A SPATIAL ANALYSIS OF FINANCIAL DEVELOPMENT AND INCOME INEQUALITY IN INDONESIA

(*ANALISIS SPASIAL DARI PEMBANGUNAN KEUANGAN DAN KETIMPANGAN PENDAPATAN DI INDONESIA*)

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ABSTRAK

Peran pembangunan keuangan dalam rangka penurunan ketimpangan pendapatan masih menjadi diskusi hangat di kalangan pembuat kebijakan karena literatur memberikan hasil yang berbeda. Fokus pada inklusivitas pasar keuangan, kami memberikan kontribusi terhadap diskusi tentang hubungan antara pembangunan keuangan dan ketimpangan pendapatan dengan mempertimbangkan analisis spasial. Kami mengidentifikasi terjadinya ketergantungan spasial antar wilayah dan pengaruhnya terhadap hubungan keduanya dengan mengaplikasikan analisis spasial panel yang mencakup data pada level kabupaten di Indonesia pada periode 2018-2020. Studi ini menemukan adanya ketergantungan spasial pada ketimpangan pendapatan di antara kabupaten dan adanya kluster wilayah dengan ketimpangan yang relatif tinggi atau rendah. Selain itu, analisis spasial ekonometri dengan metode Spasial Durbin Model (SDM) mengindikasikan adanya hubungan yang positif antara pembangunan keuangan dan ketimpangan pendapatan. Adanya efek tidak langsung yang signifikan mengindikasikan bahwa pembangunan keuangan di suatu wilayah juga mempengaruhi ketimpangan pendapatan di wilayah sekitarnya.

Kata kunci*: pembangunan keuangan; ketimpangan pendapatan; analisis spasial*

ABSTRACT

The role of financial development in reducing income inequality is still a much-heated discussion among policymakers, as the literature provides mixed findings. Focusing on the inclusiveness of the financial market, we contribute to the discussion on the relationship between financial development and income inequality by incorporating spatial considerations into the analysis. We examine the occurrence of spatial autocorrelation and its influence on the relationship by employing spatial panel analysis covering municipality-level data of Indonesia from the period 2018-2020. This research found the presence of spatial dependency on income inequality among municipalities and clusters of regions with relatively high and low Gini coefficients. Furthermore, our spatial econometrics analysis using the Spatial Durbin Model reveals a positive relationship between financial development and income inequality. The significant indirect effects indicate that financial development in a region affects the income inequality of the neighbouring regions.

Keywords: financial development; income inequality; spatial analysis

INTRODUCTION

Indonesia has maintained its relatively stable economy in the last decades, even after political and financial crises. However, its income inequality appears to be more fluctuated. There is no sign of the downward trend of Indonesia's Gini coefficients in the last decades. Governments are concerned about rising income inequality because it may signal certain groups of people in society who have been continuously disadvantaged. The government tries to maintain the level of income inequality between appropriate levels, as it is believed that excessive levels of income inequality may harm society. The target of the income inequality level in the local government development planning documents, such as the medium-term regional development planning (RPJMD), reflects the importance of income inequality for the government and policymakers.

Some level of inequality might not be a problem considering as it encourages individuals to perform well, compete, save money, and invest it to advance in life (Dabla-Norris et al., 2015), influences growth favourably by encouraging innovation and entrepreneurship (Lazear & Rosen, 2021), or allows at least for some people to gather the essential needs for starting businesses and obtaining a good education, which may especially be important for developing nations (Barro, 2000). However, high-income inequality has a detrimental impact on economic performance and growth sustainability (Berg et al., 2018). Additionally, it slows the rate of growth that makes it feasible to reduce poverty, which is a hindrance to that goal (Ravallion, 2004). Additionally, a society with severe inequality could have functioned more effectively since its policies tend to favour the affluent at the expense of the rest of society (Stiglitz, 2012) or result in policies that harm growth, such as enabling lobbyists to press for financial deregulation (Acemoglu, 2011).

Policymakers often see financial development as an effective mechanism to deal with income inequality issues. Financial development is the process of reducing the costs related to gathering information, upholding contracts, and carrying out transactions in the financial sector (The World Bank Group, 2021). Therefore, financial development is expected to lower income inequality through increasing capital allocation efficiency (Galor & Zeira, 1993). An inclusive financial system would allow all economic classes in society to get credit, therefore starting and scaling up their entrepreneurial activities and generating more income. The role of financial development in advancing other developmental objectives is recognised in the 2030 Sustainable Development Goals (SDGs), precisely the SDG 10 on reducing inequality.

Around 50 countries have adopted explicit policies to boost their financial inclusion (The World Bank Group, 2021). The Indonesian government formally established its Financial Inclusion National Strategy (FINS) in 2016 to improve the inclusiveness of the financial system in Indonesia. One of its main aims is to reduce income inequality through financial development by improving access to financial products for less wealthy people and small businesses. The NFIS as the roadmap for improving people's access to financial markets appears to be successfully implemented as there are some great signs of progress in the financial development in Indonesia. For instance, the ownership of financial institution accounts doubled from 20 % in 2011 to 49% in 2019 (The World Bank, 2022). However, while the financial development policies aim for a reduction of income inequality, there is still no agreement on whether financial development lowers (Beck et al., 2007) or widens (Jauch and Watzka, 2016) income inequality in the literature. Therefore, this relationship in Indonesia needs to be empirically verified.

Financial deepening, which refers to a financial system's expansion in size or depth, has received huge attention in research on financial development. In this term, financial development works at the intensive margin by offering people with prior access to the financial system a wider variety of services in the financial markets. Furthermore, financial development is meant to improve financial inclusion, which tends to act on the extensive margin of financial development by allowing persons previously excluded from the financial system to access financial services (Demirgüç-Kunt & Levine, 2009). Private credit and M2 are indicators that are mostly used to proxy financial deepening. However, as there is limited data on those indicators at the municipality level, this study only focuses on financial inclusion, which measures the ease of access to financial services.

Theoretical literature provides two major views about the impact of financial development on income inequality. First is the income-narrowing hypothesis proposed by Banerjee and Newman (1993) and Galor and Zeira (1993). Their theory argued that financial development negatively affects income inequality; better-developed financial systems lead to reduced income inequality. Second, Greenwood and Jovanovic (1990) introduced an inverted U-shape curve theory on the relationship. Their model predicts that financial development leads to a rise in income inequality at the early stage of development as only a small part of society gains the benefits. Then, after financial development reaches a particular level, it starts to lower income inequality as the financial system improves to a more advanced level.

In the empirical studies, previous studies on the relationship between financial development and income inequality arrive at inconclusive findings. The majority of those studies support the idea that financial development lowers income inequality by granting previously excluded poor people access to financial markets. Beck et al. (2007) suggest that the poor gain from financial development in their study using a dataset of 65 countries from 1960 to 2005. Their ability to expand their income far faster than the average per capita GDP is made possible by a highly sophisticated financial sector, which lowers income inequality. Several other studies find a favourable impact of financial development on income inequality as it improves access to the financial market for people with lower income (Clarke et al., 2006; Hamori & Hashiguchi, 2012; Kunieda et al., 2014; R. Zhang & ben Naceur, 2019). In contrast to the studies mentioned above, the second strand of the previous studies arrives at an income-widening conclusion. Jauch and Watzka (2016) examine data from 138 countries for 1960-2008 and find a positive relationship after controlling for country-fixed effects and potential endogeneity problems. Other studies by Jaumotte et al. (2013) and de Haan and Sturm (2017) find similar findings on the income-widening effects of financial development by analysing different cross-country datasets consisting of 51 countries (1981-2003) and 121 countries (1975-2005), respectively. The third group of empirical evidence supports a nonlinear inverted U-shape curve of the link between financial development and income inequality. (Kim & Lin, 2011) discover a nonlinear relationship between income inequality and financial development using a panel dataset of 65 countries from 1960 to 2005. They contend that after a nation reaches a certain level of financial development, income distribution becomes more balanced and favours the poor more than other groups. However, financial development harms the poor below this level and promotes income widening impact. Nikoloski (2013) finds similar findings on the financial development-income inequality nexus in his study using a panel of 161 countries between 1962 and 2006. In the case of Indonesia, Fitriatinnisa & Khoirunurrofik (2021) show that financial development worsens income inequality in the early phase and lowers it after a particular stage of development.

While most of the literature is cross-countries studies, several papers examine this issue in sub-national studies. Jung and Cha (2021) suggest that financial deepening fails to reduce income, while Q. Zhang and Chen (2015) observe an inverted U-curve pattern of the relationship while studying provincial-level inequality in China. In their studies for Iran and Turkey, Shahbaz et al. (2015) and Destek et al. (2020) also revealed an inverted U-curve linkage. Previous panel data studies find no significant relationship between financial development and provincial income inequality in Indonesia (Aginta et al., 2018; Zulfa Sari & Falianty, 2021), while (Fitriatinnisa & Khoirunurrofik, 2021) supports income widening hypothesis on this nexus. Jung and Vijverberg (2019) use spatial econometrics to examine this link in China between 1998 and 2014. In the presence of spatial dependence, the study shows the relevance of employing the spatial technique for assessing the impacts of financial development on income inequality. This study is closely related to those studies in Indonesia by employing spatial analysis on the financial development-income inequality nexus using municipality-level data.

In general, this paper tries to answer whether better financial development reduces income inequality at the municipality level in Indonesia. Furthermore, we consider spatial dependence in the analysis, such that the values of observations in one site may be affected by the values in other locations (J. P. LeSage, 2008). The spatial analysis is arguably a preferred approach for dealing with the presence of spatial dependence among observations. We expect two main findings from this study. First, the Gini coefficient, which is used to measure income inequality, shows a spatial dependency across municipalities. Second, we expect higher financial development to be aligned with greater income inequality as we believe Indonesia's financial system has yet to reach an advanced level. According to Greenwood and Jovanovic (1990), the expansion of the financial market would raise income inequality throughout the early phases of financial development.

Our contributions are directly related to the previous studies at the sub-national level examining the relationship between financial development and income inequality, particularly in Indonesia (Aginta et al., 2018; Fitriatinnisa & Khoirunurrofik, 2021; Zulfa Sari & Falianty, 2021). Those studies show different findings on the financial development-income inequality nexus. Our study differs from the previous research in some respects. First, we analyse regional income inequality at the municipality level, while previous studies use provincial and national level data. Furthermore, we use alternative data sources to proxy financial development at the lower administration level. We also use geographical consideration by including total land areas in the variables. Then, we apply spatial consideration to our empirical analysis to handle spatial dependencies of income inequality across regions. As far as we know, this study is the first one to examine the relationship at the municipality level and apply spatial considerations to the analysis.

The remainder of this paper is organised as follows. Section 2 explains the empirical strategies and the data. Section 3 presents the results and discussions. Finally, Section 5 summarises the study's main findings and policy implications.

METHODS

This study uses a panel dataset covering 514 Indonesian municipalities from 2018-2020. The Gini coefficients are derived from the National Socioeconomic Survey (SUSENAS) 2019, and the financial development indicators are generated from BPS's Village Potential Statistics (PODES) 2019. All control variables are obtained from official data of BPS, while the municipalities' total land areas are obtained from Permendagri 72 Tahun 2019, published by The Ministry of Home Affairs of Indonesia (Kemendagri). Overall, we use all 514 municipalities in Indonesia for the exploratory spatial data analysis and the spatial econometrics analysis. Table 1 below provides the summary statistics of the data used in this study.

Table 1. Summary Statistics

Variable	Obs.	Mean	S.D.	Min.	Max
Gini coefficient	1542	0.326	0.0456	0.186	0.508
Number of bank branches per 100.000 population	1542	9.656	6.125	0	56.351
Number of bank branches per 100 km2	1542	18.572	65.839	0	1019.473
ln GDP per capita	1542	54.006	61.592	6.17	769.827
Mean years of schooling	1542	8.210	1.652	0.85	12.650
Agriculture sector share	1542	16.351	13.01383	0.020	94.547
Government consumption share	1542	24.391	15.145	0.007	85.938

Sources: BPS, Kemendagri

This study uses the Gini coefficient to examine income distribution throughout the population as it is the most extensively used indicator of income inequality among academics and policymakers. The Gini coefficient has several important characteristics that make it a reliable indicator of income inequality. Those attributes are its independence of the size of the economy and population, meeting the transfer principle and utilising income data from the entire population (Trapeznikova, 2019). Next, we use the number of bank branches per 100.000 population to proxy financial development as it can reflect people's access to financial institutions. These measures align with the importance of financial development in facilitating wider access to financial institutions and encouraging a more inclusive financial system. Moreover, we also add geographical considerations to proxy financial development by using the number of bank branches per 100 km2. We define bank branches as branches or sub-branches that mainly operate at the lower level of administrative areas.

We include a set of control variables based on prior research (Beck et al., 2007; de Haan & Sturm, 2017; R. Zhang & ben Naceur, 2019) that are believed to influence income inequality to handle our estimation against potential omitted variable bias. Those are regional GDP per capita, share of government consumption, share of the agricultural sector, and mean years of schooling. We anticipate a positive sign for the financial development variable as we hypothesise that financial development contributes to the increasing income inequality in Indonesia.

Exploratory Spatial Data Analysis

This study applies Exploratory Spatial Data Analysis (ESDA) to depict income inequality distribution across space and identify clusters of similar Gini values. ESDA can discover distinct locations, characterise spatial distributions, and identify spatial association patterns. The approach treats data as fixed locations with a spatial weight matrix describing the neighbourhood's structure (Anselin, 2003). The standard approaches of the ESDA are the global spatial autocorrelation and the local indicator spatial autocorrelation (LISA).

This study examines the global spatial autocorrelation using Moran's I statistics (Moran, 1948), following most previous studies on identifying spatial autocorrelation. It evaluates the degree of overall similarities across spatially distributed regions. The formula of the Moran's I statistics is as follows:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(x_i - \bar{x})\,(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

where n refers to the number of regions, x_i denotes to the value of variable x taken in region i, x_j is the value of variable x taken in region j, $\bar{x}$ is the average value of variable x, and w_{ij} represents the ijth element of the spatial weight matrix W. A positive and significant value of Moran's I indicates a positive spatial autocorrelation, i.e., a region next to regions with high (low) values also has a high (low) value. In reverse, a significantly negative value describes a negative spatial autocorrelation, and the zero value of Moran's I statistics indicates that the variable x is distributed randomly over space (Kondo, 2018).

This study applies the local Moran's I (Anselin, 1995) as a LISA for the local spatial autocorrelation. One of the primary advantages of LISA lies in its ability to break down global indicators into the contribution of each observation. The formula is as follows:

$$I_i = \frac{(x_i - \bar{x})}{m_2}\sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{2}$$

where m_2 equal to $\sum_{i=1}^{n} n^{-1}(x_i - \bar{x})^2$. I_i expresses the similarity between the value's deviation from the mean and the neighbouring values' deviations from the mean. A significant positive I_i indicates that the value is similar to the neighbouring regions, while a significant negative value reflects the dissimilarity to that of the neighbouring regions. A zero value indicates that there is no relationship with the values of the neighbouring regions.

Spatial Econometrics Model

This study uses the spatial panel model to examine the effects of financial development on municipal income inequality in Indonesia. We implement a general-to-specific approach by employing Spatial Durbin Model (SDM) to investigate the relationship between financial development and income inequality with spatial considerations. Following (Elhorst, 2014), we estimate the following model:

$$INEQ_{it} = \rho\sum_{j=1}^{n} w_{ij}INEQ_{jt} + FD_{it}\alpha + X_{it}\beta + \gamma\sum_{j=1}^{n} w_{ij}FD_{jt} + \theta\sum_{j=1}^{n} w_{ij}X_{jt} + \eta_i + \varepsilon_{it} \tag{3}$$

where $INEQ_{it}$ is the income inequality in municipality i and year t, FD_{it} denotes financial development indicator in municipality i and year t, X_{it} represents the vector of control variables, $\gamma \sum_{j=1}^{n} w_{ij} FD_{jt}$ and $\theta \sum_{j=1}^{n} w_{ij} X_{jt}$ is the spatial lag of the exploratory variables, w_{ij} is the element of spatial weight matrix W that describes the degree of spatial linkage between two observations i and j, η_i is region-specific effects and $\varepsilon_{i,t}$ is the error terms. Moreover, to test the Greenwood & Jovanovic (1990) hypothesis on the nonlinear relationship between financial development and income inequality, we also estimate the following model:

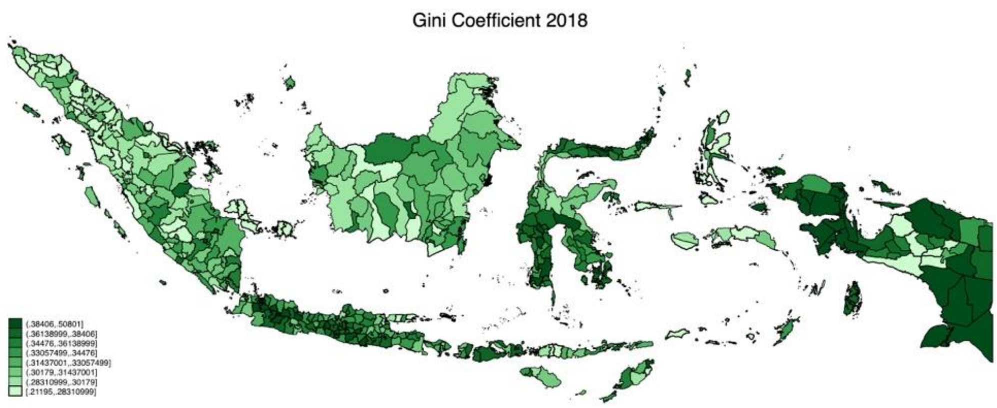
$$
\begin{aligned}
INEQ_{it} = {} & \rho \sum_{j=1}^{n} w_{ij} INEQ_{jt} + FD_{it}\alpha + FD^{2}{}_{it}\alpha + X_{it}\beta + \gamma \sum_{j=1}^{n} w_{ij} FD_{jt} \\
& + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + \eta_i + \varepsilon_{it}
\end{aligned} \tag{4}
$$

Next, we apply a common task for model comparison proposed by LeSage and Pace (2009) The task starts with the SDM as the general specification and tests for the alternatives. This study applies Wald tests to test the following hypothesises. First, we test the hypothesis of $H_0: \theta = 0$ to check whether the model can be simplified into the Spatial Autoregressive Model (SAR). Second, we test the hypothesis of $H_0: \theta = -\beta\rho$ to examine whether the model can be simplified into the Spatial Error Model (SEM). Rejection to both null hypotheses indicates that the SDM is the most preferred model in explaining the data.

The spatial weight matrix representing the degree of spatial connectivity among regions needs to be constructed to perform ESDA and spatial regressions analysis. As a central tool in spatial analysis, the matrix quantifies the notion that nearer things have more influence than farther away. The specification of the weight matrix influences both estimations and inferences (Florax & Folmer, 1992), and it is presumed to be exogenous and non-stochastic (Anselin & Bera, 2020). Nonetheless, few rules for determining the appropriate spatial weight matrix are available (Anselin, 2002). There are numerous criteria for constructing a spatial weight matrix, including inverse distance, q-nearest neighbour, contiguity-based, transport cost-based, and migration flow-based matrix ((J. P. LeSage & Fischer, 2008). Therefore, following previous spatial analysis studies in Indonesia (Santos-Marquez et al., 2022; Vidyattama, 2014), this study applies an inverse distance matrix. We measure distance as the pure physical distance between the centroid of the regions. Furthermore, we also normalised the spatial weight matrix such that the sum of the row elements is equal to one for ease of interpretation.

RESULTS AND DISCUSSIONS

Income Inequality in Indonesia



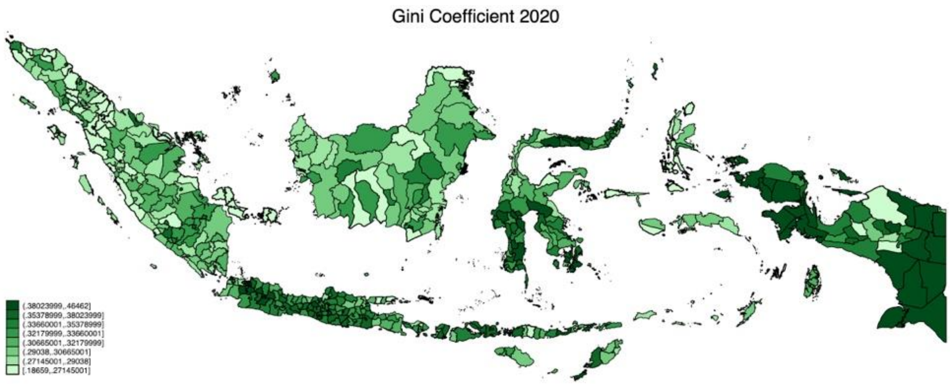


Figure 1. Income inequality in Indonesia, 2018 and 2020

Indonesia's income inequality after the Asian crisis relatively fluctuated, ranging between 0.29 in 2000 and peaked at 0.41 in 2013. For the last decade, the first half of the 2010s was marked by relatively sharp increases in Gini coefficients before they steadily declined to a level slightly above the start of the decade (The World Bank, 2022). However, income inequality at the municipality level highly varies across the regions. Figure 1 shows distributions of the Gini coefficients at the municipality level across space in 2018 and 2020. The figure shows that municipalities in Papua, Java and the southern part of Sulawesi had relatively high Gini coefficients. In contrast, those in Sumatra and a big part of Kalimantan have a relatively more equal society. In 2020, the highest Gini coefficients were recorded at Buton Municipality in Southeast Sulawesi (0.465), while Nduga Municipality in Papua (0.187), had the lowest Gini value. In the previous two years, Nduga also recorded the lowest Gini value, while Takalar (0.482) and Buton Tengah (0.508) recorded the highest Gini coefficients. Furthermore, the maps strongly indicate clustered Gini values, suggesting a region tends to have similar values to its neighbouring regions. Those preliminary trends motivate this study to examine the spatial influence on the financial development effects on income inequality and will be further analysed through spatial autocorrelation statistics and spatial regressions.

The global Moran's I statistics of the Gini coefficients verify the presence of the spatial dependence of income inequality across municipalities. Table 2 reports the values of the Moran's I statistics from 2018 to 2020 under an inverse distance spatial weight matrix. The values for those three years are positive and significant at a 1 per cent significance level, confirming the rejection of the null hypothesis that observations are randomly distributed across space. A significant positive Moran's I implies that similar Gini values tend to be clustered, that is, provinces with relatively high (low) Gini are located close to provinces with similarly high (low) Gini values. This study then considers those spatial dependencies while empirically analysing the relationship between financial development and income inequality. Furthermore, a Moran scatterplot can describe the spatial association of the observations in visual for exploratory analysis (Anselin, 2019). It divides the local Moran's I value into four quadrants, indicating spatial autocorrelation categories. In that scatterplot, a positive spatial association is located at the upper-right and the lower-left quadrants. As depicted in Figure 2, most municipalities exhibit positive spatial autocorrelation. The positive slopes correspond to the positive value of the global Moran's I statistics in the respective year. Although the distribution of the Gini values is quite different between 2018 and 2020, the slopes are relatively the same, as indicated by the Moran's I values in Table 2.

Table 2. The Global Spatial Autocorrelation on Income Inequality in Indonesia, 2018-2020

Year	Moran's I.	se (I)
2020	0.3645***	0.0232
2019	0.3900***	0.0232
2018	0.3703***	0.0232

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

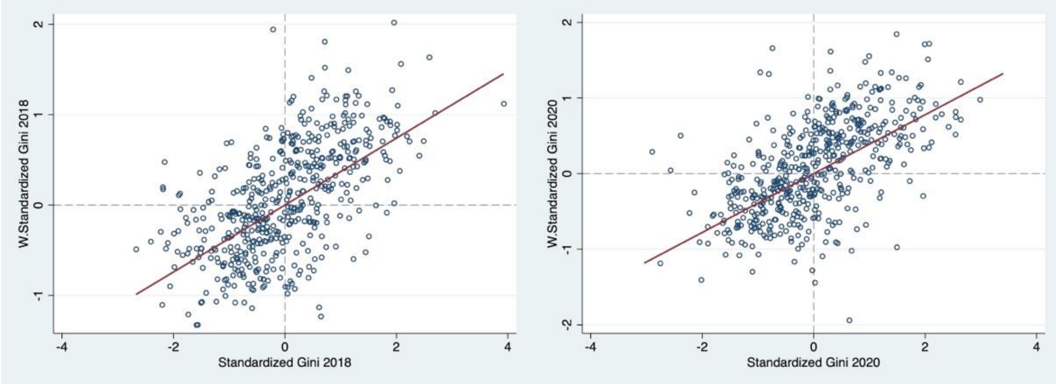


Figure 2. Moran scatterplots of income inequality in Indonesia in 2018 and 2020

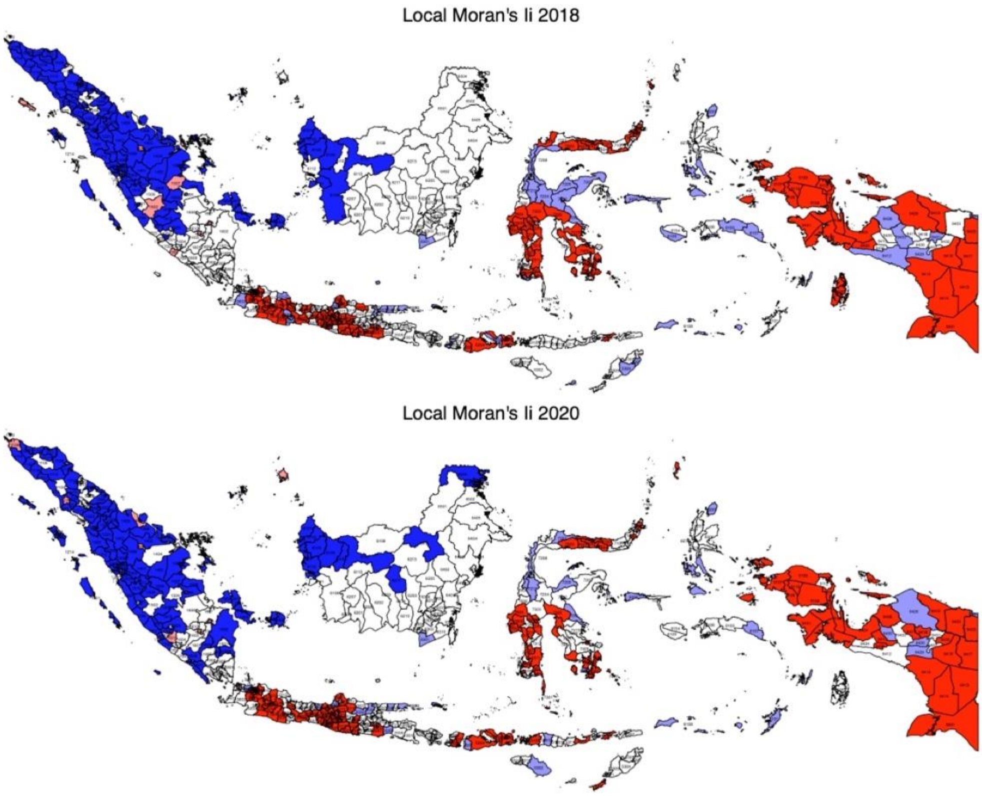


Figure 3. LISA on the income inequality in Indonesia in 2018 and 2020

LISA helps identify which parts of Indonesia form high and low Gini values clusters. This identification may help policymakers in planning specific policies to reduce income inequality. Figure 3 illustrates the identification of spatial clusters of similar Gini coefficients using LISA. They are known as the hotspots (red-coloured areas), indicating municipalities with relatively high Gini values surrounded by municipalities with high Gini values. In contrast, the coldspots (blue-coloured area) indicate municipalities with relatively low Gini values surrounded by municipalities with low Gini values. Overall, numerous hotspots and coldspots of clusters are identified based on the significant local Moran's I values. In 2018, the coldspots were formed at most of the municipalities in Sumatra and some parts of Kalimantan, indicating municipalities with relatively low Gini values surrounded by those with relatively low Gini values. Meanwhile, the hotspots are apparent in major parts of Java and Papua and several areas in Sulawesi. In general, these clusters remained for the next two years. In addition, LISA can also identify the spatial outliers marked with softer-blue colour, which are regions with Gini values dissimilar to those of neighbouring regions.

As one of the SDG's goals, reducing income inequality always be a crucial target for the central and local governments. The explanatory spatial analysis results may provide insightful views for policymakers about the geographical distribution of municipal income inequality in dealing with income inequality issues. Using information from the ESDA, they could identify which regions they should have more awareness of potential excessive income inequality and may develop more specific policies to prevent it.

Spatial Econometrics Analysis

We employ the Spatial Durbin Model (SDM) to analyse the effects of financial development on income inequality with spatial considerations. Overall, financial development has a positive relationship with income inequality, indicating that higher financial development is associated with a rise of income inequality. Moreover, the spatial lag of dependent variables ρ shows positive and significant values for all the models, verifying the necessity to include spatial considerations in the analysis. Those values indicate that the Gini value in a municipality is affected by the Gini values of its neighbouring municipalities. This study also tests the possible nonlinear relationship between financial development and income inequality by including the squared values of financial development variables in the models. The number of bank branches per 100 km2 shows a nonlinear relationship between financial development and income inequality following the hypothesis of Greenwood and Jovanovic (1990). Table 3 presents our detailed estimation results of the SDM for the two measures of financial development. The Wald tests to select the most appropriate model confirm that the Spatial Durbin Model (SDM) is the best approach for the analysis. It tests the null hypotheses of Ho: $\theta = 0$ and Ho: $\theta = -\beta\rho$ to examine whether the model can be simplified into the SAR or the SEM. The test results point to the rejection of both hypotheses at a 1 per cent significance level. Thus, we can confirm that the data is best described using the SDM rather than the SAR or the SEM to explain the relationship between financial development and income inequality in Indonesia.

The spatial lags of dependent and independent variables in the models make the interpretation of parameters more complicated. A change in the explanatory variables in a region influences the dependent variable in that region as well as in all other regions. In addition, the effect of changes in an explanatory variable varies by location (Elhorst, 2014). Thus, we follow LeSage and Pace (2009) with the direct, indirect, and total effects in explaining the magnitude of the effects of explanatory variables on the dependent variable. In the case of this study, income inequality in a region depends on the explanatory variables of that region and the neighbouring regions. The direct effects measure the effects of financial development in a region on its income inequality. In contrast, the indirect effects measure the effects of financial development in a region on the neighbouring's income inequalities.

Table 3. The Spatial Durbin Model (SDM) regressions on financial development and the Gini coefficients

Variable	Gini (3)	Gini (4)	Gini (5)	Gini (6)
Number of bank branches per 100.000 population	0.0032*** (0.0010)	0.0059** (0.0024)		
Number of bank branches per 100.000 population (squared)		-0.0001 (0.0001)		
Number of bank branches per 100 km2			0.0001 (0.0001)	0.0005*** (0.0002)
Number of bank branches per 100 km2 (squared)				- 0.0000*** (0.0000)
Regional GDP per capita (ln)	-0.0218** (0.0106)	-0.0192* (0.0107)	-0.0077 (0.0110)	-0.0028 (0.0113)
Share of the agriculture sector to regional GDP	-0.0006 (0.0005)	-0.0004 (0.0005)	-0.0005 (0.0005)	-0.0003 (0.0005)
Share of government expenditure to regional GDP	-0.0006 (0.0007)	-0.0005 (0.0007)	-0.0003 (0.0007)	-0.0001 (0.0007)
Mean years of schooling	0.0171*** (0.0059)	0.0145** (0.0063)	0.0204*** (0.0057)	0.0177*** (0.0061)
Spatial ρ	0.9674*** (0.0048)	0.9677*** (0.0048)	0.9574*** (0.0078)	0.9560*** (0.0083)
w.bank_pop	0.0091 (0.0077)	-0.0328** (0.0153)		
w.bank_area			0.0016*** (0.0004)	0.0043*** (0.0013)
w.ln_rgdpcap	-0.0540 (0.0537)	-0.0813 (0.0537)	-0.0816 (0.0556)	-0.0075 (0.0648)
w.agri_share	-0.0018 (0.0022)	-0.0002 (0.0023)	0.0031 (0.0023)	0.0069** (0.0030)
w.gov_area	-0.0003 (0.0025)	-0.0014 (0.0025)	0.0001 (0.0022)	0.0012 (0.0022)
w.mys	-0.0696*** (0.0213)	-0.0601*** (0.0219)	-0.0920*** (0.0207)	-0.1066*** (0.0218)
Year dummies	Yes	Yes	Yes	Yes
Observations	1542	1542	1542	1542
R squared	0.06	0.10	0.11	0.09
Wald test ($H_0: \theta = 0$)	0.0000	0.0000	0.0000	0.0000
Wald test ($H_0: \theta = -\beta\rho$)	0.0000	0.0000	0.0127	0.0414

Notes: standard errors are in parentheses. The values on the Wald tests are the p-values. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 4. Estimating results of the SDM regressions on financial development and the Gini coefficients

Variables	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of banks branches per 100.000 population	0.0041***	0.3896*	0.3937*			
	(0.0012)	(0.2351)	(0.2357)			
Number of bank branches per 100 km2				0.0002**	0.0423***	0.0426***
				(0.0001)	(0.0118)	(0.0118)
Regional GDP per capita (ln)	-0.028***	-2.293	-2.320	-0.013	-2.104	-2.117
	(0.0105)	(1.6536)	(1.6556)	(0.0106)	(1.3419)	(1.3428)
Share of the agriculture sector to regional GDP	-0.0007	-0.0716	-0.0723	-0.0003	0.0647	0.0643
	(0.0005)	(0.0655)	(0.0657)	(0.0004)	(0.0576)	(0.0577)
Share of government expenditure to regional GDP	-0.0006	-0.0233	-0.0240	-0.0003	-0.0015	-0.0018
	(0.0006)	(0.0672)	(0.0672)	(0.0006)	(0.0469)	(0.0469)
Mean years of schooling	0.014**	-1.645**	-1.632**	0.017***	-1.732***	-1.716***
	(0.0057)	(0.6457)	(0.6460)	(0.0055)	(0.5560)	(0.5566)

Notes: standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 reports the estimation results of the effects of financial development on income inequality from the SDM regressions. The static SDM used in this study can only estimate the long-run direct and indirect effects. The direct and indirect effects from the estimation support the notion of income-widening effects of financial development for both proxies of financial development. The direct effects indicate a significant positive effect of the number of bank branches per 100.000 population and the number of bank branches per 100 km2 on income inequality, all with a 1 per cent confidence level. A 1 unit increase in bank branches per 100.000 population is associated with 0.0041 per cent increase in income inequality. In comparison, a 1 unit increase in bank branches per 100 km2 is linked to a rise of income inequality by 0.0002 per cent. Furthermore, the spatial lag of independent variables is significant for the number of bank branches per 100 km2 as the measure of financial development with a 1 per cent significance level. The significant positive value indicates that financial development affects income inequality in the neighbouring municipalities. The total effects, which combine the direct and indirect effects, suggest income-widening effects of the number of bank branches per 100.000 population and the number of bank branches per 100 km2 with 10 per cent and 1 per cent confidence levels, respectively. Our control variables mostly show insignificant effects on income inequality except for mean years of schooling. The direct effect of education is positive, while the indirect effects negatively affect income inequality. Therefore, as the magnitudes of indirect effects are higher than the direct effects, the total effects suggest that a 1 year increase in mean year schooling reduces income inequality by 1.71 per cent.

For the robustness of the spatial econometrics results, we also analyse the model using the non-spatial fixed effects panel model. Moreover, we also perform a cross-sectional analysis as our data consist of only three years, which may not provide the best results for panel data analysis. The non-spatial fixed effect panel model suggests that the number of bank branches per 100 km2 positively affects income inequality. However, the number of bank branches per 100.000 population as the measure of financial development shows an insignificant result. The cross-sectional OLS regressions on each year also suggest the income-widening effects of financial development for both measures of financial development. Thus, we can conclude that financial development leads to increasing income inequality.

Discussion

The primary conclusion of this study indicates that higher financial development is associated with increasing income inequality. We also find an inverted U-curve relationship in the model with the number of bank branches per 100 km2 to proxy financial development. Those findings support the theoretical prediction by Greenwood and Jovanovic (1990). In the initial stage of development, when the financial system is less sophisticated, financial development will exacerbate income inequality. It needs to reach some level of development before it may successfully reduce income inequality. The results also confirm the empirical findings from the previous study in Indonesia (Khainurrafik, 2021), which used provincial income inequality. The main insight from the findings is that financial development tends to benefit the wealthy more, which is then related to the rise of income inequality as previously suggested by several studies (Nikoloski, 2013; Kim & Lin, 2011). The effect would turn at some level of financial development, marked by a more advanced and inclusive financial system. Those findings emphasise that policymakers should accelerate the improvement of the financial system to meet its objective of reducing income inequality through financial development, which is one of the main objectives of the Indonesian National Financial Inclusion Strategy (NFIS). Based on the exploratory spatial data analysis findings, the presence of high-Gini clusters at the spatial distribution indicates the dependency across regions. Then, coordination and collaboration between municipalities to create appropriate policies may help to counter possible immoderate income inequality.

Access to financial products, particularly credit, should be made available and easy for the lower level of economic society. As an important tool for people entering higher-risk businesses, credit affects employment, wages, entrepreneurship, and income distribution (Giné & Townsend, 2004). However, many poor people often need help accessing those services from financial institutions due to insufficient collateral and a lack of credit records. Data from Susenas 2020 shows that approximately merely 10.8 per cent of households from the lowest 40 per cent of income receive credit from banks, while around 14.5 per cent of the top 20% of income receive credit from banks. To make it more contrast, only 8.6 per cent of the poorest 10 per cent of households use credit from banks, while that number of the richest 10 per cent reached 14.2 per cent. The stark contrast of households who utilised bank credit shows that financial development may still benefit more wealthy people who already have access to the financial system. Less wealthy may be forced to access credit from non-banks which offer less collateral but with higher interest. Improving the microfinance market should be considered to provide less wealthy people access to credit to make new investments and grow faster. Bangoura et al. (2016) suggest that microcredit may help impoverished people improve their income, leading to lower income inequality.

Regarding the econometric results on the number of bank branches per 1002 km land area as the proxy for financial development, policymakers may create policies to improve the geographical coverage of financial services. Collaboration between government and private banks is necessary to make the expansion of the financial institution to less dense regions possible. Therefore, banks and other financial institutions with their branches or other service points are within reach for all populations, particularly those living in underdeveloped regions. Data from Podes 2020 shows that roughly 40 per cent of the districts do not have bank branches. Comparing the Java and non-Java regions, around 89 per cent of the districts in Java has at least one bank branch, while only 53 per cent of districts have at least one active bank branch in the regions outside Java. Those data indicate that the distribution of the financial service locations of banks is still unequal geographically. Often, the nearest bank branches are located far away from the villages, which requires extra transportation costs. Households' access to financial services location is crucial for people to get credit since a survey is often necessary for banks to approve the loan to consumers. Thus, increasing access to bank branches geographically could improve the chance for people in less developed areas to receive credit.

CONCLUSION

This study investigates the financial development-income inequality nexus, which remains a widely debated issue in policymaking discussions. Despite policies regarding financial development targeting a reduction of income inequality, empirical works suggest mixed findings on the effects of financial development and income inequality. We investigate the relationship using municipality-level data covering 514 municipalities in Indonesia over the period 2018-2020. Our main contributions to the literature lie in applying spatial considerations to the analysis and the usage of municipality-level rather than provincial data. The global Moran's I statistics revealed the presence of spatial autocorrelation and clusters of similar values of Gini coefficients in Indonesia. Furthermore, the LISA reveals the spatial distribution of clusters with relatively high Gini values and those with relatively low Gini values. Low Gini clusters were apparent in Sumatra, while clusters of high Gini coefficients dominated Java and Papua. Furthermore, our spatial econometrics analysis results suggest the income-widening effects of financial development by implementing the Spatial Durbin Model (SDM). The findings are consistent with the inverted U-curve theory which predicts income inequality will worsen in the early phase of financial development.

Policy implications regarding financial development policies which aim to reduce income inequality may consider the findings from this study. Albeit our findings support income widening effects of financial development, that does not mean that better financial system disbenefits the poor (de Haan & Sturm, 2017). Following the theory, Indonesia's financial system may need to be more advanced to improve capital allocations, leading to lower income inequality. The findings corroborate the necessity to accelerate financial development, particularly policies aiming to improve financial inclusion. The policies should be able to improve access to financial institutions for all parts of society regardless of their location, as the findings show that the density of financial institutions significantly affects income inequality. Hence, continuous, and sustainable financial development may help reduce income inequality as it become one of the SDGs' targets.

The limitation of this study is the use of a relatively short period of data due to the availability of data on an annual basis. A longer data period in the following years may provide stronger evidence of this financial development-income inequality nexus. Furthermore, the spatial weight matrix choice is always a central issue in spatial econometrics. This study applies an inverse distance matrix solely based on the physical distance of the municipalities' centroid, which may not be the best approach to measure the distance between municipalities. Further study may also consider the form of an archipelago of Indonesia since the distance measured between regions on the same island should be different from the distance across islands. It could be in the form of differentiating how to measure the distance between neighbours located on the same island and neighbours on different islands or measuring the distance based on driving time.

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