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Economic Agglomeration and District-Level Carbon Emissions in Indonesia

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ABSTRACT

Research Originality: This study contributes to the literature by incorporating employment density as a proxy of economic agglomeration into an extended STIRPAT framework to examine its nonlinear relationship with district-level carbon emissions in Indonesia.

Research Objectives: This study aims to investigate whether economic agglomeration promotes emission efficiency or intensifies environmental pressure, and to identify potential nonlinear dynamics across Indonesian districts.

Research Methods: This study employs a balanced panel dataset of 514 districts and municipalities in Indonesia over the period 2017–2024. A two-way fixed-effects model is estimated within an extended STIRPAT framework, with a quadratic specification to capture nonlinear effects.

Empirical Results: The results indicate that economic agglomeration is associated with lower carbon emissions per capita, suggesting efficiency effects. However, the nonlinear estimation reveals a U-shaped relationship: agglomeration reduces emissions at lower levels but increases environmental pressure beyond a threshold. The findings also indicate substantial regional heterogeneity.

Implications: The results suggest that agglomeration does not inherently lead to environmental improvements. Differentiated policies should strengthen regional growth and efficiency in low-density areas while prioritizing low-carbon transitions and congestion mitigation in dense regions.

Keywords:

economic agglomeration; employment density; carbon emissions; spatial concentration; nonlinear relationship

How to Cite:

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INTRODUCTION

Indonesia has experienced rapid urbanization and spatial concentration of economic activities over the past decade (Jamal, 2017; Wilonoyudho et al., 2017). The growing density of labor and production in urban districts has been widely associated with productivity gains, knowledge spillovers, and structural transformation (Cottineau et al., 2019). Economic agglomeration theory suggests that spatial concentration enhances efficiency through sharing of infrastructure, improved labor matching, and accelerated learning and technological diffusion (Li & Li, 2018; McCann & van Oort, 2019). Dense regions may utilize transport networks, energy systems, and public services more efficiently, potentially reducing emissions per unit of output (Fatorachian & Kazemi, 2025). However, agglomeration may simultaneously intensify environmental pressure through scale effects, rising energy demand, congestion, and industrial expansion. From a theoretical perspective, agglomeration may reduce carbon emissions through efficiency improvements, technological diffusion, and better infrastructure utilization (Resbeut et al., 2019). Dense economic areas can lower transportation costs, enhance public service provision, and promote energy efficiency. Conversely, spatial concentration may intensify emissions due to scale effects, higher energy demand, and congestion externalities (Zhou et al., 2024). The net environmental impact therefore depends on the balance between efficiency and scale dynamics.

The theoretical linkage between employment density and environmental outcomes draws on the micro-foundations of agglomeration proposed by Gilles Duranton and Diego Puga (2004), which identify three channels: sharing, matching, and learning. Through sharing, dense economic areas can operate infrastructure (such as transport systems, energy networks, and waste facilities) more efficiently, potentially lowering energy intensity per unit of output (Gatzioura et al., 2019). Through matching, thicker labor markets improve the allocation of skills, including green and energy-efficiency expertise, thereby reducing production inefficiencies (Yi et al., 2021). Through learning, spatial proximity accelerates knowledge spillovers and the diffusion of cleaner technologies (Wang et al., 2020; Yu et al., 2022). These mechanisms suggest that agglomeration may generate environmental efficiency effects. However, in contexts characterized by fossil-fuel dependence and energy-intensive production structures, scale effects may dominate these channels (Ahmad et al., 2021), making the environmental impact of agglomeration an empirical question.

Empirical evidence on the relationship between economic agglomeration and carbon emissions remains mixed and geographically concentrated. A substantial portion of the literature is based on Chinese regional data. Research in China often highlights the emission-reducing effects of density, the triggering of innovation, and the acceleration of the adoption of environmentally friendly technologies (Hong et al., 2019). On the other hand, findings in developing contexts tend to emphasize the dominance of production scale and fossil-fuel dependence (Cheng, 2016; Han et al., 2018). These findings suggest nonlinear, context-dependent dynamics in which structural conditions, energy composition, and industrial upgrading determine whether agglomeration contributes to environmental improvement (Liu et al., 2024).

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Beyond China, evidence from other countries further underscores the structural sensitivity of the agglomeration–emissions nexus. Using regional manufacturing data from South Korea, Wu et al. (2025) show that specialized industrial agglomeration tends to increase carbon emissions, whereas diversified agglomeration may reduce environmental pressure. This distinction highlights that the environmental consequences of spatial concentration depend not merely on density, but on the composition and maturity of regional economic structures. Studies in Sub-Saharan Africa, for example, indicate that economic transformation does not automatically translate into environmental improvement. Nkengfack et al. (2019) show that in many low- and middle-income countries, the scale effect remains the principal driver of rising emissions, while limited technological adoption and weak regulatory enforcement constrain the emergence of technical efficiency gains.

Despite the growing literature on agglomeration and environmental outcomes, several important gaps remain. First, existing studies are largely focused at the cross-country or provincial levels, with limited evidence at finer spatial scales in large, lower-middle-income economies. Most existing studies rely on cross-country, provincial, or metropolitan aggregates, leaving district-level dynamics underexplored, despite substantial regional disparities. In the Indonesian context, studies commonly focus on economic growth, urbanization, or energy consumption, yet rarely explicitly incorporate economic agglomeration (particularly measured by employment density) as a core explanatory variable (Kurniawan & Managi, 2018). As a result, the role of spatial economic concentration in shaping environmental outcomes remains insufficiently understood. Second, the potential nonlinear relationship between agglomeration and emissions has not been systematically examined at the subnational level in developing countries, where structural conditions differ markedly from advanced economies. Given Indonesia's substantial regional disparities and heterogeneous development patterns, understanding how agglomeration interacts with carbon emissions at the subnational level is crucial. Third, although the STIRPAT framework is widely used to analyze environmental pressures (Cooray & Özmen, 2024; Yilmaz & Sensoy, 2022), spatial economic density is rarely incorporated explicitly as a core explanatory variable (Aziz & Chowdhury, 2023; Borsha et al., 2024). Population and income are commonly included, yet the distinct role of employment density as a measure of economic concentration is seldom examined within this framework. Fourth, developing economies characterized by substantial regional disparities and fossil-fuel dependence may exhibit agglomeration dynamics that differ fundamentally from those observed in more advanced contexts.

Indonesia provides a particularly relevant setting to address these gaps. As a large, lower-middle-income country with pronounced interregional disparities, a heterogeneous industrial structure, and continued reliance on fossil fuels, Indonesia offers an opportunity to assess whether agglomeration generates environmental efficiency gains or reinforces scale-driven emission pressures. District-level analysis is especially important given the country's administrative fragmentation and uneven development trajectories.

This study addresses these gaps and contributes to the literature in three main ways. First, it provides district-level evidence from 514 districts and municipalities in

Indonesia over the period 2017–2024, offering one of the most comprehensive subnational analyses of agglomeration and carbon emissions in a developing economy. Second, it explicitly embeds employment density into an extended STIRPAT framework (York et al., 2003), integrating spatial economic concentration into a well-established environmental impact model. Third, the study examines potential nonlinear dynamics by incorporating a quadratic specification of agglomeration, thereby extending the Environmental Kuznets Curve (EKC) perspective beyond income toward spatial economic intensity (Chanda et al., 2024). Accordingly, this study aims to examine the relationship between economic agglomeration and district-level carbon emissions in Indonesia, with particular emphasis on identifying whether spatial concentration promotes emission efficiency or intensifies environmental pressure. It further evaluates nonlinear patterns and regional heterogeneity to clarify the conditions under which agglomeration may support or hinder sustainable development.

METHODS

This study employs secondary district-level panel data covering 514 districts and municipalities in Indonesia over the period 2017–2024. The observation window is selected for two main considerations. First, it captures an important phase in Indonesia's climate policy trajectory, including the implementation of Nationally Determined Contributions (NDCs) and the strengthening of green economy initiatives in the post-pandemic period. This timeframe provides a meaningful basis for assessing whether increasing economic agglomeration is associated with improvements in carbon efficiency (technique effects) or remains driven by scale-related emission pressures. Second, the selected period ensures a high degree of data consistency and comparability across districts. While some variables are available for earlier years, the coverage and harmonization of key indicators become more stable in the more recent period. Focusing on 2017–2024, therefore, allows the analysis to rely on a consistent, well-aligned dataset, thereby enhancing the robustness and reliability of the empirical results.

The data were obtained from various sources. Carbon emission data are obtained from the Emissions Database for Global Atmospheric Research (EDGAR), while socioeconomic indicators are compiled from national statistical and investment databases. The balanced panel consists of 4,112 observations. The data sourced from these institutions are predominant due to their broad global coverage (satellite data) and consistent availability across years. Table 1 presents the more detailed information about the operational variables.

As for the variables used in this study, the dependent variable is carbon emissions per capita, measured in metric tons of CO_2 per capita (Chanda et al., 2024), defined as CO_2 emissions per capita per year at the district level. For the independent variables, economic agglomeration is proxied by employment density, measured as the number of workers per square kilometer (Ercole & O'Neill, 2017; Melo et al., 2009). In the modern literature on economic agglomeration, Combes and Gobillon (2021) contend that economic density is a more canonical and superior measure than total population

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mass for capturing agglomeration effects, as it better reflects the intensity of interactions among economic agents within a given region. Following previous studies, other variables used to control for the carbon emission variable are economic growth, proxied by Gross Regional Domestic Product (GRDP) per capita at constant prices, share of manufacture industry to GDP, share of tertiary industry to GDP, and ratio of foreign direct investment to GDP (Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024). This study covers data from 2017–2024, as consistent district-level socioeconomic indicators across Indonesia have been widely available only since 2017. Although EDGAR provides emission estimates for earlier years, several explanatory variables used in this study are not consistently reported at the district level before 2017.

Table 1. Definition of variables, frequency and sources

Variables	Definitions	Measurements	Sources	References
Carbon Dioxide Emission Per Capita	CO_2 emissions per capita (metric tons of CO_2 per person per year) at the district level	Metric tons of CO_2 per capita	EDGAR	(Chanda et al., 2024; Crippa et al., 2025)
Economic Agglomeration	Employment density, measured as total number of employed workers per square kilometer	total number of employed workers/km^2	BPS	(Ercole & O'neill, 2017; Melo et al., 2009)
Gross Domestic Product Per Capita	Gross regional domestic product per capita at constant prices	IDR per capita	BPS	(Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024)
Share of Manufacture Industry to GDP	Share of manufacturing value added in total regional GDP (percent)	Total regional GDP in Manufacture Industry/GDP	BPS	(Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024)
Share of Tertiary Industry to GDP	Share of tertiary sector value added in total regional GDP (percent)	Total regional GDP in Tertiary Industry/GDP	BPS	(Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024)
Ratio of Foreign Direct Investment to GDP	Ratio of foreign direct investment in total regional GDP (percent)	Total regional FDI/GDP	BKPM / Ministry of Investment	(Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024)

Given the coverage of 514 districts and municipalities in Indonesia, which is characterized by substantial geographic diversity, heterogeneous development trajectories, and varying ecological conditions (Glaeser & Kahn, 2008), estimating the model using pooled Ordinary Least Squares (OLS) may yield biased results due to omitted variable bias. To address unobserved heterogeneity, this study employs a Two-Way Fixed Effects (TWFE) specification, formulated as follows:

$$ln(emission_{it}) = \beta_1 ln(agglo_{it}) + \beta_n lnX_{nit} + \alpha_i + \delta_t + \varepsilon_{it} \qquad (1)$$

Although the two-way fixed-effects specification helps mitigate omitted variable bias by controlling for time-invariant district characteristics and common time shocks, potential endogeneity concerns may persist. In particular, reverse causality between emissions and economic agglomeration, as well as possible measurement errors in district-level emission estimates, cannot be entirely ruled out. Therefore, the estimated coefficients should be interpreted as conditional associations rather than strictly causal effects.

To examine the relationship between economic agglomeration and carbon emissions, this study adopts an extended STIRPAT framework. Carbon emissions are modeled as a function of population size, income per capita, and structural factors. Employment density is incorporated as an additional explanatory variable to capture the spatial concentration of economic activity. This extension allows the model to distinguish between population scale effects and spatial interaction intensity, thereby enriching the conventional STIRPAT specification (Yi et al., 2021; Yu et al., 2022; Zhou et al., 2024).

Real income per capita is essential for testing the EKC hypothesis at the district and municipal levels, while ensuring that the estimated impact of agglomeration on carbon emissions is identified net of income effects. The use of constant-price GRDP is theoretically justified, as carbon emissions are more closely linked to physical output and energy consumption than to nominal price fluctuations. Following the EKC tradition, this study further incorporates a nonlinear specification of employment density ($agglo^2$) to examine whether agglomeration exhibits an inverted-U or U-shaped relationship with emissions. Consistent with the EKC literature (Shahbaz et al., 2013; Stern, 2017), the nonlinear framework allows for the possibility that environmental pressure initially rises with increasing economic intensity but declines after a certain threshold due to efficiency gains, structural transformation, and technological upgrading. In this context, the EKC concept is extended from an income–environment relationship to an agglomeration–environment relationship, where employment density captures the spatial concentration of economic activity and the identified nonlinear pattern reflects the balance between scale effects and spatial efficiency gains. With that, the model for nonlinear specification to address the EKC concept, is formulated as follows:

$$ln(emission_{it}) = \beta_1 ln(agglo_{it}) + \beta_2 ln(agglo^2_{it}) + \beta_n lnX_{nit} + \alpha_i + \delta_t + \varepsilon_{it} \quad (2)$$

All variables are transformed into natural logarithms to interpret coefficients as elasticities and to reduce heteroskedasticity. Accordingly, the estimated coefficients represent elasticities, indicating the percentage change in carbon emissions associated with a one percent change in each explanatory variable, holding other factors constant. To examine potential nonlinear dynamics in the agglomeration–emissions relationship, an alternative specification includes a quadratic term for economic agglomeration. This specification allows the analysis to assess whether increasing employment density generates diminishing environmental efficiency or reversals beyond certain density levels (Koirala et al., 2025).

To further explore regional heterogeneity, subsample estimates are conducted by dividing districts into geographic and administrative categories. First, districts are grouped into those located in Java and those outside Java, reflecting Indonesia's well-documented spatial concentration of economic activities and infrastructure in Java relative to other regions (Yunitasari et al., 2023). Second, districts are categorized by administrative classification as regencies or cities, which differ substantially in urbanization levels,

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economic structures, and population densities (Falahuddin et al., 2024). This approach allows the analysis to examine whether the agglomeration–emissions relationship varies across regions with different spatial and institutional characteristics.

The summary statistics of the variables used in this study are presented in Table 2. The average carbon emissions per capita at the district and municipal level (emission) amount to 0.471 tons per person, accompanied by a relatively large standard deviation (2.756). This pattern reflects substantial disparities in environmental pressure across regions in Indonesia. The highest emission levels are generally concentrated in areas with intensive heavy industrial activities or large-scale extractive industries, such as Bontang and Cilegon. Conversely, extremely low emission levels are observed in remote inland districts, mainly at the eastern part of Indonesia, where economic activities remain relatively limited compared with the geographic size of the administrative area.

Table 2. Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Carbon emission (emission)	4112	0.471	2.756	0.000043	49.917
Economic agglomeration (agglo)	4112	5276.153	1244.837	0.340	10754.610
Economic prosperity (gdpcap)	4112	38.662	44.868	3.969	570.117
Manufacture share (manugdp)	4112	12.766	14.538	0	83.869
Tertiary share (tertgdp)	4112	43.599	17.371	2.628	90.902
FDI-to-GDP (fdigdp)	4112	9.206	28.277	0	1040.252

Economic agglomeration (agglo) exhibits a mean value of 5,276 workers per square kilometer, with a very wide range from 0.34 to 10,754 workers per km^2. This pattern highlights a pronounced spatial polarization between major economic centers, particularly metropolitan areas in Java, and sparsely populated non-urban regions. The use of employment density as a proxy for agglomeration is consistent with the framework proposed by Duranton & Puga (2004), as variations in labor density are expected to capture mechanisms of sharing and learning that may influence regional energy efficiency and emission levels.

From an economic prosperity perspective, the average real GRDP per capita (gdpcap) across districts is approximately 38.66 million rupiah per person. Employing constant prices is methodologically essential because it removes the influence of inflation, allowing the observed variations in income levels to more accurately represent real changes in economic output that are more closely associated with energy use and carbon emissions. Consequently, this indicator provides a reliable foundation for assessing the validity of the Environmental Kuznets Curve (EKC) hypothesis within the Indonesian context. In terms of economic structure, subnational economies in Indonesia are largely dominated by the service or tertiary sector, which contributes on average 43.59 percent to regional GDP (tertgdp), substantially higher than the manufacturing sector, whose average share is only 12.76 percent (manugdp). Despite this general pattern, Indonesia's regional economies remain highly heterogeneous, with certain districts exhibiting strong industrial specialization. For instance, manufacturing activities remain relatively prominent in areas such as Kediri City and Kudus Regency, reflecting localized industrial concentration within an otherwise service-oriented national structure. The predominance of the service sector is also consistent with the phenomenon of premature deindustrialization described in the literature, where structural transformation toward services occurs before manufacturing reaches levels typical of advanced economies, potentially generating emission dynamics that differ from those commonly observed in developed countries. Finally, the ratio of foreign direct investment to regional GDP (fdigdp) averages 9.206 percent, although its distribution is highly uneven, with maximum values that exceed local GDP by several multiples. These extreme observations indicate the presence of regions that receive disproportionately large inflows of foreign investment relative to their local economies, particularly in districts hosting large-scale mining operations or strategic resource-based projects, such as Central Halmahera in early 2018 and North Maluku from early 2015 to late 2019.

RESULTS AND DISCUSSION

The empirical results reveal three main findings regarding the relationship between economic agglomeration and district-level carbon emissions in Indonesia. First, economic agglomeration, proxied by employment density, is negatively associated with per capita carbon emissions, suggesting efficiency effects arising from spatial concentration. Second, the nonlinear specification indicates a U-shaped relationship, where agglomeration initially reduces emissions but eventually increases environmental pressure beyond a certain threshold. Third, the heterogeneity analysis shows that these effects vary across regions and administrative structures, with more robust emission-reducing effects observed in non-Java regions and regencies. These findings highlight that the environmental consequences of agglomeration are not uniform but depend on the level of economic density and the characteristics of regional development.

The estimation results are presented in Table 3. Following the STIRPAT framework, the empirical specification relates environmental pressure, measured by district-level per capita carbon emissions, to economic activity, structural factors, and spatial agglomeration. All regressions, formulated in Equations (1) and (2), are estimated using a fixed-effects panel model with year dummies to control for time-specific shocks affecting all districts. To address potential heteroskedasticity and serial correlation within districts, standard errors are clustered at the district level.

The baseline estimation results in Table 3 indicate that economic agglomeration is negatively associated with district-level per capita carbon emissions. The estimated elasticity suggests that a 1% increase in employment density is associated with a modest 0.11% reduction in emissions. The negative association between employment density and per capita carbon emissions suggests that agglomeration may generate environmental efficiency gains through several channels. In line with the micro-foundations of agglomeration economies,

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higher density facilitates more efficient use of infrastructure, including transport networks and energy systems, thereby reducing energy intensity per unit of output. These findings support the presence of an efficiency effect, whereby spatial concentration improves infrastructure utilization and energy efficiency (Yi et al., 2021). Consistent with the STIRPAT framework, income per capita and energy use exhibit positive and statistically significant effects on emissions, reflecting the dominance of scale effects in driving environmental pressure (Zhou et al., 2024). In addition, denser labor markets improve the matching of skills, potentially enhancing the adoption of energy-efficient technologies and production practices. These mechanisms are consistent with recent empirical findings that highlight the role of urban density in improving energy efficiency and reducing carbon intensity in developing economies. However, the relatively small magnitude of the coefficient indicates that these efficiency gains remain limited and may not fully offset the scale effects associated with economic expansion and rising energy demand.

Table 3. The Results of OLS and Nonlinear Estimations

	TWFE ln(emission)	Nonlinear ln(emission)
ln(agglo)	-0.113*** (0.0324)	-0.343*** (0.0890)
ln($agglo^2$)		0.0358*** (0.0119)
ln(gdpcap)	0.684*** (0.0475)	0.663*** (0.178)
ln(manugdp)	-0.00387 (0.0264)	-0.00443 (0.0347)
ln(tertgdp)	0.566*** (0.0677)	0.532*** (0.189)
ln(fdigdp)	-0.00973*** (0.00253)	-0.00975** (0.00435)
Constant	-7.109*** (0.421)	-6.74040*** (1.27589)
F-Statistic	27.63	26.72
R-Square (within)	0.167	0.171
rho	0.99324256	0.99252737

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

This finding is broadly consistent with recent studies in developing economies, which document that moderate levels of economic density can contribute to lower emissions through efficiency improvements. For example, studies using regional data in China find that urban density is associated with reduced carbon intensity due to better infrastructure utilization and technological diffusion (Yu et al., 2022). However, the relatively modest effect observed in Indonesia suggests that structural factors, such as continued reliance on fossil fuels and limited technological upgrading, may constrain the extent to which agglomeration translates into environmental benefits. This contrasts with more advanced urban systems, where stronger institutional capacity and cleaner energy transitions tend to amplify the environmental advantages of spatial concentration (F. Wang et al., 2020).

Moreover, the estimation results with a quadratic specification of employment density ($agglo^2$) reveal a non-linear relationship between agglomeration and per capita carbon emissions. Employment density enters negatively and significantly, while its squared term is positive and significant, indicating a U-shaped pattern. At low to moderate densities, increased agglomeration is associated with lower per capita emissions, suggesting efficiency effects. However, beyond a certain density threshold, further agglomeration correlates with rising emissions (Shahbaz et al., 2013; Stern, 2017). Additionally, in quadratic environmental models, calculating the turning point is a standard procedure for identifying the explanatory variable level at which the marginal effect changes sign, allowing researchers to determine the threshold at which environmental improvements begin to reverse (Stern, 2004). The turning point is obtained by setting the first derivative of the estimated quadratic function equal to zero.

Formally, the turning point of a quadratic specification can be derived as follows:

$$\mathrm{TP} = -\frac{\beta_1}{2\beta_2} \tag{3}$$

where β_1 represents the coefficient of employment density, and β_2 represents the coefficient of its squared term. Applying this formulation to the estimated coefficients (converted back from the natural-log form) yields a turning point of approximately 120 workers per km², indicating the density level at which the marginal effect of agglomeration on emissions shifts from negative to positive. This suggests that, up to this threshold, the benefits of spatial concentration (such as shared infrastructure, shorter commuting distances, and more efficient use of production inputs) may help reduce per capita emissions. Once employment density exceeds this level, however, additional agglomeration tends to intensify emission pressures (Tatoğlu & Polat, 2021).

These findings suggest that agglomeration-related efficiency effects, such as shared infrastructure use and the consolidation of economic activity, operate primarily at the early stages of increasing employment density. However, at very high levels of agglomeration, such efficiency gains appear to be offset by intensified economic and energy pressures, including transport congestion, production expansion, and the continued dominance of energy-intensive sectors (X. Wang et al., 2022). Importantly, this nonlinear pattern should not be interpreted as causal evidence of an Environmental Kuznets Curve within the agglomeration context. Rather, it is more appropriately understood as an empirical relationship that reflects the dynamic balance between efficiency and scale effects, without implying the existence of a causal optimal turning point.

The identified U-shaped relationship further suggests that the environmental impact of agglomeration is highly dependent on the stage of economic density. At lower levels of agglomeration, efficiency effects dominate, as firms and households benefit from shared infrastructure, shorter commuting distances, and improved coordination of economic activities. However, as density increases beyond a certain threshold, scale effects begin to outweigh these efficiency gains. In highly concentrated areas, rising energy demand,

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transport congestion, and the expansion of energy-intensive activities may lead to increased emissions. This pattern is particularly relevant in the Indonesian context, where rapid urbanization is not always accompanied by proportional improvements in clean energy infrastructure or environmental regulation. Therefore, the impact of this cannot be assumed to be linear, uniform, or consistent across regions; it may even vary across economic sectors depending on energy intensity and the dominant technologies in each sector (Han et al., 2018). As a result, excessive agglomeration may exacerbate environmental pressure rather than alleviate it (Zhou et al., 2024).

Subsample estimations further reveal substantial regional heterogeneity in the agglomeration–emissions relationship, as presented in Table 4. The estimation results show that economic agglomeration is negatively associated with per capita carbon emissions in both Java and non-Java regions. In Java, the coefficient is –0.208 and statistically significant at the 10 percent level, indicating a relatively larger emission-reducing effect but with lower statistical precision. Outside Java, the coefficient is smaller (–0.095) yet significant at the 1 percent level, suggesting a more stable and statistically robust relationship. Although the magnitude varies across regions, the consistent negative sign indicates that higher employment density is associated with lower per capita emissions. This pattern is broadly consistent with the urban economics literature, which emphasizes that agglomeration economies, arising from mechanisms such as shared infrastructure, labor market matching, and knowledge spillovers, can enhance production efficiency and reduce energy intensity at moderate levels of spatial concentration (Duranton & Puga, 2004).

Table 4. The Results of Heterogeneity Analysis

	Java ln(emission)	Outside Java ln(emission)	City ln(emission)	District ln(emission)
ln(agglo)	-0.208* (0.118)	-0.0953*** (0.0346)	-0.161 (0.117)	-0.100*** (0.0344)
ln(gdpcap)	0.632*** (0.172)	0.649*** (0.0512)	1.006*** (0.142)	0.623*** (0.0517)
ln(manugdp)	0.115 (0.125)	-0.0223 (0.0282)	0.0205 (0.115)	0.0150 (0.0279)
ln(tertgdp)	0.356 (0.237)	0.498*** (0.0731)	0.420 (0.257)	0.545*** (0.0717)
ln(fdigdp)	0.00685 (0.00565)	-0.0120*** (0.00283)	-0.00469 (0.00527)	-0.0114*** (0.00287)
Constant	-4.403*** (1.645)	-7.211*** (0.439)	-5.100*** (1.724)	-7.483*** (0.427)
F-Statistic	4.92	58.35	8.87	53.09
R-Square (within)	0.0699	0.2007	0.1352	0.1805
rho	0.98675542	0.99309905	0.98945552	0.9912444

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

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The stronger statistical significance observed outside Java may reflect differences in the stage of urban and economic development across Indonesian regions. Java hosts the country's most mature metropolitan systems, characterized by highly complex industrial structures, extensive transportation networks, and dense economic interactions (Duranton & Puga, 2004). In such environments, the environmental impacts of agglomeration may be influenced by multiple competing forces, including congestion effects, industrial clustering, and spatial spillovers across neighboring jurisdictions (Duranton & Turner, 2011; Wang et al., 2020). These factors can introduce additional variability in emissions outcomes and reduce statistical precision. In contrast, many districts outside Java are still undergoing earlier stages of urbanization and structural transformation. In these contexts, incremental increases in employment density may more clearly reflect improvements in infrastructure utilization, production efficiency, and energy use, resulting in a more stable relationship between agglomeration and emissions (Henderson, 2003).

A similar pattern emerges when comparing cities and regencies. The agglomeration coefficient remains negative in both groups, implying that greater economic concentration tends to be associated with lower per capita emissions. In regencies, the estimated effect (–0.100) is statistically significant at the 1 percent level, whereas in cities, although the coefficient is larger in magnitude (–0.161), it is not statistically significant at conventional levels. This difference may be related to the structural heterogeneity of Indonesian cities, where variations in industrial composition, urban transport intensity, and population density can produce more complex emissions dynamics (Glaeser & Kahn, 2010; Wang et al., 2019). By contrast, regencies often exhibit lower baseline levels of agglomeration and relatively simpler economic structures, allowing the efficiency effects of spatial concentration to appear more consistently in empirical estimates (Henderson, 2003; Yu et al., 2022).

These findings in heterogeneity analysis are also consistent with the nonlinear agglomeration pattern identified in the baseline specification, suggesting that the environmental benefits of spatial concentration may diminish as urban density approaches higher levels. This result suggests that the environmental efficiency effects of agglomeration are more consistently observed in regions that are still experiencing relatively early stages of urban concentration. In such contexts, increasing employment density may improve infrastructure utilization, shorten commuting distances, and facilitate more efficient allocation of labor and capital. However, as agglomeration intensifies in highly urbanized environments, congestion externalities, expanded production scale, and rising energy demand may partially offset these efficiency gains. Similar heterogeneous patterns have been documented in recent empirical studies. For example, a city-level analysis of Chinese urban systems shows that the environmental effects of population agglomeration vary substantially across regions depending on industrial structure and technological capability, with denser cities often exhibiting lower carbon intensity due to improved industrial efficiency and technological upgrades (Yan & Huang, 2022). Likewise, research on urban agglomeration reforms in the Yangtze River Delta finds that carbon emission responses differ significantly between central and peripheral cities, highlighting the importance of

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spatial heterogeneity in understanding the environmental consequences of agglomeration (Jin & Chen, 2022). Additional evidence from spatial analyses of Chinese cities further indicates that drivers of carbon emissions exhibit strong regional variation associated with differences in economic structure, infrastructure development, and technological capacity (Guo & Yu, 2024). Taken together, these studies reinforce the interpretation that the environmental impacts of agglomeration are inherently context-dependent and may vary across regions with different stages of urbanization and economic development.

CONCLUSION

This study examines whether economic agglomeration promotes environmental efficiency or intensifies carbon emissions at the district level in Indonesia. The empirical results show that economic agglomeration, measured by employment density, is generally associated with lower per capita carbon emissions, indicating efficiency effects of spatial concentration. However, the nonlinear specification reveals that this relationship is not monotonic. At relatively low to moderate levels of agglomeration, increasing employment density reduces emissions, but beyond a certain threshold, further concentration increases emissions. These findings suggest that the environmental impact of agglomeration depends critically on the balance between efficiency gains and scale effects, and therefore does not inherently guarantee environmental improvement across all levels of economic density.

The results also indicate that the environmental effects of agglomeration vary across regions and administrative structures. The emission-reducing effect is more consistently observed in non-Java regions and in regencies, where economic concentration is still at an earlier stage. In contrast, in more developed and densely populated areas, the environmental benefits of agglomeration appear to weaken, likely due to increasing congestion, higher energy demand, and structural dependence on energy-intensive activities. These findings imply that policy strategies should adopt a differentiated and place-based approach. In regions with relatively low to moderate levels of agglomeration, policies should focus on strengthening regional growth centers, improving infrastructure connectivity, and facilitating the adoption of energy-efficient technologies to maximize efficiency gains. Meanwhile, in highly urbanized areas, policy priorities should shift toward mitigating congestion, promoting low-carbon transport systems, accelerating the transition to cleaner energy sources, and encouraging industrial upgrading toward less energy-intensive sectors. Such differentiated strategies are essential to ensure that economic agglomeration supports sustainable, low-carbon development rather than exacerbating environmental pressures.

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