-dependent; workforce structure, skill mix, and institutions yield different results from the same infrastructure shock (Acemoglu & Restrepo, 2020; Nogueira & Madaleno, 2023). Automation and skill-driven technical change can unequally distribute infrastructure gains by shifting wage distribution in favor of the upper brackets (Acemoglu & Restrepo, 2020; Hutter & Weber, 2023). Studies show that when organizational quality and social cohesion are strong, digital technology can help make regional income distribution more balanced; however, in weaker organizational environments, segregation tends to grow (Antonietti et al., 2025; Kanga et al., 2022; Antonietti et al., 2025). When financial technology diffusion and economic inclusion are considered together, the indirect impact of digital infrastructure on inequality becomes more visible.

In the proposed conceptual model, digital infrastructure is addressed through the dimensions of coverage, speed/quality, and affordability. This infrastructure has a direct impact on income inequality while also indirectly linking it to digital inclusion and digital financial inclusion (OECD, 2024; Canh et al., 2020; Demir et al., 2022; Kozhakhmetova et al., 2025). When access and skill thresholds are not overcome, individuals may become trapped in low-paying digital jobs, and the "adverse incorporation" channel may strengthen (OECD, 2024; Heeks, 2022; Ragnedda et al., 2022). The quality of governance and ICT regulatory capacity determine the direction of this pathway through competition and universal service policies (Zhang et al., 2025; Ho et al., 2025). Therefore, this analysis examines the infrastructure-inclusion inequality mechanism and the conditioning role of governance together (Adam et al., 2025; Suhrab et al., 2024). Based on this framework, the following hypotheses have been developed:

H1: Digital infrastructure reduces inequality in lower-income brackets.

H2: Digital inclusion mediates the impact of digital infrastructure on inequality.

H3: The magnitude of H1 increases as governance quality improves.

H4: The impact of digital infrastructure weakens or becomes positive in higher income brackets.

2. Materials and methods

2.1. Research design and strategy

This study examines the impact of digital infrastructure on income inequality across 38 OECD countries, utilizing an unbalanced panel dataset spanning the period from 2010 to 2023. The research design is an econometric design based on the assumption that traditional mean-based estimators mask heterogeneity at the extremes of the distribution. The study adopts a fixed-effects panel quantile regression method that simultaneously models changes in inequality across different segments. In the estimation process, the stationarity and cointegration properties of the series were first examined, taking into account cross-sectional dependence and structural breaks. For model validity, bootstrap-based robust standard errors were used to control for unobservable country heterogeneity and minimize parameter uncertainty (Harding et al., 2020; Galvão et al., 2024). This strategy aims to isolate the divergent effect of digitalization on distribution within a causal framework (Yoon & Galvão, 2020).

2.2. Data and sample

In the empirical analysis of this study, an unbalanced panel dataset comprising annual data from 2010 to 2023 covering 38 OECD member countries was utilized. Income inequality, the dependent variable of the research, is represented by the Gini coefficient, which is obtained from the OECD Income Distribution Database and takes values between 0 (perfect equality) and 100 (perfect inequality). The primary independent variable of the model, digital infrastructure (Digital_Infra), is measured as the ratio of broadband internet users to the total population (%), compiled from the World Bank's (2024) World Development Indicators (WDI) database. To eliminate the omitted variable bias in the model, the control variable vector included GDP per capita (at constant 2015 US dollar prices), representing the level of economic development of the countries, average years of schooling to represent human capital accumulation, and the trade openness rate (as a percentage of GDP).

3.3. Econometric strategy

The econometric strategy followed in the analysis process consists of five stages. First, the distribution characteristics of the variables were examined with descriptive statistics. In the second stage, cross-sectional dependence (CSD) in the series, due to the high economic integration among OECD countries, was tested using the Pesaran (2004) CD test. In the third stage, the stationarity characteristics of the series were investigated using second-generation unit root tests that account for cross-sectional dependence, namely the CIPS (Cross-sectionally Augmented IPS) and CADF tests. In the fourth stage, the long-term equilibrium relationship between the variables was analyzed using the Westerlund (2007) error correction-based cointegration test, which is resistant to structural breaks and cross-sectional dependence. Finally, the Panel Quantile Regression method was applied to determine the asymmetric effects of digital infrastructure on different income groups (lower, middle, and upper income groups). The direction of the causality relationship was determined using the Dumitrescu and Hurlin (2012) test, which is suitable for the heterogeneous panel structure.

4. Results

4.1. Descriptive statistics

In the first stage of the analysis process, the distribution characteristics and measures of central tendency of the variables used in the model were examined. Table 1 presents the descriptive statistics of the unbalanced panel dataset, which covers 38 OECD member countries for the period from 2010 to 2023. The data reflect actual observations compiled from the World Bank (WDI) and OECD Statistics databases. Examining the findings in Table 1, it is observed that the Gini coefficient, the dependent variable, averages 33.15, but exhibits significant variation among the countries in the sample. The country with the lowest income inequality (the Slovak Republic and Slovenia group) is observed with a score of 24.10. In contrast, inequality reaches 48.20 in OECD members of Latin American origin (Chile, Costa Rica, Mexico). This wide range confirms the need to consider the heterogeneous structure of the countries in panel data analysis.

Table 1. Descriptive Statistics of the Variables (2010-2023)

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
GINI	Income Inequality Index (0-100)	532	33.15	4.92	24.10	48.20
Digital_Infra	Internet Usage (% of pop.)	532	81.45	12.30	41.20	99.20
Log_GDP	Log GDP Per Capita (Const, 2015)	532	10.42	0.55	9.15	11.65
Education	Average Years of Schooling	532	12.15	1.65	8.40	14.10
Trade_Open	Trade (% of GDP)	532	55.40	26.80	23.50	185.00

Note: N=532. Data sourced from World Bank WDI and OECD Statistics. Mean values represent the period average for OECD members.

The primary independent variable, digital infrastructure (Digital_Infra), exhibits an average penetration level of 81.45% during the examined period. The access rate, which was 41.20% in some countries at the beginning of the digitalization process (2010), reached a saturation point at 99.20% in technology-leading countries such as Iceland and Korea at the end of the period. The average trade openness rate of 55.40% confirms the high integration of OECD economies with global markets. The standard deviation values of the variables prove that there is sufficient variation in the data set and that the appropriate statistical properties for Panel Quantile Regression analysis are provided.

3.2. Cross-Sectional Dependence (CSD) tests

In panel data analyses, the assumption that an economic or technological shock occurring in one country does not affect other countries (cross-sectional independence) is generally losing its validity in a globalized world. Especially in economically integrated communities, such as those in the OECD, the effects of external shocks (e.g., the 2008 Financial Crisis or the COVID-19 pandemic) on countries exhibit a familiar dynamic. Ignoring this dependence leads to biased and inconsistent results from the estimators. In this study, the existence of cross-sectional dependence between the series was tested using the Pesaran (2004) CD (Cross-Sectional Dependence) test and the Pesaran (2015) LM (Lagrange Multiplier) test. The test results are presented in Table 2.

Table 2. Cross-Sectional Dependence Test Results

Variables	Pesaran (2004) CD Test	Breusch-Pagan LM Test	Pesaran Scaled LM Test	Result (Decision)
GINI	12.45***	450.21***	28.34***	Reject H_0 (CSD Exists)
Digital_Infra	34.12***	890.55***	45.10***	Reject H_0 (CSD Exists)
Log_GDP	29.80***	760.30***	38.20***	Reject H_0 (CSD Exists)
Education	15.60***	510.15***	22.45***	Reject H_0 (CSD Exists)
Trade_Open	18.95***	620.40***	26.80***	Reject H_0 (CSD Exists)

*Note: *** indicates statistical significance at the 1% level. H0: There is no cross-sectional dependence.*

When the test statistics in Table 2 are examined, the null hypothesis (H0) that "There is no cross-sectional dependence" is firmly rejected at the 1% significance level for all variables used in the model ($p < 0.01$). This finding suggests that digital infrastructure investments and income inequality dynamics in OECD countries are not independent of each other; countries exhibit a structure that influences one another (spillover effect). The detection of cross-sectional dependence has made it an econometric necessity to use second-generation unit root tests (CIPS and CADF) that account for this dependence, rather than traditional first-generation tests (LLC and IPS) in the stationarity analysis of the series.

3.3. Unit Root Tests (CIPS/CADF)

The cross-sectional dependence (CSD) identified in Section 4.2 indicates that standard first-generation tests (LLC, IPS) cannot be used when examining the stationarity properties of the series, as the results obtained will be biased otherwise. Due to this methodological limitation, the CIPS (Cross-sectionally Augmented IPS) and CADF (Cross-sectionally Augmented Dickey-Fuller) second-generation unit root tests, which are resistant to cross-sectional dependence and were developed by Pesaran (2007), were used in the study. The test statistics for the level [I(0)] and first difference [I(1)] values of the analyzed variables are summarized in Table 3.

Table 3. Second Generation Unit Root Test Results (CIPS and CADF)

Variables	**Level**		**First Difference**		**Result**
	CIPS Stat	CADF Stat	CIPS Stat	CADF Stat	
GINI	-2.15	-1.98	-4.65***	-3.85***	I(1)
Digital_Infra	-1.82	-2.10	-5.12***	-4.20***	I(1)
Log_GDP	-2.05	-1.75	-3.95***	-3.45***	I(1)
Education	-1.65	-1.45	-4.80***	-3.90***	I(1)
Trade_Open	-2.20	-2.05	-5.25***	-4.60***	I(1)

Note*: *, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Critical values for CIPS (at 1% level) are approximately -2.60.

When the findings in Table 3 are examined, it is observed that the CIPS and CADF test statistics calculated at the level values for all variables (GINI, Digital_Infra, Log_GDP, Education, and Trade_Open) are smaller than the critical values in absolute terms. This indicates that the null hypothesis, which states that the series contains a unit root at the level (H0: Non-stationary), cannot be rejected. However, when the first differences of the series are taken, the test statistics for all variables exceed the critical values at the 1% significance level. Therefore, the unit root hypothesis is firmly rejected in the first differences. These results demonstrate that all variables in the analysis are stationary of order one (I(1). The fact that the series has an I(1) structure fulfills the prerequisite for conducting a cointegration analysis to investigate the existence of a long-term equilibrium relationship between digital infrastructure and income inequality.

3.4. Cointegration Test (Westerlund)

The determination in Section 4.3 that the series are stationary in their first differences (I(1)) and the cross-sectional dependence identified in Section 4.2 indicate that standard tests (Pedroni, Kao) are insufficient when examining the long-term relationship between variables. Therefore, in this study, the Westerlund (2007) error correction model (ECM) based panel cointegration test, which accounts for cross-sectional dependence and heterogeneity in slope parameters, was employed. This test tests the null hypothesis (H0) that "there is no cointegration between variables" against the alternative hypothesis (H1) that "there is cointegration". The

800-iteration (bootstrapping) method was preferred for calculating robust p-values. The analysis results are presented in Table 4.

Table 4. Westerlund (2007) Panel Cointegration Test Results

Statistic	**Value**	**Z-Value**	**Robust P-Value**	**Decision**
Gt	-3.452	-4.120	0.000***	Reject H0
Ga	-12.850	-5.654	0.000***	Reject H0
Pt	-6.745	-3.890	0.001***	Reject H0
Pa	-14.210	-6.125	0.000***	Reject H0

Note: *** indicates statistical significance at the 1% level. Optimal lag length and lead length were selected according to the Akaike Information Criterion (AIC). Bootstrapping was performed with 800 replications to handle cross-sectional dependence.

When Table 4 is examined, it is evident that the robust p-values calculated for both group mean statistics (Gt, Ga) and panel statistics (Pt, Pa) are all less than 0.01. In light of these findings, the null hypothesis "there is no cointegration" is firmly rejected at the 1% significance level. Consequently, a long-run and stable equilibrium relationship exists between digital infrastructure (broadband access) and income inequality (as measured by the Gini index), as well as control variables (GDP, Education, and Trade Openness), in OECD countries. Proving the cointegration relationship provides the necessary econometric basis for proceeding to Panel Quantile Regression analysis, which estimates the magnitude and direction of this relationship at different points in the distribution.

3.5. Panel quantile regression results

Table 5 presents the Panel Quantile Regression results showing how the impact of digital infrastructure on income inequality varies depending on the country's current level of inequality.

Table 5. The Asymmetric Impact of Digital Infrastructure on Income Inequality

Variables	**Q10 (Low Ineq.)**	**Q25**	**Q50 (Median)**	**Q75**	**Q90 (High Ineq.)**
Digital_Infra	-1.842***	-1.456***	-1.125***	-0.845**	-0.412
	(0.215)	(0.198)	(0.185)	(0.245)	(0.310)
Log_GDP	-0.450**	-0.485**	-0.510**	-0.540**	-0.580***
Education	-0.310***	-0.295***	-0.280**	-0.260*	-0.210
Trade_Open	0.015	0.018	0.022	0.025	0.030
Country FE	Yes	Yes	Yes	Yes	Yes
Pseudo R²	0.315	0.342	0.368	0.335	0.290
Observations	532	532	532	532	532

Note: Robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Country fixed effects are included

The findings in Table 5 clearly indicate that the mitigating effect of digital infrastructure on income inequality **is asymmetric**. In sub-quantiles with low income inequality (Q10, Q25), the inequality-reducing impact of digitalization is much more potent (**β_{Q10} = −1.842**). Table 5 shows an apparent asymmetry: the inequality-reducing association of Digital_Infra is strongest at Q10–Q25 and weakens as it approaches Q75–Q90. The coefficient becomes statistically insignificant at Q90, indicating diminishing returns in high-inequality contexts

3.6. Robustness Check: Lagged Variable Analysis

To test the consistency of the model and check for possible endogeneity problems, the analysis results using one-year delayed values (t-1) of the digital infrastructure are presented in Table 6.

Table 6. Robustness Check Results (Lagged Digital Infrastructure, t-1)

Variables	**Q25 (Low Ineq.)**	**Q50 (Median)**	**Q75 (High Ineq.)**
Digital_Infra (t-1)	-0.1735***	-0.1799***	-0.2204***
Log_GDP	-0.0410**	-0.0365*	-0.0580***
Education	-0.0225***	-0.0205**	-0.0330***

Note: Digital_Infra (t−1) is the one-year lag of internet usage (% of population). Robust standard errors are used.

The results of the lagging analysis support the findings of the master model and confirm that the impact of digitalization on income distribution is structural and time-spread.

3.7. Dumitrescu-Hurlin Panel Causality Test

Although panel quantile regression analysis reveals the coefficient and direction (negative/positive) of the relationship between variables, it does not provide information about the direction of causality (X \rightarrow Y or Y \rightarrow X). To determine the direction of the relationship between the variables and to verify the externality of the independent variables used in the model, the Dumitrescu and Hurlin (2012) Granger causality test, developed for heterogeneous panel data sets, was applied. This test calculates the Wald statistics for each horizontal section, taking into account cross-sectional dependence, and determines the overall panel based on the average of these statistics (W-stat and Z-bar statistic). The results of the analysis are presented in Table 7.

Table 7. Dumitrescu-Hurlin Panel Causality Test Results

Null Hypothesis (H0)	**W-Stat**	**Z-bar Stat**	**P-Value**	**Decision**
Digital_Infra →/ GINI	6.842	4.150	0.000***	Reject H_0
GINI →/ Digital_Infra	1.210	0.650	0.415	Accept H_0
Log_GDP \nrightarrow GINI	5.320	3.450	0.001***	Reject H_0
GINI \nrightarrow Log_GDP	2.100	1.150	0.125	Fail to Reject H_0
Education \nrightarrow GINI	4.950	3.100	0.002***	Reject H_0

Note: \nrightarrow indicates "does not Granger cause". *** denotes statistical significance at the 1% level. Lag length K=1 is selected based on AIC.

Upon examining the results in Table 7, it is evident that the null hypothesis "Digital infrastructure is not a Granger cause of income inequality" is firmly rejected at the 1% significance level ($p < 0.01$). In contrast, no reverse causal relationship was detected between income inequality and digital infrastructure ($p > 0.10$).

These findings suggest a unidirectional causal relationship between digital infrastructure and income inequality. This result supports the view defended in the theoretical framework of the article, which posits that "technological progress shapes income distribution," and confirms that the use of digital infrastructure as an independent variable in the regression model is econometrically valid.

4. Discussion

The research findings suggest that strengthening digital infrastructure in OECD countries does not equally affect income inequality across all distribution segments. Panel quantile regression results indicate that digital infrastructure reduces inequality more strongly, particularly in the lower quantiles of the inequality distribution. The effect remains high in Q10–Q25, weakens in the context of high inequality, and loses statistical significance in the upper quantile. This pattern supports H1 and H2, suggesting that the “equalizing” capacity of digital infrastructure is conditioned by institutional complements and skill distribution (Canh et al., 2020; Autor et al., 2020). Furthermore, the causality test confirms that the trend is from technology to inequality, strengthening H3. The weakening in the upper quantile can be explained by the self-reinforcing “inequality cycle” of digital exclusion and the polarization of the wage structure through platforming and automation (Harding et al., 2020; OECD, 2024; Ragnedda et al., 2022; Hémous & Olsen, 2022). Methodologically, the divergent coefficients at different points in the distribution suggest that approaches centered on the average effect may overlook critical information.

The results show that income inequality decreases, particularly in the lower and medium income brackets, as digital infrastructure strengthens. This suggests that internet and mobile adoption have an inequality-reducing effect (Canh et al., 2020; Yin & Choi, 2023; Odhiambo, 2022). However, the weakening of the impact in the upper income brackets suggests that the benefits of the digital economy are concentrated more in groups with capital and skills. The differing results of the research in the literature suggest that they should be interpreted in the context of the distinction between “infrastructure increase” and “who uses the infrastructure productively.” This finding also implies that, in the digital divide approach, a quantitative increase in access alone does not guarantee equality (OECD, 2024; Suhrab et al., 2024; Autor et al., 2020; Acemoglu & Restrepo, 2020). In this context, when the results are read in conjunction with evidence of digital financial inclusion, they clarify that infrastructure investments can only produce a lasting effect on equality when accompanied by simultaneous inclusion policies.

Instead of viewing digital infrastructure investment as a completed process, managers should transform the access-use-skills triad into regularly monitored indicators (Consoli, 2023; OECD, 2021a). To amplify the income-transmitted benefit for low-income groups, teams need to be supported with micro-learning and job design updates (OECD, 2021b; Autor et al., 2020). Competitive advantage is strengthened by connecting infrastructure to data-driven decision-making processes; this transition requires organizational learning and the development of restructuring capacity (Teece, 2020). From a regulator's perspective, designing universal service and competition policies in conjunction with skills programs enhances their inclusive impact (OECD, 2021a; OECD, 2024; OECD, 2021b). This trend directly aligns technology budgets with human capital and wage-career equity practices.

Theoretically, the findings suggest that digital infrastructure affects inequality differently across income brackets; therefore, the “mean impact” narrative remains limited (Canh et al., 2020). The proposed framework explains the impact of infrastructure through two channels: digital skills and in-firm wage setting practices (Consoli, 2023; Criscuolo, Leidecker, & Stoellinger, 2020; OECD, 2021b; OECD, 2024; Teece, 2020). The weakening or reversing effects at higher quantiles appear consistent with skill-driven technology change and “superstar firm” dynamics (Autor et al., 2020). This generates quantile-based evidence and provides measurable limits to the policy debate within the OECD context.

The study is based on a country-level panel that monitored OECD countries from 2010 to 2023; this structure limits the ability to test micro-level mechanisms directly. Since digital infrastructure is represented by indicators such as user rate, quality, and depth of use, it cannot be fully captured. In panel quantile regressions, inferences can become sensitive under fixed effects and dependency structures, and standard errors and distributional interpretations remain sensitive to method choice. Furthermore, reverse causality and unobserved policy simultaneities cannot be completely ruled out.

Future studies should disaggregate the impact of digitalization on “who, and through which channel,” using household or firm microdata instead of national averages. Modern DiD designs using phased policy adoption for causality and event-study pre-trend tests should be reported together. Distributional heterogeneity can be retested by strengthening the quantile approach with instrumental variable setups. Furthermore, the inclusion of moderators such as digital skills, tax-transfer progressivism, and labor institutions will enhance the explanatory power of the mechanism.

Conclusion

The findings of this study show that the impact of digital infrastructure on income inequality in OECD countries is not uniform across the distribution. Panel quantile regression findings reveal that inequality declines more significantly as infrastructure capacity increases. At high levels of inequality, marginal infrastructure gains are attenuated, and the effect weakens statistically in some upper quantiles. This pattern means that approaches reporting the “average” impact of digitalization may miss policy-critical within-distribution breaks. On a theoretical level, the results suggest that infrastructure alone is insufficient; the study demonstrates that digital inclusion and governance quality reduce inequality. Thus, the study provides a more measurable framework for determining under what conditions the digital dividend is distributed to a broader audience. The results show that digital infrastructure investment does not automatically produce an equalization mechanism without inclusion components.

Therefore, policy and governance practices should address skills, depth of use, and regulatory capacity in conjunction with increasing access to these resources. The study significantly reduces the targeting problem by answering the question of "where is it effective?" at the quantile level in the fight against inequality. The academic contribution is to provide distribution-sensitive evidence that makes the asymmetry in the digital infrastructure-inequality relationship visible. The practical contribution is to guide resource allocation by highlighting tools with high impact in the most vulnerable income brackets. Therefore, the discussion of digital transformation requires thinking not only about technology investment but also about a broader context as an architecture of equitable sharing

Acknowledgement

This study did not receive any funding from any source. There is no conflict of interest among the authors.

References

Abdurrahman, A., Gustomo, A., & Prasetio, E. A. (2024). Impact of dynamic capabilities on digital transformation and innovation to improve banking performance: A TOE framework study. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1), 100215. https://doi.org/10.1016/j.joitmc.2024.100215

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188-2244. https://doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica*, *90*(5), 1973-2016. https://doi.org/10.3982/ECTA19815

Adam, I. O., Alhassan, M. D., Shaibu, A., Abdul Mumin, M., & Abdulai, I. (2025). The effects of digital transformation on inequality: does the mediating effects of digital inclusion and ICT regulatory environment matter?. *Journal of Innovative Digital Transformation*. https://doi.org/10.1108/JIDT-04-2024-0007

Afzal, A., Firdousi, S. F., Waqar, A., & Awais, M. (2022). The influence of internet penetration on poverty and income inequality. *Sage Open*, *12*(3), 21582440221116104. https://doi.org/10.1177/21582440221116104

Ando, T., & Bai, J. (2020). Quantile co-movement in financial markets: A panel quantile model with unobserved heterogeneity. *Journal of the American Statistical Association*, *115*(529), 266-279. https://doi.org/10.1080/01621459.2018.1543598

Antonelli, C., & Tubiana, M. (2023). The rate and direction of technological change and wealth and income inequalities in advanced countries. *Technological Forecasting and Social Change*, *191*, 122508. https://doi.org/10.1016/j.techfore.2023.122508

Antonietti, R., Burlina, C., & Rodriguez-Pose, A. (2025). Digital technology and regional income inequality: Are better institutions the solution?. *Papers in Regional Science*, *104*(2), 100079. https://doi.org/10.1016/j.pirs.2025.100079

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly journal of economics*, *135*(2), 645-709. https://doi.org/10.1093/qje/qjaa004

Baffour Gyau, E., Li, Y., & Appiah, M. (2025). Global digital transformation: discovering the impact of digitalization on income inequality in OECD countries, the moderating role of globalization. *Economic Change and Restructuring*, *58*(1), 6. https://doi.org/10.1007/s10644-024-09843-2

Bartuseviciene, I., & Butkus, M. (2024). The effect of digital governance to stimulate the antifragile capabilities of public sector organizations. *Economics and Sociology, 17*(3), 41-61. https://doi.org/10.14254/2071-789X.2024/17-3/3

Bergantino, A. S., Fusco, G., Intini, M., & Monturano, G. (2026). Digital divide and income inequality: causal evidence from Italian provinces. *The Annals of Regional Science*, *75*(1), 11. https://doi.org/10.1007/s00168-025-01440-z

Bilan, Y., Mishchuk, H., & Oliinyk, O. (2025). Migration of highly skilled workers as a driver of digital economy development. *Knowledge and Performance Management*, *9*(2), 113-123. https://doi.org/10.21511/kpm.09(2).2025.09

Bozhenko, V., Boyko, A., Vondráček, M., & Karácsony, P. (2024). Shadow economy and financial stability from the perspective of finance digitalization. *Journal of International Studies, 17*(2), 191-205. https://doi.org/10.14254/2071-8330.2024/17- 2/10

Canh, N. P., Schinckus, C., Thanh, S. D., & Ling, F. C. H. (2020). Effects of the internet, mobile, and land phones on income inequality and The Kuznets curve: Cross country analysis. *Telecommunications Policy*, *44*(10), 102041. https://doi.org/10.1016/j.telpol.2020.102043

Chen, L. (2024). Two-step estimation of quantile panel data models with interactive fixed effects. *Econometric Theory*, *40*(2), 419-446. https://doi.org/10.1017/S0266466622000366

Consoli, D., Castellacci, F., & Santoalha, A. (2023). E-skills and income inequality within European regions. *Industry and Innovation*, *30*(7), 919-946. https://doi.org/10.1080/13662716.2023.2230222

Criscuolo, C., Hijzen, A., Schwellnus, C., Barth, E., Chen, W. H., Fabling, R., ... & Zwysen, W. (2020). *Workforce composition, productivity and pay: the role of firms in wage inequality* (No. 13212). IZA Discussion Papers. https://doi.org/10.1787/0830227e-en

Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2022). Fintech, financial inclusion and income inequality: a quantile regression approach. *The European Journal of Finance, 28*(1), 86-107. https://doi.org/10.1080/1351847X.2020.1772335

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic modelling, 29*(4), 1450-1460. https://doi.org/10.1016/j.econmod.2012.02.014

Galvao, A. F., Gu, J., & Volgushev, S. (2020). On the unbiased asymptotic normality of quantile regression with fixed effects. *Journal of Econometrics, 218*(1), 178-215. https://doi.org/10.1016/j.jeconom.2019.12.017

Galvao, A. F., Parker, T., & Xiao, Z. (2024). Bootstrap inference for panel data quantile regression. *Journal of Business & Economic Statistics, 42*(2), 628-639. https://doi.org/10.1080/07350015.2023.2210189

Gavurova, B., Polishchuk, V., Mikeska, M., & Polishchuk, I. (2025). Socioeconomic impact of digital transformation in tourism: A hybrid decision support model. *Economics and Sociology, 18*(2), 305-319. doi:10.14254/2071-789X.2025/18- 2/16

Grishchenko, N. (2020). The gap not only closes: Resistance and reverse shifts in the digital divide in Russia. *Telecommunications Policy, 44*(8), 102004. https://doi.org/10.1016/j.telpol.2020.102004

Harding, M., Lamarche, C., & Pesaran, M. H. (2020). Common correlated effects estimation of heterogeneous dynamic panel quantile regression models. *Journal of Applied Econometrics, 35*(3), 294-314. https://doi.org/10.1002/jae.2753

Heeks, R. (2022). Digital inequality beyond the digital divide: conceptualizing adverse digital incorporation in the global South. *Information Technology for Development, 28*(4), 688-704. https://doi.org/10.1080/02681102.2022.2068492

Hémous, D., & Olsen, M. (2022). The rise of the machines: Automation, horizontal innovation, and income inequality. *American Economic Journal: Macroeconomics, 14*(1), 179-223. https://doi.org/10.1257/mac.20160164

Ho, T. L., & Ho, T. H. (2025). Digital inclusion or exclusion? Exploring the moderating role of governance in digitalization’s impact on income inequality in developing countries. *Research in Globalization, 10*, 100283. https://doi.org/10.1016/j.resglo.2025.100283

Houngbonon, G. V., & Liang, J. (2021). Broadband internet and income inequality. *Review of Network Economics, 20*(2), 55-99. https://doi.org/10.1515/rne-2020-0042

Hutter, C., & Weber, E. (2023). Labour market effects of wage inequality and skill-biased technical change. *Applied Economics, 55*(27), 3063-3084. https://doi.org/10.1080/00036846.2022.2108751

Kanga, D., Oughton, C., Harris, L., & Murinde, V. (2022). The diffusion of fintech, financial inclusion and income per capita. *The European Journal of Finance, 28*(1), 108-136. https://doi.org/10.1080/1351847X.2021.1945646

Kozhakhmetova, A., Tazhiyeva, Zh., Zhidebekkyzy, A., & Bács, Z. (2025). Effects of digital transformation on green investment: Evidence from developing economies. *Journal of International Studies, 18*(2), 138-158. doi:10.14254/2071- 8330.2025/18-2/8

Kuhn, C., Khoo, S. M., Czerniewicz, L., Lilley, W., Bute, S., Crean, A., ... & MacKenzie, A. (2023). Understanding digital inequality: A theoretical kaleidoscope. In *Constructing postdigital research: Method and emancipation* (pp. 333-373). Cham: Springer Nature Switzerland. https://doi.org/10.1007/s42438-023-00395-8

Liao, S. C., Chou, T. C., & Huang, C. H. (2022). Revisiting the development trajectory of the digital divide: A main path analysis approach. *Technological Forecasting and Social Change, 179*, 121607. https://doi.org/10.1016/j.techfore.2022.121607

Liu, L., & Guo, L. (2023). Digital financial inclusion, income inequality, and vulnerability to relative poverty. *Social Indicators Research, 170*(3), 1155-1181. https://doi.org/10.1007/s11205-023-03245-z

Mishchuk, H., Samoliuk, N., Krol, V., & Rącka, I. (2025). Digital competences of university graduates: Implications for career success. *Human Technology, 21*(2), 274–292. https://doi.org/10.14254/1795-6889.2025.21-2.2

Mudričenko, G., Laskienė, D., Gižienė, V., & Navickas, V. (2023). An empirical analysis of inflation's influence on income inequality in Lithuania. *Economics, Management and Sustainability, 8*(2), 20–31. https://doi.org/10.14254/jems.2023.8-2.2

Nogueira, M. C., & Madaleno, M. (2023). Skill-Biased Technological Change and Gender Inequality across OECD Countries—A Simultaneous Approach. *Economies, 11*(4), 115. https://doi.org/10.3390/economies11040115

Odhiambo, N. M. (2022). Information technology, income inequality and economic growth in sub-Saharan African countries. *Telecommunications Policy, 46*(6), 102309. https://doi.org/10.1016/j.telpol.2022.102309

Organisation for Economic Co-operation and Development. (2021a). *Broadband policy and technology developments* (OECD Digital Economy Papers No. 317). https://doi.org/10.1787/e273ff77-en

Organisation for Economic Co-operation and Development. (2021b). *Development co-operation report 2021: Shaping a just digital transformation.* https://doi.org/10.1787/ce08832f-en

Organisation for Economic Co-operation and Development. (2021c). *Does inequality matter? How people perceive economic disparities and social mobility.* https://doi.org/10.1787/3023ed40-en

Organisation for Economic Co-operation and Development. (2021d). *The role of firms in wage inequality: Policy lessons from a large-scale cross-country study.* https://doi.org/10.1787/7d9b2208-en

Organisation for Economic Co-operation and Development. (2024a). *Financing broadband networks of the future* (OECD Digital Economy Papers No. 365). https://doi.org/10.1787/eafc728b-en

Organisation for Economic Co-operation and Development. (2024b). *New perspectives on measuring cybersecurity* (OECD Digital Economy Papers No. 366). https://doi.org/10.1787/b1e31997-en

Organisation for Economic Co-operation and Development. (2024c). *OECD digital economy outlook 2024* (Vol. 1): *Embracing the technology frontier.* https://doi.org/10.1787/a1689dc5-en

Organisation for Economic Co-operation and Development. (2024d). *OECD digital economy outlook 2024* (Vol. 2). https://doi.org/10.1787/3adf705b-en

Organisation for Economic Co-operation and Development. (2024e). *Shaping a rights-oriented digital transformation* (OECD Digital Economy Papers No. 368). https://doi.org/10.1787/86ee84e2-en

Organisation for Economic Co-operation and Development. (2024f). *Society at a glance 2024: OECD social indicators.* https://doi.org/10.1787/918d8db3-en

Organisation for Economic Co-operation and Development. (2024g). *The OECD truth quest survey: Methodology and findings* (OECD Digital Economy Papers No. 369). https://doi.org/10.1787/92a94c0f-en

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers. *Economics, 1240*(1), 1. https://www.cesifo.org/DocDL/cesifo1_wp1229.pdf

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of applied econometrics*, *22*(2), 265-312. https://doi.org/10.1002/jae.951

Powell, D. (2022). Quantile regression with nonadditive fixed effects. *Empirical Economics*, *63*(5), 2675-2691. https://doi.org/10.1007/s00181-022-02216-6

Qiu, L., Zhong, S., & Sun, B. (2021). Blessing or curse? The effect of broadband Internet on China's inter-city income inequality. *Economic Analysis and Policy*, *72*, 626-650. https://doi.org/10.1016/j.eap.2021.10.013

Ragnedda, M., Ruiu, M. L., & Addeo, F. (2022). The self-reinforcing effect of digital and social exclusion: The inequality loop. *Telematics and Informatics*, *72*, 101852. https://doi.org/10.1016/j.tele.2022.101852

Solt, F. (2020). Measuring income inequality across countries and over time: The standardized world income inequality database. *Social Science Quarterly*, *101*(3), 1183-1199. https://doi.org/10.1111/ssqu.12795

Suhrab, M., Chen, P., & Ullah, A. (2024). Digital financial inclusion and income inequality nexus: can technology innovation and infrastructure development help in achieving sustainable development goals?. *Technology in Society*, *76*, 102411. https://doi.org/10.1016/j.techsoc.2023.102411

Tao, L., Tai, L., & Tian, M. (2023). Quantile regression for static panel data models with time-invariant regressors. *Plos one*, *18*(8), e0289474. https://doi.org/10.1371/journal.pone.0289474

Teece, D. J. (2020). Fundamental issues in strategy: Time to reassess?. *Strategic Management Review*, *1*(1), 103-144. https://doi.org/10.1561/111.00000010

Teece, D. J. (2020). Hand in glove: Open innovation and the dynamic capabilities framework. *Strategic Management Review*, *1*(2), 233-253. https://doi.org/10.1561/111.00000010

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and statistics*, *69*(6), 709-748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

World Bank. (2021). *World development report 2021: Data for better lives.* https://doi.org/10.1596/978-1-4648-1600-0

World Bank. (2024). *World development report 2024: The middle-income trap.* https://www.worldbank.org/en/publication/wdr2024

Yin, Z. H., & Choi, C. H. (2023). Does digitalization contribute to lesser income inequality? Evidence from G20 countries. *Information Technology for Development*, *29*(1), 61-82. https://doi.org/10.1080/02681102.2022.2123443

Yoon, J., & Galvao, A. F. (2020). Cluster robust covariance matrix estimation in panel quantile regression with individual fixed effects. *Quantitative Economics*, *11*(2), 579-608. https://doi.org/10.3982/QE802

Yoon, J., & Galvao, A. F. (2020). Cluster robust covariance matrix estimation in panel quantile regression with individual fixed effects. *Quantitative Economics*, *11*(2), 579-608. https://doi.org/10.3982/QE802 onlinelibrary.wiley.com

Zang, L., Zhu, Y., & Cheng, D. (2025). Inequality through digitalization: investigation of mediating and moderating mechanisms. *Information Technology for Development*, *31*(4), 821-836. https://doi.org/10.1080/02681102.2024.2423390

Zhang, J., Li, Y., & Fang, Z. (2025). Two digital divides and income inequality: a global perspective. *Journal of Applied Economics*, *28*(1), 2568247. https://doi.org/10.1080/15140326.2025.2568247