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Analysis the effect of digital economy on income inequality: A study on six ASEAN countries

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ABSTRACT

The rapid development of the digital economy has reshaped labor markets and income distribution, raising concerns over whether digitalization exacerbates or reduces income inequality. While technological progress is often associated with skill-biased effects, digital technologies may also broaden access to markets, information, and economic opportunities, particularly in developing regions such as ASEAN. This study examines the impact of digital economy on income inequality in ASEAN countries and assesses whether the relationship follows a non-linear (U-shaped) pattern. Using panel data from six ASEAN countries (Indonesia, Malaysia, Singapore, Thailand, Vietnam, and Philippines) over the period 2010–2020 (66 country-year observations), the analysis employs fixed-effects panel regression models. A quadratic specification is estimated to test for non-linearity, and potential endogeneity is addressed using a two-stage least squares (2SLS) approach with telecommunication-based instrumental variables. The empirical results indicate that digital economy has a negative and statistically significant effect on income inequality, suggesting an equalizing impact across ASEAN countries. The findings imply that digitalization reduces income inequality by expanding access to digital infrastructure and economic participation, thereby enhancing labor market inclusion and income opportunities for low- and middle-income groups. However, no robust evidence of a non-linear (U-shaped) relationship is found, as the estimated turning point lies outside the observed data range.

1. Introduction

Income inequality has become a socio-economic issue faced by various countries. Income inequality is closely related to social stability, social equity, and economic development (Tian & Xiang, 2024). Income inequality refers to the gap in income distribution among populations. Income inequality has been found to reduce subjective well-being, particularly in rural populations (Zhang & Churchill, 2020). It also negatively impacts economic growth by hindering investment, which in turn affects productivity (Seo et al., 2020). In Sub-Saharan Africa, income inequality negatively affects access to electricity and human development, while good governance can help reduce inequality (Sarkodie & Adams, 2020). These findings underscore the importance of addressing income inequality through targeted policies to promote social trust, investment, and human development. Such measures could potentially lead to improvements in well-being, economic growth, and environmental sustainability.

Income inequality is a consequence of technological advancement and globalization, accompanied by biased tax policies (Polacko, 2021; Ilyasa et al., 2025). The role of globalization has led to the offshoring of jobs and wage pressures. Technological advancements have increased the demand for highly skilled workers while reducing the value of low-skilled labor, leading to skill-biased technological change. (SBTC). The advent of the digital age has placed a higher premium on the skills needed for non-routine work and reduced the value placed on lower skilled routine work, as it has enabled machines to replace jobs that could be routinised (Polacko, 2021). Technological advancements tend to benefit high-skilled labor more than low-skilled labor in the form of increasing demand in the labor market for high-skilled workers, but not for low-skilled workers, which has the potential to worsen income inequality. The development of technology can be seen from the growth of the digital economy. The digital economy generally requires workers with high skills to adapt and leverage new technologies, leading to increased productivity and income for this segment of the workforce. Unlike the conditions for highly skilled labor, low-skilled labor may face challenges such as job displacement or lower wages (Tian & Xiang, 2024). Uneven distribution contributes to income inequality. Technological advancements and skill gaps have emerged as key factors influencing income distribution in the digital economy.

Some studies have tested how the relationship between the digital economy and income inequality. Wu et al (2024), Peng & Dan (2023) and Tian & Xiang (2024) found that the digital economy can affect income inequality. Wu et al (2024) and Peng & Dan (2023) found a U-shaped relationship between the digital economy and income gap using city and provincial data in China. However, Tian & Xiang (2024) found no U-shaped relationship between the digital economy and income gap using EU28 city data. The differences may occur due to the diverse variations at the city level in the EU28 countries and China. These divergent empirical findings can be explained through classical theories of technological change and innovation. According to Kuznets (1955), an inverted U-shaped relationship between the digital economy and income inequality may occur if established industrial groups that gained surplus value from the early stages of digital economic development fail to reallocate their assets into more profitable new fields (Fuady, 2018). Meanwhile, Breschi et al (2000) demonstrate the influence of innovation and technological development through two stages, namely Schumpeter Stage I and Schumpeter Stage II, where each stage exerts a different effect on income inequality. In Schumpeter Stage I, new technologies provide greater opportunities for new entrants to enter the market, thereby reducing the level of income inequality (Fuady, 2018; Kim, 2012). In the Schumpeter II stage, established players have become increasingly entrenched with the accumulation of knowledge and technology; R&D competencies, production capabilities, distribution, and financial resources will be able to create barriers for new entrants, so that in this stage, income inequality will instead increase (Fuady, 2018; Kim, 2012; Breschi et al. 2000).

In ASEAN countries, several studies have examined the relationship between digital-related indicators and income inequality. Jing et al (2020) found that mobile-cellular telephone subscriptions and fixed telephone line subscriptions significantly reduce income inequality, while Ningsih and Choi (2019) shows that internet penetration, as a proxy for technological change, contributes to lower income inequality. However, these studies rely on relatively narrow indicators of digitalization and do not fully capture the broader and multi-dimensional nature of the digital economy. Existing studies on ASEAN do not explicitly test for potential non-linear effects between digital economy development and income inequality. The possibility of a non-linear relationship is particularly relevant for ASEAN countries, where large disparities in digital access, skills, and productive structures persist across and within economies. In such settings, early phases of digital expansion may disproportionately benefit high-skilled workers and technologically advanced firms, while broader diffusion of digital technologies may later improve market access and income opportunities for disadvantaged groups. Empirical evidence supporting this U-shaped pattern is provided by Wu et al. (2024) and Peng & Dan (2023) argued that a U-shaped relationship between digital economy development and income gaps using city- and province-level data in China, an economy that shares key structural characteristics with ASEAN, including uneven digital diffusion, regional development gaps, and segmented labor markets.

Despite these theoretical and empirical insights, empirical evidence on the relationship between the digital economy and income inequality in ASEAN remains scarce. Existing studies on ASEAN predominantly rely on single or limited digital indicators and linear model specifications, which are insufficient to capture the multi-dimensional and stage-dependent nature of digital development highlighted above. To the best of our knowledge, no study has systematically examined whether digital economy development reflecting variations in digital infrastructure, skills, innovation, adoption, and domestic digital production exhibits non-linear effects, such as U-shaped or inverted U-shaped relationships, on income inequality across ASEAN countries. By explicitly testing both negative and non-linear relationships, this study contributes to the literature by clarifying the distributional consequences of digitalization in ASEAN and by providing policy-relevant insights on how digital development strategies can be designed to promote more inclusive growth.

Based on the background, this study examines the impact of digital economy on income inequality, as well as how the relationship between the digital economy and income inequality is, whether it is a U-shaped relationship or not. This research will focus on five pillars as indicators of the digital economy index, including foundations, talent, innovation, adoption, and local production (El-Darwiche et al., 2021). To achieve this goal, this research uses the fixed effect model panel data regression method for major ASEAN countries, namely Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam from 2010 to 2020. Income inequality can have the opposite effect on the development of the digital economy (Tian & Xiang, 2024), making the regression results potentially endogenous. Based on this, the study conducts endogenous resolution using the two-stage least squares method by adding the interaction between the percentage of internet users per year (per population) and telephone subscriptions per year (per 100 people) in the same years from 2010 to 2020 as instrumental variables to address potential endogeneity issues. This approach is used because the increase in the number of phone calls can still drive the development of the digital economy through the provision of infrastructure access and connectivity, as well as digital transformation and internet dissemination. The change in the number of landline phones also does not have a direct relationship with income inequality, so the instrumental variable meets the relevant requirements and is also consistent with the assumptions about the nature of the instrumental variable. This research also uses robustness tests to ensure the reliability of the analysis results. However, before the analysis is conducted, classical assumption tests are first carried out to ensure the regression model has accuracy in estimation.

2. Literature Review

Skill-biased technical change (SBTC) is a technological change in the production sector that creates a more favorable situation for skilled labor (more educated, more capable, more experienced) with the increasing demand for skilled labor and its productivity compared to unskilled labor (Violante, 2008). The increasing demand for skilled labor will lead to polarization and income inequality (Mellacher & Scheuer, 2021). Income inequality occurs through the reduction of working hours and income for low-skilled workers. In the context of the digital economy, skill-biased technical change theory suggests that digitalization may exacerbate wage inequality and job polarization (Kolade & Owoseni, 2022). While digital technologies offer opportunities for developing countries, there are concerns about their ability to benefit equally compared to developed nations (Matthess & Kunkel, 2020). User innovation is expanding beyond businesses to include households and other economic sectors, necessitating new skills and policy considerations in the digital economy (Gault, 2019). As digitalization impacts structural change drivers, it may affect relative sectoral productivity and labor movements, potentially hindering equitable income gains and inter-firm linkages in developing countries (Matthess & Kunkel, 2020).

Nevertheless, some literature emphasizes that the distributional effects of digital technologies are not exclusively inequality-increasing. Beyond the SBTC mechanism, digitalization also generates equalizing channel that can mitigate or offset rising income inequality. Improved access to online markets allows small firms, self-employed workers, and informal producers to reach broader customer bases and reduce transaction costs, thereby enhancing income opportunities for lower-income groups (Freund & Weinhold, 2004; Goldfarb & Tucker, 2019). In addition, digital platforms facilitate access to information, training, and learning opportunities, which can gradually reduce skill gaps and improve labor market mobility. The diffusion of digital tools across households and non-firm actors further supports user innovation beyond formal businesses, expanding participation in economic activities that were previously inaccessible (Gault, 2019). These mechanisms suggest that while SBTC effects may dominate at early stages of digital adoption, broader diffusion of digital technologies and skills can generate more inclusive outcomes over time.

There are several factors found to influence income inequality, which can be grouped into macroeconomic, institutional–demographic, and technological factors. Macroeconomic factors include economic development, unemployment, globalization, trade integration, financial globalization (Furceri & Ostry, 2019), GDP, household consumption, inflation, gross savings rate, trade openness, government spending, natural resource rent, tax revenue, and GDP per capita (Yadav et al., 2020; Sarkhosh-Sara et al., 2020). These factors are closely related to the level of economic activity and labor market conditions, and therefore motivate the inclusion of GDP per capita, globalization, and unemployment as control variables.

Institutional and demographic factors include population (Butler et al., 2020), literacy, corruption, educational factors, and the growth in labor (Hoffmann et al., 2020). These factors reflect differences in demographic structure, human capital, and institutional quality that may influence income distribution across countries, which justifies the inclusion of population as a control variable. Technological factors include technological change (Antonelli & Tubiana, 2023) and the digital economy (Tian & Xiang, 2024; Wu et al., 2024; Peng & Dan, 2023; Yan et al., 2023). Unlike other factors, the digital economy has been found to exhibit a non-linear relationship with income inequality. Wu et al (2024), Peng & Dan (2023) and Yan et al (2023) documented a U-shaped relationship between the digital economy and income gap using city- and province-level data in China. In contrast, Tian & Xiang (2024) revealed no U-shaped relationship between the digital economy and income gap using EU28 city-level data. This difference may occur due to diverse structural and developmental differences across regions.

According to Tian & Xiang (2024), Wu et al (2024), Peng & Dan (2023), Yan et al (2023) found that the digital economy affects income inequality. Research by Wu et al (2024), Peng & Dan (2023) and Yan et al (2023) found a U-shaped non-linear relationship between the digital economy and income inequality using city and provincial data in China. However, Tian & Xiang (2024) found no U-shaped relationship between the digital economy and income gap using EU28 city data. Distinct divergent perspectives emerge when comparing the research trajectories of Tian & Xiang (2024), Wu et al (2024) and Peng & Dan (2023). Tian & Xiang (2024) hypothesized that in its incipient stages, the digital economy fosters new business opportunities and employment, thereby stimulating economic growth and enhancing social mobility. However, they posited that as the digital economy matures and becomes increasingly centralized, market monopolization by large corporations would trigger extreme wealth concentration. This monopolistic landscape and the resulting asymmetrical market power could exacerbate income inequality while disenfranchising marginalized groups. Paradoxically, their empirical results failed to substantiate this hypothesis. In contrast, findings from Wu et al (2024) indicate that in the early stages of development, the digital economy does not have a significant impact on income inequality. However, after a certain level of development, the digital economy will increase income inequality and will reduce income inequality as the digital economy further develops.

The digital economy contributes to the increase in the share of the workforce in areas with a high number of skilled workers, thereby reducing income inequality due to the simultaneous increase in wage income. Peng & Dan (2023) found that the U-shaped relationship between the digital economy and income inequality occurs due to different stages of urbanization. These differences may involve diverse variations at the city level in EU countries and China. Development in European Union countries is relatively equal, the social welfare system can be said to be well-developed, the education level is generally high, and the labor market is more stable. These conditions may slow down the impact of the digital economy on income inequality, creating a less pronounced U-shaped relationship in European Union countries. In China, the disparity between cities and provinces, the diversity of the population, and government policies promoting urbanization and digitalization are potential factors causing the U-shaped relationship between the digital economy and income inequality. Evidence from developing countries and ASEAN remains more limited and focuses primarily on specific digital-related indicators rather than the digital economy as a whole. For example, Jing et al (2020) found that mobile-cellular telephone subscriptions and fixed telephone line subscriptions reduce income inequality, while Ningsih and Choi (2019) shows that internet penetration, as a proxy for technological change, contributes to lower income inequality in ASEAN countries. However, these studies rely on single or narrow measures of digitalization and employ linear model specifications, without examining whether the impact of digital development varies across stages or follows a non-linear pattern.

3. Method

The type of research is quantitative research, with the research design used being causal research design. The research uses inferential statistics, testing a number of research hypotheses formulated in the study. This research uses panel data from several ASEAN countries including Indonesia, Malaysia, Singapore, the Philippines, Thailand, and Vietnam covering the period from 2010 to 2020.

Secondary data is used in this research, obtained from reliable sources such as the World Inequality Database, World Bank Database, and publications from The Global Strategy Consulting. The dependent variable in this study is income inequality. Income inequality data is taken from data on income distribution inequality, specifically the ratio of total income received by 1% of the total population. The inequality data is obtained from the World Inequality Database.

The independent variable in this study is the digital economy. The source of digital economy data is taken from the Digital Economy Index (DEI) published by Strategy&. The Digital Economy Index (DEI) is a comprehensive and empirically-based tool that measures the level of digitalization of a country based on 86 indicators that fall into five main pillars: foundations, talent, innovation, adoption, and local production. Foundations consist of investments in information and communication technology (ICT) infrastructure that enhance connectivity to provide digital coverage, improve broadband service quality, and increase affordability, along with regulations that enable the digital economy. The key assessments measured in the foundations pillar are investments, coverage, service quality, affordability, telecom and cybersecurity regulations, intellectual property regulations, and labor market regulations. Talent is the human resource that develops, operates, and maintains technology and creates innovations that produce new products and services — a factor of production that is lacking in many economies. The government, educational institutions, and companies need to develop human resources with technical skills that align with the ever-changing needs of the digital sector. The key assessments measured in the talent pillar are the quality of education, STEM graduates, basic digital skills, advanced skills, training, digital jobs across sectors, and digital jobs in ICT. Innovation is related to the scale and speed of research and development (R&D), as evidenced by the prevalence of successful startups and incubation ecosystems that provide available funding sources, mentoring, and scalability support. Advanced manufacturing and robotics, cybersecurity, and other new technologies are among the fastest-growing subsectors. In the innovation pillar, the main assessments measured are R&D, financing, ease of doing business, entrepreneurial culture, and digital growth. Adoption measures the extent to which online services, devices, and platforms are used by individuals, companies, and governments. The main assessment measured by the adoption pillar includes devices and connection, usage, entertainment, transactions, E-government, services, basic digital adoption, and advanced digital adoption. Local production refers to the level of digital products and services created domestically, as well as digital services, digital content, and software applications. DEI measures the success of locally developed internet platforms and content, as well as the export of digital goods and services. In the local production pillar, the main assessments measured are entertainment and media, telecommunications, content development, solutions development, tech exports, local emerging tech companies, and local investments in technology.

The control variables used in this study are Per Gross Domestic Product (PGDP), Globalization, Population, and Unemployment. Data for the Gross Domestic Product (GDP) per capita, population, and unemployment variables were obtained from the World Bank. The globalization variable was obtained from the KOF Globalization Index, which measures the economic, social, and political dimensions of globalization published by the Swiss Economic Institute. The data analysis technique used in this research is panel data regression with a fixed effect model. The regression model in this study also adds the square of the Digital variable to the estimated model to test hypotheses H_{2a} and H_{2b}. The equation for the study as follows:

$$inequality_{it} = \alpha_0 + \beta_1 digital_{it} + \beta_2 digital_{it}^2 + \mu_i + v_t + \varepsilon_{it} \tag{1}$$

$$inequality_{it} = \alpha_0 + \beta_1 digital_{it} + \beta_2 digital_{it}^2 + \beta Z_{it} + \mu_i + v_t + \varepsilon_{it} \tag{2}$$

$$inequality_{it} = \alpha_0 + \beta_1 digital_{it} + \mu_i + v_t + \varepsilon_{it} \tag{3}$$

$$inequality_{it} = \alpha_0 + \beta_1 digital_{it} + \beta Z_{it} + \mu_i + v_t + \varepsilon_{it} \tag{4}$$

Where μ_i is the effect of the country used as a sample and v_t is the effect of the time used as a sample. Z represents all the control variables that affect income inequality. The stages in the analysis of this research follow the methodology used by Tian & Xiang (2024), which is first to determine whether a U-shaped relationship exists, as seen in the results of equation (1). If a U-shaped relationship exists, then β_1 and β_2 in equation (1) will be statistically significant and negative and positive, respectively. Based on the regression results, if a U-shaped relationship exists, it will proceed to equation (2). To ensure the validity of the non-linear relationship results, a visual representation of the relationship between $inequality$ and $digital$ is also included in the form of a scatter plot. In addition, a turning point analysis is conducted following Wooldridge (2012) to examine whether the implied non-linear effect occurs within the observed range of the digital economy variable. If the non-linear relationship fails to be proven, the quadratic variable will be removed from the model, and a new model will be formed for re-estimation (equation 3 and 4). To assess whether the estimation is strong enough or not, by testing how sensitive the analysis results are to small changes in the data used, a robustness test is conducted. In the $inequality$ variable that previously used top 1% national income share data, it was replaced with top 10% national income share data and retested. In addition, a second robustness check was conducted by re-estimating the model after excluding Singapore from the sample to account for its distinct level of digital development and income structure within ASEAN. If the statistical test results do not change drastically after the $inequality$ variable data is replaced, it can be said that the estimation is quite strong. Conversely, if the statistical test results change drastically after the $inequality$ variable data is replaced, it can be said that the estimation is not strong enough. Before conducting the panel data regression analysis, to ensure the validity of the analysis, classical assumption tests consisting of normality test, multicollinearity test, and heteroscedasticity test are performed to avoid estimation bias.

To address potential endogeneity between digital economy development and income inequality, this study employs a two-stage least squares (2SLS) estimation strategy. The instrumental variable is constructed as the interaction between the percentage of internet users and telephone subscriptions, capturing variations in telecommunication infrastructure and connectivity that facilitate digital development. Instrument relevance is assessed through first-stage estimation, while endogeneity is evaluated using the Durbin–Wu–Hausman test. The exclusion restriction is justified by the role of telecommunication infrastructure as an enabling condition for digital transformation rather than a direct determinant of income distribution, consistent with evidence from ASEAN countries (Jing et al., 2020; Ningsih & Choi, 2019).

4. Results and Discussion

Table 1 shows that the inequality variable (income inequality) has a minimum value of 10.3 with a mean value of 16.61 and a standard deviation of 2.15. This means the mean is greater than the standard deviation, indicating low data deviation and a uniform distribution of values. The digital variable (digital economy) has a minimum value of 13 with a mean value of 31.13 and a standard deviation of 16.15. The mean is greater than the standard deviation, indicating low data deviation and a uniform distribution of values. The same condition also occurs with the control variables, namely the variables of globalization, population, and unemployment, which have mean values greater than the standard deviation. However, in the PGDP (GDP per capita) variable, the mean value is smaller than the standard deviation.

Table 1. Descriptive Statistics

a. Category	Variable Name	Measurement	Mean	Standard Deviation	Min	Max
Dependent variable	Inequality	Index	16.61	2.15	10.3	22.7
Independent variable	Digital	Index	31.13	16.15	13	74
	PGDP	US$	13966.87	20197.83	168451.63	66840.61
	Globalization	Index	68.74	11.94	51.62	87.2
Control variables	Population	People	93435744	81945353	5076732	27185797
	Unemployment	Percentage % of total labor force	2.80	1.39	0.2	5.6

Source: data processed

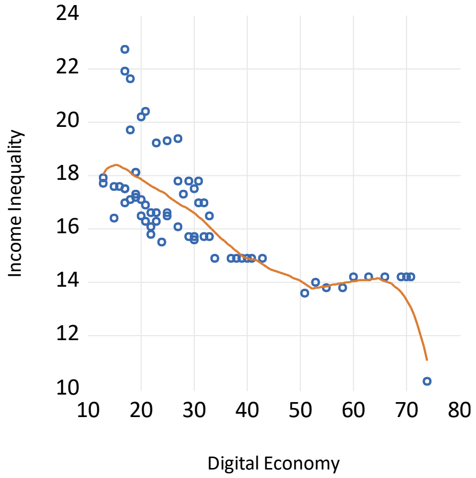
The classical assumption tests as shown in Table 2 (multicollinearity test and heteroscedasticity test) can be concluded that the residuals are normally distributed, the selected model is free from multicollinearity symptoms, and there are no heteroscedasticity issues. Based on Table 2 shows that the probability value is 0.242 > 0.05, indicating that the data is normally distributed. In the multicollinearity test, Table 2 shows that the VIF tolerance values produced by all variables < 10, which means that in the selected model, there are no signs of multicollinearity. In the heteroscedasticity test, a Glejser test was conducted with results showing that all tested variables have a probability value > 0.05, meaning there are no heteroscedasticity issues in the model used.

Table 2. Classical Assumption for the Model

	Multicollinearity test Centered VIF	Heteroscedasticity test Glejser test	Normality Test Jarque-Bera
Digital	5.45	0.4077	
PGDP	2.72	0.9230	
Globalization	1.43	0.0538	0.242
Population	4.95	0.8854	
Unemployment	2.06	0.3127	

Source: data processed

Based on Table 3 in column I, the coefficient value of the $digital$ variable was found to be statistically significant at the 1% level with a negative relationship direction, and $digital^2$ was found to be statistically significant at the 10% level with a positive relationship direction. The results shows the different directions of the relationship indicate a U-shaped effect of the digital economy on income inequality.To further assess the existence of non-linearity, a turning point test following Wooldridge (2012) was conducted using the formula $X^* = -\beta_1/(2\beta_2)$. The calculated turning point is 87.19 (Table 3), which lies outside the observed data range of the digital economy variable (minimum 13 and maximum 74). This indicates that the turning point is not empirically relevant within the sample. In addition, a visual inspection of the relationship between the digital economy and income inequality (Figure 1) does not reveal a clear non-linear pattern. Taken together, these results suggest that the U-shaped relationship is not supported empirically in the ASEAN sample.



Source: data processed

Figure 1. Scatter Plot of The Relationship Between Digital Economy and Income Inequality

The result shows there is no non-linear relationship was found between the digital economy and income inequality, the estimation continues using equation (3) and equation (4). Based on Table 3 in columns II and III, where the control variable in column II is excluded and included in column III. All estimation models show that the coefficient of the digital variable remains negative and statistically significant at the 1% level. This indicates that the digital economy can reduce income inequality and has a seemingly linear relationship. The results of the analysis support H_{1a}. The analysis of control variables in model III shows that the coefficients of GDP per capita, population, and unemployment rate are found to be positive and significant towards income inequality. Meanwhile, the coefficient of globalization indicates a negative and significant relationship with income inequality. This study conducts endogenous resolution using the two-stage least squares method (column IV in Table 3) by adding the interaction between the percentage of internet users per year (per population) and telephone subscriptions per year (per 100 people) in the same years from 2010 to 2020 as instrumental variables to address potential endogeneity issues. The explanatory variable in this study was tested for endogeneity using the Durbin-Wu-Hausman (DWH) test, which showed a DWH test statistic of 50.40, P = 0.00 < 0.01, achieving a significance level of 1 percent. Based on these results, it can be said that there is an endogeneity issue with the explanatory variables in this study. Based on the results of the two-stage least squares test, the findings indicate that the digital economy significantly affects income inequality, and this result confirms the strength of the previous test. To assess whether the estimation is strong enough or not, by testing how sensitive the analysis results are to small changes in the data used, a robustness test is conducted. Based on Table 3 in columns V and VI, the income inequality variable was replaced with the ratio of total income received by the top 10% of the total population. The test results show the same thing, namely that the digital economy coefficient is negative with statistical significance at the 1% level. Furthermore, Table 4 reports additional robustness checks by excluding Singapore from the sample to address potential sensitivity arising from a highly digitalized economy within ASEAN. The results remain qualitatively consistent with the baseline estimations. The coefficient of the digital economy variable continues to exhibit a negative and statistically significant relationship with income inequality, while the quadratic term remains statistically insignificant. This finding indicates that the main results are not driven by a single outlier country and further confirms the absence of a stable non-linear (U-shaped) relationship between digital economy development and income inequality in ASEAN countries. These results verify the validity of the previously conducted regression test.

Table 3. Results of Baseline Regression and Robustness Tests

	Baseline regression			Endogenous resolution	Robustness checks	
	Fixed Effects Model			Two-stage least squares	Variable replacement	
	I	II	III	IV	V	VI
$digital_{it}$	-0.227***	-0.126***	0.315***	-0.307***	-0.148**	-0.509***
	(-4.00)	(-5.00)	(-6.42)	(-5.925)	(-3.00)	(-5.016)
$digital_{it}^2$	0.001*	-	-	-	-	-
	(1.967)					
$PGDP_{it}$	-	-	0.003***	0.0003***	-	0.0001***
			(3.959)	(3.697)		(3.413)
$global_{it}$	-	-	-0.161***	-0.161***	-	-0.238***
			(-3.379)	(-3.366)		(-2.408)
$population_{it}$	-	-	2.390***	2.32E-07***	-	4.59***
			(4.405)	(4.126)		(4..088)
$unem_{it}$	-	-	0.836***	0.800**	-	1.994***
			(2.206)	(2.075)		(2.543)
Constant	22.053***	20.549***	8.388	9.0172*	50.16***	21.369***
	(20.203)	(25.758)	(1.662)	(1.7327)	(32.329)	(2.046)
R-squared	0.7646	0.7531	0.8556		0.7207	0.8150
Diagnostic Tools						
DWH				50.40	(p = 0.00)	
Turning Point Data Range	(Column I) (Digital) :	min = 13	max = 74	87.19		

Source: data processed

Table 4 shows the digital economy has a negative and significant impact on income inequality. This study also found that the digital economy and income inequality do not have a non-linear relationship. The negative impact indicates that the development of the digital economy can reduce income inequality. The development of the digital economy in the form of increased access to the internet and digital technology allows the public to participate in the digital economy, thereby enhancing productivity and income. The more people use digital technology for various activities, such as e-commerce, digital payments, and online government services, the more economic opportunities arise. From an educational perspective, the development of the digital economy measures the quality of education focused on STEM (Science, Technology, Engineering, and Mathematics), which will produce a skilled workforce with abilities that meet current needs. The growth of the digital economy, including advancements in research and technology development, will encourage the emergence of new innovations that can create better and more efficient products and services, as well as foster an ecosystem that supports entrepreneurship, thereby encouraging the emergence of new businesses that can create new job opportunities. Additionally, the development of the digital economy can promote the creation of jobs that are more accessible to all groups, such as jobs in the informal sector that do not require formal education, as well as jobs in the formal sector that sometimes do not prioritize formal educational backgrounds. This can provide job access to all groups, including those who cannot afford formal education.

Table 4. Robustness Checks Using Alternative Sampel Specification (Excluding Singapore)

	Fixed Effects Model		
	I	II	III
$digital_{it}$	-0.141 (-1.034)	-0.168*** (-5.689)	-0.318*** (-5.111)
$digital^2_{it}$	-0.0005 (-0.198)	-	-
$PGDP_{it}$	-	-	-0.0004 (-1.427)
$global_{it}$	-	-	-0.095*** (-2.119)
$population_{it}$	-	-	2.660*** (4.702)
$unem_{it}$	-	-	0.869*** (2.382)
Constant	21.061*** (12.414)	21.363*** (28.670)	1.971 (0.337)
R-squared	0.7162	0.7159	0.8584

Source: data processed

The findings shows the digital economy affects income inequality. These findings are in line with the research of Tian & Xiang (2024), Wu et al (2024), Peng & Dan (2023), Yan et al (2023) and Rachmawati et al (2025) found that the digital economy affects income inequality. The findings shows there is no non-linear relationship between the digital economy and income inequality, is accepted. The findings are in line with the research by Tian & Xiang (2024), but contradict the findings of Wu et al (2024), Peng & Dan (2024). The results of Tian & Xiang (2024) shows did not find a non-linear relationship between the digital economy and income inequality in cities of EU28 countries. Unlike the findings of Wu et al (2024) and Peng & Dan (2024), who discovered a non-linear influence, specifically a U-shaped relationship between the digital economy and income inequality in cities in China. These differences may involve diverse variations at the city level in EU countries and China. Development in EU countries is relatively equitable, with a well-functioning social welfare system, generally high levels of education, and a more stable labor market. These conditions might slow down the impact of the digital economy on income inequality, creating a less pronounced U-shaped relationship in EU countries. In China, the disparity between cities and provinces, the diversity of population groups, and government policies that promote urbanization and digitalization are potential factors causing a U-shaped relationship between the digital economy and income inequality.

Another findings shows that globalization exhibits an equalizing effect on income inequality in ASEAN countries. This result can be interpreted in light of the multidimensional nature of the KOF Globalisation Index, which captures trade globalization, financial globalization, Interpersonal globalization, informational globalization, cultural globalization, and political globalization (Gygli et al. 2019; Prakosa et al. 2024). In the ASEAN context, globalization has largely been associated with export-oriented manufacturing, services expansion, and foreign direct investment in labor-intensive sectors, which tend to broaden employment opportunities beyond high-skilled groups. Consistent with this mechanism, Tabash et al (2024) found that globalization can reduce income inequality in emerging economies by promoting economic growth, technological transfer, market access, and foreign direct investment, provided that governance and redistribution policies allow these gains to be more broadly shared.

5. Conclusion

This study examines the impact of the digital economy on income inequality in six ASEAN countries: Indonesia, Malaysia, Singapore, Thailand, Vietnam, and the Philippines from 2010 to 2020. The testing was conducted using fixed effect model panel data regression, classical assumption tests, and variable substitution. The relationship between the digital economy and income inequality is explored by examining factors that influence income inequality as control variables, including GDP per capita, globalization, population, and unemployment. Empirical findings support the hypothesis that the development of the digital economy can reduce income inequality, and it was found that the digital economy and income inequality have a linear relationship. This research reveals that increases in GDP per capita, population, and unemployment can worsen income inequality, while globalization can mitigate income inequality. The findings of this study provide empirical evidence about the digital economy and its potential to reduce income inequality in ASEAN countries. This research shows that the development of the digital economy can lower income inequality in the tested countries.

Based on these findings, several policy implications can be drawn for ASEAN governments. First, policies that promote inclusive digital development should be prioritized, particularly by expanding affordable internet access, digital infrastructure, and digital services to underserved and low-income populations. Second, as the digital economy is shown to reduce income inequality in a linear manner, governments should complement digital expansion with education and training programs that enhance digital and basic skills for low-skilled and vulnerable workers, enabling broader participation in digital-related economic activities. Third, given the equalizing role of globalization in this study, ASEAN countries should continue to support open trade and investment policies while ensuring that the benefits of globalization are accompanied by job creation and labor market absorption. Finally, addressing unemployment through employment-oriented digital and industrial policies is crucial, as rising unemployment is found to exacerbate income inequality. Together, these policy directions can help ASEAN countries harness the digital economy as an effective tool for reducing income inequality.

Regardless of the findings of this study, there are several limitations that are important to consider. First, the geographical and temporal scope of the research is limited to six ASEAN countries, namely Indonesia, Malaysia, Singapore, Thailand, Vietnam, and the Philippines. This research also only considers data from 2010 to 2020, which may limit the generalization of the findings. Second, the quality and availability of diverse data among ASEAN member countries have the potential to affect the accuracy of research results. The differences in data collection methodologies in each country can lead to bias in the analysis. Third, this research may not have accounted for all relevant variables, so the potential presence of hidden variables or confounding factors cannot be completely ruled out. To address these limitations, further research is recommended to expand the geographical and temporal scope. Thus, the generalization of the findings can be done more broadly. In addition, efforts to improve data quality and use more advanced analysis methods also need to be undertaken. Thus, future research is expected to provide a more comprehensive contribution to understanding the relationship between the digital economy and income inequality.

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