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Gig Economy as a Strategy for Employment Diversification in the Digital Era: A Spatial Analysis of Indonesia's Economy Using a Remote Sensing Approach

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Abstract

The rise of the digital economy has fueled the growth of gig workers as a new driver of regional economic development in Indonesia. This study examines how gig related activities influence output of the service sector and explores their spatial spillover effects across provinces. Using the Spatial Durbin Error Model (SDEM), the analysis employs output of the service sector as the dependent variable and includes Night-Time Lights (NTL), casual non-agricultural workers, internet user percentages, provincial minimum wage, average years of schooling, and micro and small industries (IMK) output as independent variables. Results reveal that NTL, casual non-agricultural workers, and average years of schooling positively and significantly affect output of the service sector, highlighting the role of gig economy and human capital in productivity growth. Conversely, internet use shows a negative effect, indicating unequal digital utilization. Spatially, the lag of casual non-agricultural workers shows a negative spillover effect, suggesting that provinces with higher service sector output tend to attract cross-regional workers, thereby reducing labor availability in neighboring areas. Meanwhile, IMK output in adjacent provinces demonstrates a positive spillover effect, indicating complementary linkages that strengthen interregional economic activity. These findings imply that the gig economy can serve as an effective mechanism to boost regional economic output through job diversification, especially amid limited formal job opportunities. Strengthening gig-based employment ecosystems may therefore become a strategic option to sustain economic growth and promote inclusive labor market development in Indonesia.

Keywords: gig economy, remote sensing, regional economy, spatial analysis

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1. Introduction

The digital economic transformation has reshaped the landscape of work through the emergence of the gig economy, a system of short-term, project-based employment mediated by digital platforms. According to Ashford, Caza, and Reid (2018), the gig economy is characterized by the dominance of independent freelance workers who operate flexibly in response to market demand through platform intermediation. Similarly, Woodcock & Graham (2020) define the gig economy as a form of service work performed by individuals through digital intermediaries. This model offers flexibility, efficiency, and broader access to economic participation, particularly for younger generations who are increasingly familiar with technology. In line with this, the IZA report emphasizes that the gig economy has evolved as an alternative safety net, enabling individuals to obtain supplemental income with high flexibility amid an increasingly competitive and unstable labor market (Oyer, 2020). The flexibility of working hours, opportunities for cross-location employment, and increased participation among young and non-formal workers make the gig economy a catalyst for digital economic inclusion (Dawid, 2024).

In Indonesia, the expansion of the gig economy has been driven by the rapid increase in internet penetration, smartphone usage, and digital service platforms. This phenomenon has become more significant in the context of the demographic dividend, as the formal sector's capacity to absorb new labor entrants remains limited. Based on the 2025 February Sakernas data, 59.40 percent of Indonesia's working population is engaged in informal activities (BPS, 2025), reflecting the strong preference and necessity for flexible employment, including gig work. Consequently, the gig economy serves as both a potential driver of service sector growth and a strategic avenue for non-agricultural employment diversification (Ode & Arafat, 2025; Fakhriyah, 2020).

The development of Indonesia's gig economy shows a high level of spatial concentration in major urban areas such as DKI Jakarta, West Java, and East Java, which have strong digital infrastructure and mature markets. In contrast, areas outside Java and underdeveloped regions continue to face challenges such as low digital literacy, limited platform penetration, and an underdeveloped digital ecosystem. These disparities have contributed to spatial inequality in the distribution of digital economic opportunities. Empirical studies have shown that the gig economy not only affects local areas but also generates spillover effects on neighboring regions, as digital activities diffuse through agglomeration, technological diffusion, and interregional production networks (Soria & Stathopoulos, 2021; Hao & Ji, 2023).

However, research that explicitly analyzes the spatial distribution of the gig economy and its impacts on regional economies remains limited, even though spatial economic theory emphasizes the importance of considering spatial dependence and interregional feedback effects in understanding digital economic development (LeSage & Pace, 2009). On the other hand, while the gig economy expands access to new employment opportunities and potentially enhances regional growth, it also introduces structural vulnerabilities for workers, such as the absence of social protection, income volatility, and exposure to uninsured occupational risks (Hafeez et al., 2023).

Measuring gig economy activity at the regional level remains challenging due to the lack of official data (Permana et al., 2023). Data reflecting the intensity of platform-based work are difficult to capture, as not all digital activities are recorded in conventional labor surveys. Therefore, this study employs Night-Time Lights (NTL) data derived from remote sensing to represent the intensity of digital economic activity, including the gig economy. Several studies have found that NTL can serve as a proxy for economic and urban activity (Fontaine et al., 2025; Addison & Stewart, 2015; Chen & Nordhaus, 2011). Given that gig economy activity is predominantly urban-based and often concentrated during nighttime hours, NTL provides a valid spatial indicator for capturing the intensity of gig economy activities.

Nevertheless, NTL data have limitations because they do not specifically measure gig related activities. NTL reflect the accumulation of various nighttime activities, such as transportation, public services, commercial lighting, and general urban infrastructure. Hence, this study combines NTL with data on Casual non-agricultural workers to represent the dimension of gig workers, given that most gig workers are categorized as informal workers without formal contracts (Kässi & Lehdonvirta, 2018). Moreover, Sultana, Rahman, and Khanam (2022) found that the expansion of informal employment contributes positively to economic growth in developing countries, reinforcing the justification for using this variable as a proxy for gig workers.

In addition to the gig economy variables proxied by NTL intensity and casual non-agricultural workers, this study includes several control variables to minimize potential omitted variable bias in estimating regional economic output, particularly in the service sector. These include internet user percentages (ICT), average years of schooling (RLS), provincial minimum wage (UMP), and micro and small industries output (IMK), as previous studies have demonstrated that these factors significantly influence regional economic performance (Li et al., 2023; Altiner & Toktas, 2017; Haelbig et al., 2023; Bayraktar & Algan, 2019).

Given the research gap and the growing need to map the spatial distribution of the gig economy in Indonesia, this study aims to examine the development and vulnerabilities of gig workers in Indonesia, analyze the impact of the gig economy on regional economic performance, particularly through the service sector, using spatial econometric approaches, and explore its role in employment diversification. By integrating remote sensing and spatial analysis, this study contributes theoretically to the literature on the gig economy in developing countries and provides policy implications for optimizing the demographic dividend and reducing spatial inequality in Indonesia's economy.

2. Research Method

2.1. Data dan Data Sources

This study uses cross-sectional data from 38 provinces in Indonesia. The data period is 2024, as it is the most recent data available from official statistics. The dependent variable used is the

Gross Regional Domestic Product (GRDP) of the service sector in each province. The service sector is closely related to gig workers, as most gig worker activities take place within service-oriented industries. There are 11 service subsectors out of a total of 17 economic sectors. These include Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; Transportation and Storage; Accommodation and Food Services; Information and Communication; Financial and Insurance Activities; Real Estate; Business Services; Public Administration, Defense, and Compulsory Social Security; Education; Health Services; and Other Services. Meanwhile, the independent variables used in this study include night-time light (NTL), casual non-agricultural workers (L), internet user percentages (ICT), provincial minimum wage (UMP), average years of schooling (RLS), and IMK output. The details of the data used are presented in Table 1.

Table 1. Details of Data and Sources

Variable	Description	Unit	Source
Output of the Service Sector (Y)	Gross Regional Domestic Product at 2010 Constant Prices	Trillion Rupiah	BPS-Statistics Indonesia
Night-Time Lights (NTL)	Average Night-Time Lights Intensity	nanoWatt/sr/ cm^2	Google Earth Engine
Casual non-agricultural workers (L)	Number of Freelance Workers in Non-agricultural Activities	Thousand person	BPS-Statistics Indonesia
Internet User Percentages (ICT)	Percentage of population aged 5+ in urban areas using mobile internet within the last 3 months	Percent	BPS-Statistics Indonesia
Provincial Minimum Wage (UMP)	Minimum wage applicable to all districts/municipalities within a province	Million Rupiah	Ministry of Manpower
Average Years of Schooling (RLS)	Average number of schooling years completed by population aged 15+	Years	BPS-Statistics Indonesia
Micro and Small Industries Output (IMK)	Output of Micro and Small Industries	Billion Rupiah	BPS-Statistics Indonesia

2.2. Research Design

In this study, gig economy activities are conceptualized as part of the dynamics of the service sector, which has expanded in line with increasing digitalization and flexible work arrangements. These activities are captured through NTL intensity. Meanwhile, the number of casual non-agricultural workers serves as a proxy for gig workers, reflecting labor participation in flexible and project-based jobs. Both indicators are employed to measure the magnitude of the gig economy's contribution to regional economic performance.

This study adopts a quantitative approach using a Cobb–Douglas production function framework that is modified for a spatial context. The model explains the relationship between output (Y), capital (K), and labor (L). In the context of the service sector and the gig economy, capital encompasses not only physical infrastructure but also digital facilities and connectivity. Therefore, the technology component (A) is measured using the internet user percentages, while capital (K) is proxied by IMK output and NTL intensity. Labor is represented by casual non-agricultural workers, with RLS serving as an indicator of labor quality and the UMP as a measure of labor costs. In general, the Cobb–Douglas production function is formulated as follows:

$$Y = AK^{\alpha}L^{\beta} \tag{1}$$

However, the standard Cobb–Douglas model is unable to capture interregional interactions. Output of the service sector across provinces may be influenced by infrastructure conditions, economic activities, and various factors in neighbouring provinces (spillover effects). Therefore, the standard Cobb–Douglas model is extended into a spatial specification to capture both the direct effects and the spillover effects of the independent variables.

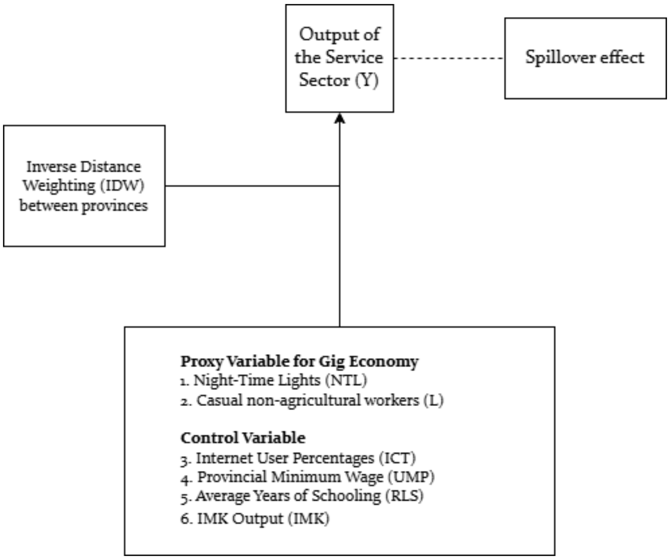


Figure 1. Research Framework

2.3. Analytical Methods

2.3.1. Spatial Weight Matrix

To capture spatial linkages among provinces more accurately, this study employs a distance-based spatial weight matrix, specifically the inverse distance weight (IDW). This approach is chosen because spatial relationships between provinces in Indonesia are not always reflected by direct geographical contiguity, as many regions are separated by sea yet maintain high levels of economic interaction. Therefore, contiguity-based weighting is considered less suitable for representing interprovincial adjacency in the Indonesian context. The inverse distance weight matrix calculates spatial proximity based on the Euclidean distance between provincial centroids (using provincial capitals as reference points), where the spatial weights are inversely proportional to geographic distance. In other words, the closer the distance between two provinces, the larger the spatial weight assigned; conversely, the farther the distance, the smaller the weight. This approach enables the model to account for cross-island spatial effects that remain economically relevant, particularly the interprovincial linkages in service-sector activities supported by improved transportation accessibility.

2.3.2. Inferential Analysis

Inferential analysis is conducted to examine the influence of economic and social factors on provincial service-sector GRDP in Indonesia while accounting for spatial dependence. Given that economic activities across regions tend to interact with one another, spatial regression methods are employed to capture two key characteristics of spatial data: spatial autocorrelation and spatial heterogeneity (Anselin, 1988). This study employs the General Nesting Spatial (GNS) model as the overarching framework for spatial regression estimation. The general form of the spatial regression model used in this study is as follows:

$$\begin{aligned} ln(Y)_i = \beta_0 + \rho \sum_{j=1}^{38} W_{ij} Y_j + \beta_1 NTL_i + \beta_2 L_i + \beta_3 ICT_i + \beta_4 UMP_i + \beta_5 RLS_i + \beta_6 IMK_i \\ + \theta_1 \sum_{j=1}^{38} W_{ij} NTL_j + \theta_2 \sum_{j=1}^{38} W_{ij} L_j + \theta_3 \sum_{j=1}^{38} W_{ij} ICT_j + \theta_4 \sum_{j=1}^{38} W_{ij} UMP_j \\ + \theta_5 \sum_{j=1}^{38} W_{ij} RLS_j + \theta_6 \sum_{j=1}^{38} W_{ij} IMK_j + \lambda \sum_{j=1}^{38} W_{ij} u_j + \varepsilon_i \end{aligned} \quad (2)$$

Explanation:

β_0	: *intercept*
$\beta_1, \dots, \beta_6$	: the regression parameter coefficients of the independent variables
$\theta_1, \dots, \theta_6$	: the spatial lag parameter coefficients of the independent variables
W_{ij}	: the values of the standardized spatial weight matrix elements
ρ	: the spatial lag parameter coefficient for the dependent variable
λ	: the parameter coefficient for the spatial effect in the error model
u	: *the error term exhibiting spatial autocorrelation*
ε	: *error term*
i	: 1,2,3,...,38 (observed provinces)
j	: 1,2,3,...,38 (neighbouring provinces)

In constructing the spatial regression model in this study, several stages are carried out as follows.

1. Forming the spatial weight matrix using the Inverse Distance Weight (IDW) method.
2. Identifying spatial autocorrelation in the dependent and independent variables using the Global Moran's I statistic as part of Exploratory Spatial Data Analysis (ESDA).
3. Building an initial regression model using the Ordinary Least Squares (OLS) method as the basis for selecting the appropriate spatial model.
4. Determining the spatial regression model based on the Elhorst (2014) framework through the Lagrange Multiplier (LM) and Robust LM tests to detect spatial effects in the lag or error components.

a) The Spatial Autoregressive (SAR) model or the Spatial Durbin Model (SDM) is applied when the LM test results indicate the presence of spatial effects in the lag component. Meanwhile, the Spatial Error Model (SEM) or the Spatial Durbin Error Model (SDEM) is used when the LM test indicates spatial effects in the error component. However, if the LM test shows spatial effects in both the lag and error components, the Robust LM (RLM) test is used to determine the more appropriate model.
b) The Autoregressive Combined (SAC) model is employed when the RLM test indicates spatial effects in both the lag and the error components.
c) The Spatial Lag of X (SLX) model is used when spatial effects are present in the independent variables, as indicated by the Global Moran's I results.

5. A comparison of model performance using log-likelihood, R-squared, and AIC is conducted when more than one model is potentially suitable.
6. The selected spatial regression model is estimated using the Maximum Likelihood Estimation (MLE) method to obtain efficient and consistent parameter estimates. Subsequently, the Wald test is performed to examine the partial significance of the parameters.

3. Results and Discussion

3.1. General Condition of Indonesia's Output of the Service Sector in 2024

Based on the plot shown in Figure 2, output of the service sector exhibits a very wide range, from approximately 8.26 trillion rupiah to nearly 1,676.12 trillion rupiah. This indicates a high degree of variation in the contribution of the service sector across regions in Indonesia. Several provinces appear as outliers, namely regions with output of the service sector that is significantly higher than others. These striking differences are generally driven by varying concentrations of economic activity across regions.

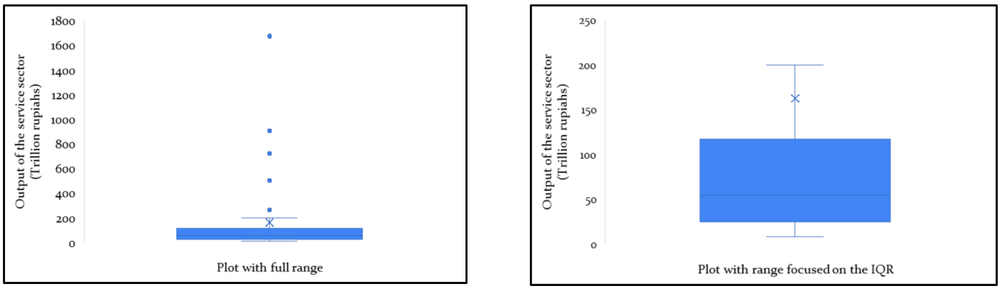


Figure 2. Boxplot output of the service sector in 2024

The province of DKI Jakarta, with output of the service sector reaching 1,676.12 trillion rupiah, serves as the largest hub for digital-based service activities in Indonesia. Meanwhile, provinces on Java Island such as East Java, West Java, Central Java, and Banten also show relatively high levels of the output of the service sector. In contrast, provinces outside Java tend to have lower output of the service sector, with their economic activities still dominated by primary sectors such as agriculture, forestry, and mining.

Furthermore, Figure 2 also shows that the interquartile range (IQR) lies between approximately 25.71 and 115.554 trillion rupiah, indicating that 50 percent of provinces in Indonesia have output of the service sector within this range. The median value of 54.30 trillion rupiah is lower than the mean value of 162.68 trillion rupiah. This condition demonstrates that the output of the service sector is right-skewed. In other words, most provinces have relatively low to moderate levels of service-sector output, while only a few provinces dominate with exceptionally high output values. This phenomenon indicates disparities in service sector contributions across regions, where provinces with concentrated economic activity such as DKI Jakarta, West Java, Central Java, and East Java serve as the primary drivers of national service sector growth. Meanwhile, provinces whose economies remain reliant on primary sectors require strengthened digital infrastructure and broader adoption of information technology.

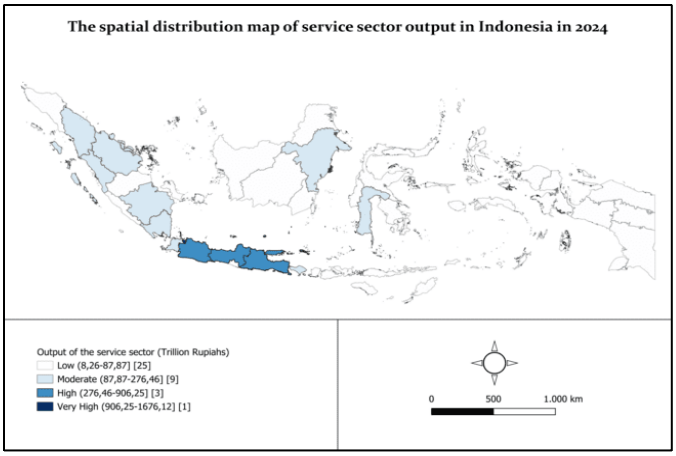


Figure 3. Map output of the service sector Distribution (Trillion Rupiah) in Indonesia, 2024

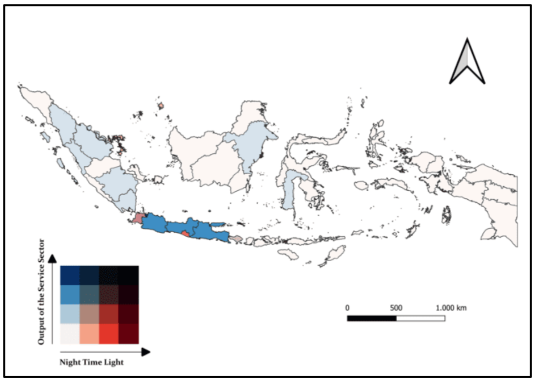
Figure 3 presents the spatial distribution of the output of the service sector for each province in 2024, classified using the natural breaks method into four categories: low, moderate, high, and very high. The visualization shows that provinces located near DKI Jakarta tend to have higher levels of the output of the service sector. Most provinces fall into the low category (8.26–87.87 trillion rupiah), particularly those in the central and eastern regions of Indonesia, such as Maluku and Papua. Very high output levels (above 906.25 trillion rupiah) are found only in DKI Jakarta, while high-category provinces include West Java, Central Java, and East Java. Finally, provinces categorized as having very high output of the service sector exceeding 906.25 trillion rupiah are found in DKI Jakarta. Meanwhile, provinces classified as having high output include West Java, Central Java, and East Java.

3.1.1. The Relationship Between the Gig Economy and output of the service sector

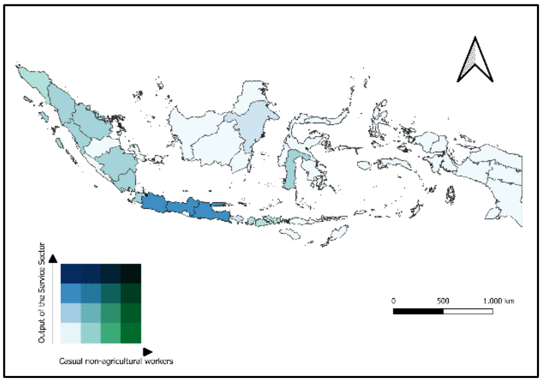
Figure 4 presents a bivariate choropleth map that illustrates the relationship between output of the service sector and the independent variables used in this study. The independent variables include NTL, casual non-agricultural workers, Internet User Percentages, Provincial Minimum

Wage (UMP), average years of schooling (RLS), and IMK output. Each variable is classified into four categories using the natural breaks method. Analysis of the distribution patterns in Figures 4(a) and 4(b) reveals a positive correlation between output of the service sector and NTL or casual non-agricultural workers. Provinces with high to very high output of the service sector, such as DKI Jakarta, West Java, and East Java, exhibit high NTL (dark blue to dark red shades), while eastern regions like Papua, Maluku, and Nusa Tenggara show low values for both. This confirms a positive relationship with NTL and a unidirectional link with large-scale casual non-agricultural workers.

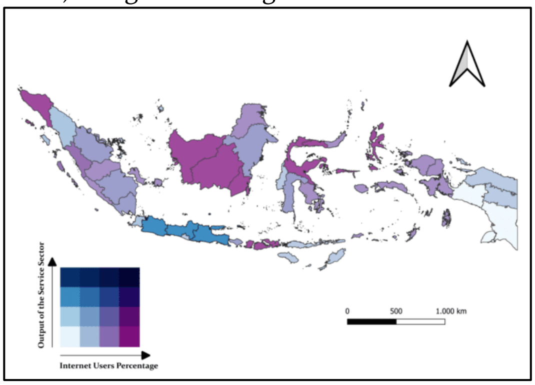
Figures 4(c) and 4(e) demonstrate positive correlations between output of the service sector and the percentage of internet users or RLS, evident from aligned distribution patterns. In contrast, Figures 4(d) and 4(f) indicate negative correlations with provincial minimum wage and IMK output. Provinces like West Java and Central Java have high output of the service sector but low minimum wages, whereas several provinces in Sumatra, Kalimantan, and Papua have low output yet high wages. High output of the service sector also tends to coincide with low IMK output, though the correlation exists but is not strong in some areas.



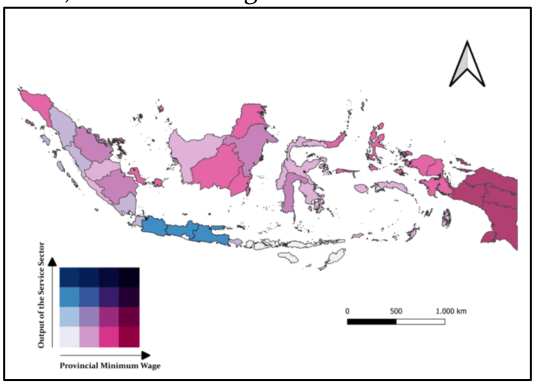
a) Night-Time Light



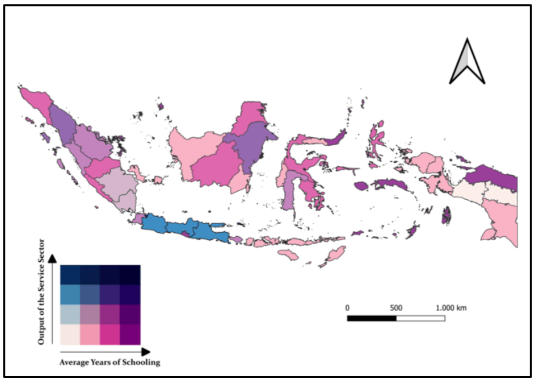
b) casual non-agricultural workers



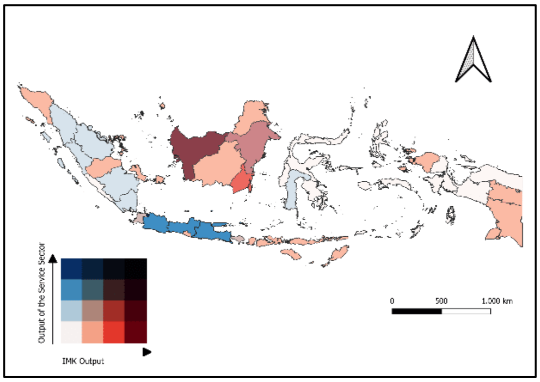
c) Internet User Percentages



d) Provincial Minimum Wage



e) Average Years of Schooling



f) IMK output

Figure 4. Bivariate Choropleth Map of the Relationship Between output of the service sector and the Gig Economy and Other Independent Variables in Indonesia, 2024

3.2. Identification of Spatial Autocorrelation Using Global Moran's I

In initiating modelling that accounts for spatial effects, the first step is to identify the presence of spatial autocorrelation in both the dependent and independent variables. This testing is conducted globally using the Global Moran's I statistic to assess the extent to which output of the service sector, the gig economy, and other independent variables in the study exhibit spatial patterns that are interrelated across provinces in Indonesia.

Table 2. Global Moran's I Testing

Variable	*Global Moran's I*	*P-value*
Output of the Service Sector (Y)	0.31934301	0.005*
Night-Time light (NTL)	0.12662055	0.001*
Casual non-agricultural workers (L)	0.16451229	0.050*
Internet User Percentages (ICT)	0.24215762	0.016*
Provincial Minimum Wage (UMP)	0.22043851	0.017*
Average Years of Schooling (RLS)	0.13661188	0.069*
IMK Output (IMK)	0.07005554	0.140

Explanation: * (significant at the 10 percent significance level)
Source: Processed

Based on the results of the Global Moran's I test presented in Table 2, the output of the service sector variable shows a Moran's I value of 0.3193 with a p-value of 0.005. This value indicates rejection of the null hypothesis (H_0) at the 5 percent significance level, leading to the conclusion that there is positive spatial autocorrelation in output of the service sector across provinces in Indonesia in 2024. This means that provinces with high levels of output of the service sector tend to be adjacent to other provinces that also have high levels of output of the service sector, and vice versa.

In addition, several independent variables also exhibit significant spatial autocorrelation. The variables NTL, ICT, and UMP each have p-values below 0.05, indicating positive spatial patterns across provinces. Meanwhile, the casual non-agricultural workers variable shows spatial autocorrelation at the 10 percent significance level, whereas RLS and IMK output do not yet show significant spatial relationships. Overall, these results confirm the existence of spatial interdependence across provinces in economic activities of the service sector, the gig economy, and other independent variables. These findings provide the basis for employing a spatial regression approach in the inferential analysis stage to accommodate the detected spatial effects in the data.

3.3. Spatial Regression Model Selection

The results of the spatial autocorrelation test indicate significant spatial interdependence in the dependent variable, namely the output of the service sector across provinces in Indonesia. This finding suggests that the Ordinary Least Squares (OLS) parameter estimation approach is no longer adequate, as it ignores spatial effects between regions. Therefore, further steps are required to identify the form of spatial dependence whether in the lag or error component in order to determine the most appropriate spatial regression model.

Table 3. Diagnostic Testing for Spatial Effects

Test	Test Statistic Value	P-value	Decision
LM-lag	3.9113	0.048	Reject H_0
LM-error	0.1051	0.746	Fail to Reject H_0
Robust LM-lag	3.8096	0.051	Reject H_0
Robust LM-error	0.0034	0.954	Fail to Reject H_0

Source: Processed

The results of the diagnostic testing for spatial effects displayed in Table 3 indicate the presence of spatial effects in the lag component of the model. This is evident from the p-value of the LM-lag test (0.048) and the Robust LM-lag test (0.051), which are significant at the 5 percent and 10 percent significance levels, respectively, leading to the rejection of the null hypothesis (H_0). In contrast, the LM-error and Robust LM-error tests show p-values well above 0.05, indicating no evidence of spatial effects in the error component.

Thus, these results suggest that the appropriate model to use is the Spatial Autoregressive Model (SAR). This model can capture spatial dependence across provinces in the output of the service sector in Indonesia in 2024, reflecting that the output of the service sector in a given region is also influenced by the output of the service sector in neighbouring regions. However, given the presence of spatial autocorrelation in the independent variables, it is necessary to construct the SLX, SDM, and SDEM models to determine the best model to be selected.

Based on the model comparison results presented in Table 4, the Spatial Durbin Error Model (SDEM) is selected as the best model. Although the AIC value of the SDEM (390.3555) is slightly higher than that of the SAR model (387.0852), the SDEM exhibits a higher log-likelihood value (-180.1778) and the highest R-Square (0.9921) among all tested models. A higher log-likelihood indicates better model fit to the data, while a larger R-Square reflects the model's superior ability to explain the variation in the dependent variable. Therefore, considering the balance between goodness of fit and explanatory power, the SDEM is deemed the most appropriate for representing the spatial relationship of the gig economy's influence on the output of the service sector in Indonesia.

Table 4. Comparison of Goodness of Fit for Spatial Models

Model	Log-likelihood	R-Square	AIC
SAR	-184.5426	0.9901	387.0852
SLX	-183.1361	0.9908	394.2721
SDM	-182.4573	0.9911	394.9146
SDEM	-180.1778	0.9921	390.3555

Source: Processed

3.4. SDEM Parameter Estimation

After determining the best model, the next step is to perform parameter estimation using the Spatial Durbin Error Model (SDEM). This estimation aims to identify the magnitude of the influence of the independent variables on the output of the service sector, both directly (direct effect) and indirectly through spatial effects (indirect effect). The SDEM enables a more comprehensive analysis by capturing spatial effects arising from errors (spatial error dependence), thereby providing a more accurate depiction of interregional spatial linkages in Indonesia's service sector economy.

Table 5. Results of SDEM Parameter Estimation

Variable	Parameter Estimation	Std. Error	P-value
(Intercept)	7367.40000	3079.20	0.017*
Night-Time Light (NTL)	61.98600	2.11	0.000*
Casual non-agricultural workers (L)	0.55297	0.02	0.000*
Internet User Percentages (ICT)	-27.74600	14.68	0.059*
Provincial Minimum Wage (UMP)	5.97410	15.21	0.694
Average Years of Schooling (RLS)	8.30620	5.01	0.098*
IMK Output (IMK)	0.00029	0.00	0.112
Lag_Night-Time Light (NTL)	-2.11270	30.58	0.469
Lag_Casual non-agricultural workers (L)	-0.15060	2.92	0.001*
Lag_Internet User Percentages (ICT)	-47.94800	0.05	0.117
Lag_Provincial Minimum Wage (UMP)	-29.17400	28.70	0.309
Lag_Average Years of Schooling (RLS)	13.97500	8.70	0.108
Lag_IMK Output (IMK)	0.00053	0.00	0.073*

Explanation: * (significant at the 10 percent significance level)
Source: Processed

The SDEM parameter estimation results show that several independent variables have a significant influence on the output of the service sector. As presented in Table 5, the effects of the independent variables are categorized into two types, direct effect and indirect effect, reflecting spatial interdependence across regions. In terms of direct effect, the variables NTL, casual non-agricultural workers, internet user percentages, and average years of schooling (RLS) have a significant impact on the output of the service sector. Meanwhile, in terms of indirect effect, Casual non-agricultural workers and IMK output (IMK) exhibit a significant indirect influence on the output of the service sector. This indicates the presence of spillover effects from these independent variables particularly Casual non-agricultural workers and IMK output (IMK) in neighboring provinces on the observed province.

The NTL variable, which serves as a proxy for gig economy activity, has a positive coefficient of 61.99 and is significant at the 5 percent significance level (p-value = 0.000), indicating that an increase in NTL intensity contributes to higher output of the service sector in the respective province. Additionally, the casual non-agricultural workers (L) variable another proxy for gig workers also exerts a positive and significant effect on the output of the service sector, with a coefficient of 0.55 and a p-value of 0.000. This finding suggests that an increase in the number of casual non-agricultural workers, many of whom are engaged in informal service activities and digital platforms, can drive growth in output of the service sector. These results are in line with Alfarizi & Arifin (2025), who state that the increasing productivity of individual gig workers can drive an overall increase in labor output, particularly in service sectors such as logistics, food delivery services, and digital content creation. These sectors contribute to the national Gross Domestic Product (GDP), especially through the added value of the service sector and the rising flow of consumption.

Job diversification needs to be a priority, given the increasingly limited availability of formal employment opportunities. The demographic bonus, which is projected to peak in 2030, further underscores the urgent need for job diversification (BPS, 2022). This challenge is exacerbated by numerous reports of layoffs in several companies. On the other hand, recruitment trends in the formal sector have declined in recent years, reducing job opportunities for new graduates (Safitri & Rezza, 2025). To address these challenges, the government can highlight the gig economy as one solution to expand employment options. This study finds that the gig economy contributes significantly to regional economic growth in Indonesia. At the same time, the workforce can utilize the gig economy sector as a temporary employment option while seeking formal sector jobs. Gig economy jobs can serve as a strategy to address the limited availability of employment in the short term (Prasojo, 2022).

Furthermore, the internet user percentages (ICT) variable exhibits a negative coefficient of -27.75, which is statistically significant at the 10 percent significance level (p-value = 0.059). These results show that the increase in the percentage of internet users has not had an impact on increasing the output of the service sector, in fact, it has led to a decline. The negative direction of the coefficient may indicate that increased internet penetration has not yet been fully accompanied by improved productivity in the service sector, possibly due to disparities in the utilization of digital technology across regions (Mun et al., 2014).

The provincial minimum wage (UMP) variable has a positive coefficient of 5.97, which is not statistically significant (p-value = 0.694), indicating that differences in wage levels have not yet had a tangible impact on increasing the output of the service sector. This can be explained by the diverse nature of jobs in the service sector, where the majority are not bound by formal minimum wage regulations. An increase in the minimum wage may boost productivity in certain service subsectors, such as hospitality and retail. This finding aligns with Croucher & Rizov (2012), who show that minimum wage increases can enhance productivity in specific service subsectors, but do not always significantly affect aggregate service sector output due to cost structure and labor adjustments at the firm level.

Furthermore, the average years of schooling (RLS) variable exhibits a positive effect on the output of the service sector, with a coefficient of 8.31, significant at the 10 percent significance level (p-value = 0.098). This finding indicates that an increase in educational attainment contributes to higher service sector output. Regions with higher average years of schooling tend to have a workforce that is more adaptable to digital technology and service-based economic innovation. This result is consistent with Altiner & Toktaş (2017), who found that human capital positively affects economic growth in developing countries.

In terms of indirect effects, the lagged Casual non-agricultural workers (L) variable has a significant negative impact on the output of the service sector, with a coefficient of –0.15 and a p-value of 0.001. This means that an increase in casual non-agricultural workers in neighboring provinces actually reduces service sector output in the observed province. This may occur because provinces with high service sector output are more attractive to cross-regional labor. Permana et al. (2022) note that the rise in gig workers is strongly correlated with urban populations, indicating that gig workers remain concentrated in areas with strong economies. In the Cobb-Douglas production function, labor is one of the driving factors of output growth that has different characteristics from capital. Labor in a given period of time are a mobile component. This means that when there is an increase in workers in one area, there will be a decrease in the number of workers in their area of origin. Given this characteristic, an increase in gig workers in one area has the consequence of a decrease in labor in other areas. This explains that an increase in gig workers in one province can cause a decline in the service sector output of surrounding provinces due to a decrease in the labor factor. Conversely, the lagged IMK output (IMK) shows a positive and significant effect at the 10 percent significance level (p-value = 0.073), meaning that an increase in IMK output in neighbouring provinces can drive growth in service sector output in the observed province. The rise in IMK output not only boosts the regional economy of the originating area but also generates spillover effects to surrounding regions.

The gig economy represents a significant potential driver for accelerating Indonesia's economic growth. This opportunity aligns with the National Medium-Term Development Plan (RPJMN) 2025–2029, which one of the targets is high and sustainable economic growth, aiming for 8 percent by 2029. The findings of this study further reinforce the role of the gig economy in expanding employment opportunities and accelerating economic growth. This is consistent with

Banik & Padalkar (2021), who argue that the gig economy helps reduce unemployment and provides alternative income sources for communities with limited access to formal employment.

However, the presence of the gig economy in Indonesia also introduces new dilemmas for job seekers. Currently, labor protections for gig workers remain extremely limited, with employment relationships governed solely through digital platform mechanisms. Putra et al. (2025) note that electronic work contracts drafted by digital platforms tend to be unfair and disproportionately favor the platform operators. Moreover, gig workers lack formal employee status and thus do not benefit from protections under the Manpower Law. This situation signals the urgent need to improve regulations to strengthen protections for gig workers. In addressing these challenges, Indonesia should look to labor protection policies for gig workers that balance freedom and welfare, as implemented by the European Union and the United States (Afifah, 2024).

The summary statistics in Table 6 indicate that the SDEM model effectively explains the variation in service sector output across Indonesia. The Nagelkerke pseudo-R^2 value of 0.9921 suggests that approximately 99.21 percent of the variation in service sector output can be explained by the independent variables included in the model. The lambda (λ) coefficient of –0.8072, which is statistically significant at the 5 percent level (p-value = 0.0150), confirms the presence of spatial autocorrelation in the error component. This implies that unobserved disturbances or factors affecting service sector output in one province are spatially correlated with those in neighboring provinces. In addition, the AIC value of the SDEM model (390.36) is lower than that of the OLS model. Furthermore, the Log-Likelihood Ratio (LR) test for the SDEM model shows statistical significance, indicating that the SDEM provides a stronger and more accurate explanation of the impact of the gig economy on service sector output.

Table 6. Summary Statistics SDEM

Statistics	value
Lambda (λ)	-0.8072
LR test	5.9166*
p-value Lambda	0.0150
AIC (SDEM)	390.36
AIC (OLS)	394.27
Nagelkerke pseudo-R^2	0.9921

Explanation: * (significant at the 10 percent significance level)

Source: Processed

4. Conclusion and Recommendations

This study highlights the significant role of the gig economy, proxied through night-time lights and casual non-agricultural workers, in promoting output growth in Indonesia's service sector. The results indicate that the gig economy contributes to strengthening service-sector output and diversifying employment opportunities. Average years of schooling positively and significantly influences service-sector output, while the percentage of internet users shows a negative effect. Furthermore, the provincial minimum wage demonstrates no significant impact, suggesting that wage policies exert limited influence within a labor market largely shaped by casual and gig-based employment structures. Spatially, IMK output generates positive spillover effects on service-sector performance in neighboring regions, whereas casual non-agricultural workers produce negative spillovers. This pattern implies that provinces with higher service-sector output attract interregional labor migration, thereby reducing labor availability in surrounding areas.

While the gig economy provides economic benefits, it also faces persistent challenges such as income instability, lack of social protection, and its concentration in urban areas, which may exacerbate regional disparities. This study contributes to the literature by examining the spatial dynamics of the gig economy in Indonesia using an integrated approach combining remote sensing and spatial econometric analysis.

Nevertheless, this study is not without limitations. The use of NTL as a proxy for gig activity captures general urban nighttime dynamics rather than platform-based work specifically, offering only an aggregated indication of regional activity. Likewise, the use of casual workers as a proxy for gig workers reflects a broader informal labor group that does not exclusively represent digital platform workers. These proxies were employed due to the absence of more precise indicators in Indonesia's official statistics. Future research may incorporate more specific measures, such as app-based mobility data, digital connectivity indicators, or micro-level platform worker datasets, and adopt spatial weight matrices based on interprovincial migration flows to more accurately capture labor mobility patterns. Based on the findings, policymakers should strengthen initiatives that improve regional digital infrastructure, expand digital literacy and reskilling programs, and design fair social protection schemes for gig workers. In addition, promoting more balanced digital development across regions and supporting micro and small industries can help ensure that the growth of the gig economy contributes to inclusive and sustainable regional development.

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