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The Effects of Agro-clusters on Rural Poverty: A Spatial Perspective for West Java of Indonesia

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Paper prepared for presentation at the 150th EAAE Seminar

**‘The spatial dimension in analysing the linkages between agriculture, rural
development and the environment’**

Edinburgh, UK, October 22-23, 2015

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Abstract

The agricultural sector plays an important role for rural economies. However, rural populations still face poverty as one main issue threatening livelihoods. Regional concentration and specialization in agricultural production and processing is referred to as agro-clusters. These clusters might generate income possibilities so that rural poverty may be reduced. We empirically analyse this question by applying spatial econometric models because neighbouring regional economies are likely to influence each other. The analysis focuses on the 545 sub-districts of the West Java province of Indonesia where about 10% of the population live in poverty. Concentration of agricultural employment is found to have significant effects on poverty reduction in the sub-district as well as its neighbouring regions. Specialisation in agricultural output is also found to cause lower poverty rates. This implies that the government should support the regional specialization in agriculture. Based on the identification of the comparative advantage of each sub-district, the government should establish regional production nuclei in agriculture in order to boost the specialization. Care has to be taken of the spillover effects the policies will have for surrounding areas.

Keywords: *agricultural production, spatial concentration, spatial dependence, clusters*

1. Introduction

The agricultural sector plays an important role for rural economies of developing countries. It often provides the major source of income for most of the rural population. This is also the case for Indonesia. West Java is a major province of agricultural production of the country in which agriculture is spatially unevenly distributed. However, the gap in the poverty rates between regions within West Java with more developed non-farm economic activities and regions with a concentrated agricultural sector is large.

Agro-clusters refer to the regional specialization and concentration of an agricultural commodity. They encompass farming activities, processing units, and trades. For example, coffee in West Java produced by farmers is a raw material for processing units. Relationship among them allows cooperation and commercialization to grow. As a local economy this specialised crop contributes higher values and employment to the whole economy of the region. Indeed, agro-clusters may play an important role for reducing poverty rates due to several reasons. Firstly, these clusters offer economic growth. Empirical evidence has explicitly proven that economic clusters in general enable smallholders to raise productivity (Barkley & Henry, 1997). The clusters may offer positive externalities and innovation (Asheim, Cooke, & Martin, 2008; Ferragina & Mazzotta, 2014). Secondly, agricultural productivity growth may be associated with higher economic performance and lower poverty rate (Abro, Alemu, & Hanjra, 2014; Datt & Ravallion, 1998; de Janvry & Sadoulet, 2010; Dolny, 1991; Gaiha, 1995; Tyler, Elghonemy, & Couvreur, 1993).

Nevertheless, this literature often neglects the importance of spatial dependence. The omission of this aspect may lead to inefficient and biased results (Fingleton, 2001; Fowler & Kleit, 2014). Spatial dependence can affect long-run steady-state growth in a closed economy

(Nijkamp & Poot, 1998). The presence of spatial dependence on economic growth has also been described widely in spatial literature (Bivand, 2006; Cravo & Resende, 2013; Tian et al., 2014). Spatial relationships between agro-clusters and poverty rates may consist of some rationales. First, the clusters contain a growth centre and its hinterlands in which innovation and knowledge spill over among them. This diffusion of knowledge occurs predictably over space and has strong connection with growth. In addition, cooperation in the clusters may reduce production costs, which help small firms to get higher revenue. Second, poverty rates are increasing incrementally along with the distance from metropolitan areas (Partridge & Rickman, 2008), but much less rates in the regions in which spatial concentration of economic activities present. In this respect, understanding the link between agro-clusters and poverty rates with considering spatial dependence is a relevant topic to address, which is rare to find, especially in the case of Indonesia.

We address the question of whether agro-clusters reduce average sub-district poverty rates by means spatial perspective. Spatial dependence accounts for assessing the relationship between agro-clusters and poverty rates. This spatial dependence captures spillover effects across area boundaries. It is essential because in fact significant dispersion exists in the distribution of the spatial concentration of farm activities and of the poverty rates within sub-districts of West Java. The agricultural productivity growth of one region is not only dependent upon its own production inputs, but also reliant on spatial networks with its surrounding regions.

On the other hand, agro-clusters also provide drawbacks for regional development. These disadvantages may affect poverty reduction. At a certain point of the density of farm concentration, the clusters increase production costs and reduce revenues due to congestion effects. This circumstance may lead to higher land prices and competition of limited resources. Additionally, the abandonment of agricultural land in developing countries occurs in large numbers. As a result, the agricultural productivity declines gradually. Those facts are most likely to be one reason why the higher concentration of farming activities is associated with the higher poverty rate. Moreover, agricultural growth may go down along with closer distance to metro-areas. Shifting from agricultural economy to more advanced non-farm economy is frequently present in the regions nearby cities. It becomes an interesting question to assess whether agro-clusters in West Java of Indonesia get equilibrium in favour of the positive and negative externalities for rural economies.

We focus on 545 sub-districts of West Java by using aggregated data at sub-district level from Statistics Indonesia. In the second section, we explore the potential relationship between agro-clusters and poverty rates. We next employ two measurements of the presence of agro-clusters in the third section and describe data and variables in the next section. In the fifth, we use Moran's I index to test for spatial autocorrelation in the variables of interest, including agro-clusters and poverty rates and then suggest six specific econometric models by accounting for spatial dependence in both dependent and independent variables. In order to estimate the models, we apply maximum likelihood estimation controlling for relevant sub-district characteristics and agricultural productivity. The last section, we deduce a number of discussion points and conclusions for policy design after interpreting our models.

2. Cluster externalities and rural poverty

Alfred Marshall introduced "localized industry" as agglomeration economies to describe the regional concentration of homogenous economic activities explained by three concepts (Krugman, 1995). First, the clusters of firms specializing in a related or even the same industry in geographical proximity are most likely to have larger supply for specialized and skilled people. Second, local industrial clusters provide interlinkages among firms to support

one to another in specialized services, for instance sharing machinery and production inputs and organizing the trade flows. Third, the clusters offer easy exchange of information and technology. Put simply, in clustering firms will perform internal and external economies of scale. The firms may earn long-run average cost decreases that correspond to increasing returns to scale in terms of outputs and may provide external economies of scale that tends to share all effective resources with other surrounding firms. Given increasing returns to scale, increases in labour, capital, and other inputs of firms may incline outputs especially when the firms are proximate each other. We here emphasize Marshallian localization economies to explain agro-clusters.

Additionally, in defining the clusters Porter (1990) sets the clusters through a strategic viewpoint. In his point clusters play an essential role in determining the competitiveness of firms. The clusters encompass an array of linked industries and other entities in the same industry. Within the numbers of firms in the same industry a firm must boost their performance to gain competitive advantages. The advantages give the firm an edge over its competitors, allowing it to generate greater margins and retain more consumers, and a capability to produce a product or service in lower costs. Considering this competitiveness, a number of firms are related to the performance of other neighboring firms and other factors tied together in the value chains, in consumer-firm network, or in regional context. Information and knowledge flow is likely present within this network to upgrade production process, products and compete in broader markets. This network is beneficial to support industrial as well as regional competitiveness.

It was outlined above that agro-clusters might provide external economies of scale within firms. With regard to regional economies of sub-districts these economies (externalities) may enhance and hinder economic development. The economic growth of sub-districts exists as a result of positive externality of the clusters. Martin and Sunley (2003) investigated that the relationship between rural clusters and poverty reduction might correlate with spatial agglomeration, industrial localization, and the importance of regional growth. Clusters enable to exchange production technology and other industry-relevant knowledge among actors (Audretsch, 1998; Dumais, Ellison, & Glaeser, 2002; Giuliani, 2007; Kajikawa, Mori, & Sakata, 2012). They therefore provide skilled labourers and opportunities to access external markets and to minimize uncertainty for the industry (Padmore & Gibson, 1998). Even if the firms are smallholders and new entry firms. These benefits occur in connection with geographical proximity and cooperation among the actors, as called collective efficiency (Schmitz & Nadvi, 1999; Visser, 1999).

In contrast, agro-clusters also provide constraints for regional economies. A region where a large population of farms exist may obtain negative external economies of scales. In this opposite case the clusters may lead to crowding and traffic congestion, pollution, and other negative externalities. Another source of these externalities is constrained access to relevant production resources and facilities. They may decrease the pricing power of farms because of many competitors and shortage of production inputs such as labour, land, machinery and fertilizers. They also reduce the flexibility of getting the inputs around the sub-district. For example, a numerous number of companies and consumers centred in cities may lead a firm to respond higher transportation costs and land prices. This condition provokes the firm to reconstruct its operations in order to re-optimize net revenues. Furthermore, the abandonment of agricultural land in Indonesia prevails massively in most of sub-districts when farmers are unwilling to pay additional costs for renting the land or even they sell their own land to property companies or other individual owners. Perhaps, the firm will change its behaviour to avoid the congestion impacts and sustain their competitiveness by shifting operations, schedules, and locations.

In terms of these externalities of clusters, our study adopts the concept of Duranton, et al. (2010). In their book, clusters are explained by the curves of productivity, cost, and profit with respect to number of firms as horizontal axis. The productivity curve explains that increase in the number of farms in a sub-district is associated with the positive productivity growth of farms. It is described above that the clustering of farms in the sub-district can gain an ability to produce and differentiate agricultural products, so that the farms could earn higher revenues. Moreover, the flexibility of input procurement allows the farms to receive more production inputs easily. The exchange of information and the appropriate size of clusters cause this procurement more flexible. One per cent of increase in the number of all resources utilised to produce a good corresponds to the increases of outputs by more than a per cent. Hence, productivity increase is possible to achieve. On the other hand, the cost curve clarifies that the increasing number of farms in a sub-district also raises production costs. It occurs as a consequence of negative externalities within a cluster. For instance, the farms must pay an additional cost to rent the land prices in the dense clusters for their main inputs. It is easy to find that farmers decide to abandon their agricultural land in sub-districts of Indonesia when input prices rise.

Additionally, a concave profit curve represents the relation between profit and the number of cluster size. There are two segments of this curve. In the first segment, profit is positive meaning that there is a tendency of profit increase when the number of farms rises. In this segment total revenue earned by farms outweigh total cost paid by the farms. Reasonably, the number of farms still generates positive external economies of scale. Nevertheless, at a certain number of farms the profit reaches a maximum value, and then decreases incorporated with the increase of farm number. This is illustrated in the second segment. This reduction happens because the production costs increase or even exceed the total revenue. In addition, the farms would get lower profit or get loss in this circumstance.

3. Cluster Measurements

In this paper we employ two measurements of the existence of agro-clusters. One measure of concentration is the location quotient (LQ_s). This measure is a broader tool that can quantify how concentrated a sub-sector in a sub-district in comparison to West Java in average. It is defined as:

$$LQ_s = \frac{\left(\frac{e_s}{E_s}\right)}{\left(\frac{e}{E}\right)} \quad (1)$$

The variable e_s denotes the number of farmers in sub-district s , $s = \{1, \dots, 545\}$ of West Java. The variable E_s denotes total number of labourers in sub-district s . The variable e is the farmer number of West Java and E is total number of labourers in West Java. The LQ_s value resulting from equation (1) indicates the importance of primary agricultural production in employment terms in a sub-district s relatively to in the average employment structure of West Java. For example, a LQ value greater than unity indicates that a higher share of total employment works in agricultural production of sub-district s than on average in West Java.

Instead of this LQ, we modify the LQ_s model in equation (1) to examine agro-clusters in West Java in which labour intensive exists. We here adopt an alternative approach called horizontal clustering (Fingleton, Iglori, & Moore, 2004) or cluster size. This measure quantifies the extent of farm labourers that may provide benefits to increase farm productivity. Additionally, the measure is calculated as follows. We determine the expected value (\hat{e}_s) for each sub-district. Fingleton et al. (2004) suggest that this value, \hat{e}_s , indicates the employment number

of a sub-district, which shares the same employee number of West Java. This definition corresponds to the LQ_s value equal to unity. If $LQ_s = 1$, so $\hat{e}_s = (\frac{e}{E})E_s$. We next measure *cluster size* (hc) by subtracting the expected number of employment \hat{e}_s from the observed number of employment e_s :

$$hc = e_s - \hat{e}_s \quad (2)$$

The equation 2 represents the size of agro-clusters in the sub-district, which contributes to improve its economic performance, especially in terms of employment number. Besides, we here also specify the square of cluster size to examine optimal number of farm labourers in order to minimize poverty. According to the profit curve, there is a turning point signifying this optimal number before profit declines. This point may reflect the change of the externalities of agro-clusters. After this point, the firms may get the loss of profits that can be one of factors increasing poverty rates in sub-districts. In our empirical model, the same case we apply to investigate is how cluster size controlling for both externalities relates to poverty rates. In this relation we expect a convex quadratic curve with cluster size as the horizontal coordinate. This assumption corresponds that the larger cluster size in the sub-district, the poverty rate goes down, and then increases after reaching the turning point. f refers to a function of poverty rates in natural logarithm, $lnpov_s$, of each sub-district with respect to cluster size (hc_s) and the square of cluster size (sq_hc_s), $lnpov_s = f(hc_s, sq_hc_s)$.

Another measure of agro-clusters we utilize in this paper is the specialization index developed in Krugman (1991). We apply this measure to capture the outputs of specialized primary agricultural production within agro-clusters in West Java. To construct this *Krugman specialization index*, we proceed as follows. We split the total primary production into the three main sub-sectors of agriculture in West Java. These sub-sectors are food crops (rice, corn, cassava, and sweet potato), horticulture (vegetables and fruits) and perennial crops (coffee, tea, sugarcane or clove). For each sub-district s , we calculate the share v_{is} of each sub-sector i in its total agricultural outputs. This variable, that is, the share of the each sub-sector in the production value, is calculated for all sub-districts. We then calculate \bar{v}_{is} as the percentage of the value created by sub-sector i in all sub-districts in the total gross production value of West Java, $\bar{v}_{is} = \frac{\sum_1^S v_{is}}{S}$ with $s = \{1, \dots, 545\}$ and S referring to total number of sub-districts in West Java $\{S = 545\}$. *Krugman specialization index* (K_s) is the absolute value of the difference between the share in sub-district s and the average share in West Java summed over all sub-sectors i , $i = \{1, 2, 3\}$.

$$K_s = \sum_{i=1}^3 |v_{is} - \bar{v}_{is}| \quad (3)$$

If the index takes value zero, the agricultural structure of a sub-district resembles the agricultural structure of West Java. The closer the index to maximum value $\frac{2(S-1)}{S} = 1.99$, the more the agricultural structure of a sub-district deviates from the average structure of West Java. In other words, the sub-district is more likely to be specialised.

4. Data and Variables

The data analysed in this paper are extracted from the Indonesia programme for the census of agriculture of the office of national statistics (BPS) in 2013, the Indonesia programme for the census of poverty of BPS in 2011 and various issues of District Statistical Yearbook published by BPS for all districts. The raw shapefile of West Java map was also obtained

from BPS. We focus on 545 sub-districts of West Java of Indonesia by using aggregated data at sub-district level.

Our study focus on West Java Province since the region, one important province of Indonesia, contributes more than 20% of total agricultural outputs of Indonesia. The province covers around 37,100 km² in total area and 72.42% of this area includes agricultural land. Geographically, the characteristics of it encompass plains and mountains, which have elevation about 0 – 1200 metres above sea level. According to Statistics Indonesia (BPS, 2013), the number of people living in this regions is more than 44.5 million. Its population density was 37,174 persons/km². In addition, agricultural sector includes the most potential sectors of West Java. This region shares approximately 17.76% of Indonesia rice production each year and contributes 20-40% of total vegetable production of Indonesia. The province produces more than 70 varied commodities in Indonesia consisting of food crops, horticulture, coffee, tea, husbandry, fishery and forestry. BPS (2013) informed that the agricultural sector provides 29.65% of West Java employment. Interestingly, some of sub-districts have developed sub-terminal agribusiness and local home industries, such as packinghouses. Our expectation of the agro-clusters present is due to the fact that firstly farms in West Java are characterized by labour intensive. Secondly, not only producing fresh products or raw materials, but farmers in a group also occupy agricultural processing and trade despite in small scales. Therefore, we can assume that the larger number of farmers signifies the higher density of agricultural production and agribusiness and then the higher possibility of existence of agro-clusters.

In addition, Poverty rates in our study reflect the ratio of poor people to total population number of West Java. In Indonesia the rates are measured by absolute poverty referring to a standard of minimum monthly expenditures of people to fulfil their basic needs. The standard, poverty line, in West Java in 2011 is around 220,098 Indonesia Rupiah a month or US \$1 a day per capita. BPS (2011) reported that 9.42 per cent of total population of West Java is categorized in poor people. Most of them are concentrated in rural areas.

Control Variables

To structure our modelling approach, we have selected a set of control variables, which have effects on poverty rates and the growth of agro-clusters accounting for agricultural productivity. The variables consist of three main categories such as farmer and farming characteristics, and sub-district properties.

We introduce 9 control variables (*i*) that may have relations with poverty rates. *pov* refers to poverty rates of each sub-district. In our study, we use poverty rates in natural logarithm (*lnpov*) to explain the ratio of number of poor people to total population of sub-districts. The growth of farmer number (*fgrowth*), the percentage of smallholders (*noland*), the proportion of farmers with age > 55 years old (*fold*), and population density (*pop*) are included to check their contribution on poverty rates. The relations assume that the higher percentage of smallholders and elderly farmers, the lower agricultural productivity is. Lower productivity may be associated with higher poverty rates. Overpopulation can result from high population density. In this paper high density is not always incorporated with higher poverty rates.

Additionally, we employ rice productivity (*prod*) to approach primarily agricultural production within agro-clusters. We select rice, which is primarily because rice as the most intensive crop of Indonesia affects all aspects of most people in Indonesia. *prod* refers to the quantity of rice production in one hundred kg per hectare. The other variables are sub-district properties consisting of total area (*area*), the percentage of wetland in total (*wet*), distance (*km*) and travel time (*trv_time*) to the nearest city (Bandung or Jakarta). We assume that the

farther distance to the city is incorporated with the higher poverty rates. Furthermore, we introduce travel time besides distance in our models to account for the quality of road and the diverse topography of West Java. We also introduce a dummy variable in the model which is $D = 1$ for rural sub-districts and $D = 0$ for urban sub-districts.

5. Model specifications

5.1. The baseline models

In this section, we set out baseline models to explain the link between agro-clusters and poverty rates. The models comprise two approaches. First, the model represents poverty rates ($lnpov$) as a dependent variable and cluster size (hc) as an explanatory variable. The changes in cluster size of sub-districts have some effects on poverty reduction. In order to confirm the externalities of agro-clusters, we envisage the quadratic relation between poverty rates and cluster size. It is because the decline of poverty rate in one region is because of larger cluster size, but at a certain size of the clusters poverty rates go up. Hence, the baseline specification used in this study takes the following forms:

$$lnpov_s = \alpha + \beta_1 hc_s + \beta_2 sq_hc_s + \sum_{i=1}^9 \mu_i X_{i,s} + \epsilon_s; \epsilon_s \sim N(0, \sigma_\epsilon^2) \quad (4)$$

In which $lnpov_s$ denotes poverty rate of a sub-district s in natural logarithm, hc_s is cluster size of a sub-district s ; $X_{i,s}$ refers to control variable i , $i \{1, \dots, 9\}$, in a sub-district s ; and ϵ_s is disturbance terms due to unobserved information. α is an intercept to be estimated. β and μ are estimated coefficients explaining the relationships among variables. From equation 4, we expect to have a negative sign for cluster size (hc) to account for positive effects of agro-clusters on poverty reduction. It means that one unit increase in cluster size decreases one per cent of poverty rate. On the other hand, we assume a positive sign for the square of cluster size (sq_hc) to justify the presence of negative externalities of agro-clusters on poverty rates.

Second, the other model explains the link between poverty rates as the dependent variable and Krugman specialization index as the independent variable. It investigates whether the specialization of primarily agricultural production can reduce poverty rates in sub-districts.

$$lnpov_s = \delta + \gamma_1 K_s + \sum_{i=1}^9 \mu_i X_{i,s} + \epsilon_s; \epsilon_s \sim N(0, \sigma_\epsilon^2) \quad (5)$$

Where K_s represents specialization index of sub district s . ϵ_s is error terms. δ denotes an intercept to be estimated. γ and μ are estimated coefficients of the relation. $X_{i,s}$ identifies control variable i , $i \{1, \dots, 9\}$, in a sub-district s . Moreover, we expect a negative sign of this index, which suggests that the more specialized in a particular sub-district, the less poverty rate it has. The more specialized in agriculture may raise agricultural productivity, which allows smallholders to get higher output values.

5.2. The model specifications with spatial dependence

Prior to performing econometric techniques for equations (4) and (5), we investigate whether the given characteristics of our spatial data have spatial dependence. We adopt a parameter and technique to test spatial dependence. In doing so, we perform the test of spatial autocorrelation to assess whether spatial dependence plays a role in the relationships between agro-clusters and poverty rates. We utilize Moran's I Index (I) and statistical tests. Furthermore, statistical tests is highlighted to investigate the presence of spatial dependence in $lnpov_s$, hc_s , and K_s . The diagnostics for spatial dependence report that there is the potential spatial dependence in our relations shown by statistically different from zero (p value < 0.01).

In other words, all variables present a positive association between the variables and their spatial lags implying one sub-district may depend on its surrounding sub-districts.

In order to construct our spatial models, we add spatial parameters into the equations (4) and (5) to deal with spatial random error biases for the relations. We perform a spatial lag model (SAR) in equations (6) and (7), a spatial Durbin model (SDM) in equations (8) and (9), and a spatial error model (SEM) in equations (10) and (11) to determine the effects of our poverty rate variable in one region on that in surrounding regions, so that:

$$(I - \rho W_s) \ln pov_s = \beta_1 hc_s + \beta_2 sq_hc_s + \sum_{i=1}^9 \mu_i X_{i,s} + \alpha + \varepsilon_s \quad (6)$$

$$(I - \rho W_s) \ln pov_s = \gamma_1 K_s + \sum_{i=1}^9 \mu_i X_{i,s} + \delta + \varepsilon_s \quad (7)$$

$$(I - \rho W_s) \ln pov_s = \rho W_s \beta_1 hc_s + \beta_2 hc_s + \beta_2 sq_hc_s + \sum_{i=1}^9 \mu_i X_{i,s} + \varepsilon_s \quad (8)$$

$$(I - \rho W_s) \ln pov_s = \rho W_s \gamma_1 K_s + \beta_2 K_s + \sum_{i=1}^9 \mu_i X_{i,s} + \varepsilon_s \quad (9)$$

$$\ln pov_s = \beta_1 hc_s + \beta_2 sq_hc_s + \sum_{i=1}^9 \mu_i X_{i,s} + \alpha + \lambda W_s \varepsilon_s \quad (10)$$

$$\ln pov_s = \gamma_1 K_s + \sum_{i=1}^9 \mu_i X_{i,s} + \delta + \lambda W_s \varepsilon_s \quad (11)$$

In which, $\varepsilon_s \sim N(0, \sigma_\varepsilon^2)$ and $\varepsilon_s \sim N(0, \sigma_\varepsilon^2)$; λ is the scalar spatial disturbance coefficient for SEM. α and δ are an intercept to be estimated. β , γ , and μ are estimated coefficients. ρ and λ are the scalar spatial disturbance coefficient. W_s is a spatial weight matrix. We start our economic analysis by fitting cross sectional regression models into the data. Additionally, we estimate the spatial regression models by using maximum likelihood (ML) estimation. We test the models by utilizing *spautoreg* command in Stata 13.

In our study the values of spatial weights reflect spatial connections among 545 sub-districts. Considering the topographical diversity and natural properties of West Java, the spatial weight matrix W_s we apply is calculated based on spatial contiguity weights. It simply indicates whether sub-districts share a boundary or not. Contiguity is to expose the interaction among sub-districts. We calculate spatial weight matrix by using a *spmat* command in Stata 13 based on a *shapefile* of West Java map.

6. Results and Discussions

Unlike OLS implicitly assuming that the outcomes of all independent variables are different of each other, spatial regression allows getting spillover effects in this interaction. This spillover effects refers to the impacts of spatial proximity one sub-district to another sub-district. Our results are illustrated in Tables 1. In general, all parameters of spatial effects (ρ and λ) are statistically significant from zero and positive at 95% of confidence level. The significances signify that spatial dependence is a matter to assess the relation models. The results implies that poverty rate in one district is not only influenced by its own properties, but also affected by the properties of its surrounding sub-districts.

6.1. The effects of cluster size on poverty rates

The results in Table 1 confirm three spatial regression models. All models are highly significant to explain the relation between poverty rates and cluster size by controlling for spatial dependence. First, three models consistently show that cluster size has significant negative effects on poverty rates of sub-districts. The negative sign means that the higher dense of cluster size is incorporated with the lower poverty rate. Second, the consistently significant results are also reported from *fgrowth*, *fold*, *pop*, *wet*, *prod* and *trv_time*. The estimations suggest that poverty rates have a positive relation with the *fgrowth*, *wet*, and *trv_time*. The higher poverty rates may associate with the higher growth of farmers, the larger proportion of wetland in a sub-district, and the longer time to travel to the nearest city. On the other hand, *pop*, *prod* and *fold* are inversely associated with poverty rates. In terms of this spatially lagged variable, the poverty rates are a negative function of travel time. The shorter hours to travel from the neighbouring sub-districts to the nearest city are associated with the lower poverty rates. In other words, the neighbouring effects also reduce poverty rate.

We next compare 3 approaches of estimation in order to select the best alternative model that can estimate the relation between poverty rates and cluster size. We performed Akaike Criterion (AIC) and Schwarz Criterion (BIC). The lowest AIC and BIC values reflect the best-fitting specification. The result informs that the SAR model with 0.1242 of AIC value and 0.1377 of BIC value can be the preferred estimation model. From this comparison, we perform marginal effects analysis using the partial derivative of the SAR as the preferred model with respect to independent variables. These effects investigate to what extent that cluster size and other control variables provides impacts on poverty rates. The marginal effects comprise direct and spillover effects by considering average values as a reference. Direct effects clarify the impacts of own properties of a sub-district on its poverty rate. Moreover, spillover effects mean that the poverty of a sub-district may be affected by the properties of surrounding sub-districts. In Appendix 1, we obtain that all explanatory variables have larger direct effects than spillover effects on poverty. It means that the properties of own sub-districts provide higher influence on reducing poverty of this sub-district than that of its neighbouring sub-districts.

Let us consider the impacts of cluster size on poverty rates. From the Table 3 we observe that the impacts of cluster size are negative and significant. It implies that at the mean of cluster size, 2.90 labourers, there is an approximate decrease in poverty rates of a sub-district by 3.30 per cent. Additionally, with respect to equation 2, on average 2.90 of cluster size represents about 3,760 farm employees. Increase in 3,760 persons of total farm labourers of a sub-district and its surrounding sub-districts is associated with poverty rate at around 11.10% of total population in the sub-district. In Table 3, these effects comprise of direct and spatial spillover effects. The direct impact of cluster size is negative and significant suggesting a negative effect on poverty rate by 2.04% and contributes larger impact than the spillovers. Furthermore, the spatial spillover effect of cluster size is also negative and significant. This indicates that cluster size in the neighbouring sub-districts has a negative impact on poverty rate by nearly 1.26 per cent.

Table 1. Estimation results of the relations between poverty rates and agro-clusters

Variable (Dependent variable = <i>lnpov</i>)	Equation 4 (<i>hc</i> as independent variable)			Equation 5 (<i>Ks</i> as independent variable)		
	SAR	SEM	SDM	SAR	SEM	SDM
Original variables						
Cluster size (<i>hc</i>)	-0.0342***	-0.0379***	-0.0363***			
Square cluster size	0.0039**	0.0038**	0.0035**			
Krugman index (<i>Ks</i>)				-0.1007**	-0.1026**	-0.0929**
Growth of farmer number	0.0004***	0.0004***	0.0004***	0.0003**	0.0003***	0.0003***
% of smallholders	-0.0860	-0.0199	-0.0584	-0.1134	-0.0533	-0.0784
% of farmers with age > 55 years	-0.9116***	-1.0880***	-0.8526***	-0.8930***	-0.9704***	-0.8324***
Population density	-0.0390***	-0.0372***	-0.0394***	-0.0293***	-0.0286***	-0.0301***
Total area of sub-district	0.0008*	0.0010**	0.0007	0.0005	0.0007	0.0004
% of wetland in total	0.0021***	0.0025***	0.0019***	0.0017**	0.0021***	0.0015**
Productivity	-0.0036***	-0.0028**	-0.0035***	-0.0024**	-0.0020*	-0.0024**
Distance to the nearest city	-0.0002	-0.0003	-0.0001	-0.0002	-0.0001	-0.0000
Travel time	0.0897***	0.1192***	0.1142***	0.0746***	0.1001***	0.0994***
Dummy (Rural = 1, Urban = 0)	0.0658	0.0763	0.0768	0.0146	0.0297	0.0261
Spatially lagged variables						
Cluster size (<i>hc</i>)			0.0102			-0.0131
Krugman index (<i>Ks</i>)						
Population density			0.0047			0.0049
Travel time			-0.0510**			-0.0486*
Intercept (α or δ)	1.7599***	2.5814***	1.6542***	1.8900***	2.6569***	1.7605***
Log likelihood	-136.5778***	-133.3234***	-133.7716***	-145.8532***	-143.5917***	-143.1207***
ρ (SAR and SDM)	0.4039***		0.4469***	0.3864***		0.4350***
λ (SEM)		0.5015***			0.4741***	
AIC	0.1242	0.1276	0.1252	0.1260	0.1296	0.1272
BIC	0.1377	0.1414	0.1421	0.1385	0.1424	0.1432

Note: One, two and three asterisks denote significance at the 10%, 5% and 1% level, respectively.

6.2. The effects of agricultural specialization index on poverty rates

The other objective of our study is to assess the effects of regional specialization of primarily agricultural production on poverty rate and to investigate the spatial neighbouring effects within this relationship. Table 1 also describes the results of spatial regression assessing the link between K_s and poverty rates with controlling for other control variables. First, Krugman index has a negative impact on poverty rate of a sub-district. The sub-district, which has tendency to be specialized in primarily agricultural crops experiences lower poverty rate. In other words, agro-clusters with specialised agricultural production are most likely to reduce poverty in a sub-district. Second, the SDM regression suggests that the spatial lags of all independence variables are not statistically significant. It signifies that the spatially lagged explanatory variables in one sub-district may not decrease poverty rates in other surrounding sub-district. However, the significance of ρ and λ gives evidence that spatial dependence in this relation is essential to consider.

Third, it is interesting to note that the same results as the models of cluster size are given from the independence variables. *fgrowth*, *fold*, *pop*, *wet*, and *trv_time* have a significant influence on poverty reduction. Furthermore, poverty rate has a positive relation with the *fgrowth*, *wet*, and *trv_time*. The higher growth of farmer number, the larger proportion of wetland in a sub-district, and the longer time to travel to the nearest city may raise poverty rate of the sub-district. On the other hand, *pop* and *fold* are inversely associated with poverty rates.

Even though spatially lagged control variables are insignificant, we assess the effects of neighbouring sub-districts through analysing direct and spatial spillover effects of independence variables on poverty rates. In order to investigate these impacts, we also compare 3 regression models by applying several model selection procedures. The results of AIC and BIC indicate that SAR model is also the best-fitting specification because of the lowest AIC and BIC values, which are 0.1260 and 0.1385 respectively. In Appendix 2 we see that the direct effects of all independent variables are likely higher impacts than their spatial spillover effects on poverty reduction. These marginal effects imply that at the mean of Krugman index, 0.4562, there is a negative impact of Krugman specialization index on poverty rates of a sub-district by approximately 9.76 per cent. This effect includes the negative effects on poverty rates from its own sub-district and its neighbouring sub-districts, which are about 6.18 per cent and 3.58 per cent, respectively. It asserts that a sub-district, which is more likely to be specialised has lower poverty rate.

6.3. The negative externality of agro-clusters

It has been discussed above that agro-clusters can provide negative externalities for sub-districts. In order to assess an appropriate size of agro-clusters, we then perform an adjusted model according to the result of SAR model. The model estimates the maximum size of agro-clusters that has profit for firms by applying a quadratic function of hc .

$$Adj \ln pov = 1.7599 - 0.0342hc_s + 0.0039sq_hc_s \quad (12)$$

In other words, the adjusted poverty rates are computed simply by nullifying the effects of other variables than cluster size. Thus, there is a solution to the quadratic form because of quadratic model specification ($\beta_2 \neq 0$ and $0 \leq \beta_1 - 4\beta_2\alpha$). The turning point of this quadratic curve (Figure 1) signifies the optimal number of cluster size before the poverty rate go up. This point (hc_p) is solved using the first derivative of the equation (12) with respect to hc .

We assume that negative externalities occur when the number of cluster size reaches more than the optimal number (hc_p). Appendix 3 illustrates this optimal number, which is 4.385.

Recall the equation (2), we calculate adjusted farm employees, \hat{e}_s , reflecting the optimal number of farmers in average by applying $\hat{e}_s = hc_p + \left(\frac{e}{E}\right)\bar{E}_s$. We suggest that in average the adjusted number of farm labourers of a sub-district is around 8,108 people. Furthermore, negative externalities of agro-clusters present if the number of farmers exceed this number

7. Conclusions and Policy Remarks

Rural populations are highly reliant upon agricultural sector, which is spatially unevenly distributed. In fact, they still confront the higher poverty rates. This paper uses two measures, cluster size and the Krugman Specialization Index, to assess the impact of clusters, which are spatial concentrations of farm activities on poverty rates for 545 sub-districts of West Java. Cluster size is an input-oriented measure quantifying the concentration of agricultural employment. The Krugman Specialization Index is an output-oriented concentration measure, which provides evidence on the difference between the share of agricultural production values of each sub-district and the average share in West Java.

We estimate six specifications of spatial econometric models: a spatial lag model, a spatial Durbin model, and a spatial error model by using a contiguity spatial weights matrix. We emphasize two key findings. First, there is a significant negative effect of cluster size in a sub-district and its neighbouring sub-districts on poverty rates. The higher number of farm labourers, the lower poverty is, but after reaching the optimal average number, the poverty rate rise. Second, the Krugman specialization index leads to the same negative impact on poverty rates in the sub-district as well as negative spillover effects on the poverty in neighbouring sub-districts. The more specialization in agriculture or non-agriculture, sub-district may experience the lower poverty rate. In addition, the direct effects of agro-clusters on poverty rates in the sub-district itself are larger than the spillover effects. In other words, the properties of a sub-district are more influential on reducing its poverty rates rather than the properties of its surrounding sub-districts. On the other hand, political interventions for lowering poverty do not need to target each sub-district since they will also exert significant negative effects in the surrounding of the targeted region.

These findings indicate that government planners of West Java can successfully reduce poverty by fostering the specialisation of the sub-districts. The government should improve farmers' capabilities and knowledge by establishing on-spot targeted extension services as well as other education channels. This can also be attained by enforcing networks with universities or other research institutions. Additionally, the government should control input availability and prices and improve market access. Since agro-clusters result in spatial spillovers for local economic development, improving the availability and quality of infrastructures connecting sub-districts is also a promising strategy for poverty reduction.

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Appendix 1. Marginal effects of cluster size and control variables on poverty rates

	Total Effects	Direct Effects	Spillover Effects
Cluster size (hc)	-0.0330	-0.0204	-0.0126
Square cluster size	0.0037	0.0023	0.0014
Growth of farmer number	0.0003	0.0002	0.0001
% of farmers with age > 55 years	-0.8804	-0.5434	-0.3371
Population density	-0.0376	-0.0232	-0.0144
% of wetland in total	0.0020	0.0013	0.0008
Productivity	-0.0035	-0.0021	-0.0013
Travel time	0.0866	0.0535	0.0332

Appendix 2. Marginal effects of Krugman index and control variables on poverty rates

	Total Effects	Direct Effects	Spillover Effects
Krugman index (Ks)	-0.0976	-0.0618	-0.0358
Growth of farmer number	0.0003	0.0002	0.0002
% of farmers with age > 55 years	-0.8654	-0.5480	-0.5480
Population density	-0.0284	-0.0180	-0.0180
% of wetland in total	0.0016	0.0010	0.0006
Productivity	-0.0024	-0.0015	-0.0009
Travel time	0.0723	0.0458	0.0265

Appendix 3. Cluster size in relation to adjusted poverty rates

