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The Impact of ICT on Regional Economy in Indonesia Through MSEs as Mediators: Application of Causal Mediation Analysis in Instrumental-variable Regressions

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Abstract

Introduction/Main Objectives: The development of information and communication technology (ICT) and small and micro enterprises (SMEs) can encourage regional economic growth. **Background Problems:** Studies on the impact of ICT on the rural economy at the village level are very limited. Furthermore, the Indonesian study neglects to tackle the endogeneity issue associated with this variable and the indirect effects of ICT on the regional economy. **Novelty:** Using SMEs as a mediator, this study examines the impact of ICT (internet signal strength) on the village's local economy (nighttime light), both directly and indirectly. ICT is considered to be endogenous. **Research Methods:** This study employs causal mediation analysis in instrumental-variable (IV) regressions at the village level in 2018 and 2021, using lightning strike intensity as IV. **Finding/Results:** Internet signal strength can increase the number of SMEs, and this increase can positively and significantly impact the local economy. In addition, the direct impact of internet signal strength on the local economy is significantly negative. However, the total impact of internet signal strength is significantly positive.

1. Introduction

Development is critical to a country's sustainability. The objectives of this development are high economic growth, poverty alleviation, and improving the quality of human resources (HR) [1]. In developing countries, such as Indonesia, the primary goal of development implementation is economic growth, as it can bridge Indonesia's gap with developed countries. The realization of this condition can occur when the processing industry sector demonstrates satisfactory performance [2].

The manufacturing industry has been the most significant contributor to the Indonesian economy, as evidenced by data from BPS-Statistics Indonesia. The manufacturing industry's contribution to Indonesia's Gross Domestic Product (GDP) in 2022 was 18.34 percent, which was significantly higher than the other two highest sectors (agriculture at 12.4 percent and trade at 12.85 percent) [3]. The manufacturing industry sector also has an impact on job creation [4]. In 2023, this sector was capable of accommodating 14.17 percent of the total working population in Indonesia. Consequently, this sector ranks third in labor absorption, following the agriculture and trade sectors [5].

BPS-Statistics Indonesia classifies manufacturing industry enterprises into four categories: large industry (100 or more workers), medium industry (20-99 workers), small industry (5-19 workers), and micro industry (1-4 workers). Small and micro enterprises (SMEs) are the most significant of the four categories, as they account for 99 percent of manufacturing industry enterprises and employ 60 percent of the industry's workforce [6]This demonstrates that SMEs can be a solution to economic issues, including poverty and unemployment. To optimize SMEs' potential, it is imperative that they are provided with the necessary ICT infrastructure.

Many previous studies have shown that ICT plays an important role in the manufacturing industry [7-9] because ICT can increase productivity, encourage innovation, and create new jobs [10-14]. Furthermore, ICT can assist enterprises in identifying strategic locations for economic activities [15]. Therefore, we suppose that the increase in ICT stimulates the growth of SMEs and indirectly boosts the regional economy.

Multiple studies have examined the impact of ICT on the regional economy [41–43]. Nonetheless, these studies have just examined the direct effects of ICT. In actuality, ICT can impact the regional economy through both direct and indirect means [16–20]. Mediation analysis can elucidate these effects; however, it neglects to address the endogeneity of ICT. The strength of the internet signal, serving as a proxy for the ICT variable, is not wholly arbitrary. This variable may exhibit endogeneity and non-randomness [21-22].

Regions with higher populations, superior infrastructure, and income levels may exhibit enhanced signal strength. This could make signal strength endogenous, as the decision to develop communications infrastructure could correlate with the error term, potentially influencing the outcome variables in our study. Indonesia frequently encounters several natural disasters. Anticipating such catastrophes would diminish the motivation for telecommunications firms to invest in infrastructure in regions with a higher likelihood of natural disasters, resulting in worse signal strength and related consequences. Reverse causality also skews the results since regions with superior social development circumstances may exhibit robust mobile phone signals [28]. Neglecting these problems may result in bias within the mediation analysis [27]. This study will utilize an instrumental variable approach to mitigate these issues by using the fluctuation in lightning strike intensity. Reduced connectivity is attributable to a rise in lightning occurrences. This study forecasts that the intensity of lightning strikes may affect signal quality in Indonesia, a tropical area marked by considerable geographical diversity [28]. Furthermore, previous studies did not utilize village-level data. Given these limitations, this study will utilize causal mediation analysis within instrumental-variable (IV) regressions to investigate the direct and indirect impacts of ICT on the village economy. This study employs nighttime light (NTL) data as an indicator of the village economy [23] and utilizes the number of SMEs as a mediating variable.

Economic growth theory and location theory can elucidate the relationship between ICT, SMEs, and regional economies. Location theory functions as a conceptual framework for examining the factors that influence the location decisions of enterprises [24]. Neoclassical, institutional, and behavioral theories are the three theories that Hayter discusses regarding the location of economic activities [25]. Neoclassical theory aims to maximize profits or minimize costs by selecting the optimal location based on economic agglomeration factors, technology, and human resources. The network of economic relations determines profit and cost functions in institutional theory, which is the basis for location determination. Conversely, behavioral theory underscores the significance of individual preferences. Dicken observed the influence of ICT on enterprise location decisions, specifically the necessity for technology-based labor, internet connectivity, and access to technological infrastructure [26].

Meanwhile, the Solow model explains the relationship between ICT and regional economies. The model explains how capital stock, labor force, and technological progress interact with the economy, as well as how they affect the total output of goods and services in a country [27]. However, the Solow Model still has gaps because it assumes that technological growth is an exogenous variable, meaning that technology is considered something that occurs outside the economic system. The endogenous growth theory serves as a complementary theory to address the shortcomings of the Solow model. In this theory, technology is considered an endogenous variable where economic factors, such as investment, human resource development, and economic policy, directly affect the rate of technological growth [27]. This theory also links the role of industrial innovation with economic growth. The industrial sector's innovation development through technology adoption can accelerate economic growth. The difference between the Solow Model theory and the Endogenous Growth theory reflects the different approaches to the role of technology in explaining long-term economic growth.

2. Material and Methods

2.1. Scope of Study

This study focuses on analyzing the impact of ICT on the development of SMEs and regional economies at the village level in Indonesia in 2018 and 2021. The strength of the Internet signal is a proxy for ICT; the number of SMEs is a proxy for SMEs' development; and NTL data is a proxy for the village economy (known as the Gross Regional Domestic Product (GRDP)). The idea that villages with higher levels of illumination tend to exhibit greater economic dynamism is the foundation of the correlation between NTL and economic output. Higher population density, improved infrastructure, and increased industrial activity typically attribute this association. We overcome the endogeneity problem in the internet signal strength variable by using the instrument variable, lightning strike intensity, at the village level [28]. The study also includes several control variables, such as demographic, government, and geographic characteristics.

2.2. Data dan Data Sources

The majority of data used in this study are secondary data sourced from BPS-Statistics Indonesia. In addition, this study also uses satellite imagery data obtained from Earth Observation Group (EOG) [29], NASA's Global Hydrometeorology Resource Center (GHRC) [30], WorldPop [31], and WorldClim [32]. Table 1 provides details of the data used.

Table 1. Data and Data Sources

Variable	Definition	Data Level	Data Source
Main variables			
T	Internet signal strength (1 = signal is strong, 0 = otherwise)	Village	BPS-Statistics Indonesia
M	The number of SMEs (unit)	Village	BPS-Statistics Indonesia
Y	NTL data (nW/cm^2/sr)	Village	BPS-Statistics Indonesia
Z	Lightning strike intensity (flash per village)	Village	GHRC NASA
Demographic and government characteristics (X_1)			
$agri$	Main income sources (1 = The majority of the population is employed in agriculture, 0 = otherwise)	Village	BPS-Statistics Indonesia
$muslim$	Muslim dummy (1 = the majority of the population is Muslim, 0 = otherwise)	Village	BPS-Statistics Indonesia
$christian$	Christian dummy (1 = the majority of the population is Christian, 0 = otherwise)	Village	BPS-Statistics Indonesia
$ethnic$	Ethnic dummy (1 = the population consists of several ethnic groups, 0 = otherwise)	Village	BPS-Statistics Indonesia
age	Age of the village head (year)	Village	BPS-Statistics Indonesia
sex	Sex of the village head (1 = if the village head is male, 0 =otherwise)	Village	BPS-Statistics Indonesia
$educ$	Education of the village head (1 = if the village head's education is high school or below, 0 = otherwise)	Village	BPS-Statistics Indonesia
Demographic characteristics in the previous year (X_2)			
$lagpop$	The number of populations in the previous year (persons)	Village	WorldPop
RLS	Years of schooling in the previous year (years)	District	BPS-Statistics Indonesia
Geographic characteristics (X_3)			
$temp$	Average temperature (°C)	Village	WorldClim
$elevation$	Average elevation (m)	Village	WorldClim
$rainfall$	Average rainfall (mm)	Village	WorldClim
$flatland$	Topography (1 = if the village topography is flatland, 0 = otherwise)	Village	BPS-Statistics Indonesia

2.3. Causal Mediation Analysis in Instrumental-variables Regressions

In many contexts, researchers often seek to comprehend the process that explains the estimated effect of a treatment on an outcome. In this study, we are interested in the hypothesis that ICT, as a treatment variable (T), affects the regional economy as an outcome variable (Y), through the number of SMEs as an intermediate variable (M). Since the distribution of SMEs across villages is probably not random, we present an IV (Z) to prove that ICT contributes to an increase in the number of SMEs, thereby stimulating economic growth. In IV regressions, this method is known as causal mediation analysis.

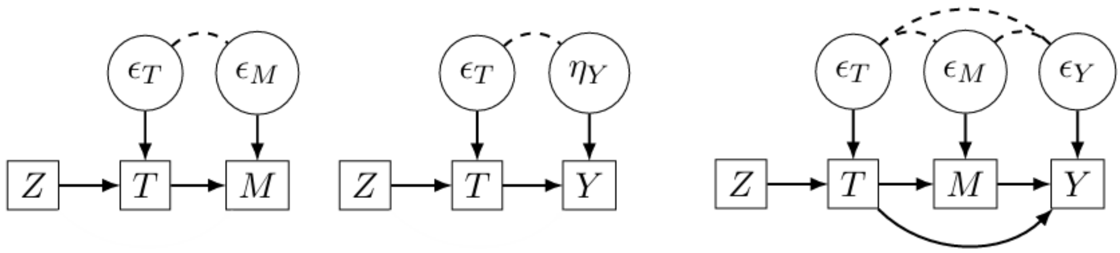
Figure 2 illustrates the identification challenge described above. Model A is a standard instrumental variable two-stage least squares (IV-2SLS) model. This model allows us to identify the causal effects of T on M. Model B is the standard IV-2SLS model that enables the identification of T's causal effects on Y. Model C is the IV mediation model, with an instrumental variable Z. It estimates three separate 2SLS regressions: the effect of T on M, the effect of T on Y, and the effect of M on Y conditional on T. Model C can decompose the total effect of T on Y into an indirect effect of T on Y that operates through M and a direct effect that does not work through M [33].

Prior to employing the IV-2SLS model, we conduct endogeneity tests to ascertain whether an explanatory variable in a regression model is endogenous. The Wu-Hausman test is one of the most commonly used tests for endogeneity. It checks explicitly whether the difference between the OLS and IV-2SLS estimates is statistically significant. The test employs the following hypothesis:

H_0: The difference between the OLS and IV-2SLS estimates is zero (endogeneity is not present).

H_1: The difference between the OLS and IV-2SLS estimates is non-zero (endogeneity is present).

If the test statistic is significant, it suggests that the OLS estimates are inconsistent due to endogeneity, and IV-2SLS estimation is necessary. Even though the test result is not statistically significant, this study maintains the assumption that ICT is endogenous, as other variables can indeed affect it. Previous studies that used the IV mediation method did not conduct the Hausman test [28, 44].



(a) Model A (b) Model B (c) Model C

Figure 2. The Identification Problem of Causal Mediation Analysis

Under linearity, we can write the causal relations in Model C in Figure 2 as

$$\begin{bmatrix} Z \\ T \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ \beta_T^Z & 0 & 0 & 0 \\ 0 & \beta_M^T & 0 & 0 \\ 0 & \beta_Y^T & \beta_Y^M & 0 \end{bmatrix} \cdot \begin{bmatrix} Z \\ T \\ M \\ Y \end{bmatrix} + \begin{bmatrix} \epsilon_Z \\ \epsilon_T \\ \epsilon_M \\ \epsilon_Y \end{bmatrix} \quad (1)$$

Parameter β_M^T is identified by the standard IV-2SLS model, described by the following equations:

First stage: $T = \beta_T^Z . Z + \epsilon_T$ (2)

Second stage: $M = \beta_M^T . \hat{T} + \epsilon_M$ (3)

$\hat{T}$ are the estimated values of T in the first stage. β_Y^M and β_Y^T can be fit by the following IV-2SLS model:

First stage: $M = \gamma_M^Z . Z + \gamma_M^T . T + \epsilon_M$ (4)

Second stage: $Y = \beta_Y^M . \widehat{M} + \beta_Y^T . T + \epsilon_Y$ (5)

$\widehat{M}$ stands for the estimated values of M in the first stage.

There are two first stages (Equation 2 and Equation 4). Causal mediation analysis assesses weak identification by reporting the corresponding F statistics on the excluded instrument. A rule of thumb is that an F test of the excluded instrument in the first stage should yield an F statistic of 10 or more [34]. When using a robust standard error, the regression output presents the F statistic calculated by Kleibergen-Paap Wald (KPW) [35]. There is a link between equations 2-5 and the direct estimation of the total effect in Model B of Figure 2. We obtain Model B from Model C by substituting Equation 3 into Equation 5.

$$Y = \beta_Y^M.(\beta_M^T.T + \epsilon_M) + \beta_Y^T.T + \epsilon_Y = (\beta_Y^M.\beta_M^T + \beta_Y^T)T + \beta_Y^M.\epsilon_M + \epsilon_Y \quad (6)$$

Equation 6 shows that the estimate of the total effect produced by Model B is identical to the product of estimates $\beta_Y^M.\beta_M^T + \beta_Y^T$ produced by Model C (equations 2-5). In Model C, the direct effect is shown by β_Y^T, while the indirect effect is shown by $\beta_Y^M.\beta_M^T$. By incorporating the control variable vectors $\boldsymbol{X_1}$, $\boldsymbol{X_2}$, and $\boldsymbol{X_3}$ into Equations 2-6, Equations 2-6 is transformed as follows:

$$T = \beta_T^Z.Z + \boldsymbol{\beta_T^1 X_1} + \boldsymbol{\beta_T^2 X_2} + \boldsymbol{\beta_T^3 X_3} + \epsilon_T \quad (7)$$

$$M = \beta_M^T.\hat{T} + \boldsymbol{\beta_M^1 X_1} + \boldsymbol{\beta_M^2 X_2} + \boldsymbol{\beta_M^3 X_3} + \epsilon_M \quad (8)$$

$$M = \gamma_M^Z.Z + \gamma_M^T.T + \boldsymbol{\beta_M^1 X_1} + \boldsymbol{\beta_M^2 X_2} + \boldsymbol{\beta_M^3 X_3} + \epsilon_M \quad (9)$$

$$Y = \beta_Y^M.\hat{M} + \beta_Y^T.T + \boldsymbol{\beta_Y^1 X_1} + \boldsymbol{\beta_Y^2 X_2} + \boldsymbol{\beta_Y^3 X_3} + \epsilon_Y \quad (10)$$

$$Y = \beta_Y^M.\left(\beta_M^T.T + \boldsymbol{\beta_M^1 X_1} + \boldsymbol{\beta_M^2 X_2} + \boldsymbol{\beta_M^3 X_3} + \epsilon_M\right) + \beta_Y^T.T + \boldsymbol{\beta_Y^1 X_1} + \boldsymbol{\beta_Y^2 X_2} + \boldsymbol{\beta_Y^3 X_3} + \epsilon_Y = (\beta_Y^M.\beta_M^T + \beta_Y^T)T + (\boldsymbol{\beta_M^1} + \boldsymbol{\beta_Y^1})\boldsymbol{X_1} + (\boldsymbol{\beta_M^2} + \boldsymbol{\beta_Y^2})\boldsymbol{X_2} + (\boldsymbol{\beta_M^3} + \boldsymbol{\beta_Y^3})\boldsymbol{X_3} + \epsilon_M + \epsilon_Y \quad (11)$$

Equation 11 shows the same result. The indirect effect is β_Y^T, while the indirect effect is $\beta_Y^M.\beta_M^T$.

3. Results and Discussion

3.1. NTL as a Proxy for Regional Economy

As previously explained, researchers use NTL data to approximate the regional economy (GRDP) in regions with limited or inaccurate economic data [23]. BPS-Statistics Indonesia has not yet provided GRDP data at the village level. This study demonstrates the relationship between GRDP and NTL data at the district level using thematic maps, scatter plots, and Pearson correlation calculations. Figure 3 and Figure 4 are thematic maps showing the distribution of GRDP and NTL data in each district in Indonesia in 2022. The redder the color, the higher the GRDP and NTL values. Based on these two figures, the majority of districts in western Indonesia are red. This means that the majority of districts in this region have high GRDP and NTL values. On the other hand, the majority of districts in eastern Indonesia are green, indicating that the GRDP and NTL values in this region are relatively low. The similar distribution of GRDP and NTL data demonstrates that NTL data can represent GRDP data.

Table 2. Pearson Correlation between GRDP and NTL Data at the District Level in Indonesia by Year

Year	Pearson Correlation	p-value
2017	0.747***	0.000
2018	0.758***	0.000
2019	0.750***	0.000
2020	0.744***	0.000
2021	0.733***	0.000
2022	0.717***	0.000

Note: *** denotes 1% significance level.

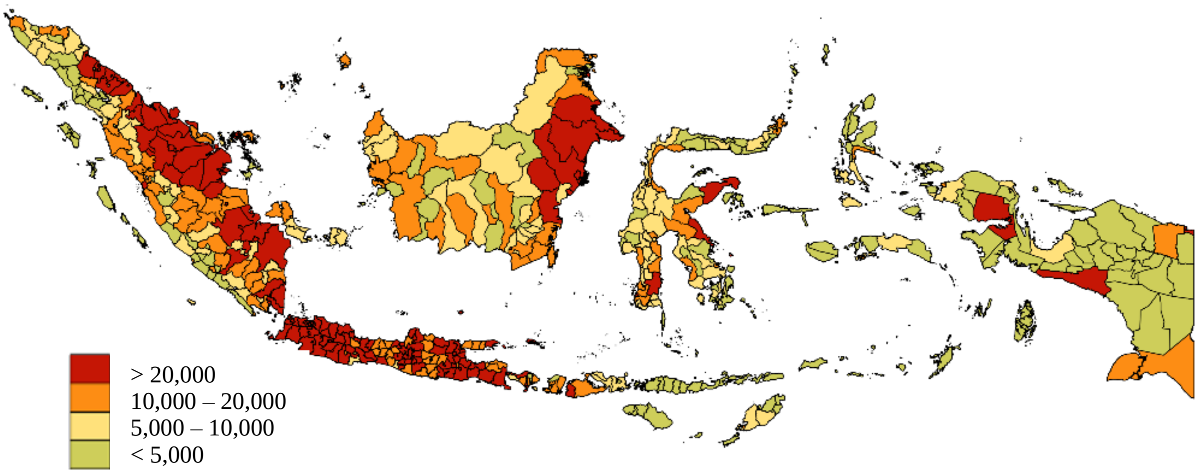


Figure 3. GRDP in Indonesia in 2022 by District (Billion Rupiah)

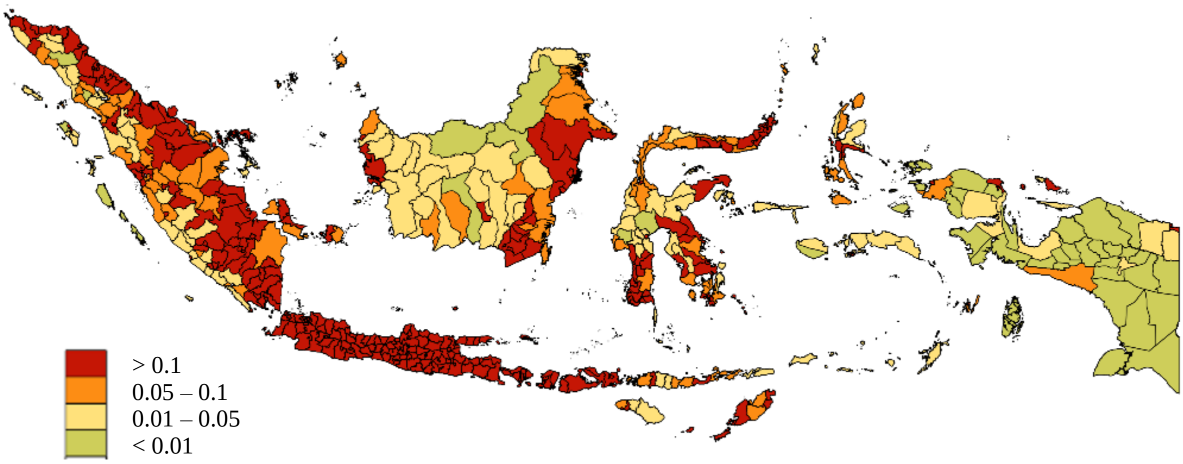


Figure 4. NTL data in Indonesia in 2022 by District (nW/cm^2/sr)

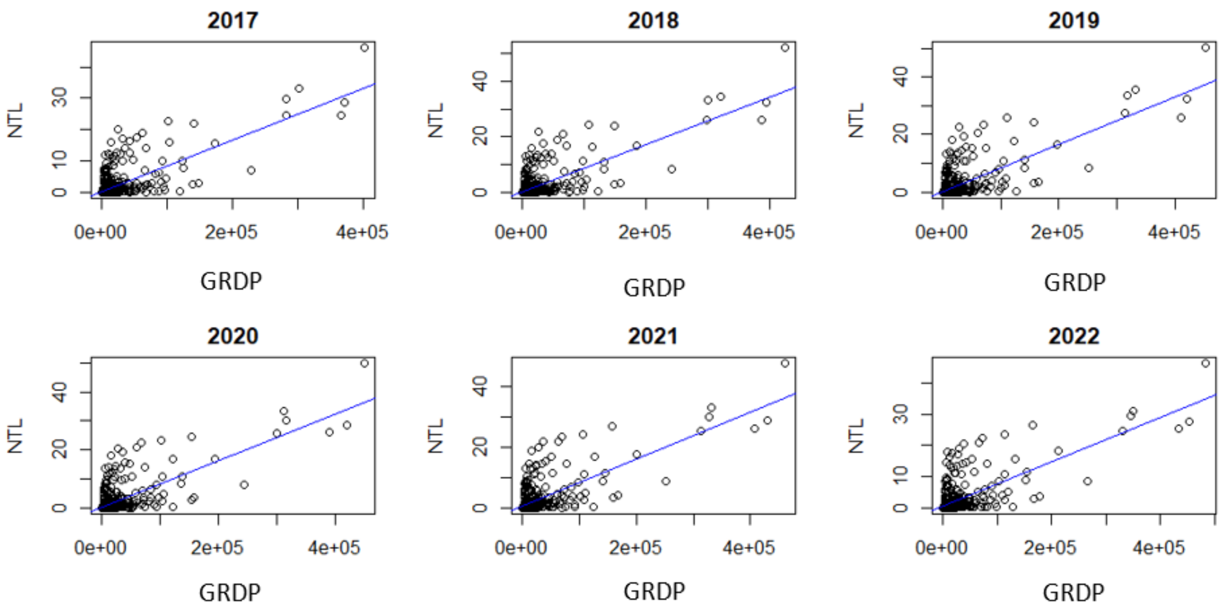
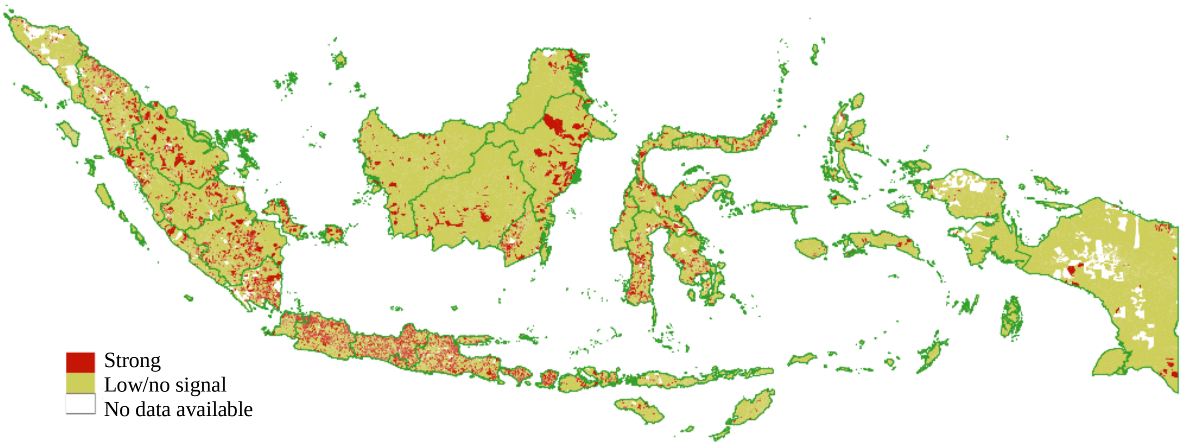


Figure 5. Scatter Plot between GRDP and NTL Data in Indonesia in 2017-2022

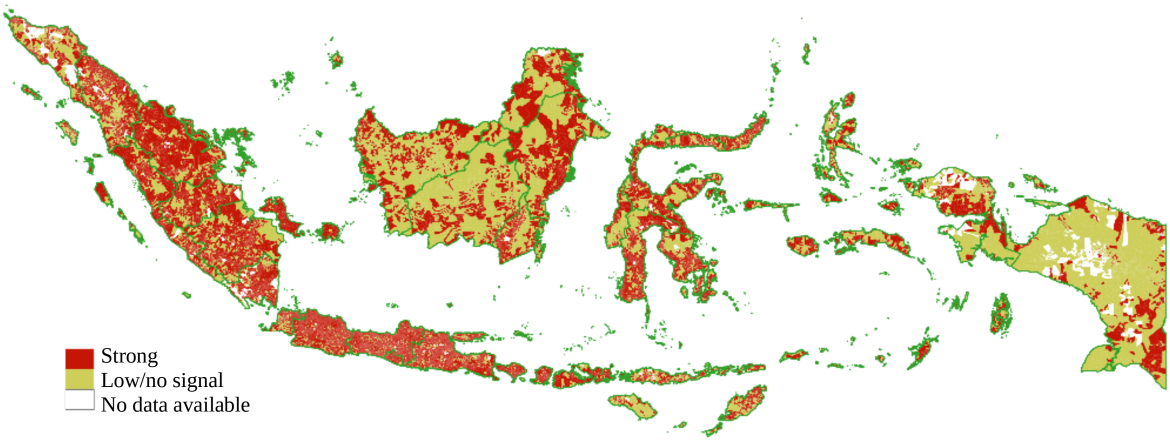
The relationship between NTL data and GRDP is clearly visible in the scatter plot in Figure 5. During the 2017-2022 period, NTL data and GRDP have a positive relationship. The NTL data increases in tandem with the district's GRDP value. In line with this argument, the Pearson correlation between PDRB and NTL data at the district level also provides similar results, as shown in Table 2. During 2017–2022, the Pearson correlation value of these variables was always greater than 0.7 and had a p-value of less than 1%. It shows that at a significance level of 1%, PDRB data is positively and significantly correlated with NTL data. Therefore, we can use NTL data as a proxy for PDRB data.

3.2. Lightning Strike Intensity, Internet Signal Strength, the Number of SMEs, and Regional Economy in Indonesia by Regions

Figure 6 presents the results of mapping the internet signal strength in each village in 2018 and 2021. The red color indicates areas with strong internet signals, while the green color indicates areas with weak or no internet signals. The map reveals that the distribution of strong signals remained uneven in 2018. However, very rapid development occurred in 2021. The distribution of strong internet signals is much more even, especially in areas located on the islands of Java and Sumatra. However, some areas, such as Papua Island, continue to experience weak or no internet signals. This is likely due to the conflict in the Papua region, which has made it difficult for the government to carry out development. Topographically, Papua also has many mountainous areas. Furthermore, the government may still excessively focus on advancing development in Western Indonesia, causing the Eastern region to lag behind. Several areas on the island of Kalimantan still lack a strong internet signal. However, the distribution is still more evenly distributed than on Papua Island.



2018



2021

Figure 6. Internet Signal Strength at the Village Level in Indonesia in 2018 and 2021

A map of the distribution of NTL values in each village in Indonesia in 2018 and 2021 is showcased in Figure 7. In general, the distribution pattern of NTL in 2018 and 2021 does not exhibit any substantial differences. The thematic map in Figure 7 suggests that the distribution of NTL is more extensive in Sumatra and Java. The NTL value decreases as one moves further east. The East and South Kalimantan regions of Kalimantan Island are the primary locations for NTL distribution. Consequently, the distribution of NTL in Sulawesi Island is confined to the North and South Sulawesi regions. In the interim, the vast majority of Papua Island is devoid of any NTL value. The NTL value can offer a glimpse into the economic activity of a given region. Therefore, it is possible to infer that a high level of economic activity characterizes Western Indonesia. Economic activity decreases as one moves eastward. The distribution pattern of NTL data is quite similar to the distribution pattern of internet signal intensity data. Consequently, there is a suggestion of a unidirectional relationship between the NTL's value and the internet signal's intensity.

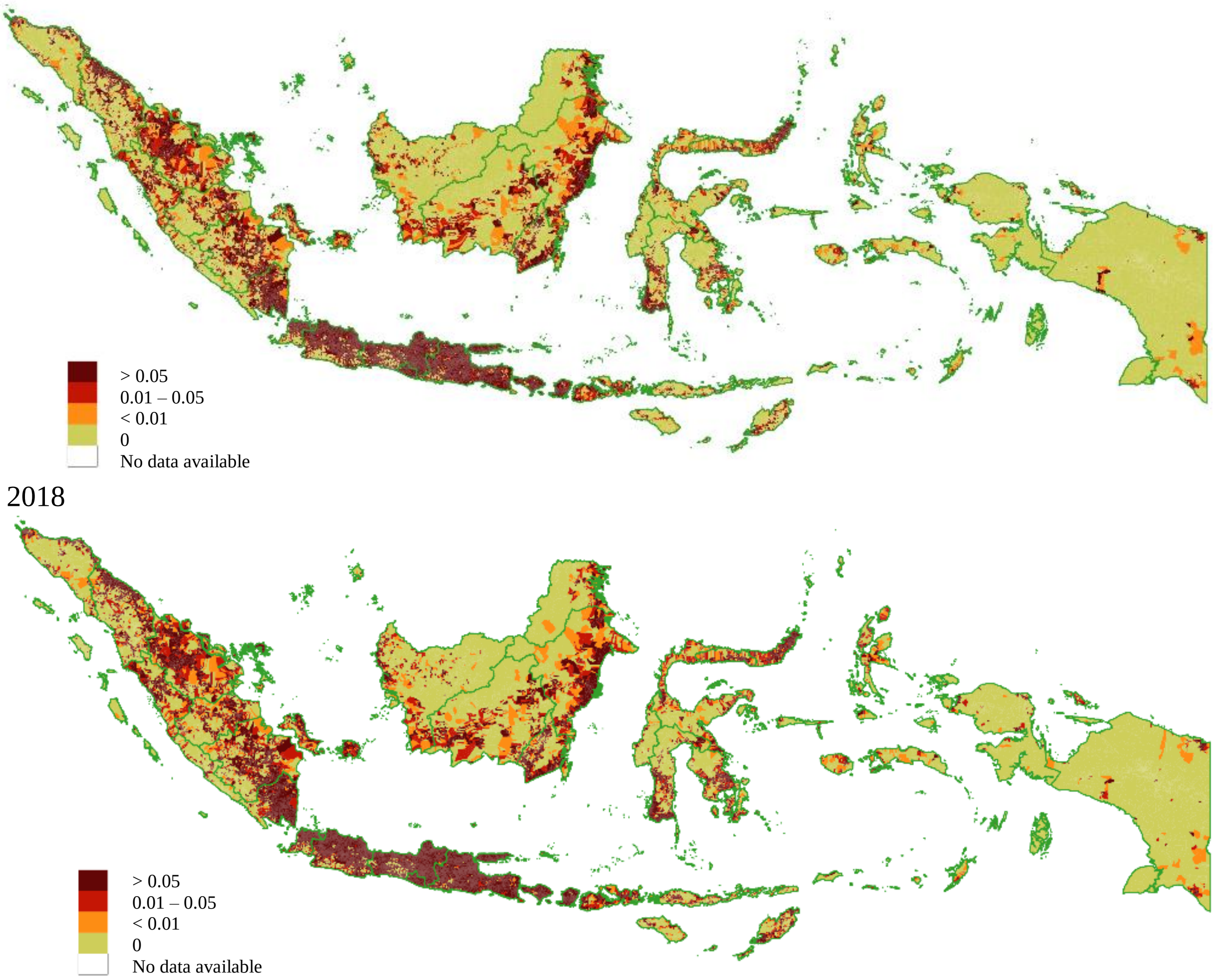
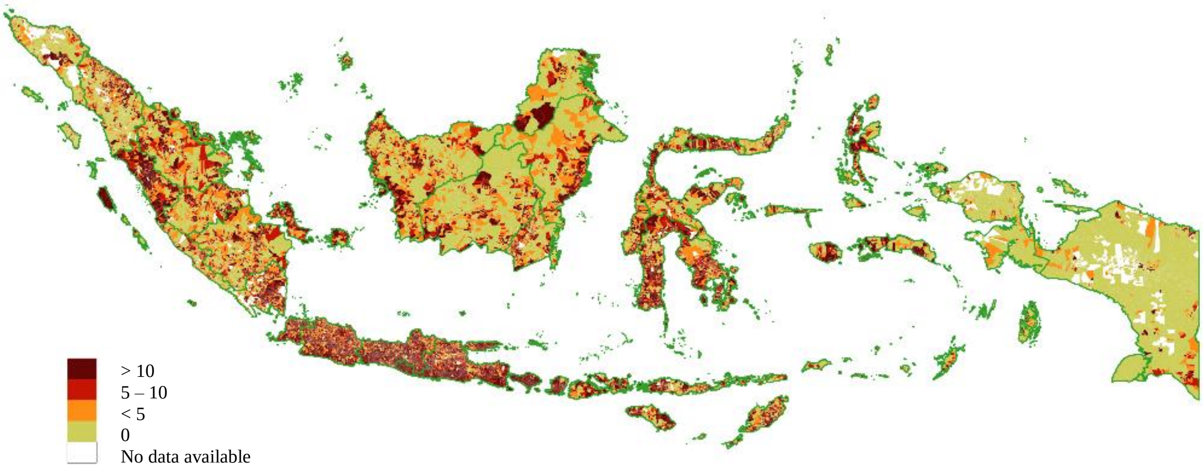
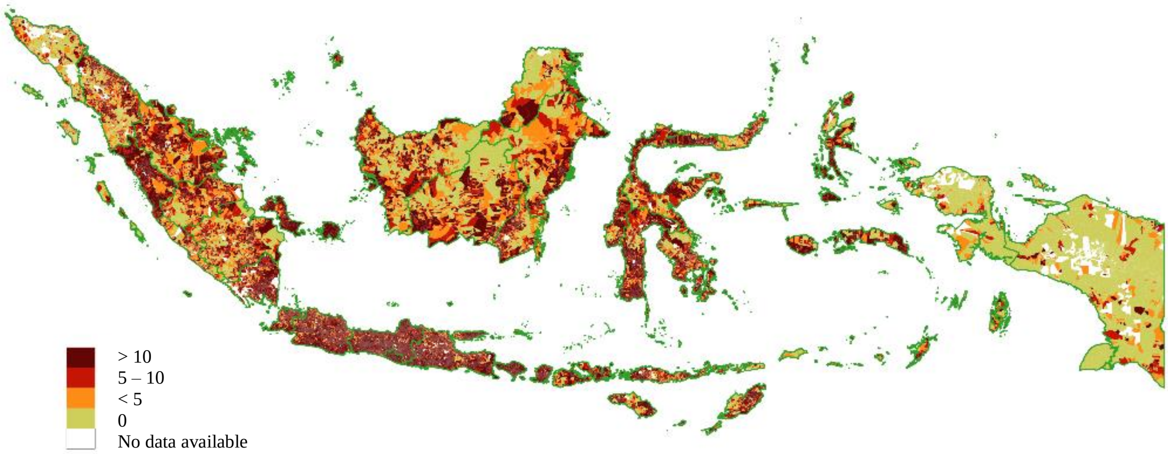


Figure 7. NTL at the Village Level in Indonesia in 2018 and 2021

The results of the mapping of the number of SMEs in each village in 2018 and 2021 are depicted in Figure 8. The data distribution pattern regarding the number of SMEs generally remains consistent between 2018 and 2021. Nevertheless, the coverage area of SMEs in 2021 appears to be more extensive than in 2018. The majority of SMEs are situated in the western regions of Indonesia, specifically in Java and Sumatra, similar to the two preceding variables. Nevertheless, the Kalimantan and Sulawesi islands have a more extensive coverage. In the interim, the Papua Island region maintains a minimal distribution, which is consistent with the two preceding variables. The similarity in the data distribution pattern between the number of SMEs, internet signal intensity, and NTL demonstrates the unidirectional relationship between the three variables.



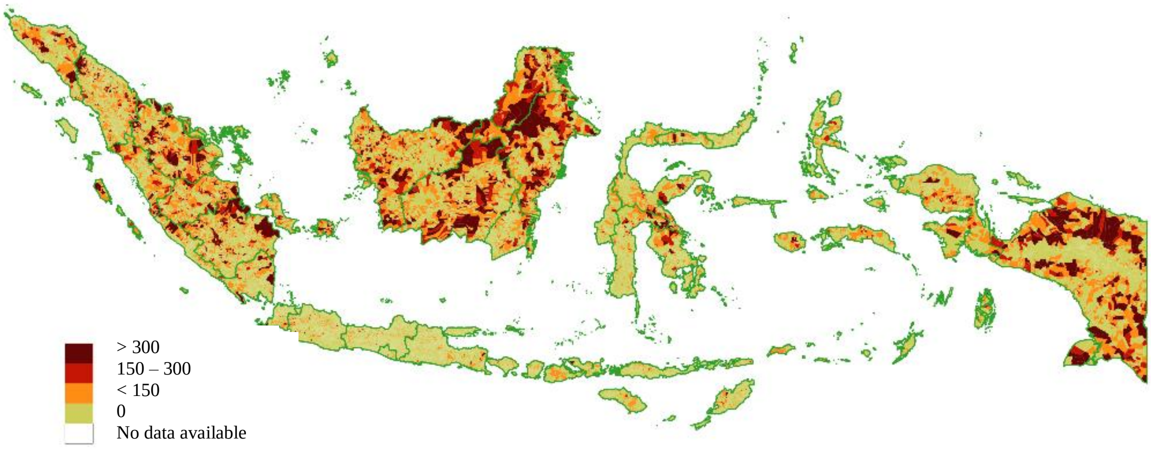
2018



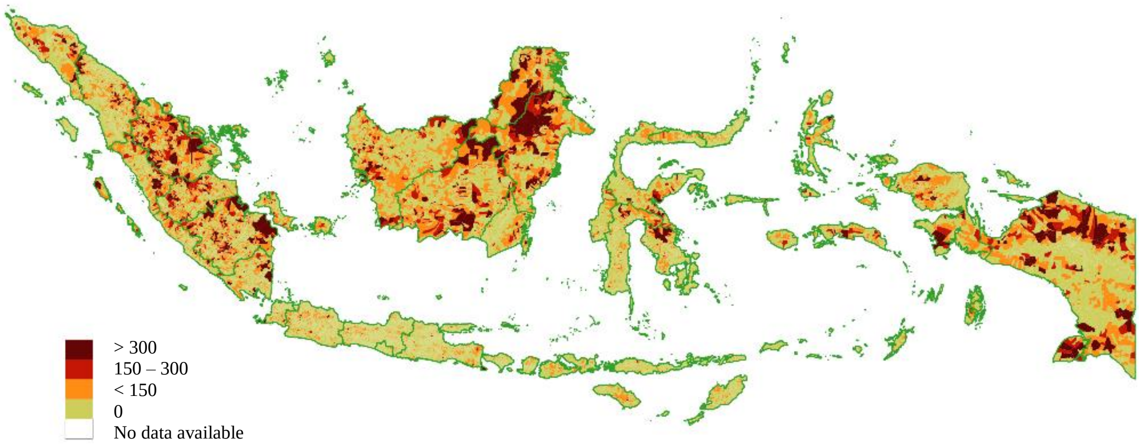
2021

Figure 8. The Number of SMEs at the Village Level in Indonesia in 2018 and 2021

Lastly, Figure 8 illustrates a depiction of the number of lightning flashes in each village in Indonesia between 2018 and 2021. There are no substantial distinctions between the data patterns of 2018 and 2021. The distribution pattern of lightning flashes is distinct from that of the preceding three variables, particularly in Java. The situation is reversed in this instance, as Java had the highest distribution in the preceding three variables. Compared to other regions, Java has the lowest distribution of lightning bolts. In contrast, the distribution of lightning bolts is particularly high in Kalimantan and Papua. The distribution of lightning flashes is more pronounced in regions with reduced internet signal strength when correlated with this variable. This suggests that the intensity of the internet signal is inversely proportional to the number of lightning flashes.



2018



2021

Figure 8. Lightning Strike Intensity at the Village Level in Indonesia in 2018 and 2021

3.3. Correlation between Lightning Strike Intensity, Internet Signal Strength, the Number of SMEs, and Regional Economy

Figure 9 presents a descriptive analysis of the relationship between the variables of lightning strike intensity, internet signal strength, the number of SMEs, and NTL. Because internet signal strength data is categorical, descriptive analysis uses bar graphs. Villages with strong internet signals have higher NTL values. There are intriguing results. In 2021, the average NTL value was smaller than in 2018. This is likely due to the uneven distribution of strong internet signals in 2018. Furthermore, the majority of villages in urban areas have strong internet signals. These regions tend to have higher levels of economic activity than rural areas, as indicated by high NTL values.

Both in 2018 and 2021, villages with strong internet signals tend to have a greater number of SMEs compared to villages with weak or no internet signals. In 2018, villages with weak or no internet signals had an average number of 18 SMEs, and in 2021, the value dropped to 16 units. Then, in 2018 and 2021, villages with strong internet signals had the same average number of SMEs, namely 32. Based on these results, there is an indication of a positive relationship between internet signal strength and the number of MSMEs. A stronger internet signal will correspond to an increase in the number of SMEs.

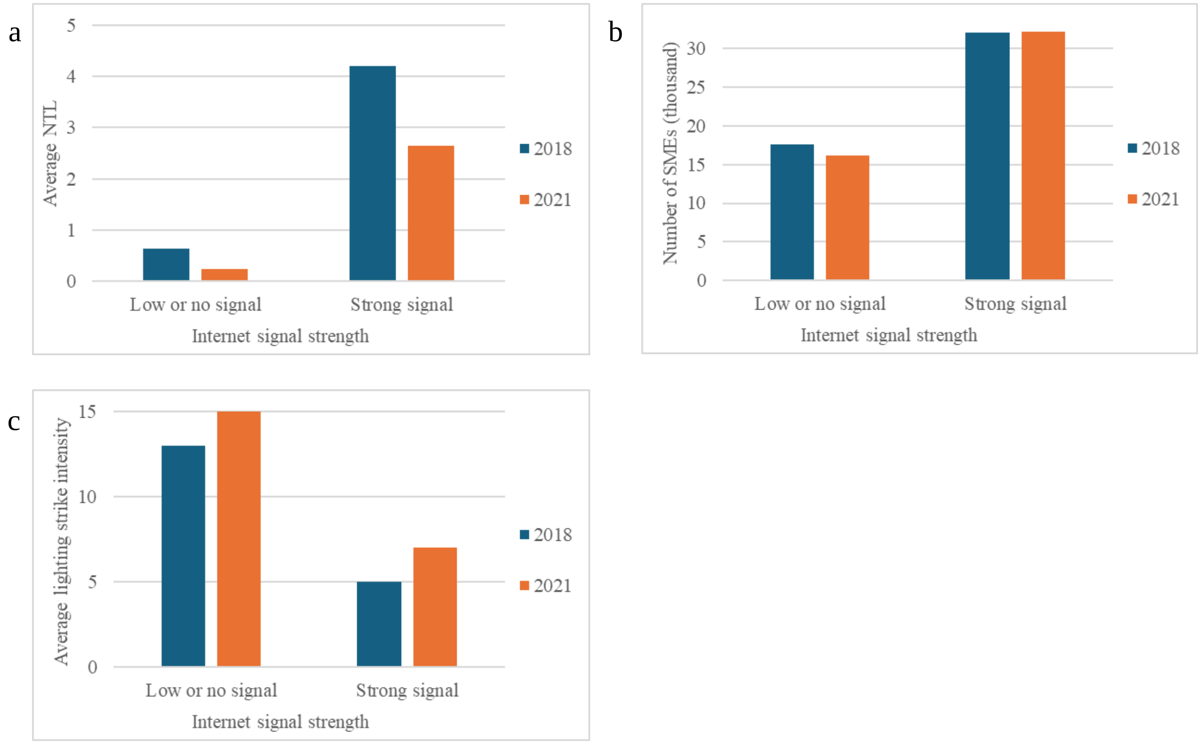


Figure 9. (a) Average NTL by Internet Signal Strength Category and Year; (b) the Number of SMEs per Village by Internet Signal Strength Category and Year; (c) Lightning Strike Intensity by Internet Signal Strength Category and Year.

The next analysis looks at the relationship between internet signal strength and the instrument variable, namely the number of lightning flashes. Based on the visualization results in Figure 9c, villages with strong signal strength tend to have a lower average number of lightning flashes compared to villages with weak or no internet signals. Both in 2018 and 2021, the relationship between internet signal strength and the number of lightning flashes has the same pattern. In 2018, villages with strong signals had an average number of lightning flashes that was 59.34% lower than villages with weak or no internet signals. Meanwhile, in 2021, the difference in the number of lightning flashes was 52.47%. It indicates a negative relationship between the number of lightning flashes and internet signal strength.

3.4. Endogeneity Test

Before modeling, we first used the Wu-Hausman test to conduct an endogeneity test of the internet signal strength variable. The null hypothesis of the test states that the internet signal strength variable is not endogenous. After the calculation, the test statistic value was 733.799, with a p-value of less than 1%. As a result, we can conclude that the internet signal strength variable is endogenous. This is in line with Rezki's research in 2023 [28]Therefore, to overcome this endogeneity, we need an analysis method involving instrument variables, such as causal mediation analysis in instrumental-variable regressions.

3.5. The Impact of Internet Signal Strength on the Regional Economy

We use the IV-2SLS estimation method to demonstrate how internet signal strength impacts NTL. The first stage involves regressing the number of lightning strike intensity, an instrument variable, and other exogenous variables against the internet signal strength, an endogenous variable. This study formed four models using different control variables for the robustness check. We use this method to verify the consistency of the estimated parameter values generated [13, 28, 36]. Table 3 presents the results of the first stage regression estimation.

The coefficient estimation results in Table 3 show that the number of lightning flashes has a significant negative effect on internet signal strength. The estimated value is also consistent across all models. In model 4, the lightning flash coefficient estimate is -0.00034. This means that a 1-point increase in lightning flash intensity will reduce the village's chance of having a strong internet signal by

0.034 percentage points. This result aligns with Rezki's study, which shows that higher lightning strike intensity can reduce the strength of mobile phone signals [28]. To see how strong the instrument variable can explain the strength of the internet signal, we conducted an identification test by looking at the value of the KPW F test statistic. For testing, the critical point limit is 16.38 [34]. Model 4's KPW F test statistic yields a value higher than 16.38, indicating the strength and relevance of the instrument variable in predicting internet signal strength.

Table 3. The Results of the First Stage Regression Estimation using IV-2SLS Method

Dependent Variable: Internet Signal Strength	Model 1	Model 2	Model 3	Model 4
Lightning strike intensity	-0.00043^{***} (0.00002)	-0.00032^{***} (0.00002)	-0.00037^{***} (0.00002)	-0.00034^{***} (0.00002)
Demographic and government characteristics	No	Yes	Yes	Yes
Demographic characteristics in the previous year	No	No	Yes	Yes
Geographic characteristics	No	No	No	Yes
KPW F-statistic	315.329	216.837	290.187	263.269
Observations	160,680	160,680	160,680	160,680

Note: *** denotes 1% significance level. Clustered standard errors at village level are in parentheses.

Table 4 presents the estimation results for the impact of internet signal strength on NTL as a proxy for economic growth. We obtained these results from stage 2 regression using the IV-2SLS method. Table 4 also presents four models with different control variables for robustness checks. All models show the same results, namely that internet signal strength has a positive and significant effect on NTL, with a value of 3.863-4.959. For example, in Model 4, the estimated coefficient of the internet signal strength variable is 4.224. This means that the NTL value in villages with strong internet signals is 422.4 percent higher than in villages with weak or no internet signals. Therefore, a village's economy becomes more developed as its internet signal strength increases.

Table 4. The Results of the Second Stage Regression Estimation using IV-2SLS Method

Dependent Variable: ln NTL	Model 1	Model 2	Model 3	Model 4
Internet signal strength	4.441^{***} (0.3680)	4.959^{***} (0.4753)	3.863^{***} (0.3657)	4.224^{***} (0.4065)
Demographic and government characteristics	No	Yes	Yes	Yes
Demographic characteristics in the previous year	No	No	Yes	Yes
Geographic characteristics	No	No	No	Yes
Observations	160,680	160,680	160,680	160,680

Note: *** denotes 1% significance level. Clustered standard errors at village level are in parentheses.

3.6. The Number of SMEs as a Mediator

This section presents the results of causal mediation analysis in instrumental-variable regressions. This study adopted the method from Dippel et al. in 2020 [33]. The number of SMEs is the mediating variable, while the number of lightning flashes is the IV. This study divides the total impact of internet signal strength on NTL (see Table 4) into two categories: a direct effect from other unspecified pathways and an indirect effect from the number of SMEs. The results of this decomposition are presented in Table 5.

Table 5, column 3, shows the total effect of internet signal strength on NTL. It has the same value as the estimated results of the IV-2SLS method in Table 4, column 5 (model 4). Table 5, column 2, displays the effect of internet signal strength on the number of SMEs. The results show that internet signal strength has a positive and significant effect on the number of SMEs, namely 3.857. This means villages with strong internet strength have 385.7% more SMEs than villages with weak or no internet signals. These results are in accordance with the theory of industrial location. According to this theory, technological advances are one of the factors that influence the location of an industry's economic activities. Mack and Grubesic in 2009 [37] and Duvivier in 2021 [38] both demonstrated similar results.

Table 5, column 4, second row, shows the effect of the number of SMEs on NTL. We conclude that the number of SMEs acting as mediators between internet signal strength and NTL has a positive and significant effect on NTL, with a significance level of 1% and a coefficient value of 1.168. This means that increasing the number of SMEs in a village by 1% will increase the village economy by 1.168%, assuming other variables are constant.

Table 5. The Results of the Causal Mediation Analysis in Instrumental-variable Regressions

	Ln SME	Ln NTL	Ln NTL
Internet signal strength	3.857*** (0.1944)	4.224*** (0.4065)	-0.280*** (0.0313)
Ln SME			1.168*** (0.1004)
KPW F-Statistics in the first stage regression estimation	263.269	263.269	263.269
KPW F-Statistics in the first second regression estimation			452.403

Note: *** denotes 1% significance level. Clustered standard errors at village level are in parentheses.

The coefficient estimate in the first row of column 4 in Table 5 is equivalent to the direct influence value in the second row of column 5 in Table 6. The calculated value is -0.280. Villages with strong internet signals have a 28% lower NTL than villages with weak or no internet signals. Therefore, the internet signal's strength can potentially reduce the regional economy directly. This discovery is consistent with the research findings of Atkinson and McKay in 2007 [39] and Bakari and Tiba in 2019 [40]. Atkinson and McKay attributed this phenomenon to the disparity in technology. The unequal distribution of technology and information adoption can worsen income inequality, which has the potential to cause a deterioration in the economy [39]. Meanwhile, Bakari and Tiba argued that the detrimental impact of the internet on the economy arises from its utilization in non-productive pursuits, such as engaging in social media and playing online games [40].

Table 6. The Total, Direct, and Indirect Effects of Internet Signal Strength on the Regional Economy using Causal Mediation Analysis in Instrumental-variable Regressions

Dependent Variable: Ln NTL	Model 1	Model 2	Model 3	Model 4
Total effect	5.087*** (0.4229)	5.795*** (0.5653)	3.863*** (0.3657)	4.224*** (0.4065)
Direct effect	-1.055*** (0.1147)	-0.882*** (0.0845)	-0.255*** (0.0302)	-0.280*** (0.0313)
Indirect effect	6.142*** (0.5938)	6.677*** (0.7451)	4.118*** (0.4008)	4.504*** (0.4487)
Demographic and government characteristics	No	Yes	Yes	Yes
Demographic characteristics in the previous year	No	No	Yes	Yes
Geographic characteristics	No	No	No	Yes

Note: *** denotes 1% significance level. Clustered standard errors at village level are in parentheses.

Additionally, Table 6 displays the indirect impact. The findings indicate that the number of MSEs has a positive and statistically significant effect on NTL, indirectly influencing internet signal strength. To determine this impact, for instance, we obtain the result by multiplying the coefficient representing the influence of internet signal intensity on the number of SMEs in column 2 of Table 5, with the coefficient representing the effect of the number of SMEs on NTL in column 4 of the same table. The calculated coefficient value is 4.504, indicating that villages with strong internet signals have an NTL value of 450.4 percent greater than villages with weak or no internet signals.

3.7. The Impact of Internet Signal Strength on the Number of SMEs

This section estimates the impact of internet signal strength on the number of SMEs using causal mediation analysis in instrumental-variable regressions. The first-stage modeling yields the same results as those listed in Table 3. At a significance level of 1%, the number of lightning strikes has a positive and significant effect on internet signal strength. The identification test results with the F KPW test statistic are also greater than 16.38, indicating that the instrumental variable is considered strong and relevant.

Table 7. The Impact of Internet Signal Strength on the Number of SMEs using Causal Mediation Analysis in IV Regressions

Dependent Variable: Ln SME	Model 1	Model 2	Model 3	Model 4
Internet signal strength	2.756^{***} (0.1244)	2.773^{***} (0.1671)	3.972^{***} (0.1823)	3.857^{***} (0.1944)
Demographic and government characteristics	No	Yes	Yes	Yes
Demographic characteristics in the previous year	No	No	Yes	Yes
Geographic characteristics	No	No	No	Yes
KPW F-statistic	315.329	216.837	290.187	263.269
Observations	160,680	160.680	160.680	160.680

Note: *** denotes 1% significance level. Clustered standard errors at the village level are in parentheses.

Table 7 presents the effect of internet signal strength on the number of SMEs. The estimation result in column 5 of Table 7 is the same as the estimation result in column 2 of Table 5, both of which are 3.857. Models 1-4 provide the same results, with internet signal strength having a positive and statistically significant effect on the number of SMEs at a significant level of 1%. These results suggest that entrepreneurs will tend to determine the location of their enterprises in areas with strong internet signal strength. This is consistent with the theory of industrial location, in which ICT is one of the determining factors in enterprise location decisions, as previously explained.

4. Conclusion

Based on the research results, villages with strong internet signals, as an indicator of ICT improvement, tend to have higher NTL values and the number of SMEs compared to villages with weak internet signals. ICT's indirect role through SMEs has the potential to enhance the regional economy, whereas its direct impact actually diminishes it. The greater indirect influence leads to a positive total effect of ICT. The disparity in ICT adoption and utilization, which often results in non-productive activities, has the potential to directly reduce the regional economy [39-40]. However, by increasing the number of SMEs, we can mitigate this negative impact, which also contributes to improving the regional economy. The increase in the number of SMEs occurs because the development of ICT in a region can encourage new industries in the region.

Improving ICT infrastructure is crucial, particularly in underdeveloped regions, as it can potentially increase the regional economy. Building more high-speed internet networks, expanding cellular telecommunications coverage, and improving accessibility can accomplish this. Training and mentoring activities for SMEs should accompany the increase in SMEs, enabling them to innovate effectively and market products using ICT, such as e-commerce. Thus, increasing the number of SMEs can boost the regional economy.

Unfortunately, this study has limited information about SME data. We hope that additional studies will shed light on how ICT can enhance MSE performance and how this enhancement could potentially contribute to regional economic development. Additionally, ICT can affect the labor market by enabling the entrance of new firms. Indonesia has not yet conducted studies on this subject.

Ethics approval

Not required.

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All the authors declare that there are no conflicts of interest.

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Credit Authorship

Luthfio Febri Trihandika: Conceptualization, Data Collection, Writing – Original Draft, Visualization. **Ribut Nurul Tri Wahyuni**: Methodology, Formal Analysis, Writing – Review and Editing, Supervision. **Meilinda Fitriani Nur Maghfiroh:** Writing – Review and Editing, Supervision.

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