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AGRO-CLUSTERS AND RURAL POVERTY: A SPATIAL PERSPECTIVE FOR WEST JAVA

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Neighbouring economies are likely to influence one another. The concentration of farming activities referred to as an 'agro-cluster' generates opportunities for income and employment in a given region and its surrounding area. We analyse the link between poverty rates and agro-clusters by accounting for spatial spillovers. To quantify agro-clusters, we employ one input-oriented and one output-oriented measure. Our analysis applies six spatial econometric specifications and focuses on 545 subdistricts of West Java, where about 10% of the population live in poverty. We find that the concentration of agricultural employment substantially reduces poverty in a subdistrict as well as in neighbouring subdistricts. We also find that specialisation in crop outputs has positive impacts on poverty reduction and that localisation externalities are fundamental to agriculture's success. These findings imply that policy interventions may be applied in a spatially selective manner because they will generate spatial-spillover effects on poverty reduction in surrounding areas.

Keywords: *clusters*, *farming activities*, *poverty*, *spatial dependence*, *Indonesia*

JEL classification: C31, I32, Q11, R12

INTRODUCTION

The agricultural sector plays an important role in rural economies; it is often the primary income source for most of the rural population. Of all sectors, it has the most potential to accelerate rural development (Anríquez and Stamoulis 2007). The World Bank (2008) states that when GDP grows in the agricultural sector, the positive impacts on poverty reduction are three times greater than that of growth in other sectors. However, over 68% of poor people in Southeast Asia live in rural areas, which have concentrated agricultural sectors (Alkire and Robles 2015); rural

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people have a higher risk of being poor than urban people do (ADB 2015). In Indonesia, agriculture is evenly concentrated, in spatial terms, in most rural regions.

The geographical concentration of agriculture can be interpreted as the formation of agro-clusters. We define agro-clusters as regional concentrations and specialisations in agricultural production, processing, or marketing. Our initial question is whether agro-clusters reduce poverty in a region as well as in its neighbours. Agro-clusters offer various advantages in terms of improving agricultural productivity and reducing poverty (Kiminami and Kiminami 2009; Brasier et al. 2007); such clusters generate income opportunities for farmers and create employment opportunities for other rural people. Income generation and employment creation assist rural households to move out of poverty (Estudillo and Otsuka 2010).

According to Barkley and Henry (1997), proximate farmers are likely to support one another in order to raise productivity. Such mutuality may advance production processes and outputs, even if the companies involved are small or passive (Knorringa and Nadvi 2016). Sato (2000) claims that adjacent rural firms benefit from these potential linkages via an increase in targeted product sales. Additionally, such firms place relatively greater value on attitudes that reduce market and financial risks, increase access to credit or new technology, or strengthen commitments from buyers (Umberger et al. 2015).

In analysing the spatial concentration of economic activity, some of the literature assesses the relations between firm benefits, employment, population concentration, and economic development. Some studies seek to identify the determinants of firms' decisions to cluster. In Indonesia, manufacturing firms have been shown to concentrate owing to access to more centralised locations, lower wages, larger local markets, better infrastructure (Henderson and Kuncoro 1996), greater technological spillovers, a higher degree of labour pooling, or a larger supply of inputs (Amiti and Cameron 2007). In addition, Deichmann et al. (2008) point out that, in horizontal clustering, natural-resource-based industries benefit from what the authors call 'localisation effects'—that is, that farmers benefit from having neighbours with similar specialisations.

Our second question is whether agro-clusters in West Java benefit rural economies, or whether they are counterproductive owing to the dense population of farmers. Farmers in densely clustered markets can face intense competition (Folta, Cooper, and Baik 2006; Crozet, Mayer, and Mucchielli 2004), which may create a difficult operating environment (Stucke 2013; Coad and Teruel 2013). Such circumstances are likely to be why the density of farmer concentration can reduce farmers' profitability and, ultimately, raise poverty rates.

Our study differs from previous studies in two main ways. First, in focusing on the spatial concentration of agriculture, it considers the effects of agglomeration on poverty reduction with respect to spatial interactions among neighbouring subdistricts. Henderson and Kuncoro (1996) argue that researchers looking to examine industrial concentration should analyse agriculture separately from other economic sectors because of its specific production system and its dependence on land. Thus, our core interest is the link between the concentration of farming activities and the incidence of poverty.

Second, our study is more concerned with the effects of spatial spillovers between neighbouring subdistricts on poverty reduction. The literature on the relation between spatial concentration and the incidence of poverty often neglects the importance of spatial effects (see, for example, Cali and Menon 2013; Giang, Nguyen, and Tran 2016). These spatial effects show the spatial interactions in which endogenous variables of different regions may be dependent (Anselin and Bera 1998). Such interactions are referred to as spatial-spillover effects.

The effects of spatial spillovers on economic growth have been acknowledged in the literature (Cravo and Resende 2013; Tian, Wang, and Chen 2010). Spatial relations may exist for various reasons. First, neighbouring economies are likely to influence each other; in Indonesia, for example, districts may grow faster if their neighbours are growing quickly (McCulloch and Sjahrir 2008). Second, spatial agglomeration and economic distance have a strong connection with regional growth in terms of competitive advantage, productivity, and employment growth (Fan and Scott 2003). Third, geographical proximity to urban regions has a spatial effect on rural incomes (Day and Ellis 2014). Finally, economic transactions cross geographic space, because of geographical and institutional diversity (Wood and Parr 2005). For Indonesian districts, the effects of neighbours extend beyond levels of and growth in gross regional domestic product per capita; they also affect demographics, human capital, and infrastructure (Day and Lewis 2013).

With respect to spatial distribution, we employ spatial econometric regressions from regional aggregated data for 545 subdistricts of West Java to assess the concentration of farming activities and poverty rates. These regressions allow us to assess the link between our key variables and to investigate the spatial spillovers across adjacent subdistricts. Examining the link between the spatial concentration of agriculture and poverty while accounting for spatial dependence is an original contribution to the literature.

THEORETICAL FRAMEWORK

Cluster Externalities and Rural Poverty

Alfred Marshall introduced the term 'localised industry' to describe agglomeration economies, or the regional concentration of homogenous economic activities, and explained them using three concepts (Krugman 1995). First, neighbouring firms are likely to have a large supply of skilled people. Second, such firms can establish reciprocity in offering specialised services—for instance, by sharing machinery and production inputs and improving market access. Third, in clustering, the exchange of expertise and information fosters cooperation.

Increasing returns make it profitable for firms to cluster production (Krugman 1991). Additionally, clustered firms tend to have skilled labourers and access to external markets (Padmore and Gibson 1998). These benefits are connected to geographical proximity and cooperation among the actors, or 'collective efficiency' (Schmitz and Nadvi 1999). Farmers can obtain the advantages of agglomeration if they are located in regions with natural cost advantages (Ellison and Glaeser 1999), such as good soil quality, ample farmland, and a favourable climate.

Porter (1990) defines clusters as a competitiveness-enhancing array of linked industries and other entities in the same industry. Industries in a strong cluster often share higher levels of employment and patenting growth (Delgado, Porter, and Stern 2014). In relatively large clusters, farmers can gain an advantage over their competitors and thereby generate greater margins, retain more consumers, and produce their products at lower costs (Porter 1998; Braguinsky and Rose 2009). These farmers are often linked in the same value chain, a consumer farm network, or a regional economy. Knowledge flow along these links may also improve production processes (Aydogan and Lyon 2004; Vissers and Dankbaar 2013).

Contrarily, agro-clusters can also hinder local economies. A region with a large number of farmers may encounter negative externalities such as congestion and pollution (Duranton et al. 2010, 31). Another negative externality is constrained access to production resources and facilities, which reduces bargaining power. Stuart and Sorenson (2003) argued that new-entry firms suffer if there is a heavy concentration of competitors nearby. This growth leads to shortages in labour, land, machinery, and fertilisers, as well as to increased land rents and transport costs (Deichmann et al. 2008; Miron 2010). Hence, farmers will be less flexible when sourcing production inputs and may need to alter their behaviour by shifting operations, schedules, or locations in response to the impacts of congestion in order to maintain their competitiveness and therefore their revenue.

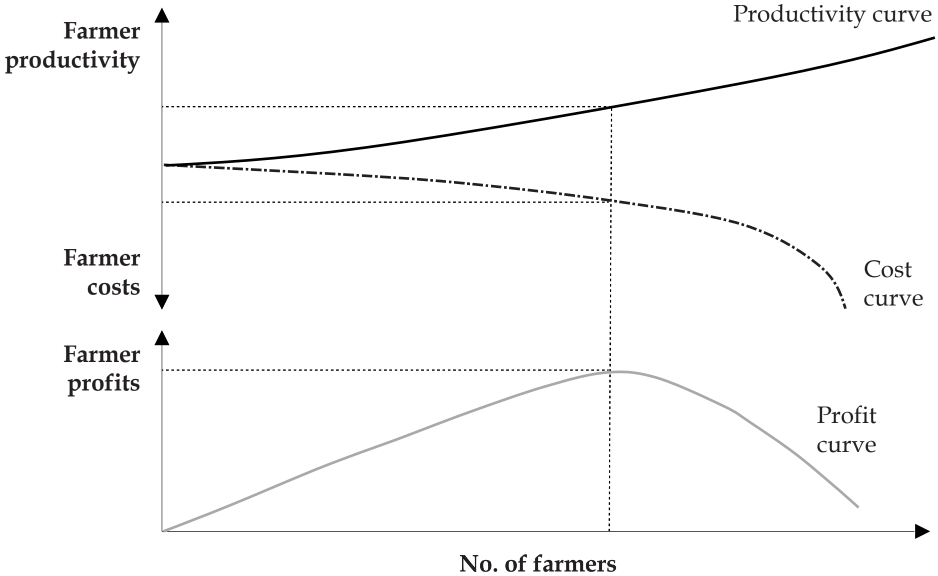
To explore both positive and negative externalities of clusters, we have adapted the concept of Duranton et al. (2010), who argue that agricultural clusters can be explained by the curves of productivity, cost, and profit (figure 1).

The productivity curve reveals that an increasing number of farmers in a subdistrict is associated with positive productivity growth. As described above, the clustering of farmers in a subdistrict enables them to produce and differentiate agricultural products and earn more revenue. In an optimally sized cluster, the sharing of information allows farmers to be flexible in sourcing inputs. An increase of 1% in the number of resources used to produce goods corresponds to an increase of more than 1% in output (Duranton et al. 2010). The cost curve, however, shows that increasing the number of farmers in a subdistrict also raises production costs, as a consequence of the negative externalities within clusters, as discussed above.

The concave profit curve represents the relation between profit and the concentration of farmers. This curve consists of two segments. In the first segment, profit is positive, meaning that farmers' profits rise when the number of farmers increases. In this segment, the total revenue earned by farmers outweighs their total costs—this number of farmers still generates reasonably positive external economies. Conversely, in the second segment, after the optimal number of farmers (e_p) has been reached, profits fall as the number of farmers increases, owing to congestion and its impacts on production costs. Poverty rates are therefore likely to be higher in the second segment than in the first.

Fowler and Kleit (2014) investigated the relation between farming clusters and poverty reduction and found that it correlates strongly with spatial agglomeration, industrial localisation, and regional growth. At the regional level, multiple types of externalities—including knowledge, skills, and input–output linkages—may arise in farming clusters (Delgado, Porter, and Stern 2014). These externalities have strong links to regional competitiveness (Porter 1998). Proximity and abundant resources affect competitive advantage through their influence on productivity growth. This productivity is derived from the capacity of agents to use production factors, and prosperity depends on the productivity with which production factors are used and upgraded in particular regions (Porter 2000). We infer that the more resources a subdistrict uses for productivity gains, the larger its share of employment and income gains will be.

FIGURE 1 *Clusters and Economic Performance*



Source: Adapted from Duranton et al. (2010, 34).

Cluster Measures

In the literature, one measure of economic concentration is the location quotient (LQ) of subdistrict *s* (LQ_s). We use this measure to quantify how concentrated a subsector in a subdistrict is, in comparison with the West Javan average. It is defined as

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

In equation (1), the variable e_s denotes the number of farmers in subdistrict *s*, $s = \{1, \ldots, 545\}$, of West Java; E_s refers to the number of total employees in subdistrict *s*; *e* is the number of farmers in West Java; and *E* is the number of total employees in West Java. If subdistrict *s* has an agricultural LQ value greater than unity, its agriculture sector is said to be economically concentrated, because it has above the average proportion of employment of West Java. An LQ value greater than unity points to the importance, in employment terms, of primary agricultural production in that subdistrict. However, there are two main limitations of using the LQ to measure concentration. First, unity in the LQ is defined arbitrarily; there is no theoretical consensus of LQ cut-off values (Martin and Sunley 2003). Second, the measure cannot inform the absolute size of local industries, because it ignores the presence of 'mass effects' in larger workforce industries (Fingleton, Igliori, and Moore 2004). Therefore, it is possible to obtain high LQ values for subdistricts that have a small number of farmers.

Regardless, we use a modified LQ_s model to examine the relation between farm employment and the spatial concentration of agriculture in West Java—or 'horizontal clustering' (hc_s)—following the measure of Fingleton, Igliori, and Moore (2004). They suggest that the hc_s measure takes into account the relative local importance of an industry and the size of agglomeration with respect to the number of employed farmers. Their suggestion is relevant for our study for two reasons. First, we look at a variety of subdistricts with different farmer population sizes, from 8 farmers to 29,241 farmers (BPS 2013b). We obtain higher LQ values for agriculture in urban and peri-urban subdistricts, which have a relatively small number of farmers. Second, we analyse only the horizontal interactions between farmers in subdistricts, who use productive resources to produce and sell similar products.

The variable hc_s is defined as the observed number of farmers in subdistrict e_s that exceeds its expected number, $\hat{e}_s$. Fingleton, Igliori, and Moore (2004) suggest that the quantity $\hat{e}_s$ indicates the number of farmers in a subdistrict; the same value is used to describe the number of farmers in West Java. This definition corresponds to the LQ_s value being equal to unity. If $LQ_s = 1$, then

$$\hat{e}_s = \left(\frac{e}{E}\right)E_s.$$

We measure the hc_s of subdistrict s by subtracting the expected number of farmers, $\hat{e}_s$, from the observed number of farmers, e_s:

$$hc_s = e_s - \hat{e}_s. \tag{2}$$

Equation (2) is our input-oriented measure. The hc_s value of subdistricts is positive, indicating the presence of farmer concentration in those subdistricts.

Our other measure of economic concentration is output-oriented. We quantify this measure by adapting Krugman's (1991) relative specialisation index. Our adapted index takes into account the share of a subdistrict's agricultural production outputs that would have to be relocated in order to achieve an agricultural structure equivalent to the average structure of West Java (Krugman 1991, 76; Combes and Gobillon 2015). In other words, it calculates the relative specialisation of a subdistrict's primary agricultural outputs in relation to West Java's agricultural outputs.

We divide the primary agricultural subsectors, i, into the three major subsectors of West Java, $i = \{1, 2, 3\}$: food crops, horticulture, and perennial crops. Following Combes and Gobillon (2015, 274), we adapt Krugman's specialisation index (K_s) as follows. For subdistrict s, we calculate the share, v_{is}, of the agricultural subsector outputs, y_{is}, of that subdistrict in relation to its total agricultural outputs, Y_s,

$$v_{is} = \frac{y_{is}}{Y_s}.$$

We then compute $\bar{v}_s$ as the average share of the agricultural outputs of subsector i across West Java, y; Thus,

$$\bar{v}_s = \frac{\sum_{n=1}^{N} v_{is}}{N}.$$

The variable N denotes the number of subdistricts in West Java, $n = \{1, \ldots, 545\}$. The K_s is the absolute value of the difference between the share of the outputs in subdistrict s and the average share across West Java:

$$K_s = \sum_{i=1}^{3} \left| v_{is} - \overline{v}_s \right| . \tag{3}$$

If the index takes the value of zero, the agricultural structure of subdistrict *s* resembles the agricultural structure of West Java. The closer the ratio is to the maximum value,

$$\frac{2(S-1)}{S} = 1.99,$$

the more the agricultural structure of subdistrict *s* deviates from the average agricultural structure of West Java. A subdistrict is more likely to be specialised in agriculture if it has the close-to-zero value of the relative specialisation index.

DATA AND VARIABLES

The data analysed in this article are extracted from Sensus Pertanian (Agricultural Census), carried out for Statistics Indonesia (BPS), the central statistics agency, in 2013; the 2011 Pendataan Program Perlindungan Sosial (Data Collection for Social Protection Programs); and various BPS statistical yearbooks at the *kabupaten* (district) and *kota* (city) level. We distinguish 545 subdistricts of West Java by using aggregated data at the subdistrict level and referring to the geospatial 'shapefile' of West Java.

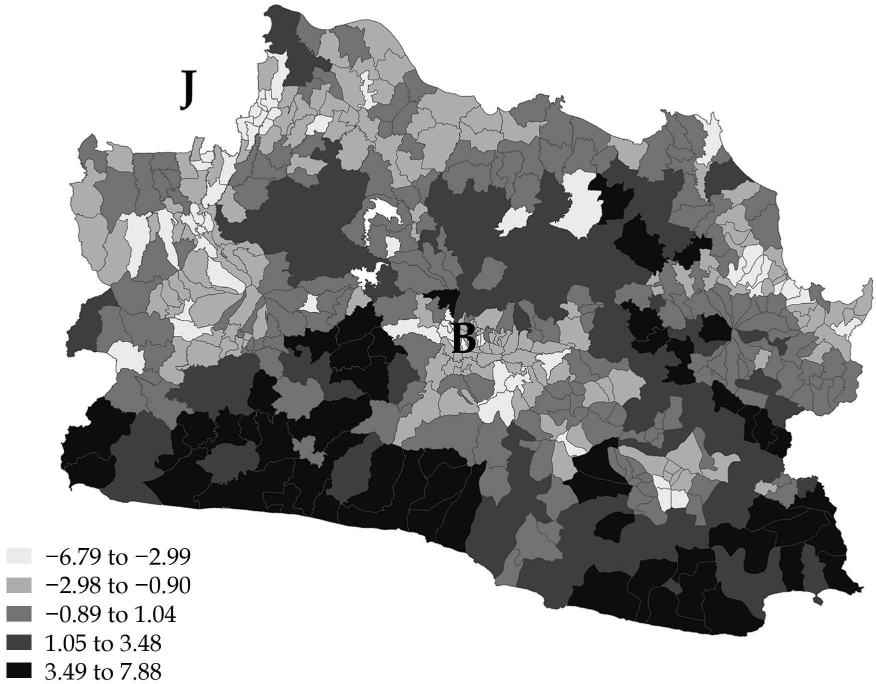
Our study focuses on West Java, which covers around 37,000 square kilometres, 72% of which is agricultural land. The province contributes around 15% of Indonesia's GDP (BPS 2013b) and more than 20% of its agricultural output. It also produces more than 70 agricultural commodities each year; it contributes approximately 18% of Indonesia's rice and around 30% of its vegetables. BPS (2013c) reported that the agricultural sector provides 30% of West Java's total employment. Some of its subdistricts have developed subterminal agribusinesses and local home industries, such as packing houses. These industries often have contracts with exporters, wholesalers, and retailers.

Furthermore, two of Indonesia's largest cities are in or near West Java. The city of Bandung, in the centre of the province, has a population of around 2.6 million (BPS 2013b). The other city is Jakarta, which borders West Java and has around 9.8 million residents (BPS 2013a). Both cities have influenced agricultural development in the province. For instance, they supply a large number of consumers of farm products but also create urban sprawl that reduces farmland productivity. West Java is also home to some of Indonesia's leading universities, from which many technology transfers to farmers originate.

Agro-clusters in West Java

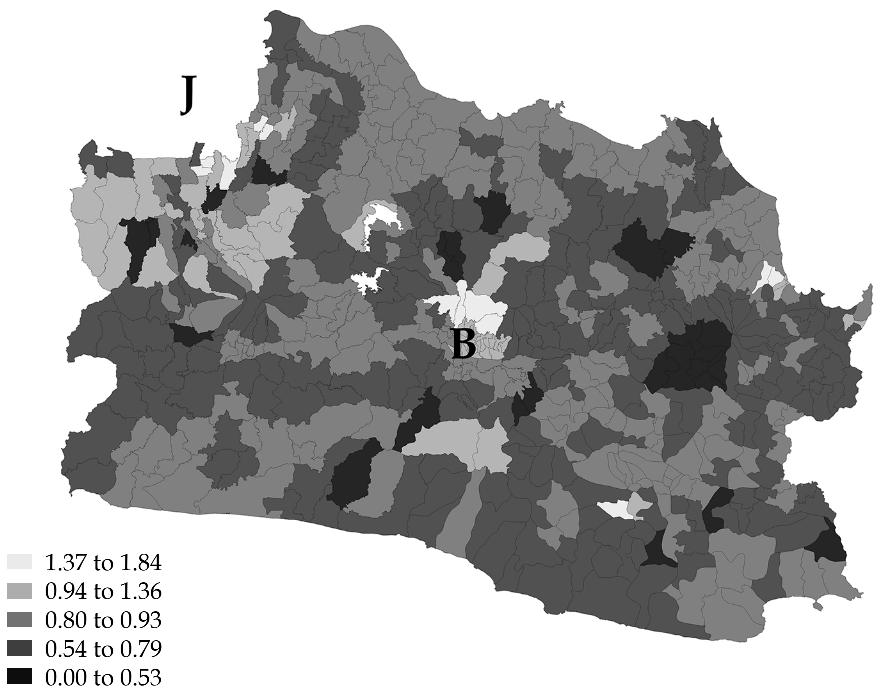
The number of farm households in West Java was about three million in 2013. Figures 2 and 3 depict the spatial distribution of agro-clusters in West Java on the basis of equations (2) and (3). Figure 2 shows the hc_s distribution, and figure 3 shows the specialisation distribution. The darker regions in figures 2 and 3 represent, respectively, denser agro-clustering and greater specialisation in agriculture.

FIGURE 2 *Horizontal Clustering, West Java, 2013 (1,000 people)*



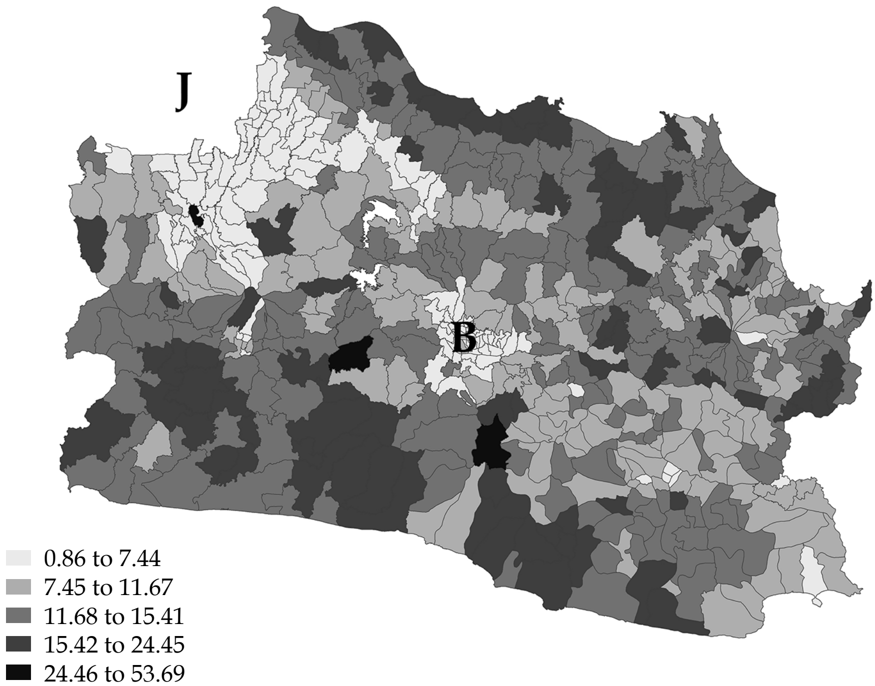
Note: Authors' calculations. J = Jakarta; B = Bandung Metropolitan Area.

FIGURE 3 *Relative Specialisation Index, West Java, 2013*



Note: Authors' calculations. J = Jakarta; B = Bandung Metropolitan Area.

FIGURE 4 *Poverty-Rate Quintiles, West Java, 2011 (% of population)*



Note: Authors' calculations. J = Jakarta; B = Bandung Metropolitan Area.

In the hc_s map (figure 2), agro-clusters are concentrated mostly in the southern subdistricts of West Java, suggesting that these subdistricts have above-average potential for agricultural production. The clusters have a magnitude of hc_s. Subdistricts with positive values of hc_s have a larger number of farmers than those with negative values. Our expectation is that farmers in West Java are characterised by labour intensiveness. The southern subdistricts of West Java include more than 57% of the province's total farm households. Therefore, we interpret a larger number of farmers as signifying a higher density of agricultural production and, consequently, a greater likelihood that agro-clusters are present. Furthermore, as shown in the specialisation map (figure 3), agro-clusters exist mainly in the southern subdistricts. The specialisation index records the relative output share of agricultural products in the total agricultural output of West Java.

Poverty in West Java

In Indonesia, poverty rates are measured by absolute poverty, which refers to a standard of minimum monthly expenditure needed for people to fulfil their basic needs. In West Java in 2011, the standard—the poverty line—was defined as around Rp 277,000 per month, or about $1 per day, per capita. Around 9.4% of the West Java's population was categorised as poor, most of whom were in rural areas (BPS 2011). As shown in figure 4, the subdistricts closest to Bandung and Jakarta have lower poverty rates than those farther away. Nearly all of the southern and northern subdistricts have high poverty rates.

TABLE 1 *Summary Statistics*

Variable	Unit	Mean	CV	Median	Min.	Max.
Poverty rates (pov_s)	%	11.44	0.42	11.67	0.86	53.69
Horizontal clustering (hc_s)	1,000 people	0.01	877	−0.16	−6.79	7.88
Squared horizontal clustering (sq_hc_s)		6.47	1.48	2.62	0.00	62.18
Specialisation index (K_s)		0.46	0.82	0.35	0.06	1.79
Proportion of smallholders	%	0.76	0.18	0.80	0.18	1.00
Proportion of aged farmers	%	0.36	0.25	0.36	0.17	0.66
Population size	1,000 people	73.81	0.74	58.40	10.76	46.97
Total area of subdistrict	hectares	601,293	0.78	47.60	1.56	304.75
Proportion of paddy field	%	24.93	0.91	19.54	0.00	97.32
Travel time	hours	2.39	0.57	2.37	0.02	6.17
Capital-city effects		79,715	0.92	51,446	26,462	514,467

Note: Authors' calculations. CV = coefficient of variation.

Control Variables

To structure our modelling approach, we select a set of control variables that affect poverty rates and the concentration of farming activities. Table 1 summarises our key variables: pov_s, hc_s, and K_s.

Table 1 also shows our control variables ($X_{i,s}$) which fall into three categories: farmer characteristics, subdistrict properties, and urbanisation economies. The category of farmer characteristics includes two variables. The first is the share of farmers aged 55 or older, which, in West Java, is nearly 36% (BPS 2013c). This farmer group's footprint is considerable for agricultural growth and the farmers in this group tend to be wealthier than their younger counterparts (El-Osta and Morehart 2008). The second variable is the proportion of smallholders in a subdistrict. We define smallholders as farmers who manage less than 0.5 hectares, independently of whether they own or rent the land. The proportion of smallholders to the total number of farmers in West Java is around 76% (BPS 2013c). There is a positive relation between the incidence of poverty and the number of smallholders (Fan and Chan-Kang 2005). IFAD (2013) reported that supporting smallholders financially could help to lift more than 5% of people in Asia out of poverty. However, the production efficiency of small farms in many Asian countries has decreased relative to large farms, and hence they are likely to lose comparative advantage (Otsuka, Liu, and Yamauchi 2016).

The second category of variable is subdistrict properties, including the distance to the nearest city (Bandung or Jakarta), the population size, the proportion of paddy fields, the total area of subdistricts, and a rural–urban distinction. Travel time to the nearest city is measured from the centroid of the subdistrict to the centroid of the city, for an average one-way trip. We use the centroids' GPS coordinates to measure the distance in Google Maps. A shorter travel time to the nearest city may help to lift rural regions out of poverty (Day and Ellis 2014; Partridge and Rickman 2008). This variable accounts for the quality of the roads and the diverse topography of West Java.

We also consider the population size of each subdistrict, which may indicate urbanisation effects within the subdistricts and the size of potential markets for agricultural products. The other subdistrict variable is the percentage of rice fields in the total area. In West Java, the average share is around 26%, spread unevenly across subdistricts (Ministry of Agriculture 2014).

Third, we control for the capital-city effect on farming activities in West Java by introducing the population size of Jakarta (*pop_size*$_j$). We apply a gravity measure to weight the strength of the effect on agricultural activities in the nearest subdistricts,

$$GI_s = \sum_j \frac{pop\_size_j}{km_{sj}}$$

(Day and Ellis 2013, 2014). The variable GI_s is the gravity measure of the capital-city effect on agriculture in subdistrict *s* relative to the distance, km_{sj}, to Jakarta.

Last, we add a dummy variable, *D*, which equals one for rural subdistricts and zero for urban subdistricts, to analyse the interaction between urban and rural regions in the concentration of farming activities. To distinguish such regions, we define an urban region as one that satisfies certain criteria, including having a population density of at least 5,000 people per square kilometre; a share of less than 25% of farm households; and accessibility to urban facilities, such as roads, public health services, and education facilities (BPS 2010).

MODEL SPECIFICATIONS

Baseline Models

In this section, we set out two baseline models by which to examine the link between agro-clusters and poverty rates. In the first, we use poverty rates ($lnpov_s$) as a dependent variable and horizontal clustering (hc_s) as an explanatory variable. In figure 1's profit curve, the optimal number of farmers signifies the turning point from positive to negative externalities for agro-clusters. The loss of profits is one factor that increases regional poverty rates. In this model, we investigate how horizontal clustering influences poverty rates, by controlling for these externalities—having assumed that changes in horizontal clustering in a subdistrict can either increase or decrease poverty rates. On the basis of this relation, we apply the square of horizontal clustering (sq_hc_s) to the models, which, as expected, return convex quadratic curves. The first baseline model takes the following form:

$$lnpov_s = \alpha + \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{8} \mu_i X_{i,s} + \varepsilon_s;\ \varepsilon_s \sim N\left(0, \sigma_\varepsilon^2\right), \tag{4}$$

in which $lnpov_s$ denotes the poverty rate of subdistrict *s* in the natural logarithm; $X_{i,s}$ refers to control variable *i*, *i*{1, …,7}, in subdistrict *s*; and ε_s is a disturbance term, to account for unobserved information. The symbol α is an estimated intercept, while β and μ are estimated coefficients explaining the relations among variables. From equation (4), we expect hc_s to have a significant negative magnitude, to account for the positive effects of agro-clusters on poverty reduction. We assume the opposite for sq_hc_s, to account for the negative effects.

The second baseline model explains the link between $lnpov_s$ as the dependent variable and K_s as the independent variable. We use it to investigate whether the relative specialisation of primarily agricultural production can reduce poverty rates in subdistricts:

$$lnpov_s = \delta + \gamma_1 K_s + \sum_{i=1}^{8} \theta_i X_{i,s} + \epsilon_s;\ \epsilon_s \sim N\left(0, \sigma_\epsilon^2\right), \tag{5}$$

where ϵ_s is an error term, δ denotes an intercept to be estimated, and γ and θ are estimated coefficients for the relation between $lnpov_s$ and K_s. We expect this specialisation index to have a positive sign, which suggests that the more specialised a subdistrict's farm outputs are (relative to those of West Java as a whole), the lower its poverty rate will be.

Spatial Dependence Tests

Spatial Weight Matrix

Although there is no consensus for standardising spatial weights, defining a weight parameter (w_s) is a common way of modelling a spatial structure. We examine the values of w_s in the spatial connections among 545 subdistricts in West Java. Considering the topographical diversity and natural properties of West Java, we apply spatial contiguity weights to compute a spatial weight matrix, W_s. Such a weight indicates whether subdistricts share a boundary. Suppose we have a set of boundary points between two subdistricts, $s_{(1)}$ and $s_{(2)}$. The contiguity weights are defined by

$$\begin{cases} 1, s_{(1)} \cap s_{(2)} \neq \varnothing \\ \\ 0, s_{(1)} \cap s_{(2)} = \varnothing . \end{cases} \tag{6}$$

We use these weights to expose the interactions among subdistricts: w_s will equal one if subdistricts $s_{(1)}$ and $s_{(2)}$ are neighbours, and zero otherwise. Moreover, w_s will equal zero for each subdistrict itself. We calculate W_s by using row normalisation procedure.

Spatial Autocorrelation

Before calculating equations (4) and (5), we investigate whether the given characteristics of our spatial data have spatial dependence. We adopt a parameter and a technique to test spatial autocorrelation. For spatial effects, we adjust equations (4) and (5) to examine spatial dependence in our data on agro-cluster indices and poverty rates:

$$I = \left(\frac{S}{W_s}\right) \frac{\sum_{s(2)} \sum_{s(1)} w_s \left(V_{j,s(1)} - \bar{V}_j\right)\left(V_{j,s(2)} - \bar{V}_j\right)}{\sum_{s(2)} \left(V_{j,s(1)} - \bar{V}_j\right)^2}, \tag{7}$$

where I refers to Moran's index; S is the number of subdistricts indexed by $s_{(1)}$ and $s_{(2)}$; V_j represents our variables of interest, j, $j\{1, 2, 3\}$, which are $lnpov_s$, hc_s, and K_s; $\bar{V}_j$ is the mean of V_j; w_s is an element of a matrix of spatial weights; and W_s is the spatial weight matrix,

$$W_s = \sum_{s(1)} \sum_{s(1)} w_s.$$

Furthermore, we investigate the presence of spatial dependence within our variables. We estimate Moran's I error and the Lagrange multiplier to test the null hypothesis with regard to no spatially lagged dependent variables.

According to our test results, statistical evidence confirms the spatial dependence of our variables at a 5% significance level. This affirms the importance of accounting for spatial dependence when estimating our models. Moran's *I* scatterplots for $lnpov_s$, hc_s, and K_s(figure 5) illustrate the significance of a positive association between the variables and their spatial lags. This finding verifies that the properties of a subdistrict can affect efforts to reduce poverty in neighbouring subdistricts. It also means that the effects of a cluster in one region can influence surrounding regions.

Model Specifications with Spatial Dependence

As discussed above, we are confident that spatial effects are significant in our models. Accordingly, we add spatial parameters to equations (4) and (5) to deal with spatial correlation of the error terms. We develop three spatial specifications for the two baseline models. First, we use spatial autoregressive (SAR) models to control for spatial spillovers in the dependent variable when determining the effects of the poverty-rate variable in one region on surrounding areas (Anselin and Bera 1998). The SAR models are as follows:

$$\left(I-\rho W_s\right) lnpov_s = \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{8} \mu_i X_{i,s} + \alpha + \varepsilon_s;\ \varepsilon_s \approx N\left(0,\sigma^2 I\right), \tag{8}$$

$$\left(I-\rho W_s\right) lnpov_s = \gamma_1 K_s + \sum_{i=1}^{8} \theta_i X_{i,s} + \delta + \epsilon_s;\ \epsilon_s \approx N\left(0,\sigma^2 I\right). \tag{9}$$

Second, we use spatial Durbin models (SDMs) to examine spatial lags on our dependent and explanatory variables (Mur and Angulo 2006). The SDMs capture feedback influences between variables—that is, the impacts passing through neighbouring subdistricts and back to a subdistrict itself (Elhorst 2010). We verify spatial lags on all variables, except sq_hc_s and the rural–urban dummy. The SDMs are as follows:

$$\begin{aligned}\left(I-\rho W_s\right) lnpov_s = \rho W_s\left(hc_s + \sum_{i=1}^{7} X_{i,s}\right) + \beta_1 hc_s + \sum_{i=1}^{8} \mu_i X_{i,s} + \\ \beta_2 sq\_hc_s + \alpha + \varepsilon_s;\ \varepsilon_s \approx N\left(0,\sigma^2 I\right)\end{aligned} \tag{10}$$

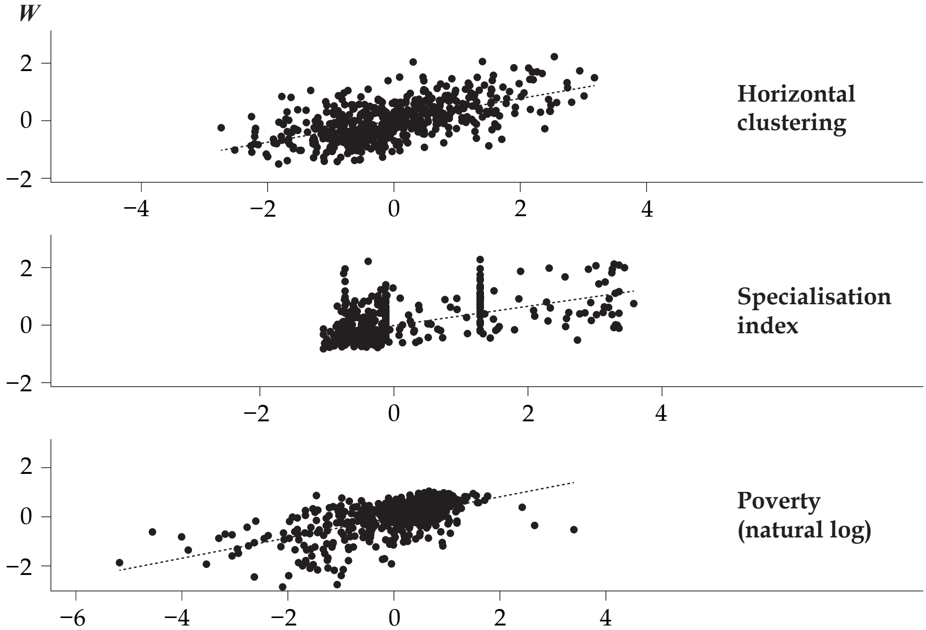
$$\left(I-\rho W_s\right) lnpov_s = \rho W_s\left(K_s + \sum_{i=1}^{7} X_{i,s}\right) + \gamma_1 K_s + \sum_{i=1}^{8} \theta_i X_{i,s} + \delta + \epsilon_s;\ \epsilon_s \approx N\left(0,\sigma^2 I\right), \tag{11}$$

where ρ is the scalar-spatial-disturbance coefficient for our SAR and SDM models. It equals one if a variable is spatially dependent, and zero otherwise. If ρ equals zero, this implies that there are no spatial effects; it would thus be better to estimate these models using conventional ordinary least squares. We also consider the zero value of ρ, to check for the presence of spatial dependence in our models.

Last, we use a spatial error model (SEM) to specify a random shock that would lead to inefficiency (Anselin and Bera 1998). The SEM investigates spatial dependence in the residual term; λ is the scalar-spatial-disturbance coefficient for SEM:

$$lnpov_s = \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{8} \mu_i X_{i,s} + \alpha + \lambda W_s \varepsilon_s;\ \varepsilon_s \approx N\left(0,\sigma^2 I\right), \tag{12}$$

FIGURE 5 *Moran's* I *Scatterplots*



Note: Authors' calculations. Moran's *I* scatterplots of the variables are significantly different from zero at the 1% level.

$$lnpov_s = \gamma_1 K_s + \sum_{i=1}^{8} \theta_i X_{i,s} + \delta + \lambda W_s \epsilon_s;\ \epsilon_s \approx N\left(0, \sigma^2 I\right). \tag{13}$$

All models above allow us to assess the degree of spatial dependence while we control for the effects of other variables. To estimate these spatial models, we employ maximum-likelihood estimation. This involves maximising the log-likelihood function with respect to the parameters ρ or λ concentrated with estimated coefficients β and the noise of variance, σ^2, in error terms ε_s or ϵ_s.

We also address heteroskedastic disturbances in our spatially lagged models by applying the Hall-Pagan Lagrange-multiplier test. These disturbances lead to inefficient parameter estimates and inconsistent covariance-matrix estimates (White 1980). We therefore draw fault inferences when testing our hypothesis. Where fault inferences exist, we use a weight procedure to transform our dataset. It is implied that multiple residuals are combined into one variable—that is, the weight ω,

$$\omega = \sqrt{\hat{e}^2}\,.$$

In our analysis, we introduce analytic weights.

RESULTS

In the interactions between agro-clusters and poverty rates, spatial-regression specifications allow us to measure the spatial-spillover effects, or the impacts of spatial proximity of one subdistrict on another. Tables 2 and 3 show the results of our structural variants, using spatial weights with row-standardised contiguity.

The result tables confirm that all our regression estimations are highly significant in clarifying the spatial relations between subdistricts, shown by the log-likelihood values that are statistically different from zero at the 1% level. From these results, the coefficients of our variables that typically feature in our spatial models have the expected signs. We observe consistent signs of the β and γ coefficients in the variables of horizontal clustering and the specialisation index, respectively, for all specifications. Additionally, the coefficients of the shares of farmers aged 55 or older, smallholders, population size, the total area of subdistricts, the proportion of rice fields, and travel time are consistent in explaining the incidence of poverty in a subdistrict and its surrounds.

Farmer Concentration (Horizontal Clustering)

The relations between horizontal clustering (hc_s) and the poverty rate ($lnpov_s$) are reported in table 2. The concentration of farmers is statistically significant in reducing poverty rates of subdistricts. The hc_s variable has a negative sign, meaning that the greater the farmer concentration in a subdistrict, the greater the decreases in the poverty rate of that subdistrict. In our SDM estimation, however, we do not find significance in the link between the poverty rate and spatially lagged horizontal clustering. Our findings suggest that farmers influence each other by increasing their income, if they are proximate to one another within a particular region and are not greatly affected by farmers in neighbouring regions. At close distances, the positive externalities of agro-clusters may appear.

For further interpretation, we compare the three specifications and select the one that best explains the relation between our variables. To do so, we apply the Akaike information criterion (AIC) and Schwarz's Bayesian information criterion (BIC). The lowest values reflect the preferred specification, which, in this case, is the SEM (table 2). From this specification, we analyse the marginal effects on a particular independent variable in order to investigate the impact of horizontal clustering and other variables on poverty rates.

Since the coefficients and from a SEM are total effects, we can report the total effect of a change in the error term ε_s by using the relevant estimate of λ. For instance, the total effect of a 1.00% increase in ε_s is a 0.34% increase in the poverty rate of a subdistrict. This is due to an own direct effect. In other words, there are fewer spatial-spillover effects and no indirect effects. From table 2 we infer that a 1.00% increase in the concentration of farmers in a subdistrict will lead to a 0.12% reduction of poverty in that region.

Agricultural Specialisation (Specialisation Index)

The other objectives of our study are to assess the effects of regional specialisation of primarily agricultural production on poverty rates and to investigate the spatial neighbouring effects within this relation (table 3). In general, the results point towards a statistically significant correlation between relative specialisation indices and poverty rates, after we control for other explanatory variables. This is shown by the significance of ρ for SAR and SDM and of γ for SEM at the 1% level. The results also provide insight into the importance of spatial dependence in this context.

The specialisation index (K_s) has a positive impact on the poverty rate of a subdistrict. The subdistrict, which has a tendency to produce the primarily agricultural outputs of West Java, retains a lower poverty rate. In other words, agro-clusters

TABLE 2 *Spatial Models of the Relation between the Poverty Rate and Horizontal Clustering*

Variable (dependent variable = *lnpov*)	SAR	SEM	SDM
Original variables			
Horizontal clustering	−0.1227***	−0.1211***	−0.1144***
Horizontal clustering^2	0.0137***	0.0148***	0.0133***
Smallholders	0.6476***	0.4409**	0.2141
Farmers aged ≥55	−1.9138***	−1.8409***	−1.3404***
Population	−0.0053***	−0.0056***	−0.0055***
Subdistrict size	0.0034***	0.0036***	0.0028***
Paddy field	0.0053***	0.0053***	0.0036***
Travel time	0.0107	0.0199	0.0061
Capital-city effects	−0.0000***	−0.0000***	−0.0000***
Dummy (rural = 1; urban = 0)	0.2966***	0.2895***	0.3378***
Spatially lagged variables			
Horizontal clustering			−0.0043
Smallholders			1.3045***
Farmers aged ≥55			−1.5892***
Population			0.0019**
Subdistrict size			−0.0001
Paddy field			0.0053***
Travel time			0.0198
Capital-city effect			−0.0000
Others			
Intercept (α or δ)	1.5486***	2.4630***	1.0826***
ρ(SAR and SDM)	0.3341***		0.3132***
λ(SEM)		0.3416***	
Akaike information criterion	0.0700	0.0665	0.0753
Bayesian information criterion	0.0763	0.0725	0.0874

Note: SAR = spatial autoregressive (model); SEM = spatial error model; SDM = spatial Durbin model.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

that specialise in agricultural production are most likely to decrease the poverty rate. The results show that specialisation in agriculture seems beneficial to reducing poverty if spatial dependence is controlled for in the analysis.

The relation between specialisation and poverty is not straightforward: the K_s measure correlates strongly with farm outputs that themselves correlate strongly with productivity. If farmers tend to specialise in activities that produce specific crops, they have opportunities to improve their productivity. In raising productivity, specialised farmers benefit more from resource-sharing and from proximity to production inputs, farm workers, food industries, and crop markets.

After comparing three spatial models by applying AIC and BIC model-selection procedures, we confirm that the SEM is also the best-fitting specification in table 3. Once again, since the SEM result represents only the direct effects of the variables,

TABLE 3 *Spatial Models of the Relation between the Poverty Rate and the Specialisation Index*

Variable (Dependent variable = *lnpov*)	SAR	SEM	SDM
Original variables			
Specialisation index	0.1764**	0.2066**	0.1596**
Smallholders	1.8778***	0.5739*	1.0869***
Farmers aged ≥55	−2.0665***	−0.4289	−0.5423
Population	−0.0073***	−0.0073***	−0.0069***
Subdistrict size	0.0025**	0.0052***	0.0050***
Paddy field	0.0129***	0.0108***	0.0106***
Travel time	0.0158	0.0896**	0.0949**
Capital-city effect	−0.0000***	−0.0000***	−0.0000***
Dummy (rural = 1; urban = 0)	0.5032***	0.5829***	0.4969***
Spatially lagged variables			
Specialisation index			−0.0676
Smallholders			1.3402***
Farmers aged ≥55			−4.6096***
Population			0.0095***
Subdistrict size			−0.0083***
Paddy field			0.0029
Travel time			−0.0605
Capital-city effect			−0.0000***
Others			
Intercept	0.2353	1.0252***	0.5297
ρ(SAR and SDM)	0.3771***		0.4867***
λ(SEM)		0.6336***	
Akaike information criterion	0.2798	0.2578	0.3363
Bayesian information criterion	0.3028	0.2789	0.3877

Note: SAR = spatial autoregressive (model); SEM = spatial error model; SDM = spatial Durbin model.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

we use the γ coefficients in table 3 as marginal effects explaining the impacts of our explanatory variables on poverty reduction. At the mean of K_s, 0.46, a 1.00% increase in the degree of relative specialisation in agriculture may reduce a region's poverty rate by nearly 0.20%.

The result of the SDM regression in table 3 suggests that the spatial lags of the specialisation index are not statistically significant in clarifying the extent of poverty reduction. This finding is consistent with the result in table 2; farmers interact more frequently to boost their crop productivity if they live in the same region. Although specialising in agriculture has its benefits, it can be a challenge for farmers near urban regions. In Indonesia, farming activities take place amid high levels of risk and uncertainty, owing to limited insurance and credit markets, large fluctuations in weather and crop prices, and different skill levels of individual farmers (Umberger et al. 2015).

Negative Externalities of Agro-clusters

In this section, we examine the negative externalities of agro-clusters. As discussed above, we expect to have a convex quadratic function of horizontal clustering on poverty rates to control for these externalities. Applying the preferred model, the SEM, we estimate the poverty rates of subdistricts to investigate positive and negative externalities. Figure 6 shows the quadratic curve of the estimation result.

A vertical line signifying the curve's turning point, $e_p = -2.07$, indicates the optimal concentration of farmers for poverty rates. The e_p is solved using the first derivative of equation (12) with respect to hc_s; therefore,

$$e_p = \frac{-\beta_1}{2\beta_2},$$

or around 5,608 farmers. The segment to the left of the vertical line signalises the positive externalities of the clusters: as the number of farmers in a subdistrict increases, the poverty rate decreases.

In the segment to the right of the vertical line, however, the poverty rate rises alongside the concentration of farmers, owing to negative externalities from the congestion effects of agro-clusters. As agro-clusters grow beyond the optimal number, the poverty rate increases. In other words, in any subdistrict an agro-cluster will create negative externalities if the number of farmers exceeds the turning point. In such circumstances, farmers will incur higher costs for production, land rent, and transport, reducing their revenues and thus raising the subdistrict's poverty rate.

Smallholders and Older Farmers

From tables 2 and 3 we find that a larger share of smallholders has an adverse effect on poverty but that a larger share of farmers aged 55 or older has a positive effect on poverty. Additionally, the results of the SDM show a statistically significant link between the poverty rate and the spatial lags of both variables at the 1% level, most likely owing to spatial spillovers.

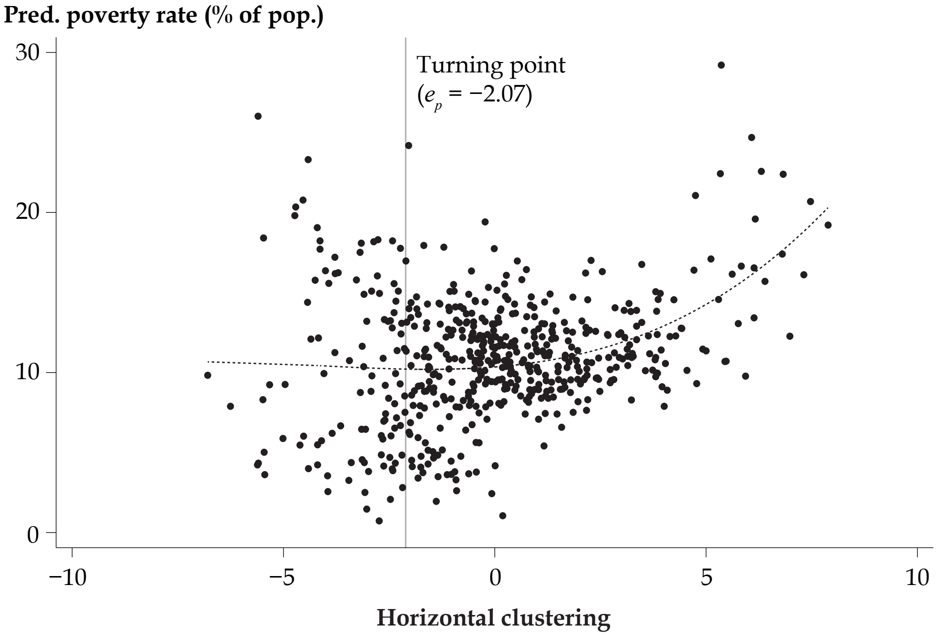
From this finding, we infer that subdistricts with a smaller share of smallholders have lower poverty rates and affect poverty reduction in neighbouring subdistricts. This inference is most likely related to the operating size of farms: Fan and Chan-Kang (2005) found that farm size corresponds positively with income. In subdistricts with a high concentration of farmers, smallholders face competition for limited land resources (IFAD 2013) and may struggle to raise their income owing to fewer yields. IFAD (2013) suggested that investing in farm infrastructure that supports smallholders can increase income and thus reduce poverty.

Tables 2 and 3 also show us that a higher share of older farmers in a subdistrict is associated with decreased poverty in that subdistrict and its neighbours. This can be explained by the lack of a general pension scheme in Indonesia; most Indonesians do not receive government support when they retire. Instead, many generate income by establishing their own businesses—or, in rural regions, by continuing to farm.

Agro-clusters and Urban Proximity

This section elaborates on the influence of proximity to urban regions on poverty if agro-clusters are present. We use the variables of population size, travel time to the nearest big city, and the capital-city effect to indicate this urbanisation (Day and

FIGURE 6 *Horizontal Clustering versus the Predicted Poverty Rate*



Note: Authors' calculations.

Ellis 2013, 2014). Our results are consistently significant for these three variables at the 5% level, except for the travel-time variable.

In these results, an increase in a subdistrict's population size reduces its poverty rate. We infer that being geographically adjacent to a city has a positive effect on poverty reduction in a subdistrict. This inference is also shown from the β and γ coefficients of the dummy variable in tables 2 and 3. All results seem intuitively plausible, since these subdistricts have more diverse services and more job opportunities, as shown by the lower *Ks*. They therefore have lower poverty rates.

Significant impacts of travel time are found by the SEM and SDM specifications of the model, linking the poverty rate and the specialisation index. If travel time increases by one hour, for example, then the poverty rate is expected to rise, according to the results of the SEM in table 3, by 0.09 percentage points. That is, the farther away a subdistrict is from Bandung and Jakarta, the higher its expected poverty rate will be, ceteris paribus. This implies that a shorter commute between a subdistrict and the nearest city is associated with a lower incidence of poverty in that subdistrict. Travel time between regions relies on road availability and quality; subdistricts with the lowest levels of income have the least access to such infrastructure (Day and Ellis 2014). Better access to roads could facilitate specialisation in agriculture and thus reduce rural poverty—especially in regions with natural advantages (Qin and Zhang 2016).

On the capital-city effect, we estimate that its economic magnitude is negligible for all models. That is, we obtained an effect that is statistically significant but not economically significant. In tables 2 and 3, we observe different signs of the effects of this variable on the poverty rate in two cluster models. In our estimations of the input measure, the capital-city effect is negative: subdistricts with high levels of market gravity tend to have lower-than-average poverty rates. Farmers concentrated in subdistricts around Jakarta have access to a larger pool of consumers and suppliers than those farther away—proximity to the city increases crop sales and production inputs (Cali and Menon 2013).

Despite this advantage, the capital-city effect can also have drawbacks for farming practices, as shown in table 3. The effect is associated with increased poverty rates in relation to output measures. The capital-city effect is slightly larger than that of the models of the input measure in table 2. Specialised subdistricts close to Jakarta may face greater competition for inputs and have higher output prices, alongside easier access to infrastructure and better market opportunities. Farmers in these subdistricts often struggle to generate improvements, having only limited farm resources. Urban sprawl and urbanisation cause this shortage, by converting farmland into non-farm areas. The rate of farmland conversion in West Java was about 6.7% per year during 1997–2000 (UNEP 2005).

This is the case for rice farming. The cumulative area of rice fields in West Java shrank by more than 2% during 2009–13 (Ministry of Agriculture 2014). As figure 2 shows, the concentration of farmers decreases if the subdistricts are proximate to Jakarta or Bandung. Tables 2 and 3 show that subdistricts with higher shares of rice fields have higher poverty rates. This suggests that subdistricts in which farmers specialise in rice tend to have slightly higher poverty rates. This finding signals the inability of rice farmers to increase their income. Owing to the size of their land tenure (less than 0.5 hectares per farm household), rice farmers could generate revenue of less than Rp 1 million per month (Darwis 2009), which was below the minimum wage in West Java at the time (Rp 1.31 million per month).

We find that population size and the capital-city effect have a smaller impact than horizontal clustering and the relative specialisation index on poverty reduction. This indicates that Marshall–Arrow–Romer (Glaeser et al. 1992) spatial externalities are the predominant force behind farmers' success. In other words, farmers are expected to perform well if they are close to each other and therefore able to share inputs, knowledge, information, or labour (Krugman 1991). This finding may also reflect that agriculture tends to thrive in more economically specialised regions rather than in more industrially diverse regions, like cities. Localisation economies seem to be stronger in regions dominated by small firms (Capello 2002). We infer that, regardless of geographical proximity, farmers may concentrate farther away from cities owing to the abundance of farm resources elsewhere.

SIMULATING POLICY SCENARIOS

This section discusses potential policy recommendations for reducing poverty in Indonesia. Ideally, such recommendations should decrease average poverty rates considerably and, simultaneously, shift the poverty rate in each subdistrict towards the area below the mean.

To prioritise these recommendations, we simulated our regression results, corresponding to SEM specifications, for both the input-oriented equation (12) and the output-oriented equation (13). These simulations allowed us to ascertain any changes in the effects of our key variables, and other explanatory variables, on poverty rates. The selected variables included travel time and the share of farmers

TABLE 4 *Simulation Scenarios*

Scenario	Simulated policy measure
Equation (8)	
S1	10% increase in horizontal clustering in each subdistrict
S2	10% increase in the number of farmers aged ≥55 in each subdistrict
S3	10% reduction in travel time
S4	S1, S2 & S3 combined
Equation (9)	
S5	10% increase in the specialisation index of each subdistrict
S6	10% increase in the number of farmers aged ≥55 in each subdistrict
S7	10% reduction in travel time
S8	S5, S6 & S7 combined

aged 55 or older. On the basis of our estimations, we chose these variables because they have (or contribute to) the greatest impact on poverty reduction and are more applicable to policy interventions. To simplify the simulations, we held constant the effects of other control variables on poverty rates.

As shown in table 4, we divided the simulations into eight scenarios. Each scenario reflects a change in horizontal clustering, travel time, the specialisation index, or the number of older farmers. We applied an unrealistic assumption in order to attempt a realistic forecast for policy recommendations. Before running the simulations, we predicted the poverty rate in each subdistrict by using the SEM, the best-fit estimation. We then compared this initial condition with our other simulated outcomes and assigned policy priority to each.

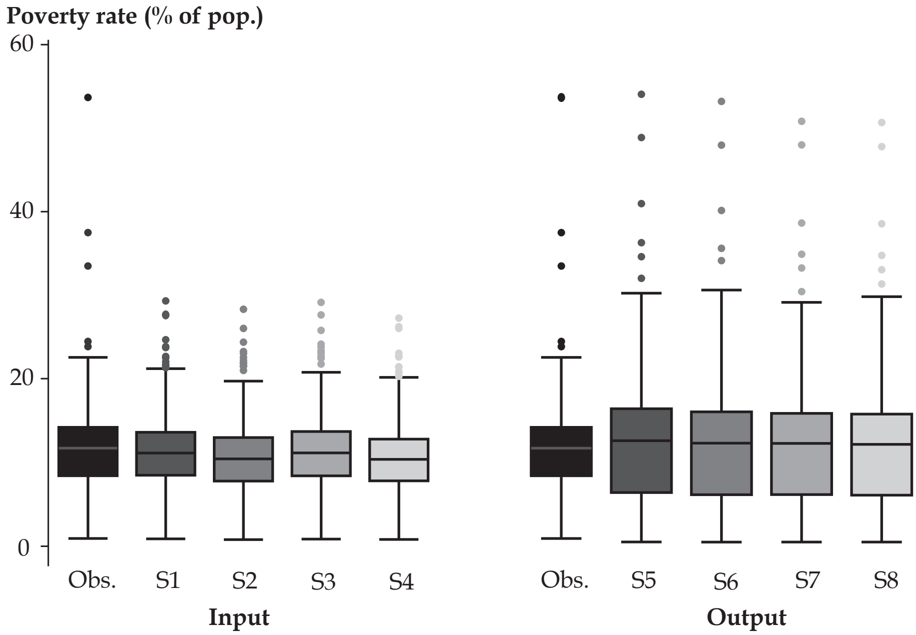
Figure 7 shows a statistical summary of predicted poverty rates at the 5% level. We determined the first box plot as the initial condition. We observe a decreasing trend in both graphs. Since the distribution of the box plots seems uniform, we selected policy priorities by using the median and range effects of the simulation results. Compared with the initial state, the policy priority encompasses (a) the smallest mean of poverty rates, (b) the smallest range of poverty rates, and (c) the smallest range between the mean and the 75th percentile. In other words, the policy would be more beneficial if it could shift subdistricts with high poverty rates as many as possible towards the area below the average estimated poverty rate, represented by the dashed line in figure 6.

Simulation Results

Input-Oriented Model

Observing the mean of the predicted poverty rates in equation (8), we see S4—the combination of 10% increases in travel time, horizontal clustering, and the number of farmers aged 55 or older—as the policy priority. In our simulation, this scenario brings about relatively large declines in the average poverty rate, compared with other scenarios. We used size effects based on the mean values to check the average difference between the initial condition and the simulation results. In this comparison, the larger absolute value of Cohen's *d* indicates the stronger effect and may signify the preferred simulation; the *d* value of S4, 0.27, is greater than those of the other simulations. Figure 7 shows that S4 also has the largest gap if

FIGURE 7 *Poverty Rates Predicted by Input- and Output-Oriented Models*



Note: Authors' calculations.

we compare the mean of all simulation results of input-oriented model with the mean of the initial condition (the 'Obs.' box plot).

The range effects also show a tendency to decrease the maximum values of poverty rates, and the range of poverty distribution becomes narrower compared with the initial condition. Policymakers should therefore aim to narrow the distribution of the poverty rate as much as possible—at present, wealth is unevenly distributed throughout subdistricts. Figure 6 shows that S4 would be the most efficient policy for reducing the range of wealth distribution, followed by S2 (increasing the number of farmers aged 55 or older). Accordingly, S4 and S2 are likely to be the most favourable mean-based policies for policymakers.

The emphasis, however, should be placed on S2, because implementing S4 would be too costly. Both the central and regional governments could provide incentives for older farmers to continue working, in order to reduce the number of poor people in each subdistrict. Policies could include stimulating farming practices in both rural and urban regions for this age group by, for example, strengthening the Kelompok Rumah Pangan Lestari (Sustainable Food House Group) program. This program aims to establish groups of people, including older people, in particular regions to engage in cooperative farming activities. Governments are often willing to provide inputs and extensions for such initiatives because of the flow-on effects for food security and income of the older population in the long term.

Output-Oriented Model

Recalling equation (9), we emphasise that the output-oriented model relates to productivity. The more productive the production process, the higher the income earned by the farmers. In this sense, policymakers should focus on increasing the number of skilled workers by providing subsidies for training farmers. According to the mean-based policy targets, policymakers should focus on S8 (the combination of 10% increases in travel time, the specialisation index, and the number of farmers aged 55 or older), followed by S6 (a 10% increase in the number of farmers aged 55 or older). Comparing *d* value of the simulation results of output oriented models, we find that S8 has the largest *d* value. This finding suggests that S8 may be the preferred policy to reduce poverty rates. In addition, corresponding to the range-based targets, the range of the poverty rates of the policy simulations is smaller than that of the initial condition, as shown by a decrease in the maximum poverty rate of each policy simulation. Although reducing poverty rates, S8 may be less attractive to policymakers, who may prefer S6—increasing the number of older farmers in each subdistrict—because it would reap less cost of policy implementation. Improving the quality of roads between subdistricts and to the nearest city, or introducing other policies that respond to S7 (decreasing travel time) would enable farmers to commute at a lower cost and could also reduce poverty in subdistricts.

CONCLUSIONS

A subdistrict's resources influence not only its agricultural growth but also that of its neighbours. Farming activities in most subdistricts are spatially concentrated. Under certain conditions, this concentration reduces poverty rates. This article uses two measures, horizontal clustering and the relative specialisation index, to assess the impact of agro-clusters on poverty rates for 545 subdistricts of West Java. Horizontal clustering is an input-oriented measure quantifying the concentration of agricultural employment. The specialisation index is an output-oriented measure that provides evidence on the difference between the share of agricultural production values of each subdistrict and the average share in West Java.

We estimate six specifications of three spatial econometric models: spatial lags, spatial Durbin, and spatial errors. These models account for spatial dependence in the link between poverty rates and agro-clusters. We emphasise three key findings. First, horizontal clustering has a significant adverse effect on poverty rates in a subdistrict. Higher numbers of farmers are associated with lower poverty rates in these subdistricts. Second, specialisation in agriculture in a subdistrict relative to West Java reduces the poverty rate of that subdistrict. Third, localisation externalities appear to support agricultural growth. Enabling policy that works towards empowering farmers could be seen as a priority to increase farmers' welfare. policymakers should also prioritise infrastructure improvements to enhance connectivity between neighbouring regions.

Further research could focus on determining the geographical cores, as well as the borders, of the agricultural clusters in West Java or in Indonesia as a whole. This research could be undertaken for either separate commodities or entire commodity groups. Similarly, insights gained from this analysis of West Java could be assessed and tested in future analyses on a national scale. Further research could shed light on other measures of urban proximity—that is, the strength of attraction to cities of various sizes.

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