STUDIES

The impact of urban characteristics on the spread of Covid-19 in 2020: The case of Java Island cities, Indonesia

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The world has been combating the Covid-19 global pandemic for almost a year, with cities being at the centre of the fight against the pandemic. However, variations in urban characteristics, population, economic size, and connectivity have led to different impacts of the pandemic's dispersion between cities. The pandemic has disrupted social and economic activities in the Java metropolitan area, which accounts for more than 60% of the national economy and boasts a population of more than 60 million people. Using spatial and econometric analysis on the Java metro area as a case study, this paper shows that large cities and core-metropolitan areas are more prone to the pandemic due to higher population density and commuter rate; these factors determine the number of positive cases. This study highlights the importance of spatial and economic activities in urban policies for the containment of the spread of Covid-19.

Keywords:
urban characteristics,
Covid-19,
mobility,
population density,
Java Island

Introduction

Covid-19 (hereafter, 'Covid' as well) caused a global pandemic due to its rapid infection rate and extensive dispersion. Since urban economies are driven by urbanisation and agglomeration, governments' attempts to reduce the spread of this pandemic with policies such as social distancing and urban lockdowns has led to the restriction and global disruption of economic and social activities.

In Indonesia, Covid-19 caused significant health problems with a growing number of patients and costs for health workers, as well as the occurrence of economic challenges with an increased number of the unemployed due to a decline in business activities. Furthermore, considering its wide area and population, the pandemic's impact varied across the country. Over 151 million people (more than 56% of the Indonesian population) reside on Java Island (BPS 2021); consequently, most of the impact of the pandemic has been on cities on the island. This study specifically focuses on the largest metropolitan area in Indonesia, i.e., the Jakarta Metropolitan Area (JMA). JMA has a population of more than 15 million and produces 30% of the national economic output. Notably, decentralisation implemented in 2001 has resulted in the government delegating development functions to the districts, which led to a variety of urban policies during the pandemic, such as mobility restriction policies, social safety net regulations, and economic-health expenditures. Therefore, as the metropolitan area continues to have crowded commutes and offices, these local policies determine the number of cases in the areas.

Currently, there are limited studies on the impact of urban characteristics on Covid-19 cases and how decentralisation plays a critical role in setting up those characteristics. Using spatial and econometric analysis at the city level, this study aims to examine the variation of urban characteristics which determine the number of Covid-19 cases in districts across Java Island. The island was specifically selected as a case study for two reasons. First, more than 56% of the population in the country lives on Java Island. Second, the island has the best transportation infrastructure with districts that are spatially connected, allowing us to capture the spread of Covid-19 on the island. Furthermore, the hypothesis states that large cities are vulnerable to a high infection rate due to large economic activities and high connectivity rates.

The structure of the study is as follows. Firstly it reviews literature on urban characteristics and how it may determine the spread of Covid-19. Secondly describes the study's data sources and analysis methods. Thirdly discusses the econometric models and spatial analysis results. Finally, I present the conclusions and policy implications.

Literature review

The following discussion explores the challenges and potential impact of the spread of Covid-19 due to urban characteristics and decentralisation.

Effects of urban characteristics on the spread of Covid-19 cases

Recent studies have shown the impact of urban lockdowns on well-being. One of these studying states in the USA and European countries also shows evidence of the negative effect of lockdown on general well-being due to persistent boredom and worrying (Brodeur et al. 2020). Despite this, there is still a strong significant correlation between mobility pattern and reduction of Covid-19 cases (Badr et al. 2020). Therefore, urban characteristics determine the spread of Covid-19 cases throughout cities across the globe. Pierantoni et al. (2020) suggest several conditions of urban areas that make them vulnerable to the pandemic, such as the size of the economy, persistent social gatherings, mobility, and economic dynamics. Another factor is population density which strongly influences the disease outbreak due to a higher and faster infection rate (Jabareen–Eizenberg 2020).

Another concern is the disparity of physical and social neighbourhoods. In terms of physical neighbourhood, variations in facilities and infrastructure determine how the epidemic spreads across neighbourhoods. Meanwhile, health facilities and shopping centres are more likely to be accessible in a rich neighbourhood. Wide-open spaces such as peripheral areas and mountains are associated with lower Covid-19 cases, suggesting the importance of open space and distancing. Consequently, this raises the importance of green and blue networks for sustainable mobility such as pedestrian and cycle paths that create more space to individualise running trails and widen paths (Honey-Rosés et al. 2020).

Furthermore, there is the concern that shopping centres make rich neighbourhoods more vulnerable because these closed-space malls allow for the easier spread of the virus between visitors. A recent study by Deaton (2021) suggests that the virus spreads easily in metropolitan areas, meaning poor neighbourhoods are suspected to be less vulnerable than rich ones. In this sense, urban form is inflexible, unresponsive, and dysfunctional in its role to serve the inclusive neighbourhood. For instance, in the case of USA, the poor neighbourhoods which are dominated by African-Americans with the lowest median income are the most vulnerable neighbourhoods (Jabareen–Eizenberg 2020). As such, the importance of more open spaces and effective distancing between cities has increased during the pandemic to reduce the spread across regions, whilst also improving decent housing and access to hospitals (Lak et al. 2020). Overall, these studies confirm Rodríguez-Pose–Burlina's (2021) findings which suggests institutional inequality affects the capacity to effectively fight the pandemic.

Decentralisation's effect on urban characteristics

The above discussion highlights the impact of urban characteristics on the spread of Covid-19 cases. This study argues that the critical role of urban governance and its institutional setting is to fully understand how urban characteristics determine the number of Covid-19 cases.

Since 2001, the promulgation of decentralisation was to meet the high demand for local authority and to attempt to provide an alternative administration to keep Indonesia intact through a democratic government (Alm et al. 2001, p.100). Decentralisation refers to the delegation of state authority and responsibility to the lower tiers of government, consisting of de-concentration and devolution. De-concentration refers to the role of local governments that administer the central government policies and development programs in their respective regions. Meanwhile, devolution is the full delegation of authority to local government to administer development programs.

The main argument is that decentralisation promotes economic efficiency (Calamai 2009). Furthermore, it is the devolution of social capital, which in turn serves as the most effective monitoring tool for government performance based on the people and society. Finally, the establishment of transparent and good governance will then lead to better public service. The impact of devolution on regional convergence depends on how decentralisation is implemented (Pepinsky–Wihardja 2011). Aziz (2013) found that decentralisation outcomes in Indonesian regions are determined by economic, administrative, and institutional factors; people's participation plays the most critical role.

However, decentralisation also magnifies differences in institutional capacities and social endowments which potentially lead to policies that improve public services (Rodríguez-Pose–Ezcurra 2010, 2011). Naturally, richer regions have more resources, opportunities, and capital to develop economic activities and absorb skilled labour. These more dynamic regions have a bigger capacity to mobilise resources such as tax collection and human capital (Özyurt–Daumal 2013). Subsequently, in less developed regions, the lack of expertise and human capital may hinder the government's capacity to promote efficient allocation of resources to deliver better policies and strategies (Rodríguez-Pose–Ezcurra 2010).

Thus, uneven development shifts the structure of relationships and interactions between regions. Therefore, decentralisation has allowed rich regions' economic growth at the cost of neighbouring regions' development. Core regions experience economic overflow and value-added concentration, which lead to polarisation and development concentration (Rustiadi et al. 2010, p. 24). In turn, neighbouring regions became more dependent due to the concentration of infrastructure and job opportunities in the core-metropolitan ones. This is seen in the weakening of hinterlands resulting from the excessive transfer of resources and a high commuting rate of its population.

Recently, spatial regression models have been widely used to account for spatial interactions' effects among regions. For instance, Álvarez-Díaz et al. (2017) found that demand for inter-regional domestic tourism depends on income and is highly price elastic. Járosi (2017) also examined spatial interdependencies of employment and industrial product in the USA. Using spatial regressions, Egri–Tánczos (2018) found evidence of social well-being being much more balanced compared with gross domestic product per capita in Central and Eastern Europe.

Decentralisation and urban characteristics' effect on the spread of cases in Java cities

The decentralisation laws (*undang-undang*) 22/1999 and 25/1999 are responsible for regional autonomy and fiscal decentralisation. In particular, the decentralisation law 22/1999 regulates decentralisation as a form of devolution which delegates local development to municipalities and regencies.

Studies of regional economic convergence in Indonesia showed several dimensions while examining geographical variation, such as Java-biased, Jakarta-biased, urban-biased, and terrestrial-biased (Aritenang 2016, McCulloch–Sjahrir 2008, Rustiadi et al. 2010). Various studies on the regional economy using panel regression analysis discovered that decentralisation exaggerates regional disparities (Aritenang 2016, Akita 2002, Resosudarmo–Vidyattama 2006). McCulloch–Sjahrir (2008) found that while districts located on the Java Island had lower economic growth, disparities remained persistent across Indonesia due to large economic growth variation in districts, e.g., the Papua provinces which have the lowest economic growth per capita.

Moreover, there has been concern over the limited sources of revenues for government districts because of lack of public finance which limits a region's ability to implement a credible and effective development budget (Aritenang 2020, Suwanan–Sulistiani 2010). In particular, this was because property taxes continued to remain under the central government. Thus, local governments struggled to generate alternative sources of revenue. This finding may be explained by Aritenang (2016): the type of administration in local governments (regency and municipality) is insignificant for economic growth; the author suggested that more urbanised areas in municipalities are not necessarily associated with higher economic growth when compared with rural-dominated regency districts. Furthermore, on the impact of fiscal decentralisation on regional economic growth, there were attempts to recognise spatial dependence, especially between adjacent regions (Oates 2006, Setiawan–Aritenang 2019).

Conversely, decentralisation led to a variation of local responses to the pandemic, with each district having its own lockdown policies. For instance, urban lockdowns found in Jakarta or Bandung could not take place in Surakarta due to a lack of funding in that city. The local government calculated that the lockdown would require about 49 billion IDR, out of which more than 10 billion IDR would be spent on household subsidy within a month [2]. Another small city, Sleman, argued that it did not implement urban lockdowns due to being part of a greater urban area, the Jogjakarta metropolitan one, which required other cities to apply mobility restrictions. During the New Year holiday, the district introduced its restriction regulation which limited the mobility of people entering and leaving the district. However, the cost was high and in the last four months, the district has observed the highest number of cases compared to other metropolitan areas [3]. Conversely, throughout the pandemic, the city of Bandung, a large metropolitan area, implemented various types of city lockdown from full, transitioning to proportional, with differences in commercial stores opening hours and regulations on access to the city's main streets [4].

Data and Methodology

To examine urban characteristics, we use several indicators that have been applied in previous studies such as population characteristics (age, size, and density) and infrastructure (Konecka-Szydłowska et al. 2018, do Carmo Dias Bueno–de Souza Lima 2018). Other urbanisation indicators are migration share, public employment support, and education background (Kóti 2018).

This study employed urban characteristics statistics and Covid-19 case data at the district level. There are 123 districts in Java Island within 6 provinces. The descriptive statistics of selected urban characteristic variables are presented in Table 1.

Table 1

Summary statistics

Variables	MEAN	STD DEV	MIN	MAX
Number of daily Covid-19 cases	1161.439	2797.693	1	15619
Population density	3251.715	4458.745	278	20813
Share of informal workers	27.077	8.762	12.75	50.12
Commuter rate	3.907	3.607	0	18.52
Ratio of health facilities per population	0.000184	0.00028	0.000018	0.0022
Internet speed	10.117	0.925	8.7	11.6

A cross-sectional analysis was used for econometric models between districts. The dependent variable was the average number of daily Covid-19 infections per district from August to December 2020. The data were obtained from various Covid-19 province and district websites (See the Databases/Websites for the list of websites).

The independent variables which include data on urban characteristics with the most recently available years from various sources are as follows. First, the urban characteristics data obtained from the Statistic Bureau (Badan Pusat Statistik – BPS) include population density data, share of the population working in the informal sector, and the commuter rate. The former captures data which show the impacts of population density within a district, whilst the latter are based on surveys carried out by the BPS on respective issues. Second, the ratio of the total number of health units (including hospitals, general practitioners, and small health centres) per population from the Ministry of Health was used. Internet speed is also included as an explanatory variable to capture information access and the district's level of information and communication technology (ICT) infrastructure. These data were made available by the Ministry of Communication and Information Technology.

This study was carried out in three stages of analysis. First, descriptive statistics using commuting maps and population mobility rates were examined to explore the urban connectivity of each district. Next, spatial statistics using Moran's I-statistic were used to examine districts' clustering in the number of Covid-19 cases. However, Moran's scatterplot visualises the I-statistic and characterises spatial autocorrelation in the case study area. The local indicators of spatial association (LISA) were examined for each spatial unit (districts) to evaluate evidence of spatial autocorrelation in Covid-19 cases of individual districts that would have similar conditions with their neighbours. As the inference for Moran's I is based on a null hypothesis of spatial randomness, the distribution of the statistic under the null can be derived using randomisation (permutation with the value which is equally likely to occur at any location) or an assumption of normality.

The last analysis employed econometric analysis on the determinants of Covid-19 cases in the context of city characteristics. The following are the econometric equations that were carried out by the ordinary least squares (OLS) and spatial models to capture the spatial effects of each region at the local level. In addition, spatial models are econometric models widely used in many studies to capture spatial differences in object analysis with two models, namely spatial lag and spatial error. The selection of an appropriate spatial model was based on the largest test statistics and the significance of Robust Lagrange Multiplier (RLM) tests (Osland 2010). The OLS general model is presented in the following equation.

$$\text{Number\_Covid\_cases}_{it} = \beta 0 + \beta 1\ (\ln \text{population\_density}_{it-1}) + \beta 2\ (\text{Share\_informal\_worker}_{it-1}) + \beta 3\ (\text{Commuter\_rate}_{it-1}) + \beta 4\ (\text{Ratio\_Health\_Facilities/population}_{it-1}) + \beta 5\ (\text{Internet Speed}_{it-1}) \tag{i}$$

Analysis

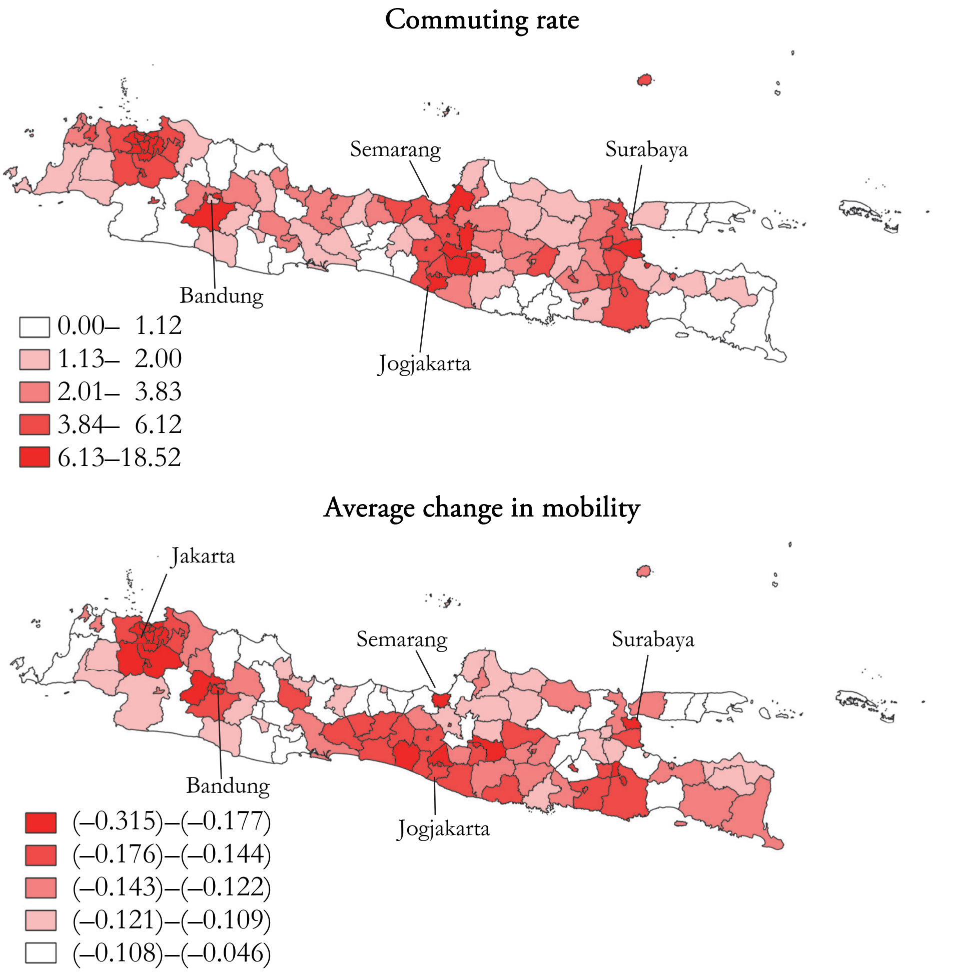
This section analyses the effect of urban characteristics on the share of positive cases in the total population of each district (Figure 1). To compare people's mobility, the New Normal period which started in August 2020 was used as mobility restrictions were considered less important compared to the lockdown period, and therefore, may capture a relatively similar comparison.

First, the urban characteristics of each district were examined. The first map in Figure 1 shows a high commuting rate in all core cities of metropolitan areas: Jakarta, Bandung, Semarang, Jogjakarta, and Surabaya[1]. The second map depicts changes in population mobility on average obtained from the Facebook Movement Range Maps [5] available at the district level. This map shows the change in movement, i.e., how much people are moving around compared to the baseline period before most social distancing measures. Notably, the highest decline in mobility was observed in the core metropolitan areas, especially Jakarta, Semarang, and Surabaya.

[1] Each of these metropolitan spatial development plans are regulated by a Presidential Regulations; Presidential Regulation 60/2020 on Jakarta metropolitan, Presidential Regulations 45/2018 on Bandung metropolitan, Presidential Regulations 78/2018 on Semarang metropolitan, Presidential Regulations 5/2019 on Yogyakarta metropolitan, Presidential Regulations 80/2019 on Surabaya metropolitan.

Figure 1

Maps of commuting rate in 2019 and average changes in movement compared with baseline for August–December 2020



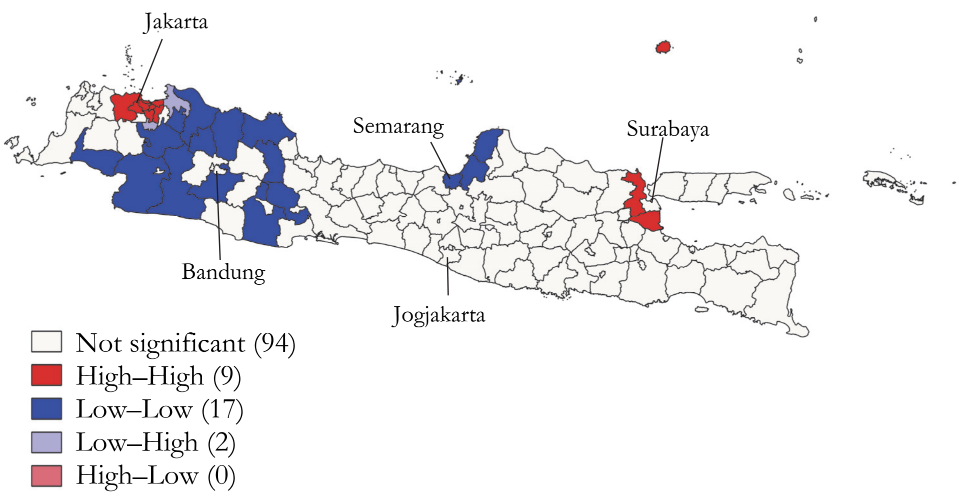
Second, spatial autocorrelation of Covid spread was analysed in the first map of Figure 2. The LISA cluster map shows spatial autocorrelation, suggesting that the pandemic's spread is determined by spatial proximity. This is mainly found in Jakarta districts, where there is a high-high (H-H) category, whilst its surrounding metropolitan districts have a low-high (L-H) category. Furthermore, in the West Java province, including Bandung city (as the core district in Bandung metropolitan), there is low Covid spread; therefore, it is categorised as low-low (L-L). A similar phenomenon occurs in the Semarang Metropolitan area in the north part of Central Java. Finally, districts in the north part of East Java are found to be in the high-high (H-H) Covid spread category, suggesting the Covid spread in Sidoarjo and Gresik districts, which are part of the Surabaya Metropolitan, resulted in high Covid cases. This was confirmed through various news media which reported that the national Covid task force demanded strict prevention policies and evaluation in these districts [6].

The Moran Scatterplot in the second graph in Figure 2 suggests the presence of spatial autocorrelation in districts having high Covid cases similar to their neighbours. We take the number of Covid cases as the conditioning variable for the x-axis, and its neighbours[2] Covid cases as the conditioning variable for the y-axis. The value of the statistic for the actual data is 0.548 and is well to the right of the reference distribution, suggesting a strong rejection of spatial randomness. Furthermore, the model has a pseudo p-value of 0.001 for 999 permutations. This suggests that not a single statistic computed from the randomly generated samples exceeded the actual statistics. This was confirmed using the z-value of 9.1749 that suggests the rejection of spatial randomness.

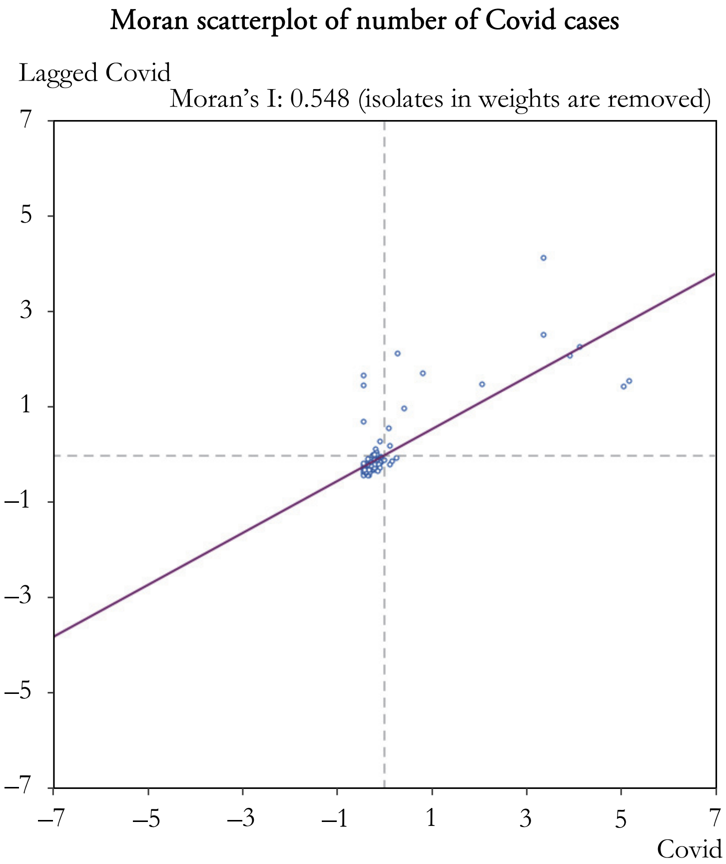
Figure 2

LISA spatial autocorrelation map and Moran scatterplot of number of Covid cases, August–December 2020

LISA spatial autocorrelation



[2] We construct a queen contiguity weight that includes common vertices, thus will result in eight neighbours [7].



Lastly, the determinants of the average number of daily Covid-19 infections per district in the Java Island ones were analysed (Table 2). Furthermore, tests were performed to check whether urban characteristics presented in the previous section are associated with the Covid-19 spread in Java Island. The OLS regression model was used and corrected for heteroskedasticity by including robust standard errors. Subsequently, the analysis corrected spatial autocorrelations through the estimation of econometric models by first running the Lagrange multiplier (LM) and likelihood ratio (LR) tests to examine spatial lag and error, and then estimating spatial lag (SAR) and spatial error (SEM) models. Our analysis of the RLM tests suggests that the spatial lag model is preferable to the spatial error model due to its greater value.

First, there is evidence of spatial lag and error in the average number of daily Covid-19 infections in some districts of Java Island. This confirms the LISA map cluster, that spatial autocorrelations are only found in metropolitan areas such as Jakarta, Bandung, Semarang, and Surabaya. Second, the results highlight urban characteristics such as the economy and infrastructure in advanced districts are associated with higher average number of daily Covid-19 infections. This is also reflected by the higher population density and access to high-speed internet being linked with a higher average number of daily Covid-19 infections.

Table 2

Determinants of share of Covid-19 cases, OLS, and spatial lag models

	OLS model	Spatial lag model	Spatial error model
Spatial lag/Lambda		0.651*** (0.067)	0.720*** (0.0641)
Population density	0.440*** (0.0711)	0.2644*** (0.0563)	0.239*** (0.065)
Share of informal workers	–14.558 (34.5266)	–11.395 (26.715)	2.442 (34.137)
Commuter rate	–139.172* (82.1302)	–176.074*** (63.528)	–147.961** (70.778)
Ratio health facilities per population	–1.39E+06* (746520)	–710088 (581160)	–712615 (612807)
Internet speed	596.667** (235.03)	370.829** (184.845)	339.034 (323.205)
CONSTANT	–5113.73** (2300.61)	–3083.06* (1803.9)	–2771.99 (3282.91)
Number of observation	123	123	123
Moran's I	4.481***		
LM lag	33.340***		
RLM lag	26.366***		
LM error	15.330***		
RLM error	8.355***		
AIC		2213.09	2221.81
LR test		42.317 ***	31.596***
R2	0.354	0.610	0.589

Notes: Dependent variable is the average daily number of Covid-19 cases in the population. Estimation is by OLS robust standard error. The standard errors in parentheses *, **, and *** are 10%, 5%, and 1% significance, respectively.

Conversely, there is a negative relationship between the commuter rate and the spread of Covid cases. Consequently, it is expected that commuters are the ones who spread the virus most easily, implying higher infection rates in districts with a large number of commuters. This counter intuitiveness may be due to the commuter rate capturing the effect of lower population density or worse access to health care in non-core districts with high commuter rates (those with a higher share of informal workers). Furthermore, as expected, districts with a lower ratio of health facilities per population have higher Covid cases; this indicates their incapacity to address the pandemic.

Comparing OLS and spatial models on the number of Covid cases, there is evidence of the presence of autocorrelation among districts. This indicates that the number of Covid cases determines spatial proximity. However, this finding is only true in a large part of West Java province, Jakarta, Semarang, and Surabaya metropolitan areas. According to the LISA map, regression analysis results suggest that geographical proximity is the cause of spatial autocorrelation due to the remaining significant and coefficient of spatially lagged share of Covid-19 cases differing from zero after controlling the urban characteristics.

Conclusion

This study analysed the effects of urban characteristics on the average number of daily Covid-19 infection cases' dispersion throughout districts of Java Island, Indonesia. First, spatial analysis found autocorrelation in a few areas such as Jakarta and Surabaya metropolitan areas; in these areas, the H-H category was applied, suggesting that core and peripheral metropolitan areas are hotspots of Covid cases. Meanwhile, in Bandung and Semarang metropolitan areas, the L-L category was applicable; this indicates low daily infection rate of Covid-19 in both core and peripheral metropolitan areas.

Second, the above findings were confirmed by the econometric analysis. I found that large and core-metropolitan cities are associated with a higher number of average daily Covid-19 infections. This subsequently explains that core-metropolitan cities reflect higher economic connectivity and higher rate of entry-exit of commuters within metropolitan districts. As such, this reveals that core-metropolitan districts become vulnerable due to high infection rates via the mobility due to infrastructure and economic activities. Consequently, this provides supporting evidence that there are higher Covid cases in cities with high density and high-speed internet access.

This study highlights how critical decentralisation is in determining how local governments respond to the spread of Covid-19 via spatial and economic policies. Therefore, two policies are proposed to handle the pandemic. First, tight spatial mobility restrictions between core and neighbouring metropolitan districts are needed to further contain the spread of Covid cases. This study reveals that despite more strict regulations on mobility, the number of Covid cases in large cities and metropolitan areas remains higher. Second, there is a need for more funding and institutional capacities to improve health services, as districts with fewer health facilities are more prone to the disease. In particular, core-metropolitan districts with higher population density and commuters are more vulnerable to infection rates through backbone mobility and economic activities such as trains, public buses, offices, and restaurants.

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