Spatial Analysis of Youth Unemployment in Indonesia: Minimum Wages and Industrial Mix

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Abstract

This study examines the spatial distribution of youth unemployment rates (15–24 years old) and the impact of wages and industrial composition on these rates in Indonesian provinces. The persistently high youth unemployment rate and uneven distribution of youth labor across provinces have motivated this research. Data from 2010 to 2018, sourced from Sakernas and other BPS publications, were analyzed for 33 Indonesian provinces. This study employed Moran's index and spatial panel data regression methods. The findings reveal a clustered spatial pattern of youth unemployment rates among provinces. The best-fitting model, identified as the Spatial Durbin Model (SDM) with random effects, indicates that increasing the minimum wage ratio significantly contributes to higher youth unemployment rates. Conversely, higher real wages lead to a slight decrease, whereas greater industrial sector absorption reduces youth unemployment. However, increased absorption in the service sector amplifies youth unemployment.

Keywords: Youth Unemployment, Minimum Wages, Industrial Mix, Spatial Panel

JEL Classification: C23, J30, J46

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I. Introduction

At present, Indonesia is in the initial stages of the peak of the second demographic dividend, which is projected to occur from 2020 to 2030. Demographic dividend can be both an opportunity and a threat to the economy. It can be an opportunity or demographic window of opportunity because the greater the number of working-age productive population, the greater the savings that can be allocated as investments, which will ultimately result in economic growth. Conversely, it will be a threat to the economy if the increase in the population of productive age is not followed by an increase in the quality of human resources and the availability of jobs, which will bring about the problem of unemployment. Such problem would ultimately result in an economic burden.

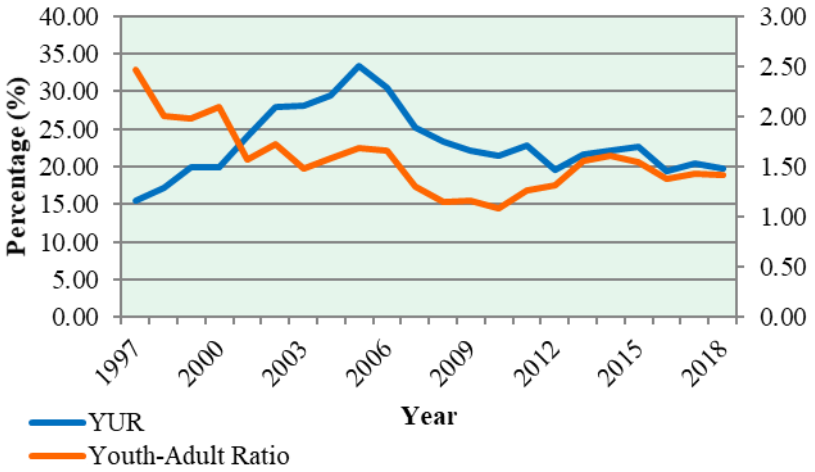
If we look at the age composition of Indonesia's productive population, it is indisputable that the largest part are the age group of 15-19 years old and 20-24 years old, comprising 22 percent of the total productive age population (BPS 2018). Therefore, it is not surprising that young people issue is one of the issues that receive attention because they are the group with the most potential to become unemployed. This is reflected in the eighth goal of the Sustainable Development Goals (SDG's) Agenda. This goal has five targets, one of which is related to the decline in youth unemployment rate.

According to ILO (2017, 1), young people are three times more likely to be unemployed than adults due to several reasons. The first is related to the quality of human capital. According to Demidova and Signorelli (2012), although in general the level of education of young labor is better, their general work experience and job-specific experiences are still very limited. This limitation also causes low productivity of young labor. The second reason is related to the minimum wages system and temporary contracts, which make the costs of young labor relatively higher and make them more vulnerable to termination of employment (Gorry 2013; Specks and Mysíková 2015; and Gontcovicova et al. 2015). Finally, according to ILO (2017, 21); and Banerji, Huidan, and Saksonovs (2015), in general, young labor are concentrated in the informal sector and the economic sector which are more sensitive to the business cycle.

Indonesia's youth unemployment rate has a downward trend. In 2018, the youth unemployment rate is 19.68 percent, which means that 4.10 million young people are unemployed (50 percent of the total open unemployment, BPS 2018). When compared with other ASEAN countries, such as Malaysia (11.20 percent), Vietnam (7.00 percent), and the average youth unemployment rate of developing countries (14.90 percent), it is clear that Indonesia's youth unemployment rate is still quite high. This condition provides a simple illustration that unemployment at a young age is still a chore that the government needs to finish.

In addition, the ratio of youth to adult unemployment suggests that there has been an upward trend since 2008 (Figure 1). In 2010, the ratio of youth unemployment to adult employment was 1.08, went up to 1.31 in 2012, then to 1.41 in 2018. This condition means that, although the unemployment rates of young people and adults are declining, the decline is slower among youth. According to Smyth (2008), this condition indicates that

the adult labor force is actually benefiting more from increased labor absorption, indicating that the economy is still less friendly to the younger labor force, which is dominated by newcomers (school-leavers). Marelli et al. (2012) concluded that the young labor force faces a labor market that is different from the adult labor force.



Note.: YUR: Youth Unemployment Rate (15-24 Years Old)

Figure 1. The Youth Unemployment Rate and Ratio of Youth to Adult Unemployment in Indonesia, 1997-2018 (BPS 2019, processed)

The problem of youth unemployment is very complex because it has very broad social and economic implications (Gontcovicova et al. 2015). Serious long-term implications, such as impeded accumulation of work experience and income, reduced employment opportunities and the possibility of future unemployment (Rodriguez-Modroño 2018), increased tendency to resort to criminal acts (Narayan and Smyth 2007), decreased human capital and social capital, and physical and mental health issues (Ningrum 2013).

In general, unemployment can be explained through the characteristics of the labor market, namely the interaction between demand, supply of labor, and wages. According to Breen (2005) and Seth (2017), employment, especially the employment of young labor, is strongly influenced by labor market flexibility. There are two things that cause the labor market to become inflexible or rigid, namely the wages level and the labor absorption structure or industrial mix. This labor absorption structure reflects the composition of each economic sector the labor they can absorb.

In Indonesia, the level of wages formed on the market cannot be separated from the minimum wages policy that is set annually by the government. From Figure 2, it is clear that the Provincial Minimum Wages increases every year. Put simply, higher minimum wages means higher labor costs. This minimum wages applies to all groups of labor. As a result, the young labor force, with all its characteristics, becomes less competitive when compared to the adult labor force. Employers or companies can choose to recruit new and experienced labor or substitute young labor with adult labor when wages level increase. This is indicated by the ever-increasing ratio of unemployment between the youths and adults. On the other hand, a high wages level is an opportunity cost for young people to start working immediately, resulting in the increasing supply of young labor.

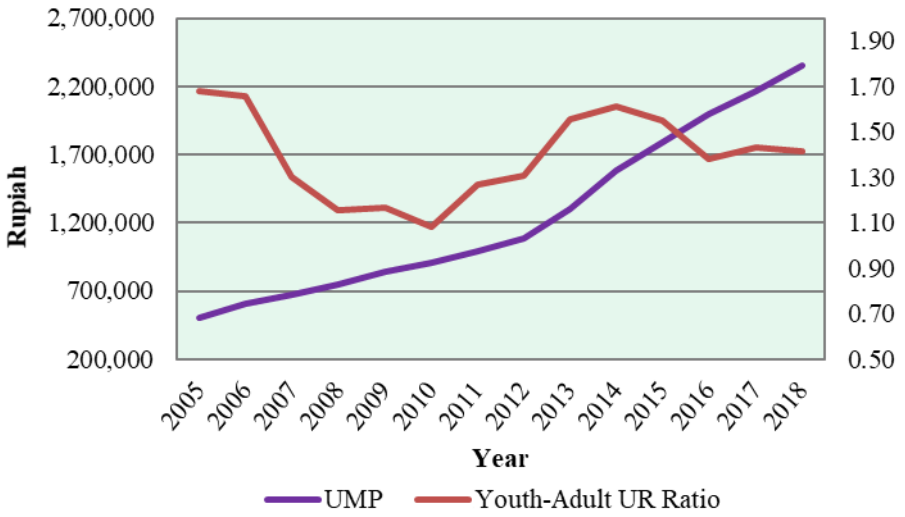


Figure 2. Minimum Wages and Ratio of Youth to Adult Unemployment in Indonesia, 2005-2018 (BPS 2019, processed)

The effect of wages level and minimum wages on unemployment/young labor is still being debated. A number of researchers found evidences that increased minimum wages means increased youth employment. In other words, no negative effects (Card 1992; Pereira 2003; Chuang 2006; Putra and Iskandar 2018; etc.). Other researchers found evidences suggesting to the contrary, namely that increased minimum wages adversely affects youth unemployment (Neumark and Wascher 2004; Kalenkoski and Lacombe 2008; Sen, Rybczynski, and Waal 2011; Laporsek 2013; Liu, Hyclack, and Regmi 2016; etc.). Thus their effects are still not clear (Soest 1994; and Zavodny 2000).

Labor market flexibility is determined from the structure of labor absorption (industrial mix). Industrial mix can influence employer behavior (demand side) and job search behavior (supply side) of the young labor force. Changes in the composition of the industry can cause skills to be less suitable and cause an increase in unemployment from the economic sector which experiences a decline in performance. In addition, in a regional context, a region's specialization in a certain sector may cause the labor market to become inflexible so that when shocks occur in the sector, the rate of unemployment will increase.

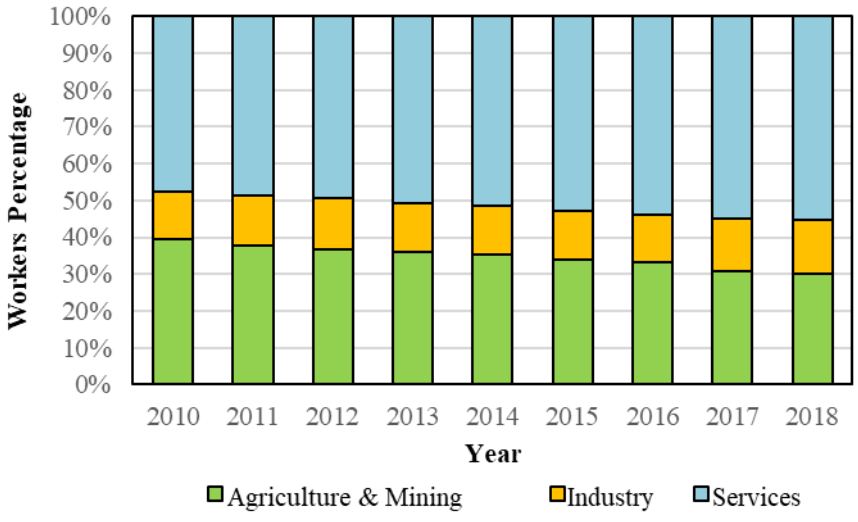


Figure 3. Trend of Industrial Mix in Indonesia, 2010-2018 (BPS 2019, Processed)

The figure above shows that there has been a sectoral shift in Indonesia. The agriculture and mining sectors experience a downward trend, while the industrial and service sectors experience an upward trend. Until 2018, the percentage of workers in the primary, industrial and services sector is 29.96 percent, 14.71 percent and 55.33 percent respectively.

The phenomenon of national youth unemployment certainly cannot be separated from similar phenomena at the provincial level. Figure 4 shows that some provinces have very high youth unemployment rates, while other provinces have fairly low youth unemployment rates. This condition indicates that there is a disparity in the absorption of young labor between provinces. Disparity in the absorption of young labor between provinces can occur due to the different characteristics of the labor market between one province and the others (Breen 2005).

In addition, it is also indicated that provinces that have relatively high youth unemployment rates tend to be in close proximity to other provinces that also have high youth unemployment rates, such as Riau and West Java. Likewise, provinces that have relatively low youth unemployment rates tend to be in close proximity to provinces that also have low youth unemployment rates, such as Bali and West Sulawesi. This indicates that the characteristics of the labor market in one province can also affect the performance of other provinces because of the proximity of the regions. The influence of other regional characteristics is also referred to as an indirect impact or spillover. This can occur through a process of migration, information dissemination and/or knowledge transfer (Oktafianto, Achsani, and Irawan 2019).

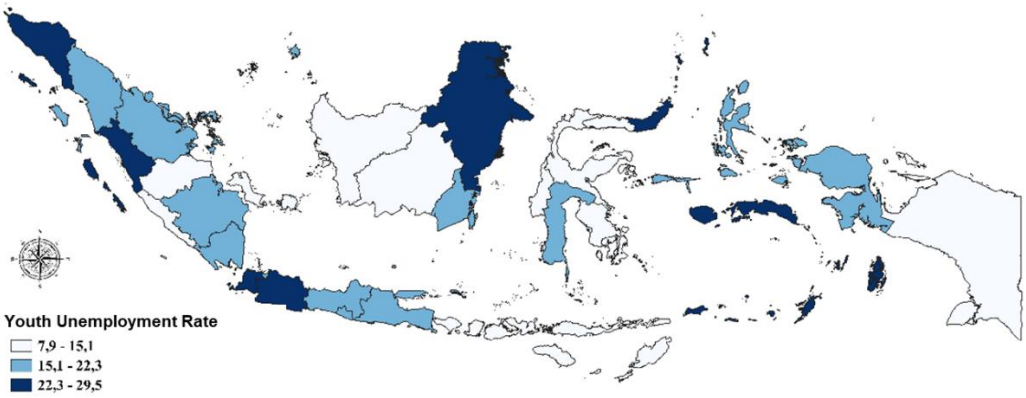


Figure 4. Thematic Map of Average of Youth Unemployment Rate by Province in Indonesia, 2010-2018 (BPS 2019, processed)

As technology advances, the current labor force's decision making is no longer limited by territory. People can also consider the possibility of moving to another region due to, for example, higher wages or greater opportunities to find work in other provinces (Semerikova 2015; and Monras 2015). That possibility is still very rarely considered in analyzing the problem of unemployment, especially youth unemployment. This is important to consider because young people are considered to have high motivation to migrate.

The problem of unemployment at the regional level must be viewed comprehensively since each province can interact with each other due to spatial dependencies or spatial autocorrelation. This interaction may cause changes in unemployment in a province not only due to the changes in the characteristics of the labor market in the province itself, but also the changes in the characteristics of the labor market of the neighboring (closest)

provinces, both directly or indirectly (spillover). According to Elhorst (2003), capturing this interaction requires a spatial econometric analysis approach.

Based on the explanation of the problem and the gap of literature that has been described, the purpose of this study is to find out the spatial pattern of youth unemployment rates and the influences of wage rates and industrial mix on youth unemployment rates (15-24 years) in Indonesian provinces with a spatial econometric analysis approach.

II. Literature Review

This study uses a measure of open youth unemployment, which is the percentage of youth unemployment within the young labor force. Referring to the UN definition, the age range of young people is 15-24 years old.

The phenomenon of youth unemployment cannot be separated from the interaction between supply and demand of labor and the level of wages in the labor market. In the Neoclassical model, an increase in wages causes unemployment because the amount of labor supply is greater than its demand, especially the low-skilled worker group that is dominated by the young labor force. Employer will tend to have a preference for recruiting adult labor compared to younger labor with the same wages (Card and Kruenger 1995). Several studies supported this model, such as Naumark and Wascher (2004) in 17 OECD countries, 1975-2000; Allegretto, Dube, and Reich (2011) in a number of countries from 1990-2009; Sen, Rybczynski, and Waal (2011) in Canada, 1981-2004; Gorry (2013) in France and the United States, 2007 and 2009; Laporsek (2013) in 18 European countries, 1996-2011; Rataj and Magda (2015) in Poland, 2003-2011; and Liu, Hyclack, Regmi (2016) in the United States, 2000-2009.

In the monopsony market theory, an increase in minimum wages will simultaneously increase wages and employment because companies have a market power (Card 1992; Strobl and Walsh 2016). This theory is developed as a new economic theory of minimum wages, as in the study of Card (1992) in California, United States, 1987-1989; Soest (1994) in the Netherlands, 1994-1997; Zavodny (2000) in the United States, 1979-1993; Pereira (2003) in Portugal, 1986-1989; Chuang (2006) in Taiwan, 1973-2004; and Putra and Iskandar (2018) in Indonesia 2012-2016.

Strobl and Walsh (2016) argued that not all sectors are covered by the minimum wages policy. Welch (1974) developed a two-sector model or a model of partial-coverage minimum wages by considering that there are economic sectors that are not covered by the wages policy, such as the informal sector. In general equilibrium, setting minimum wages can have positive, negative, or no impact on the unemployment rate. Mincer (1976) developed this model by adding the assumption that labor laid off from covered sectors do not immediately switch jobs to sectors that are not covered but would wait until they get jobs with a desirable wages. This leads to frictional unemployment.

Furthermore, according to the theory of labor heterogeneity which assumes that the labor force is not homogeneous, the effect of wages regulation on labor is quite small and only reflects the balance of inactivity between labor who are benefited and labor who have lost their jobs (Deere et al. 1995; Freeman 1996). If the minimum wages set is relatively low, it will only affect a small number of labor and the effect on the total number of labor is quantitatively insignificant (Card and Kruenger 1995, 361-364).

According to the theory of efficient wages (Mankiw 2007, 164-165), paying wages higher than the expected value can increase labor productivity, efficiency and loyalty, and decrease costs. In addition, turnover

rates would be lower because labor no longer have the incentive to quit or look for another job. Higher wages will also attract more job seekers, thus providing companies with many labor to choose from, which in turn reduce unemployment. Conversely, in the theory of human capital, an increase in the wages of labor with low education will cause a decrease in the investment in education because the opportunity cost to work is greater than opportunity cost of staying in school. Young people, especially those at school age, will choose to quit school and start working, which will eventually increase the supply of young labor and results in more youth unemployment.

According to Neumark (2018), the Neoclassical model does not yet accommodate the possibility of a sectoral shift, i.e. changes in the composition of demand between industries or regions. In Lewis migration theory (1955 in Arsyad 2016, 352), labor from the traditional sector move slowly to the modern or industrial sector. Labor move from one area to another area that is dominated by the modern sector. Companies in the modern sector will try to maximize profits by paying wages according to the labor's marginal physical product. The profit obtained is then reinvested to increase the capital and output of the modern sector, which in turn drives an increase in the demand for labor. Furthermore, according to Todaro (1970 in Arsyad 2016, 352), labor force migration occurs due to the difference between the "expected" income and the current income. Some studies that are in line with this theory are researches by Perrugini and Signorelli (2010) in 19 European countries in 1996-2006; Dietrich (2013) in 23 European countries in 2001-2010; Baah-Boateng (2016) in 41 African countries in 2000-2010; Bradley, Migali, and Paniagua (2019) in Italy, Spain, and England in 1993-2011; and Oktafianto, Achsani, and Irawan (2019) in Indonesia in 2008-2017.

According to Marston (1985), there are two views that can explain the disparity in the regional unemployment rate, namely equilibrium and imbalance or disequilibrium. The equilibrium view assumes that external shocks or economic shocks to the labor market only has short term effects, and the unemployment rate will return to the natural level (average level). According to this view, in stable equilibrium, each region has its own average unemployment rate (natural rate). The average regional balance depends on amenities or facilities which can further hamper the inter-regional migration process. This difference in regional average values is also an indication of differences in employment (industrial mix) and wages level. If the labor market can work perfectly and labor can freely migrate, there will be no regional unemployment disparity.

The disequilibrium view assumes that the regional unemployment rate will be the same only in the long run and that the adjustment process may proceed very slowly. The unemployment rate is very dependent on the speed of adjustment between regional labor markets. Therefore, the migration process must be taken into account in this view. According to Semerikova (2015), a factor that plays a major role in the disequilibrium view is the characteristic of labor supply because companies cannot react quickly due to the high costs of relocating businesses. The pattern of returning to equilibrium is largely determined by wages flexibility, migration decisions, labor force participation, and business location, which indirectly influence job search (Aragon et al. 2003).

According to Allegretto, Dube, and Reich (2011) the lack of control a researcher has over spatial dependencies in employment trend results in estimation bias. Therefore, some researchers consider the effect of spatial interactions in looking at the effect of wages rate and industrial mix on youth unemployment rates, such as a study conducted by Kalenkoski and Lacombe (2008) in the United States in 2000 using the Spatial Autoregressive (SAR) model and Innocence-Prucha (SAC); a study by Kalenkoski and Lacombe (2012) in the United States from 1990 to 2004 that uses the SAR data panel and Spatial Durbin Model (HR) model; a study by Tamayo, Melguizo, and Ramos (2017) in Spain in 2006-2015 that uses the SAR and HR panel data model; a study

by Perrugini and Signorelli (2010) in 19 European countries in 1996-2006 that uses the SAR model with GMM; a study by Bradley, Migali, and Paniagua (2019) that uses the panel data SAR model; and a study by Oktafianto, Achsani, and Irawan (2019) that uses the HR model.

In addition to being influenced by minimum wage rates and real and industrial mix wages, previous studies have shown that there are many other factors that affect youth unemployment, such as the vulnerability factors of labor proxied through the informal labor share variables (Anyanyu 2013; Baah- Boateng 2016), information and communication technology proxied through internet penetration variables (Ebaidalla 2017), education proxied through average length of school variables (Choudry et al. 2013; and Tamayo, Melguizo, and Ramos 2017), and demographics which are indicators of the large supply of young labor proxied through the number of young people (Perugini and Signorelli 2010; and Demidova and Signorelli 2012). These variables are used as control variables in this study.

III. Methodology

The data used are annual secondary data obtained from the Central Statistics Agency (BPS). The unit of analysis is the 33 provinces in Indonesia during the 2010 to 2018 data period chosen so as to create a balanced panel data with a total of 297 observations. The minimum wages variable used in this study is the relative provincial minimum wages, which is the ratio of the minimum wages to average nominal wages. The use of these variables is to anticipate potential biases due to the endogeneity of the minimum wages variable, i.e. when policy makers increase the minimum wages while the economy is relatively strong and stable (Naumark and Wascher 2004; Laporsek 2013).

3.1 Analytical method

The analytical method used is the spatial autocorrelation analysis and spatial panel data regression. Spatial autocorrelation is used to see the pattern of spatial spread of youth unemployment. Meanwhile, spatial panel data regression analysis is used to examine the effect of wages and industrial mix on youth unemployment rate.

The spatial influence in the model was accommodated through a weighting matrix or spatial weighing (W) in the form of an inverse matrix of the distance between provinces (distance weight). The use of the weighting matrix refers to previous studies in Indonesia, namely a research by Anglingkusumo, Winarno, and Ariyanti (2013) and Oktafianto, Achsani, and Irawan (2019). Interprovincial distances were measured from the distance between the centroids, or geometric centers, of provincial polygons and are calculated using the Kernel Nearest Neighbor method (Anselin 2018).

Spatial autocorrelation was calculated using the Moran's Index. The calculation formula is (Lee and Wong 2001, 157):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

where y is the observed variable. In this study, the youth unemployment rate $\bar{y}$ is the average of variable y, w_{ij} is an element of the spatial weighting matrix $i, j = 1, 2, \ldots n$; $i \neq j$, and n is the number of provinces. Moran's index is between -1 and 1. An index value close to one indicates strong positive spatial autocorrelation and has a clustered pattern. An index value close to minus one indicates a strong negative spatial autocorrelation and has a

dispersed pattern. In addition, the Moran's index can be displayed in the form of scatterplots to facilitate interpretation.

Based on the literature and previous research, the basic model used in this study is:

$$YUR_{it} = \beta_0 + \beta_1 rasio\_upah_{it} + \beta_2 ln\_wage_0 + \beta_3 industri_{it} + \beta_4 jasa_{it} + \beta_5 informal_{it} + \beta_6 inet_{it} + \beta_7 mys_{it} + \beta_8 ln\_youth_{it} + \varepsilon_{it} \quad (2)$$

where $\beta_0, \beta_1, \ldots, \beta_8$ is the regression coefficient, *YUR* is the youth unemployment rate, *rasio_upah* is the ratio of provincial minimum wages to average nominal wages, *ln_wage* is the natural logarithm of real wages, *industri* is the share of industrial sector workers, *jasa* are the share of workers in the service sector workers, *informal* are the share of informal workers, *inet* is internet penetration, *mys* is the mean years of schooling, *ln_youth* is the natural logarithm of the young population, and ε_{it} is the error term.

The basic model was estimated using the spatial panel data regression approach. The complete form of the spatial panel data regression model or General Nesting Spatial (GNS) is (Elhorst 2014, 38):

$$Y_{it} = \alpha_{lN} + \rho \boldsymbol{WY}_{it} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \boldsymbol{WX}_{it}\boldsymbol{\theta} + u_{it}$$
$$u_{it} = \lambda \boldsymbol{W}\boldsymbol{u}_{it} + \varepsilon_{it} \quad (3)$$

where *Y* is a vector (NT x 1) of the dependent variable, variable X is the independent variable, ρ represents the spatial autoregressive coefficient, λ represents the spatial autocorrelation coefficient, $\boldsymbol{W}$ is the weighting matrix (N x N), and β, θ is the regression coefficient. The specification of the spatial panel data model used is (Elhorst 2014, 44):

1. *Spatial Autoregressive Model* (SAR)

   Often referred to as the Spatial-lag Model. The SAR model shows that the dependent variable of an area depends on the dependent variable of a neighboring region and a set of local characteristics observed;

2. *Spatial Error Model* (SEM)

   SEM model is a model that has a spatial variable in the error term or can be interpreted as a link between regions that occur in the error term, which is a characteristic of unobservable variables;

3. *Spatial Durbin Model* (SDM)

   A development of SAR model made by adding spatial lag of independent variables to accommodate the effects of exogenous interactions simultaneously.

The statistical tests used to determine the effects of spatial interactions are Lagrange Multiplier (LM), LM-Lag and LM-Error. This LM test is based on the non-spatial model residuals (Elhorst 2014, 57). If the standard LM test results provide an ambiguous conclusion, then it must be continued with the LM robust test (Elhorst 2014, 58).

The best spatial panel data regression model was determined based on three criteria, namely (1) using the Likelihood Ratio (LR) test of the basic HR model; (2) comparing the value of Root Mean Square Error (RMSE); and (3) the value of Akaike's Information Criterion (AIC) for each regression model (Elhorst 2012; Purwaningsih 2014; and Belotti, Hughes, and Mortari 2017). After the best spatial panel data regression model was determined, the direct, indirect, and total effects of each independent variable were calculated (LeSage and Pace 2009, 37).

IV. Result and Discussion

The growth of the provinces' youth unemployment rate from 2010 to 2018 is shown in Figure 5. Based on the thematic map, it appears that youth unemployment remains a problem in almost all provinces. There are several provinces that have become the hotspot of youth unemployment, such as Banten, West Java, East Kalimantan, North Sulawesi, and Maluku. The youth unemployment rate in those provinces is much higher than that of the surrounding provinces. During the 2010-2018 period, youth unemployment rates in almost all provinces experiences a decline, although still very small, except in Riau, Riau Islands, West Kalimantan, South Kalimantan, Gorontalo, West Papua and Papua which experiences an upward trend.

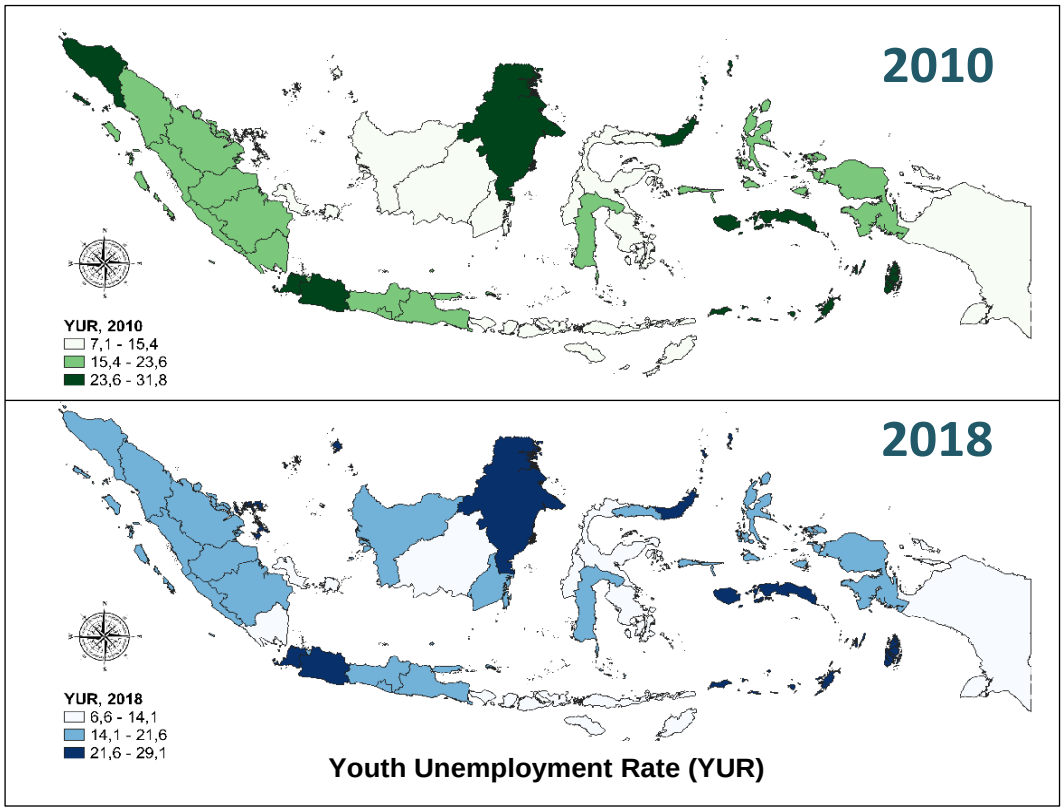


Figure 5. Thematic Map of Youth Unemployment Rate by Province, in 2010 and 2018 (BPS 2019, Processed)

Some provinces have youth unemployment rates that are still very high until 2018, including Riau Islands (23.17 percent), Banten (29.13 percent), West Java (28.62 percent), North Sulawesi (28.24 percent), and Maluku (24.27 percent). In contrast, some provinces have relatively low youth unemployment rates, including Bali (6.60 percent) and East Nusa Tenggara (9.29 percent). This indicates that there are differences in the characteristics of the young labor market and there is a disparity in the absorption of young labor between the provinces in Indonesia.

4.1 Youth Unemployment Rate and Wages

During the 2010-2018 period, the provincial minimum wages set by the government continues to increase with an average growth of 11.41 percent per year, and reaches its highest growth in 2014 with a 22.17 percent increase. The average wages of formal labor only grows 5.68 percent per year so the ratio of the provincial minimum wages to the average nominal wages tends to increase, as evident in the boxplot ratio of the minimum wages in Figure 6. This increase in the minimum wagse ratio makes the younger labor force less competitive. It is clear that companies prefer to pay labor who have more ability and experience than new migrant labor with the same wages.

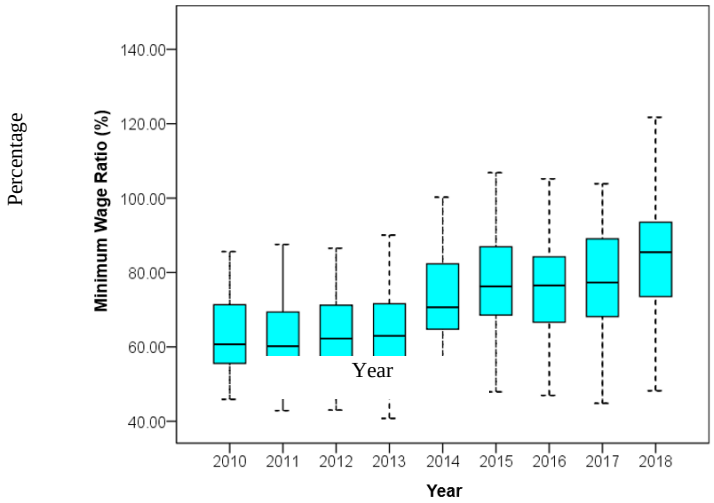


Figure 6. Boxplot of Ratio Between Minimum Wages and Nominal Wages, 2010-2018 (BPS 2019, Processed)

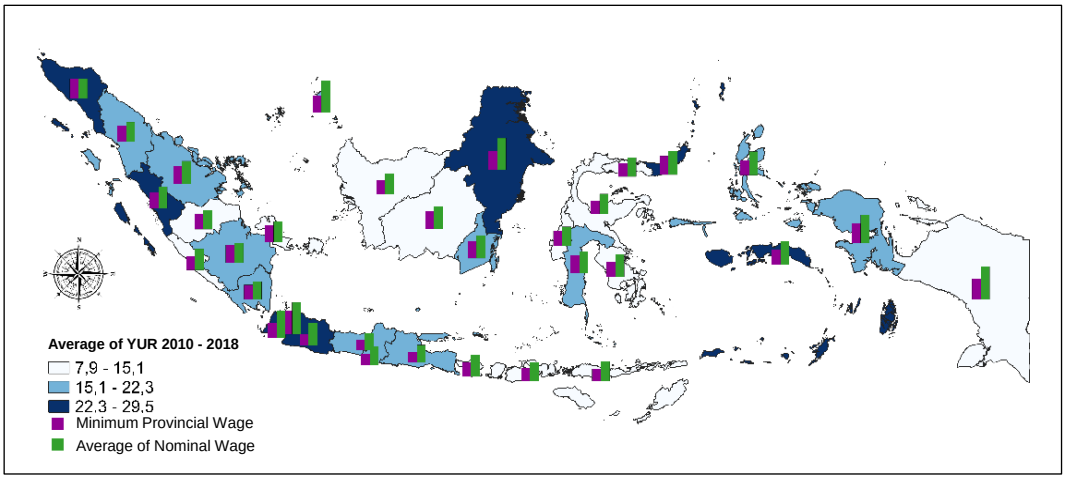


Figure 7 Thematic Map of Average of Youth Unemployment Rate and Wages by Province, 2010-2018 (BPS 2019, Processed)

When juxtaposed between the average minimum wages and the youth unemployment rate (Figure 7), it is clear that provinces with high minimum wages have a high youth unemployment rate. Provinces that have high youth unemployment rates and high minimum wages include Aceh, East Kalimantan, Banten, and Jakarta.

4.2 Youth Unemployment Rate and Industrial Mix

Elhorst (2003) emphasized the importance of the role of industrial mix. Regions that specialize in "poor" economic sectors will tend to have higher unemployment rates than regions that specialize in "prosperous" sectors or prosperous economic sectors, such as the industrial sector (manufacture). However, when an economic sector is less diversified, it becomes more sensitive to external shocks and job vulnerability. In addition, the industrial mix also influences young labor force job seeking behavior.

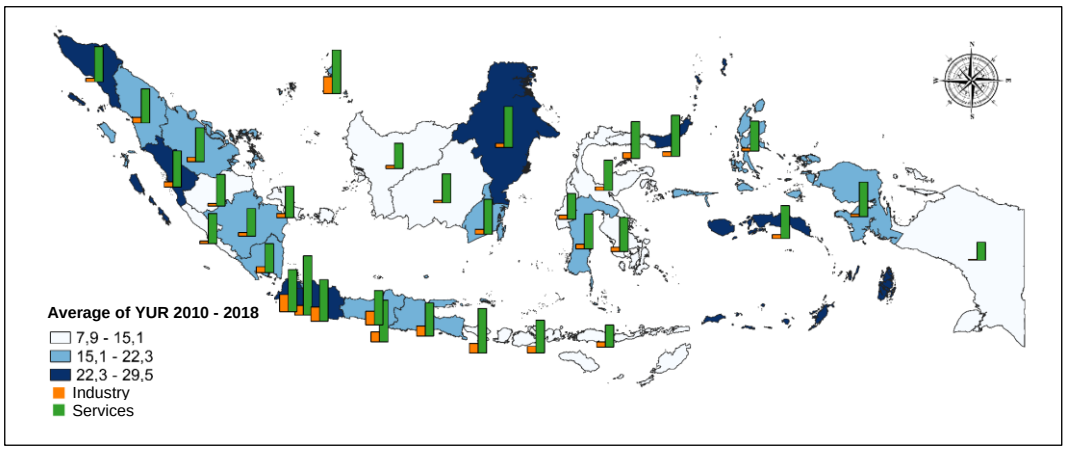


Figure 8. Thematic Map of Average of Youth Unemployment Rate and Industrial Mix by Province, 2010-2018 (BPS 2019, Processed)

When juxtaposed with the youth unemployment rate, as shown in Figure 8, it appears that provinces that have high youth unemployment rates, such as Aceh, DKI Jakarta, East Kalimantan, North Sulawesi, and Maluku have an economic sector composition that is dominated by the service sector. According to Martin (1997 in Semerikova 2015), the effect of an economic sector composition is the main factor behind the differing labor demand and unemployment rate between regions.

4.3 Spatial Pattern of Youth Unemployment Rate

The Moran index of the youth unemployment rate for each year and panel data is positive and significant, except for 2012 and 2015. These results indicate the spatial autocorrelation of the provincial youth unemployment rate in Indonesia. Spatial patterns that are formed are clustered. Adjacent or neighboring provinces tend to have similar youth unemployment rates. This is in line with the findings in the study of Demidova and Signorelli (2012); Demidova, Marelli, and Signorelli (2015).

Table 1. Spatial Autocorrelation (Moran's Index) of Provincial Youth Unemployment Rate in Indonesia

Years	Moran's Index	Spatial Pattern
2010	0.1993**	Clustered
2011	0.1621*	Clustered
2012	0.0666	Clustered
2013	0.1637*	Clustered
2014	0.2001**	Clustered

2015	0.1123	Clustered
2016	0.2031**	Clustered
2017	0.1875**	Clustered
2018	0.1913**	Clustered
Panel	0.1836***	Clustered

Source: Processing result obtained using *RStudio 1.2.5*

Note: (***) significant at $\alpha = 0.01$; (**) $\alpha = 0.05$; (*) $\alpha = 0.10$

Judging from Moran's scatterplot, during 2010 to 2018, most of the observation points are in quadrants I (high-high) and III (low-low), which is more than 70 percent. Around 34 percent of the provinces are in quadrant I and 39 percent of the provinces are in quadrant III. Quadrant I (high-high) shows that provinces that have high youth unemployment rates tend to be around provinces that also have high youth unemployment rates. In contrast, quadrant III (low-low) shows that provinces that have low youth unemployment rates are around provinces that also have low youth unemployment rates.

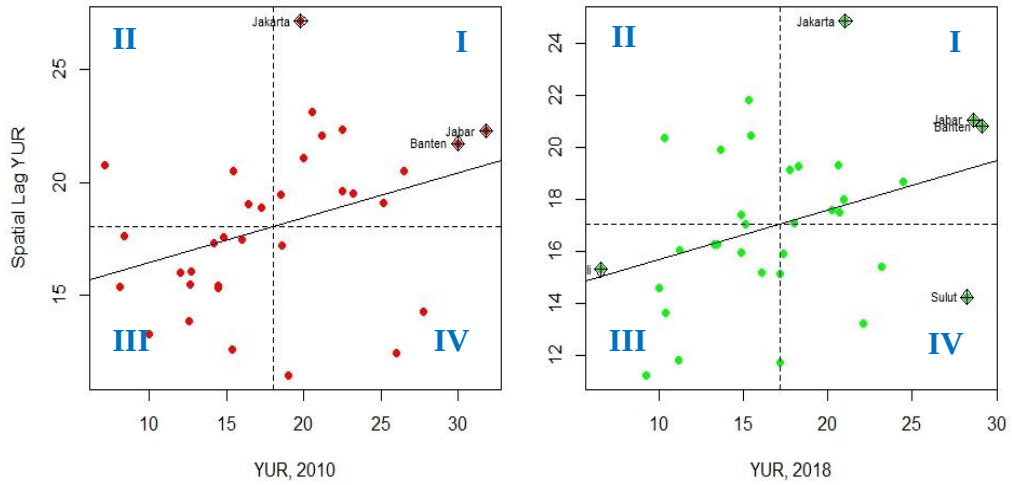


Figure 9. Moran's Scatterplot of Youth Unemployment Rate, 2010 and 2018 (Processing Result with *Rstudio 1.2.5*)

The figure also shows that the provinces of Jakarta, West Java, and Banten, from 2010 to 2018, are listed in quadrant I with asterisks, which means that the three provinces have a large influence on the surrounding provinces (their local Moran is significant in the high-high group). For the government, the making of policies related to young people is focused on the provinces in quadrant I, specifically the three provinces.

4.4 Non-spatial Panel Data Regression Results

The initial stage in examining the effect of wage rates and industrial mix on youth unemployment rates with a spatial econometric approach was determining the best non-spatial panel model. Based on the results of the REM-0 panel data regression (see Appendix 2), it appears that the minimum wages ratio variable is significant at alpha 0.01, while the real wages variable is not significant with a very high p-value. These results indicate the problem of multicollinearity on both of these wages level variables.

This is also confirmed by the research conducted by Anglingkusumo, Winarno, and Ariyanti (2013); and Liu, Hyclak, and Regmi (2015). Their results showed that minimum wages is strongly correlated with average

real wages. The increase in the UMP (Provincial Minimum Wages) affects the amount of real wages received by labor and the impact of the increase is transmitted in the same year. Therefore, the estimation is then made through two models that separate the minimum wages ratio variable and the real wages variable so that the effects of the two variables can be seen.

The selection of the initial model of non-spatial panel data was carried out using statistical tests, namely the Chow test, the Lagrange Multiplier (LM) test, and the Hausman test (see Appendix 2). A Chow test is performed to choose between the common effect and fixed effect models. In the test, a p-value smaller than alpha 0.01 was obtained for both models. Therefore, it can be concluded that the best model in this study is the fixed effect model. Next, an LM test was performed to choose between the common effect and random effect models. In the test, the p-value is smaller than alpha 0.01 for both models. Thus, the random effect model is better than the common effect model. Finally, the Hausman test was conducted to choose the best model between the fixed effect and random effect models. In the test, a p-value greater than alpha 0.05 was obtained. In conclusion, the right panel data regression used for both models is the random effect model. The estimation results of the parameters of the effect of the ratio of minimum wages, real wages and industrial mix on youth unemployment rates in Indonesia in 2010-2018 using the random effect model are presented in Table 2.

From Table 2, it is known that the Wald Chi-square probability of the two models is smaller than the alpha significance level of 0.01. Therefore, it can be concluded that all independent variables have a significant effect on the unemployment rate of young labor in Indonesian provinces, with a confidence level of 99 percent. Preliminary results show that the provincial minimum wages ratio variable has a positive and significant effect (at alpha 0.01) on youth unemployment. That is, the higher the ratio of the minimum wages set to the average nominal wages, the higher the youth unemployment rate will be. Conversely, the real wages variable has a negative and significant effect (at alpha 0.05) on youth unemployment. That is, the higher the average real wages received by labor, the lower the youth unemployment rate will be.

Table 2. The Results of Non-Spatial Panel Data Regression with Random Effects
Dependent variable: youth unemployment rate

Variable	REM-1		REM-2	
	Coefficient	Sig.	Coefficient	Sig.
Ratio of minimum wages	0.0669	***	-	
Natural logarithm of real wages	-		-3.4357	**
Share of industrial sector labor	-0.1635	*	-0.2258	**
Share of service sector labor	0.2180	***	0.2193	***
Share of informal labor	0.0284		0.0237	
Internet penetration	-0.1075	***	-0.0542	**
Mean years of schooling	1.2918		1.5527	*
Natural logarithm of young people	2.7339	***	2.6110	***
Wald Chi-Square	45.28		36.63	
Probability	0.0000		0.0000	
R-Square	0.2916		0.2946	
Number of observations	297		297	

Source: Processing result obtained using *Stata 15.1*

Note: (***) significant at $\alpha = 0.01$; (**) $\alpha = 0.05$; (*) $\alpha = 0.10$

Furthermore, the share of industrial sector labor variable has a negative and significant effect (at alpha 0.10) on youth unemployment. That is, an increase in employment in the industrial sector causes a decrease in youth unemployment. On the other hand, the service sector labor share variable actually has a positive and significant effect (at alpha 0.01) on youth unemployment. This means that an increase in employment in the service sector actually causes an increase in youth unemployment.

The classic assumption test results for the panel data regression model show that there is no assumption violation. Next, a cross-sectional dependency test was performed using the Magnification test. The results show that there are cross-sectional dependencies. The test results are an early indication for the application of spatial panel data regression analysis.

4.5 Spatial Panel Data Regression Results

Before entering into the spatial panel data regression analysis, a Lagrange Multiplier (LM) test was performed to see the spatial dependency in the lag and in the errors of the non-spatial model. The two LM tests used are the standard LM test and the LM robust test. The standard LM test results (Appendix 3) show that the LM-lag and LM-error values are equally significant at alpha 0.01 for both models. Therefore, it is necessary to do a robust LM test to determine the spatial panel data regression model that will be used. The robust LM test results indicate that the LM-lag robust value is significant at alpha 0.10, while the LM-error robust value is not significant. Therefore, the next spatial data regression model used is the Spatial Autoregressive (SAR) and Spatial Durbin Model (SDM).

The estimation results of the spatial panel data regression model using the SAR and HR random effects model are presented in Table 3. The SAR model shows the effect of wages level and industrial mix on the provincial youth unemployment rate by considering the effects of spatial interactions, while the HR model considers the effects of spatial interactions and spatial lag of the independent variable.

Based on the SAR-1, SAR-2, SDM-1, and SDM-2 models in Table 3 it is evident that the spatial coefficient rho (ρ) of the four models is positive and significant (at alpha 0.01). The direction of the sign of the spatial coefficient rho can be interpreted that a decrease in the unemployment rate of young people in a province will cause a decrease in the unemployment rate in the nearest province, or vice versa. Spatial rho coefficient value of 0.2629 to 0.3391 shows the value of the interaction between the unemployment rate of a province with the unemployment rate of the other provinces. Thus, it can be said that the determinants that play a role in reducing the youth unemployment rate in a province by one percent will also help reduce the youth unemployment rate in the nearest province by 0.2629 to 0.3391 percent, or vice versa, ceteris paribus. This is in line with the results of research conducted by Kalenkoski and Lacombe (2008); Perugini and Signorelli (2010); Kalenkoski and Lacombe (2012); Tamayo, Melguizo and Ramos (2017); and Bradley, Migali, and Paniagua (2019). According to Kalenkoski and Lacombe (2012), these results are in line with the idea of economic agglomeration which drives companies to look for locations that are close to one another and create work centers that can cross boundaries.

From the SAR-1 and SAR-2 models, it is clear that the estimated coefficient of the influence of the ratio of minimum wages, real wages, share of industrial sector labor, and share of service sector labor on the youth unemployment rate shows a direction consistent with the estimation results of the non-spatial panel data regression that do not consider the effects of spatial interactions. The minimum wages ratio has a positive effect, the real wages has a negative effect, the share of industrial sector labor has a negative effect, and the share of service sector labor has a positive effect.

Table 3. The Results of Spatial Panel Data Regression, SAR and SDM Model with Random Effect

Dependent variable: youth unemployment rate

Variable	SAR-1		SDM-1		SAR-2		SDM-2	
	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
[Main]								
Ratio of minimum wages	0.0485	***	0.0446	**	-		-	
Natural logarithm of real wages	-		-		-2.4993		-2.1475	
Share of industrial sector labor	-0.1254		-0.0881		-0.1694	*	-0.1171	
Share of service sector labor	0.2183	***	0.1986	***	0.2182	***	0.2027	***
Share of informal labor	0.0250		0.0309		0.0208		0.0301	
Internet penetration	-0.0908	***	-0.0065		-0.0513	**	0.0142	
Mean years of schooling	1.0273		0.8917		1.1846		1.1507	
Natural logarithm of young people	2.5119	**	3.0406	***	2.4123	***	2.8812	***
[Wx]								
Ratio of minimum wages			0.0201				-	
Natural logarithm of real wages			-				-1.3097	
Share of industrial sector labor			-0.2989	*			-0.3400	*
Share of service sector labor			-0.0781				-0.0238	
Share of informal labor			0.0951				0.1043	
Internet penetration			-0.1173	**			-0.1060	*
Mean years of schooling			3.4233	*			4.1581	**
Natural logarithm of young people			0.5984				0.0100	
Spatial Rho	0.3164	***	0.2629	***	0.3391	***	0.2845	***
R-Square	0.3160		0.3383		0.3036		0.3553	
Log-Likelihood	-700.49		-693.76		-702.71		-696.18	
Number of observations	297		297		297		297	

Source: Processing result by *Stata 15.1.* Note: (***) significant at *alpha* 0.01; (**) significant at *alpha* 0.05; (*) significant at *alpha* 0.10

Furthermore, from the SDM-1 and SDM-2 models that consider the spatial lag of the independent variable, it is known that the direct effect (shown in line [Main]) of the ratio of minimum wages, real wages, share of industrial sector labor, and share of service sector labor variables towards the youth unemployment rate still shows the direction that is consistent or equal to the spatial model without the lag of the independent variable. Furthermore, the coefficient value becomes smaller. Then, judging from the spatial lag of the independent variable (shown in line Wx), all variables show the same effect as the direct effect, except the spatial lag of the service sector labor share variable which actually has a negative effect on youth unemployment rates.

After estimating the spatial panel data regression model on the SAR model and the HR model, the best model must be chosen. Based on the LR test results and the good category of the spatial panel data regression model, it can be concluded that the best spatial panel data regression model is the HR model (Appendix 4).

4.6 Direct, indirect, and total effects

According to LeeSage and Pace (2009, 34) it is not appropriate if the regression coefficient of the spatial model is interpreted directly because there are effects of spatial interactions. For this reason, a partial derivative approach is used (marginal form). The marginal effect of the independent variables on the dependent variable can be divided into direct impacts, indirect or spillover impacts, and total impacts.

The total impact can be interpreted as the average effect of the independent variables in all provinces on the youth unemployment rate in a province. Table 4 and Table 5 show that the total impact of the minimum wages ratio and the share of industrial sector labor variables has a significant effect (at alpha 0.05) on youth unemployment. In contrast, the total impact of the real wages variable and the share of service sector labor variable does not have a significant effect on the youth unemployment rate of provinces in Indonesia.

Table 4. Direct, Indirect, and Total Effects of SDM-1's Model

Variable	Direct Effects		Indirect Effects		Total Effects	
Ratio of minimum wages	0.0474	**	0.0437		0.0911	**
Share of industrial sector labor	-0.1103		-0.4040	*	-0.5144	**
Share of service sector labor	0.2034	***	-0.0346		0.1685	
Share of informal labor	0.0384		0.1415		0.1799	
Internet penetration	-0.0152		-0.1589	***	-0.1741	***
Mean years of schooling	1.1372		4.9286	**	6.0658	**
Natural logarithm of young people	3.1185	***	1.6907		4.8091	*

Source: Processing result obtained using *Stata 15.1*.

Notes: (***) significant at $\alpha = 0.01$; (**) $\alpha = 0.05$; (*) $\alpha = 0.10$

Table 5. Direct, indirect, and total effects of SDM-2's model

Variable	Direct Effects		Indirect Effects		Total Effects	
Natural logarithm of real wages	-2.1951		-2.3528		-4.5479	
Share of industrial sector labor	-0.1448		-0.4841	**	-0.6289	**
Share of service sector labor	0.2113	***	0.0419		0.2532	
Share of informal labor	0.0389		0.1572		0.1961	
Internet penetration	0.0055		-0.1369	**	-0.1314	**
Mean years of schooling	1.4694		6.0504	**	7.5199	**
Natural logarithm of young people	2.9275	***	0.8968		3.8243	

Source: Author's calculation using *Stata 15.1.*

Notes: (***) significant at $\alpha = 0.01$; (**) $\alpha = 0.05$; (*) $\alpha = 0.10$

The total impact of the minimum wages ratio variable has a positive effect of 0.0911. That is, if the ratio of the minimum wages to the average nominal wage or the relative minimum wages of all provinces in Indonesia goes up by 10 percent, the youth unemployment rate in a province will increase by 0.91 percent, ceteris paribus. The increase in the provincial minimum wages relatively inhibits the absorption of young labor. This is in line with the findings of the researches conducted by Neumark and Wascher (2004); Sen, Rybczynski, and Waal (2011); Gorry (3013); Laporsek (2013); Liu, Hyclack, and Regmi (2016); etc. An increase in the minimum wages will result in higher young labor cost, which, when combined with all of their characteristics, will make the young labor become less attractive when compared to adult labor. Eventually, they become uncompetitive.

From the estimation results above, it is also visible that the total effect of the minimum wages on youth unemployment rates calculated by considering the effects of spatial interactions is greater than the total effect calculated without considering the effects of spatial interactions (in the non-spatial regression model of 0.67). This is in line with the results of research conducted by Kelenkoski and Lacombe (2012). Therefore, spatial aspects are very important to consider in formulating policies, especially when those policies are related to the problem of youth unemployment in Indonesia.

The total impact of the share of industrial sector labor variable has a negative effect of -0.5144 to -0.6289. That is, if the absorption of industrial sector labor in all provinces increases by 10 percent, the youth unemployment rate in a province falls by around 5.14 to 6.29 percent, ceteris paribus. This is in line with the findings of research conducted by Perugini and Signorelli (2010); Bradley, Migali, and Paniagua (2019); and Oktafianto, Achsani, and Irawan (2019). When compared with the effect of the service sector, the influence of the industrial sector on youth unemployment in Indonesia is far greater.

The direct impact is interpreted as the average effect of the independent variable on the level of youth unemployment in the same province, including the effect of feedback as the effect of spatial dependence. Conversely, the indirect effect is interpreted as the average effect of an independent

variable of a province on youth unemployment in another province. Based on Table 4 and Table 5, it can be seen that the direct impact of the minimum wages ratio and the share of service sector labor variables has a significant effect (at alpha 0.05 and 0.01) on youth unemployment. Conversely, the indirect impact of the share of labor in the industrial sector actually has significant (at alpha 0.05) on youth unemployment.

The direct impact of the minimum wages ratio variable has a positive effect of 0.0474. That is, if the ratio of the minimum wages to the average nominal wages or relative minimum wages in a province increases by 10 percent, the youth unemployment rate in the province concerned will increase by 0.47 percent, ceteris paribus. The direct impact of the share of service sector labor variable has a positive effect of 0.2034 to 0.2113. That is, if employment in the service sector in a province increases by 10 percent, the youth unemployment rate in the province will increase by around 2 percent, ceteris paribus. Conversely, the indirect effect of the share of industrial sector labor variable has a negative effect of -0.4040 to -0.4841. That is, if the average absorption of labor in the industrial sector in the neighboring (nearest) province increases by 10 percent, the youth unemployment rate in the province concerned will fall by around 4 percent, ceteris paribus.

The significant effect the absorption of labor in the industrial sector in the neighboring province has on youth unemployment is most likely due to the province being the center of national industrial growth, such as Banten (share of industrial labor: 25 percent and share of industrial sector GRDP: 35 percent), West Java (share of industrial sector labor: 21 percent and share of industrial sector GRDP: 43 percent), Riau Islands (share of industrial sector labor: 24 percent and share of industrial sector GRDP: 38 percent) (BPS 2019). The existence of this industrial sector growth centers attracts young labor force from other provinces to look for jobs in these provinces.

Real wages has a negative effect on youth unemployment, but is not significant in all impact categories. The estimation results are not in accordance with what was hypothesized. According to Kalenkoski and Lacombe (2008), one possibility that can explain the findings is that real wages actually reflect economic conditions in general and the level of wages or income of parents that can be a factor among young people to decide whether to work immediately or not. Young people who live with low-income parents have a higher potential ("forcing" them) to immediately find work compared to younger people who live with higher-income parents. Therefore, an increase in real wages has a negative effect on youth unemployment. In addition, according to Semerikova (2015), real wages reflect the cost of living and house prices. This has led to insignificant direct and indirect impacts from real wages on the unemployment rate of Indonesia's young workers.

In addition to wages and industrial mix levels, from the spatial regression model, it can also be seen that internet penetration, average length of schooling, and the number of young people have a significant effect on youth unemployment. Internet penetration has a negative effect on youth unemployment. That is, increased access to information will reduce youth unemployment. Conversely, the average length of schooling and the number of young people have a positive effect.

Greater young population means more supply of labor force that has the potential to become unemployed.

V. Conclusions and Policy Implications

5.1 Conclusions

From the results of the analysis and discussion, it can be concluded as follows:

1. The youth unemployment rate of Indonesian provinces during the period of 2010 to 2018 tends to decrease. Spatial patterns of distribution are clustered, i.e. provinces that have a high youth unemployment rate are surrounded by neighboring provinces that also have a high youth unemployment rate and vice versa.
2. An increase in the ratio of the minimum wages or an increase in the provincial minimum wages relative to the average nominal wages leads to an increase in the youth unemployment rate and is significant. Conversely, an increase in real wages causes a decrease in the youth unemployment rate, but not significantly.
3. Increased employment absorption in the industrial sector which is proxied from the share of labor in the industrial sector significantly causes a decrease in youth unemployment. On the contrary, the increase in employment absorption of the service sector, which is proxied from the share of labor in the service sector, actually causes a significant increase in youth unemployment.
4. The ratio of minimum wages and labor absorption in the service sector is only significant through its direct impact, while employment in the industrial sector is only significant through its indirect impacts, and real wages are not significant in terms of both direct and indirect impacts.
5. Other conclusions: (a) an increase in internet penetration has a significant effect on reducing the level of youth unemployment; (b) an increase in average length of schooling and the number of young people having a significant effect on the increase of the level of youth unemployment.

5.2 Policy Implications

Based on the results of the study, several policy implications can be made:

1. A synergy between local governments is needed. In addition to that, there is a need to consider the factors related to spatial interaction in formulating and implementing policies to reduce youth unemployment.
2. Uniform minimum wages policies need to be reviewed. One of them is by considering the special minimum wages for young labor. In addition, the use of average nominal wages data

as a correction factor to the results of minimum wages calculated based on economic growth and inflation needs to be considered.

3. Efforts should be focused on the development of the industrial sector through, among others: modernization and industrial revolution so as to increase productivity and competitiveness; enhancement of the integration between the industrial sector and the world of education, especially with Vocational High Schools (SMK), Vocational Schools, and Vocational Training Centers (BLK); as well as the augmentation of the potential of the Micro Small Industry (IMK) which is capable of absorbing a large workforce.
4. Access to information needs to be expanded and facilitated.

5.3 Research limitations and suggestions for further research

This research still contains several limitations both in terms of data availability and the research methods used. The limitations of this study are as follows:

1. The spatial unit used is a province whose scope is still very broad so that the effect of the spatial interaction captured is small. In addition, the analysis in this study has not separated the spatial units of East Kalimantan and North Kalimantan Provinces.
2. In this study, there is no control variable of the quality of the labor force, specifically the quality of the young labor force. Additionally, this study has not considered reservation wages that can influence the decision of the young population in choosing whether to work.
3. In terms of methodology, this study only focuses on two possible spatial interaction effects, namely the spatial lag and the spatial lag of the independent variable.

Some suggestions for further research are as follows:

1. Where possible, it is recommended to use district and municipal spatial units or other smaller spatial units to be able to capture stronger spatial effects.
2. Quality control variables need to be added to the specific young labor force, such as the percentage of the young population according to the level of last education completed.
3. Future researchers can try to develop the Spatial-Prucha (SAC) or Spatial Durbin Error Model (SDEM) so that they can accommodate the possibility of spatial lag and spatial error simultaneously.

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Appendix 1. Panel data regression model *REM-0*

Variable	REM-0			
	Coefficient	Std. Err.	*P*>|*z*|	Sig.
Ratio of minimum wages	0.0651	0.0229	0.005	***
Natural logarithm of real wages	-0.3508	2.0583	0.865	
Share of industrial sector labor	-0.1697	0.0970	0.080	*
Share of service sector labor	0.2175	0.0601	0.001	***
Share informal labor	0.0274	0.0532	0.607	
Internet penetration	-0.1041	0.0278	0.000	***
Mean years of schooling	1.2797	0.9388	0.173	
Natural logarithm of young people	2.7285	0.9547	0.004	***
Wald Chi-Square	44.80	***		
R-Square	0.2869			
Chow test	39.29	***		
LM test	727.26	***		
Hausman test	12.02			

Source: Processing result obtained using *Stata 15.1*

Note: (***) significant at α = 0.01; (**) α = 0.05; (*) α = 0.10

Appendix 2. Selection procedure of non-spatial panel data regression models

Statistic Test	Chow Test	LM Test	Hausman Test
Model 1	40.27	736.36	11.22
p-value	(0.0000)	(0.0000)	(0.1293)
Model 2	37.94	714.00	8.94
p-value	(0.0000)	(0.0000)	(0.2567)

Source: Processing result obtained using *Stata 15.1.*

Note: Model 1: ratio of minimum wages; Model 2: Natural logarithm of real wages

Appendix 3. Results of Lagrange Multiplier test

Dependency Test	REM-1		REM-2	
LM-Lag	27.24	***	32.61	***
LM-Error	23.89	***	29.54	***
Robust LM-*Lag*	3.40	*	3.23	*
Robust LM-*Error*	0.05		0.16	

Source: Processing result obtained using *RStudio 1.2.5*

Note: (***) signifikan pada α = 0,01; (**) α = 0,05; (*) α = 0,10

Appendix 4. Selection procedure of spatial panel data regression models

	Criteria	SAR-1	SDM-1	SAR-2	SDM-2
-	LR Test ($\mathbf{H_0}: \boldsymbol{\theta} = \mathbf{0}$)	-	13.19*	-	13.89*
	($\mathbf{H_0}: \boldsymbol{\theta} + \boldsymbol{\rho\beta} = \mathbf{0}$)	-	14.51**	-	12.70*
-	RMSE	1.9481	1.8876	1.9754	1.9169
-	AIC	1422.97	1423.52	1427.42	1428.35

Source: Processing result obtained using *Stata 15.1*.

Note: (***) significant at α = 0.01; (**) α = 0.05; (*) α = 0.10