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HAVE DIGITALIZATION AND CREDIT ACCESS ACCELERATED GROWTH PERFORMANCE IN EAST JAVA? : A SPATIAL ECONOMETRIC AND GOOGLE TREND ANALYSIS

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ABSTRACT

This article evaluates the effect of digitalization and credit access in boosting regional growth performance across 38 districts in East Java over the 2010-2021 period. Using google trend analysis, we capture the pattern and spatial distribution of main explanatory variables, which are digitalization and credit access to support our empirical findings. Results show that overall the google trends' portraits indicate adequate similarities in credit access, which declare the negative yet significant effect to growth. We also find interesting findings to be highlighted for internet access. Both google trends and empirical data show negative correlation between digitalization and credit access. From the standpoint of spatial spills-over effect, there is significant and positive spatial autocorrelation in internet access across districts in Indonesia. Applying spatial econometric model, two key factors appear to boost economic growth in the recovery period, which are digitalization and education-related variable. This article concludes that digitalization can not work itself. The inclusion of spills-over effect and spatial dependence across districts is needed to accelerate regional growth. Thus, from policy perspectives, our findings suggest that spatial-based policies by combining digitalization with human capital are more appropriate to boost growth performance in East Java.

Keywords: *Digitalization; Credit Access; East Java; Google Trend; Spatial Econometrics*

ABSTRAK

Artikel ini mengevaluasi pengaruh digitalisasi dan akses kredit dalam mendorong kinerja pertumbuhan daerah di 38 kabupaten di Jawa Timur periode 2010-2021. Menggunakan analisis Google trend, kami menangkap pola dan distribusi spasial variabel penjelas utama, yaitu digitalisasi dan akses kredit untuk mendukung temuan empiris kami. Hasil menunjukkan bahwa secara keseluruhan potret Google trend menunjukkan kesamaan yang memadai dalam akses kredit, yang menyatakan efek negatif namun signifikan terhadap pertumbuhan. Kami juga menemukan temuan menarik untuk disoroti untuk akses internet. Google trend dan data empiris menunjukkan korelasi negatif antara digitalisasi dan akses kredit. Dilihat dari spill-over effect spasial, terdapat autokorelasi spasial yang signifikan dan positif pada akses internet antar kabupaten di Indonesia. Dengan menerapkan model ekonometrika spasial, muncul dua faktor utama yang mendorong pertumbuhan ekonomi pada masa pemulihan, yaitu digitalisasi dan variabel terkait pendidikan. Artikel ini menyimpulkan bahwa digitalisasi tidak dapat berjalan sendiri. Dimasukkannya spill-over effect dan ketergantungan spasial antar kabupaten diperlukan untuk mempercepat pertumbuhan daerah. Dengan demikian, dari perspektif kebijakan, temuan kami menunjukkan bahwa kebijakan berbasis spasial dengan menggabungkan digitalisasi dengan sumber daya manusia lebih tepat untuk mendorong kinerja pertumbuhan di Jawa Timur.

Kata Kunci: *Digitalisasi; Akses Kredit; Jawa Timur; Google Trend; Ekonometrika spasial*

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Introduction

Economic development is an ongoing issue in both the government and private sectors. The new normal era changes human activities and lifestyles around the world. The government and the private sector have to plan the economic policies to survive. East Java Province has a strategic role in the national economy. Its geographical position is a gateway for the economy of the eastern region of Indonesia giving the benefit for East Java especially as both an industrial center and a trade route. According to Statistics Indonesia, the contribution of Jawa Timur to national GDP is about 14.48 percent and to Java, Bali and Nusa Tenggara (Jabalnusra) region is about 25.01 percent in 2021. Its contribution is in second place after DKI Jakarta. Economic growth rate of Jawa Timur is about 3 percent as well as when compared to the national rate and other provinces in java such as DKI Jakarta, West Java and Central Java. During the COVID-19 pandemic, the economy of East Java contracted about 2.33 percent in 2020 and accelerated in 2021 about 3.57 percent. The economic structure of East Java is mainly driven by several industries including the manufacturing industry, trade, and agriculture. During the pandemic, the agricultural industry had a positive growth rate despite a slowdown while the manufacturing and trade industries contracted. However, in 2021 these three industries accelerated.

The economic potential of East Java based on the input output table analysis has several leading commodities in the agricultural industry and manufacturing industry, including sugarcane, animal feed, slaughtering animals, cattle, goats, sheep, and chickens, ice cream industry, rice milling industry, processing industry. rice, and the cigarette industry (Nurhayati & Suryantini, 2015). The economic in East Java spatially is leaded by City of Surabaya (24.07 percent), Sidoarjo Regency (8.56 percent), Pasuruan Regency (6.32 percent), Gresik Regency (5.83 percent), the City of Kediri (5.75 percent), Malang Regency (4.43 percent), Mojokerto Regency (3.56 percent), and Banyuwangi Regency (3.52 percent). Meanwhile, the other regency/city have an aggregate contribution less than 3.5 percent. This fact shows that the economy of East Java is concentrated in the city of Surabaya and its surrounding area. The manufacturing industry, which is supported by around 30.72 percent to the East Java economy, is also clustered in Surabaya and its surroundings. It is in line with research by Kyswantoro (2016) that the manufacturing industry as the leading sector tends to be concentrated in Gresik - Surabaya - Sidoarjo which is also supported by the availability of facilities and easy access to input sectors (backward linkages) and other sectors. The agglomeration of the East Java economy in some areas is caused by a spillover effect of the growth pole. Sidoarjo and Gresik regencies receive the highest growth spillover effect from the city of Surabaya (Wibisono & Kuncoro, 2015).

The inequality of East Java economy spatially is also caused by various factors. Solow's growth theory states that output and growth over time are also influenced by factors of capital, labor, and technological progress. The main focus of the Solow growth model is not on capital and labor growth but focuses on technological advancements and improving the skills of its workforce.

The population of East Java in 2020 is widely spread in the city of Surabaya and other areas that have a high contribution to the East Java economy. These areas also have the high education quality which is proxied by the mean school years (RLS) above 10 years while other areas even below 10 years and many areas below the province rate (7,88 years). These pole economic areas also have a higher coverage of information technology than other areas. These coverage of information technology is approached by a variable population over five years old who access the internet. These facts show that there are inequality and disparities of human capital and technological developments in East Java spatially.

One of the local government policy in dealing with economic equity in East Java is develop a Regional Spatial Plan (RTRW) which divides 38 regencies/cities into 9 Development Area Units (SWP), including Gerbangkertosusila Plus, Malang Raya, surrounding Madiun, Kediri and its surrounding, Probolinggo-Lumajang, Blitar, Jember and its surrounding, Banyuwangi, and Madura Islands (Yordani & Sugiarto, 2016). Each SWP has an urban area as a source of growth and supports the surrounding area to grow. It is relevant to Richardson's theory about growth poles (1978: 164–165) which is considered capable of creating dynamic economic growth as a result of the application of high technology and the rapid growth rate of innovation with close inter- sectoral relationships and providing a spillover effect from growth centers to surrounding regions. In this regard, the information and communication sector grows along with the development of technology. Ease of access to information is experienced by various groups, both across ages, education, and professions.

Moreover, during the last 5 years, even during the COVID-19 pandemic, the information and communication industry had a positive growth rate above 5 percent both at the East Java level and in all districts/cities. This fact is also in line with the increasing e-commerce activities. Since 2017, there have been around 70.8 million e- commerce users and it grows every year. Statista predicts the e-commerce users will reach 180.6 million users by 2024 (Christy, 2020). In East Java, enterprises using e-commerce reached 467,996 business units in 2020 or around 19.82 percent of all e-commerce businesses in Indonesia with the education background of users dominating the high school/vocational/equivalent education (BPS, 2021). This potential will continue to grow along with the increasing number of centers of economic growth and spillover effects between regions, both as inputs and outputs between sectors. A previous study conducted by Falentina et al. (2020) regarding the digitization and performance of micro and small enterprises in Yogyakarta showed that internet utilization has enabled Micro and Small Enterprises to engage in the digital economy and has improved labor productivity and exports. The associated monetary benefit due to internet utilization is substantial for local people.

Moreover, the ease of access to credit funding for small and micro enterprise (KUR) and credit funding to group enterprise (KUBE) for the poor has become an economic stimulus to the micro scale. The collaboration between information technology that encourages the culture of e- commerce and the ease of funding for Micro and Small Enterprises boost the economy growth and spatial effect on surrounding regions.

The use of the internet in daily life through various platforms and devices produces the data in big volume, big variety, and big velocity. We can call these concepts big data. One of the utilizations of big data is analysis by google trends. Google is the most popular company that leads the internet development. Google records the activity of users in search engines and quantifies automatically as an index of Google Trends. It can be studied and analyzed for various purposes like adsense, business, marketing, and others. The Google Trends index is useful to support analysis as has been done by previous research including predicting car purchases, retail sales, and housing purchases in America (Choi & Varian, 2012), estimating unemployment in Spain (Vicente et al., 2015), and GDP forecasting (Patricia, 2021). Figure 1 is the Google Trends index from January 2010 to December 2021 in East Java and Indonesia which shows the number of searches for the keyword "Kredit Usaha Rakyat" on Google. The search rate of the keyword "Kredit Usaha Rakyat" increased until December 2021, both at the national level and at the East Java level. This is in line with the recovery of the national and regional economy in the fourth quarter of 2021. The pattern of these indexes in East Java and Indonesia is similar. It means that the keyword "Kredit Usaha Rakyat" is a hot issue at the national and regional level.

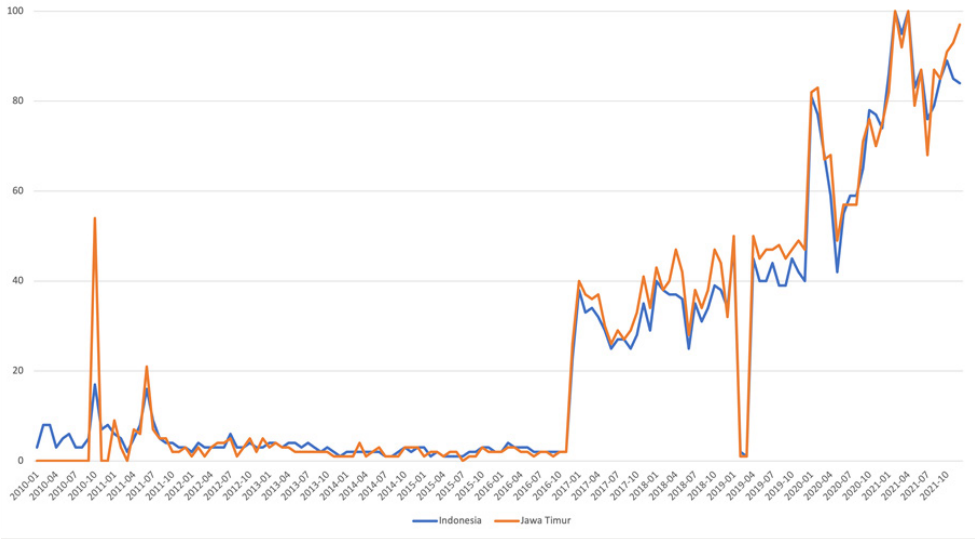


Figure 1: Google Trends with Keywords "Kredit Usaha Rakyat" in East Java and Indonesia

Based on these explanations, this research focuses on how digitization and credit funding can encourage economic growth based on Solow's growth theory by involving spatial effects andthe support of google trends.

Literature Review

Regional Disparities in East Java

Regional disparities according to the ILO (International Labor Organization) are differences in economic performance and welfare between regions. According to Karin Vorauer (2007) in Aprianoor & Muktiali, (2015), regional inequality is an imbalance in the spatial structure within a region or between regions. East Java has 38 regencies/cities which are the largest number in Indonesia. This gives rise to cultural differences that make the economic activities of each region different, thus making the economic performance between regions in East Java indicated to be different. Research on regional inequality in East Java was conducted by Islami & Nugroho (2018) about the factors that influence it, namely investment, labor force, and the human development index. In addition, research has also been conducted by Noto (2016) who concluded that the factors that influence regional inequality in East Java include the regional minimum wage, the working force, the human development index, and government spending.

Growth Theories and Its Determinants

According to Solow's Growth Theory, economic growth depends on availability of factors of production: population, labor and capital accumulation and the level of technological progress. This model explains that the technology used determines the amount of output produced from a certain amount of capital and labor.

Its theory presented in the Cobb-Douglas function emphasizes the role of capital formation as one of the important factors in growth. Solow (in Jhingan, 1983; Mankiw, 2007) emphasizes long-term growth and the role of capital, labor and technology as factors of production. Furthermore, according to Solow, growth will occur if there is capital, there is population growth and there is technology, although technology is still considered as an exogenous factor. Thus the production function can be formulated into the following Equation:

$$Y = F(K, L\,x\,E) \quad (1)$$

where E is a variable called labor efficiency. L x E measures the number of effective workers taking into account the number of workers L and efficiency of each worker. This production function states that the total output Y depends on the number of units of capital K and the number of effective workers L x E. This means that the increase in labor efficiency E is in line with the increase in workforce L (Mankiw, 2007). In this model, savings will encourage temporary economic growth, but increasing returns on capital decline will ultimately encourage the achievement of a stable economy that will depend on technological progress (exogenous).

The Use of Big Data to Deliver Phenomenon

Big Data is a wealth (asset) of information that has large volumes, high speeds, and large variety, which demands innovative and cost-effective forms of information processing, which can be used to improve insight and quality of decision making (Gartner, 2014). Big Data is a popular phrase used to describe a massive volume of structured data and unstructured data, which due to their size is difficult to process with traditional database and software techniques. The characteristics used to distinguish Big Data from ordinary data are the presence of a larger 3-V or Volume, more Variety and higher Velocity (UN Global Pulse, 2012).

The use of big data in the digital era is starting to be widely used to support official statistical data. Research using big data has been conducted by Duha et al. (2022) regarding the implementation of big data technology in the digital era, stating that companies involved in the business sector can take opportunity of the valuable information provided by Big Data to optimize the process of decision-making, so that the target is to maximize profits. Meanwhile, institutions involved in public services can use information output from Big Data to optimize the level of service satisfaction to their clients/customers. In addition, research on the use of big data was also conducted by Putra & Wulandari (2021) on the use of MPD in estimating economic growth which concluded that an approach in predicting economic activity in Indonesia is represented by the value of Gross Regional Domestic Product (GRDP), which is approximated from the measurement value based on Mobile Positioning Data (MPD). By using the OLS method and cluster analysis, the research shows that MPD can be a good predictor of provincial GRDP, especially during pandemic conditions.

Methods, Data and Stylized Facts

Exploratory Spatial Data Analysis (ESDA)

Several statistical tests have been guiding the way to evaluate the existence of spatial dependence in a dataset. The most popular one is Moran's I test, which can be defined as:

$$I_x = \sum_i \sum_j w_{ij} \cdot (x_i - \mu) \cdot \frac{(x_j - \mu)}{\sum_i (x_i - \mu)^2} \quad (2)$$

where w_{ij} reflects the spatial structure of the data, and it is derived from a spatial weight matrix, x_i is the value of the variable x at location-*i*, x_j is the value of the same variable at location j, and μ is the cross-sectional mean of the data. Statistical inference for Moran's I can be applied using both a simulation of a reference distribution and an assumption of normality based on random permutation (Anselin, 1995).

A local analysis of spatial autocorrelation equilibrates the analysis of global dependence by identifying the specific location of spatial clusters and outliers. Specifically, local spatial patterns such as hot spots (cluster of high values), cold spots (cluster of low values), and

spatial outliers can be delivered using the methods developed by (Anselin, 1995). The local version of Moran's I for each spatial unit defined as:

$$I_i = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij} \cdot (x_j - \mu) \quad (3)$$

Statistical inference is based on a conditional permutation approach. One of the most appealing features of local spatial dependence analysis is those statistically significant values can be plotted in a map. Thus, it greatly facilitates the spatial identification of hot spots, cold spots, and spatial outliers.

The Use of Google Trend Analysis

Google trends provides access to a mostly unfiltered sample of search queries on google. This sample search query data is anonymized (none is personally identifiable), categorized (determining the topic of the search query), and grouped/aggregated. *Google trends* makes it possible to show interest in a particular topic from around the world, or to a specific geographic area of a country. There are 2 (two) sample data provided by *Google Trends*:

a. Real Time Data, sample data covering the last 7 (seven) days.

b. Non-Real Time Data, sample data separate from Real Time Data, i.e. from 2004 to 36 hours prior to tracing.

There are several things that need to be underlined when using google trends data. *Google trends* data has the potential to predict in the short term, but not in the long term. Google trend data is still rarely used to predict macroeconomic variables such as inflation, industrial production and others. However, in line with the development of research using *google trends* data, severalliteratures/ references were found that conducted research using *google trends* to predictmacroeconomic indicators (Nooraeni et al., 2019).

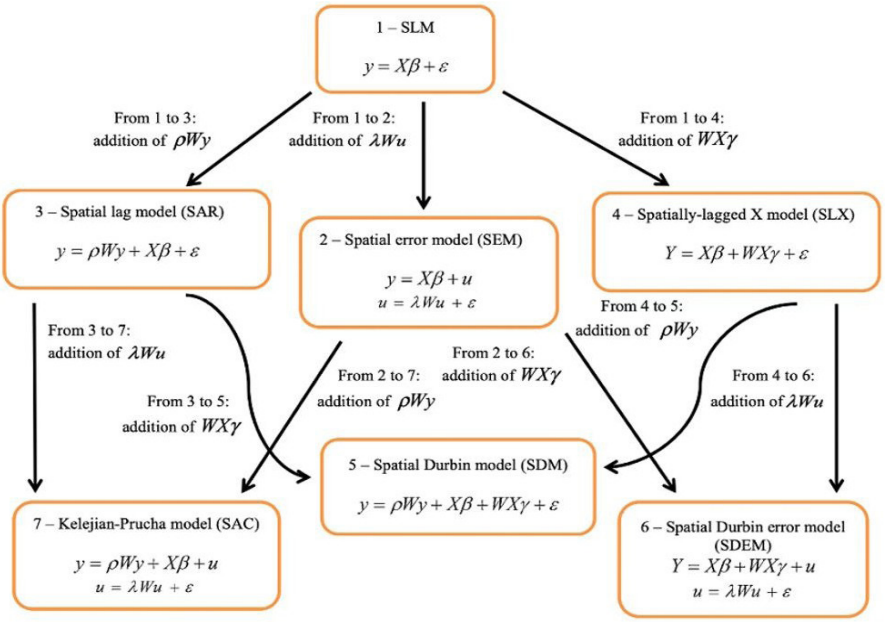
Previous research on *Google Trends* conducted by Nuti et al. (2014) on the use of google trends in health care research concluded that *google trends* can be used to study health phenomena in various topic domains. in many ways. *Google trends* has the potential to be a free and easily accessible tool for accessing search data of large populations to gain meaningful insights into population behavior and its relationship to health and healthcare. However, *Google Trends* has a weakness, namely the lack of transparency so thatthe results of the analysis are inconsistent, so that more transparency is needed from the *GoogleTrends* data by multiplying keywords.

Spatial Panel Models

Recent growing studies take attention to the role of spatial dependence in economies among countries (Fingleton & López-Bazo, 2006; LeSage & Fischer, 2008). These concerns may emerge due to pecuniary externalities from the neighbour regions. Those externalities consist of spatial lag and spatial errors. The spatial externalities ought to be included in the regression, since if it is not fulfilled, it will provide inconsistent and biased estimates. Inaccurate correlation between explanatory variables and spatially lagged dependent variables tend to generate overestimated or underestimated parameters.

The development of spatial convergence has mostly been reviewed in the spatial econometric literature over the past years. Nevertheless, in the present study, we just address some prominent and important spatial econometrics methods. Figure 4.1 summarizes all the

specifications of the spatial regression framework through the scheme suggested by Golgher and Voss (2016):



Source: Figure 2 is adapted from Golgher and Voss (2016)

Figure 2: Some spatial methods

Sub-national level studies provide a better look at the differences among regions in the same country. For example, Rey & Montouri (1999) evaluate the United States covering states over the 1994-2004 periods. They use an unconditional convergence model, which assumes that the growth is only affected by the initial income level as the explanatory variables. They reveal the existence of spatial autocorrelation and conclude that the spatial effect is associated with regional incomes in the country. Another growing body of literature which includes Bernat (1996), Funke & Niebuhr (2000), and Arbia et al. (2003), drew attention to panel studies on state- based spillovers in West Germany, Italy, and the United States.

Fewer researchers evaluate the outcomes for developing countries at the sub-national level. These issues come from the constraint in data availability. Among these few studies, Magalhaes et al. (2005) evaluate growth in Brazilian states encompassing over the 1975-1995 periods and examine the existence of spatial effects by applying a convergence regression. Results found that spatial autocorrelation existed on growth rates among the states in Brazil. A study across Chinese regions by Ying (2003) applied a spatial convergence model to a data set covering the 1978-1998 periods to examine the spill-overs effect on GDP growth among Chinese regions. The findings suggest that there are significant coefficients of GDP growth in neighboring regions, leading to polarization, which affects the growth of more developed regions and harm of peripheral regions.

Recent studies show growing interest in the relationship between spatial spillovers and regional growth performance. Tian et al. (2010) and Bai et al. (2012) reveal that the externalities factor positively influences economic growth in a region in China. Also, the studies of Cravo et al. (2015), Resende et al. (2016), and Lima & Silveira Neto (2016) studied economic growth convergence at the sub-national level in Brazil and revealed the existence of spatial spill-over effects on growth. Torres-Preciado et al. (2014) presented that spatial dependence in terms of per capita income is found across Mexico regions. Spatial growth spillovers were also emphasized by Mohl & Hagen (2010) and Cuaresma et al. (2014) through studies of European regions.

There are numerous studies attempting to incorporate spatial effects into growth models at the sub- national level, specifically in Indonesia (Rumayya et al., 2005; Mcculloch Bambang & Sjahrir, 2008; Day & Lewis, 2013; Day & Ellis, 2014). However, all of those studies only concern on the economic condition of neighbouring regions, neglecting other spillover effects. Mcculloch Bambang & Sjahrir (2008) documents that the closeness to a growing region has increased economic growth. Rumayya et al. (2005) found that spill-over effects, spatial clusters, and spatial outliers occurs on GDP per capita, showing the distinct administrative classification into two main groups: poor and rich groups. The findings of Day & Lewis (2013) suggest that various spillover effects affect a region through different stages. Moreover, assuming various stages in growth regressions leverage the effectiveness of those models. The findings show that spatial effects exist not only on GRDP growth but also on and infrastructure, human capital, and demographic variables. There are significant spatial effects across Indonesian districts regarding those conditioning factors.

Data

As seen in Table 1, regional development in this paper is measured through GDP growth in East Java over the 2012-2020 period. We employ the change of access to credit and the change of access to internet as our key explanatory variables. Following the original Solow growth model, we append physical capital, human capital, and population as the control variables. All data are obtained from the Central Bureau of Statistics of Indonesia.

Table 1: Data and sources

Name	Description	Source
GDP growth	The change of GDP during 2010-2021	BPS
Change in access tointernet	The difference of percentage household accessinternet in a district from t to t-1	BPS
Change in accessto credit	The difference of percentage household accesscredit for business in a district from t to t-1	BPS
Change in investment share	The difference of public investment ratio to GDP(percentage point) from t to t-1	BPS
Change in population	The difference of number of populations betweenfinal and initial year (in person) from t to t-1	BPS
Mean Years of Schooling	Average number of completed years of education of a country's population	BPS

The data used, before the analysis is carried out, it is necessary to know how the general description uses descriptive statistics. The discussion regarding the characteristics of the data used is shown in Table 2.

Table 2: Descriptive statistics

Variable	Symbol	N	Min	Max	Mean	Std. Dev
Growth of GDP (%)	g_GDP	418	-6.460	21.950	4.955	2.937
Change in Access to Internet	chg_inet	418	-7.250	12.760	3.283	4.375
Change in Access to Credit	chg_credit	418	-42.360	33.790	-1.286	7.940
Change in Investment Share	chg_inv	418	-0.613	0.666	-0.003	0.087
Change in Population	chg_pop	418	2283	-166.675	155.059	50814.12
Mean Years of Schooling	mys	418	23.54	32.77	9729.80	24215.19

Table 2 shows that the average economic growth of 38 districts/cities in East Java for the 2010-2021 period is 4.955 percent. This value is below the average economic growth of East Java itself in the same period, which is 4,968. During the period 2010 to 2021, the low-

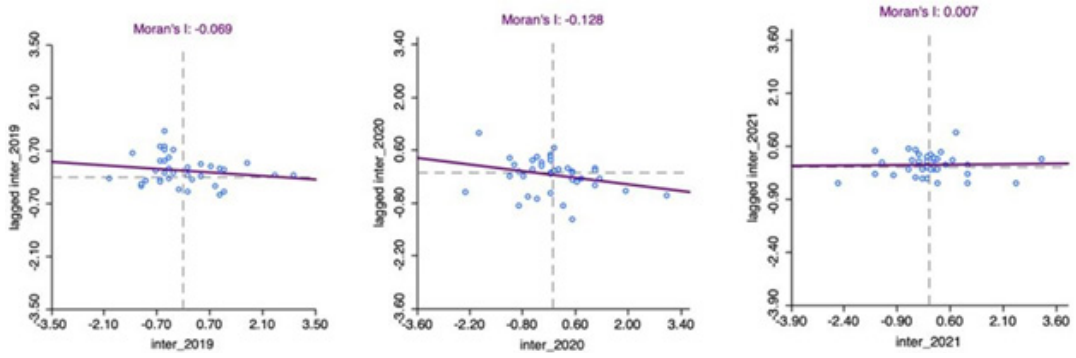
est economic growth was in Batu City in 2020 of -6.460 while the highest was in Bojonegoro Regency in 2016. The distribution of economic growth in districts/cities in East Java was 2.937 during the 2010- 2021 period. This shows that the variability of economic growth in East Java still tends to be high, so that it can be said that there is an imbalance in the economic area in East Java in terms of economic growth.

In the variable of change in the percentage of the population aged 5 years with internet access, the variation that is formed also tends to be high with a variance value of 4.375 where the average is 3.283 percent. The highest percentage change was 12.760 percent and the lowest was -7.250 percent. In the variable of change in the percentage of credit described in the People's Business Credit and Joint Business Credit, the average for the 2010-2021 period is -1.286 percent with a variation of 7.940. The highest percentage change was 33,790 percent and the lowest was -42,360 percent. In the variable of changes in investment share, the average is -0.003 with a variation of 0.087. The lowest change was -0.613 while the highest was 0.666. In the variable of changes in population, the average in East Java is 155.059 with the highest change of 2283 and the lowest of -166.675. The variance of the spread is 50814.12 which is a very high number for the distribution. For the variable mean years of schooling, the average in East Java is 9729.80 with a very high variability as well as 24215.19 percent. The highest change was 32.77 and the lowest was 23.54.

Stylized Facts

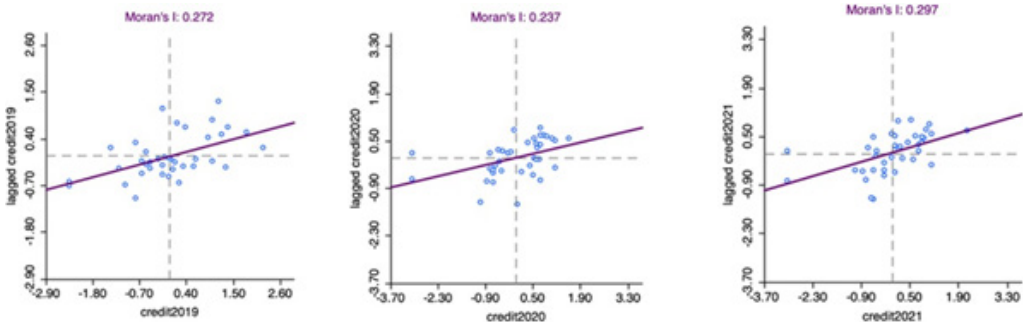
Moran's Scatter Plot across Years for Internet Access, Credit Access, and GDP per Capita using Google Trend

Figures 3, 4, 5 and 6 present apparent trends of global spatial autocorrelation. Global spatial autocorrelation is evaluated based on the value of the Moran's I indicator. Figure 3 and 4 using data from google trend analysis, meanwhile figure 5 and 6 using empirical data.



(a) (b) (c)

Figure 3: Moran's Scatter Plot for Internet Access using Google Trend, 2019-2021

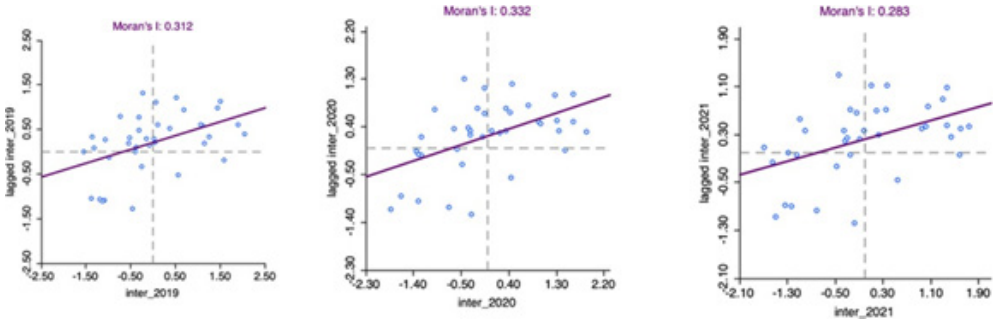


(a) (b) (c)

Figure 4: Moran's Scatter Plot for Credit Access using Google Trend, 2019-2021

In figure 3, we find that internet access using google trend data has a low global spatial autocorrelation with the rate of Moran's I close to zero point. In 2019 and 2020, it showed a negative pattern but turned to positive pattern in 2021 although providing a low spatial autocorrelation. This implies the positive role of internet access on growth in the transition of new normal era, as information and communication technology has been drastically penetrating.

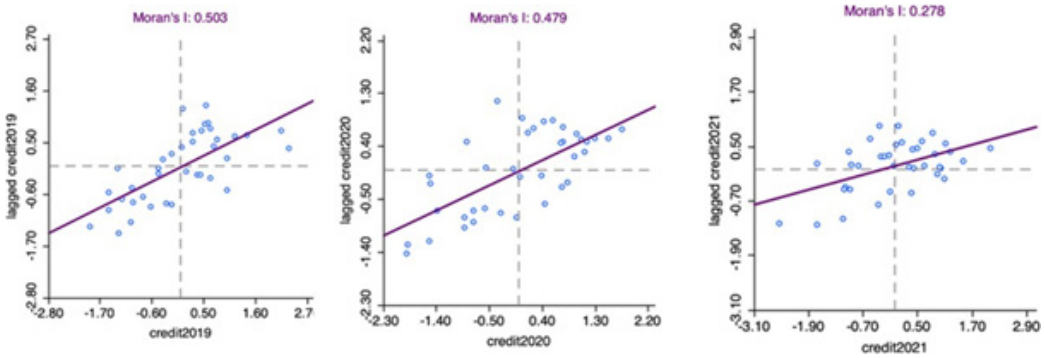
In figure 4, we find that credit access using google trend data has a moderate global spatial autocorrelation with the rate of Moran's I between 0,2 to 0,3 point. The pattern shows a positive and persistent pattern during 2019-2021 period.



(a) (b) (c)

Figure 5: Moran's Scatter Plot for Internet Access using Empirical Data, 2019-2021

In figure 5, we find that internet access using empirical data has a moderate and positive global spatial autocorrelation with the rate of Moran's I. Moran's I statistics during 2019-2021 is higher than that of google trend data. google trends data have the positive pattern of Moran's I in recovery period.



(a) (b) (c)

Figure 6: Moran's Scatter Plot for Credit Access using Empirical Data, 2019-2021

In figure 6, we find that credit access using empirical data has a positive global spatial autocorrelation with the rate of Moran's I. Its pattern is similar to google trend data.

Based on these figures, we find that the global spatial autocorrelation have the low Moran's I rate both google trend and empirical data from 2019-2021. The similar pattern and direction also supplement each other.

Local Indicators of Spatial Autocorrelation (LISA)

The analysis of local spatial autocorrelation proposed by Anselin (1995) is recommended to allocate the existing clustering patterns and find out both spatial clusters and spatial outliers. In general, as proposed by Anselin et al. (2007), there are four notable features generated from LISA analysis. It consists of two spatial clusters (hot-spots and cold-spots) and two spatial

outliers (high-low clusters and low-high clusters). Hot-spots are the clusters with high values of observations surrounded by other high values of observations, while cold-spots are the clusters of low values surrounded by other low values of observations). Meanwhile, high-low clusters are groups of high values rounded by other low values of groups. Low-high clusters are groups of low values rounded by other high values of observations. In this study, the application of LISA refers to the work of Kondo (2015), who divide clusters only based on two most common features; hot- spots with 1% and 5% significance level and cold-spots with 1% and 5% significance level.

Figure 7-10 below shows the spatial distribution of internet access and credit access both using empirical data and google trend.

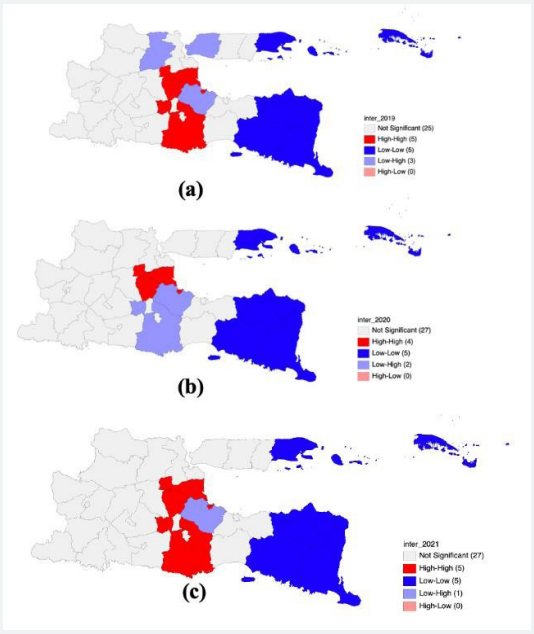


Figure 7: LISA of Internet Access using Empirical Data,2019-2021

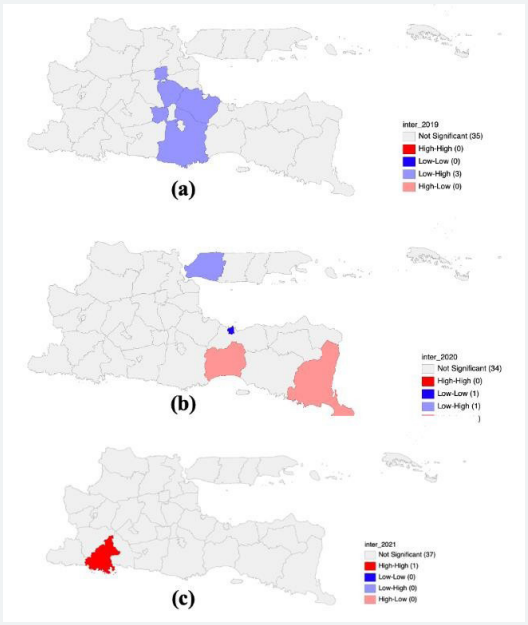


Figure 8: LISA of Internet Access using Google Trend,2019-2021

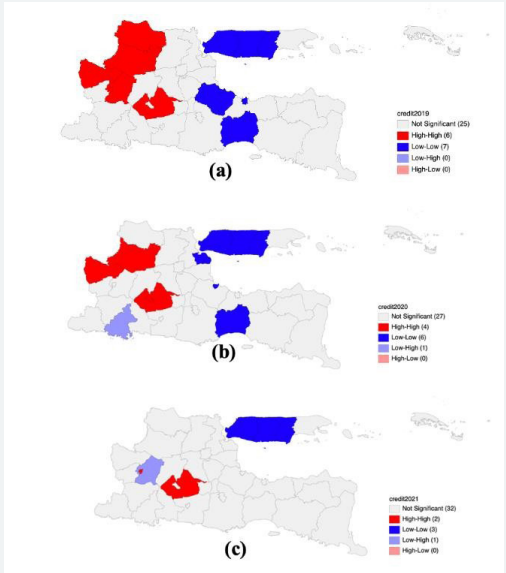


Figure 9: LISA of Credit Access using Empirical Data, 2019-2021

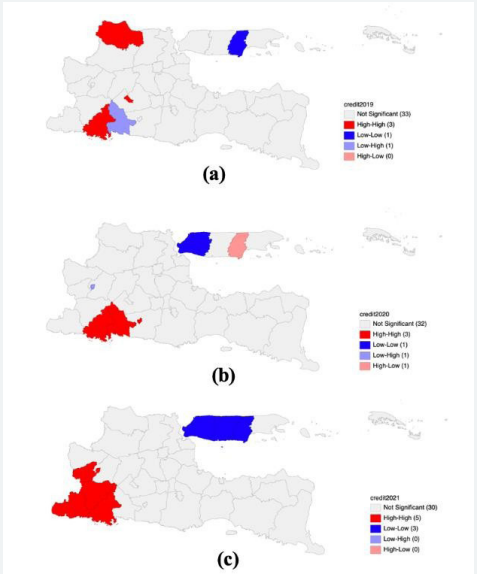


Figure 10: LISA of Credit Access using Google Trend, 2019-2021

Figure 7 and 8 indicate the pattern of internet access generated from Empirical Data and Google Trend. Both shows that there are spatial outliers, however only using empirical data we find cold-spots and cold-spots. It implies that although Google Trend data helps to capture and support the phenomena, empirical data analysis provides more fruitful information regarding the spatial mapping of dependence from digitalization.

The similar occurs with Figure 9 and 10 where the spatial distribution of credit access is portraited. However, on the spatial distribution of credit access, we can still find cold-spots and hot-spots both using empirical data and google trends. From these figures, we can conclude thatdata from google trends provide a similar pattern with empirical data from the perspectives of exploratory spatial data analysis.

Results and Discussion

Google Trends Analysis

Characteristics of Google Trends Data

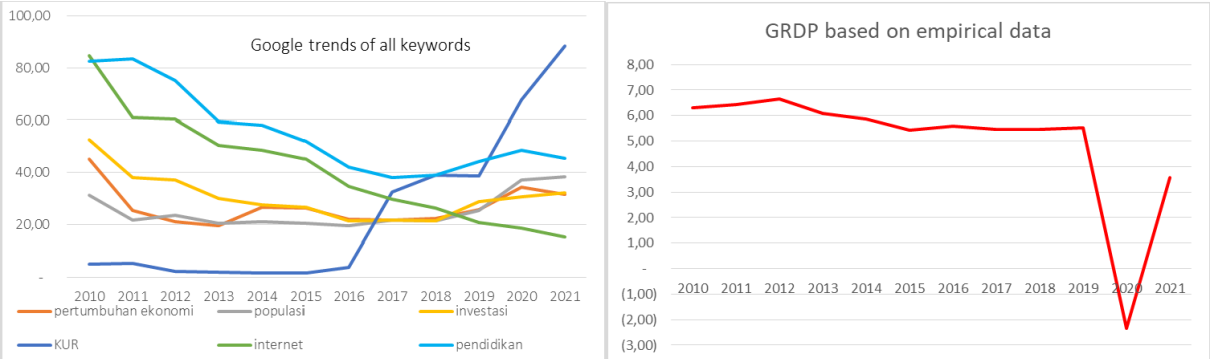


Figure 11: Google Trends of All Variables Based on Keyword Searches

First, we need to know how the google trends graph is based on each keyword against the GRDP figure in the province of East Java. From the graph, it is known that from 2011 to 2019, most keywords have the same pattern of direction as GRDP, except for “kredit usaha rakyat” which have surged since 2017. This is due to changes in people’s business credit policy targeting the production sector which began in that year, Initially, KUR was only intended for the trading sector. In 2020, some keywords have a pattern that is inversely proportional to the GRDP of East Java, except the “internet”.

Visually, the google trends index in the 2011-2019 follows the East Java GRDP pattern. This can be used to support empirical data, but in 2020 due to the COVID-19 pandemic, the pattern has changed.

Relationship between Variables (Using Google Trends)

In this study, the use of big data is used to support the results of the analysis of empirical data, namely google trends. The keywords used refer to the independent variables of empirical data, where the keywords used are “populasi”, “investasi”, “kredit usaha rakyat”, “internet”, and “pendidikan”. This google trends data is analyzed to see if it has the same pattern as the results of the empirical data correlation analysis. The pattern of the relationship between google trends data on economic growth in East Java is as follows.

In Figure 12, the relationship between the independent variables from Google Trends on economic growth tends to have the same pattern, namely clustering at a point. From this pattern, it is not known how the direction of the relationship is formed, so that a scatterplot is formed with a curve estimation with a linear model.

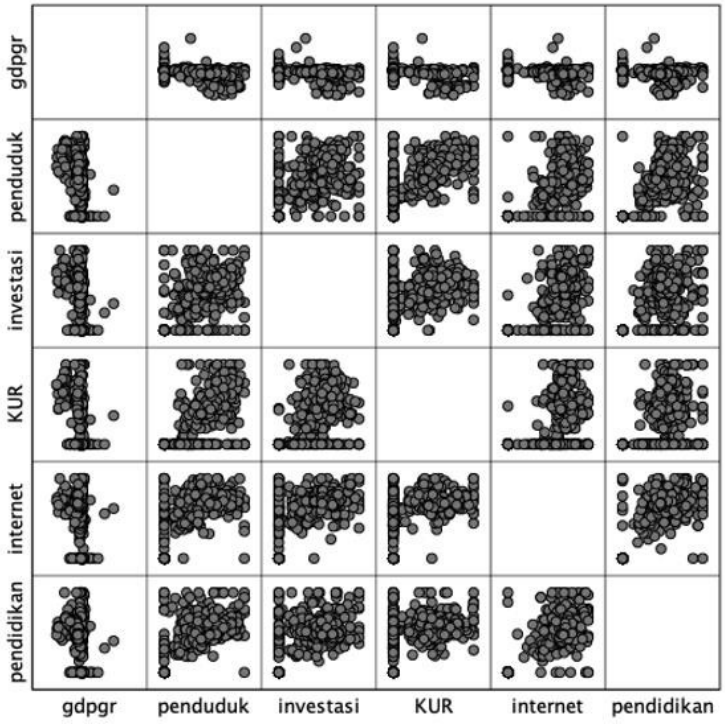


Figure 12: Scatter Plot across The Keywords of Google Trends and Dependent Variable

From the curve estimation in Figure 13, it can be observed that the pattern of google trends variable has an inverse relationship with economic growth. To know for sure the relationship between the google trends variable on economic growth, then look at the correlation coefficientfrom the following correlation analysis.

Table 3. Pearson Correlation across Google Trends and Dependent Variable

		penduduk	investasi	KUR	internet	pendidikan
gdpgr	**Pearson correlation**	-.439**	-.398**	-.414**	-.309**	-.270**
	Sig. (2-tailed)	.000	.000	.000	.000	.000

**. Correlation is significant at the 0.01 level (2-tailed).

Based on the results of the correlation in Table 3, it can be seen that all the keywords from google trends that are used to support official statistics are significant for economic growth in East Java. From the correlation coefficient, it can be seen that all keywords from Google Trends also have a non-unidirectional relationship with economic growth. This result is in accordance with the previously described curve estimation.

When compared with the results of the correlation of empirical data, the correlation coefficient has the same direction on the keywords “populasi”, “investasi”, and “kredit usaha rakyat”. For the keyword “internet” which represents the empirical variable the percentage of internet use in the population aged over 5 years and “pendidikan” which represents the empirical variable the mean years of schooling has a different direction of relationship with the results of the correlation of empirical data. This indicates that there is a discontinuity of public searches on Google with empirical data. While empirical data shows an increase, people’s searches for the keywords “internet” and “pendidikan” are decreasing. However, overall they still have the same pattern of relationships and have a significant relationship, so google trends data can be used to support the analysis.

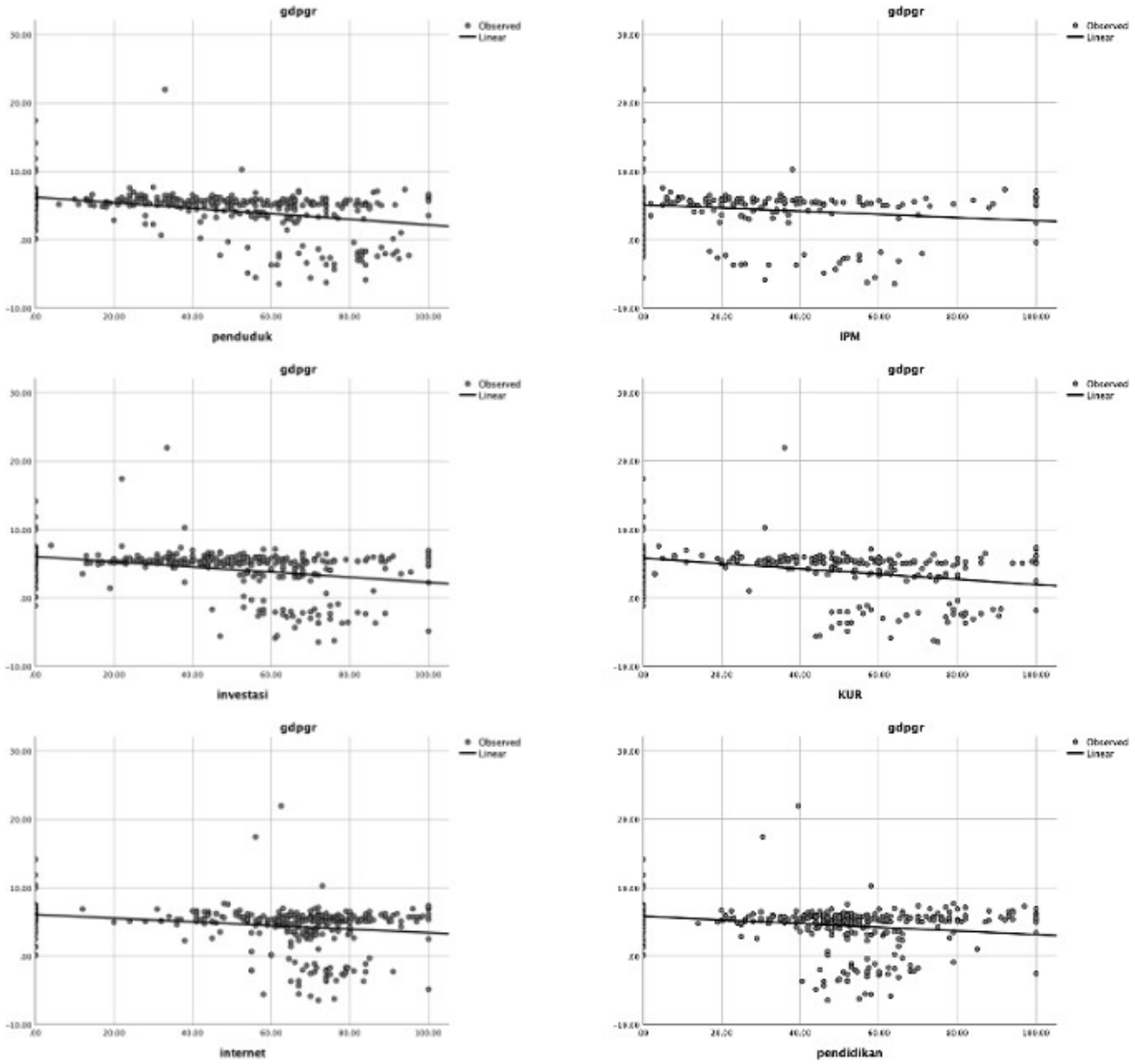


Figure 13: Curve Estimation of Regression across The Keywords of Google Trends and Dependent Variable

Panel Regression Model from Google Trends

Panel regression analysis was performed by Google Trends search on the economy in East Java. Google Trends data is compiled based on keywords consisting of "populasi", "investasi", "kredit usaha rakyat", "internet", and "pendidikan". The keywords are searched using the Indonesian language since our observation unit is located in Indonesia. In addition, Google Trends records people's search activities according to the keywords entered in Google searches, so that keyword searches are specifically made to only use Indonesian, which is more familiar.

Table 4: Panel Regression Test Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.306929	0.201306	31.33012	0.0000
PENDUDUK	-0.024722	0.007409	-3.336730	0.0009
INVESTASI	-0.028149	0.006696	-4.203744	0.0000
KREDIT_USAHA_RAKYAT	-0.017579	0.006284	-2.797541	0.0054
PENDIDIKAN	0.019711	0.006903	2.855545	0.0045

The panel regression results for the Google Trends index data show that there are only 4 keywords that are significant to East Java's GRDP, with the direction of the coefficients being inversely proportional, except "pendidikan". For example, people's business credit has a coefficient of -0.018, which means that every one unit increase in the Google Trends index will reduce East Java's GRDP by 0.018 percent. This is due to several assumptions, firstly because the public's interest shows negative sentiment, meaning that many people seek investment when the GRDP is down. The second assumption is that there is no spatial effect in panel regression, so it is necessary to model with a spatial model. Meanwhile, based on the results of panel regression with the Fixed Effect Model (FEM), the model formed is as follows:

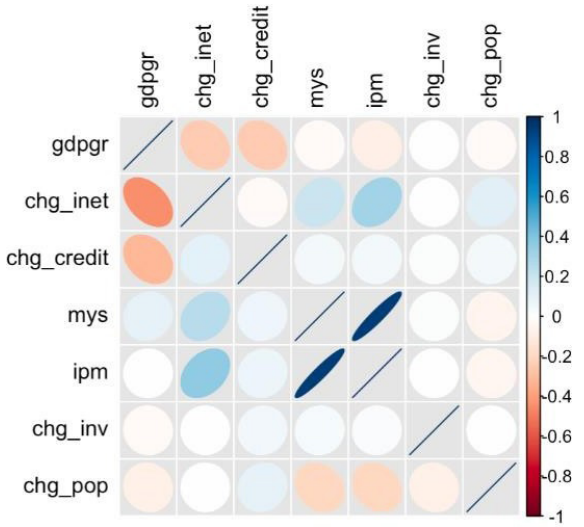
$$g\_GDP_{it} = 6.306929 - 0.024722\ (populasi)_{it} - 0.028149\ (investasi)_{it} - 0.017579\ (kredit\ usaha\ rakyat)_{it} + 0.019711\ (pendidikan)_{it} \quad (4)$$

where;

i = *38 regencies/cities in East Java Province*
t = *Period (year)*

The google trends analysis here does not involve empirical predictor variables. Therefore, to find out whether the use of the google trends index can support empirical data, a comparisonof the results of the analysis with empirical data is carried out.

Relationship between Variables (Using Empirical Data)



Exploration of dataset can be accessed through this link: https://chan912.shinyapps.io/application/

Figure 14: Correlation Matrix across Variables

Spatial Econometric Model

Testing Cross-sectional Dependence in Spatial Panel Models

Evaluating the pattern of spatial dependence is essential to estimate panel data models. When the time period (T) of the panel is larger than the cross-sectional dimension (M), we should use the Lagrange multiplier test. On the contrary, when T < M, the Lagrange Multiplier statistic does not fulfill any desirable statistical terms which indicate substantial size distortions. Thus, Pesaran's Test is preferable to cover that shortcoming. In this study, we use Pesaran's Test to examine the existence of spatial dependence in the panel poverty data. Based on Table 5, we can see that Pesaran's test results do not accept the null hypothesis of cross-sectional dependence's inexistence at 1% level of significance.

Table 5: Pesaran's Test Result

Variable	Statistics
Pesaran's Test statistics	74.261
Average absolute value	0.845
p-value	0.000***

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

By rejecting the null hypothesis of cross-sectional independence, we can conclude that our data (growth and its determinants) are spatially related to each other. It also supports the findings of global and local spatial autocorrelation in a similar direction, emphasizing that the spatial dependence across districts in East Java forces regions to respond to social, economic, and policy changes in a more similar fashion or direction.

Choosing the Best Model and Application of Region-Fixed Effect Spatial Model

In the literature, there is an emerging agreement to determine the best model to estimate. It should pass through some goodness of fit tests. In linear models, the AIC, BIC, $R2$, and Log- likelihood are commonly used. In this study, only AIC, BIC, and $R2$ are exhibited to cover the OLS estimation method. Table 5 shows the best specification model through the smallest value of AIC and BIC and the largest value of $R2$ is Spatial Durbin Model on the model of regional growth across districts in East Java. Using the Spatial Durbin Model as the best specification model, we find that change in access to the internet and mean years schooling affect the GDP growth significantly and positively. Related to spatial autocorrelation parameters, all spatial autocorrelation parameters are significant in all spatial models. In this paper, we use the Spatial Panel Model with region- fixed effect since including fixed-effects in our model allows us to decompose the effect of spatial interaction from that of spatial heterogeneity and of omitted variables.

According to the determinants, specifically, change in access to the internet and human capital (in this case, approached by mean years of schooling) indicate the positive and significant effects on economic growth while change in investment share has positive but insignificant effects on economic growth. However, credit access is significant but affects growth performance negatively. Previous literature of Miranti et al. (2021) across districts in Sumatra using Geographically Weighted Regression has presented the effect of credit access on regional growth is diverse across regions, yet on average it shows negative effect on growth. The positive effect of credit is mostly pronounced along the southern and middle parts of Sumatera, negative in all districts in Aceh, and insignificant in a few districts in Sumatera Utara.

These findings depict pronounced evidence that in new normal era, the use of internet, in this case, digitalization as a set of process has emerged the productivity and movement in cross-sectoral sectors. The high productivity and movement in many sectors help to improve economic output across districts in East Java entirely. This finding is confirmed by various studies across countries. Solomon & van Klyton (2020) examined and analyzed the impact of the use of digital technology on economic growth in 39 African countries, from 2012 to 2016. In the case of East Java, Fahta et al. (2022) suggest that high utilization of internet access at the city/district level in East Java Province is able to dramatically increase GRDP per capita.

Qian et al. (2020) also record that the digital economy promotes regional economic growth in China by promoting regional entrepreneurship and innovation. Recent studies from Sumatra region of Indonesia conducted by Miranti et al. (2021) confirms that internet contributes a great role in spreading literacy in an economy. Besides, economic growth is positively related with digitalization.

Table 6. Goodness of Fit Test and Region-Fixed Effect Spatial Models

Variable	OLS	SLM	SEM	SAC	SDM
Number of observations	418	418	418	418	418
Chg_internet	0.047	0.008	0.070*	0.074*	0.087**
Chg_credit	0.046***	-0.015	-0.027**	-0.027**	-0.027**
Chg_Pop	-0.000*	-0.000	-0.000	-0.000	-0.000
Chg_Inv	-0.231	0.091	0.282	-0.000	0.311
Mean years ofschooling	3.919***	-0.462	0.587	0.642	0.846*
R2 between	0.116	0.118	0.113	0.108	0.095
R2 overall	0.004	0.150	0.003	0.002	0.308
AIC	1930.858	519.986	1517.457	1516.448	1512.522
BIC	1955.07	1548.235	1545.705	1548.732	1560.948
Spatial rho (SLM)		0.874*** (0.026)			
Spatial Lambda(SEM)			0.911***(0.019)		
Spatial rho (SAC)				0.865***	
				(0.002)	
Spatial Lambda (SAC)				0.909***	
				(0.032)	
Spatial Cross-regressive (SDM)					0.851*** (0.029)

Note: Values in parentheses are robust standard errors
**** p < 0.01, ** p < 0.05, * p < 0.1*

In terms of mean years of schooling, improving mean years schooling accompanied by the inclusion of digitalization help to accelerate growth performance across districts in East Java. This is in line with Ravallion (2012) stating that human capital is useful to achieve the growth in the region's economy. In an emerging country like Indonesia, the optimization of human capital and knowledge transfer is still essential. Due to insular geography of Indonesia, the equality in the level of human capital across regions in Indonesia remains big challenge. Therefore, to achieve growth equality, it is needed to increase knowledge spillovers as a strategy to leverage regional economies.

Conclusion and Policy Implication

Conclusion

Reducing regional inequalities is the main concern for the sustainable development in Indonesia, including East Java. This paper evaluates the spill-over effect of digitalization and credit access in accelerating growth performance across 38 districts in East Java over the 2010-2021 period. This paper also examines the magnitude of control variables which are adapted from Solow growth model, including human capital and physical capital. To strengthen our findings, we both compare the digitalization and credit data from google trend analysis and empirical data. From the analysis, we find that both these data sources could give complementary support to enrich our paper.

Results from exploratory spatial data analysis indicate that spatial autocorrelation or dependence does exist globally and locally, by using google trends and empirical data. Due to the similarity, we proceed to continue the existence of spatial dependence by using spatial

econometric models. Results from spatial econometric models show that the Spatial Durbin Model is the best specification model to bring out the main key factors to boost the growth in East Java. The spatial autocorrelation parameter from the Spatial Durbin Model is positive, showing that the increase of internet access in a district would lead to an increase in internet access in neighboring regions. It implies that the inclusion of spills-over effect helps knowledge spills-over is utilized optimally. As expected, internet access has positive promising effects on growth across districts in East Java. This is supported by the endogenous growth model by Romer (1986, 1990) stating that balanced growth is affected by knowledge spillover positively. As we expect, internet delivers a vital message in deploying references and information in an economy. Also, empirically, economic growth is positively related with the use of the internet. Finally, our particular finding supports the role of internet access on economic growth which encourage most of the evidence reported in previous studies (Skordili, 2008; Jiménez et al., 2014).

Policy Implication

Our results from exploratory spatial data analysis highlight the importance of arranging regional development policies in at least two matters. First, local governments are urged to synergize and coordinate cross-sectoral policies, specifically on related-significant key variables. Second, policies should facilitate the need of population in all parts of East Java in accessing technology. In addition, the implementation of internet usage with low fee is worth to note. By applying these, digital literacy rate could be improved and eventually boost economic and social productivity.

Finally, some caveats in this paper call for specific emphasizes. First, the variable of internet access in this paper does not thoroughly reflect the use of the internet for economic activities. For future research, productive use of the internet, such as online transactions in marketplaces at district level. Second, the alternative to modify this research from the perspective of spatial heterogeneity using GWR, confirming that some variables tend to indicate diverse effect in terms of direction at the district level.

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