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Spillover Effects of Social and Economic Interactions on COVID-19 Pandemic Vulnerability Across Indonesia's Regions

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Abstract: *This research study focuses on measuring the possible spillover effects of socio-economic interactions on COVID-19 pandemic vulnerability across Indonesia's regions by utilising a spatial simultaneous model. The COVID-19 pandemic vulnerability level here is used to indicate the extent to which a region is susceptible to the spreading COVID-19 pandemic, as determined by not only the region's COVID-19 related epidemiological factors but also by its relevant socio-demographic and economic aspects, housing, environmental health, and availability of health facilities. High COVID-19 pandemic vulnerability levels were mostly found in districts in Java Island and southern Sumatera, suggesting high population density and mobility in both regions. It was revealed that 31 districts have low COVID-19 risk levels (from epidemiological indicators-related measurements), but they have high COVID-19 vulnerability levels (from epidemiological and socioeconomic indicators-based measurements). Labour productivity was found to have a reciprocal relationship with COVID-19 vulnerability, proving that the COVID-19 pandemic has a significant impact on labour productivity and vice versa. On the other hand, regional independence affects COVID-19 vulnerability, but this does not apply the other way around. Moreover, this study has also proven that COVID-19 pandemic vulnerability levels have socio-economic spillover effects on neighbouring areas in Indonesia.*

Keywords: Spillover Effects; Spatial Simultaneous Model; COVID-19 Vulnerability Levels

JEL Classification: C31; R23; R53

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1. Introduction

The COVID-19 pandemic outbreak has severely affected almost all countries in the world, including Indonesia. As of 28 March 2021, there were over 1.5 million positive cases, with 41,242 deaths, spreading over all districts across Indonesia (Indonesian Health Ministry). Jakarta, the country's capital, has suffered the worst with a total of 380,706 positive cases, or nearly a quarter of the total positive cases in Indonesia. Significant numbers of positive cases were also recorded in other big cities in densely populated provinces, such as in East Java, West Java, and South Sulawesi, but these have slowed recently.

In Indonesia, the COVID-19 pandemic has brought about an unprecedented health crisis, a worsening of the economy, and impacts on Indonesian people's well-being. The percentage of poor people in March 2020 was 9.78%, an increase of 0.37% from March 2019. The government predicts that poverty incidence in Indonesia will reach above 10% and the open unemployment rate will also soar due to the COVID -19 pandemic until 2021.

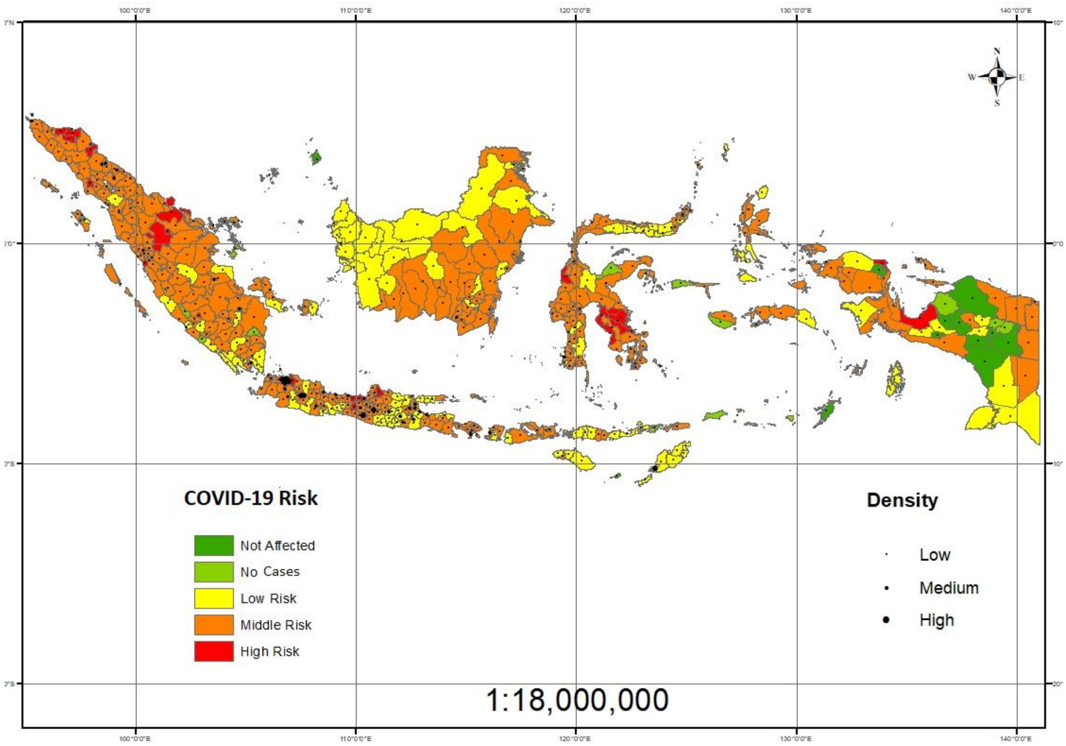
In quarter 2 (Q2) 2020, Indonesia's gross domestic product (GDP) growth dropped to –1.26% from Q1 2020, and the rate is expected to continue declining given the prolonged health and economic impacts of the pandemic. The government has aimed to mitigate the prolonged impacts of the pandemic with integrated health and economic mitigation measures and by establishing the National Economic Recovery and COVID-19 Response Team, consisting of the Economic Recovery Task Force and COVID-19 Handling Committee. In July 2020, the government began implementing 'new normal' conditions by reactivating economic activities. Macroeconomic indicators during Q3 2020 showed bleak performance. Exports in Q2 2020 dropped by 17.1% compared to Q1. Likewise, imports declined by 19.0% in the last quarters (BPS-Statistics Indonesia, n.d.). Whilst household consumption also decreases, government spending is expected to improve in balancing the drops in both international trade and household consumption.

Ten months after it started affecting Indonesia, the pandemic has had domino effects on decreasing regional incomes, increasing unemployment rates, and decreasing people's purchasing power. Sudden economic disruptions caused by COVID-19 have created spillover socio-economic implications leading to demand

and supply shocks in almost all human endeavours (El-Erian, 2020). Through its regular monitoring, the COVID-19 Handling Committee maps out the COVID-19 Risk Index in all districts in Indonesia.[1] This so-called COVID-19 Risk Index is calculated using a weighted composite index of various epidemiological, public health surveillance, and health services indicators and is currently used for mapping out the COVID-19 pandemic risk into three levels of risk, namely high, medium, and low.

Figure 1 visualises the zoning of COVID-19 risk levels in 514 districts in Indonesia, categorised into low risk (22.1%), medium risk (66.9%), and high risk (6.2%), combined with the population density by district. This grouping, however, needs to be re-examined by considering others factors that likely influence the risk of the virus spreading in an area, including population mobilisation.

Figure 1. Map of COVID-19 Risk Levels and Population Density by District in Indonesia



Source: https://covid19.go.id; BPS-Statistics Indonesia (n.d.).

[1] See https://covid19.go.id.

Previous studies on the regional zoning of COVID-19 pandemic vulnerability include those by Acharya and Porwal (2020); Mishra, Gayen, and Haque (2020); and Rahman, Islam, and Islam (2020). Various vulnerability indices of COVID-19 have been formulated in India and Bangladesh using vulnerability zoning and management approaches to modelling the regional spread of the pandemic. Populations exposed to COVID-19 cases tend to be in regions with relatively highly concentrated economic activities, and thus have high population mobility. The combination of economic agglomeration and population mobility accelerates the regions' vulnerability toward the spread of COVID-19 cases. Pujari and Shekatkar (2020) analysed a multi-city modelling of the COVID-19 pandemic using spatial networks in India. Veneri and Ruiz (2013); Kahsai (2009); Bill (2005); and Bhandari et al. (2007) used interlinkages across neighbouring areas, including urban-rural interactions for the spatial dependency modelling of local economic interrelationships. It is quite challenging to examine the spillover effects of interregional socio-economic interactions and the extent to which these interactions have an impact on the increase in COVID-19 pandemic vulnerability in all districts in Indonesia, with different magnitudes depending on regional socio-economic characteristics.

Moreover, Ozili and Arun (2020) focus on the spillover effects of COVID-19 on the global economy, suggesting that restrictions on internal movement and fiscal policy due to COVID-19 had a positive spillover impact on the level of economic activities. Cross-country evidence shows that COVID-19 adversely affected socio-economic, demographic, and environmental aspects (Caraka et al., 2020; Fernandes, 2020; Narayanan et al., 2020; Ozili, 2020; Sannigrahi et al., 2020; Zhang, Qian, and Hu, 2020). These studies find that each region has a different level of severity of the pandemic and also a different level of associated socio-economic vulnerability. Therefore, a more in-depth study on the level of pandemic-related regional vulnerability and its possible spillover impacts on multidimensional aspects at the district level is needed to support well-informed and targeted policymaking in response to effectively handling the COVID-19-related health and socio-economic impacts across the regions of Indonesia.

A COVID-19 pandemic vulnerability index is developed in this study to indicate the extent to which a region is susceptible to the spread of the COVID-19 pandemic, as determined by not only the region's COVID-19-related epidemiological factors – as in the case of measuring the COVID-19 risk level – but also by its relevant socio-demographic and economic aspects, housing, environmental health, and number of health facilities.

Based on the research problem described above, the main objectives of this study are the following:

1. Map out COVID-19 pandemic vulnerability groupings based on the epidemiological and socio-economic characteristics in Indonesia's districts;
2. Identify the interactions between interregional socio-economic dimensions and COVID-19 pandemic vulnerability levels; and
3. Develop a model for measuring the possible spillover effects of interregional socio-economic interactions on COVID-19 pandemic vulnerability levels across Indonesia's districts.

This paper is structured as follows. Following the background and objectives of the study, the next section details the data sources and analytical methods used in the study. The third section presents the study results and their discussion. A conclusion and related policy implications are given in the final section.

2. Data and analytical methods

Following Acharya and Porwal (2020), the regional COVID-19 pandemic vulnerability index/level in this study is constructed from five dimensions, namely socio-economic conditions, demographic composition, housing and hygienic conditions, availability of healthcare facilities, and COVID-19-related epidemiological factors. The variables from each dimension along with their definitions/measurements data sources are presented in Table 1.

Table 1. Dimensions of the Regional COVID-19 Pandemic Vulnerability Index

Dimension	Xi	Variable	Description	Source
Socio-economic	X1	POVERTY	% of poor people	BPS-Statistics Indonesia
	X2	LESS EDUCATION	% of population older than 15 years not completed primary school	BPS-Statistics Indonesia
Demographic	X3	ELDERLY	% of population aged 60 and above	BPS-Statistics Indonesia
Housing and hygiene conditions	X4	LESS FLOOR	% of households with floor area less than 7.5 m^2/capita	BPS-Statistics Indonesia
	X5	NO TOILET	% of households with no access to improved sanitation	BPS-Statistics Indonesia
	X6	NO WATER	% of households without access to safe drinking water	BPS-Statistics Indonesia
Availability of healthcare	X7	NO INSURANCE	% of population without health insurance	BPS-Statistics Indonesia
	X8	LESS HOSPITAL BED	Total population divided by number of hospital beds	Ministry of Health of the Republic of Indonesia
	X9	LESS DOCTORS	Total population divided by number of doctors	BPS-Statistics Indonesia
	X10	LESS NURSES	Total population divided by number of nurses	BPS-Statistics Indonesia
Epidemiological	X11	MORBIDITY	Morbidity rate	BPS-Statistics Indonesia
	X12	SMOKING	% of population aged 10+ smoking every day	RISKESDAS Result Report 2018
	X13	CFR	Case fatality rate: number of COVID-19 deaths divided by total cases	Datawrapper KawalCovid19 (https://datawrapper.dwcdn.net/BA77E)
	X14	INCREASE IN CASES	Increase in COVID-19 cases from 31 October to 5 December 2020	Datawrapper KawalCovid19 (https://datawrapper.dwcdn.net/BA77E)

In answering the first objective, the study employs a factor analysis method for creating the COVID-19 pandemic vulnerability index in all districts in Indonesia. For the second and third objectives, the study develops a spatial simultaneous econometric model in order to identify the interaction between interregional socio-economic dimensions and COVID-19 pandemic vulnerability levels and analyse the socio-economic spillover on these vulnerability levels in all districts in Indonesia. The spatial model is widely used because it can capture the effect of neighbouring locations according to the patterns of the spread of COVID-19 through population mobility and interactions in social and economic activities. Moreover, in this study, a simultaneous spatial model is developed using spatial weights adjusted for population mobilisation.

In the regional development literature, growth centres can produce spreading effects to neighbouring areas if the two regions complement each other (Ke and Feser, 2010). The theoretical framework of interregional spillovers in this study is built upon the dynamics of multiregional population systems, economic geography, and spatial econometrics (see Cordey-Hayes (1975) and Fingleton (2001)). Moreover, the variables in each of dimensions apply the spatial simultaneous relations of social capital and poverty (Harrison, 2019); space and the location changes of jobs and people (Hoogstra, 2012); population migration and housing prices (Jeanty, Partridge, and Irwin, 2010); and regional employment, income growth, and migration (Gebremariam et al., 2010; Gebremariam et al., 2011). Based on the spatial simultaneous relation paradigm, considering the spillover calculations of the COVID-19 vulnerability level in district *i* ($\overline{\mathrm{Y}}_{1\mathrm{i}}^{*}$), labour productivity in the district *i* ($\overline{\mathrm{Y}}_{2\mathrm{i}}^{*}$), and regional independence of district *i* ($\overline{\mathrm{Y}}_{3\mathrm{i}}^{*}$) from the agglomeration centre to the neighbouring regions, the district balance model can be written as follows:

$$\begin{cases} \mathrm{Y}_{1\mathrm{i}}^{*} = \mathrm{f}_1(\mathrm{A}_{1.\mathrm{i}}, \mathrm{Y}_{2\mathrm{i}}^{*}, \mathrm{Y}_{3\mathrm{i}}^{*}, \overline{\mathrm{Y}}_{1\mathrm{i}}^{*}) \\ \mathrm{Y}_{2\mathrm{i}}^{*} = \mathrm{f}_2(\mathrm{A}_{2.\mathrm{i}}, \mathrm{Y}_{1\mathrm{i}}^{*}, \overline{\mathrm{Y}}_{2\mathrm{i}}^{*}) \\ \mathrm{Y}_{3\mathrm{i}}^{*} = \mathrm{f}_3(\mathrm{A}_{3.\mathrm{i}}, \mathrm{Y}_{1\mathrm{i}}^{*}, \overline{\mathrm{Y}}_{3\mathrm{i}}^{*}) \end{cases}$$

where $\overline{\mathrm{Y}}_{1\mathrm{i}}^{*}$, $\overline{\mathrm{Y}}_{2\mathrm{i}}^{*}$, and $\overline{\mathrm{Y}}_{3\mathrm{i}}^{*}$ are the spatial lags of endogenous variables, as the product of a spatial weight matrix W of size nxn from the dependent variable Y, which is a vector of size nx1.

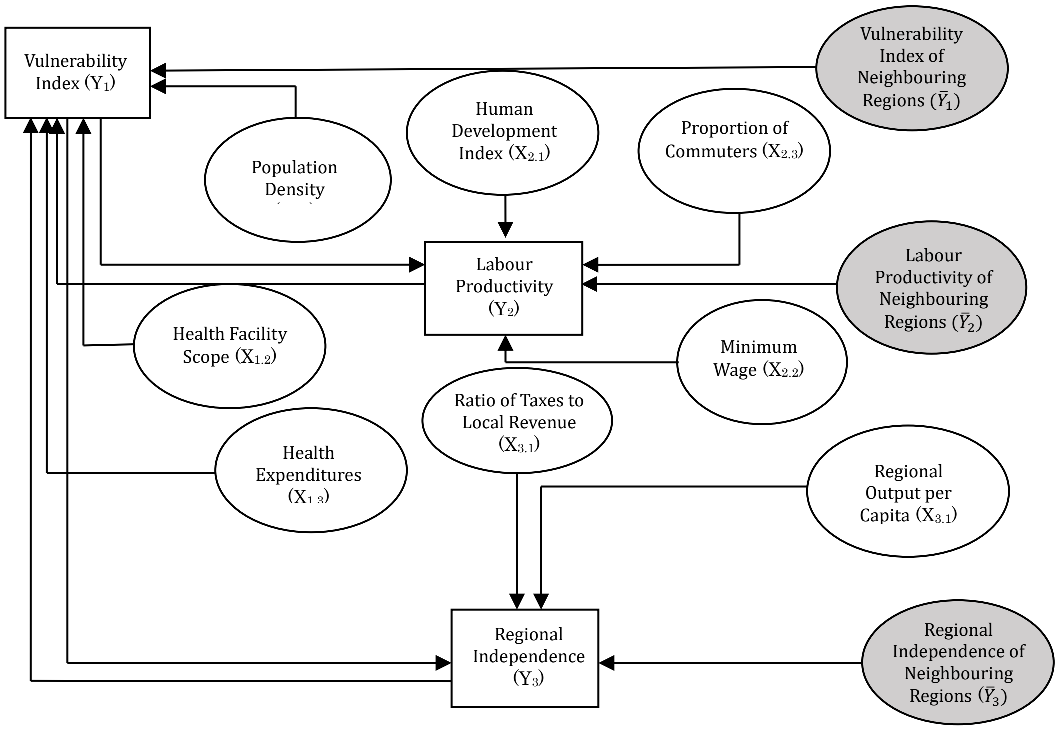
$$\overline{\mathrm{Y}}_{1i} = \mathrm{W_i} Y_1$$

$$\bar{Y}_{2i} = \mathrm{W_i} Y_2$$

$$\bar{Y}_{3i} = \mathrm{W_i} Y_3$$

An asterisk (*) indicates the balance level. The terms $\mathrm{A_{1.i}}$, $\mathrm{A_{2.i}}$, and $\mathrm{A_{3.i}}$ are composite variables, which are efficiency p'arameters to capture the influence of the locational characteristics of the region, such as accessibility, urban and regional infrastructure, labour productivity, and regional output (GRDP). Thus, the simultaneous equation model used to test the spillover hypothesis by including spatial elements is depicted in the theoretical framework as in Figure 2.

Figure 2. Theoretical Framework of Spillover Effects of Interregional Socio-economic Interactions on COVID-19 Pandemic Vulnerability Levels across Indonesia's Districts



Source : Authors.

As presented in Figure 2, this study uses three dependent variables (Y1, Y2, and Y3) and spatial lag dependent variables ($\overline{Y}_1, \overline{Y}_2$, and $\overline{Y}_3$) on the right-hand side. To provide consistent results, estimates using simultaneous equations must be used (Rey and Boarnet, 2004). Kelejian and Prucha (1998; 2010) to construct estimates for the simultaneous equations using a generalised spatial two-stage least-square (GS2SLS) method. The Kelejian-Prucha method produces a better estimate that uses reduced form to get an estimate of all dependent variables re-entered as predetermined variables. Meanwhile, other predetermined variables used in the model to capture the influence of regional local characteristics include accessibility, regional infrastructure, labour productivity, and sociodemographic factors (i.e. population density, school participation, regional minimum wages, hospital capacity, and a lag dependent as a variable for its spatial aspects).

The endogenous variables are the level of vulnerability, human capital, and local income, with the following explanations:

1. Vulnerability level (Y_1): influenced by the population density of district i in year t (X_{11}), number of health facilities (X_{12}), government health expenditures (X_{13}), handwashing (X_{14}), labour productivity (Y_2), regional independence (Y_3), and vulnerability levels of neighbouring regions ($\overline{Y}_1$).
2. Labour productivity (Y_2) as a proxy of human capital: influenced by the Human Development Index (X_{21}), minimum wage ($X_{2.2}$), proportion of commuters ($X_{2.3}$), vulnerability level (Y_1), regional independence (Y_3), and labour productivity in neighbouring regions ($\overline{Y}_2$).
3. Regional independence (Y_3) as a proxy of local income: influenced by the ratio of taxes to local revenues (X_{31}), regional output per capita (X_{32}), vulnerability level (Y_1), labour productivity (Y_2), and regional independence in neighbouring regions ($\overline{Y}_3$).

A complete list of dependent and independent variables can be seen in the Table 2.

Table 2. Variables of the Interregional Spillover Analysis

Variable	Symbol	Description	Source
Vulnerability Level	Y_1	The extent to which a region is susceptible to the spread of the COVID-19 pandemic, as determined by not only the region's COVID-19-related epidemiological factors – as in the case of measuring the COVID-19 risk level – but also by its relevant social-demographic and economic aspects, housing, environmental health, and number of health facilities.	Measured by researchers
Labour Productivity	Y_2	Total current price gross domestic regional product (GDRP) divided by number of workers (million rupiah)	BPS-Statistics Indonesia
Regional Independence	Y_3	% of district's self-generating revenue divided by its total income	Ministry of Finance of the Republic of Indonesia
Population Density	$X_{1.1}$	Number of people per unit area (square kilometres)	BPS-Statistics Indonesia
Health Facility Coverage	$X_{1.2}$	Number of population divided by number of health facilities	Ministry of Health of the Republic of Indonesia
Health Expenditures	$X_{1.3}$	Proportion of health expenditure to district's total expenditure	Estimated by researchers
Handwashing	$X_{1.4}$	% of households with basic handwashing facilities at home	BPS-Statistics Indonesia
Human Development Index	$X_{2.1}$	A composite index for measuring decent living standards, healthy and long lives, and knowledge	BPS-Statistics Indonesia
Minimum Wage	$X_{2.2}$	Regional monthly minimum wage (million rupiah)	Districts' manpower offices
Proportion of Commuters	$X_{2.3}$	Proportion of district's commuters to its total population	BPS-Statistics Indonesia
Regional Output per Capita	$X_{3.1}$	Total current price GDRP divided by number of district's population (million rupiah)	BPS-Statistics Indonesia

Ratio Tax of Revenue	$X_{3.2}$	Ratio of taxes to district's total local revenue	Ministry of Finance of the Republic of Indonesia
Vulnerability Level of Neighbouring Regions	$\overline{Y}_1$	Proposed COVID-19 pandemic vulnerability level of neighbouring regions	Measured by researchers
Labour Productivity of Neighbouring Regions	$\overline{Y}_2$	Total of current price GDRP divided by the number of workers of neighbouring regions (million rupiah)	BPS-Statistics Indonesia
Regional Independence of Neighbouring Regions	$\overline{Y}_3$	% of neighbouring district's self-generating revenue to its total income	Ministry of Finance of the Republic of Indonesia

3. Results and discussion

This section provides the results from the data analysis for answering the three objectives of this research study. In addressing Objective 1, Subsection 3.1 critically assesses the government's current use of COVID-19 risk levels by proposing a new alternative measure of COVID-19 pandemic vulnerability levels for mapping out the extent of susceptibility to the pandemic across all districts in Indonesia. Following this, Subsection 3.2 attempts to answer Objective 2 for identifying the spatial interaction between interregional socio-economic dimensions and the COVID-19 vulnerability level by using Moran's Indicator with the best spatial weight. Finally in addressing Objective 3, Subsection 3.3 focuses on the development of the spatial simultaneous model for measuring the possible spillover effects of interregional socio-economic interactions on COVID-19 vulnerability levels across Indonesia

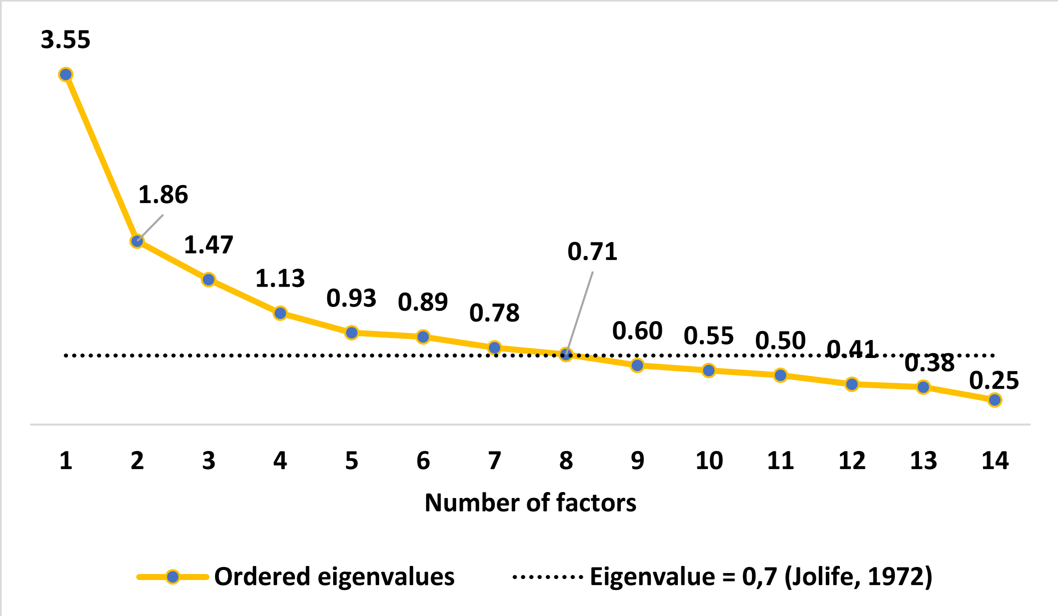
3.1. Regional COVID-19 pandemic vulnerability groupings based on the epidemiological and socio-economic characteristics in Indonesia's districts

As mentioned earlier, in measuring the extent to which a region is susceptible to the spread of the COVID-19 pandemic, this study develops a COVID-19 pandemic vulnerability index composed from both the epidemiological and socio-economic indicators for all 514 districts in Indonesia. This vulnerability level is constructed using a factor analysis method, according to the degrees of correlations (Johnson and Wichern, 2002). The variance of the variables in the same group can be represented only by a random quantity, called a factor.

The factor analysis reduces the number of variables and summarises the variance of the data into a standardised index value. The estimation method used is the principal component method. Data feasibility for the analysis factor is evaluated using Bartlett's test, Kaiser-Meyer-Olkin (KMO), and the measure of sampling adequacy (MSA). Bartlett's test produces a statistic $X^2 = 1756.897\,; df = 91\,; p - value < 2{,}22e - 16$. It is concluded to reject the null hypothesis, as the correlation matrix between the variables is not an identity matrix. The statistic KMO = 0.709 and MSA for all variables are more than 0.5, indicating that all variables are feasible for factor analysis.

Jolife (1972) determines the number of factors by excluding those with eigenvalues below 0.7 from the result of the scree plot in the factor analysis. Jolife (1972) defines the minimum variance above 70% of the total variance, as compared to 75% according to Morrison (1990) and Johnson and Wichern (2002). Based on these criteria, Figure 3 shows the number of factors selected was eight factors with an eigenvalue above 0.7.

Figure 3. Scree Plot of the Eigenvalues of Factors



Source: Data processed by authors.

The resulting factor analysis model using varimax rotation is presented in Table 3. Each factor is characterised by the corresponding variables, representing a portion of the variance. The factor scores are estimated as values of the common factor (Johnson and Wichern, 2002).

Table 3. Resulting Factor Scores of COVID-19 Pandemic Vulnerability Levels and the Proportion of Variance Explained by Each Factor

Factor Scores	Variables	Proportion of Variance Explained	Cumulative
F1	Poverty Less education Less floor No toilet	0.14	0.14
F2	Less doctors Less nurses	0.12	0.26
F3	Elderly Morbidity rate Case fatality rate	0.12	0.38
F4	Increase in cases	0.10	0.48
F5	Smoking	0.09	0.57
F6	No water	0.09	0.65
F7	No insurance	0.08	0.73
F8	Less hospital beds	0.07	0.81

Source : Data processed by authors.

The vulnerability index is extracted by aggregating the factor scores weighted by the proportion of the variance explained in each factor. The level of total data variance explained is 81%, meaning that 81% of the information can be explained by the COVID-19 pandemic vulnerability level, with the following model:

$$Unstandardised\ COVID-19\ Pandemic\ Vulnerability\ Index$$

$$= (0.14 \times F1) + (0.12 \times F2) + (0.12 \times F3) + (0.10 \times F4)$$

$$+(0.09 + F5) + (0.09 \times F6) + (0.08 \times F7) + (0.07 \times F8)$$

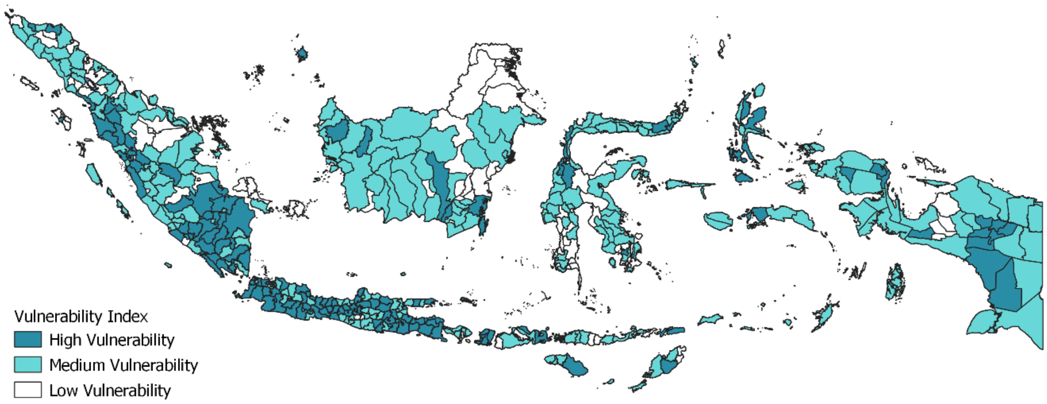
The analysis reveals that the unstandardised COVID-19 pandemic vulnerability level scores range from -0.937 (least vulnerable) to 1.048 (most vulnerable). These scores are then standardised by applying minimum-maximum values with a range from 10 (least vulnerable) to 100 (most vulnerable), with the following procedure.

$$Standardised\ COVID-19\ Pandemic\ Vulnerability\ Index$$
$$= \left[\frac{Unstandardised\ VI - (-0.937)}{1.048}\right] \times (100 - 10) + 10$$

The lowest vulnerability is found in Tarakan City (South Kalimantan), whereas the highest vulnerability is found in Dogiyai (Papua). Furthermore, the overall calculated COVID-19 vulnerability levels of the 514 districts in Indonesia can be presented in a thematic map using the Jenks natural break classification method, as shown in Figure 4. Based on this method, the COVID-19 vulnerability index can be classified into three groups: districts with a 'low vulnerability' level (less than 44.4637), districts with a 'medium vulnerability' level (between 44.4637 and 60.8392), and districts with a 'high vulnerability' level (above 60.8392). It was found that 140 districts are in the 'low vulnerability' group, 242 districts are grouped into 'medium vulnerability', and 132 districts grouped into 'high vulnerability'.

Figure 4 highlights that districts with high vulnerability levels (shaded in dark blue) are heavily concentrated in Java and southern Sumatera. Amongst the 119 districts in Java, 59 are classified into high vulnerability, and only 8 are classified into low vulnerability. In Jakarta, all cities have high vulnerability levels. This finding is most likely related to high population density and mobility, parallel to the extensive economic concentration in both Java and southern Sumatera. Such a situation consequently indicates the susceptibility of the population to the massively quickly spreading COVID-19 pandemic in both regions.

Figure 4. District Mapping of COVID-19 Regional Vulnerability Levels in Indonesia, 2020



Source : Data processed by authors.

Meanwhile, most districts in Kalimantan, Sulawesi, Maluku, and Papua are dominated by a medium level of vulnerability (shown in light blue). Bali and Nusa Tenggara have an almost balanced proportion between high and low vulnerability. Cross tabulation of the COVID-19 pandemic vulnerability level versus the currently used COVID-19 risk level categorisation is presented in Table 4.

Table 4. Cross Tabulation of the COVID-19 Vulnerability Level and COVID-19 Risk Level Categorisation in Indonesia's 514 Districts

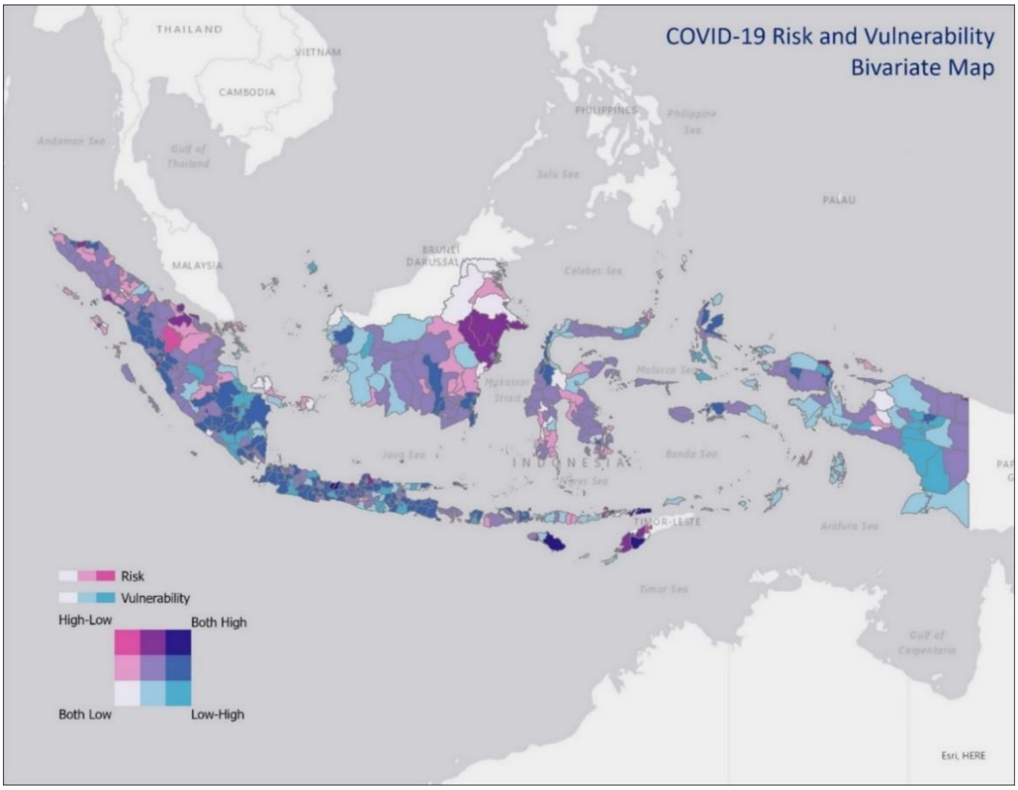
Cross Tabulation		Risk Categorisation			Total Districts	Percentage of Mismatch
		Low	Medium	High		
Vulnerability Index	Low	**28**	107	**5**	140	21.79%
	Medium	58	**167**	17	242	14.59%
	High	**31**	96	**5**	132	24.71%
Total Districts		116	370	28	514	61.09%

Source : Data processed by authors.

There are 28 districts classified as 'low vulnerability–low risk', 167 districts classified as 'medium vulnerability–medium risk', and 5 districts classified as 'high vulnerability–high risk', whilst the rest are mismatched. Of the 514 districts, 61% are classified into different groups for the vulnerability level and risk level categorisation. When socio-economic conditions, demographic composition, housing and hygiene conditions, availability of healthcare facilities, and COVID-19-related epidemiological factors are considered in handling the pandemic, the classifications for districts are quite different from the existing risk categorisation. This means that classification by looking only at the epidemiological conditions (risk categorisation) is not sufficient. In other words, the classification of the COVID-19 risk zoning categories by the COVID-19 Handling Committee needs to be re-examined.

The association between COVID-19 the pandemic vulnerability level and COVID-19 risk levels can be seen in the bivariate choropleth in Figure 5. Most districts in Indonesia are classified into the 'high vulnerability–medium risk' (shown in blue) and 'medium vulnerability–medium risk' (shown in purple) groups. Some districts are in the 'high vulnerability–high risk' group (deep purple-blue). Only a few districts have opposite categories for vulnerability and risk (shown in dark pink and light blue). This indicates that the correlation between the vulnerability and risk levels is positive, but the relationship is not strong. Districts in Papua and West Papua are dominated by light blue (high vulnerability but low risk). In this region, the categories of the vulnerability and risk levels are opposite. Although Papua and West Papua are not too severe in terms of their numbers of positive COVID-19 cases, the readiness of health facilities and personnel, poverty levels, and other socio-economic variables are still poor.

Figure 5. Bivariate Map of COVID-19 Pandemic Vulnerability Levels versus Existing Risk Categorisation



Source : Data processed by authors.

Table 5 provides an interesting finding, with 31 districts being mismatched as having low risk levels (i.e. from the epidemiological indicators-related measurement), but high vulnerability levels (from both the epidemiological and socio-economic indicators-based measurements). This finding suggests that these 31 districts do not appear to be at risk from an epidemiological perspective, but they are not ready, and are thus very vulnerable, for dealing with the pandemic when further assessment takes account of other relevant socio-economic conditions.

Table 5. Number of Districts with Mismatches between Risk and Vulnerability Level Categorisations

Mismatch between Risk and Vulnerability	Number of Districts	Names of Districts
Low risk level, but high vulnerability level	31	Tebo, Banyu Asin, South Ogan Komering Ulu, Ogan Ilir, West Lampung, Way Kanan, West Tulang Bawang, West Pesisir, Natuna, Cianjur, Indramayu, Banyumas, Ponorogo, Trenggalek, Malang, Bojonegoro, Sampang, Central Lombok, Sekadau, Bolaang Mongondow, East Bolaang Mongondow, South Halmahera, Pegunungan Arfak, Jayawijaya, Mappi, Asmat. Tolikara, Nduga, Lanny Jaya, Yalimo, Dogiyai
High risk level, but low vulnerability level	5	Kampar, Pekanbaru City, Belu, Pontianak City, Kendari City,

Source : Data processed by authors.

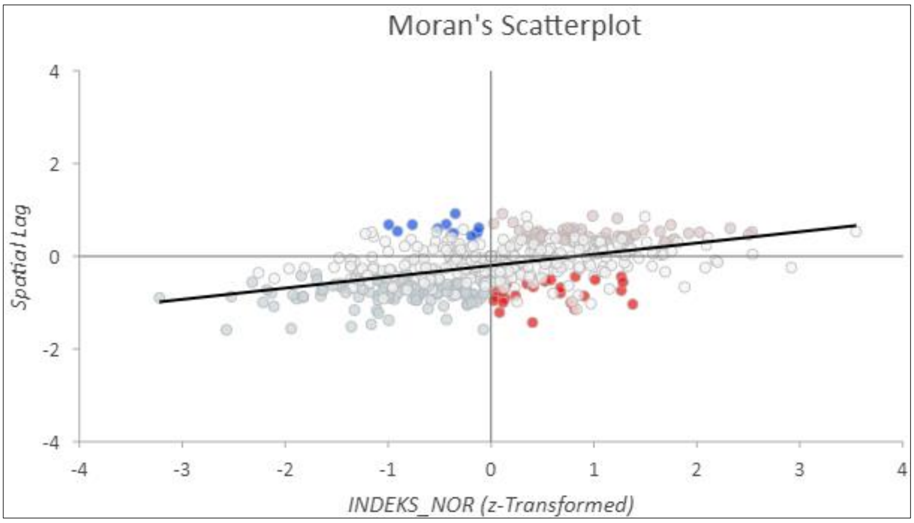
On the contrary, Table 5 also reports 5 districts being mismatched as falling into high-risk level categories but with low vulnerability levels. One of the crucial factors in handling the pandemic is a district's capacity for budgeting/spending management. These five districts categorised as high risk but with low vulnerability show that they can manage the pandemic well due to having better socio-economic conditions, thus allowing them to best use their budgeting/spending capacity in minimising the high risk of the pandemic spread and its associated socio-economic impacts. The policy measures would be different between these 31 and 5 districts, focusing on the importance of further improving people's socio-economic aspects as the foremost and pre-condition for handling the situation in the former, whilst exploring the lessons learned from the latter.

3.2. The interaction between the interregional socio-economic dimension and COVID-19 pandemic vulnerability levels

In this study, spatial autocorrelation to measure similarity/correlation between nearby districts uses Global Moran's I, with a value close to 1 indicating strong positive spatial autocorrelation, 0 showing random spatial distribution, and -1 showing strong negative spatial autocorrelation (Lloyd, 2010). The spatial weight matrix is first calculated before testing the spatial autocorrelation and forming the spatial regression model. This matrix is defined as the spatial dependence relationship between observations (Anselin, 1988), with the row as the observed regions *i* and the column as the neighbouring regions. The conceptualisation of spatial relationships as defined in the weight matrix are often based on geographical aspects, such as contiguity and distance. Another conceptualisation used in constructing the weight to see spatial effects is W-Customised (Pasaribu, 2015), which can be used as an alternative when geographical distances or neighbours are not able to explain the relationship between regions. Even though an area is geographically close or neighbouring, it is possible that two regions have infrequent interactions – thus, the interaction is not strong. With this possibility, the weight can be constructed from another method, namely from factors other than geographical distance, such as economic factors.

This study uses W-Customised, which describes population mobilisation as indicated by recent migration and the proportion of commuters in each district in Indonesia. This weight calculates the population mobilisation between certain districts that intersect with the proportion of commuters, which is then normalised to obtain the population interaction proximity matrix. From the results of the spatial autocorrelation for formulating a spatial regression model with the combined weighting factors of recent migration and commuters in this study, Figure 6 presents the scatterplot of Moran's I, and the obtained Moran's I value is 0.8820 with a 99% statistical significance level (Table 6).

Figure 6. Scatterplot of Moran's I with the Weight of Combined Recent Migration and Commuters



Source : Data processed by authors.

Table 6. Moran's I, Z Scores, and P-values

Weight	Moran's I	Z Score	P-value
Combination of recent migration and commuters	0.8820	43.1817	0.0000*

Source: Data processed by authors.

The obtained Moran's I value at 0.8820 indicates positive spatial autocorrelation, in which similar values of districts and their neighbouring districts with either high values or low values are spatially clustered. In other words, COVID-19 pandemic vulnerability levels are similar amongst districts and their neighbouring districts, partly due to factors related to recent migration and the commuting of people residing and working in the same districts or surrounding areas. As argued by Liem et al. (2020), migrant workers tend to be more vulnerable than non-migrants, either directly or indirectly, to COVID-19 infections. Oztig and Askin (2020) explained that the higher the population mobility in an area, the greater the acceleration of the spread of COVID-19 in that area.

With this resulting positive spatial autocorrelation, Objective 3 can be followed up by fitting a simultaneous spatial model for measuring the possible spillover effects of interregional socio-economic interactions on COVID-19 pandemic vulnerability levels across Indonesia's districts.

3.3. Spillover effects of vulnerability to COVID-19 between districts in Indonesia

In measuring the spillover effects of socio-economic interaction on COVID-19 vulnerability levels across 514 districts in Indonesia, this study uses three dependent variables, namely the vulnerability model (Y1), labour productivity (Y2), and regional independence (Y3). Having detected the existence of spatial dependence between districts in Indonesia, using Lagrange multiplier (LM) and Lagrange multiplier robust tests, all three variables in Table 7 show values for the LM spatial lag test and LM test spatial error below $\alpha = 5\%$, which rejects H0 or the spatial autoregressive (SAR) model and spatial error model (SEM).

Table 7. Dependency Test Results for Y1, Y2 and Y3

Spatial Lag/Spatial Error	Vulnerability to COVID-19		Labour Productivity		Regional Independence	
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
LM test, no spatial lag	46.0476	0.000*	31.6075	0.000*	272.0919	0.000*
Robust LM test, no spatial lag	4.3787	0.036*	3.0643	0.000*	35.7856	0.000*
LM test, no spatial error	93.1909	0.000*	32.4363	0.000*	326.8306	0.000*
Robust LM test, no spatial error	51.5219	0.000*	3.8930	0.048*	90.5243	0.000*

Note: * indicates significance at $\alpha = 5\%$.
Source : Data processed by authors.

The vulnerability spillover model is generally estimated through a simultaneous spatial equation model with generalised spatial two-stage least squares (GS2SLS). The resulting model is then tested to ensure that it has accurate estimation results for all districts in Indonesia. The Arcmap application is used to visualise the spillover impact of COVID-19 vulnerability across the 514 districts in Indonesia.

The use of the spatial autoregressive model results in consistent conclusions with the LM test for the Y1, Y2, and Y3 models, by which the models are spatial autoregressive (SAR). The next step is to estimate the parameters of these three models. The results from the parameter estimations show that the Y1 and Y2 models produce direct impacts and indirect impacts on the surrounding districts, whilst the

Y3 model only produces a direct impact on the concerned districts. These finding are elaborated further as below.

COVID-19 vulnerability model of districts in Indonesia

Table 8 indicates that districts' vulnerability toward the spread of the COVID-19 pandemic is significantly affected by the variables of health facility coverage (X12), health expenditures (X13), handwashing (X14) and labour productivity (Y2). Health facility coverage has a positive relationship with COVID-19 vulnerability, and the three other remaining variables have negative relationships with COVID-19 vulnerability. These findings suggest that the higher the ratio of a district's public health spending and the larger proportion of its population regularly practicing handwashing, the lower level of COVID-19 vulnerability in that district.

Table 8. Results of the Parameter Estimation for Y1, Y2, and Y3

Variable	Direct Effect		Indirect Effect		Total	
	Direct	t-stat	Indirect	t-stat	Total	t-stat
Vulnerability to COVID-19 (Y1)						
Population Density (X_{11})	0.0002	0.9973	-0.0001	-0.9626	0.0001	0.9724
Health Facility Coverage (X_{12})	0.0005	7.8263*	-0.0002	-6.1248*	0.0003	6.1045*
Health Expenditures (X_{13})	-9.6681	-2.4846*	3.7348	2.3280*	-6.0569	-2.4396*
Handwashing (X_{14})	-0.1495	-4.4524*	0.0566	4.1558*	-0.0928	-3.9754*
Labour Productivity (Y2)	-0.5999	-5.2759*				
Regional Independence (Y3)	0.0766	0.9139				
Intercept	36.1881	9.8525*				
Rho	0.4571	6.9901*				
Labour Productivity (Y2)						
Human Development Index(X_{21})	0.1436	1.7622	-0.0322	-1.7568	0.1114	1.7176
Minimum Wage (X_{22})	2.4770	3.0923*	-0.5620	-2.9226*	1.9150	2.9300*
Proportion of Commuters (X_{23})	-0.7528	-4.1673*	0.1724	3.5011*	-0.5805	-3.9316*
Vulnerability to COVID-19 (Y1)	-0.3010	4.3231*				
Regional Independence (Y3)	0.7665	11.1440*				
Intercept	-4.3676	0.5466				
Rho	0.4020	6.1471*				
Regional Independence (Y3)						
Regional Output per Capita (X_{31})	0.0159	3.0279*	0.0019	1.3048	0.0177	2.8921*
Ratio Tax of Revenue (X_{32})	0.1821	9.1664*	0.0204	1.5802	0.2025	0.9043
Vulnerability to COVID-19 (Y1)	0.1000	1.7641				
Labour Productivity (Y2)	0.6190	8.5078*				
Intercept	-15.7194	5.1769*				
Rho	0.5788	12.3460*				

Note: * indicates significance at $\alpha = 5\%$.

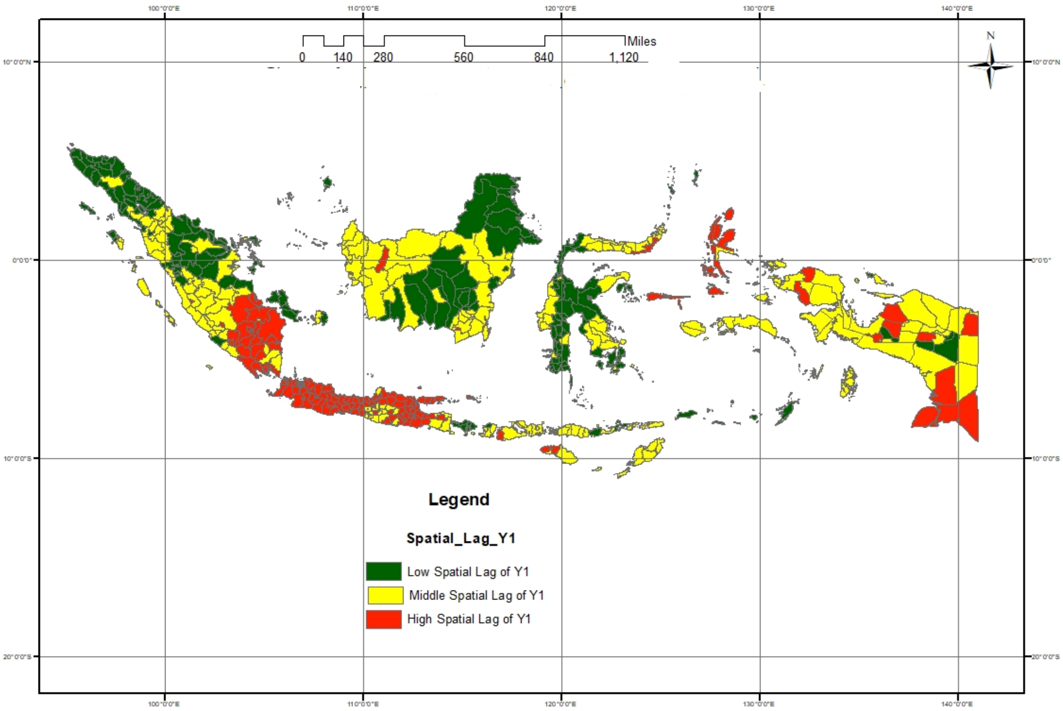
Source : Data processed by authors.

In general, the COVID-19 vulnerability model in Indonesia with a spatial lag model is:

$$y\hat{}\_1i=36.1881+0.457WY1j+0.0002X11i+0.005X12i-9.668X13i-0.145X4i-0.6Y2i+0.0766Y3i$$

Table 8 also provides the dependent spatial lag coefficient with a value of Rho at 0.4571, indicating that an increase in the COVID-19 vulnerability level of a district by 1 point will simultaneously increase the vulnerability to COVID-19 in the neighbouring/other districts with high population interactions by 0.4571 points. High population interactions between districts, such as through migration and commuting between Jakarta and other cities in Java and North and West Sumatera, etc., become a pivotal factor in causing a potential spillover effect on the vulnerability to COVID-19 from one district to its neighbouring districts and beyond. This suggests that the vulnerability to COVID-19 in a district is not solely due to proximity to the surrounding districts but rather to the population interaction between districts in Indonesia. This result is in line with research conducted in the Appalachia region (Wood, 1999) in which the spreading effect is not evenly distributed, and even the closest areas do not always have the same impacts as areas with higher population interactions. This might be due to the influence of agglomeration, in which urban areas often share connectivity with areas outside regional boundaries and even national borders. Furthermore, the overall results of the parameter estimations for the COVID-19 vulnerability model in the 514 districts show that almost all districts show significant results for all independent variables at $\alpha = 5\%$. Figure 7 presents the highest spatial effect of vulnerability to COVID-19, as indicated by the value of Rho, is in Pasuruan City (East Java), whereas the lowest is in Tana Tidung (North Kalimantan). Districts with high interactions of COVID-19 vulnerability (high spatial lag of Y1), as highlighted in red, are mostly located in Java, Southern Sumatera, and several districts in Papua Province.

Figure 7. Spatial Lag of Vulnerability Index



Source : Data processed by authors.

Labour productivity model of districts in Indonesia

The labour productivity model is estimated by the spatial autoregressive (SAR) method, providing significant results for several independent variables and the dependent spatial lag. Labour productivity in districts will increase if it has high migration interactions with the surrounding districts. The estimated spatial lag coefficient generated in this model is much lower than the estimated spatial lag coefficient generated in the COVID-19 vulnerability model. This indicates a greater influence of the spatial linkages of COVID-19 vulnerability between regions that have high inter-district population migration. The highest spatial lag coefficient estimate is in Tambrauw, West Papua, whilst the lowest is in East Manggarai, East Nusa Tenggara.

The minimum wage (X_{22}) has a significant (a = 5%) positive relationship with labour productivity with a coefficient value of 2.477, suggesting that every additional Rp1 million of minimum wages will increase labour productivity by 2.477 points. The proportion of commuters (X_{23}) has a significantly negative relationship with labour productivity with a coefficient value of 0.753, indicating that each increase in the proportion of commuters by 1% will reduce labour productivity by 0.753 points.

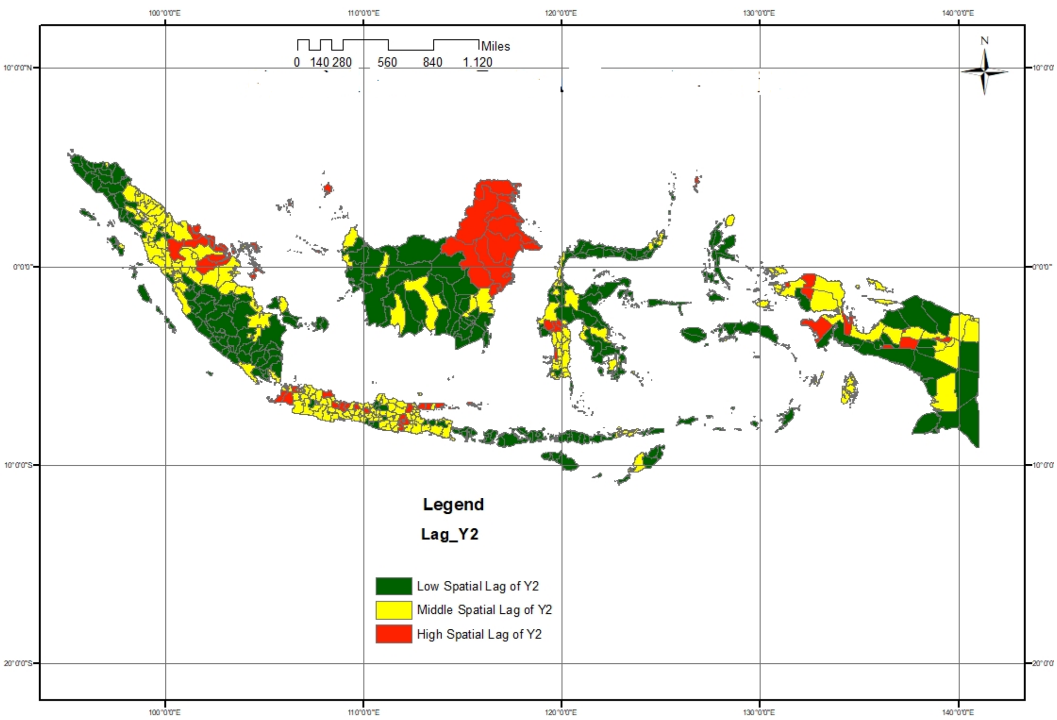
The feedback effect between labour productivity and vulnerability to COVID-19 occurs in a negative direction, showing that vulnerability to COVID-19 directly affects labour productivity, and vice versa. This further indicates that when vulnerability to COVID-19 increases in districts, it will reduce labour productivity in that region. In other words, the decreased labour productivity is related to limited economic activity due to pandemic-related disruption in Indonesia.

In general, the labour productivity model in Indonesia with spatial autoregressive is:

$$\hat{y}_{2i} = -4.368+0.402\mathrm{WY}_{2j}+0.143X_{21i}+2.477X_{22i}-0.753X_{23i}-0.301Y_{1i}+0.766Y_{3i}$$

The spatial lag of labour productivity in Figure 8 shows that districts with high spatial relationships from labour productivity, as indicated in red for a high spatial lag of Y2, are mostly located in East and North Kalimantan, as well as in several districts in Java, Papua, Sumatra, and Sulawesi.

Figure 8. Spatial Lag of Labour Productivity



Source : Data processed by authors.

Model of regional independence of districts in Indonesia

Regional independence refers to a district's capacity in generating its own revenue for financing its routine and development budgets, independent from the central government's funding support. Application of the SAR model on regional independence produces a positive value of 0.5788, indicating that the regional independence of a district increases by 0.5788% from the addition of 1% of regional independence of its neighbouring districts that have inter-district population interactions.

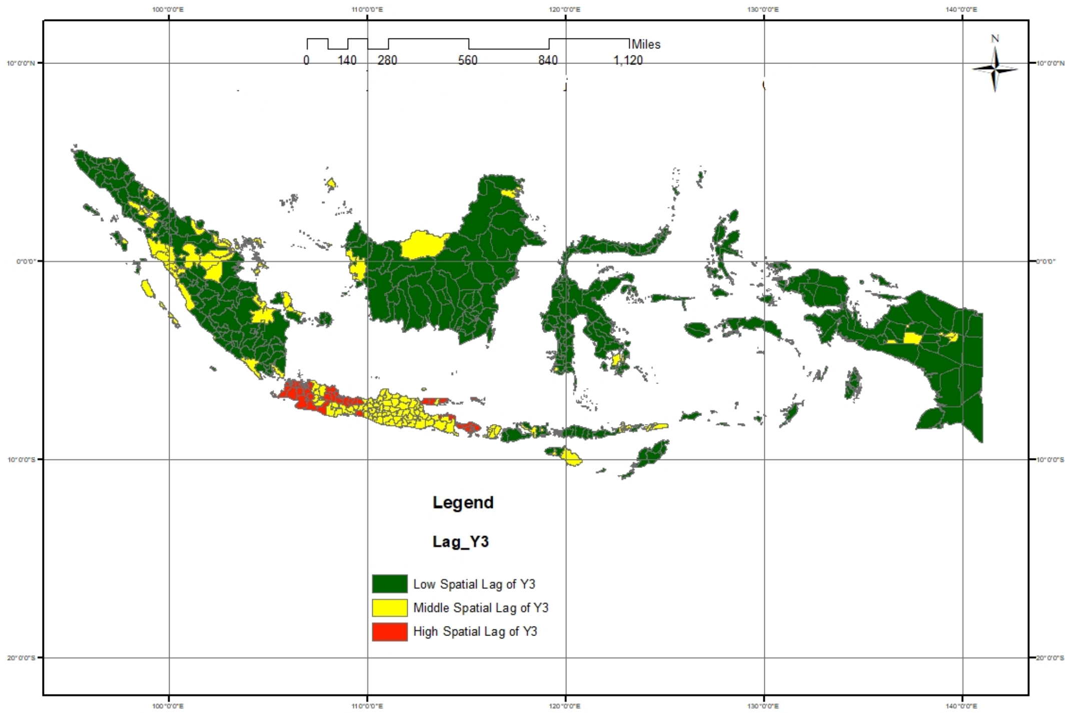
The highest spatial effect of regional independence is observed in Tabanan (Bali), whereas the lowest is in Sarmi (Papua). The estimation of the spatial lag model for regional independence proves that in addition to the dependent spatial lag, both GDRP per capita and the tax ratio significantly ($\alpha = 5\%$) positively affect regional independence. This shows that an increase of 1 unit in each variable, ceteris paribus, will increase the independence of the region in accordance with the resulting parameter coefficient. For every Rp1 million, regional output per capita will increase regional independence by 0.0159 points.

A feedback effect between regional independence and vulnerability to COVID-19, however, does not occur, suggesting that vulnerability to COVID-19 does not directly affect regional independence. On the other hand, a feedback effect occurs between regional independence and labour productivity. This shows that when labour productivity decreases due to the COVID-19 pandemic, regional independence will also decrease by 0.619 points. The model for regional independence in Indonesia is as follows:

$$\hat{y}_{3i} = -15.7194 + 0.579WY_{3j} + 0.0159X_{31i} + 0.1821X_{32i} + 0.10Y_{1i} + 0.619Y_{3i}$$

The lag of regional independence in Figure 9 shows that districts that have a high spatial relationship with regional independence are only in some areas in the western part of Java, Madura, and Bali.

Figure 9. Spatial Lag of Regional Independence



Source : Data processed by authors.

4. Conclusion and policy implications

4.1. Conclusion

Attempts have been made in the data analysis to answer three objectives in this study. The main findings can be summarised according to these objectives. With regard to addressing Objective 1, the findings are as follows.

First of all, the COVID-19 pandemic vulnerability level is believed to be a better composite index for measuring the extent to which a region is susceptible to the spread of the COVID-19 pandemic. This index is determined by not only the region's COVID-19-related epidemiological factors – as in the case of measuring the COVID-19 risk level – but also by its relevant social-demographic and economic aspects, housing, environmental health, and number of health facilities.

Secondly, the study found that 242 out of a total 514 districts (47%) in Indonesia are categorised as having 'medium vulnerability', whereas the rest are grouped into 'low vulnerability' (140 districts) and 'high vulnerability' (132 districts). Thirdly, on the association between the COVID-19 pandemic vulnerability level and COVID-19 risk level categorisation, 31 districts were found to be mismatched with low risk levels but high vulnerability levels, whereas 5 districts were mismatched by falling into high-risk level categories but having low vulnerability levels. These 31 districts are not at risk from an epidemiological perspective, but they are vulnerable to dealing with the pandemic when further assessment takes account of other relevant socio-economic conditions. On the contrary, five districts with high risk and low vulnerability levels potentially provide a good case showing they can well manage the pandemic due to having better socio-economic conditions, thus allowing them to best use their budgeting/spending capacity to minimise the risk of the pandemic's spread and its associated socio-economic impacts.

In identifying the interactions between interregional socio-economic dimensions and the COVID-19 pandemic vulnerability level (Objective 2), the study ran a spatial autocorrelation for formulating a spatial regression model weighted by recent migration and commuting, and produced Moran's I value at 0.8820. This positive value indicates that similar values of districts and their neighbouring districts are spatially clustered. The COVID-19 pandemic vulnerability levels are similar amongst districts and their neighbouring districts, partly due to factors related to the recent migration and commuting of people residing and working in the same districts or surrounding areas. Migrant workers tend to be more vulnerable than non-migrants, either directly or indirectly, to COVID-19 infections.

In addressing Objective 3, the study found some interesting evidence. For measuring the spillover effects of socio-economic interactions on COVID-19 vulnerability levels across the 514 districts in Indonesia, this study used three dependent variables: vulnerability level, labour productivity, and regional independence. The results from the parameter estimations show that the vulnerability and labour productivity models indicate direct impacts and indirect impacts (spillover effects) of a district's values on its neighbouring or inter-connecting districts, whilst the regional independence model only indicates direct impacts.

Firstly, analysis of the COVID-19 vulnerability model in the 514 districts confirms that districts' vulnerability to the spread of the COVID-19 pandemic is significantly affected by the variables of health facility coverage, health expenditures, handwashing practices, and labour productivity. The last three variables have a negative relationship with COVID-19 vulnerability, suggesting that the higher the ratio of a district's public health spending and the larger proportion of its population regularly practicing handwashing, the lower level of COVID-19 vulnerability in that district.

The analysis also produces a dependent spatial lag coefficient with a value of Rho at 0.4571, indicating that an increase in the COVID-19 vulnerability level of a district by 1 point will simultaneously increase the vulnerability to COVID-19 in the neighbouring districts or other inter-connecting districts by 0.4571 points. High population interactions between districts/cities, such as through migration and commuting between districts/regions, become a pivotal factor in causing a potential spillover effect on the vulnerability to COVID-19 from one district to its neighbouring districts and beyond. Districts with high spillover effects of COVID-19 vulnerability are mostly located in Java, Southern Sumatera, and several districts in Papua Province. The highest spatial effect of vulnerability to COVID-19, as indicated by the value of Rho, is for Pasuruan City (East Java), whereas the lowest is for Tana Tidung (North Kalimantan).

Secondly, analysis of the labour productivity model indicates a feedback effect between labour productivity and vulnerability to COVID-19 occurring in a negative direction, showing that vulnerability to COVID-19 directly affects labour productivity, and vice versa. When the vulnerability to COVID-19 increases in a district, it will reduce labour productivity in the district. In other words, the decreased labour productivity is related to limited economic activity due to pandemic-related disruption in Indonesia. Thirdly, analysis of the regional independence model produces a positive Rho value of 0.5788, indicating that the regional independence of a district increases by 0.5788% from the addition of 1% of the regional independence of its neighbouring districts. The highest spatial effect of regional independence is observed in Tabanan (Bali), whereas the lowest is in Sarmi (Papua).

4.2. Policy implications

The important findings as highlighted above are necessary to draw policy implications for further improvements in handling the impacts of COVID-19 in Indonesia.

- The COVID-19 vulnerability level can be potentially used as an alternative measure for monitoring the dynamic COVID-19 pandemic and its impacts, as this measure provides more comprehensive dimensions by including both epidemiological and socio-economic indicators at the district level in Indonesia.
- On the mismatched categorisation of districts between the two indices of COVID-19 risk and vulnerability, it is crucial to re-emphasise the importance of further improving the people's socio-economic aspects as the pre-condition for handling any unexpected and sudden pandemic outbreak in the future, both at the regional and national levels.

On the contributions of population migration and commuting to the interactions between interregional socio-economic dimensions and the COVID-19 pandemic vulnerability level, there is a need for addressing the presence of migrant workers in particular districts/cities, as they tend to be more vulnerable than non-migrants, either directly or indirectly, to COVID-19 infections. This might include policy measures related to better and safer conditions for their accommodation and modes of transportation.

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Appendix 1. Vulnerability index – Highest and lowest

25 Highest	Vulnerability Index	25 Lowest	Vulnerability Index
Dogiyai, Papua	100.000	Toba Samosir, North Sumatera	30.841
Empat Lawang, South Sumatera	91.646	Payakumbuh City, West Sumatera	30.329
Situbondo, East Java	86.647	Solok City, West Sumatera	30.257
South Ogan Komering Ulu, South Sumatera	86.555	Palangka Raya City, Central Kalimantan	28.763
Indramayu, West Java	86.111	Tanjung Pinang City, Riau Islands	28.564
Garut, West Java	83.767	Binjai City, North Sumatera	28.560
Jember, East Java	82.135	Pekanbaru City, Riau	28.321
West Pesisir, Lampung	81.822	Banda Aceh City, Aceh	27.709
Ogan Ilir, South Sumatera	80.872	Nunukan, North Kalimantan	27.543
Wonosobo, Central Java	80.680	Barru, South Sulawesi	27.235
Asmat, Papua	80.529	Bulungan, North Kalimantan	27.010
Pandeglang, Banten	79.815	Bontang City, East Kalimantan	26.712
Central Mamberamo , Papua	78.558	Klungkung, Bali	24.839
Tasikmalaya, West Java	78.401	Langsa City, Aceh	24.777
Nduga *, Papua	78.170	Pakpak Bharat, North Sumatera	24.696
Musi Rawas Utara, South Sumatera	77.861	Pematang Siantar City, North Sumatera	24.470
Probolinggo, East Java	76.974	Palopo City, South Sulawesi	23.898
Banjarnegara, Central Java	76.572	Parepare City, South Sulawesi	23.371
East Sumba, East Nusa Tenggara	76.571	Jambi City, Jambi	22.784
Sukabumi, West Java	76.315	Anambas Islands, Riau Islands	22.374
East Bolaang Mongondow, North Sulawesi	76.180	Sabang City, Aceh	22.034
Lebak, Banten	76.087	Lhokseumawe City, Aceh	21.978
Grobogan, Central Java	75.364	Pangkal Pinang City, Bangka Belitung Islands	19.280
Seram Bagian Barat, Maluku	75.351	Malinau, North Kalimantan	18.656
East Jakarta City, Special Capital Region of Jakarta	75.286	Tarakan City, North Kalimantan	10.000

Appendix 2. Spillover estimation model

Spatial Dependency Test Result for Y1

```
T = 1
LM test no spatial lag, probability     =  46.0476,  0.000
robust LM test no spatial lag, probability  =  4.3787,  0.036
LM test no spatial error, probability    =  93.1909,  0.000
robust LM test no spatial error, probability =  51.5219,  0.000
```

Spatial Dependency Test Result for Y2

```
T = 1
LM test no spatial lag, probability     =  31.6075,  0.000
robust LM test no spatial lag, probability  =  3.0643,  0.080
LM test no spatial error, probability    =  32.4363,  0.000
robust LM test no spatial error, probability =  3.8930,  0.048
```

Spatial Dependency Test Result for Y3

```
T = 1
LM test no spatial lag, probability     = 272.0919,  0.000
robust LM test no spatial lag, probability  =  35.7856,  0.000
LM test no spatial error, probability    = 326.8306,  0.000
robust LM test no spatial error, probability =  90.5243,  0.000
```

Y1 Spatial Simultaneous

```
Spatial autoregressive Model Estimates
Dependent Variable =    Y1
R-squared     =  0.3452
Rbar-squared    =  0.3374
sigma^2     = 115.3078
Nobs, Nvars    =  514,   7
log-likelihood   =    -1953.3823
# of iterations  =    1
min and max rho  =  -1.0000,  1.0000
total time in secs =  1.3606
No lndet approximation used
***************************************************************
Variable    Coefficient Asymptot t-stat  z-probability
intercept    36.188169     9.852547     0.000000
X1.1      0.000217     0.997353     0.318593
X1.2       0.000464     7.939084     0.000000
X1.3      -9.668071    -2.461480     0.013837
X1.4      -0.145067    -4.371259     0.000012
y2hat      -0.599924    -5.275873     0.000000
y3hat       0.076575     0.913892     0.360774
rho       0.457127     6.990110     0.000000
***************************************************************
  direct  t-stat  indirect  t-stat  total   t-stat
  0.0002  0.9782  -0.0001  -0.9626  0.0001  0.9724
  0.0005  7.8263  -0.0002  -6.1248  0.0003  6.1045
  -9.7917  -2.4846  3.7348  2.3280  -6.0569  -2.4396
  -0.1495  -4.4524  0.0566  4.1558  -0.0928  -3.9754
```

Y2 Spatial Simultaneous

```
Spatial autoregressive Model Estimates
Dependent Variable =    Y2
R-squared     =  0.4248
Rbar-squared    =  0.4191
sigma^2      =  80.0916
Nobs, Nvars    =  514,   6
log-likelihood   =    -1858.7908
# of iterations  =   1
min and max rho  =  -1.0000,  1.0000
total time in secs =  0.4463
No lndet approximation used
***************************************************************
Variable    Coefficient Asymptot t-stat  z-probability
intercept    -4.367591    -0.546622     0.584639
X2.1       0.139465     1.718469     0.085711
X2.2        2.414758     3.021677     0.002514
X2.3       -0.730101    -4.060619     0.000049
y1hat      -0.301009    -4.323141     0.000015
y3hat       0.766514    11.144047     0.000000
rho        0.402035     6.147086     0.000000
***************************************************************
  direct  t-stat  indirect  t-stat  total   t-stat
  0.1436  1.7622  -0.0322  -1.7568  0.1114  1.7176
  2.4770  3.0923  -0.5620  -2.9226  1.9150  2.9300
  -0.7528  -4.1673  0.1724  3.5011  -0.5805  -3.9316
```

Y3 Spatial Simultaneous

```
Spatial autoregressive Model Estimates
Dependent Variable =    Y3
R-squared     =  0.6544
Rbar-squared    =  0.6517
sigma^2      =  48.4892
Nobs, Nvars    =  514,   5
log-likelihood   =    -1733.3893
# of iterations  =   1
min and max rho  =  -1.0000,  1.0000
total time in secs =  0.4996
No lndet approximation used
***************************************************************
Variable    Coefficient Asymptot t-stat  z-probability
intercept    -15.719435    -5.176857     0.000000
X3.1       0.015938     2.995656     0.002739
X3.2       0.180643     9.372919     0.000000
y1hat       0.100025     1.764139     0.077709
y2hat       0.619032     8.507767     0.000000
rho        0.578762    12.345964     0.000000
***************************************************************
  direct  t-stat  indirect  t-stat  total   t-stat
  0.0159  3.0279  0.0019  1.3048  0.0177  2.8921
  0.1821  9.1664  0.0204  1.5802  0.2025  8.9043
```

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