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Spatial Interactions between Planned Settlements and Small Businesses: Evidence from the Jakarta Metropolitan Area, Indonesia

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Abstract: Rapid urban growth is reshaping cities and promoting economic development in low and middle-income countries throughout Southeast Asia, with the prevalence of Micro-, Small-, and Medium-sized Enterprises (MSME) emerging as a crucial factor. This study explores the complex relationship between MSMEs and planned settlements within the Jakarta Metropolitan Area (JMA), Indonesia. Utilizing official government data and extensive GIS sources analyzed using a Spatial Lag Model, the research assessed the spatial interactions between MSMEs and sixteen variables, revealing the statistical significance of eight of these variables. Notably, the study identified a negative correlation between the prevalence of planned settlements and the number of MSMEs, indicating that areas with a higher proportion of planned settlement land use tend to have fewer MSMEs. Emphasizing the importance of land use and built environment policies, the findings underscore MSMEs' preference for locations with a greater share of commercial land uses. Moreover, the research highlights the localized nature of MSMEs, suggesting a tendency to cluster in specific areas. As Indonesia and other Global South countries experience rapid urbanization and potential increases in planned settlements, the study underscores the need for policymakers to develop strategies that foster a synergistic relationship between planned settlement development and MSME growth to support sustainable urban development.

Keywords: MSMEs; planned settlements; spatial regressions; Jakarta Metropolitan Area

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1. Introduction

1.1. Background

Rapid growth is transforming urban landscapes and fostering socioeconomic development for residents in low and middle-income cities across Southeast Asia. A key driver in this context is the prevalence of Micro-, Small-, and Medium-sized Enterprises (MSME), constituting a significant percentage of enterprises in countries like Vietnam (approximately 60%) and Indonesia (around 95%) [1].

The development of MSMEs is intricately linked to the nature of urban form, where specific urban characteristics may either facilitate or hinder their growth. Urban development trajectories in developing countries vary, with planned settlements [2], colloquially known as private cities [3], master-planned communities [4,5], and company towns [6], among others, emerging as a consistent feature. Conversely, informal and unplanned development has traditionally shaped existing urban morphologies [7]. While their definitions may vary, the nature of planned settlements, particularly, can be understood from their morphological features and procedural perspectives associated with their development [2,3,8,9], and potentially from the way they impact MSMEs.

The ubiquity of MSMEs, particularly in developing countries [10,11], positions them as significant catalysts and beneficiaries of urbanization. This dynamic interaction extends to the juxtaposition of planned and unplanned settlement strategies. Planned settlements

maintain physical and spatial features that exhibit clear boundaries emanating from deliberate plans from their inception [3]. This deliberate planning typically entails, although not always, that these settlements manage to ensure the provision of basic physical services more so than informal or unplanned settlements [12]. In contrast, unplanned settlements emphasize "actor-centered analyses" [2] and highlight the agency of non-government entities [3] as an alternative to formal control of the state [8]. Unplanned settlements thus tend to develop incrementally and exhibit "unauthorized and self-organized [neighborhood] production" [13].

The Interrelationship between MSMEs and the nature of settlements, thus, motivates this study's research questions. That is, how do planned settlements interact spatially with MSMEs? Does the prevalence of planned settlements lead to a lower number of MSMEs in the area—or vice versa? If so, to what extent?

To address these questions, the study focuses on the Jakarta Metropolitan Area (JMA), encompassing the region's nine urban districts, including five in the Jakarta province and four in surrounding areas (see Figure 1). The JMA is a compelling case for investigation due to, at least, the following reasons. Firstly, it maintains a large population of around 30 million people, with approximately 5.3 million households in the study area (Figure 1). Secondly, rapid urban expansion in the region has produced a substantial number of planned settlements of a range of sizes [3,14], facilitated by large-scale and smaller private developers [15]. Thirdly, the JMA is consistently ranked first in the country in terms of housing acquisition from private developers [16] and is expected to grow in the coming years [14,17]. Historical assessments of the JMA's land use dynamics further support these patterns [18]. The case study, thus, offers valuable insights applicable to other metropolitan regions globally, where planned settlements are prevalent.

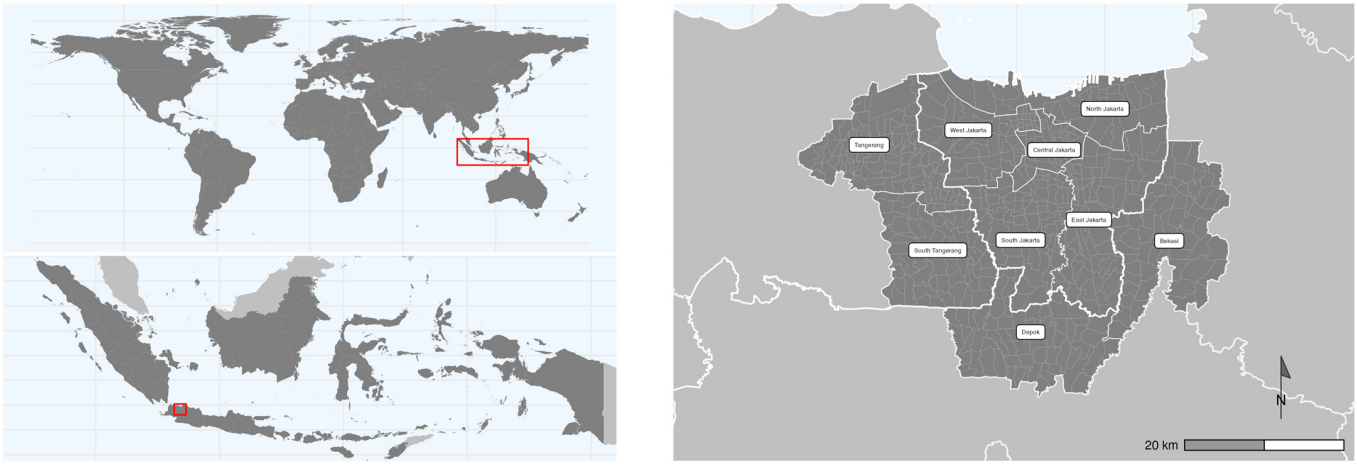


Figure 1. The Jakarta Metropolitan Area (JMA) case, as adopted in this study, is composed of nine urban districts that include five districts in the Jakarta province and four districts that surround it as shown. Insets: Red boxes denote Indonesia in the global context (upper left) and JMA within Indonesia (lower left) (Source: Authors' analyses).

To understand the interrelated patterns of MSMEs and planned settlements, we employed an innovative approach to analyzing their spatial distribution using statistical methods with official government and big open GIS data sources. The analyses compared three categories of MSMEs to 16 independent, literature-driven variables representing four urban domains: land use, built environment, and economic and demographic characteristics. Prior to the statistical analysis, we conducted a literature review to inform our approach and the selection of relevant variables.

1.2. Literature Review

To incorporate the aforesaid indicators, we drew on literature related to MSMEs, linking it to the established theory on firms' location choice, dating back to classic studies from the early 1900s [19,20]. Firms' location choice theory suggests that businesses make deliberate decisions in determining their placement due to, in large part, profit-maximization reasons [21], as they simultaneously consider *range* and *threshold* [19,22]. Range refers to customers' willingness to travel, while threshold indicates the minimum number of patrons required to sustain a business [19,21–23]. Recent empirical studies have emphasized the importance of proximity to markets or populations served and the role of agglomeration effects in shaping businesses' location decisions [23–25].

Even though there is an established body of literature on business location decisions, as noted earlier, there is a notable scarcity of studies specifically examining the spatial determinants of small businesses or MSMEs. Furthermore, a significant proportion of the existing studies on business location decisions disproportionately focus on the Global North. Given that MSMEs make up nearly 90% of the world's enterprises and contribute to nearly 60% of the world's GDP [26], the need to empirically assess MSMEs' spatial pattern and its drivers, particularly in under-researched regions, has never been greater.

Of the few studies on MSMEs' spatial pattern and their drivers [24,25], they all adopted empirical models and their results largely follow and mirror the findings of firms' location choice theory. For example, a 2020 study in Poland revealed that MSMEs tend to concentrate in areas with a high degree of development, as measured using the percentage of built areas [25]. The study suggested that proximity to nearby patrons, or *range* [19], influences MSMEs' location decisions. Similarly, a study in the Philippines found that access to nearby labor markets serves as an important contributor to MSMEs' location choice [24]. Finally, a combined observational and field experiment study on MSMEs in the agriculture sector based in India also showed how spatial factors drive MSMEs spatial distribution [27].

These existing studies tend to adopt spatial units that are either coarse, e.g., city or regional level [24,28] or only focus on a single community [27]. Coarse-level spatial units may mask the variability in MSME spatial patterns. Fine-scale studies have shown that small businesses, akin to MSMEs, commonly cater to local, neighborhood-level markets, and therefore, spatial clustering tends to operate at a neighborhood level, including at certain urban nodes such as plazas and street corners [23,29]. Given these drivers, it is imperative that studies on MSMEs are conducted at such a fine-scale geographic resolution.

Another key gap in the literature is the absence of studies specifically examining spatial interactions between MSMEs and planned, formal settlements. The proliferation of such settlements in the Global South [3], including the JMA [16], highlights an important gap in both MSME and planned settlement literature.

Collectively, the literature review underscores the lack of research on MSME spatial patterns and their drivers, despite the established literature on firms' location choice. This study addresses this gap, representing one of the initial research efforts to specifically investigate MSME spatial patterns and their interaction with planned settlements while taking into account a suite of mediating, literature-driven variables within the four domains: Land use, Built environment, Economic, and Demographic, as outlined in the conceptual framework (Figure 2). The following section will further elaborate on the data and methods used to operationalize the conceptual framework.

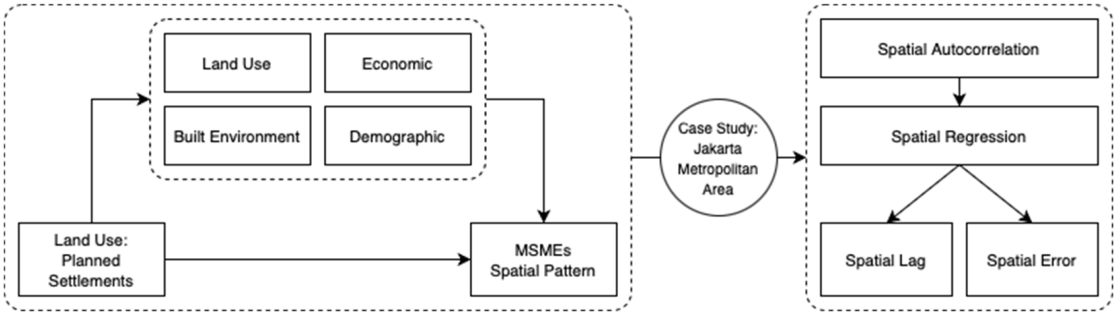


Figure 2. Conceptual framework (Source: Authors).

2. Data and Methods

In this section, we offer detailed information on the data and methods employed to address the research objective of unraveling the spatial interaction between planned settlements and small businesses, following the conceptual framework (Figure 2). To accomplish this, we acquire and link spatially embedded, highly granular data from multiple sources and apply a suite of statistical techniques, namely spatial autocorrelation tests and subsequently, spatial regressions, taking into consideration the nature of the data.

2.1. Data

The analysis was underpinned by spatially embedded data on enterprises from Indonesia's 2016 Economic Census, maintained by Statistics Indonesia/*Badan Pusat Statistik*. The data capture a comprehensive list of enterprises across the country including neighborhood (or *kelurahan*) locations, as well as quantity, size (micro, small, medium, and large) and type (i.e., food and beverages, retail). The neighborhood level at a village/*kelurahan* resolution represents the lowest administrative geographical units in Indonesia and enables much finer and more detailed observation than found in previous district-level studies [24,28]. The 2016 data may seem slightly outdated, given that it is collected every 10 years, and the next iteration is likely to occur in 2026. However, it provides details and spatial resolution suitable for the purpose of this study.

The urban districts portion of the JMA as our study area comprised of 538 neighborhoods. The spatial distribution of MSMEs is represented in Figure 3, showing the simulated dot density distribution (Figure 3, left) and total number of MSMEs (Figure 3, right) at a neighborhood level.

We assessed the relationship between planned settlements and MSMEs following three distinct categories of MSMEs: All MSMEs, F&B (Food and Beverage) MSMEs, and Retail Trade MSMEs. The F&B and retail trade represent the two largest enterprise sectors, out of the 18 enterprise sectors captured in the 2016 Economic Census data.

In assessing these associations, we account for 16 literature-driven variables, grouped into four domains: Land use, Built environment, Economic, and Demographic. The first domain, Land use, is hypothesized as influencing MSMEs' spatial pattern following findings derived from the firms' location choice literature [23,30]. In this study, the land use domain was derived primarily from the 2016 land use data for the Jakarta Metropolitan Area, which was developed as part of the second iteration of the Jabodetabek Urban Transportation Policy Integration (JUTPI) [31]. The data capture 14 land use categories including planned settlements as the main indicator of interest, as well as other typical land use classifications such as commercial, industrial, agriculture, *kampong*, and transportation infrastructure, among others. The spatial distribution of planned settlements, as the key variables of interest in this study, is depicted in Figure 4.

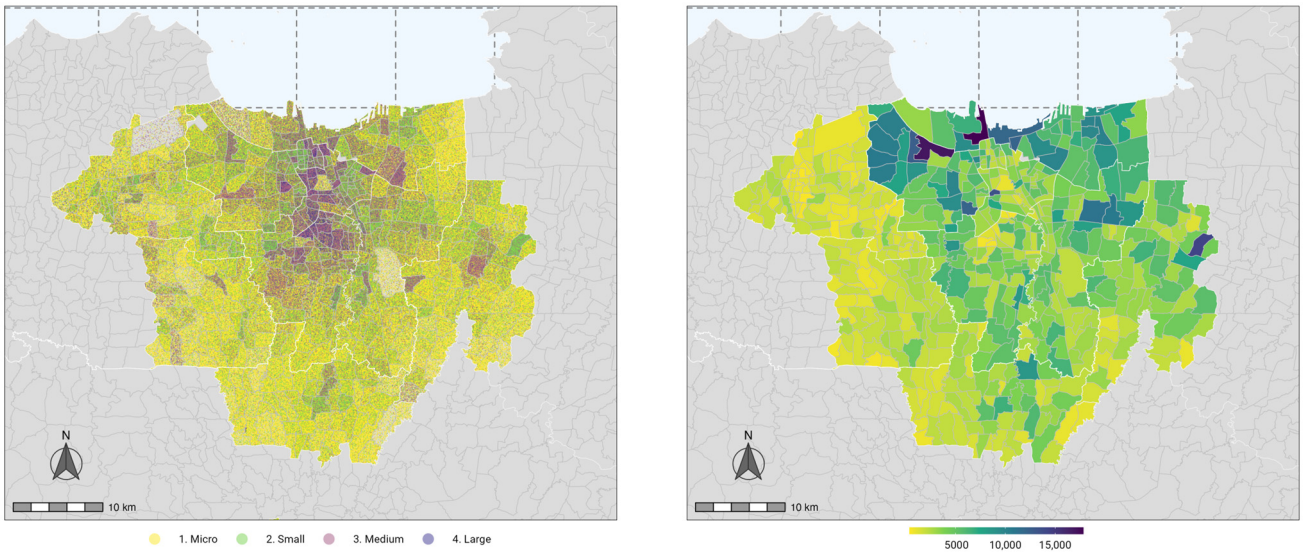


Figure 3. Dot density map of MSMEs spatial pattern (left) and aggregate number of MSMEs (right), both populated at a neighborhood level. (Source: Author's analyses using 2016 Economic Census data).

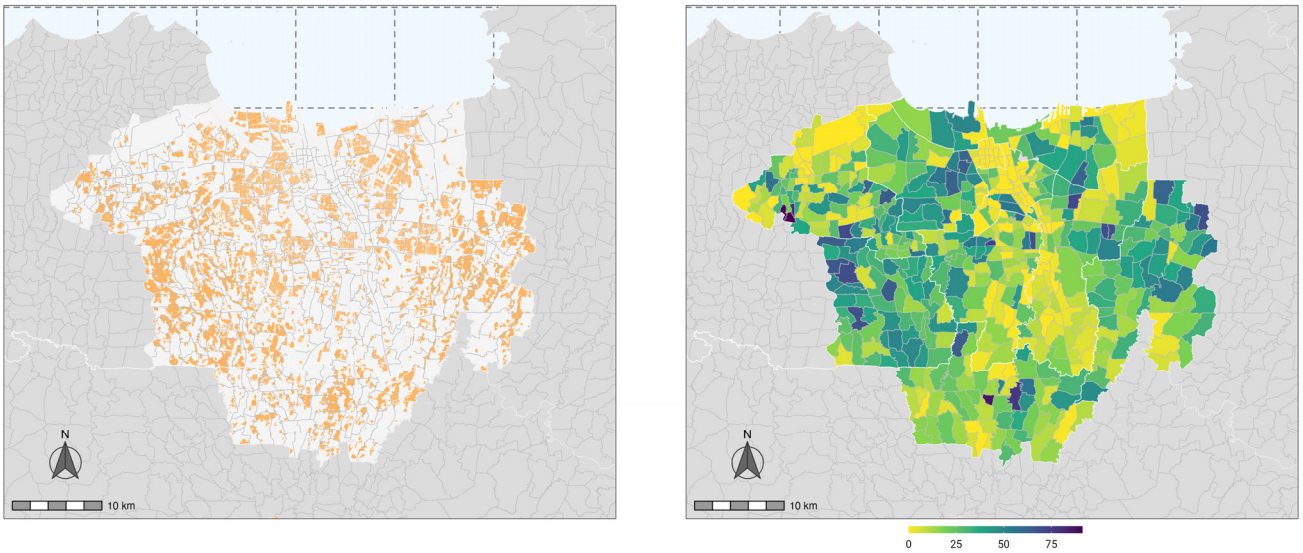


Figure 4. Distribution of planned settlements (left) and percentage of planned settlements from total land use area (right) at a neighborhood level. (Source: Author's analyses using land use data for the JMA).

The next domain, Built Environment, describes various aspects of urban morphology that have been found to influence the spatial patterns of enterprises [23,25,30,32]. In this study, this domain includes four variables: household density, land use entropy, street node density, and Connected Node Ratio (CNR). Household density was derived from the Village Potentials/*Potensi Desa* (PODES) data. Land use entropy measures the degree of land use mixing based on the measure calculated as follows [33,34]:

$$Land\ Use\ Entropy_j = -\frac{\sum_i \left[(P_{ij})\ln(P_{ij})\right]}{\ln(I)} \quad (1)$$

where P_{ij} is the proportion of land use i from the total land use area in the neighborhood j; I refers to the number of land use categories incorporated in the computation. An entropy measure ranges from 0 to 1 where 0 indicates that the neighborhood is occupied with only

one land use category and 1 represents an equal share of each land use category in the neighborhood.

Street node density and CNR variables were used to unravel the relationship between street network configuration and the prevalence of MSMEs. These measures were derived from OpenStreetMap (OSM) and retrieved using a Python-based OSMNx package [35]. Street node density is simply a measure of the total number of street nodes, including intersections and Cul-de-Sacs, divided by the neighborhood area, as applied in multiple studies [36,37]. CNR captures the ratio between all street intersections divided by the sum of the street intersections plus Cul-de-Sacs. Larger CNR values (maximum = 1.0) indicate higher street connectivity and less dead ends [36,37].

Drawing from previous studies aimed at disentangling the association between economic factors and enterprises' spatial pattern [23,30], for the Economic domain three variables were derived: number of traditional markets, number of Traditional markets (30-min), and number of large enterprise employees. The 2016 Economic Census provides the number of employees working at large enterprises. Village-level number of traditional markets was derived from the PODES data. While, the cumulative accessibility to traditional markets within a 30-min time band is computed following methods derived from Palacios and El-Geneidy [38], which follow earlier works by Hansen [39] and Levinson and King [40], as shown as follows:

$$C_i = \sum_j A_j f(C_{ij}) \tag{2}$$

where C_i represents cumulative accessibility from geographic boundary (e.g., neighborhood, census tract) i; A_j accounts for the number of amenities (A) at destination j; C_{ij} represents the cost incurred to travel from i to j, typically quantified as travel time (e.g., minutes, hours); and $f(C_{ij})$ is an impedance function. This impedance function is specified by the following equation where the value would either be 1 or 0 depending on a threshold travel time t [38,41]:

$$f(C_{ij}) = 1 \text{ if } C_{ij} \leq t, \text{ else } f(C_{ij}) = 0 \tag{3}$$

The r5r package [41] based on the R programming language [42] in RStudio [43], was used to compute cumulative accessibility (C_i) derived from travel time matrices between neighborhoods in the JMA. The resultant matrices were used to compute cumulative numbers of traditional markets, or other indicators, for that matter, from each neighborhood's centroid that could be reached given a particular time threshold.

Following studies that posit the relative importance of demographic factors in shaping the spatial pattern of enterprises [30], the final domain, Demographic, was composed of two variables: households in poverty (%) and the Gini index. These variables were derived from the 2015 SMERU Poverty and Livelihood Map of Indonesia [44].

2.2. Statistical Analysis

For the statistical analyses, we first calculated the descriptive statistics for all variables. Next, and as outlined in the conceptual framework (Figure 2), we assessed the spatial autocorrelation of the outcome variables, encompassing both the total number of MSMEs and sector-specific MSMEs. In the final step, we performed spatial regressions between the MSME combinations and the 16 explanatory variables. Our approach to empirically estimating the spatial interaction between planned settlements and MSMEs adopts the analytical methods developed by Anselin [45], and later on by Burkey [46].

The spatial autocorrelation analyses estimated whether MSMEs were distributed randomly across neighborhoods or whether there is an underlying spatial pattern that exhibit certain degrees of clustering [45–48]. Such spatial clustering was assessed through a Moran's I test, as shown in the equation below, adopted from related studies [47–49]:

$$Moran's\ I = \frac{n\sum_i\sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{(\sum_i\sum_j w_{ij})\sum_i (x_i - \overline{x})^2} \tag{4}$$

where x_i and x_j refer to the spatial settings of i and j, correspondingly; w_{ij} represents spatially defined weight given distinct geographic boundaries, which in this case is the 538 neighborhoods in the study area; and n is the unit of the said geographic boundaries. Values derived from Moran's I test range from -1 to 1, with zero indicating a lack of spatial autocorrelation, positive values indicating spatial clustering, and negative value indicating the data are dispersed. Moran's I was tested using the 'spdep' package [50] in R. In addition, statistically significant spatial clusters were mapped with Moran's I cluster analyses using 'rgeoda' package [51].

Aside from offering valuable insights into spatial patterns, conducting tests for spatial clustering is critical for the next step. This is because conventional linear models, such as Ordinary Least Squares (OLS), are unsuitable when spatial clustering exists, and their use can introduce biases. In addition, because our assessment revealed that the dependent variables do not follow a Poisson distribution, we adopted methodologies that revolve around spatial regression analyses [45,46,52].

To alleviate such issues and as an alternative to OLS, the Spatial Lag Model (SLM) and Spatial Error Model (SEM) [53] were used. The SLM is expressed as follows:

$$y = \rho W y + X\beta + \varepsilon \tag{5}$$

where y represents the dependent variable, ρ captures the spatial autocorrelation parameter for the spatial weight matrix of Wy, in which a statistically significant value of ρ indicates the presence of spatial dependence; X refers to the matrix of explanatory variables and β is the regression coefficients; and ε is a random error term. The SLM posits that the dependent variable is correlated with and influenced by neighboring locations [54,55].

SEM, in contrast, posits that the spatial autocorrelation is explained by the interaction between error terms across neighbors [54,55]. The SEM is expressed as follows:

$$y = X\beta + \gamma W\varepsilon + \delta \tag{6}$$

where γ is the spatial autocorrelation parameter, in which a statistically significant value suggests that certain factors are responsible for the presence of spatial autocorrelation between error terms; $W\varepsilon$ is the spatial weight matrix; and δ refers to the error terms.

In the spatial regressions, we applied a log transformation to the outcome variables, encompassing both all and sector-specific MSMEs, given their non-normally distributed nature. Another consideration stemming from this transformation is the aim of facilitating a more intuitive interpretation of the results.

The choice of which spatial regression approach to use was based on an assessment of parsimony conducted with Lagrange Multiplier (LM) tests [52] with the 'spdep' package in R [50]. The tests yield Lagrange multiplier and p-values derived using "LM" and "robust LM" tests to compare between SEM and SLM. The preferred model is the one with higher LM values and greater statistical significance.

We also conducted two further tests contingent on whether SLM was the recommended model. The first test assesses the indirect and direct effects of planned settlements on MSMEs' spatial patterns. The final test performed was a comparison between OLS, SEM, and SLM models to evaluate the sensitivity of applying models with and without spatial autocorrelation.

3. Results

3.1. Descriptive Statistics

The descriptive statistics of the outcome and independent variables describe the overall patterns of the spatial data for the 538 neighborhoods incorporated in this study (Table 1). For the outcome of variables of the number of all MSMEs, on average, neighborhoods have nearly 3439 MSMEs (Table 1). The variability of MSMEs is substantial with a minimum value of approximately 400 MSMEs (i.e., Nambojaya, Tangerang) and a maximum value

of nearly 18,000 MSMEs (i.e., Penjaringan, North Jakarta). Substantial variability in the distribution of MSMEs is also observed within F&B and retail trade.

Table 1. Descriptive statistics of the outcome variable and the 16 Independent variables for the 538 neighborhoods.

	N	Mean	SD	Min	Max
Outcome variables					
MSMEs	538	3439.4	2477.2	392	17,817
MSMEs, food and beverages	538	921.3	722.3	97	6335
MSMEs, retail trade	538	1327.2	1105.4	101	11,767
Independent variables					
Neighborhood area (km^2)	538	2.6	1.9	0.3	17.6
Land use					
Planned settl. (%)	538	22.0	19.1	0.0	91.3
Industrial (%)	538	6.1	13.3	0.0	86.8
Commercial (%)	538	9.4	12.5	0.0	87.4
Built environment					
Household density (per km^2)	538	5049.3	4670.5	120.9	54,053.1
Land use entropy	538	0.5	0.1	0.1	0.8
Street nodes density (per km^2)	538	312.7	341.3	20.6	6806.0
Connected Node Ratio	538	0.8	0.1	0.6	1.0
Economic					
Number of traditional markets	538	2.1	2.7	0	36
Number of accessible traditional markets (30-min)	538	693.1	213.6	100	1041
Large ent. Employees	538	3087.2	5927.5	0	50,037
Demographic					
Households in poverty (%)	538	3.0	2.2	0.02	13.6
Gini index	538	0.3	0.03	0.2	0.5

In terms of the key independent variable of interest, Table 1 shows that, on average, 22.0% of land in the 538 neighborhoods is classified as planned settlements. Cibodasari, in Tangerang City, had the highest percentage of planned settlements at nearly 92%. The spatial distribution of planned settlement can be seen in Figure 4, which shows a substantial spatial variability that is also reflected by its standard deviation of 19.1% (Table 1). Similar variability was found in the distribution of other land use categories, namely industrial and commercial land uses (Table 1). The corresponding indicator of land use entropy had an average value of 0.5 and a standard deviation of 0.1, indicating that most neighborhoods exhibit a reasonable level of land use mixing.

Taken together, most indicators exhibit considerable variability stemming from, in some parts, their non-normal distribution. This observation underscores the likelihood of spatial clustering. The presence of clustering is not too surprising given the spatially embedded nature of the indicators, as would be expected with any geographical phenomenon according to Tobler's first law of geography [56].

3.2. Tests for Spatial Autocorrelation

The Moran's I analysis indicates that spatial autocorrelation is present for all and sector-specific MSMEs (Table 2). More specifically, for all F&B sector MSMEs, the Moran's I value was 0.457 ($p < 0.01$) and 0.490 ($p < 0.01$), respectively, which indicates a moderately positive spatial autocorrelation. The retail trade MSMEs also had positive and significant spatial autocorrelation though to a lesser degree.

Table 2. Moran's I test for all and sector-specific MSMEs.

	Moran's I	*p*-Value	Significance
All MSMEs	0.457	0.000	***
F&B MSMEs	0.490	0.000	***
Retail trade MSMEs	0.305	0.000	***

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Figure 5 depicts the geographical locations of MSMEs' spatial clustering. The spatial clustering appears to be largely consistent across all sector-specific MSMEs. As shown in Figure 5, areas classified as 'high-high' indicate locations where MSMEs are most prevalent and are found in North Jakarta. In contrast, neighborhoods classified as 'low-low' are where MSMEs tend to be least prevalent and are found in the western part of the JMA.

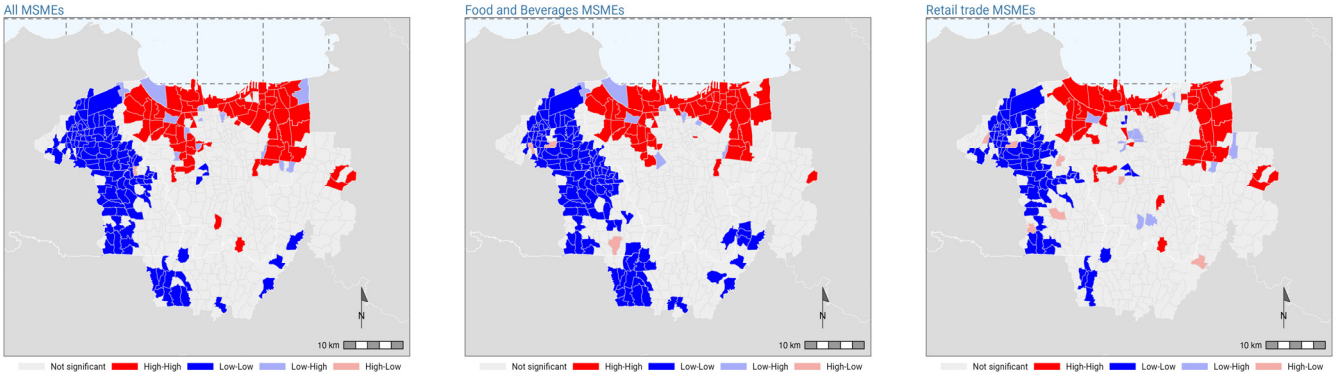


Figure 5. Spatial clustering of all MSMEs (left), F&B MSMEs (middle), and retail trade MSMEs (right) (Source: Author's analyses).

3.3. Spatial Regression

3.3.1. Choice of Spatial Regression Model

The outcome of the comparison between the two spatial regression models, SLM and SEM, using the Lagrange Multiplier (LM) is shown in Table 3. The Lagrange Multiplier test demonstrated that SLMs outperform SEMs for every model, and this difference is clear when evaluated through robust Lagrange Multipliers values. Given these results, the SLM was the chosen model, and subsequent analyses and observed insights were derived only from SLM models.

Table 3. Lagrange Multiplier (LM) tests for spatial dependence for all and sector-specific MSMEs.

		Lagrange Multiplier	*p*-Value	Sig.
All MSMEs	LM (SLM)	59.198	0.000	***
	LM (SEM)	35.715	0.000	***
	Robust LM (SLM)	25.969	0.000	***
	Robust LM (SEM)	2.486	0.115	
Food and Beverages MSMEs	LM (SLM)	54.361	0.000	***
	LM (SEM)	35.398	0.000	***
	Robust LM (SLM)	21.994	0.000	***
	Robust LM (SEM)	3.029	0.081	*
Retail trade MSMEs	LM (SLM)	26.944	0.000	***
	LM (SEM)	13.189	0.000	***
	Robust LM (SLM)	13.755	0.000	***
	Robust LM (SEM)	0.000	0.992	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

3.3.2. SLM Assessment

The spatial interaction between planned settlements and All MSMEs, analyzed with SLM shows that 8 of the 16 variables and the constant were statistically significant, with the majority of variables statistically significant to $p < 0.01$ (Table 4), including the relative importance of planned settlements emerging as a key driver which reduced MSMEs. Specifically, the results indicate that a larger share of planned settlements correlates with a reduced likelihood of MSMEs locating in an area. To be more precise, the estimated coefficients reveal that for each additional one percentage unit increase in planned settlements, the number of MSMEs decreases by 0.3% for all MSMEs, 0.3% for the F&B, and 0.2% for the retail trade sector.

Table 4. SLM regression results predicting log transformed number of all and sector-specific MSMEs.

	All		**F&B**		**Ret. Trade**	
	Coef.	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Neighborhood area (log)	0.720 ***	(0.037)	0.661 ***	(0.037)	0.778 ***	(0.046)
Land use						
Planned settl. (%)	−0.003 ***	(0.001)	−0.003 **	(0.001)	−0.002 *	(0.001)
Industrial (%)	−0.003 *	(0.002)	−0.001	(0.002)	−0.0002	(0.002)
Commercial (%)	0.009 ***	(0.002)	0.007 ***	(0.002)	0.013 ***	(0.002)
Built environment						
Household density (log)	0.526 ***	(0.029)	0.549 ***	(0.031)	0.492 ***	(0.036)
Land use entropy	−0.150	(0.142)	−0.144	(0.148)	−0.153	(0.183)
Street nodes density (log)	−0.049	(0.034)	−0.121 ***	(0.036)	−0.026	(0.044)
Connected Node Ratio	1.219 ***	(0.248)	1.456 ***	(0.259)	1.082 ***	(0.316)
Economic						
Number of trad. markets	0.016 ***	(0.006)	0.011 *	(0.006)	0.021 **	(0.008)
Number of accessible trad. markets (30-min)	0.0003 ***	(0.0001)	0.0004 ***	(0.0001)	0.0001	(0.0001)
Large ent. employees	−0.00000	(0.0000)	0.0000	(0.0000)	−0.00001 **	(0.0000)
Demographic						
Households poverty (%)	−0.002	(0.007)	−0.005	(0.007)	−0.005	(0.009)
Gini index	−1.128	(0.695)	−1.148	(0.720)	−0.413	(0.892)
Constant	−3.069 ***	(0.502)	−4.062 ***	(0.524)	−4.279 ***	(0.645)
N	538		538		538	
Log Likelihood	−174.391		−194.218		−307.587	
Wald Test (df = 1)	56.440 ***		54.409 ***		28.999 ***	
LR Test (df = 1)	53.586 ***		50.474 ***		26.159 ***	
AIC	380.782		420.436		647.173	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Coef. refers to Coefficients while Std. Error stands for Standard Error.

In general, most variables exhibited similar patterns, in terms of direction or significance, regardless of whether the dependent variable was all or sector-specific MSMEs (Table 4). Furthermore, the explanatory variables patterns yield results that are largely expected and intuitive. For example, neighborhoods predominantly zoned for commercial and business land use tend to host a larger number of MSMEs compared to otherwise similar neighborhoods with fewer areas zoned for commercial and business use. Notably, the magnitude of this effect appears to be larger than the influence of planned settlements; that is, for every one percentage unit increase in the share of land classified as commercial and business, the share of MSMEs increases by 0.9% for all MSMEs, 0.7% for the F&B sector, and 1.3% for the retail trade sector. This finding reinforces the notion that land use policy plays a significant role in facilitating, or hindering, the growth of MSMEs.

It is evident from the results that the built environment plays a significant role in influencing the location choices of MSMEs (Table 4). The findings posit a positive association, with a substantial magnitude, between MSMEs and household density, suggesting that MSMEs tend to cater to local customers. Specifically, for every 1 percent increase in

household density, the number of MSMEs is likely to increase by 0.53% for all MSMEs, 0.55% for the F&B sector, and 0.49% for the retail trade sector.

In the context of the built environment measures, another noteworthy finding is the positive impact of street network connectivity. Urban villages (*kelurahan*) that maintain a more connected street configuration with fewer Cul-de-Sacs may have a higher number of MSMEs. It is also worth noting the insignificant influences of the degree of land use mixing and the density of road infrastructure. As shown in Table 4, land use entropy appears to have no significant influence on the location choice of MSMEs and, in fact, exhibits a negative correlation.

From an economic perspective, the presence of traditional markets, measured both in terms of the absolute number within the village and how many can be accessed within a 30-min threshold, is likely to attract MSMEs to locate in the area. The results suggest that an additional traditional market is associated with an increase in the number of MSMEs by 1.6% for all MSMEs, 1.1% for MSMEs in the F&B sector, and 2.1% for MSMEs in the retail trade sector, all else being equal.

The analysis based on SLM exclusively shows the direct effects of the coefficients (Table 4) and, therefore, the next analyses delved deeper into the results to shed light on both the direct, indirect, and total effects of planned settlements on MSMEs (Table 5 and Figure 6). The indirect effects of planned settlements on the propensity of MSMEs' location choices indicate that for every one percentage unit increase in planned settlements, the number of MSMEs in neighboring villages may decrease by 0.1% for both all and sector-specific MSMEs (i.e., F&B and retail trade sectors). This additional insight into indirect effects showed how planned settlements exert influences on MSMEs in adjacent and nearby villages.

Table 5. Direct and indirect effects of planned settlements for all and sector-specific MSMEs.

	All		F&B		Ret. Trade	
	Coef.	Std. Eror	Coef.	Std. Eror	Coef.	Std. Eror
Direct effect	−0.003 ***	(0.001)	−0.003 **	(0.001)	−0.002 *	(0.001)
Indirect effect	−0.001 ***	(0.000)	−0.001 **	(0.001)	−0.001 *	(0.000)
Total effect	−0.004 ***	(0.001)	−0.004 **	(0.002)	−0.003 *	(0.002)

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Coef. refers to Coefficients while Std. Error stands for Standard Error. These regression results as shown above exclude other explanatory and control variables for brevity.

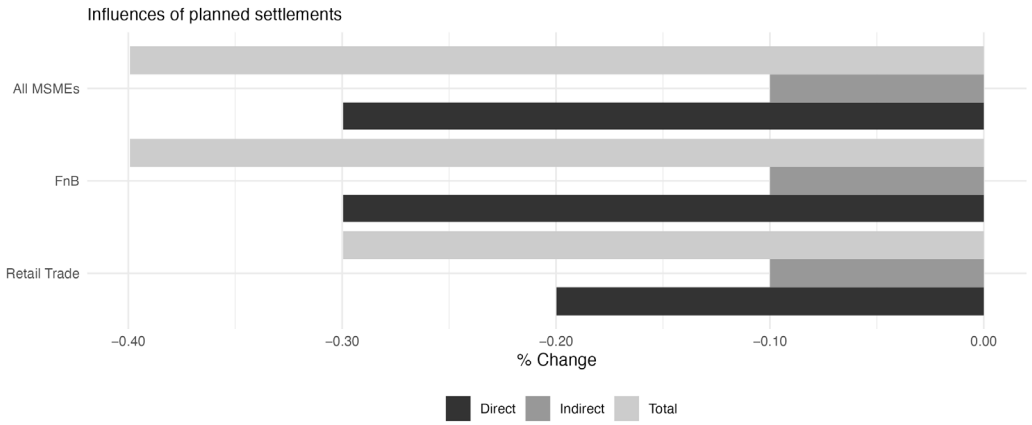


Figure 6. Direct, indirect, and total effects of planned settlements on all and sector-specific MSMEs. (Source: Author's analyses).

3.3.3. Sensitivity of OLS and SEM

Table 6 compares the sensitivity of the results from the SLM to the OLS and SEM. It is evident from the primary independent variable of interest, i.e., the share of planned settlements, and the other variables exhibit similar direction and statistically significant

findings across these different models, with the magnitude of the effects remaining notably similar. For the OLS model, the results suggest that for each one percent increase in the area zoned as planned settlement, there is a potential decrease of 0.3% in the number of MSMEs. Likewise, in the SEM model, this reduction is observed to be slightly larger, with a magnitude of 0.4%. This consistency across findings derived from SLM, OLS, and SEM reinforces the robustness of the primary independent variable's (i.e., share of planned settlements) influence on the number of MSMEs.

Table 6. OLS, SEM, and SLM regression results predicting log transformed number of all MSMEs.

	OLS		**SEM**		**SLM** †	
	Coef.	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Neighborhood area (log)	0.870 ***	(0.032)	0.814 ***	(0.037)	0.720 ***	(0.037)
Land use						
Planned settl. (%)	−0.003 ***	(0.001)	−0.004 ***	(0.001)	−0.003 ***	(0.001)
Industrial (%)	−0.003 **	(0.002)	−0.003 **	(0.002)	−0.003 *	(0.002)
Commercial (%)	0.011 ***	(0.002)	0.010 ***	(0.002)	0.009 ***	(0.002)
Built environment						
Household density (log)	0.641 ***	(0.027)	0.581 ***	(0.031)	0.526 ***	(0.029)
Land use entropy	−0.155	(0.153)	−0.118	(0.152)	−0.150	(0.142)
Street nodes density (log)	−0.079 **	(0.037)	−0.085 **	(0.040)	−0.049	(0.034)
Connected Node Ratio	1.688 ***	(0.259)	1.435 ***	(0.277)	1.219 ***	(0.248)
Economic						
Number of trad. markets	0.010	(0.006)	0.015 **	(0.006)	0.016 ***	(0.006)
Number of accessible trad. markets (30-min)	0.0004 ***	(0.0001)	0.0004 ***	(0.0001)	0.0003 ***	(0.0001)
Large ent. employees	−0.00000	(0.0000)	−0.00000	(0.0000)	−0.00000	(0.0000)
Demographic						
Households poverty (%)	0.002	(0.008)	−0.005	(0.008)	−0.002	(0.007)
Gini index	−1.596 **	(0.745)	−0.870	(0.760)	−1.128	(0.695)
Constant	−2.854 ***	(0.539)	−2.413 ***	(0.604)	−3.069 ***	(0.502)
N	538		538		538	
R-squared	0.718					
Adj. R-squared	0.711					
Log Likelihood			−182.289		−174.391	
Wald Test (df = 1)			56.633 ***		56.440 ***	
LR Test (df = 1)			37.790 ***		53.586 ***	
AIC			396.579		380.782	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Coef. refers to Coefficients while Std. Error stands for Standard Error. † Chosen model (shown in Table 4).

4. Discussion

4.1. Overall Patterns of MSMEs and Planned Settlements

In terms of overall patterns, firstly, the descriptive statistics for the 538 neighborhoods showed that significant variation exists, with total MSMEs ranging from approximately 400 to 18,000, and significant hotspot clusters were identified in the north and cold spots in the west of the study area. The percentage of planned settlements averages 22.0% across the 538 neighborhoods, with Cibodasari in Tangerang City having the highest percentage at nearly 92%.

The SLM assessment of the spatial interaction between MSMEs and the 16 variables representing a range of neighborhood-level urban characteristics, revealed that 8 of the variables, including the prevalence of planned settlements, were statistically significant. Planned settlements emerged as a key factor, inversely related to the total number of MSMEs, with each one percentage unit increase leading to a decrease of 0.3% in all MSMEs, 0.3% in the F&B sector, and 0.2% in the retail trade sector (Table 4). Further indirect effects analyses (Table 5 and Figure 6) derived from the SLM provide indicative evidence that a higher prevalence of planned settlements is associated with a decreased likelihood of

MSMEs choosing to establish themselves in a given area. It is also worth noting that commercial and business land use zoning exhibited a larger impact on MSME distribution than planned settlements, increasing their prevalence by 0.9% for all MSMEs, 0.7% for the F&B sector, and 1.3% for the retail trade sector per one percent of unit increase. In sum, these results demonstrate the relative importance of land use and, therefore, spatial planning and policy on the distribution of small businesses, echoing findings from previous studies [11,25].

Household density, street network connectivity, and the presence of traditional markets also significantly influenced MSME location choices. The tested independent variables affirm firm location choice theory [19,22], indicating that businesses prioritize proximity or accessibility to their target markets or populations. This is evident as higher numbers of MSMEs were observed in commercial areas, areas with higher population density, and locations closer to or with significant traditional market presence [23–25].

Planned settlements, arguably have nuanced influences, both positive and negative, on MSMEs. On the positive side, well-planned infrastructure, zoning regulations, and strategic locations could enhance efficiency, market access, and collaboration opportunities, as exemplified by the positive impact of the variable CNR (Table 4). However, challenges may arise in the form of high land costs, which can be a barrier for MSMEs, particularly for startups and small businesses with limited financial resources and where access to bank loans and financing remains a challenge [57]. Not to mention the emerging gentrification phenomenon, as identified in Indonesian-based studies [58,59], which may displace MSMEs as property values rise, making it difficult for smaller businesses to afford space.

Another significant obstacle to MSME development in planned settlements is that, as their name implies, they often adopt and adhere to zoning regulations designed strictly to provide residential land uses, following what is typically labeled as the Euclidean zoning approach [60]. These regulations, in turn, act as a barrier that limits the propensity of MSMEs to locate in the area and may also reduce residents' inclination to establish small, home-based businesses. This situation likely stands in contrast to informal settlements that grew organically [3,7], where land use regulations were relatively loosely defined and enforced, hence, facilitating a low barrier of entry for establishing small businesses. The proximity of businesses to customers and the ability to establish market linkages are influenced by the structure of these urban areas.

4.2. Implications

The findings outlined above hold substantial implications for policymakers, particularly in the context of the ongoing expansion of planned settlements not only in the JMA but also in other cities across Indonesia—and globally, for that matter, that have also experienced the proliferation of planned settlements, e.g., Mexico City, Mexico [61]; Accra, Ghana [9]; to name a few. Our study, thus, also extends the growing literature on small businesses, and informal street vending to be more specific, that underscores the relative influence of built environment attributes on the spatial pattern of street vendors [10,25,62].

In light of this, it is crucial for policymakers and relevant stakeholders to implement measures and planning policies that encourage a mutually beneficial relationship between planned settlements and MSMEs, especially considering the observed patterns in other parts of the world where land use and spatial planning could serve as a tool for the systematic exclusion of small businesses [63,64].

As these settlements continue to proliferate, there is an opportunity to design policies that foster synergy between urban planning initiatives and the growth of small enterprises, which in turn provide important economic benefits to local and surrounding communities. This may involve integrating supportive infrastructure, revisiting zoning regulations, or *Rencana Detail Tata Ruang* (RDTR) in the Indonesian contexts [65], to accommodate MSMEs-driven commercial activities, and strategically position planned settlements to enhance accessibility for MSMEs. Indeed, given that the production of planned settlements is primarily driven by private developers [3], it is also imperative to bridge the dialogue

between public and private stakeholders. By adopting such measures, policymakers and relevant stakeholders can contribute to the creation of more inclusive and economically vibrant urban environments that simultaneously accommodate planned settlements and provide conducive conditions for the establishment and flourishing of small businesses.

5. Conclusions

This study marks the first empirical assessment of the spatial interactions between planned settlements and the spatial distribution of MSMEs. Utilizing the JMA as a case study, a comprehensive spatial analysis was conducted capturing diverse factors encompassing land use, the built environment, socioeconomic, and demographic elements.

This study contributes to the existing MSME literature in three significant ways. It establishes a negative correlation between the prevalence of planned settlements and MSMEs, suggesting that areas with a larger share of planned settlement land use may have fewer MSMEs. The findings also highlight MSMEs' preference for locations with a higher proportion of commercial land uses, emphasizing the crucial role of land use and built environment policies. Lastly, the study underscores the localized nature of MSMEs, emphasizing their tendency to cluster in specific areas.

While the current study provides valuable insights on a topic of critical importance, and the sensitivity analyses confirmed the consistency of the results regardless of the model applied, future research could benefit from refinements on several fronts. Firstly, the dynamic nature of planned settlements and urbanization in rapidly growing cities like Jakarta highlights the need to explore the temporal stability of interactions between planned settlements and MSMEs. Investigating whether older planned settlements evolved to accommodate a higher proportion of MSMEs than in the past emerges as a crucial avenue for research in this context.

Secondly, considering that the next iteration of the Economic Census data may likely occur in 2026, a subsequent analyses would be of great interest. Doing so may shed further light on whether and how the interaction between planned settlements and MSMEs evolves over time, particularly against the backdrop of the COVID-19 pandemic.

Thirdly, expanding the analyses to encompass additional cities and regions, either within Indonesia or similar Global South countries, would enhance the external validity of the findings. Indonesia's secondary cities have also witnessed the proliferation of planned settlements [3], making it even more pertinent to extend this study to other regions within the country.

Fourthly, an important avenue for further analysis is evaluating the implications for residents of planned settlements who may not have the same access to MSMEs as their counterparts in unplanned, informal settlements. Questions regarding increased travel, potentially leading to higher pollution emissions, raise concerns about the sustainability of planned settlements compared to informal ones, presenting fertile ground for further research. For example, would these planned settlement residents need to travel more by automobile or motorcycle, potentially leading to increased pollution emissions? What does this mean for assessing the sustainability of planned settlements compared to informal ones?

Taken together, as Indonesia and other Global South countries undergo rapid urbanization, potentially leading to an increase in planned settlements, it becomes imperative for policymakers and relevant stakeholders to formulate policies that foster a synergistic relationship between planned settlement development and the growth of MSMEs.

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