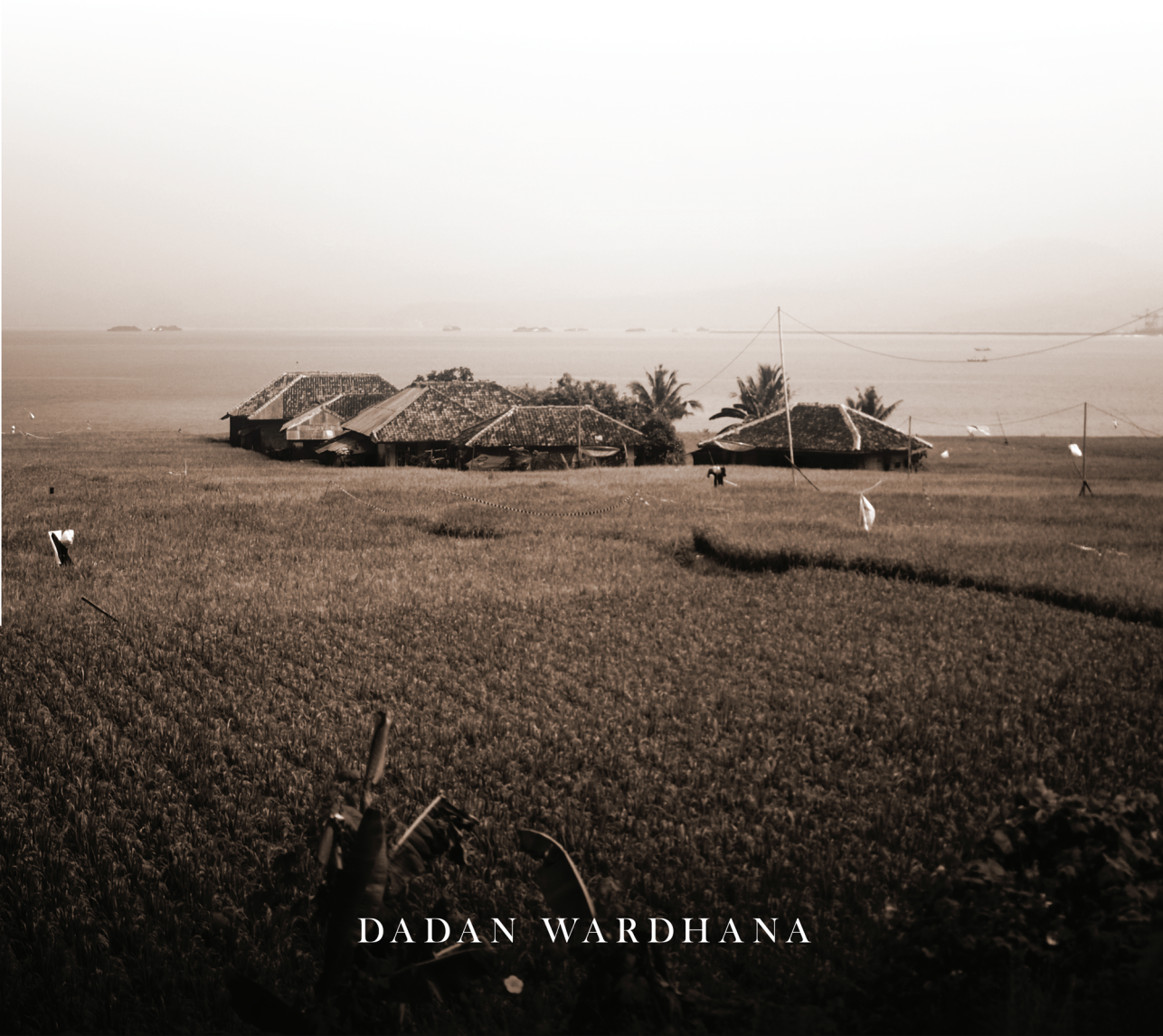
AGRO-CLUSTERS

for Rural Development in the Indonesian Province of West Java



DADAN WARDHANA

Propositions

1. External economies of scale are a predominant force behind farmers' success.
   (this thesis)

2. For farmers located in agricultural agglomerations of high density, cooperation leads on average to an increase of their income.
   (this thesis)

3. Farmer's participation in the development of agricultural policies is a necessary condition for the success of the policies.

4. A theory in economics is only of temporary relevance.

5. Neighbours that are helping each other reduce the need for insurance.

6. Pursuing a PhD expands your comfort zone.

Propositions belonging to the thesis entitled
'Agro-clusters for Rural Development
in The Indonesian Province of West Java'

Dadan Wardhana
Wageningen, 9 October 2018

Agro-clusters for Rural Development in the Indonesian Province of West Java

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Agro-clusters for Rural Development in the Indonesian Province of West Java

Dadan Wardhana

Thesis

submitted in fulfilment of the requirements for the degree of doctor
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CHAPTER 1
Introduction

1.1. Problem Definition

UN (2015) has declared with the formulation of the SDGs framework that eradicating poverty is the central challenge for sustainable development in all countries – a vision which is also shared by the government of Indonesia. Although the poverty rate of Indonesia decreased from 23.43% of total population in 1999 to 10.12% in 2017, its pace has been slowing down since 2010 (BPS, 2017). BPS (2018) reports that this pace is about 20.18% from 2010 to 2017, compared to the period 1999-2009 (39.61%). An et al. (2015) highlight that the number of poor people found in rural regions is higher than in urban regions. About 61% of all Indonesian poor live in rural regions (16 m), and around 44% of them are located on Java island (BPS, 2018). According to West Java BPS (2018), 53% of total poor people living in Java island dwell the Indonesian province of West Java. McCulloch et al. (2007) point out that the Indonesian rural poor are engaged in low productivity agricultural activities due to limited access to production inputs and markets.

Due to the widespread lack of alternatives for income generation in rural areas of developing countries, agriculture often remains the dominant economic activity. However, the role of agriculture in rural poverty reduction remains much debated in the current literature. On one hand, Besley et al. (2007) unveil that such role is minor in Indian rural regions. Hence, some studies propose that transitioning to non-farm activities is the best way to decrease the poverty incidence of rural regions (Besley et al.,

2007; Reardon et al., 2001). McCulloch et al. (2007) and others, on the other hand, emphasize the positive impacts of agricultural growth on poverty reduction. According to Wiggins and Proctor (2001), rural regions may have comparative advantages only in the primary sector, due to immobile natural resources. They suggest that productivity increases in farming activities directly contribute to pathways out of poverty in rural regions. Following the latter argument, this thesis assesses the potential and the impact that ways of boosting agricultural productivity have on poverty reduction in the context of Southeast Asia.

USDA (2017) reports that the growth rate of the agricultural total factor productivity of Indonesian agriculture from 1991 to 2014 was on average about 1.8% per year, that is the second lowest compared to other southeast Asian countries after the Philippines (1.5% per annum). In addition, crop productivity has advanced at a much slower pace: productivity of rice farming - rice being the strategic staple of Indonesia - increased by only 0.87% per year from 1993 to 2015 (BPS, 1993, ..., 2015). FAO (2015) also reports that the Indonesian rice production slightly increased to around 250 kg per capita per year in the years 2000-2012. This pace was the lowest compared to other southeast Asian countries, such as Cambodia, Thailand, Lao PDR, Myanmar, and Viet Nam that experienced an increase from 400 to 600 kg per capita over the same period.

Barkley and Henry (1997) underline that rural areas with declining or slowly growing economic activities, such as agriculture, should continue to promote rural clusters with small business development to reduce poverty. Such rural clusters are geographical concentrations of agriculture-based economic activities including rural firm and farmer collabourations in production and value chain links (Barkley & Henry, 1997). Such agglomerations are also called agro-clusters. According to Folta et al. (2006), the advantages of agro-clusters allow farmers to increase productivity by

generating larger margins and to reduce production costs. This point has been proven for the secondary sector: Porter (1990) argues that geographically concentrated industries stimulate their growth pathways and general economic activity in the regions in which they are located. However, literature on these economic agglomerations has been more concerned with the phenomena of industrial clusters in urban settings (Duranton et al., 2010; Porter, 1990). This thesis thereby contributes to the existing literature on agglomerations economics by examining effects of clustered farming activities on farm productivity and on poverty reduction in rural regions. It also contributes to the literature on rural development in Southeast Asia.

Barkley and Henry (1997) also point out limitations of such agro-clusters. Weak relationships among rural firms hinder cluster development. Tambunan (2005) observes that the failure of cluster development policy in Indonesia occurs mostly due to neglecting linkages between involved actors. Burger et al. (2001) and Najib and Kiminami (2011) also show that most of the Indonesian agro-processing clusters do not involve interactions between firms. These weak relationships between neighbouring farmers may influence the productivity from which the individual farmer may profit. As found by Folta et al. (2006), the productivity of farmers is, among other factors, dependent upon the number and performance of their neighbours since they are tied together in agricultural value chains and in regional economies. This result suggests that a suitable and effective way to promote agro-clusters in the early stage of their development is to focus on improving farmers' productivity and strengthening their institutions, which are exactly the aspects with which this thesis is concerned.

1.2. Research Objective and Research Questions

Within the strands of the literature on economic agglomerations and rural development, this thesis addresses to what extent agglomerations of

farming activities in the form of agro-clusters increase farm productivity and therefore contribute to reducing rural poverty. This objective is assessed by answering the following four research questions, which are elaborated upon as self-contained contributions to these two strands of literature in chapters 2 to 5 of this thesis:

Q1. To what extent do agro-clusters influence rural poverty? (Chapter 2)

Q2. What are the determinants influencing farmers to cooperate with their peers within agro-clusters? (Chapter 3)

Q3. To what extent does economic pressure within agro-clusters affect farmer behaviour towards their neighbouring farmers? (Chapter 4)

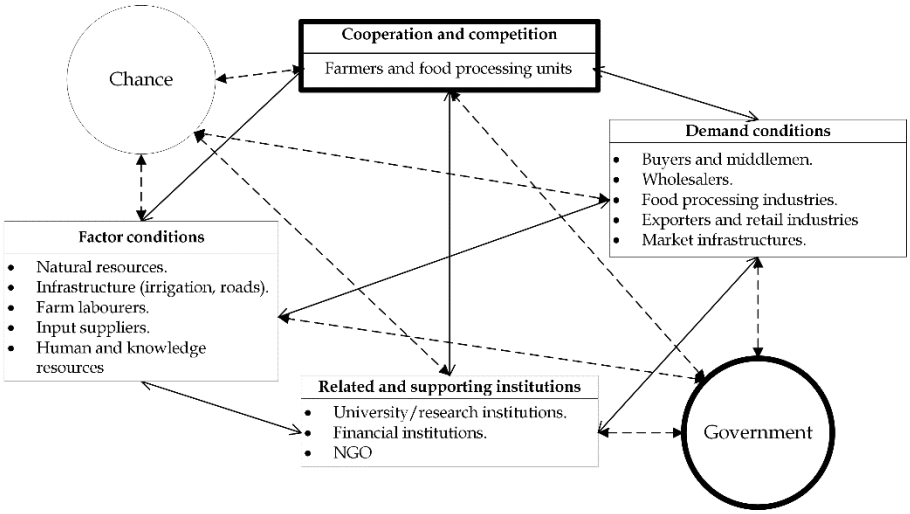
Q4. How can existing policies supporting agro-cluster development be improved? (Chapter 5)

In order to answer each of these research questions, this thesis takes into account the crucial attributes of agro-clusters, which are spatial proximity and cooperation-competition between farmers. These attributes are related to the development of farmer institutions within agro-clusters. The following analyses shed light on positive and negative economic externalities of agro-clusters and provide insight into their consequences for rural policies in West Java.

1.3. Theoretical Framework

Building on Porter (1990) and Krugman (1991), an agro-cluster is defined as a geographical concentration and specialisation of farming activities which involves farmers, buyers, food processing industries, and exporters/retail industries. Figure 1.1 illustrates the attributes of agro-clusters according to Porter (1990) which are crucial for increasing farm productivity. These attributes encompass factors of production (e.g. natural resources, input suppliers, technologies), demand conditions (buyers,

market infrastructure), cooperation and competition among farmers leading to farmer institutions, and supporting institutions (research institutions, finance, NGOs). They reinforce each other and proliferate over time in fostering productivity. Besides these four attributes, Porter also suggests two additional attributes – government and chance events – influencing the crucial attributes to develop. For example, governments create innovations in production processes and production outcomes and stimulate infrastructure enhancing productivity. This thesis focuses on the attributes of cooperation and competition between farmers as suggested by Barkley and Henry (1997) being key attributes bringing agro-clusters to a more advanced and sustainable level (the bold-lined shapes in Figure 1.1).



Source: Author adapted from Porter (1990).
Note: The shapes with bold lines are two attributes of agro-clusters focused on in this thesis. Solid arrows denote the relationships between the crucial attributes and dashed arrows indicates the role of two additional attributes (government and chance) in encouraging the development of all crucial attributes.

Figure 1.1. The Attributes of Agro-clusters.

1.3.1. Agro-clusters and Rural Development

Barkley and Henry (1997) argue from a regional science perspective that agglomerations of farming activities play a positive role in an industry's employment growth, labour productivity, and wage rate; subsequently, rural poverty declines. This role is related to the presence of economic externalities resulting from knowledge spillovers and the pool of labourers and suppliers (Krugman, 1991). Chapter 2 studies this aspect at the regional level. Farmers located in clusters may be able to buy production inputs more cheaply due to the suppliers nearby, or they may benefit from good agricultural infrastructure -for example irrigation. Barkley and Henry (1997) emphasize that such clusters enhance the spread of technology and information among neighbouring rural firms, thereby facilitating rural development.

The literature on rural agglomerations has recently much debated the role of these externalities in regional economies including Marshall-Arrow-Romer (MAR) externalities, Porter externalities, and Jacobs externalities (De Groot et al., 2009). MAR and Porter externalities stress knowledge spillovers between firms in an industry stimulating economic growth. Both types of externalities emphasize the positive role of industrial specialisation in growth. Jacobs externalities, on the other hand, highlight the diversity of geographically proximate industries as the most significant knowledge transfer for growth (De Groot et al., 2009). The first two types of externalities describe localisation economies, while the last type explains urbanisation economies. To investigate these externalities, Chapter 2 examines how neighbouring regions influence one another in terms of agricultural growth.

1.3.2. Agro-clusters, Cooperation and Competition

Huggins and Thompson (2017) claim that rural development is crucially determined by farmer behaviour. They argue that socio-economic interactions between proximate farmers are influenced by their behaviour towards each other. The level of such interaction needs to be chosen between the extremes of complete cooperation and complete competition, depending on which strategy farmers consider to be most beneficial for them to achieve income improvements. Nooteboom (2006) points out that farmers may strategically decide whether to cooperate or to compete with neighbours for the sake of increasing their own income. Considering prospect theory (Kahneman, 2011), farmers make this decision by underweighting gains and losses that probably or certainly happen in relation to risk aversion and risk seeking from cooperation. In other words, farmers may choose to cooperate when they consider the economic benefits they expect to realize from this choice to outweigh the economic costs they would incur. Thereby, "[...] economists expect the benefits of competition to come at the costs of cooperation – hence the need to 'find the right balance'" (Braguinsky & Rose, 2009, p. 361).

Combined with the benefits of economic externalities (Krugman, 1991), an agro-cluster can facilitate cooperation between involved actors, for instance, by sharing resources, collective production and joint marketing (Li & Geng, 2012). Schmitz (1995) argues that such cooperation is particularly pronounced in regions where a high density of farmers exists. Geldes et al. (2015) stress that spatial proximity allows farmers to build frequent interactions which facilitate sharing knowledge or joining forces in production and marketing. Nonetheless, examining determinants influencing neighbouring farmers at the individual farmer level to establish such cooperation in geographically concentrated farming regions is barely addressed in the current literature. Thus, Chapter 3 explores these

determinants and investigates whether such collective action affects farmers' income.

Braguinsky and Rose (2009), however, find that competition between farmers also appears inside densely geographically concentrated farming clusters. Coad and Teruel (2013) maintain that this competitive pressure is not only an innovation source, but also a challenging operating environment for farmers due to the limitation of the resources they depend upon. Staber (2007a) points out that the cluster can foster rivalry and predation that increase social conflict between neighbouring firms. James and Hendrickson (2008) emphasize that farmers perceiving higher competitive pressure tend to re-adjust their attitude towards cooperative behaviour. Agro-clusters with distrust-based relationships are likely to be weak and to fail (Barkley & Henry, 1997; Staber, 2007b). Chapter 4 therefore studies behaviour towards neighbouring farmers when farmers are operating subject to such competitive pressure.

1.3.3. Roles of the Government in Agro-cluster Development

Figure 1.1 highlights that governmental policies may influence the advancement of clusters by creating a business-friendly environment for facilitating cluster attributes to develop. For example, the government of India has been a crucial actor in the success of the Maharshtra grape cluster through developing cooperation between farmers and exporters (Galves-Nogales, 2010). Porter (2000) suggests that governments should prioritise promotion of networks and collective action, infrastructure improvements, regulatory policy support as well as research and technical progress in order to enhance productivity within agro-clusters. Therefore, governments in developing countries in particular may realise substantial benefits from paying more attention to strengthening networks between the involved rural

communities, as such links are generally weak in their countries (Galves-Nogales, 2010).

Porter (2000) points out that governments are sometimes unable to identify crucial constraints that impede productivity and innovation progress inside clusters. Complex governmental regulations may hinder the creativity of firms to create innovation, for example, or create unfair competition among firms. Crucial infrastructure might be neglected because the government underestimates the effort of creating or maintaining it during policy development. Porter (2000) emphasises the importance of regional properties for agro-cluster development. Every region has distinctive characteristics that shape such development. With a focus on increases in crop productivity, Chapter 5 assesses the effectiveness of existing policy instruments and suggests improvements for strengthening farmer institutions inside agro-clusters at national and regional levels. As stated by MoA (2016, p. 1), both national and regional governments are responsible for agro-cluster development in the Indonesian context.

1.4. Research Methodology

In order to answer the four above-mentioned research questions, this thesis uses four methodological approaches. Table 1.1 summarises the research focus, the data and the method of each chapter. The empirical analysis focuses on the Indonesian province of West Java (see Figure 1.2). This region was chosen, firstly because it has been declared a national strategic region for the economy of Indonesia (GoWJ, 2010). Secondly, its agriculture contributes to about 13% of total Indonesian GDP, and 9% of total Indonesian employment (World Bank, 2015). Thirdly, around 10% of the total population, or 4.3 million people in this province, however, live below the poverty line – 1.25 USD per day – and the number of the poor of this province is around 15% of all poor Indonesian population.

Table 1.1. Research Methodology

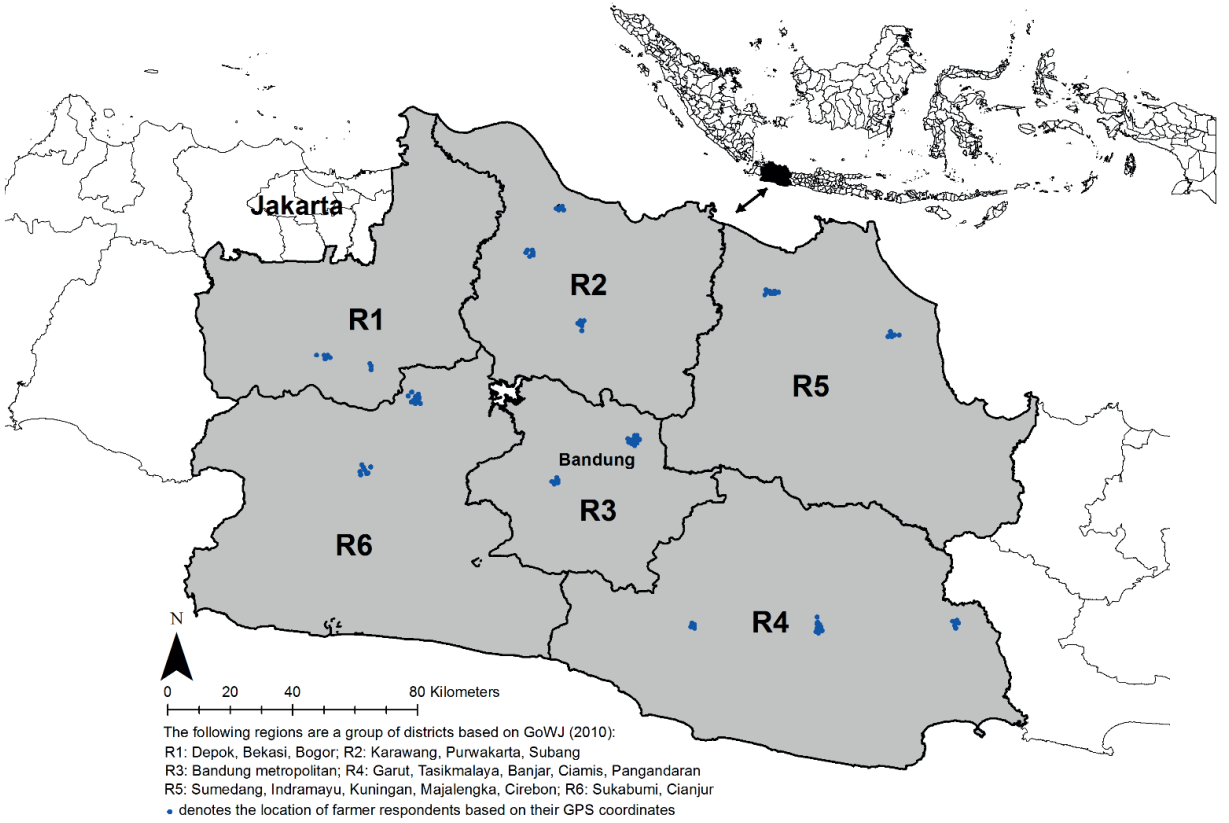
Chapter	Focus	Data Collection	Level of Analysis	Data Analysis
Chapter 2: Q1	Links between agro-clusters and poverty rates	Secondary data from BPS	Sub-district	Spatial econometric regression models
Chapter 3: Q2	Determinants of cooperation, effects on farmer income	Primary survey data	Individual farmer	1. Heckman selection model based on a two-stage decision process model of cooperation 2. OLS regressions
Chapter 4: Q3	Determinants of economic pressure within agro-clusters on farmer behavioural patterns, effects on farmer income	Primary survey data	Individual farmer	OLS regressions based on the models of planned behaviour and the behavioural interaction
Chapter 5: Q4	Quality of existing policy framework and feasible improvements	1. Secondary data from BPS and the national and provincial governments 2. Primary survey data	District and individual farmer	1. OECD's policy evaluation criteria for evaluating the existing rice policies 2. Propensity score matching and OLS regressions

Source: Author.

Several datasets are used for the analyses of this thesis: primary data gathered based on a self-designed and self-implemented survey and secondary data gathered by the Indonesian Statistics Agency (BPS) at the national and provincial levels. For the collection of the primary data, an one-round survey was conducted from May to September 2016. The survey

collected responses to 58 questions grouped in 5 categories from 1,250 farmers located in 15 of the 27 districts of West Java. The selection of the regions covered was determined by three indicators: poverty rates, agro-cluster density, and whether a sub-district is classified by BPS (2010) to be mainly rural or mainly urban. The selection also considered six groups of districts (Regions R1, …, R6 as shown in Figure 1.2) which have been identified by GoWJ (2010) to have similar regional properties. Figure 1.2 also shows the locations of the farmer respondents in the selected villages represented by blue dots. This survey consisted of a structured questionnaire on the basis of face-to-face interviews. Appendix D shows the detailed questionnaire. The questionnaire inquired with farmers about their social economic profile and perceptions about their attitudes towards cooperation, the extent of their actual cooperation, the motivation of their decision in favour of cooperation, and the economic pressure they perceive from neighbouring farmers. The resulting dataset from the survey is used in Chapters 3, 4, and 5.

The three secondary datasets are mainly used in Chapters 2 and 5. First, the database of 'registration for agriculture' in 2013 (BPS, 2013c) consists of detailed information on the socio-economic characteristics of farming activities, such as the number of farmers, farmer income, crops, farmer households, and land tenure. Second, the database of 'registration for poverty' in 2011 (BPS, 2011) contains all socio-economic aspects related to Indonesian poverty. Third, 'West Java in Figure' in the years 1990 – 2017 (Statistics Agency of West Java, BPS, 1990 – 2017) comprises regional properties including population, economic activities, employment, social aspects and education.

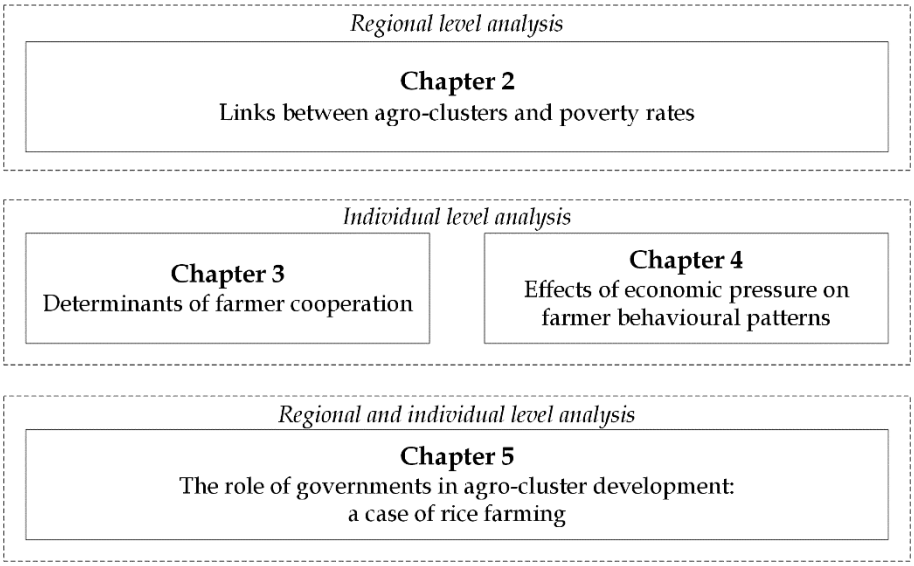


Source: Author

Figure 1.2. Location of the Province of West Java in Indonesia

1.5. Thesis Outline

Figure 1.3 summarizes the structure of this thesis as elaborated in Table 1.1. This thesis starts in Chapter 2 with the analysis of economic externalities of agro-clusters for agricultural growth with a focus on poverty reduction at the sub-district level. Through the lens of individual perception, Chapters 3 and 4 provide an in-depth analysis of the importance of such externalities by examining the interactions between neighbouring farmers for the sake of income improvements. These interactions are closely related to two crucial attributes of agro-clusters, that is, cooperation and competition, as illustrated in Figure 1.1. Chapter 5 assesses the role of governments in strengthening farmer institutions with regards to the findings of Chapters 3 and 4. In the following, the contents of all chapters are explained in more detail.



Source: Author.

Figure 1.3. Thesis Structure

Chapter 2 focuses on the links between agro-clusters and poverty rates. It applies spatial econometric regression models at the regional level from the about 600 sub-districts of West Java. According to Anselin and Bera (1998), these models capture the spatial interactions of neighbouring regions which are often neglected in OLS specifications. They stress that endogenous variables of neighbouring regions may be dependent. Day and Lewis (2013) emphasize that such spatial-spillover impacts should be taken into consideration when analysing economic development in Indonesia.

Chapters 3 and 4 examine the effects of agro-clusters on cooperation and competition between neighbouring farmers in the context of their effects on enhancing farmers' income. Chapter 3 analyses the determinants of farmer cooperation within agro-clusters. This analysis models the behaviour of individual farmers towards making a decision on cooperation with their neighbours. The model is based on a two-stage decision process based on the model of behavioural interactions of Rabbie (1991). Chapter 4 analyses the effects of economic pressure that farmers perceive within agro-clusters. The conceptual model of this analysis is based on the behavioural interactions models (Rabbie, 1991) and the planned behaviour model of (Ajzen, 1991). These theories help to deduce several hypotheses which are explicitly tested based on the OLS models estimated.

Chapter 5 focuses on assessing the quality of the existing policy frameworks and its feasible improvements in terms of agro-cluster development. It is especially concerned with rice farming, as rice is the Indonesian food staple of strategical importance that has manifold impacts on incomes, rural employment, and food self-sufficiency. This chapter is divided into three sub-objectives. First, it evaluates the existing Indonesian policies of rice self-sufficiency in West Java at the national and regional levels by applying OECD's policy evaluation criteria (OECD, 2014). Second, this chapter investigates the impact of farmer organisations within agro-

cluster regions on increased farm productivity. To this end, propensity score matching and OLS specifications are applied. Last, this chapter provides feasible policy improvements for sustainably achieving the Indonesian rice self-sufficiency targets based on the previous findings.

Chapter 6 synthesises the conclusions from the analysis of the four single research questions formulated in section 1.2. Furthermore, it adds a critical reflection on the limitations of the research and places them into the existing literature. Following this, it opts for further research.

CHAPTER 2

Agro-clusters and Rural Poverty: A Spatial Perspective for West Java

Abstract

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 sub-districts 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 sub-district. 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.

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2.1. 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 & Stamoulis, 2007). 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 & Robles, 2015); rural 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 (Brasier et al., 2007; Kiminami & Kiminami, 2009); 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 & 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 & 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 & Kuncoro, 1996), greater technological spillovers, a higher degree of labour pooling, or a larger supply of inputs (Amiti & 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 (Crozet et al., 2004; Folta et al., 2006), which may create a difficult operating environment (Coad & Teruel, 2013; Stucke, 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 sub-districts. 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 sub-districts 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) and Giang et al. (2016)). These spatial effects show the spatial interactions in which endogenous variables of different regions may be dependent (Anselin & 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 (Tian et al., 2010; Cravo & Resende, 2013). 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 & 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 & Chan-Kang, 2005). Third, geographical proximity to urban regions has a spatial effect on rural incomes (Day & Ellis, 2014). Finally, economic transactions cross geographic space, because of geographical and institutional diversity (Wood & 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 & Lewis, 2013).

With respect to spatial distribution, we employ spatial econometric regressions from regional aggregated data for 545 sub-districts 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 sub-districts. Examining the

link between the spatial concentration of agriculture and poverty while accounting for spatial dependence is an original contribution to the literature.

2.2. Theoretical Framework

2.2.1. 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 & Gibson, 1998). These benefits are connected to geographical proximity and cooperation among the actors, or "collective efficiency" (Schmitz & Nadvi, 1999). Farmers can obtain the advantages of agglomeration if they are located in regions with natural cost advantages (Ellison & 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 et al. 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,

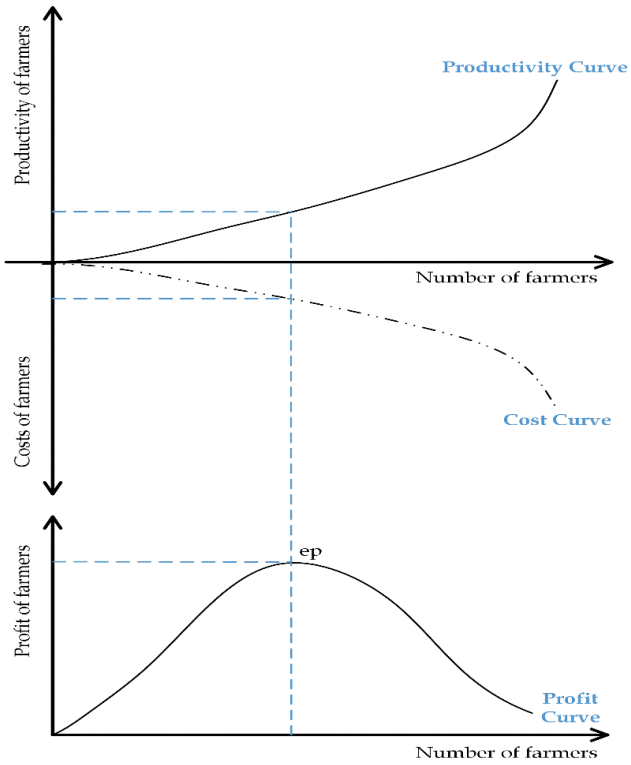
1998; Braguinsky & Rose, 2009). These farmers are often linked in the same value chain, a consumer farm network, or a regional economy. Knowledge flow along these links may also improve production processes (Aydogan & Lyon, 2004; Vissers & Dankbaar, 2013).

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). 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 2.1).

The productivity curve reveals that an increasing number of farmers in a sub-district is associated with positive productivity growth. As described above, the clustering of farmers in a sub-district 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 sub-district also raises production costs, as a consequence of the negative externalities within clusters, as discussed above.



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

Figure 2.1. Clusters and Economic Performance

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 (ep) 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 et al., 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 sub-district uses for productivity gains, the larger its share of employment and income gains will be.

2.2.2. Cluster Measures

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

$$LQ_s = \frac{\left(\frac{e_s}{E_s}\right)}{\left(\frac{e}{E}\right)} \tag{2.1}$$

In equation (2.1), the variable esdenotes the number of farmers in sub-district s, s = {1, ..., 545}, of West Java; Esrefers to the number of total employees in sub-district s; $e$is the number of farmers in West Java; and $E$is

the number of total employees in West Java. If sub-district *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 sub-district. 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 & 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 et al., 2004). Therefore, it is possible to obtain high LQ values for sub-districts that have a small number of farmers.

Regardless, we use a modified LQ_smodel 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 et al. (2004). They suggest that the hc_smeasure 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 sub-districts with different farmer population sizes, from 8 farmers to 29,241 farmers (BPS, 2013c). We obtain higher LQ values for agriculture in urban and peri-urban sub-districts, which have a relatively small number of farmers. Second, we analyse only the horizontal interactions between farmers in sub-districts, who use productive resources to produce and sell similar products.

The variable $hc_s$is defined as the observed number of farmers in sub-district $e_s$that exceeds its expected number, $\hat{e}_s$. Fingleton et al. (2004) suggest that the quantity $\hat{e}_s$ indicates the number of farmers in a sub-district; 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

$$\hat{e}_e = \frac{(e)}{(E)} E_s$$

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

$$hc_s = e_s - \hat{e}_s \tag{2.2}$$

Equation (2.2) is our input-oriented measure. The hc_s value of sub-districts is positive, indicating the presence of farmer concentration in those regions.

Our other measure of economic concentration is output-oriented. We quantify this measure by adapting Krugman (1991) relative specialisation index. Our adapted index takes into account the share of a sub-district'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; Combes & Gobillon, 2015). In other words, it calculates the relative specialisation of a sub-district'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, p. 274), we adapt Krugman's specialisation index (K_s) as follows. For sub-district s, we calculate the share, v_{is}, of the agricultural subsector outputs, y_{is}, of that sub-district 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 sub-districts in West Java, $n = \{1, \dots, 545\}$. The K_s is the absolute value of the difference between the share of the outputs in sub-district s and the average share across West Java:

$$K_s = \sum_{i=1}^{3} |v_{is} - \bar{v}_s| \tag{2.3}$$

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

2.3. 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

sub-districts of West Java by using aggregated data at the sub-district level and referring to the geospatial "shapefile" of West Java.

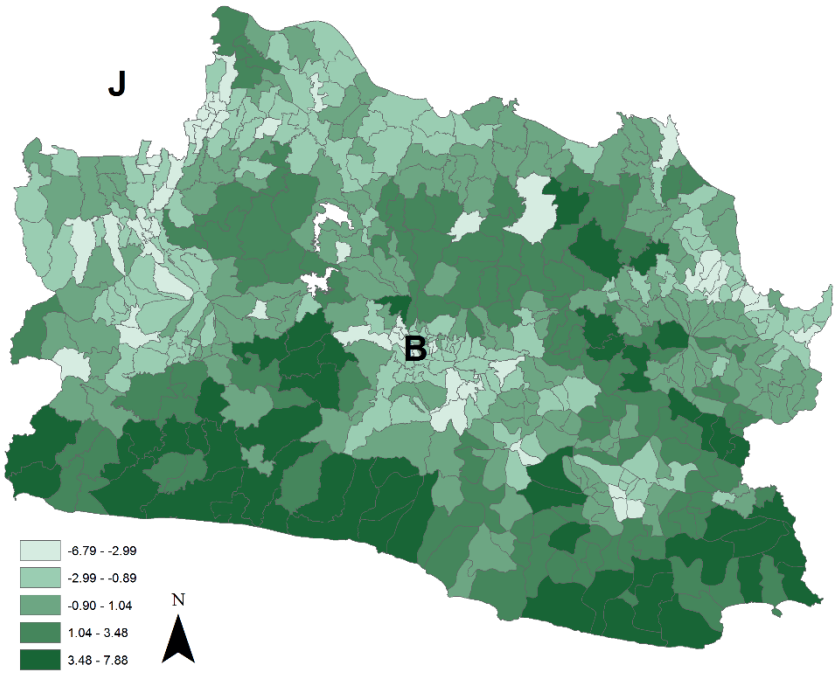
Our study focuses on West Java, which covers around 37,000 square kilometres, 72% of which is agricultural land. The province contributes around 15% of Indonesia's GDP (BPS 2013b) and more than 20% of its agricultural output. It also produces more than 70 agricultural commodities each year; it contributes 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 sub-districts have developed sub-terminal 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.

2.3.1. Agro-clusters in West Java

The number of farm households in West Java was about three million in 2013. Figures 2.2 and 2.3 depict the spatial distribution of agro-clusters in West Java on the basis of equations (2.2) and (2.3). Figure 2.2 shows the hc_sdistribution, and Figure 2.3 shows the specialisation distribution. The

darker regions in Figures 2.2 and 2.3 represent, respectively, denser agro-clustering and greater specialisation in agriculture.

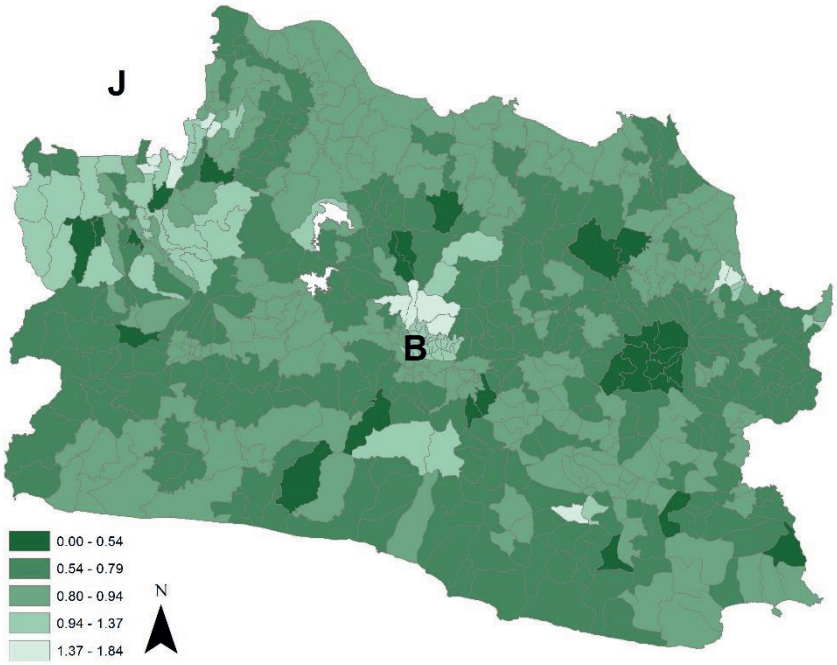


Source: Authors' calculations.
Note: J = Jakarta; B = Bandung Metropolitan Area

Figure 2.2. Horizontal Clustering, West Java, 2013 (1,000 people)

In thehc_s map (Figure 2.2), agro-clusters are concentrated mostly in the southern sub-districts of West Java, suggesting that these sub-districts have above-average potential for agricultural production. The clusters have a magnitude of hc_s. Sub-districts 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 sub-districts 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.



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

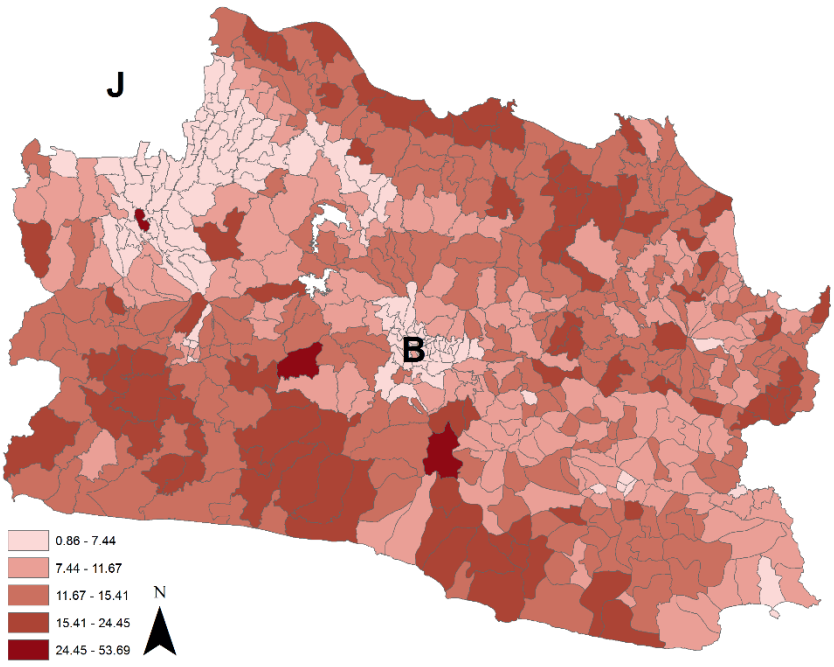
Figure 2.3. Relative Specialisation Index, West Java, 2013

Figure 2.3 representing the specialisation map shows agro-clusters exist mainly in the southern sub-districts. The specialisation index records the relative output share of agricultural products in the total agricultural output of West Java.

2.3.2. 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 Rp277,000 per month, or $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 2.4, the sub-districts closest to Bandung and Jakarta have lower poverty rates than those farther away. Nearly all of the southern and northern sub-districts have high poverty rates.



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

Figure 2.4. Poverty-Rate Quintiles, West Java, 2011 (% population)

2.3.3. 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 2.1 summarises our key variables: pov_s, hc_s, and K_s. Table 2.1 also shows our control variables ($X_{i,s}$) which fall into three categories: farmer characteristics, sub-district 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 & Morehart, 2008). The second variable is the proportion of smallholders in a sub-district. 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 & 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 et al., 2016).

The second category of variable is sub-district properties, including the distance to the nearest city (Bandung or Jakarta), the population size, the proportion of paddy fields, the total area of sub-districts, and a rural–urban distinction. Travel time to the nearest city is measured from the centroid of the sub-district 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 (Partridge & Rickman, 2008; Day & Ellis, 2014). This variable accounts for the quality of the roads and the diverse topography of West Java.

Table 2.1. Summary Statistics

Variable	Unit	Mean	CV	Median	Min.	Max.
Poverty rate (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
Smallholders	%	76.16	0.18	80.01	18.18	100
Farmers aged ≥55	%	36.39	24.82	35.87	16.82	65.85
Population	1,000 people	73.81	0.74	58.40	10.76	46.97
Sub-district size	100 ha	60.13	0.78	47.60	1.56	304.75
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

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

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

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

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

Last, we add a dummy variable, D, which equals one for rural sub-districts and zero for urban sub-districts, 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).

2.4. Model Specifications

2.4.1. 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 sub-district 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:

$$lnpov_s = \alpha + \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{8} \mu_i X_{i,s} + \varepsilon_s;\ \varepsilon_s \sim N(0, \sigma_\varepsilon^2) \tag{2.4}$$

in which $lnpov_s$denotes the poverty rate of sub-district s in the natural logarithm; $X_{i,s}$refers to control variable i, i{1, …, 8}, in sub-district s; and $\varepsilon_s$is a disturbance term, toaccount for unobserved information. The symbol $\alpha$is an estimated intercept, while β and μ are estimated coefficients explaining

the relations among variables. From equation (2.4), we expect $hc_s$to have a significant negative magnitude, to account forthe 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 sub-districts:

$$lnpov_s = \delta + \gamma_1 K_s + \sum_{i=1}^{8} \theta_i X_{i,s} + \epsilon_s;\ \epsilon_s \sim N(0, \sigma_\epsilon^2) \tag{2.5}$$

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 sub-district's farm outputs are (relative to those of West Java as a whole), the lower its poverty rate will be.

2.4.2. 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 sub-districts 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 sub-districts share a boundary. Suppose we have a set of boundary points between two sub-districts, $s_{(1)}$ and $s_{(2)}$. The contiguity weights are defined by

$$\begin{cases} 1, s_{(1)} \cap s_{(2)} \neq \emptyset \\ \\ 0, s_{(1)} \cap s_{(2)} = \emptyset \end{cases} \tag{2.6}$$

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

Spatial Autocorrelation

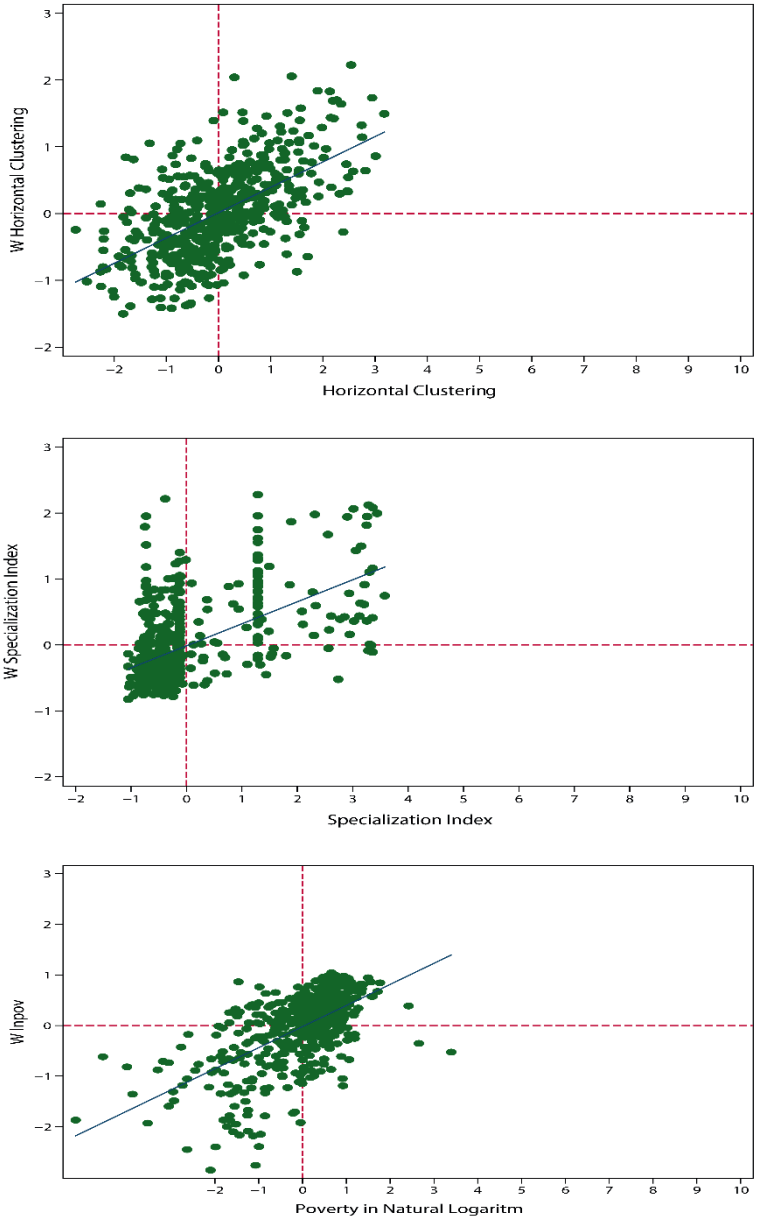
Before calculating equations (2.4) and (2.5), we investigate whether the given characteristics of our spatial data have spatial dependence. We adopt a parameter and a technique to test spatial autocorrelation. For spatial effects, we adjust equations (2.4) and (2.5) to examine spatial dependence in our data on agro-cluster indices and poverty rates:

$$I = \left(\frac{S}{Ws}\right) \frac{\sum_{s(2)} \sum_{s(1)} w_s \left(V_{j,s(1)} - \bar{V}_j\right) \left(V_{j,s(2)} - \bar{V}_j\right)}{\sum_{s(2)} \left(V_{j,s(1)} - \bar{V}_j\right)^2} \tag{2.7}$$

where I refers to Moran's index; S is the number of sub-districts 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; $\acute{V}_j$ 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,

$$Ws = \sum_{s(1)} \sum_{s(1)} w_s$$

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.



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

Figure 2.5. Moran's I Scatterplots

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 2.5) illustrate the significance of a positive association between the variables and their spatial lags. This finding verifies that the properties of a sub-district can affect efforts to reduce poverty in neighbouring sub-districts. It also means that the effects of a cluster in one region can influence surrounding regions.

2.4.3. 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 (2.4) and (2.5) 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 & Bera, 1998). The SAR models are as follows:

$$(I - \rho W_s) lnpov_s = \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{6} \mu_i X_{i,s} + \alpha + \varepsilon_s;\ \varepsilon_s \approx N(0, \sigma^2 I) \tag{2.8}$$

$$(I - \rho W_s) lnpov_s = \gamma_1 K_s + \sum_{i=1}^{6} \theta_i X_{i,s} + \delta + \epsilon_s;\ \epsilon_s \approx N(0, \sigma^2 I) \tag{2.9}$$

Second, we use spatial Durbin models (SDMs) to examine spatial lags on our dependent and explanatory variables (Mur & Angulo, 2006). The SDMs capture feedback influences between variables – that is, the impacts passing through neighbouring sub-districts and back to a sub-district itself

(Elhorst, 2010). We verify spatial lags on all variables, except sq_hc_s and the rural–urban dummy. The SDMs are as follows:

$$(I - \rho W_s) lnpov_s = \rho W_s \left(hc_s + \sum_{i=1}^{6} X_{i,s} \right) + \beta_1 hc_s + \sum_{i=1}^{6} \mu_i X_{i,s} + \beta_2 sq\_hc_s + \alpha + \varepsilon_s;\ \varepsilon_s \approx N(0, \sigma^2 I) \quad (2.10)$$

$$(I - \rho W_s) lnpov_s = \rho W_s \left(K_s + \sum_{i=1}^{6} X_{i,s} \right) + \gamma_1 K_s + \sum_{i=1}^{6} \theta_i X_{i,s} + \delta + \epsilon_s;\ \epsilon_s \approx N(0, \sigma^2 I) \quad (2.11)$$

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 & Bera, 1998). The SEM investigates spatial dependence in the residual term; λ is the scalar-spatial-disturbance coefficient for SEM:

$$lnpov_s = \beta_1 hc_s + \beta_2 sq\_hc_s + \sum_{i=1}^{6} \mu_i X_{i,s} + \alpha + \lambda W_s \varepsilon_s;\ \varepsilon_s \approx N(0, \sigma^2 I) \quad (2.12)$$

$$lnpov_s = \gamma_1 K_s + \sum_{i=1}^{6} \theta_i X_{i,s} + \delta + \lambda W_s \epsilon_s;\ \epsilon_s \approx N(0, \sigma^2 I) \quad (2.13)$$

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

λconcentrated 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.

2.5. 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 sub-district on another. Tables 2.2 and 2.3 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 sub-districts, 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 sub-districts, the proportion of rice fields,

and travel time are consistent in explaining the incidence of poverty in a sub-district and its surrounds.

2.5.1. Farmer Concentration (Horizontal Clustering)

The relations between horizontal clustering (hc_s) and the poverty rate ($lnpov_s$) are reported in Table 2.2. The concentration of farmers is statistically significant in reducing poverty rates of sub-districts. The (hc_s) variable has a negative sign, meaning that the greater the farmer concentration in a sub-district, the greater the decreases in the poverty rate of that sub-district. 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 2.2). 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 $\varepsilon_s$by using the relevant estimate of λ. For instance, the total effect of a 1.00% increase in $\varepsilon_s$is a 0.34% increase in the poverty rate of a sub-district. This is due to an own direct effect. In other words, there are fewer spatial-spillover effects and no indirect effects.

From Table 2.2 we infer that a 1.00% increase in the concentration of farmers in a sub-district will lead to a 0.12% reduction of poverty in that region.

Table 2.2. Spatial Models of the Relation between the Poverty Rate and Horizontal Clustering

Variable (Dep. variable = *lnpov*)	**SAR**	**SEM**	**SDM**
Original variables			
Horizontal clustering	-0.1227***	-0.1211***	-0.1144***
Squared horizontal clustering	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***
Sub-district 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**
Sub-district size			-0.0001
Paddy field			0.0053***
Travel time			0.0198
Capital-city effect			-0.0000
Intercept (α or δ)	1.5486***	2.4630***	1.0826***
ρ(SAR and SDM)	0.3341***		0.3132***
λ(SEM)		0.3416***	
AIC	0.0700	0.0665	0.0753
BIC	0.0763	0.0725	0.0874

Source: Authors' calculations.
Note: SAR = spatial autoregressive (model); SEM = spatial error model; SDM = spatial Durbin model.* p < 0.10; ** p < 0.05; *** p < 0.01.

2.5.2. 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 2.3). 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 sub-district. The sub-district, which has a tendency to produce the primarily agricultural outputs of West Java, retains a lower poverty rate. In other words, agro-clusters 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 2.3. Once again, since the SEM result represents only the direct effects of the variables, we use the γ coefficients in Table 2.3 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%.

Table 2.3. Spatial Models of the Relation between the Poverty Rate and the Specialisation Index

Variable (Dep. 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***
Sub-district 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***
Sub-district size			-0.0083***
Paddy field			0.0029
Travel time			-0.0605
Capital-city effect			-0.0000***
Intercept	0.2353	1.0252***	0.5297
ρ(SAR and SDM)	0.3771***		0.4867***
λ(SEM)		0.6336***	
AIC	0.2798	0.2578	0.3363
BIC	0.3028	0.2789	0.3877

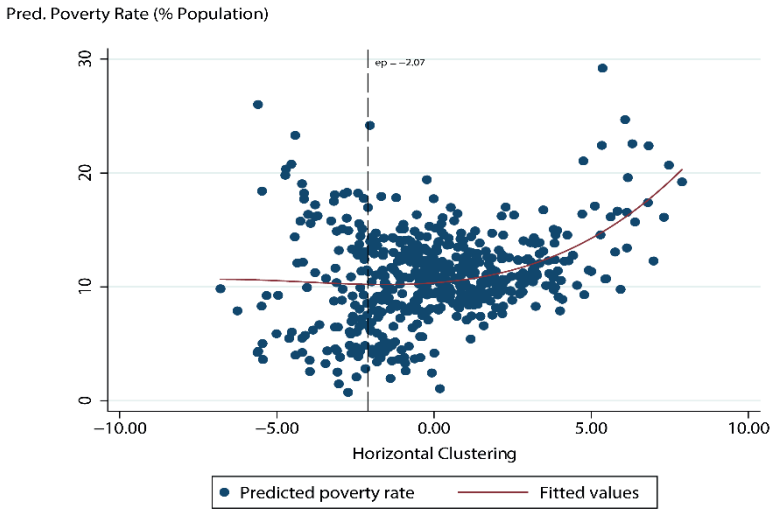
Source: Authors' calculations.
Note: SAR = spatial autoregressive (model); SEM = spatial error model; SDM = spatial Durbin model. * p < 0.10; ** p < 0.05; *** p < 0.01.

The result of the SDM regression in Table 2.3 suggests that the spatial lags of the specialisation index are not statistically significant in clarifying the extent of poverty reduction. This finding is line with the result in Table

2.2; 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).

2.5.3. 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 sub-districts to investigate positive and negative externalities. Figure 2.6 shows the quadratic curve of the estimation result.



Source: Authors' calculations.

Figure 2.6. Horizontal Clustering versus the Predicted Poverty Rate

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 (2.12) 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 sub-district 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 sub-district 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 sub-district's poverty rate.

2.5.4. Smallholders and Older Farmers

From Tables 2.2 and 2.3 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 sub-districts with a smaller share of smallholders have lower poverty rates and affect poverty reduction in neighbouring sub-districts. 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 sub-districts 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 2.2 and 2.3 also show us that a higher share of older farmers in a sub-district is associated with decreased poverty in that sub-district 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.

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

In these results, an increase in a sub-district'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 sub-district. This inference is also shown from the β and γ coefficients of the dummy variable in Tables 2.2 and 2.3. All results seem intuitively plausible, since these sub-districts have more diverse services and more job opportunities, as shown by the lower K_s. 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 sub-district is from Bandung and Jakarta, the higher its expected poverty rate will be, ceteris paribus. This implies that a shorter commute between a sub-district and the nearest city is associated with a lower incidence of poverty in that sub-district. Travel time between regions relies on road availability and quality; sub-districts with the lowest levels of income have the least access to such infrastructure (Day & Ellis, 2014). Better access to roads could facilitate specialisation in agriculture and thus reduce rural poverty—especially in regions with natural advantages (Qin & 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 2.2 and 2.3, 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: sub-districts with high levels of market gravity tend to have lower-than-average poverty rates. Farmers concentrated in sub-districts 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 & Menon 2013).

Despite this advantage, the capital-city effect can also have drawbacks for farming practices, as shown in Table 2.3. 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 2.2. Specialised sub-districts 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 sub-districts 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 annual rate of farmland conversion in West Java was about 6.7% 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 (MoA, 2014). As Figure 2.2 shows, the concentration of farmers decreases if the sub-districts are proximate to Jakarta or Bandung. Tables 2.2 and 2.3 show that sub-districts with higher shares of rice fields have higher poverty rates. This suggests that sub-districts 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 1 million IDR per month (Darwis, 2009), which was below the minimum wage in West Java at the time (Rp1.31 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 rich farm resources elsewhere.

2.6. 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 sub-district towards the area below the mean.

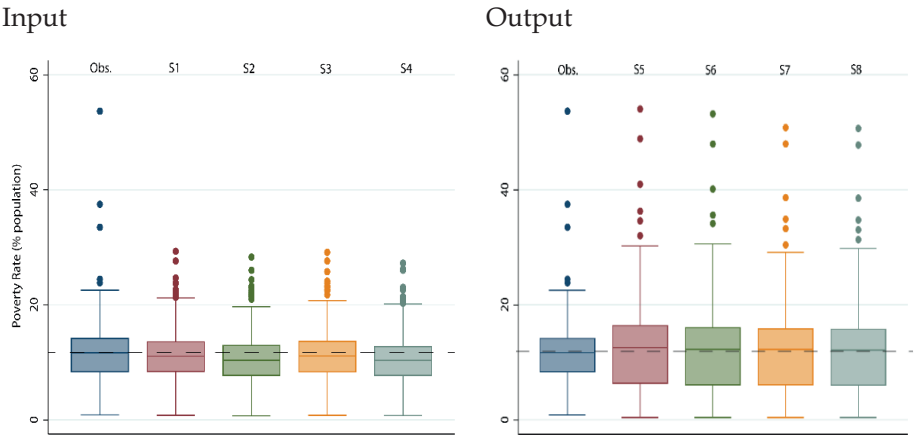
To prioritise these recommendations, we simulated our regression results, corresponding to SEM specifications, for both the input-oriented equation (2.12) and the output-oriented equation (2.13). These simulations allowed us to ascertain any changes in the effects of our key variables, and other explanatory variables, on poverty rates. The selected variables included travel time and the share of farmers 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.

Table 2.4. Simulation Scenarios

Scenario	**Simulated Policy Measure**
Equation (2.12)	
S1	10% increase in horizontal clustering in each sub-district
S2	10% increase in the number of farmers aged ≥55 in each sub-district
S3	10% reduction in travel time
S4	S1, S2 & S3 combined
Equation (2.13)	
S5	10% increase in the specialisation index of each sub-district
S6	10% increase in the number of farmers aged ≥55 in each sub-district
S7	10% reduction in travel time
S8	S5, S6 & S7 combined

As shown in Table 2.4, 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 sub-district 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 2.7 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. Comparing to the initial state, the policy priority encompasses (1) the smallest mean of poverty rates, (2) the smallest range of poverty rates, and (3) the smallest range between the mean and the centile, at 75%. In other words, the policy would be more beneficial if it could shift sub-districts with high poverty rates as many as possible towards the area below the average estimated poverty rate, represented by the dashed line in Figure 2.7.



Source: Authors' calculations.
Note: Obs. = estimated poverty rates.

Figure 2.7. Simulation Results

Input-Oriented Model

Observing the mean of the predicted poverty rates in equation (2.12), 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 2.7 shows that S4 also has the largest gap if 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 sub-districts. 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 sub-district. 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 (2.13), 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 sub-district—because it would reap less cost of policy implementation. Improving the quality of roads between sub-districts 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 sub-districts.

2.7. Conclusions

A sub-district's resources influence not only its agricultural growth but also that of its neighbours. Farming activities in most sub-districts 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 sub-districts 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 sub-district 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 sub-district. Higher numbers of farmers are associated with lower poverty rates in these sub-districts. Second, specialisation in agriculture in a sub-district relative to West Java reduces the poverty rate of that sub-district. 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.

CHAPTER 3

Farmer Cooperation in Agro-clusters

Abstract

Collective action in geographically concentrated farming regions can lead to improvements in farmers' incomes. We model farmers' cooperation as a two-stage decision process inside agro-clusters. Survey data from 1,250 farmers in West Java, Indonesia confirms that being located in an agro-cluster increases farmers' likelihood towards cooperation. Positive attitudes towards cooperation are influenced by farmer's gender, assets, and household food vulnerability. Working time in farms and the frequency of face-to-face meetings also raise the probability of engaging in cooperation. A higher cropping diversity reduces this probability. Reinventing agro-clusters for fostering farmer cooperation remains a promising initiative for increasing income of farmers.

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3.1. Introduction

Smallholder cooperation has been often seen as possible institutional innovation to enhance access to knowledge and technology as well as markets, particularly in developing countries (Markelova et al., 2009). Bolwig et al. (2009) and Fischer and Qaim (2012b) suggest that cooperation could raise smallholders' income[1]. We address how farmers as an individual could establish cooperation with other farmers when they are spatially close to each other. By "cooperation" in the context of this paper we mean farmer-to-farmer cooperation, that is, one farmer works together with one or more other farmers without any payment taking place. She may cooperate with her neighbouring farmers by sharing knowledge on crop production technology. However, if a farmer sells some of her time as a day labourer to other farmers, this would not be considered cooperation in this study. Such cooperation may refer to reciprocity to improve access to agricultural resources, collective production and joint marketing.

Farmers are geographically concentrated in regions with agricultural resources (Deichmann et al., 2008). This geographical concentration is referred to as agro-cluster. Following Porter (1990) and Krugman (1991), we highlight that agro-cluster includes: (1) social and economic interactions between farmers, (2) mutual relationships between farmers and related actors at a given level of the food supply chain (horizontal) or along it (vertical), that is, in agricultural production, food processing, and processes of food marketing, (3) linkages with supporting actors, for instance, research institutions/universities and government bodies, and (4) connections between farming activities and other sectors. This cluster could foster the cooperation as a result of frequent interactions between farmers (Ostrom, 2010). Some studies acquaint positive relationships between spatial

[1]Smallholders refer to farmers who operate farmland less than half a hectare (the Agency for Indonesian Statistics Agency, 2013).

concentration, cooperation, and income growth (Torre & Rallett, 2005; Geldes et al., 2015; Opper & Nee, 2015; Lazzeretti & Capone, 2016). Humphrey and Schmitz (2001) and Vissers and Dankbaar (2013) claim that clusters allow for building complex network relations, thereby creating innovation through knowledge exchange. Additionally, firms inside clusters could benefit from collective efficiency (H. Schmitz, 1995).

However, the failure of cooperation could happen due to increasing distrust between involved agents (Staber, 2007a; Graham, 2014). Ostrom (2010) and Hakelius and Hansson (2016) suggest that cooperation is structured by trust-based reciprocal interactions and commitment that are affected by individual behaviour. Farmers may decide to cooperate with peers because they believe that they will grasp benefits from such cooperation. Similarly, Lajili et al. (1997) argue that individuals' characteristics, preferences, and beliefs shape cooperative behaviour. Interpersonal trust and commitments strengthen cooperation (Osterberg & Nilsson, 2009). In detail, Dowling and Chin-Fang (2007, p.5) also suggest that the psychological attributes of individuals could shape cooperation. For instance, Raya (2014) finds that chili farmers in Yogyakarta of Indonesia often adjusted their behaviour as a member of farmer organisations when they found inequality in terms of economic and societal benefits among all members. The member farmer changes her attitude toward the organisation when other members cheat on her, for example, if she finds that other farmers withhold all information related to government subsidies.

Recent literature on clusters has paid less attention to the significant heterogeneity of smallholder farmers. Farmer heterogeneity particularly relates to individual access to productive resources and, perhaps more importantly, to farmers' decision process on establishing cooperation for advancing their crop production and marketing. The emergence of successful clusters in particular regions highlights the efforts of individuals

by industrial structure, skills, and knowledge (Isaksen, 2016). Nooteboom (2006) indicates the different behaviour of neighbouring firms within clusters in relation to income improvements. We, therefore, investigate the determinants of cooperation between neighbouring farmers by controlling for farmer heterogeneity in terms of their decision on such cooperation. The analysis considers spatial, cognitive, organisation, and institutional proximity between farmers, reflecting neighbouring effects between farmers. In the final purpose, we examine the effect of such cooperation farmer's income level. Our study differs from previous studies in three ways. First, we provide empirical evidence of how agro-clusters promote farmer cooperation as well as their resulting benefits from increased income. Second, we model a two-stage process of an individual farmer's decision with regard to cooperation. Third, we apply survey data taken from farmers at the individual level to control for farmer's behaviour toward cooperation.

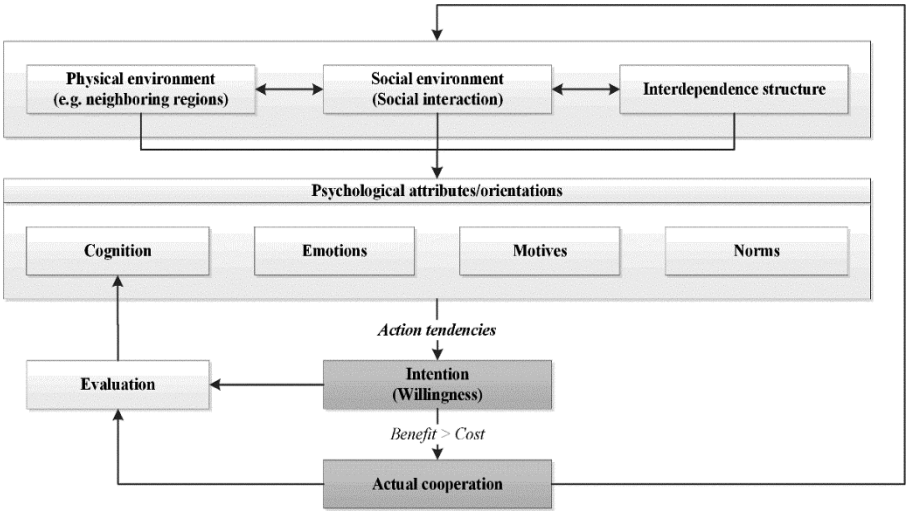
The remaining sections are organised as follows: The next section outlines the conceptual framework upon which the empirical models are based and discusses empirical specifications. We then define our variables and explore data used in the empirical analysis. The fourth section provides a brief background on agro-clusters and farmer cooperation in West Java, Indonesia as our study focus. Subsequent sections elaborate on the estimation results as well as deduce some discussion points and policy implications at the end.

3.2. Conceptual Framework

3.2.1. Farmer's Decision Process on Cooperation

As mentioned in Section 3.1, we define cooperation as cooperation between farmers for the aim of increasing income. This cooperation includes, for example, sharing knowledge and working together on providing

production inputs and farm workers as well as on harvesting, storing, or marketing. In this study, we emphasize that farmers decide on an individual basis whether or not they participate in cooperation. In order to analyse the cooperation decisions of farmers, we adapt the behaviour interaction model of Rabbie (1991) as shown in Figure 3.1. It suggests that cooperative behaviour can be modelled as a function of individual psychological attributes in relation to desirable and undesirable trade-offs, which are influenced by the external environment. Likewise, Hansla et al. (2008), Stallman and James (2015) and Tsusaka et al. (2015) identify that an individual decision on cooperation is subject to personal characteristics, economic factors, and neighbouring effects.



Source: Authors based on Rabbie (1991, pp.242).

Figure 3.1.Determinants of Farmer's Decision on Cooperation

We observe from Figure 3.1 two major stages of the decision process. The first stage is related to farmer's willingness to cooperate. Rabbie (1991) find that this willingness is influenced by individual psychological attributes

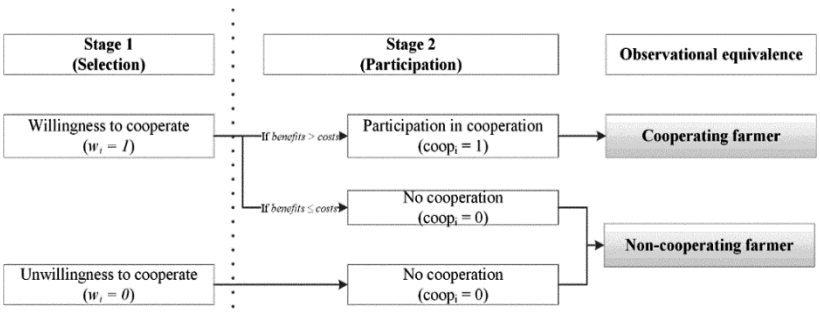
including cognitive, emotional, motivational, and normative orientations. For example, farmers living close to urban regions are aware of collective production and marketing due to limited agricultural resources (Curran-Cournane et al., 2016). Additionally, Chaserant (2003) argues that willingness to cooperate is related to individual utility. Following Dowling and Chin-Fang (2007), farmers may act in their own self-interests to maximize their utility. In other words, individuals are likely to cooperate when they see ways of improving their performance (Rabbie 1991). Owing to Figure 3.1, the second stage refers to actual cooperation. Only if farmers have a positive attitude toward cooperation after forming expectations about potential losses and gains, would they actually engage in cooperation. If they have a negative attitude towards cooperation, they will not engage in it no matter how large potential gains might be. Dowling and Chin-Fang (2007) emphasize that individuals perceive losses and gains differently when making decisions about how to get their expected utility maximization. Given that farmers are rational, they intend to build collective crop production with others, when they subjectively expect that the gains they reap as individuals exceed the costs and efforts they have to incur in order to make joining cultivation happen.

In relation to physical and social environments (Figure 3.1), Ostrom (2007) and Pacheco et al. (2008) identify that face-to-face interactions and communication foster cooperation. Likewise, Braguinsky and Rose (2009) and Tsusaka et al. (2015) argue that neighbouring farmers are more likely to interact with one another to consolidate the trust among them. These social interactions allow those farmers to engage in actual cooperation, for example, collective production and joint marketing. However, farmers working with a large number of partners may also encounter the presence of free riders (Kandel & Lazear, 1992). According to Duranton et al. (2010), competition between individuals within high density of clusters may lead to

unfair environment. The competition, such as intensive competition for water irrigation shortage and farmland, may influence some farmers to exploit their neighbouring farmers or to hide information on government subsidies from the others (Raya 2014).

3.2.2. Models of Farmer Cooperation

This sub-section aims at theoretically modelling determinants of farmer cooperation. Based on Figure 3.1, we model farmers' decision whether to cooperate or not as a two-stage process. Figure 3.2 elaborates this modelling framework. As discussed above, farmers may have differing attitudes towards cooperation. This farmer heterogeneity forms farmer's willingness to cooperate and thereupon farmer's participation in cooperation. In the first stage, we distinguish two groups of farmers, based on their willingness to cooperate (Figure 3.2). Farmers are distinguished into those who do and do not have willingness to cooperate. In stage 2, we split those farmers who wish to cooperate into two groups according to their actual cooperation (Figure 3.2). This two-stage classification yields to the observational differentiation between farmers who actually cooperate and those that do not.



Source: Authors.

Figure 3.2. Farmer's Cooperation Decision Process

Suppose that farmer i, $i = \{1, \dots, N\}$, intends to maximize her profit subject via participation in peer-to-peer cooperation. In doing so, she considers to work together with her neighbouring farmers j, $j = \{1, \dots, J\}$. Let the variable π_i be the profit of farmer i when participating in cooperation. Farmer i's profit is a function of her input costs and outputs of production and summed by a function of cooperation:

$$\pi_i = \prod f_{prod}(c_{mi}, y_{mi}) + f_{coop}(b_{ij}, c_{ij}) \tag{3.1}$$

$f_{prod}(.)$ is the function of farmer i's production in relation to the production input costs c_{mi} and production outputs y_{mi} of crop m, $m = \{1, \dots, M\}$. The function $f_{coop}(.)$ is the observed cooperation in which farmer i decided to participate in cooperation, in relation to gains b_{ij} and costs c_{ij} due to this cooperation.

Figure 3.2 clearly indicates that farmers must pass two distinct hurdles (stages 1 and 2) before they actually decide to cooperate. These two hurdles allow for the grouping of farmers based on their attitudes toward cooperation and the investigation into the farmers' characteristics determining this group. We model this cooperation decision, as follows:

$$coop_i = \begin{cases} 1, & if\ b_{ij} \geq c_{ij} \Big| w_{ij} = 1 \\ 0, & if b_{ij} \leq c_{ij} \\ \\ 0, & if b_{ij} \geq c_{ij} \Big| w_{ij} = 0 \end{cases} \tag{3.2}$$

The variable $coop_i$ is a discrete random variable which can be observed. If the value of $coop_i$ is unity, this means that farmer i engages in cooperation with at least one of her peers; otherwise, $coop_i$ equals zero. The variable b_{ij} denotes the expected benefits farmer i will receive from cooperation with farmer j. The variable c_{ij} is the expected costs and risks that farmer i will incur when she becomes involved in cooperation with

farmer j. We measure b_{ij} and c_{ij} based on monetary and non-monetary equivalents.

The first hurdle corresponds to the willingness of farmers to cooperate. It determines whether the farmer is willing or not to build the cooperation. In this hurdle, farmers assess their attitude toward cooperation measured by the observed w_i. The variable $w_i = 1$ denotes the positive attitude of farmer i to engage in cooperation with farmer j; $w_i = 0$ otherwise. We investigate the characteristics of farmers that shape this attitude. As outlined in Sub-section 3.2.1, these characteristics are primarily related to farmers' personal traits and experiences. We formulate the willingness equation (willingness stage) as:

$$w^* = \alpha z_i + \epsilon_i, \qquad w_i = \begin{cases} 1 \, if \; w^* > 0 \\ 0 \, if \; w^* \leq 0. \end{cases} \tag{3.3}$$

The variable w^* is the unobserved latent dependent variable corresponding to the observed binary outcome of w_i describing whether or not farmer i has a positive attitude towards cooperation. This attitude stage explains the outcome of a binary choice. The vector z_i represents observable variables that affect the value of w^*. They comply with farmer i's willingness to cooperate or not with any of her peers, as framed in Figure 3.2. The parameters α and ϵ_i denote the estimated coefficient vector and disturbance term vector, respectively.

Meanwhile, the second hurdle relates to whether or not farmers take the decision to actually cooperate with peers, given that they are willing to cooperate. When farmers have this willingness, they will consider their resources in order to assess benefits they believe they will gain and costs they believe they will incur if they decide to participate in cooperation. For rationale economic agents, farmer i will choose to work with peers if the benefits she expects from cooperation are larger than the costs she believes

to have to incur. We observe this second hurdle, if the sample selection in the first hurdle is introduced. We formulate the cooperation equation (cooperation stage) as:

$$coop_i^* = \gamma y_i + \varepsilon_i coop_i \; = \begin{cases} 1 \; if \; coop_i^* > 0 \\ 0 \; if \; coop_i^* \leq 0 \end{cases}$$
$$corr(\varepsilon_i, \epsilon_i) = \rho \tag{3.4}$$

The variable $coop_i^*$ denotes the unobserved latent dependent variable associated with the observed binary outcome of $coop_i$. The vector y_i refers to explanatory variables that influence the cooperation decision of the farmer. The parameters γ and ε_i denote the estimated coefficients and disturbance terms vectors, respectively. The disturbance terms in equations (3.3) and (3.4) are assumed to be independent and distributed as $\epsilon_i \sim N(0,1)$ and $\varepsilon_i \sim N(0,1)$, since both models utilize a binary model. The parameter ρ is a variance correlation for both error terms. Therefore, the probabilities of being willing and actually cooperating can be correlated as either sign and any magnitude, e.g., a strong positive correlation implies that farmers who are willing to cooperate are more likely to have actual cooperation.

For estimating determinants of farmer cooperation, we combine the relationships in equations (3.3) and (3.4) by employing the Heckman selection procedure (Heckman, 1979). It allows us to model a dichotomous dependent variable in order to obviate sample selection bias and to attain more robust outcomes, particularly for small sample sizes (Bolwig et al., 2009). It also provides consistent and asymptotically efficient estimates for all parameters in the model (Miyata et al., 2009; Zheng et al., 2011). When $\rho \neq 0$, standard OLS regression techniques applied to equations (3.3) and (3.4) yield biased results; the Heckman model is then superior.

3.2.3. The Link Between Farmer Cooperation and Income Level

This sub-section aims at analysing the effects of farmer cooperation on farmers' income level. We apply two measures of cooperation. First, we quantify cooperation by observing whether or not farmers are in actual cooperation, i.e. $Coop_i$, as discussed in Sub-section 3.2.2. Recalling equations (3.1) and (3.2), we specify a model to explain the relationship between farmers' income level and cooperation decision. The model is as follows:

$$\pi_i = \beta_0 + \beta_1 Coop_i + \beta_2 x_i + v_i \tag{3.5}$$

The vector x_i quantifies explanatory variables that influence farmer i's income. These variables comprise the characteristics of the farmer, her farm, and the region in which it is located. β_1 and β_2 are the estimated parameters. The parameter v_i is the disturbance terms assumed to be independent and distributed as $v_i \sim N(0, \sigma^2)$, and β_0 is the intercept.

As already discussed, we are interested in examining the effects of agro-clusters on the increased incomes of farmers when they actually cooperate with peers. For this purpose, we employ two approaches. First, we add an agro-cluster indicator as regional density (rd_s)[2] and the interaction between $Coop_i$ and rd_s to equation (3.5). These additional variables aim at controlling for the effects of agro-clusters. Second, we modify equation (3.5) by introducing a quadratic form of rd_s to account for the presence of negative externalities inside agro-clusters. As mentioned earlier, agro-clusters with a high number of farmers can also evoke negative externalities. These externalities may reduce income (Duranton et al. 2010). We accordingly specify the modified model as:

[2] See Appendix A.1.

$$\pi_i = \beta_0 + \beta_1 Coop_i + \beta_2 rd_s + \beta_2 Coop_i rd_s + \beta_3 Coop_i sq\_rd_s + \sum_{k=1}^{2} \beta_k d_{ik} + \beta_6 x_i + v_i \qquad (3.6)$$

The variable sq_rd_s denotes squared regional density, capturing the negative externalities. The "distance" variables d_{ik} indicate spatial proximity, measured as travel time from farmer i to her closest partner (d_{i1}) and nearest economic center (d_{i2}). $Coop_i rd_s$ is the interaction variable of farmer i's decision on actual cooperation across regional density of farmer concentration. $Coop_i sq\_rd_s$ is the combination between farmer i's participation in cooperation and squared regional density. We run OLS specification to estimate the coefficients of all variables introduced in equation (3.6). Second, we elaborate the effect of cooperation on farmer i's income level by using another cooperation measure, that is the strength of cooperation measured as following (Marsden & Campbell, 1984). This measure differs from the first measure in equations (3.5) and (3.6) as it captures the intensity of cooperation farmers perceive when they have cooperation with peers. We specify the empirical model as:

$$\pi_i = a + \beta_1 tie_i + \beta_2 rd_s + \sum_{k=1}^{2} \beta_k d_{ik} + \sum_{p=1}^{p} \beta_p X_{ip} + u_i \qquad (3.7)$$

The variable tie_i denotes the strength of cooperation that farmer i perceives. Following Marsden and Campbell (1984), we measure tie strength by controlling for proximity, i.e. cognitive, institutional, and organisational proximity (Boschma, 2005; Geldes et al., 2015). Additionally, we quantify these proximity measures by questions related to partnerships with families and neighbours, amity intensity, frequency of face-to-face meetings, and membership of farmer organisations. We assume that the stronger tie may be reflected by a more intense friendship and more frequent meetings. Farmers having partnerships with family, neighbours, and other farmers in

the same organisation may also experience stronger cooperation. To quantify the tie strength measure, we apply a Likert scale from 1 to 5 and utilize principal component analysis to calculate the score of all proximity measures. In addition, We suggest several control variables X_{ip} including the characteristics of farmers, farms, and regions. The parameter β_i and u_i are estimated coefficients and a disturbance term, respectively.

3.3. Data and Variables

3.3.1. Data Sources

The analysis is based on a survey conducted by the authors between May and August 2016 in West Java. Data has been gathered from about 1,250 questionnaires filled-in as a result of face-to-face interviews of farmers. The survey covers information on the socio-economic profile of farmers, including demographics, farm area, farming activities, and farm incomes. It also consists of information about farmers' attitudes toward cooperation and their actual cooperation. The survey was designed to collect comprehensive data on cooperation, that is, details related to motivation, intensity, benefits, costs, and risks linked with cooperation by using a Likert's scale from 1 to 5. Appendix A.2 shows the respondents surveyed based on their GPS coordinates.

We applied a two-step procedure to select our respondents. The first step was to group the sub-districts of West Java based on 18 regional categories. This regional selection considers all possible combinations of regional density (high, medium, and low)[3], poverty rates (high, medium, and low), as well as whether the sub-district is classified by the Statistics

[3]The range of probability distribution of this regional measure is divided into three categories with mean values as a reference point. We set the range of > 2.5% of the mean as the "high" category, between -2.5% and 2.5% of the mean as the "medium" category, and < -2.5% of the mean as the "low" category.

Agency of Indonesia, BPS (2010) to be mainly urban or mainly rural. The combination of these categories yielded 18 dimensional vectors of regional characteristics. The 626 sub-districts of West Java were then categorized according to these 18 categories. One sub-district of each category was selected to be surveyed. The second step was randomly selecting about 70 farmers in each sub-district as the respondents. Our selected respondents represent individual farmers who actively operate cropping farms. As a complement, we also use primary data from West Java Statistical Yearbooks, the Indonesian program for agricultural census (BPS, 2013), and other documents from government institutions.

3.3.2. Variable Definitions

The definition of all variables introduced in our models is shown in Table A.1 in Appendix A. We designed measures of cooperation and agro-cluster as our key variables. The first variable is w_i signifying farmer's willingness to cooperate. We approach it by asking a respondent to indicate whether or not she has this willingness. To indicate this measure, each respondent is asked to answer the question: "*do you wish to cooperate with other farmers*?" The value of w_i is unity if she has this intention, otherwise zero. In order to complement this indicator, we operationalize a 5-point Likert's scale from responses given to four sets of questions related to expectations, estimated risks, expected benefits, and estimated costs. Each set represents the perception of the farmer on the prospective cooperation. We assume this perception as a proxy of psychological attributes affecting farmer's willingness. The second variable is actual cooperation $coop_i$. For quantifying this variable, we developed a question: "*are you currently working together with other farmers*?" Similar to the measure of the "willingness" variable, $coop_i$ equals to unity if the farmer is actually participating in cooperation, otherwise zero. We also observe the perception

of each farmer on her motivations to cooperate or to not cooperate with other farmers by utilizing a 5-point Likert's scale (where 5 represents the acceptable statement). Additionally, we asked respondents to indicate on a 5-point Likert's scale "*the degree to which she believes that she benefits from or incurs costs due to the cooperation she participates.*"

The last key variable is agro-clusters. For indicating agro-clusters, we use regional density and local density. The regional density rd_s refers to the concentration of farmers at the level of a sub-district s in relation to the average employment in West Java (Appendix A.1). We indicate that farmers living in the same sub-district are subject to the same regional density rd_s. The relationship between rd_s and cooperation is expected to be positive, meaning that the higher the regional density, the larger the likelihood of farmers to actually cooperate with peers will be (Geldes et al., 2015). Furthermore, we impart the second measure of agro-clusters as local density, using a "distance" variable d_{ik}. This distance variable explains spatial proximity. We utilize GPS coordinates to estimate the spatial distance from farmer respondents to their nearest partner d_{i1} and the nearest perceived center of economic activity d_{i2}[4]. These distance variables are measured by travel time between the two places via public transportation. Table 3.1 statistically summarizes all variables applied.

We also apply as our explanatory variables some relevant characteristics of farmers and their farming activities that may influence the willingness of farmers to cooperate and her decision on actual cooperation. Greve and Salaff (2003) find that gender shapes social networks in the phase of entrepreneurship. Age and education affect the traits of entrepreneurial personality and networking activities that have an impact on firm growth (Davidsson & Honig, 2003).

[4]The perceived center of economic activities d_{i2} refers to the closest place where the farmer more frequently purchases her daily household needs. It also offers urban-like facilities, such as marketplaces and banks.

3.1. Summary Statistics

	Obs.	Min	Max	Mean	Coef. Of variation
Cooperation					
Willingness to cooperate	1151	0	1	0.94	0.24
Actual cooperation	1151	0	1	0.81	0.39
Cooperation strength*	1151	-8.02	5.23	0	n.a.
Organisation membership	1151	0	1	0.62	0.78
Number of family partners					
1. Living in the same village	1151	0	140	8.98	1.79
2. Living in the different village	1151	0	50	1.16	4.24
Number of non-family partners					
1. Living in the same village	1151	0	256	20.21	1.22
2. Living in the different village	1151	0	47	5.14	0.85
Frequency of cooperation	1151	0	3	1.20	0.86
Agro-clusters					
Regional density	1151	-6.79	4.15	-0.77	-3.68
Distance to partner (minutes)	1151	0	26	2.91	1.47
Distance to economic centre (minutes)	1151	1	135	28.01	0.97
The Characteristics of Farmers and Farms					
Agricultural income (million IDR)	1151	0.02	80.6	2.94	1.95
Gender	1151	0	1	0.78	0.53
Age	1151	18	81	50.31	0.20
Year of schooling	1151	0	18	7.18	0.45
Main occupation	1151	0	1	0.64	0.74
Household size	1151	0	12	3.97	0.54
Working hours in agriculture	1151	1	12	6.15	0.37
Food vulnerability*	1151	-4.91	8.86	0	-1.36e+06
Production satisfaction*	1151	-5.33	3.90	n.a	-1.39e+08
Farmer's assets	1151	0	2920	278.69	1.04
Farmland size	1151	0	19	0.72	1.42
Rice farmer dummy	1151	0	1	0.74	0.58
The number of cultivated crops	1151	1	3	1.38	0.73
Regional Properties					
Poverty rate	1151	4.66	17.99	11.58	0.38
Rural dummy	1151	0	1	0.40	1.23
Regional dummy					
1. R1	210	0	1	0.18	2.12
2. R2	180	0	1	0.16	2.32
3. R3	151	0	1	0.13	2.57
4. R4	200	0	1	0.17	2.18
5. R5	230	0	1	0.20	2.00
6. R6	180	0	1	0.16	2.32

Source: Authors' calculation.
Note: * We quantify variables measured by their principal component score from a 5-point Likert's scale.

We also introduce food vulnerability[5] and the level of satisfaction from the last season's production, economic pressure that farmer perceives during the decision process. Regarding actual cooperation, Fan and Chan-Kang (2005), Lee and Tsang (2001), and Zheng et al. (2011) find a positive association between farmers' age, farm size, and the number of partners with increased likelihoods of farmer participation in cooperatives and firm growth. In addition, we add other variables, such as frequency of face-to-face meetings and the memberships of farmer organisations, into equation (3.4).

Based on our observation, about 94% of all farmer respondents are willing to cooperate with peers, and around 81% of these farmers are actually cooperating. Within the ratio of cooperation farmers, around 76% of farmers join farmer organisations. Table 3.1 also shows that farmers mostly establish peer-cooperation with someone living in the same village, either with their relatives or their neighbours. Additionally, around 64% of the respondents consider agriculture as their main occupation. Over 78% of all respondents are male farmers.

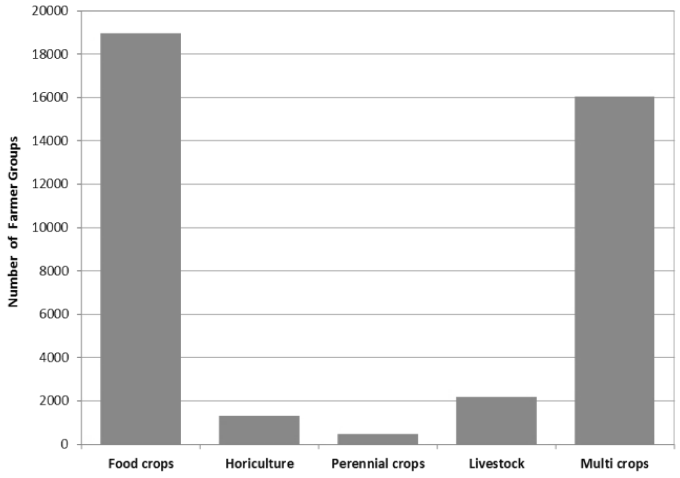
3.3.3. Agro-clusters and Farmer Institutions in West Java

West Java is one of the major agricultural production regions of Indonesia. BPS (2013) reported that its agricultural sector employs more than 3.6 million farmers. Referring to the agro-cluster measure in Appendix A.1, we propose that the higher number of farmers may indicate a higher density of agro-clusters. Sub-districts with a higher density are mostly placed in southern sub-districts and some parts in the northern regions.

[5] We measure the variable of food vulnerability by applying a 5-point Likert's scale. For this variable, we adapted FAO survey module to design our questionnaire. The module explains individual experiences in accessing daily food for herself as well as for her household members due to her resource constraints (Ballard et al., 2013).

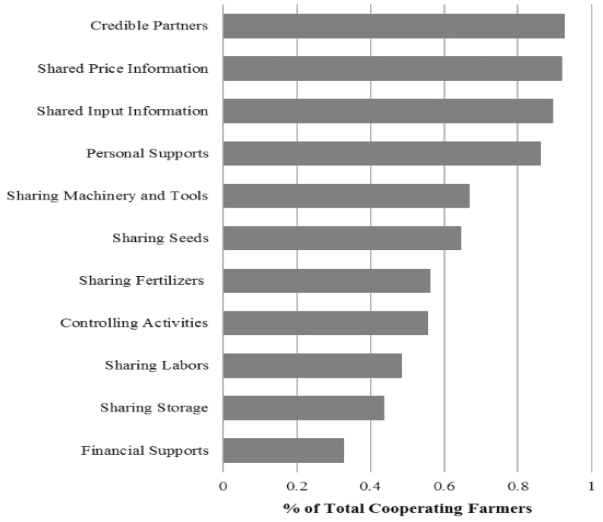
Indonesian farmers are often organised by farmer organisations (FOs) in order to facilitate cooperation between farmers. These organisations are normally based on single crops. The number of farmer groups in West Java has reached over 42 thousand groups (Board of Agricultural Extensions of West Java, 2015). Figure 3.3 illustrates this number in connection with different cultivated crops. About 44% of all farmer groups cultivate food crops, such as rice, corn, cassava, and sweet potatoes, as their main crop. According to the Indonesian Ministry of Agriculture Decree No. 82/2013, the FOs aim at empowering farmers to build farmer cooperation. Figure 3.4 describes several reasons for farmers to work with peers based on our interview. Over 80% of all respondents commit to collaboration peers mostly because of having responsive partners to help their farms, share information about input choice and crop selling prices, and support each other even with regard to their personal life. Around 60% of the respondents believe that they will benefit from cooperation by sharing production inputs, such as machinery and tools, seeds, and fertilizers.

Table A.2 in Appendix A shows that socio-economic characteristics of cooperating and non-cooperating farmers differ on average when compared with each other. The two groups differ in income, age, asset, farm size, and number of crops. On one side, cooperating farmers have relatively higher income, asset, and farm size. They feel more confident to secure adequate food for their household members. On the other side, non-cooperating farmers tend to farm multi-crops to improve their income. They are more afraid of daily food insecurity in their household. This insecure feeling may be due to low income. Around 20% of them are worried of suffering this problem. The average score of food vulnerability of this group is larger than the counterpart group (Table A.2). However, there is no significant difference between the two groups in gender, years of schooling, the number of household members, working hours in agriculture, and main occupation.



Source: Authors based on data from the Board of Agricultural Extensions of West Java (2015).

Figure 3.3. Farmer Groups based on Crops



Source: Authors based on authors' survey.

Figure 3.4. Farmer's Motivation to Cooperate

3.4. Results

3.4.1 Determinants of Farmer Cooperation

The determinants of cooperation are assessed by a two-step Heckman selection model. Table 3.2 presents the estimation results. We find that the model is statistically significant at the 5% level to explain determinants of farmer cooperation. We also confirm no selection bias in the model because of the significance in lamba and Wald χ^2 at the 5% level. It means that the Heckman model is more superior than OLS specification to detect the "cooperation" model under the "willingness" selection assumption because of covariance between errors of the two models, as in equations (3.3) and (3.4).

We indicate two major findings in relation to the two-stage decision process of farmers. The first result is related to willingness stage shown in columns (2) and (3) in Table 3.2. This result presents the effects of farmers' characteristics on their willingness to cooperate, as in equation (3.3). This willingness has a positive association with male dummy and assets, but having an opposite direction to food vulnerability and rice farmer dummy. We find that the variable "male dummy" has a positive link with farmers' willingness to cooperate at the 5% level. This implies that male farmers are more likely to prefer to work with other farmers than female farmers. This result is in line with the finding of Schubert et al. (1999), which suggests that males tend to be more risk-prone toward gains in decision making, while females are rather more risk-prone toward losses. Table A.2 in Appendix A shows that the male group expects to obtain more benefits from the cooperation (*male's expected gains* = 0.01) than the female does (*female's expected gains* = - 0.32). Female farmers view that the cooperation is too risky as their average score of estimated risk (*female's estimated risk* = 0.79) are significantly higher than the male's score (*male's estimated risk* = -0.47). Based

on our data survey, around 27% of female respondents are afraid that other farmers will control all their production decisions. Over 26% of the females are concerned that other farmers will take advantage of them, and 21% of them argue that they will have conflicts within cooperation. If they have to cooperate, they prefer to work with their family members (93% of all female respondents).

Contrarily, Table 3.2 reports the negative relationship between willingness to cooperate and food vulnerability. One-unit reduction in the degree of food vulnerability is associated with increased willingness of the farmer to work with peers by about 9 percentage points. Similarly, Morris et al. (2013) find causes of food insecurity within coffee farmer cooperatives. Vulnerable farmers may assume that cooperation is too risky; they perceive insecure to satisfy daily food for their household members. Put differently, these farmers are more likely to be risk averse by exhibiting saving behaviours onto uncertain income generation from crop production. Deaton (1992) argues that household's saving motive is associated with increased degree of risk aversion. Similar point is highlighted by Yesuf and Bluffstone (2009) suggesting links between risk aversion and poverty traps.

The second main finding is related to the determinants of farmers' engagement in actual cooperation, as estimated in "cooperation" stage. We assume in Section 3.2 that farmers decide to actually cooperate with peers when they are willing to cooperate and see the benefit in cooperation. This decision is affected not only by farmers' characteristics, but also by their external environment, as mentioned in Figure 3.1. Accordingly, we suggest agro-clusters and other regional properties as control variables that may influence farmers' actual cooperation. Columns (4) and (5) in Table 3.2 show that farmers base their actual cooperation significantly at the 5% level on agro-cluster indicators, farmers' characteristics (age, farm size, working hours, and number of crops), and frequency of face-to-face meetings.

Table 3.2. Estimation Results of Determinants of Farmer Cooperation

Dependent Variables ($Coop_i$)	**Heckman Selection (two-step)**			
	Willingness Eq. (3.3)		**Cooperation Eq. (3.4)**	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**
Cooperation				
Frequency of face-to-face meetings				
2	-	-	-0.19	(0.12)
3	-	-	0.16*	(0.08)
4	-	-	0.15*	(0.08)
5	-	-	0.22***	(0.08)
Agro-cluster indicators				
Regional density	-	-	0.02***	(<0.01)
Distance to the nearest partner	-	-	0.004*	(<0.01)
Distance to the economic centre	-	-	0.0005	(<0.01)
The characteristics of farmers				
Male dummy	0.44***	(0.14)	-0.04	(0.03)
Age	-0.0006	(<0.01)	0.005***	(<0.01)
Years of schooling	-0.003	(0.02)	0.004	(<0.01)
Assets	0.20**	(0.08)	0.001	(0.02)
Household size	-0.03	(0.02)	-0.0008	(<0.01)
Food vulnerability	-0.09***	(0.02)	-	-
Production satisfaction	0.09	(0.06)	-	-
Agriculture as a main job	0.10	(0.14)	0.008	(0.02)
Farm size	0.11	(0.08)	0.02**	(0.01)
The number of cultivated crops	-0.06	(0.16)	-0.10***	(0.02)
Rice farmer dummy	-0.74***	(0.28)	0.003	(0.04)
Working hours in agriculture	-	-	0.02***	(<0.01)
The regional properties				
Poverty rate	-	-	0.06*	(0.03)
Rural dummy	-	-	-0.23***	(0.02)
Regional dummy				
R1	-	-	-0.05	(0.04)
R2	-	-	0.22***	(0.05)
R4	-	-	0.005	(0.05)
R5	-	-	-0.32***	(0.04)
R6	-	-	0.19***	(0.04)
Intercept	1.21*	(0.69)		
Observations	1145			
Lamba	-0.30**			
Wald chi2	711.25***			

Source: Authors' calculations.

Note: One, two and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. R3 is our referent region.

Supporting the suggestion of Geldes et al. (2015) and Lazzeretti and Capone (2016) that geographical proximity has a positive effect on cooperation, we provide evidence that agro-clusters offer opportunities for farmers to build and strengthen cooperation. Table 3.2 indicates that the relationship between actual cooperation $coop_i$ and regional density rd_s is positive at the 5% level based on the Heckman model. The denser the farmer population in a region, the higher the likelihood the farmers in that given region establish peer cooperation. We indicate that farmers living in the higher concentrated regions are most likely to engage in cooperation.

As proximity is an advantage, adjacent farmers can interact with one another more intensively. Spatial proximity reduces barriers to establishing networks over regional administrative boundaries (Boschma, 2005). Table 3.2 also shows a positive association between actual cooperation and meeting frequency at the 5% level. This finding indicates that farmers meeting one another more intensely raises the probability of them actually building partnerships. From Table 3.2, farmers who have meetings with peers at least once a week have over a 22% higher likelihood of actually cooperating with peers than those who rarely meet with other farmers. Rotemberg (1994) suggests that cooperation arises in equilibrium because of repeated interactions between individuals. Likewise, adjacent farmers establishing frequent meetings are able to strengthen their cooperation, as shown in positive correlation coefficient in Table A.3 in Appendix A. Ostrom (2007) highlights that future contact has a linear relationship with the frequency of past contact, which might facilitate cooperative behaviour. Furthermore, Dowling and Chin-Fang (2007, p. 307) point out that if individuals recognize similar cooperative traits in others, they would be enthusiastic to build the self-organised cooperation.

Observing the result of the variables "farmer characteristics" in Table 3.2, we imply that cooperation is seen by senior farmers with larger farm

size and more hours working (per day) on a few or only one crop as a social insurance mechanism against economic pressures. It means that a cooperative shift in allocating resources and sharing risks between farmers may provide an equilibrium for every farmer to maximize their income. One example of this mechanism may relate to crop marketing. Over 65% of the cooperating farmers believe that cooperative behaviours in marketing make it easier to sell their products, and about 77% of them perceive that marketing costs are decreasing.

3.4.2. Impacts of Farmer Cooperation on Income Levels

Table 3.3 reports the estimation results of the relationship between cooperation and farmers' income, as specified in equations (3.5) and (3.6). We run two models to control for agro-cluster impacts on this relationship. We indicate two main results. First, the finding indicates that the squared R of both models is around 0.6, meaning that all independent variables together could explain about 60 percentage points of farmer's income level. Second, the coefficient directions of all variables are consistent.

Although there is no partial effect of the variable "actual cooperation" on farmer's income, we report a significant effect of the interaction variable between cooperation and agro-clusters on income improvements at the 5% level, as shown in the estimation result of equation (3.6) in Table 3.3. This result gives us the insight that agro-clusters play a role in increasing the likelihood of farmers actually cooperating with peers in order to increase income. Based on the result of equation (3.6), we suggest negative and positive links between income and two variables of interaction terms, that are, with original and quadratic forms of regional density rd_s, respectively. These relationships, representing the effect of cooperation in agro-clusters on income level, show a convex quadratic function of farmers' income with respect to these interaction variables, paribus ceteris.

Table 3.3. Estimation of the Effects of Farmer Cooperation on Income Levels

Dependent Variables (Agr. Income in Natural Log)	**Equation (3.5)**		**Equation (3.6)**	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**
Cooperation				
Actual cooperation ($Coop_i$)	0.04	0.06	-0.08	0.07
$Coop_i * rd_s$	-	-	-0.04**	0.02
$Coop_i * sq\_rd_s$	-	-	0.005**	<0.01
The number of family partners				
Living in the same village	-0.004**	<0.01	-0.003*	<0.01
Living in different villages	-0.003	<0.01	-0.003	<0.01
The number of non-family partners				
Living in the same village	0.01***	<0.01	0.004***	<0.01
Living in different villages	0.001	<0.01	0.003	<0.01
Frequency of cooperation	-0.003	0.02	0.01	0.02
Agro-clusters Indicators				
Regional density	0.09***	0.01	0.13***	0.02
Distance to partner	-0.003	<0.01	-0.003	<0.01
Distance to economic centre	0.004***	<0.01	0.004***	<0.01
The characteristics of farmers				
Male dummy	0.01	0.05	0.006	0.05
Age	0.0008	<0.01	0.001	<0.01
Years of schooling	0.01*	<0.01	0.01*	<0.01
Farmer's assets	0.21***	0.03	0.21***	0.03
Farm size	0.46***	0.03	0.46***	0.03
The number of cultivated crops	0.26***	0.04	0.22***	0.04
Working hours in agriculture	0.06***	0.01	0.06***	0.01
The regional properties				
Rural dummy	-0.006	0.06	-0.02	0.06
Intercept	12.58***	0.23	12.66***	0.23
Observations		1145		1145
R-squared		0.56		0.57

Source: Authors' calculations.
Note: One, two and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

From these quadratic links, we find two segments with a turning point at minimum level. Similar to the finding of Schmit and Hall (2013), our model seems to explain both positive and negative externalities of agro-clusters. In the first segment, cooperating farmers may generate lower income alongside increased regional density of agro-clusters up to a turning point. Negative externalities may dominate in this segment. Smallholder farmers have many constraints to boost their productivity when they are

forced by unfriendly environments within agro-clusters. Beside technical issues, their constraints include maintaining good relationships with other neighbouring farmers. Although they are inside agro-clusters offering more opportunities to build cooperation, as shown in Table 3.2, their relationship seems fragile. Over 22% of farmers said, "*I am concerned that other farmers will take advantage of me and they will exhibit selfishness*," and about 28% of them argue, "*Unlike me, I am afraid that other farmers will not share their resources with me*." Even more than 10% of respondents had conflicts with other farmers when they actually cooperated. These constraints may hinder them from attaining the advantages of collective action for their performance.

In contrast, the second segment indicates a positive relationship between income and regional density. It means that after a turning point, the income of cooperating farmers rises as regional density increases. Farmers inside high density may have more opportunities to get credible partners and access to knowledge than they expect because of the many options available. Braguinsky and Rose (2009) and Tsusaka et al. (2015) claim that cooperation spontaneously emerges from sharing technical know-how, demonstrating how best to spur industrial development based on the effects of neighbouring farmers. Accordingly, they are able to support each other for income improvements. Active cooperation within clusters may generate collective efficiency or, in other words, achieve productivity improvements (Schmitz, 1995). This finding implies that farmers are not "truly rivals" and they benefit from agro-clusters by strengthening their cooperation, for example, through knowledge exchange. According to Humphrey and Schmitz (2002), inter-firm cooperation could upgrade firm productivity because of knowledge transfers and collective action. In detail, Songsermsawas et al. (2016) suggest that farmers have an information channel from their peers for learning about new technologies. Cooperation

in crop production, for example, offers a profit-sharing mechanism to improve income (Fitzroy & Kraft, 1987).

3.4.3 Effects of Cooperation Strength on Income Levels

This sub-section captures the second measure of cooperation, i.e., tie strength. This variable is measured as tie_i in equation (3.7). Table 3.4 reports the estimation result of the effects of tie strength on farmers' income from the robust OLS estimation. We indicate that tie strength has a positive relationship with farmers' income. The stronger the cooperation between farmers, the higher the income that farmers generate. One unit increase in cooperation strength perceived by farmers leads to an increase of two percentage points of farmers' income. Similar to the estimation result of the first measure in Sub-section 3.4.2, cooperation allows farmers to raise income. We find that all these findings together verify that the estimated coefficients of independent variables in all models are able to explain a substantial proportion of variation in the dependent variable. Both results confirm that farmers working in peers have a higher income than those who work independently.

Similar to the result in Table 3.3, we also find a positive coefficient between income and regional density at the 5% level. Therefore, we could confirm that agro-clusters facilitate farmers to raise income. Agro-clusters may strengthen ties between farmers, so that knowledge exchange appears. We indicate this finding from the positive correlation coefficient between tie strength and regional density, as shown in Table A.3.

Table 3.4. Estimation Results of the Link between Income and Tie Strength

Dependent Variable (Agr. Income)	Coefficient	Standard Errors
Cooperation		
Tie Strength	0.02***	(<0.01)
The number of family partners		
Living in the same village	-0.004**	(<0.01)
Living in different villages	-0.01**	(<0.01)
The number of non-family partners		
Living in the same village	0.003**	(<0.01)
Living in different villages	0.002	(<0.01)
Frequency of cooperation	-0.007	(0.02)
Agro-cluster indicators		
Regional density	0.08***	(0.01)
Distance to partner	-0.001	(<0.01)
Distance to economic center	0.001	(<0.01)
Farmers' characteristics	Yes	Yes
Regional properties	Yes	Yes
Intercept	12.84***	(0.28)
Observations	1145	
R^2	0.60	

Source: Authors' calculations.
Note: One, two and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

3.5. Summary and Conclusions

As a major consequence of knowledge exchange and collective action, adjacent farmers tied in partnerships in agro-clusters are able to reach institutional innovation and then boost their productivity (Humphrey & Schmitz, 2002). In this paper, we address how farmers' attitude and perceptions influence the establishment of peer-to-peer cooperation in agro-clusters and assess the effect of this cooperation on farmers' income levels. Our central finding is that smallholder farmers located in agro-clusters have a higher probability of actually cooperating with peers which is shown to result in income improvements.

We model farmers' decision process with respect to cooperation as a two-stage process. The first stage is whether or not they are willing in

principle to cooperate with other farmers. This predisposition is modelled as being influenced by farmers' motivations. The following stage refers to whether or not farmers take the decision to actually engage in cooperation. Farmers will only cooperate with peers, if they are willing to cooperate in principle and expect to reap more benefits than they have to invest in such collective action. This two-stage model provides three major findings. First, we find that male farmers who are richer show a higher willingness to cooperate. In contrast, rice farmers suffering from food vulnerability in their household have a smaller willingness. The latter result confirms Yesuf and Bluffstone (2009), who also find that increased vulnerability is associated with higher risk aversion such that vulnerable farmers tend to perceive more threats than benefits from cooperation. Second, the decision to engage in actual cooperation is found to rise with farmers' age, working hours dedicated to the farm, and the frequency of peer-to-peer meetings. It is negatively related to an increased cropping diversity. This finding suggests that cooperation with peers might be seen by farmers as an insurance mechanism against income shocks. Third, cooperating farmers are likely to have a higher income than those who do not participate in cooperation. Such cooperation provides a means to build collective action when negotiating with input suppliers and marketing clients such that farmers are able to realize competitive prices. Hence, agro-clusters allow smallholders to benefit from the cooperation by leading to income improvements.

Policy makers might take some of our results into account for policy measures. The policy, for instance, aims at building trust-based inter-relationships between farmers. As stated in Section 3.4, farmers inside agro-clusters have the advantage of geographical proximity, which stimulates them to establish collective production and joint marketing. Promoting a strong farmer organisation might be a fruitful initiative which attracts many farmers to engage in active cooperation. This initiative is for example

through profit-cost sharing schemes and expressive communication between farmers, thus reducing mismanagement and conflicts inside the farmer organisations. Porter (2000) argues that cooperation, especially between small-medium firms in agriculture could influence competitive advantage leading to cluster development.

Appendix A

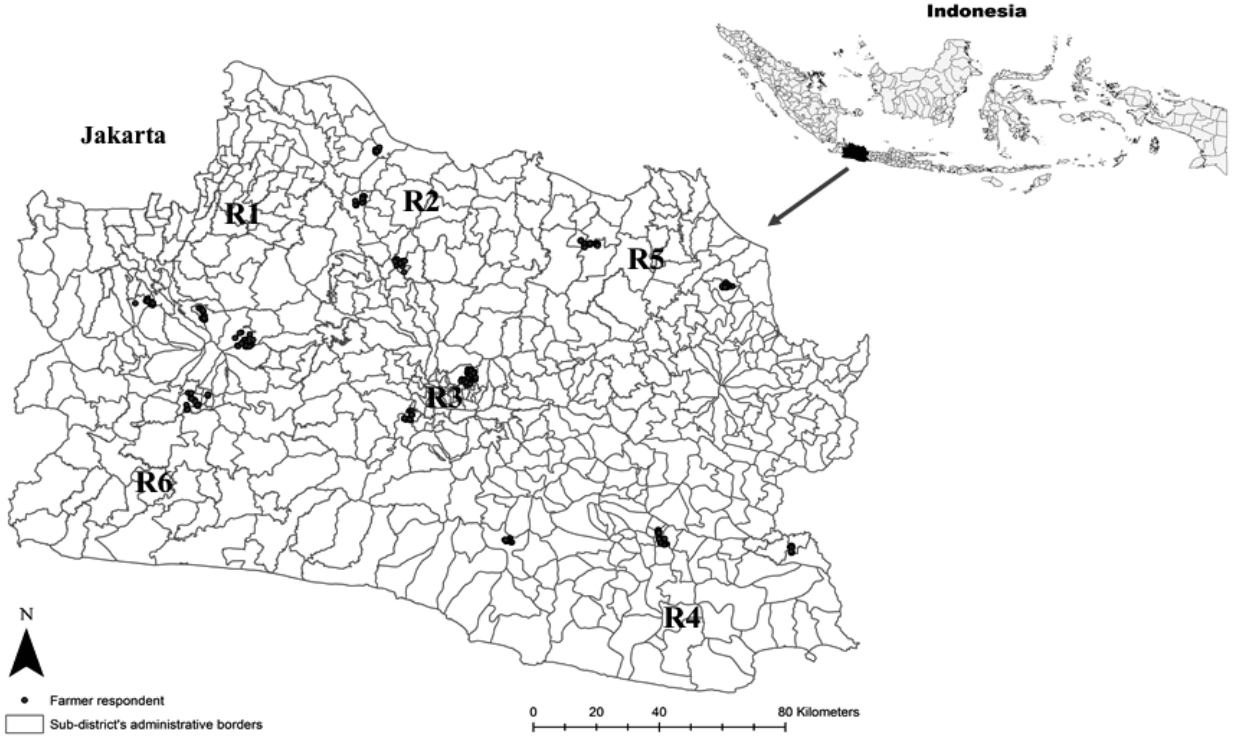
A.1. Measurement of regional density

Fingleton et al. (2004) specify the measure of rd_s as:

$$rd_s = e_s - \left(\frac{e}{E}\right) E_s$$

The variable e_s denotes the observed number of farmers in sub-district s. E_s is the total employment number of that sub-district. Meanwhile, the variable e indicates the number of farmers in West Java, as our reference region, and E signifies the total employment number of West Java. The measure means that the higher the value of rd_s in a sub-district, the higher the density of the agro-cluster in that given region. Hence, agriculture in that region is found to be the most influencing sector for its economy in terms of employed farmers.

A.2. Study Sites in the Indonesian Province of West Java



Source: Authors based on respondents' GPS coordinates.
Note: The map shows the borders of the 626 sub-districts of West Java.

Table A.1. Variables Definitions

Variable Name	Definition
Attitudes towards cooperation	
1. Willingness for cooperation	The willingness of farmer *i* to cooperate with other farmers.
	1 = will; 0 = neglect
2. Expected benefits	Expected benefits from cooperation that farmer *i* perceives.
	Likert's scale 1-5. Cronbach's alpha = 0.89.
3. Estimated risk	Estimated risk from cooperation that farmer *i* incurs
	Likert's scale 1-5. Cronbach's alpha = 095.
4. Estimated costs	Estimated cost from cooperation that farmer *i* incurs
	Likert's scale 1-5. Cronbach's alpha = 0.89.
Actual cooperation	
1. Cooperation	The actual cooperation that farmer *i* has.
	1 = yes; 0 = no
2. Tie Strength	The strength of cooperation that farmer *i* perceives.
	Likert's scale 1-5. Cronbach's alpha = 0.99.
3. Organization memberships	The participation in farmer organizations
	1 = join; 0 = not join
4. The number of partners	The number of family partners who live in the same village (persons).
	The number of family partners who live in the different village (persons).
	The number of non-family-partners who live in the same village (persons).
	The number of non-family-partners who live in the different village (persons).
5. Meeting frequency	Frequency of face-to-face meetings with other farmers
	1 = never; 2 = once a year; 3 = once a season; 4 = once a month
	5 = more than one a week.
6. Frequency of cooperation	The frequency of cooperation that farmer *i* experienced in the last year.
Agro-cluster Index	
1. Regional density	The concentration of farmers in a sub-district *s* where farmer *i* lives relative to the number of West Javan Famers.
2. Local density	The distance from farmer *i* to the nearest his/her farmer partner (minutes).
	The distance from farmer *i* to the nearest economic activity (minutes).

Table A.1. (Continued)

Variable Name	Definition
The characteristics of farmers	
1. Agricultural Income	Farmer *i*'s agricultural income in the last season (million Indonesian Rupiahs). It is measured by the subtraction between total revenue and total costs.
2. Gender	Farmer *i*'s gender 1 = male; 0 = female.
3. Age	Farmer *i*'s age.
4. Year of schooling	The number of schooling years that farmer *i* attended.
5. Main occupation	The main occupation that farmer *i* has. 1 = agriculture; 0 = other economic sectors.
6. Household size	The number of household members with whom farmer *i* lives.
7. Working hours in agriculture	The number of hours farmer *i* works in agriculture in a day.
8. Farmer's assets	The estimated values of farmer *i*'s asset (million IDR).
9. Farmland size	The size of agricultural land that farmer *i* operates (hectares).
10. Rice farmer dummy	Whether or not farmer *i* cultivates rice. 1 = rice farmers; 0 = not rice farmers.
11. Number of crops	The number of crops that farmer *i* cultivates in the season. 1 = one crop; 2 = two crops; 3 = ≥ three crops.
Regional characteristics	
1. Poverty rate	The incidence of poverty of a sub-district s in which farmer *i* lives.
2. Rural dummy	The dummy variable of rural-urban identity of a sub-district in which farmer *i* lives. 1 = rural; 0 = urban.
3. Regional dummy	R1: Regions including Bogor, Cianjur, Depok, Bekasi take 1; 0 otherwise. R2: Regions including Purwakarta, Subang, and Karawang take 1; 0 otherwise. R3: Regions including Bandung Metropolitan Area take 1; 0 otherwise. R4: Regions including Ciamis, Tasikmalaya, Banjar, Garut take 1; 0 otherwise. R5: Regions including Majalengka, Indramayu, Cirebon, Kuningan take 1; 0 otherwise. R6: Regions including Sukabumi and surrounding take 1; 0 otherwise.

Table A.2. Comparison between Cooperating and Non-cooperating Farmers

	Cooperating Farmers			Non-cooperating Farmers			Cooperating farmers	Non-cooperating farmers	t-stat
	Male	Female	t-stat	Male	Female	t-stat			
Cooperation Indicators									
Tie Strength	1.74	2.07	3.96***	-	-	-	-	-	-
Expected gains	0.01	-0.32	-4.40***	-	-	-	-0.06	0.25	3.92***
Estimated costs	0.05	0.13	0.76	-	-	-	0.07	-0.31	-3.95***
Estimated risks	-0.47	0.79	5.62***	-	-	-	-0.21	0.93	5.31***
Meeting frequency	4.53	4.52	-0.34	-	-	-	4.53	4.40	-2.26**
Farmers' Characteristics									
Farmer's agricultural income	2.86	1.89	-4.14***	3.73	5.18	0.81	4.14	2.66	3.41**
Male	-	-	-	-	-	-	0.79	0.72	-2.34
Age	50.78	50.39	-0.48	48.10	49.83	1.25	50.70	48.59	-2.83***
Year of schooling	7.30	7.03	-1.06	7.27	5.85	-3.14***	7.25	6.87	-1.57
Main occupation	0.64	0.70	1.75*	0.61	0.65	0.57	0.65	0.62	-0.81
Household size	3.95	3.92	-0.30	3.85	4.83	1.58	3.94	4.13	1.16
Working hours in agriculture	6.33	5.56	-3.97***	6.47	5.25	-4.91***	6.17	6.12	-0.27
Food vulnerability	-0.11	0.14	1.48	0.13	0.55	1.11	-0.06	0.24	1.81*
Farmer's assets	326.57	211.49	-4.71***	180.36	154.85	-1.06	302.65	173.18	-5.97**
Farmland size	0.78	0.62	-2.40**	0.69	0.40	-1.15	0.74	0.61	-1.77*
Rice farmer dummy	0.78	0.77	-0.31	0.54	0.68	1.88*	0.78	0.58	-6.15***
Number of crops	1.70	1.32	0.95	1.91	1.52	-2.77***	1.28	1.80	9.70***

Table A.3. Correlation Coefficients

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
A	Cooperation	1														
B	Tie strength	0.97	1													
C	Farmer's income	0.15	0.11	1												
D	Regional density	0.12	0.07	0.48	1											
E	Distance to partner	0.03	0.04	0.03	-0.07	1										
F	Distance to city centre	0.10	0.12	0.13	-0.11	0.37	1									
G	Meeting frequency	0.07	0.05	0.09	0.18	-0.06	-0.14	1								
H	Crop diversity	-0.28	-0.26	0.18	0.23	0.05	-0.11	0.05	1							
I	Working hours	0.01	-0.05	0.22	0.12	0.08	0.04	0.15	0.28	1						
J	Farm size	0.19	0.16	0.64	0.32	0.04	0.15	0.09	0.00	0.09	1					
K	Assets	0.20	0.19	0.40	0.24	-0.04	-0.04	-0.02	-0.21	-0.13	0.42	1				
L	Education years	0.05	0.07	0.15	0.00	0.01	0.15	-0.10	-0.10	-0.12	0.17	0.23	1			
M	Farmer's age	0.08	0.07	-0.09	-0.03	-0.02	-0.15	0.02	-0.09	0.02	-0.12	0.00	-0.33	1		
N	Male dummy	0.07	0.04	0.16	0.16	0.01	0.07	-0.03	0.01	0.16	0.13	0.17	0.07	0.00	1	
O	Household size	-0.03	-0.01	-0.04	-0.20	0.05	0.08	-0.02	0.00	0.05	-0.02	0.01	0.05	-0.08	-0.04	1

CHAPTER 4

Farmer Performance under Peer Pressure in Agro-clusters

Abstract

The higher the density of farmers in agricultural agglomerations, the higher the competition between them. This competition results in pressure from peers with respect to purchasing production inputs or marketing output. We assess whether and how such competitive pressure from peers is perceived by farmers and how it affects their behaviour. We focus on the two aspects that farmers may either cooperate with peers by sharing knowledge or they may act in self-interest refusing any cooperation. Building on the theory of planned behaviour and the behavioural interaction model, we develop a conceptual model which we econometrically test based on primary data taken from 1,250 farmers in Indonesia. We find robust evidence that both the various aspects of peer pressure measured as well as the density of agricultural agglomerations impact the behaviour of farmers. In a agglomeration of high density, lower degrees of peer pressure foster cooperative behaviour, while higher degrees tend to produce self-interest. As Indonesian farm policies aiming at increasing cooperation between farmers in order to ease the spread of innovations and knowledge, they should aim at decreasing peer pressure perceived in order to facilitate cooperation.

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4.1. Introduction

Fierce economic competition between densely clustered economic agents of one industry tends to erode profits (Porter, 1990; Duranton et al., 2010). Despite that relation, from the aggregate perspective such an economic race is beneficial because it ensures efficient resource allocation and market efficiency. From the individual agent's perspective it implies a harsh environment. Output prices tend to be driven downwards due to the competition between the actors to sell their produce (Alcacer, 2006), while prices for production inputs tend to be driven upwards because each actor tries to ensure that she has the inputs that she needs for production (Meyer-Stamer, 1998; Kim et al., 2000). The more homogenous the output products marketed and the production factors required are, the more pronounced these effects will be, for example in agricultural production.

The resulting economic pressure a farmer perceives could result in that farmer changing her attitudes and behaviour related to, for instance, her currently used production technology or output marketing. This decision would be a rational response as she might believe that this change could improve her income. Kandel & Lazear (1992) or Binmore (2009) find that individuals respond differently from one another to such economic pressure. Some farmers might engage in cooperative behaviour by sharing information relevant for their economic success with neighbours (Braguinsky & Rose, 2009). Others may exhibit self-interest behaviour such as withholding such information in order to exploit it themselves and enlarge their individual benefit vis-à-vis competing peers. Porter (1998) and Boari et al. (2003) indicate that such economic pressure from peers tends to be higher in the region in which a large number of closely adjacent firms are located, that is, in regions which are more densely clustered.

Deichmann et al. (2008) stress that farmers are likely to concentrate in naturally advantageous regions. This geographical concentration is often

referred to as an 'agro-cluster'. Following Porter (1990), Krugman (1991) and Duranton et al. (2010), we define an agro-cluster as the geographical concentration of crop specialization involving socio-economic interactions between farmers, business networks between food producers and buyers as well as processing industries. Our study analyses the interactions between peer farmers by accounting for the density of the agro-cluster they are located in. According to Staber (2007a), a cluster leads to social capital (e.g. distrust, reciprocity) of the involved agents who selectively perceive the ideas that affect individual attitudes and behaviour.

Besides obtaining the advantage of knowledge exchange (Barkley & Henry, 1997; Lissoni, 2001; Morosini, 2004), farmers inside the cluster could perceive social and economic pressure from their peers in the neighbourhood. According to Staber (2007b), the social organisation of the cluster can involve rivalry and predation that may increase distrust among agents. Pouder and StJohn (1996) and Folta et al. (2006) suggest that as the cluster grows, competition for resources, such as labour, and marketing opportunities, such as consumers or output prices, increases. Furthermore, Porter (2000) argues that such pressure intensifies inside a cluster when local rivals have similar general circumstances (e.g. production input supply, market access and technology). Specifically, Coad and Teruel (2013) explicitly prove that within a cluster a rival's growth corresponds to a decrease in a firm's growth.

We interpret this pressure as "peer pressure" between farmers caused by the highly competitive environment. Fishbein and Azjen (2010) refer to it as perceived social pressure. It comprises an individual farmer's behaviour toward other farmers with regard to the production process and output marketing. Individual farmers therefore may be forced to alter their attitudes and behaviour, replicating other farmers' actions. Porac et al. (1995) and Suire and Vicente (2009) argue that firms assess the similarities and

differences from other firms and imitate others' actions because of social interactions between them. In addition, Boari et al. (2003) claim that peer pressure involves a cognitive and social dimension that affects a firm's orientation toward other firms. For example, a farmer applies a new production technology, such as a variety of seeds and a fertilizing technique, because her neighbours use it to increase crop productivity. In another case, she feels that she has to improve the quality of the product because other farmers who produce a similar crop seem to market products of higher quality than hers.

The literature reports two opposite impacts of the pressure on farmer performance. On the one hand, Porter (1998) and Alpmann and Bitsch (2015) suggest that peer pressure could be a source of innovation that improves income. In like manner sharing knowledge between firms in highly competitive markets inside clusters may increase the adoption of new technologies (Braguinsky & Rose, 2009). If farmers are altruistic, they might share all agricultural information, such as selling prices, input use and knowledge of how to receive government subsidies. Songsermsawas et al. (2016) indicate that farmers are more likely to increase income from higher selling prices if their peers earn more too. On the other hand, such pressure could evoke a challenging operating environment for individual firms (Coad & Teruel, 2013). Hendrickson and James (2016) argue that farmers subjectively perceive unfairness from their neighbours. According to Shleifer (2004), peer pressure may prompt firms to expose dishonesty. For example, a farmer supposes that her neighbouring farmers withhold crucial information. Hence, she feels taken advantage of and cheated. In other words, this farmer perceives unfair competition within the cluster, due to e.g. free riders (Fehr & Schmidt, 1999) and selfish behaviour (Gino et al., 2013; Harbaugh & To, 2014).

Our study addresses how peer pressure due to a high density of an agro-cluster affects a farmer's individual behavioural pattern. We account for the fact that farmers will respond differently to peer pressure with regard to income generation based on their personal characteristics. Bommer et al. (1987) argue that personal environments affect the behavioural patterns of decision-makers in industrial organisations. We analyse how such pressure influences a farmer's behavioural patterns and subsequently affects income. Adriani and Sonderegger (2015) suggest that inequality among individuals in a group will directly impact their behaviour towards income improvements. According to Kandel and Lazear (1992), peer pressure can be an effective force in firms to establish partnerships and reduce free rider problems. We therefore hypothesize that farmers with cooperative behaviour may generate a higher income than those who are selfish.

Understanding peer pressure between farmers allows us to obtain a critical insight into which institutional innovations reduce conflicts among farmers. This innovation is an essential part of agro-cluster development in rural areas in the context of a developing economy (Barkley & Henry, 1997). Our study makes three contributions to this inquiry. First, we are unique in that we focus on interactions between smallholder farmers when they are geographically clustered. Second, we assess the effects of perceived peer pressure on a farmer's behaviour. Third, we empirically assess the impacts of such behaviour on a farmer's income by controlling for regional heterogeneity.

The reminder of this paper is structured as follows: The next section elaborates on the conceptual framework linking peer pressure, farmer's behaviour and agro-cluster density. We then describe the data analysed and define the variables used in the empirical analysis. In the following section, we present the estimation results. Finally we discuss implications and policy recommendations.

4.2. Conceptual Framework

Here we conceptualize a farmer's behavioural responses to peer pressure in the context of agro-clusters. Farmer interactions are likely to influence a farmer's decision on which behaviour to perform as a response to her peers' behaviour. We differ from James and Hendrickson (2008) by assuming that the farmer's perception of an increase of pressure inside an agro-cluster will influence her behaviour, expressed by either cooperative or self-interest behaviour. A farmer may share agricultural information on input supply, a new technology, selling prices, new marketing options or government subsidies with peers for free. Others might display selfishness by keeping such crucial information that are decisive factors for individual income for themselves. Also, farmers might encounter disadvantages when they notice that their peers are withholding crucial information from them.

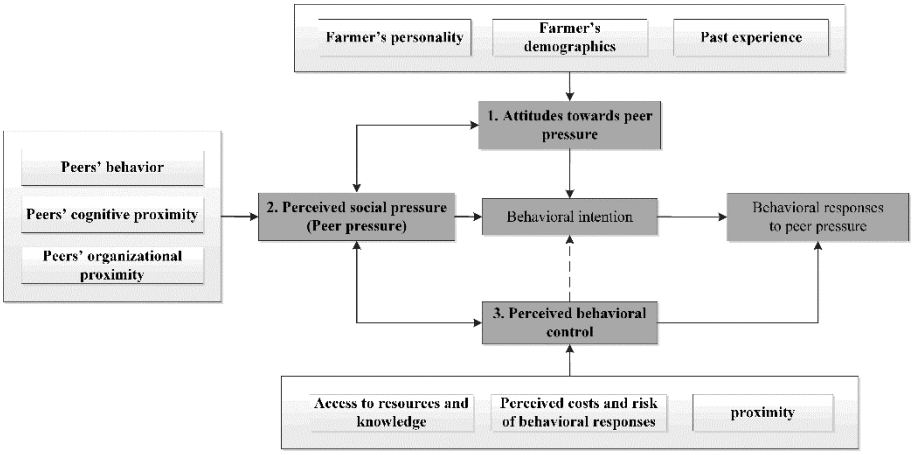
The conceptual framework of our study as shown in Figure 4.1 is based upon the theory of planned behaviour (Ajzen, 1991) and the behavioural interaction model (Rabbie, 1991). Figure 4.1 illustrates the resulting conceptual framework of how a farmer's behaviour is determined subject to peer pressure. Ajzen (1991) emphasizes that individual behaviour depends jointly on behavioural intention and perceived behavioural control (ability). The key factors of a farmer's behavioural intention are attitudes, perceived social pressure and perceived behavioural control. In other words, the intention of a farmer to perform a given behaviour is a combination of these three factors. This behavioural intention is likely to be determined by personal traits and the external environment (Rabbie, 1991).

Figure 4.1 shows that the first factor of a farmer's intention is the individual attitudes towards peer pressure. Holm et al. (2013) suggest that farmers have different attitudes toward competing with peers. Building on Rabbie (1991), a farmer is more likely to share information with other farmers if she has positive attitudes toward such behaviour. According to

Hansla et al. (2008) and Fishbein and Ajzen (2010, p. 22-25), individual personality, demographic characteristics and past experience influence these attitudes. When the farmer has a bad experience, such as cheated by peers, she is more likely to be prudent towards peers. In addition, the demographic characteristics, e.g. age, gender, education, socio-economic status and organisation memberships, as well as personality and emotions, could potentially affect the attitudes of individuals (Fishbein & Ajzen, 2010). The second factor influencing a farmer's behavioural intention is the perceived peer pressure. A farmer may share information with peers because she has the willingness to conduct this behaviour, whereas other farmers may do so because of perceived peer pressure, that is, the behaviour of their peers. However, under certain circumstances she may deny (continuing) sharing (more) information because she perceives social pressure against that behaviour. For example, other farmers conceal government subsidies from her. Thus, she may choose which behavioural response to show when she perceives such dishonest behaviour.

We indicate that this perceived pressure is potentially stronger inside agro-clusters because of geographical proximity. We refer to this pressure as peer pressure as defined in Section 4.1. An agro-cluster may allow farmers to establish frequent face-to-face contact that may stimulate socio-economic ties between them (Breschi & Lissoni, 2001). However, adjacent farmers are not always embedded in trust-based networks. Bergstrom (2002) suggests that individual payoffs in a multiplayer prisoner's dilemma depends linearly on the number of cooperating persons. Staber (2007a) argues that geographical proximity is not necessarily strongly correlated with social proximity, i.e. the cognitive and organisational proximity of peers. Farmers under pressure may conceal information from peers when they believe it is the best option for increasing their income. Lissoni (2001) finds that only a few Italian firms within the cluster could access knowledge for free. Accordingly, we

hypothesize that farmers located in agro-clusters may share or not share crucial information if they are under pressure.



Source: Authors adapted from Ajzen (1991) and Rabbie (1991)[6]

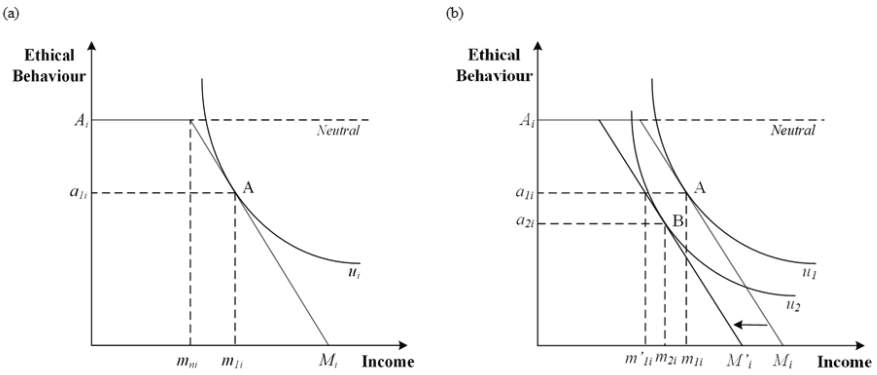
Figure 4.1. Farmer's behavioural pattern due to peer pressure

The last factor of a farmer's behavioural intention and responses is the perceived behavioural control. Some farmers may fail to share information because of, for instance, their limited access to resources, money or time shortage or distance constraints. So prior to performing an action, an individual will assess the benefits and costs that she might incur with respect to income growth (Kahneman & Tversky, 1979). Figure 4.2 shows the expected utility and behavioural patterns.

According to Rotemberg (1994), individuals have a tendency to be cooperative toward others. This attitude drives farmers to share resources with one another in the form of cooperation. Given that the farmer is neutral

[6]We combine the theory of planned behaviour (Ajzen, 1991) and behavioural interaction model (Rabbie, 1991) in order to conceptually frame our models, which explore the relationship between peer pressure, agro-clusters and behaviour.

or fully ethical, she will always share all information even if she is under peer pressure, as shown in the "neutral" line A_i in Figure 4.2 panels (a) and (b). At point A_i, she gains wealth due to her ethically neutral activities, specifically $0 \rightarrow m_{ni}$. Contrarily, if the farmer has a lower level of ethics, for example at a_{1i}, for instance determined by withholding information, she may have additional profit specified as m_i.



Source: Authors adapted from James and Hendrickson (2008) and Binmore (2009).
Note: u_i denotes farmer i's expected utility. u_{1i} and u_{2i} denote farmer i's expected utility under no pressure and pressure, respectively. A_i refers to farmer i's fully ethical behaviour. a_{1i} and a_{2i} denote farmer i's less than fully ethical behaviour. M_i is the total income of farmer i. M'_i is farmer i's income due to pressure. m_{1i} and m_{2i} signify farmer i's income at a_{1i} and a_{2i}, respectively. m'_{1i} is income due to pressure.

Figure 4.2. Income, Ethical Behaviour and Expected Utility

As illustrated in Figure 4.2, the expected utility $u_i$may refer to the indifferent curve of an individual farmer, reflecting her disposition to lower her ethics in exchange for a given increase in income. Graafland (2002), James and Hendrickson (2008) and Graham (2014) claim that an increase in pressure that a farmer perceives reduces that farmer's ethics. Similar to James and Hendrickson (2008), we assume that farmers with relatively steep indifferent curves slightly increase their profit as a result of a large decrease of their ethics. Figure 4.2 panel (a) illustrates a farmer's ethical behaviour

against income. Figure 4.2 panel (b) depicts that such pressure reduces farmer's wealth (income) from M_i to M'_i, and the expected utility curve will also move to the left. In this case, the farmer will earn less income from m_{1i} to m'_{1i}. Then in order to raise income, she will adjust her behaviour when she knows her peers have forced on her behavioural decision. This adjustment may reduce her ethics from a_{1i} to a_{2i} at point B, but she thus could raise her income to m_{2i}. In other words, a farmer under peer pressure could increase her income by decreasing her level of cooperative behaviour.

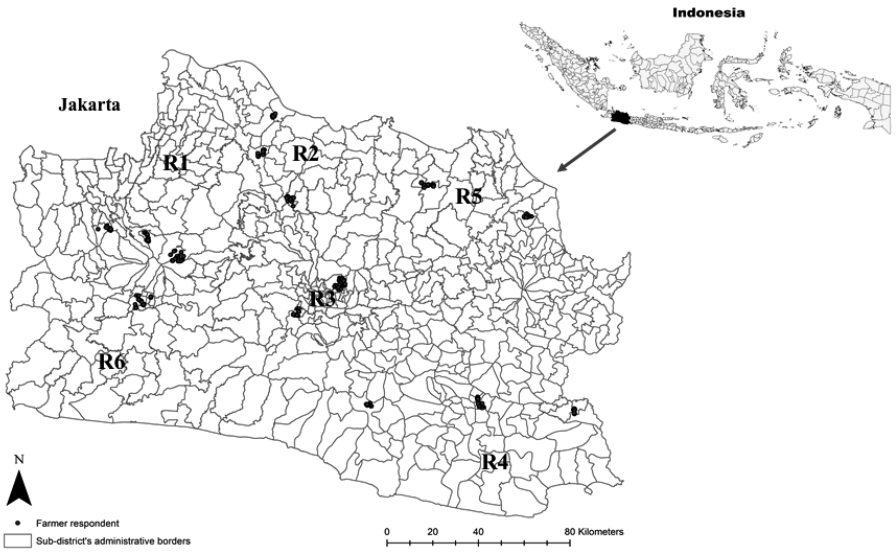
4.3. Methods

4.3.1. Data and Variables

The province of West Java is one of the most important agricultural production regions of Indonesia. According to Statistics Agency of Indonesia (BPS, 2015a), it contributes to more than 15% of the Indonesian annual rice production and 20-40% of the Indonesian horticultural production. BPS (2013c) reports that about 4 million households in this region, which correspond to approximately 23% of all Indonesian households, are directly reliant upon the agricultural sector. This region supplies commodities such as food staples, coffee, tea, vegetables and fruits. The production of these crops is geographically clustered across West Java based on topography and agricultural resources, such as soil quality and water resources.

To obtain data for analysis, we conducted from May to August 2016 a survey of 1,250 farmers located in 15 sub-districts of West Java based on face-to-face interviews. The sample was selected by applying a two-step selection procedure to ensure representativeness. Firstly, we chose 15 sub-districts out of the total number of about 600 sub-districts

of the province[7]. In each sub-district, we randomly selected 70 to 80 farmers as respondents. Figure 4.3 illustrates the locations of respondents surveyed.



Source: Authors based on respondents' GPS coordinates.
Note: R1 denotes districts close to DKI Jakarta, such as Bekasi, Depok and Cianjur. R2 includes Karawang, Purwakarta and Subang. R3 is Bandung Metropolitan. R4 comprises Tasikmalaya, Ciamis, Banjar, Garut and Pangandaran. R5 denotes Kuningan, Indramayu and Cirebon. R6 comprises Sukabumi.

Figure 4.3. Respondents Surveyed in West Java

We present descriptive statistics of the key variables. The first key variable is farmer's behaviour, which is used as a dependent variable. As explained in Section 4.2, we distinguish such behaviour into two types: cooperative and self-interest behaviour. We measure cooperative behaviour as whether or not respondents share information related to farming practices

[7]This choice is based on 18 possible combinations defined by the density of agro-clusters, poverty rates (high, medium and low) and whether a sub-district is classified as mainly rural or mainly urban by BPS (2010). As 3 combinations did not have corresponding regions, we thus selected 15 sub-districts.

with peer farmers. Self-interest behaviour refers to withholding this information from peer farmers.

To operationalize these behavioural variables, we design two sets of question items with a 5-point Likert scale as summarized in Sets A and B of Table 4.1. These sets contain items quantifying cooperative and self-interest behaviour, respectively. Table B.1 in Appendix B reports the results of the underlying principal component analysis defining Sets A and B. We accept question items with factor loadings of more than 0.4 (Streiner, 1994). The analysis suggests two factors: cooperative behaviour (b_{1i}) and self-interest behaviour (b_{2i}). The variables b_{1i} and b_{2i} explain about 56% and 73% of the variation in farmer's behaviour, respectively. Cronbach's alpha of both variables b_{1i} and b_{2i} is above 0.70, meaning that sets A and B have relatively high internal consistency (Vaske et al., 2017) which implies that all items of each set can be reliably summarized into one variable.

The second key variable is peer pressure. We operationalize peer pressure by two measurements: the perceived degree of peer pressure and the perceived comprehensiveness of peer pressure. Each approach measures the respondent's perception of such pressure. The first variable, the perceived degree of peer pressure of farmer$i$, is denoted as $dpress_i$. The pressure is quantified on a continuous scale between 0 and 10. Zero represents no perceived pressure, while 10 signifies extremely high perceived pressure. It was measured by asking every respondent to mark a point on a line ranging between 0 and 10. This measure indicates to what extent farmers generally feel pressure from their peers as a result of economic competition.

Table 4.1. Questions Items of Farmer's Behaviour and Peer Pressure

Farmer Behaviour				Comprehensiveness		
Set	**Question Item**	**Var.**	**Set**	**Question Item**	**Var.**	
A	Sharing knowledge with other farmers for free	b_{1i}	**I**	Seed application	z_{1i}	
	Sharing knowledge with family farmers	Cooperative behaviour		Application of new fertilizer technology	z_{2i}	Production technology
	Sharing knowledge with farmers of the same village			Application of a new production technology		
	Sharing knowledge with farmers of the same groups			Application of a new technology of crop processing and handling		
	Sharing knowledge with the rest of farmers			Improving the quality of the products		
B	Withholding information on production technology	b_{2i}		Limited farmland resources due to high competition	z_{3i}	Input supply and crop marketing
	Concealing information on processing technology	Self-interest behaviour		Shortage of production inputs in the markets		
	Keeping information on seeds applied from others			Shortage of hired farm labourers		
	Withholding knowledge on buyers			Water shortage for irrigation		
	Keeping information on government's subsidies			Storing crop products due to high competition for selling		
	Withholding information on prices			Difficulty to find buyers		
	Concealing information for specific buyers			No option to sell products with higher selling prices		
			II	Access to production technology	y_i	Knowledge accessibility
				Access to market information		
				Access to production inputs		
				Access to government's subsidies		
			III	Increasing seed costs	x_{1i}	Production inputs
				Increasing fertilizer costs		
				Increasing pesticide costs		
				Increasing costs of labours		
				Increasing machinery costs		
				Increasing costs of land rent		
				Higher yield of the crop	x_{2i}	Income
				Higher selling price		
				Larger sold quantity		

Source: Authors.

The second measure of peer pressure is the perceived comprehensiveness ($cpress_i$). This measure contains six variables: z_{1i}, z_{2i}, z_{3i}, y_i, x_{1i} and x_{2i}, as described in Sets I, II and III of Table 4.1. They differ from the first variable as they capture a farmer's behavioural responses to other farmers' actions related to specific farming practices, such as production technology application, input supply, crop markets and knowledge accessibility. According to Breschi and Lissoni (2001), knowledge exchange is the major advantage of economic clusters since it can upgrade the performance of firms. We therefore designed three different sets of questions with regard to a farmer's perception of knowledge exchange. Table 4.1 lists 25 items corresponding to the three sets of items. Appendix B.1 describes the approach taken from measuring the six variables of the comprehensiveness measure based on a 5-point Likert scale.

We apply principal component analysis with varimax rotation to identify underlying variables of the question items listed in Table 4.1. Table B.2 in Appendix B presents detailed results. Set I is split into three variables: seed application (z_{1i}), production technology (z_{2i}) and input supply and crop marketing (z_{3i}, Table 4.1). Meanwhile, set II consists of only one variable: knowledge accessibility (y_i). A farmer may feel that she has limited access to information due to her neighbours' selfishness. Table 4.1 also summarizes that set III consists of two variables: the change of production inputs (x_{1i}) of income opportunities (x_{2i}). Cronbach's alpha of all these factors exceeds the acceptable reliability coefficient of 0.70. For regression analysis, we calculate a single component score for each observation on each of the underlying variables, including farmer behaviour (cooperative vs. self-interest behaviour) and the perceived comprehensiveness of peer pressure (z_{1i}, z_{2i}, z_{3i}, y_i, x_{1i} and x_{2i}). The scores are computed by summing the standardized scales corresponding to all of the question items weighted by the factor loadings of the variables (Grice, 2001).

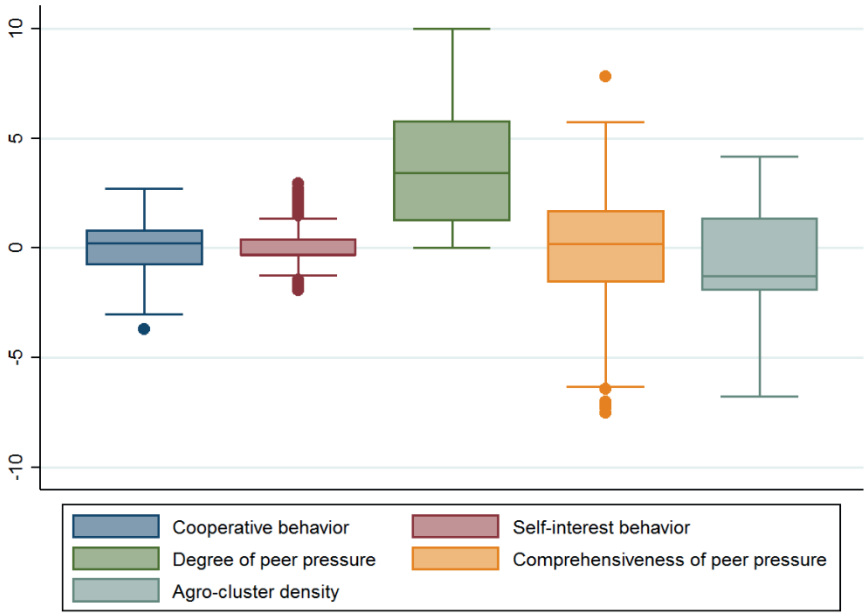
Furthermore, the last key variable is agro-cluster density (rd_s). Appendix B.2 describes its construction which is based on Fingleton et al. (2004). This measure refers to regional density of farmer concentration in a sub-district relative to the number of farmers at province level. This variable is useful as farmers living close to each other in one agro-cluster operate under identical socio-economic conditions and agro-cluster density.

Figure 4.4 presents boxplots of these key variables. The medians of the variables representing farmer behaviour and the comprehensiveness of peer pressure are close to zero, meaning that the values of these variables has a systematic distribution across zero. The number of farmers who have a lower level of cooperative behaviour, for example, is relatively the same number as those who have a higher level. The degree of peer pressure is balanced about 3.5. The boxplot of this variable suggests that half of the respondents perceive peer pressure of a magnitude between 1.2 to 5.8. This implies that that three quarters of the farmers typically feel rather low pressure, that is, less than 5.8 on a scale between zero and ten. We find agro-cluster density to be heavily skewed to the left, that is, half of respondents live in regions with agro-cluster density above the median of -1.29.

Finally, we consider a number of control variables. They include the socio-economic characteristics of farmers and properties of the regions in which they live. For instance, the variable of 'crop diversity' represents the number of crops which a farmer cultivated in the last season. The variable 'food vulnerability' indicates the inability of farmers to provide daily food for their household members. Farmers categorized as poor have the problem of food insecurity, which influences behavioural decisions (Brañas-Garza, 2006). Adapted from FAO's survey module[8], we quantify food vulnerability

[8] The FAO's survey module, that is referring to the Food Insecurity Experience Scale, contains eight questions which refer to individual experiences in accessing food for herself as well as for her household members due to her resource constraints (Ballard et al., 2013).

by using a 5-point Likert scale. Detailed descriptive statistics of all variables are given in Table B.3.

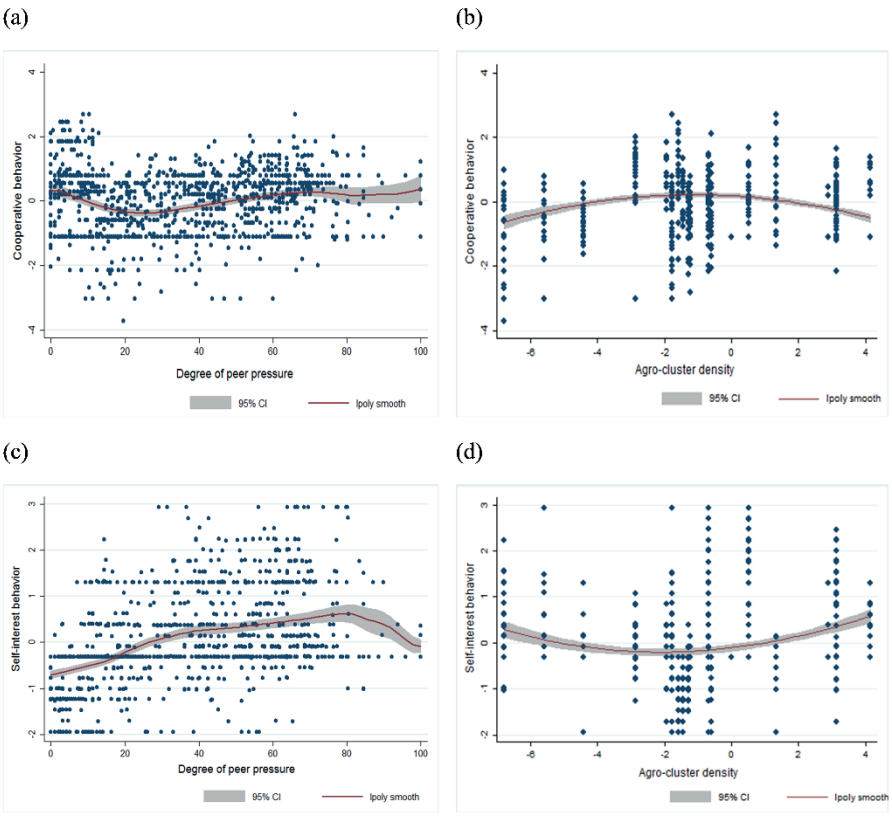


Source: Authors' calculation.
Note: Comprehensiveness of peer pressure is the summation of the six separate scores (z_{1i}, z_{2i}, z_{3i}, y_i, x_{1i} and x_{2i}) of each observation.

Figure 4.4. Boxplot of Key Variables

Figure 4.5 illustrates selected nonparametric bivariate relations between the key variables. Figure 4.5(a) shows within a wide range a concave-upward correlation between cooperative behaviour and the degree of peer pressure. The slope of this relationship increases until a peer pressure degree of 6. Hence, an increase in the degree of peer pressure is associated with on average an increased level of farmer cooperation for lower levels of pressure, while for higher levels of pressure cooperative behaviour barely changes. Contrarily, the correlation between self-interest behaviour and the degree of peer pressure is concave-downward (Figure

4.5(c)). Until a peer pressure degree of 8, an increase in the degree of this pressure continually increases the level of farmer selfishness, while selfishness gets reduced for pressure levels beyond 8.



Source: Authors.
Note: CI denotes the 95% confidence interval around the nonparametric estimate. *Ipoly* smooth refers to locally weighted scatterplot smoothing.

Figure 4.5. Bivariate Relations between Behaviour, Peer Pressure and Cluster Density

Figure 4.5(b) indicates a concave-downward association between cooperative behaviour and agro-cluster density. As agro-cluster density increases, the level of cooperative behaviour also goes up until reaching the

density of around -2. Afterwards, its average value declines. In contrast, we find a concave-upward correlation between self-interest behaviour and agro-cluster density (Figure 4.5(d)). The level of self-interest behaviour decreases as agro-cluster density rises, but beyond -2 it increases with agro-cluster density. Hence, the two aspects of farmer's behaviour studied does indeed depend on the level of competitive pressure as well as on the density of the agro-cluster in which the farmer is located.

To be precise, Table 4.2 shows the correlation matrix of these key variables. We find that all variables statistically correlate with each other at the 5% level, but the correlations are weak, specifically below 0.50. Therefore, we suggest no multi-collinearity in their relationships.

Table 4.2. Correlation Matrix of Key Variables.

		A	B	C	D	E
A	Cooperative behaviour	1.00				
B	Self-interest behaviour	-0.19*	1.00			
C	Degree of Pressure	0.08*	0.43*	1.00		
D	Comprehensiveness	0.36*	0.22*	0.40*	1.00	
E	Agro-cluster density	-0.05*	0.15*	-0.23*	-0.20*	1.00

Source: Authors' calculation.
Note: Asterisks denote statistical significance at the 95% confidence level.

4.3.2. Empirical Model Specifications

Pursuant to the discussion in Section 4.2, we set up two empirical models that consider the variables of perceived peer pressure as key explanatory variables. These models are designed to quantitatively assess the effect of such pressures on a farmer's behavioural patterns. We model the relationship between a farmer's behaviour and the degree of peer pressure as:

$$b_{ni} = \beta_0 + \beta_1 dpress_i + \beta_2 sq\_dpress_i + \beta_3 rd_s + \sum_{p=1}^{6} \beta_p^c cpress_{pi} + \sum_{p=1}^{6} \beta_p^{sq} sq\_cpress_{pi} + \sum_{f=1}^{2} \beta_f^d d_{fi} + \sum_{x=1}^{10} \beta_x^v V_{xi} + \varepsilon_i \quad (4.1)$$

The dependent variable b_{ni}, having subscript n, measures two aspects of farmer i's behaviour, that is, either cooperative behaviour b_{1i} or self-interest behaviour b_{2i}, as discussed in sub-section 4.3.1. These two behavioural variables differ from each other by measuring to what extent she is willing to share information with peers. The variable $dpress_i$ signifies the *degree of peer pressure* as subjectively perceived by farmer i. As illustrated in Figure 4.5, the relationship between farmer's behaviour and peer pressure shows non-constant marginal effects. Therefore, we introduce the square of both key explanatory variables: sq_dpress_i and sq_cpress_i. The quadratic form allows for the possibility to identify the turning point of the effect of peer pressure, that is, the change of a farmer's behavioural tendency.

The perceived comprehensiveness of peer pressure is denoted by $cpress_{pi}$, which comprises six variables. These variables measure complementary sources of peer pressure caused by competition in the areas of seed application (z_{1i}), production technology (z_{2i}), crop input and markets (z_{3i}), knowledge accessibility (y_i), change of production inputs (x_{1i}) and the change of income opportunities (x_{2i}, details in Appendix B.1). Again, we include the squares of these variables sq_cpress_{pi} because we are also interested in their potentiality for changing marginal effects on behaviour.

The variable rd_s captures agro-cluster density (details on the measurement in Appendix B.2). We explicitly account for this variable because the higher the agro-cluster density, the stronger the pressure from peers the farmers perceive (Boari et al., 2003; Porter, 1998). Also, an increase in agro-cluster density leads to a higher level of cooperation (Barkley &

Henry, 1997). Spatial proximity between farmers within economic centres has been reported to have a positive effect on cooperation, since it leads to frequent interactions (Geldes et al., 2015). Similarly, Ostrom (2010) and Mani et al. (2013) argue that interactions with peers promote an individual's cooperative behaviour. The term d_{fi} contains the distance d_{1i} between farmer i to her closest neighboring farmer and distance d_{2i} between farmer i to the regional economic centre located closest to her farm. These distance variables are measured by a respondent's reported travelling time in minutes. Finally, the term V_{vi} contains ten control variables including the eight socio-economic characteristics of farmer i and her farm as well as the two properties of the region where she lives in. The β's are the coefficients to be estimated by OLS and ε_i is the error term.

We also assess the effects of farmer's behaviour on farmer's income. Figure 4.2 suggests that farmer i as an individual will increase the level of self-interest behaviour in order to raise income if she perceives pressure. Otherwise, she will always exhibit cooperative behaviour no matter how large the pressure she perceives. This farmer may take advantage of such pressure to raise income (Braguinsky & Rose, 2009; Songsermsawas et al., 2016). This relationship can be modelled as:

$$\pi_i = \gamma_0 + \sum_{n=1}^{2} \gamma_n^b b_{ni} + \sum_{x=1}^{7} \gamma_x^v X_{xi} + \epsilon_i \tag{4.2}$$

The dependent variable π_i measures farmer i's income from her farm in the period of January to March 2015 in million Indonesian rupiah (IDR)[9]. The variable b_{ni} is the same as in (4.1), and quantifies two aspects of farmer's behaviour: cooperative behaviour (b_{1i}) and self-interest behaviour (b_{2i}). The term X_{xi} are seven control variables which carry subscript x and influence farmer's income. These variables include the characteristics of a

[9] 10,000 IDR was in 2016 on average equivalent to 0.76 US$ or 0.72 Euros.

farmer's business activities as well as characteristics of the region in which the farm is located. We also add a dummy for membership in a farmer group, farmer association or cooperative to equation (4.2) to control for whether being a member of such a farmer organisation is associated with an increase of farmer's income. Verhofstadt and Maertens (2014) and Ahmed and Mesfin (2017) emphasize that membership in farmer organisations increases a farmer's income level. These control variables are complementary to those used to explain farmer's behaviour in equation (4.1), since in (4.2) these two behavioural variables are the key explanatory ones. The γ's are the coefficients and ϵ_i is the error term.

However, as OECD (1998) emphasizes that the diversity of regional properties is a significant determinant of farm income inequality, instead we do not estimate (4.2), but its augmented version (4.3), which accounts for such regions in West Java. Based on Regulation No. 22 (GoWJ, 2010) on the spatial planning of West Java[10], we group the sub-districts of this province into 6 large regions named R1, R2, R3, R4, R5 and R6 (Figure 4.3). Each region contains several districts that have relatively homogenous characteristics relevant for the income generation of farmers.

As this regional heterogeneity might also yield regionally varying partial effects of the explanatory variables on farmer income, we augment equation (4.2) by these region-dependent intercepts and slope coefficients introduced as separate dummies and interaction terms between each regional dummy and all explanatory variables, respectively.

[10] This regulation is to be a guidance for the government of West Java to arrange land use so as to maximize people's welfare.

Hence, the model finally estimated is the following:

$$\pi_i = \gamma_0 + \sum_{n=1}^{2} \gamma_n^b b_{ni} + \sum_{x=1}^{7} \gamma_x^v X_{xi} + \sum_{r=1}^{5} \gamma_r^R R_{ri} + \sum_{r=1}^{5} \sum_{n=1}^{2} \gamma_{r,n}^{Rb} R_{ri} b_{ni} + \sum_{r=1}^{5} \sum_{x=1}^{7} \gamma_{r,x}^{RX} R_{ri} X_{xi} + \epsilon_i \quad (4.3)$$

The variable R_{ri} denotes a regional dummy with subscript r indicating in which of these six regions (R1, R2, R4, R5 and R6) farmer i's farm is located in. This variable captures the heterogeneity of regional effects and allows us to test whether equation (4.3) can be simplified to equation (4.2). The data gathered in our survey confirms the finding of OECD (1998): regions, such as R1 and R3, located in the neighbourhood of the two largest cities of Indonesia (Jakarta and Bandung) have an average farm income of about 1.89 m IDR with the median around 1.50 m IDR. This income generation is relatively lower than farms located in regions distant from the cities, where the average income is more than 3.41 m IDR and with a median value of about 1.90 m IDR. This discrepancy is plausible because farmers next to the cities are subject to many constraints due to urban growth effects, such as smaller farm sizes, higher land rents, a low quality of land and more intensive production processes (Satterthwaite et al., 2010).

4.3.3. Hypotheses Specification

Models (4.1) and (4.3) allow us to test a number of meaningful economic hypotheses about the relationships of the estimated coefficients with the dependent variables. For this purpose, we conduct a number of F-tests to acquire statistical evidence on the following economically meaningful null hypotheses which are either derived from our conceptual

framework in Figure 4.1 or from literature findings on behavioural determinants:

Hypothesis 1: Our conceptual framework based on Ajzen (1991) and Rabbie (1991) in Figure 4.1 suggests that the coefficients of the variables measuring the degree of peer pressure are jointly statistically significant, that is, both variables have a significant effect on cooperative as well as self-interest behaviour (Ho: $\beta_1 = \beta_2 = 0$).

Hypothesis 2: Figure 4.1 also suggests that the coefficients of the variables measuring the comprehensiveness of peer pressure are jointly statistically significant, that is, they have an effect on cooperative and self-interest behaviour (Ho: $\beta^c_{1,2,..6} = \beta^{sq}_{1,2,..6} = 0$).

Hypothesis 3: Furthermore, we test whether the coefficients of all variables measuring either the degree or the comprehensiveness of peer pressure are jointly statistically significant (Ho: $\beta_1 = \beta_2 = \beta^c_{1,2,..6} = \beta^{sq}_{1,2,..6} = 0$).

Hypothesis 4: Fischer and Qaim (2012b) argue that distance has a negative effect on collective action and group memberships. Hence, it is reasonable to assess whether distant farmers might show a lower level of cooperative behaviour due to their less frequent interactions with peers and additional travelling costs. Therefore, we test whether the distance variables d_{1i} and d_{2i} are jointly statistically significant (Ho: $\beta^d_1 = \beta^d_2 = 0$).

Hypothesis 5: Brañas-Garza (2006) finds that poverty reduces individual generous behaviour. Therefore, we test whether the variables quantifying food vulnerability, the poverty rate and the location of a household in a rural region are jointly statistically significant in explaining farmer behaviour (Ho: $\beta^v_7 = \beta^v_9 = \beta^v_{10} = 0$).

Hypothesis 6: Figure 4.1 suggests too that the characteristics of farmers (e.g. age and gender) influence their behaviour. The variables of age and gender jointly affect both types of farmer behaviour (Ho: $\beta_1^v = \beta_2^v = 0$).

As discussed in Sub-section 4.3.2, OECD (1998) highlights that the income of farmers is heterogeneous across regions. Accordingly, we assess whether the partial effects of the explanatory variables of model (4.3) are spatially homogenous across the six regions R1 to R6, such that model (3) allows us to test whether it can be simplified to equation (4.2). For that end, we carry out the following F-test:

Hypothesis 7: The partial effects of farmer's behaviour on their income levels do statistically differ by region (Ho: $\gamma_{1,\dots,5}^R = \gamma_{1,1}^{Rb} = \cdots = \gamma_{5,2}^{Rb} = \gamma_{1,1}^{RX} = \cdots = \gamma_{5,7}^{RX} = 0$), that is, (4.3) can be simplified to (4.2).

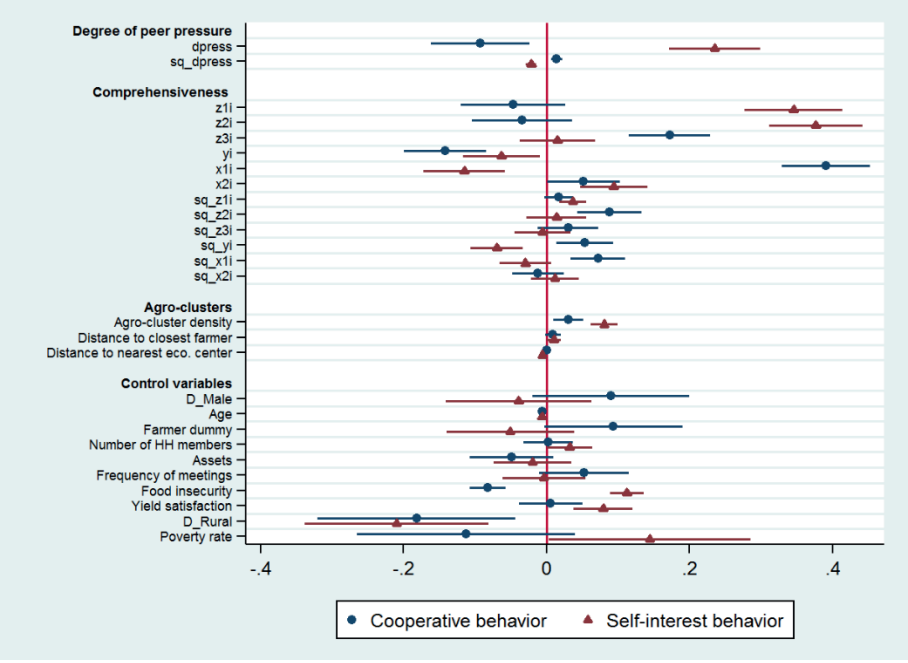
4.4. Results

4.4.1. Effects of Peer Pressure on Farmer's Behaviour

Figure 4.6 presents the estimation results of model (4.1): the effects of peer pressure and agro-cluster density as well as the effects of the control variables on farmer's cooperative and self-interest behaviour. The detailed results are shown in Table B.4 in Appendix B. Figure 4.6 illustrates the significance of the estimated coefficients and compares both versions of model (1). The difference between the two models is solely the dependent variable, being either cooperative or self-interest behaviour. Overall F-tests for both models are statistically significant at the 5% level, showing that both models are meaningful explanations of the variation of farmer's behaviour.

Figure 4.6 shows that the effect of the degree of peer pressure $dpress_i$ on both types of farmer's behaviour is statistically significant at the 5% level. These findings are in line with Azjen (1991), Rabbie (1991) and Binmore

(2009). However, the sign of this partial effect is opposite for both dependent variables. The partial impacts of the squared terms are both significant and of opposite sign and have much narrower confidence intervals. Thus, the marginal effect of the degree of peer pressure on cooperative behaviour is not constant: it is upward U-shaped, that is, for low levels of peer pressure until about 4.3 (Figure 4 shows that about 60% of the observations lie in this range) cooperative behaviour is markedly reduced, while it rises strongly for levels of peer pressure beyond that point.



Source: Authors' calculations.
Note: The circles represent the point estimates of the coefficients for explaining the partial impacts of the explanatory variables on cooperative behaviour. The triangles denote the point estimates for the coefficients in the equation that explain self-interest behaviour. The lines to both sides of each of the point estimates indicate the lower and upper bounds for its 95% confidence intervals. The variables which do not have the lines across the zero line are statistically significant at the 5% level.

Figure 4.6. The Effects of Peer Pressure on Farmer Behaviour.

The marginal effect of the degree of peer pressure on self-interest behaviour is not constant: it is downward U-shaped, that is, selfish behaviour rises strongly until a level of peer pressure of about 6, while it reduces beyond that level. This finding confirms Bergstrom (2002), who finds that farmers undergoing low peer pressure typically raise their selfishness towards peers because they believe to be better able to earn more benefits from doing so than being cooperative. This finding is also in line with Hendrickson and James (2005) and Graham (2014), who emphasize that perceived pressure increases selfishness (Figure 4.2). However, the partial effect of the perceived level of peer pressure is higher for selfishness than for cooperation. Very high levels of perceived peer pressure tend to foster cooperation and to reduce selfishness.

Several aspects of the comprehensiveness of peer pressure also significantly affect cooperative behaviour with the largest coefficient being about 0.4 for the pressure as a result of the changes of production inputs (x_{1i}). Furthermore, they significantly influence self-interest behaviour with the largest coefficients being about 0.4 for competition for seed application (z_{1i}) and on production technology (z_{2i}). Pressure from competition in seed application z_{1i} does not affect cooperative behaviour; competition from crop inputs and markets z_{3i}does not affect self-interest. Aspects z_{2i}, y_iandx_{1i}show quadratic effects on cooperation and $z_{1i}$and$y_i$on self-interest. However, as seen in Figure 4.6, many quadratic terms are not significant. In addition, agro-cluster density rd_s shows a positive effect on both types of farmer's behaviour. Thus, a higher agro-cluster density is associated with an increased level of cooperative as well as self-interest behaviour. The two distance variables only affect self-interest behaviour. Moreover, Figure 4.6 highlights the wide confidence intervals of many of the control variables, leaving them often insignificant.

In order to get a better idea of the economic relevance of the various variables, we calculate the highest potential effect of each variable on both dependent variables by multiplying the estimated coefficients significant at the 5% level by the observed range (maximum minus minimum) of each variable. That is, Table 4.3 reports the ordered partial effect of the maximum observed range of each variable on each type of farmer's behaviour. As we explain above, the variables of farmer's behaviour are factors composed of several questionnaire items. The variable measuring cooperation takes values between -3.7 and 2.7, the one quantifying self-interest varies between -1.9 and 2.9 (see also Figure 4.4). For example, Table 4.3 shows that the comprehensiveness effect of the smallest and the largest observation of variable x_{1i} changes the level of cooperative behaviour by 2.92, which is almost half of the observed range of the cooperative behaviour variable amounting to 6.4. Therefore, Table 4.3 allows insight into the economic relevance of the expected effects of the maximum observed ranges of the explanatory variables on farmer's behaviour.

Table 4.3 suggests that two of the variables quantifying the comprehensiveness of peer pressure exert the largest maximum partial effect on both behavioural variables. Competition in production inputs x_{1i} is the most prominent factor that influences farmers to engage in more cooperation, followed by competition for getting information on input supply and crop marketing z_{3i}. This finding is supported by evidence from the survey: over 73% of respondents reported to getting informed by their neighbours regarding cheaper inputs, and around 40% of respondents realized higher selling prices because their peers shared crucial information on crop marketing. Competition in seed application z_{1i} gives the highest total positive effect on selfishness (4.77), followed by production technology z_{2i} (2.13). However, the two variables with the largest negative economic

relevance for self-interest are two other variables quantifying comprehensiveness of peer pressure.

Table 4.3. Economic Relevance of Peer Pressure on Farmer's Behaviour.

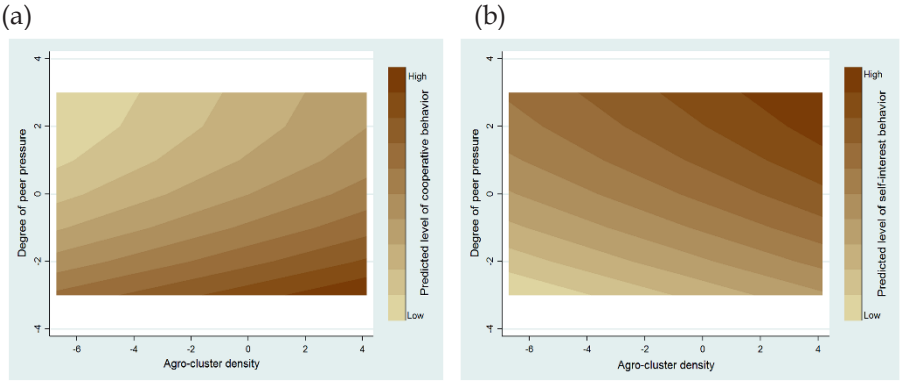
Cooperative behaviour			Self-interest behaviour		
Variable	Abs. Effect	Rel. Effect	Variable	Abs. Effect	Rel. Effect
Change of inputs (x_{1i})	2.92	45%	Seed application (z_{1i})	4.77	98%
Input supply and crop marketing (z_{3i})	1.42	22%	Prod. technology (z_{2i})	2.13	44%
Degree of peer pressure ($dpress_i$)	0.51	8%	Food vulnerability	1.55	32%
Prod. technology (z_{2i})	0.51	8%	Agro-cluster density	0.88	18%
Agro-cluster density	0.34	5%	Output satisfaction in the last yield	0.73	15%
Change of income opportunities (x_{2i})	0.16	2%	Change of income opportunities (x_{2i})	0.70	14%
Rural dummy	-0.18	-3%	Household members	0.36	7%
Knowledge accessibility (y_i)	-0.35	-5%	Distance to closest farmer	0.27	6%
Age	-0.36	-6%	Degree of peer pressure ($dpress_i$)	0.22	4%
Food vulnerability	-1.13	-18%	Poverty rate	0.20	4%
			Rural dummy	-0.21	-4%
			Age	-0.40	-8%
			Distance to eco. centre	-0.78	-16%
			Change of inputs (x_{1i})	-0.95	-19%
			Knowledge accessibility (y_i)	-1.00	-20%

Source: Authors' calculation.
Note: Only variables that are statistically significant at the 5% level are included. The column 'relative effect' reports the share of the absolute effect of each variable divided by the range of the dependent variable.

The variable with the third-largest economic relevance for self-interest behaviour is food vulnerability, although it has the largest economic negative effect on cooperation. That is, the more food vulnerable a farmer's household is, the more self-interest and the less cooperation the farmer will show. The economic relevance of the perceived degree of peer pressure is fourth-largest for cooperative behaviour (0.51), but has a much smaller absolute effect (0.22) and a much lower ranking (13 of 15) among all the

relevant determinants of self-interest behaviour. The effect of agro-cluster density on self-interest behaviour is almost three times larger than on cooperative behaviour (0.34 vs. 0.88).

These findings still leave the question of to what extent agro-cluster density determines farmer's behaviour when taking peer pressure into consideration. In order to obtain evidence on these partial effects, we use model (4.1) for predicting the expected effects of these two characteristics on cooperative and self-interest behaviour, as respectively shown in Figures 4.7(a) and 4.7(b). Farmers located in sub-districts of higher agro-cluster density show the highest level of cooperative behaviour when they perceive lower degrees of peer pressure, as shown in Figure 4.7(a). This confirms Balland (2012) and Cassi and Plunket (2014), who find that geographical proximity directly induces individuals to strengthen cooperation. The level of cooperation decreases as the degree of pressure rises. Figure 4.7(b) indicates that farmers are more likely to show the highest levels of self-interest if they perceive higher degrees of peer pressure again in a high-density agro-cluster environment.



Source: Authors' calculation.
Note: The more positive the peer pressure score, the higher the pressure that a farmer perceives.

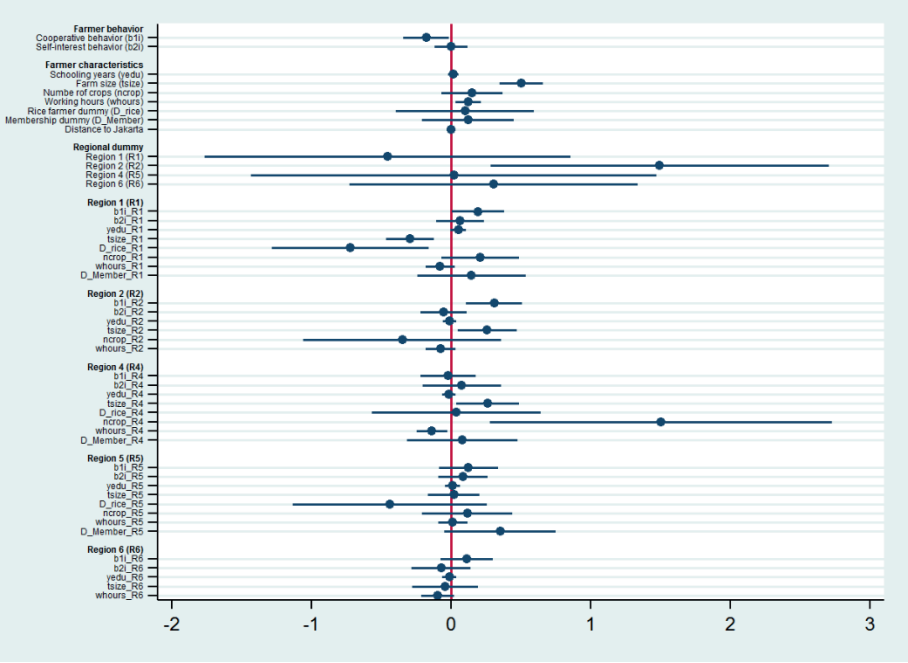
Figure 4.7. The Effect of Agro-cluster and Pressure on Farmer's Behaviour

4.4.2. Effects of Farmer's Behaviour on Income Levels

Figure 4.8 reports the estimation result of model (4.3), that is, the effects of farmer's behaviour (cooperative and self-interest behaviour) and all control variables on farmer's income level. The detailed results are given in Table B.5 in Appendix B. The overall F-test of this model is statistically significant at the 5% level, shown by a p-value of <0.01. Hence, this model is meaningful for explaining the variation of farmer's income. Figure 4.8 shows that the partial effect of cooperative behaviour on income is statistically significant at the 5% level for three regions, but self-interest behaviour is not for any region.

The effects of cooperative behaviour on farmer's income is heterogeneous across the six regions. Similar to Figure 4.2(b), the impact of cooperative behaviour in the reference region R3 (Bandung Metropolitan Area) is negative, meaning that farmers engaging in increased cooperation have a lower expected income. However, cooperation is found to have a significantly positive impact on income in regions R1 (sub-districts near Jakarta) and R2 (coastal-northwest sub-districts). Farmers in these two regions generate more income if they cooperate.

Figure 4.8 and Table B.5 suggest that the partial effects of the explanatory variables are markedly varying by region. This is shown by the finding that in the reference region R3 farm size is the variable having the strongest effect on income, while it is being a rice farmer in R1, cooperative behaviour in R2, the number of crops in R4 and association membership in region R5 having the strongest effect.



Source: Authors' calculation.
Note: The circles represent the point estimates of the coefficients for explaining the partial impacts of the explanatory variables on farmer's income. The lines to both sides of each of the point estimates indicate the lower and upper bounds for its 95% confidence intervals. The variables which do not have the lines across the zero line are statistically significant at the 5% level. Region 1 denotes sub-districts close to Jakarta, such as Bekasi, Depok and Cianjur. Region 2 includes Karawang, Purwakarta and Subang. Region 3 is Bandung Metropolitan. Region 4 comprises Tasikmalaya, Ciamis, Banjar, Garut and Pangandaran. Region 5 denotes Kuningan, Indramayu and Cirebon. Region 6 Sukabumi. Region 3 is the reference category in model (4.3).

Figure 4.8. The regionalized determinants of farmer income

4.4.3. Results of the Hypotheses Tests

As mentioned in Sub-section 4.3.3, we aim to test hypotheses 1 to 7 regarding the partial effects estimated by models (4.1) and (4.3). Table 4 reports the results of the F-tests for all hypotheses. The F-tests of hypotheses 1, 2 and 3 give robust evidence that both the degree as well as the comprehensiveness of peer pressure matter for determining farmer's

behaviour—cooperative as well as self-interest behaviour. Thus, we can confirm this aspect of our conceptual framework based on Ajzen (1991) and Rabbie (1991).

Table 4.4. F-test Results.

Model (4.1): Dependent variable: farmer's behaviour					
Cooperative behaviour			**Self-interest behaviour**		
	p-value	Interpretation		p-value	Interpretation
Hypothesis 1	<0.01	$dpress_i$ affects cooperative behaviour	Hypothesis 1	<0.01	$dpress_i$ affects self-interest behaviour
Hypothesis 2	<0.01	$cpress_i$ jointly influence cooperative behaviour	Hypothesis 2	<0.01	$cpress_i$ jointly influence self-interest behaviour
Hypothesis 3	<0.01	$dpress_i$ and $cpress_i$ jointly affect cooperative behaviour	Hypothesis 3	<0.01	$dpress_i$ and $cpress_i$ jointly influence self-interest behaviour
Hypothesis 4	0.24	Distance does not influence cooperation	Hypothesis 4	<0.01	Distance affects selfishness
Hypothesis 5	<0.01	Poverty influences cooperation	Hypothesis 5	<0.01	Poverty affects selfishness
Hypothesis 6	0.02	Farmer characteristics jointly influence cooperative behaviour	Hypothesis 6	<0.01	Farmer characteristics jointly influence selfishness
Model (4.3): Dependent variable: Farmer's income					
	p-value	Interpretation			
Hypothesis 7	0.00	The partial effects of farmer's behaviour on income levels do statistically differ by region.			

Source: Authors' calculation.

Distance to the closest partner and to the nearest perceived economic centre does not matter for cooperation, but impacts self-interest behaviour. Hence, we only partly can confirm Fischer and Qaim (2012). We need to

reject hypothesis 5 for both types of farmer's behaviour, thus confirming the findings of Brañas-Garza (2006) who argues that poverty affects individual behavioural patterns. Also, we reject hypothesis 6, that is, farmers' personal characteristics influence their behavioural patterns as hypothesized in our conceptual framework illustrated in Figure 4.1. Finally, hypotheses 7 is rejected at the 5% level. In other words, the effects of farmer's behaviour on income level statistically differ across the various regions of Indonesia. These findings affirm OECD (1998), which highlights regionally heterogeneous determinants of income.

4.5. Summary and Conclusions

In many social interactions, an individual's best behavioural response depends on the actions taken by others (Bergstrom, 2002). Farmers may exhibit cooperative behaviour or self-interest as a response to pressure from peers. Porter (2000) argues that economic clustering leads to peer pressure, which ultimately influences the involved agents' behavioural patterns. This pressure could be advantageous (Porter, 1998; Alpmann & Bitsch, 2015) as well as disadvantageous (Shleifer, 2004; James & Hendrickson, 2008; Graham, 2014) for farmers in generating income. We therefore estimate the effects of agro-cluster density and various aspects of peer pressure as perceived by farmers on their willingness to behave cooperatively or selfishly. For this purpose, we draw on the theory of planned behaviour of Ajzen (1991) and the behavioural interaction model of Rabbie (1991) to develop a theoretical model underlying the empirical analysis assessing the relationships between peer pressure and farmer behaviour while controlling for agro-cluster density.

To that end, we estimate two models. One model quantifies the impacts of various aspects of perceived peer pressure and a number of

control variables on farmer's behaviour that are measured as factors composed of several Likert-scaled items. The second model relates the behavioural variables with a different set of control variables with regard to farmer's income and focuses on quantifying potential regionally heterogeneous determinants of farmer's income as suggested by OECD (1998). After the estimations, we deduce seven hypotheses from our theoretical framework as well as from the literature. We econometrically assess these hypotheses using a number of F-tests. We also predict the combined effect of the density of agro-clusters and the perceived degree of peer pressure on both cooperative and self-interest behaviour. This empirical analysis is based on primary data collected by a survey of 1250 farmers located in 15 sub-districts of the province of West Java in Indonesia.

Our analysis yields three major findings. Firstly, the various aspects of perceived peer pressure and the density of the agro-cluster have been shown to be decisive factors for farmer's behaviour. Farmers located in regions of high agro-cluster density show cooperative behaviour if they perceive low pressure from peers, while they show the lowest levels of cooperation in environments of low density and high peer pressure. Farmers engage in more cooperation due to a higher competition for production inputs and competition for obtaining information on input supply and crop marketing. Farmers show the highest levels of self-interest in regions of high agro-cluster density and high peer pressure. Competition for seed application exerts the most relevant effect on raising self-interest, followed by the competition for production technology. Secondly, poverty, a household's food insecurity and a farm's location in a rural area significantly affect farmer's cooperative and self-interested behaviour, which confirms the findings of Brañas-Garza (2006). Thirdly, we find strong evidence in accordance with OECD (1998), namely that the effect of farmer's behaviour

on her income significantly varies by region as many other income determinants show clear regional effects.

To translate these findings into policy implications, it is necessary that we look at the viewpoint of policy-makers. Coming from a social behaviour perspective, farmers within agro-clusters are better off if they all show cooperative behaviour and gain higher income (Bergstrom, 2002). Yet, the worst can happen if cooperative behaviour is only exhibited by a few farmers. Boschma and Lambooy (2002) highlight that dynamic networks are a key success of agro-clusters. They are driven by trust-based relationships between farmers. In the case of Indonesia, farmers are organised in formal organisations for facilitating cooperation between them. According to Law No. 19 on the protection and empowerment of farmers (Government of Indonesia, 2013) and Act No. 67 on the empowerments of farmer organisations (MoA, 2016a), agricultural policies related to the empowerment of farmers aim to increase cooperation between farmers through farmer organisations. Such organisations are to exchange knowledge, disseminate new production technologies, distribute government subsidies and join crop production and marketing. However, the Board of Agricultural Extension of West Java (2015) reports that less than 25% of all West Javanese farmers join such organisations. From our survey, about 37% of all respondents do not cooperate with peers due to the high potential for conflicts between them, and about nearly 48% of non-cooperating farmers perceive a lot of cheating behaviour from peers towards them.

Therefore, policies supporting agro-clusters should aim at decreasing peer pressure perceived by farmers and ultimately increasing cooperation between them. For example, a policy provides infrastructure or stimuli to face competition both within and outside agro-clusters. This infrastructure makes it easier for farmers to gain access to production inputs, information,

markets and irrigation. Hence, farmers are motivated to join farmer organisations on a basis of individual benefits. Also, the policy should phase out bureaucratic stages of the utilization of extension services, so that farmers would have good contact with extension officers.

Appendix B

B.1. Measuring the perceived comprehensiveness of peer pressure

For measuring the perceived comprehensiveness of peer pressure, we designed three sets of questions with a 5-point Likert scale.

(1) The first set is related to the effect of this pressure on a farmer's behaviour as a response to other farmers' actions. We set up a general question: "*How does peer pressure from other neighbouring farmers impact your farming practices?*". This question is divided into 13 relevant question items. To quantify it, we apply a 5-point Likert's scale. The lowest point, quantified by 1, represents "strongly disagree" and the highest point, quantified by 5, is "strongly agree". Based on the result of principal component analysis, we group this set into 3 variables, which are seed application (z_{1i}), production technology (z_{2i}) and input supply and crop marketing (z_{3i}). The variables z_{1i}, z_{2i} and z_{3i} explain about 8.56%, 42.35% and 11.40% of the variation in the perceived pressure, respectively.

(2) The second set captures a farmer's perception of knowledge accessibility due to her peers' actions. This set consists of 5 question items. We asked each respondent to scale each item by using a 5-point Likert's scale. The lowest point, quantified by 1, represents "strongly disagree" and the highest point, quantified by 5, denotes "strongly agree". Based on the result of the principal component

analysis, we group this set of items into one variable: knowledge accessibility (y_i), which explains about 78.73% of the variance.

(3) The third set indicates a farmer's perception on the change of production inputs and income opportunities due to peer pressure. This last set is approached by the questions: "*How did peer pressure on you change your production inputs in the last five years*?" and "*How did peer pressure on you change your income opportunities in the last five years*?". We design 5 scenarios to approach each question. A 5-point Likert scale is applied to quantify the extent to which respondents believe their production cost and yield are decreasing. 1 is quantified as the lowest point, or increasing. 5 is qualified as the highest point. We obtain two variables of this set: change of production inputs (x_{1i}) and change of income opportunities (x_{2i}). They clarify about 60.74% and 58.29% of the variation, respectively. Observing the two latter factors, around 70% of the respondents consider that the costs of production inputs have been increasing, yet income has been decreasing during the last five years.

B.2. Measuring agro-cluster density

We quantify agro-cluster density with the variable rd_s by measuring regional density in terms of the number of farmers. This measure refers to how large the number of farmers in a sub-district is relative to the total number of employees on the provincial level. In other words, it indicates the regional concentration of farmers. We follow Fingleton et al. (2004) to specify it as:

$$rd_s = e_s - \left(\frac{e}{E}\right) E_s$$

The variable e_s denotes the observed number of farmers in sub-district s. E_s is the total employee number of that sub-district. The variable e indicates the number of farmers in West Java, taken as our reference region, and E refers to the total employment number of West Java. The measure means that the higher the value of rd_s in a sub-district, the higher the density of the agro-cluster in that given region is. Hence, agriculture in that region is found to be the most influential sector for its economy in terms of employed farmers.

Table B.1. Farmer's Behaviour with Principal Component Analysis

Factor	Question items	Notation	Mean (scale 1-5)	% indicating 4 or 5	Factor Loading
Cooperative behaviour (α = 0.79)	A farmer shares all knowledge with other farmers for free.	b_{1i}	3.55	54.30	0.66
	A farmer shares knowledge with family farmers.		3.74	65.25	0.81
	A farmer shares knowledge with farmers living in the same village.		3.70	62.73	0.86
	A farmer shares knowledge with farmers belonging to the same groups.		3.62	58.99	0.86
	A farmer shares knowledge with the rest of farmers.		3.14	27.80	0.44
Self-interest behaviour (α = 0.94)	A farmer holds information on production technology.	b_{2i}	2.17	5.20	0.86
	A farmer holds information on processing technology.		2.16	5.60	0.86
	A farmer holds information on a new variety of seeds applied.		2.17	6.00	0.85
	A farmer holds information on buyers.		2.23	6.00	0.84
	A farmer holds information on selling prices.		2.24	6.00	0.83
	A farmer holds information on product requirements for specific buyers.		2.25	5.50	0.85
	A farmer holds information on government's subsidies.		2.15	5.60	0.86

Source: Authors' calculation.

Note: αrefers to Cronbach alpha. We apply a principal component analysis with varimax rotation to identify underlying dimensions of farmer's behaviour. We accept scale items with factor loadings > 0.40.

Table B.2. The Comprehensiveness of Peer Pressure with Principal Component Analysis

Factor	Question item	Notation	Mean (scale 1-5)	% indicating 4 or 5	Factor Loading
Seed application	A farmer uses a new variety of seed.	z_{1i}	3.13	40.05	0.82
Production technology (α = 0.82)	A farmer applies new fertilizer technology.	z_{2i}	3.03	32.84	0.80
	A farmer utilizes a new production technology.		3.06	30.84	0.71
	A farmer applies a new technology of crop processing and handling.		3.11	35.45	0.84
	A farmer believes that improving crop quality could increase selling prices.		3.34	49.00	0.72
Input supply and crop marketing (α = 0.85)	A farmer cannot enlarge farmland due to high competition.	z_{3i}	2.88	26.50	0.44
	A farmer feels the shortage of production inputs in the markets.		2.78	18.85	0.68
	A farmer feels that having a difficulty in providing hired farm labourers.		2.92	29.28	0.75
	A farmer feels water shortage for irrigation.		2.70	22.07	0.67
	A farmer prefers to store crop products due to high competition to sell directly.		2.66	19.03	0.73
	A farmer feels a difficulty to find buyers.		2.50	12.42	0.80
	A farmer has no option to sell products with lower selling prices.		2.61	14.34	0.53
Knowledge accessibility (α = 0.91)	A farmer has access to information on production technology.	y_i	2.98	23.20	0.85
	A farmer has access to market information.		3.04	27.28	0.90
	A farmer has access to information on production inputs.		3.07	27.19	0.89

Table B.2 (Continue)

Factor	Question item	Notation	Mean (scale 1-5)	% indicating 4 or 5	Factor Loading
	A farmer has access to information on government's subsidies.		3.08	28.58	0.89
The change of production inputs (α = 0.89)	Seed costs have been	x_{1i}	3.76	69.24	0.80
	Fertilizer costs have been		3.87	76.02	0.89
	Pesticide costs have been		3.87	73.41	0.89
	Labour costs have been		3.84	70.81	0.82
	Machinery costs have been		3.75	64.38	0.78
The change of Income opportunities (α = 0.74)	Farmland has been	x_{2i}	3.07	30.58	0.59
	Yield of the crop has been		3.31	35.88	0.83
	Selling price of the crop has been		3.26	33.54	0.78
	Sold quantity of the crop has been		3.21	31.36	0.83

Source: Authors' calculation.

Note: For the first three factors, a higher scale indicates a higher perceived pressure. For the change of production inputs, a higher scale means an increasing cost of production inputs. Meanwhile, for income opportunities, a lower scale indicates decreasing income opportunities due to pressure. αrefers to Cronbach's alpha.

Table B.3. Statistics Summary of All Variables

Variable	Obs.	Min	Max	Mean	Coef. of variation
Farmer's behaviour					
Cooperative behaviour	1151	-3.72	2.69	n.a.	1.80e06
Self-interest behaviour	1151	-1.94	2.93	n.a.	1.91e06
Perceived peer pressure					
Degree of peer pressure	1511	0	10	35.66	0.70
Comprehensiveness of peer pressure					
Seed application	1151	-6.71	2.30	n.a.	3.97e-06
Production technology	1151	-2.54	2.81	n.a.	-1.15e08
Crop inputs and markets	1151	-3.02	3.30	n.a.	1.15e07
Peer's behaviour	1151	-3.00	2.89	n.a.	1.24e06
Change of inputs	1151	-3.31	2.14	n.a.	6.22e05
Change of income opportunities	1151	-2.44	3.51	n.a.	-4.11e07
Agro-clusters					
Agro-cluster density	1151	-6.79	4.15	-0.77	-3.68
Distance to partner (minutes)	1151	0	1	2.89	1.47
Distance to economic centre (minutes)	1151	26	135	28.01	0.97
The characteristics of farmers and farms					
Agricultural Income (million IDR)	1151	0.02	80.6	2.94	1.95
Male dummy	1151	0	1	0.78	0.53
Age (years)	1151	18	81	50.31	0.20
Schooling years (years)	1151	0	18	7.18	0.45
Farmer dummy	1151	0	1	0.64	0.74
Household members (persons)	1151	0	12	3.97	0.54
Working hours in agriculture (hours)	1151	1	12	6.15	0.37
Food Vulnerability[1]	1151	-4.91	8.86	n.a.	-9.73e06
Assets (million IDR)	1151	0	2920	278.69	1.04
Farm size (hectares)	1151	0.01	19	0.72	1.42
Rice farmer dummy	1151	0	1	0.74	0.58
Number of crops[2]	1151	1	3	1.38	0.73
Meeting frequency[3]	1151	1	5	4.51	0.17
Distance to Jakarta (minutes)	1151	72	406	199.58	0.39
Regional Properties					
Poverty rate	1151	4.66	17.99	11.58	0.38
Rural dummy	1151	0	1	0.40	1.23
Region 1 (R1)	210	0	1	0.18	2.12
Region 2 (R2)	180	0	1	0.16	2.32
Region 3 (R3)	151	0	1	0.13	2.57
Region 4 (R4)	200	0	1	0.17	2.18
Region 5 (R5)	230	0	1	0.20	2.00
Region 6 (R6)	180	0	1	0.16	2.32

Source: Authors' calculations.

Note: [1] Food vulnerability indicates how capable a farmer is in satisfying the daily food needs of her household members. It is measured by a 5-point Likert's scale. [2]Crop diversity is the number of cultivated crops in the last season. [3] Meeting frequency categorizes a 5-point scale, that is 1: never, 2: at least once a year, 3: at least once in a season; 4: at least once in a month and 5: at least once a week.

Table B.4. OLS Estimations of the Effect of Peer Pressure on Farmer's Behaviour

	Dependent variable			
	Cooperative behaviour (b_{1i})		**Self-interest behaviour (b_{2i})**	
	Coef.	p-value	Coef.	p-value
Degree of peer pressure ($dpress_i$)	-0.09***	<0.01	0.23***	<0.01
$dpress_i$ squared	0.01***	<0.01	-0.02***	<0.01
Comprehensiveness of peer pressure				
Seed application (z_{1i})	-0.04	0.22	0.35***	<0.01
Production technology (z_{2i})	-0.03	0.36	0.38***	<0.01
Crop inputs and markets (z_{3i})	0.17***	<0.01	0.01	0.60
Knowledge accessibility (y_i)	-0.14***	<0.01	-0.06**	0.02
Change of inputs (x_{1i})	0.39***	<0.01	-0.11***	<0.01
Change of income opportunities (x_{2i})	0.05**	0.04	0.09***	<0.01
z_{1i}squared	0.02*	0.09	0.04***	<0.01
z_{2i}squared	0.09***	<0.01	0.01	0.51
z_{3i}squared	0.03	0.16	-0.006	0.77
$y_i$squared	0.05***	<0.01	-0.07***	0.02
x_{1i}squared	0.07***	<0.01	-0.03*	0.09
x_{2i}squared	-0.01	0.62	0.01	0.47
Agro-clusters				
Agro-cluster density (rd_s)	0.03***	<0.01	0.08***	<0.01
Distance to closest farmer (d_{1i})	0.01	0.13	0.01**	<0.05
Distance to nearest eco. centre (d_{2i})	0.00005	0.96	-0.006***	<0.01
The characteristics of farmers and farm				
Male dummy (D_Male)	0.09	0.10	-0.04	0.44
Age	-0.01**	0.02	-0.006***	<0.01
Farmer dummy (D_farmer)	0.09*	0.06	-0.05	0.26
Household members	0.003	0.85	0.03**	<0.05
Assets	-0.0002**	0.04	-0.00004	0.63
Meeting frequency	0.05	0.13	-0.004	0.89
Food vulnerability	-0.08***	<0.01	0.11***	<0.01
Output Satisfaction	0.008	0.73	0.08***	<0.01
Regional properties				
Rural dummy (D_Rural)	-0.19***	<0.01	-0.21***	<0.01
Poverty rate	-0.10	0.18	0.14**	<0.05
Intercept	0.10	0.73	-0.17	0.51
Observations	1151		1151	
R-squared	0.47		0.54	
F-test	36.39***		48.60***	
p-value (F-test)	0.00		0.00	

Source: Authors' calculations.

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

Table B.5. The OLS Estimations of the Effects of Farmer's Behaviour on Income.

	Dependent variable: income in natural logarithm	
	Coefficient	p-values
Farmer's behaviour		
Cooperative behaviour (b_{1i})	-0.17**	0.03
Self-interest behaviour (b_{2i})	0.001	0.98
The characteristics of farmers and farm		
Years of schooling ($yedu_i$)	0.02	0.38
Farm size ($tsize_i$)	0.50***	<0.01
Rice farmer dummy (D_rice_i)	0.10	0.69
Number of crops ($ncrop_i$)	0.15	0.18
Working hours on farms ($whours_i$)	0.13***	<0.01
Membership dummy (D_Member_i)	0.122	0.46
Distance to city ($dist\_city_i$)	0.0003	0.76
Regional Variables†		
R1	-0.45	0.50
R2	1.49**	0.02
R5	0.02	0.98
R6	0.31	0.56
Regional interaction terms		
Region 1 (R1)		
b_{1i} x R1	0.19**	0.04
b_{2i} x R1	0.06	0.45
$yedu_i$ x R1	0.05*	0.07
$fsize_i$ x R1	-0.29***	<0.01
D_rice_i x R1	-0.72**	<0.01
$ncrop_i$ x R1	0.21	0.14
$whours_i$ x R1	-0.08	0.15
D_Member_i x R1	0.14	0.46
Region 2 (R2)		
b_{1i} x R2	0.31***	<0.01
b_{2i} x R2	-0.05	0.53
$yedu_i$ x R2	-0.008	0.73
$fsize_i$ x R2	0.26**	0.02
$ncrop_i$ x R2	-0.35	0.34
$whours_i$ x R2	-0.07	0.17
Region 4 (R4)		
b_{1i} x R4	-0.02	0.82
b_{2i} x R4	0.08	0.59
$yedu_i$ x R4	-0.02	0.47
$fsize_i$ x R4	0.26**	0.02
D_rice_i x R4	0.04	0.90
$ncrop_i$ x R4	1.50**	0.02
$whours_i$ x R4	-0.14**	0.02
D_Member_i x R4	0.08	0.68

Table B.5. (Continued)

	Dependent variable: income in natural logarithm	
	Coefficient	**p-values**
Region 5 (R5)		
b_{1i} x R5	0.12	0.24
b_{2i} x R5	0.08	0.34
$yedu_i$ x R5	0.11	0.67
$fsize_i$ x R5	0.02	0.84
D_rice_i x R5	-0.44	0.22
$ncrop_i$ x R5	0.12	0.48
$whours_i$ x R5	0.01	0.82
D_Member_i x R5	0.35*	0.08
Region 6 (R6)		
b_{1i} x R6	0.12	0.23
b_{2i} x R6	-0.07	0.52
$yedu_i$ x R6	-0.01	0.62
$fsize_i$ x R6	-0.04	0.72
$whours_i$ x R6	-0.10	0.11
Intercept	13.16***	<0.01
Observations	1151	
R-squared	0.62	
F-test	37.94***	
p-value (F-test)	<0.01	

Source: Authors' calculation.

Note: One, two, three asterisks denote the significance at 10%, 5% and 1%, respectively. The analysis drops some variables due to collinearity. † Regional variables include R1, R2, R4, R5,and R6. R3 (Bandung Metropolitan Area) is set as our referent region.

CHAPTER 5

The Potential of Agro-cluster Policies for Improving Productivity of Rice Farming

Abstract

Rice self-sufficiency becomes a challenging policy target for Indonesia. Rice production was predicted to decrease by 768,808 tons over the years 2011 – 2015 due to the decline of rice productivity in almost all regions of West Java compared to its trend prior to 2011. This loss corresponds to 2.2% of the total actual rice production, or the annual consumption of 9 million inhabitants. The policies of UPSUS swasembada padi and rice cluster development are currently aimed at raising rice productivity. By applying OECD policy evaluation criteria, this paper evaluates whether both policies are effective for this aim. We identify that none of 17 policy instruments of both programs meets all five criteria of OECD. The government has paid less attention to empowering farmers in its policy instrument. Although the latter program could address the lack of the first program, no specific budgets are allocated for its implementation. For policy improvements, this paper also analyses the effects of farmer organisations on increased rice productivity when farmers are geographically clustered. We suggest that farmer organisations within rice clusters allow farmers to increase rice productivity. The government should not undertake large investments in subsidised inputs and agricultural infrastructure in the absence of strong farmer organisations in order to attain the sustainable improvements in rice productivity. Introducing the notion of agro-clusters could be an alternative policy option to strengthen farmer cooperation, and thus such policy could return to the level of rice productivity growth before 2010.

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5.1. Introduction

Rice is an economically and politically crucial crop of Indonesia that has manifold impacts on incomes, rural employment, and food self-sufficiency (MoA, 2016c). FAO (2015) reported that Indonesia slightly increased rice production at around 250 kg rice per capita and per year, having an average productivity[11] of about 5.2 tons/hectare over the period 2000-2012. This progress falls behind other Southeast Asian countries, such as Cambodia, Thailand, Laos, Myanmar, and Viet Nam which enhanced rice production by 50% to 600 kg per capita until 2012. Simatupang and Timmer (2008) find that the slow growth of Indonesian rice production results mainly from declining productivity and limited available arable land. BPS (2015) reported that rice productivity of the province of West Java rose slightly at 0.9% per year over the last five years. In addition, smallholders[12] with low productivity, low input uses, and low skills characterise the majority of West Javanese farmers (BPS, 2013b; Hazell & Rahman, 2014, McCulloch & Timmer, 2008).

As the province of West Java accounts for about 16% of total national rice production[13], this stagnation may result in a challenge for Indonesia to keep national production growth at the pace of annual population growth of 1.1% (BPS, 2016). As a consequence, Indonesia is predicted to undergo rice shortage in the future. Rice import is likely to be less politically favoured as a way for the Indonesian government to address rice shortage. Simatupang and Timmer (2008) point out that such import has recently become a political debate of rice policy in Indonesia: allowing rice import is

[11] In this paper, rice productivity is defined as the average quantity of rice produced by one farmer per unit of land in a given year.
[12] Smallholders are farmers who operate less than a half hectare (BPS, 2013). According to BPS (2013), their share in total Indonesian and West Javanese farmers was 55% and 76%, respectively.
[13] This production corresponds to the second largest provincial contribution to national Indonesian rice production after East Java.

considered anti-farmer. Despite such little progress, FAO (2015) suggests that Indonesia could potentially raise rice productivity to 8-10 tons/hectare, that is, virtually double its average productivity of 2012, due to its abundant agricultural resources.

The Indonesian government, therefore, is heavily concerned with improving rice self-sufficiency as emphasized by OECD (2015, p. 1): "the new Indonesian government has revised the timeframe for achieving self-sufficiency to 2017 for rice […]". To that end, it has set up the program of *UPSUS swasembada padi* (Bahasa Indonesia for "special efforts for rice self-sufficiency")to accelerate rice production in the years of 2017-2019 (MoA, 2015b, 2015c). The policy aims at reaching about 78 million tons of paddy as the annual production target of Indonesia (MoA, 2015a). It facilitates farmers to widen rice planted areas through land optimisation and machinery facilitation and to increase rice productivity by subsidised production inputs and the application of new production technology. The second policy set up for reaching the goal of rice self-sufficiency is the rice cluster development (MoA, 2016b). This policy aims to increase rice productivity and farmers' income. Both *UPSUS swasembada padi* and the rice cluster policy are highly expected to build a strong collaboration among various stakeholders such as universities, research and military institutions. Additionally, regional governments, either at provincial or district levels[14], also have a mandate and a politically defined role in the implementation of both policies.

Recent scientific literature stresses the benefits of farmer cooperation for realizing such intended productivity improvement which is especially facilitated in regions of production concentration. Deichmann et al. (2008)emphasise that farmers typically concentrate in particular regions due to their high dependency on natural resources, such as topography, water

[14] Indonesia has one national government. Moreover, each of the 34 provinces has an own provincial government. Each province consists of 5 to 38 districts each of which has also an own government.

resources, and fertile lands. Wardhana et al. (2017) define such geographical concentrations, often referred to as agro-clusters, as the spatial concentration and specialisation of agricultural-based economic activities involving farmers, buyers, suppliers, and supporting actors who develop collaborations with mutually advantageous impacts. Recent literature suggests that cooperation could help smallholder farmers in particular to increase rice productivity (Galves-Nogales, 2010). World Bank (2007) emphasizes that cooperation offers advantages for farmers due to economies of scale in input and output markets. Schmitz (1995) and Fischer and Qaim (2012a) also highlight that firms could enjoy joint-action advantages in agglomeration economies. Ainembabazi et al. (2017) find that farmers in an organisation raise productivity through better knowledge exchange. Farmers located in such geographical concentrations are more likely to be closely located to other farmers and can therefore be expected to easily establish cooperation.

Galves-Nogales (2010) observes the crucial factors driving the success of Thailand's clusters of fruits and vegetables, Viet Nam's root crop processing clusters, the Maharashtra grape cluster of India, and Chinese livestock clusters. These factors embrace farmers and their cooperation as the main priority in agro-cluster development. She also stresses that the governments of these countries persuade many external institutions to support farmers in creating product and processing innovations and in opening global markets. Studying the One Village One Product program of Japan and Thailand, Mukai and Fujikura (2015) point out human resource development, such as self-reliance and creativity, as the key objectives of sustainable clusters. In other words, all actors in these clusters acquire knowledge and skills including business, managerial and leadership capacity and production, which are likely to raise productivity. Additionally, Porter (2000) and Galves-Nogales (2010) suggest that

strengthening cooperation between involved actors is essential for incipient clusters to carry out productivity improvements.

Increasing rice productivity as a central goal of these policies faces several challenges. These challenges are especially prevalent in West Java, that is why this paper focusses in its empirical analysis on this Indonesian province. First, 76% of West Javanese farmers are smallholders (BPS, 2013c) and, therefore, are likely to have a low farm productivity(Paul & wa Gĩthĩnji, 2017). Second, MoA (2014) reported that West Java faces a decrease in the total area of productive rice fields (*sawah*) by about 1.3% in the period 2009–2014. Third, the dissemination of technological innovation is uneven among Indonesian farmers(Simatupang & Timmer, 2008). OECD (2012) notes that the public spending for agricultural research on productivity technologies is, with a share of only 0.3% of total agricultural GDP, substantially smaller than in Malaysia (1.9%) or the Philippines (0.5%). This may hamper technological progress in Indonesian rice productivity. Fourth, Indonesia has a low quality of irrigation infrastructure. GoWJ (2014) records that 40% of the total irrigation infrastructure of West Java was in damaged condition. Fifth, Indonesia applies a multi-regulatory system inducing low participation of the public and private sector for improving farm productivity (OECD, 2012; Quincieu, 2015). Consequently, a wide diversity of rice productivity occurs across regions of West Java ranging from 4.5 to 7.1 tons/hectare (BPS, 2016).

UPSUS swasembada padi and the rice cluster development policy are expected to overcome these challenges farmers face to reach a substantial increase in Indonesian rice productivity. This paper makes two major contributions: First, it analyses the existing policy schemes and suggests alternative policy options for raising rice productivity, and therefore enhancing rice domestic production. The analysis applies the evaluation criteria of OECD (2007) at all levels of Indonesia governance. Second, it

provides an insight into the role of agro-clusters in building farmer cooperation for productivity improvements. Empirical evidence on the benefits of such cooperation for rice productivity gained from propensity score matching and an OLS regression justifies strengthening farmer cooperation in both policy programs.

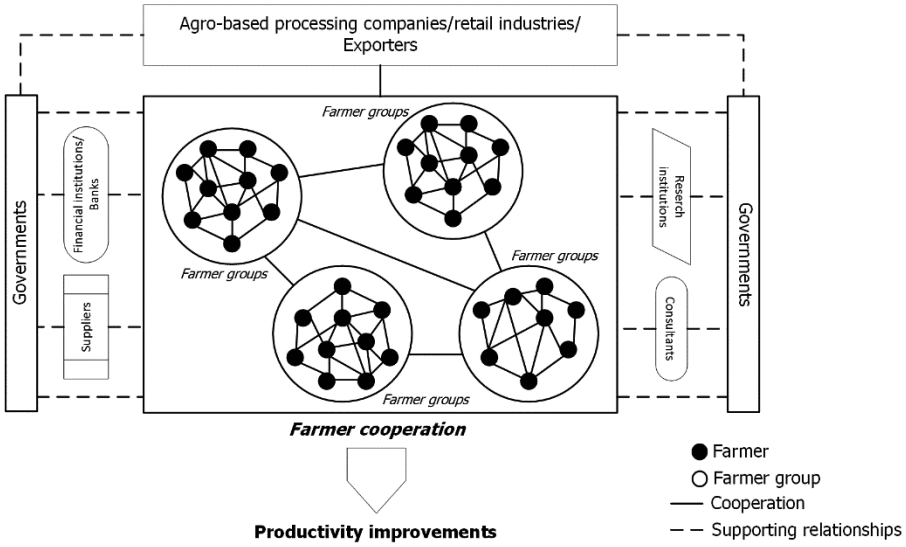
5.2. The Role of Agro-clusters for Rice Productivity

In this section, we provide the theoretical background underpinning the potential role of farmer cooperation resulting from agro-clusters for influencing rice productivity. According to OECD (2001a), productivity is the ratio of the quantity of total crop outputs to all factor inputs, such as labour, land and capital. Mundlak (1992) and OECD (2001a) give an overview of various ways to measure it. Total factor productivity (TFP) is a multifactor productivity measure tracing technological changes (OECD, 2011). However, OECD (2011) point out that TFP is a theoretical construction that often uses unrealistic and aggregate assumptions which can be inadequate to reflect the essential properties of technological improvements and requires significant data. Therefore, OECD (2011) suggests single factor measures, such as yield per hectare, yield per labour unit, and capital productivity, reflecting partial effects of a factor input on gross outputs. Besides the ease of measurement and less data requirements, they simplify determining the ratio of the quantity of total outputs and input. Our study utilizes yield quantity per hectare for quantifying observable rice productivity. This measure represents an individual farmer's ability to convert one hectare of farms into tons of rice. Although it is not the ideal measure of rice productivity, it gives a good picture of the actual productivity of farmers. Additionally, this measure is commonly used in governments' statistical documents.

Building on Porter (1990) and Krugman (1991), agro-clusters characterize increasing returns to scale, explaining increased farm productivity. Schmitz (1999) suggests that farmers benefit from collective efficiency resulting from agro-clusters, that is, that the competitive advantages of farmers are derived from cooperation between proximate farmers and economic externalities. Li and Geng (2012) highlight that cooperation increases the willingness of farmers to share information and resources with one another through the motive of increased productivity. Adapted from Porter (1990), Figure 5.1 illustrates cooperation between farmers and their relationships with supporting institutions within an agro-cluster. There can be two types of cooperation inside agro-clusters: horizontal and vertical cooperation. The former concerns individual farmers cooperating, such as sharing production inputs and exchanging crucial information, and groups of farmers joining together in farmer organisations. The latter can be explained by cooperation between farmers and input suppliers or agro-based processing companies, retails, and exporters. Humphrey and Schmitz (2002) emphasise that agro-clusters allow for establishing a complex, strong network relation, thereby fostering innovation for improving productivity.

Krugman (1991) highlights that farmers could attain the advantages of economic externalities inside agro-clusters, that is, that spatially neighbouring farmers influence each other for productivity growth. He explains that economic externalities within cluster regions arise because of knowledge spillovers and the pool of production inputs. Fujita and Thisse (2002) argue that the economic gains of personal interactions between farmers are generally greater if they are located spatially closer to one another. Such interactions allow these farmers to exchange knowledge leading to innovation creation, and thus, increasing returns to scale (Krugman, 1991). Based on Fujita and Thisse (2002) and World Bank (2008),

agro-clusters help in accelerating knowledge spillovers and allowing farmers to learn from each other. For example, new production technologies from research institutions are diffused among farmers due to their frequent face-to-face contacts within geographically concentrated farming activities.

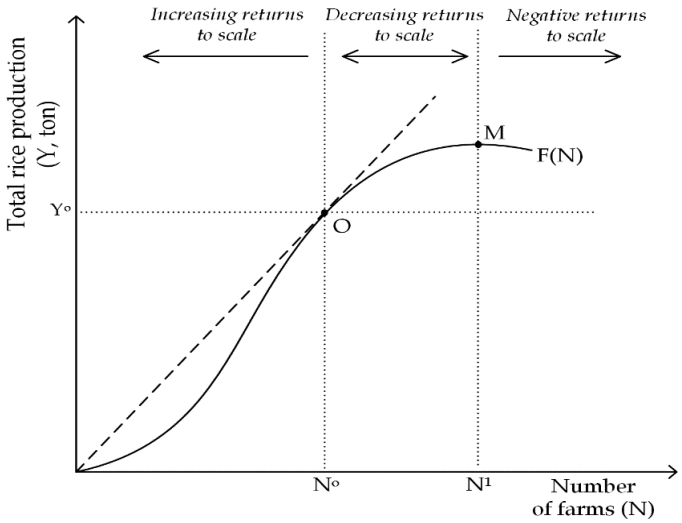


Source: Authors adapted from Porter (1990).

Figure 5.1. Agro-cluster Institutions.

Figure 5.2 illustrates the relationship between agro-clusters and rice production growth. It shows that the growth of total rice production changes depending on the farm number. Suppose an agro-cluster region i consists of the certain number of farms N. The total land size of this region is fixed due to limited agricultural land available. All these farms are identical in terms of operated land sizes. If this region has one hundred hectares for the total land size of rice from 100 farms, each farm, thus, operates a hectare. Additional farm numbers in the region reduce the operated land size of each farm. Hence, an increase in rice production in the region represents the

increase in its rice productivity. Furthermore, the F(N) curve represents the total quantity of rice production (Y) in a region which farms can produce, under its certain number of farms (N).



Source: Authors based on Fujita and Thisse (2002, pp. 106-113).

Figure 5.2. Agro-clusters and Returns to Scale

Based on Figure 5.2, the curve is divided into three phases. These are increasing returns, decreasing returns, and negative returns. In the first phase, the curve is convex, meaning that the total rice production increases by more than the proportional rise in the farm population density. Krugman (1991) argues that farms could produce rice at an increasing rate because of economic externalities within agro-clusters. For example, farms apply a new production technology disseminated by the government, such as *jajar legowo super*[15], and learn from each other due to knowledge spillovers within such

[15]*Jajar legowo super* is an Indonesian new technology of rice cultivation, which is a rice planting system of a specific row crop cultivated pattern, integrated with the technologies of rice seeds, organic fertilizers, and natural pesticides (AIAT, 2016).

clusters. Therefore, these farms may have better opportunities to raise rice productivity. As Schmitz (1999) explains, cooperation is also associated with increasing returns to scale because of sharing new technologies. Ye et al. (2016) argue that increasing returns to scale occur as the number of co-operators increases. The increasing growth of rice productivity will be turned to a decreasing slope after reaching to optimal rice production at point O (N^o, Y^o). This turning point represents the optimal quantity of total production (Y^o) produced by the optimal number of farms (N^o).

After the point O, the second phase graphically shows decreasing returns to scale. The slope of total production curve gets flatter, and the curve becomes concave. This concavity indicates marginal increases in farm numbers in relation to marginal decreases in total production. This change happens due to the negative impact of competition between proximate farmers. Martin and Sunley (2003) point out the high competition for farm labourers and on production inputs within agro-clusters. Since there is limited land available, smallholders cultivating rice in smaller land size were a result of the high competition on this land. This small size of the agricultural land reduces rice productivity. Similarly, Folta et al. (2006) find that the higher competition for inputs and marketing opportunities, such as marketing prices and clients, is associated with the higher number of neighbouring farms. Staber (2009) notes that social conflicts also arise within cluster regions which may prevent the knowledge exchange. Farmers tend to hide crucial knowledge from their neighbours when they perceive higher economic pressure (James & Hendrickson, 2008). Based on Figure 5.2, the decreasing returns occur until point M, that is, the maximal total rice production that farmers could produce at N^1 farmer numbers. Thereafter, the curve has negative returns to scale, meaning that rice production decreases as the number of farms increases.

5.3. Rice Farming in West Java

Figure 5.3 panel (a) shows the growth of rice production of all provinces located on the island of Java. Combined with Central and East Java, the province of West Java contributes to almost half of national rice production. As the second largest contributor to Indonesian rice production, it annually produces about 11 million tons or about 16% of national rice production. Figure 5.3 panel (b) shows the relative changes of rice production across the six provinces of West Java. Rice production in these provinces – except for Jakarta - has risen by 40 to 55% during the past 25 years. West Java realised the smallest increase of about 38%. Its rice production was roughly stable until the end of the economic crisis in 2003 and significantly took off afterwards.

As total rice production is the product of total land harvested and average productivity in tons per hectare, our special interest lies in the contribution of the productivity growth to the development of total rice production. According to BPS (1993, 2016), rice productivity of West Java was on average 5.0 tons/hectare in 1993 and increased to an average of 5.8 tons/hectares in 2015. Figure 5.4 summarises the relative changes of the distribution of rice productivity and area across the 27 districts[16] of West Java since 1993. Although variation in harvested area across the districts is much higher than variation in productivity, this distribution remains roughly constant during these 25 years while the distribution of productivity changes markedly. Rice productivity in all districts has experienced a substantial increase between 1998 and 2010. While productivity per hectare in the district with the minimum productivity was 17% below the median productivity in 1993, minimum productivity in 2010 had risen to 7% above

[16]The district number of West Java changes due to its regional proliferation. It had 21 districts in 1993, excluding 4 districts which after the year 2000 became a part of the province of Banten. This number increased to 27 districts in 2015.

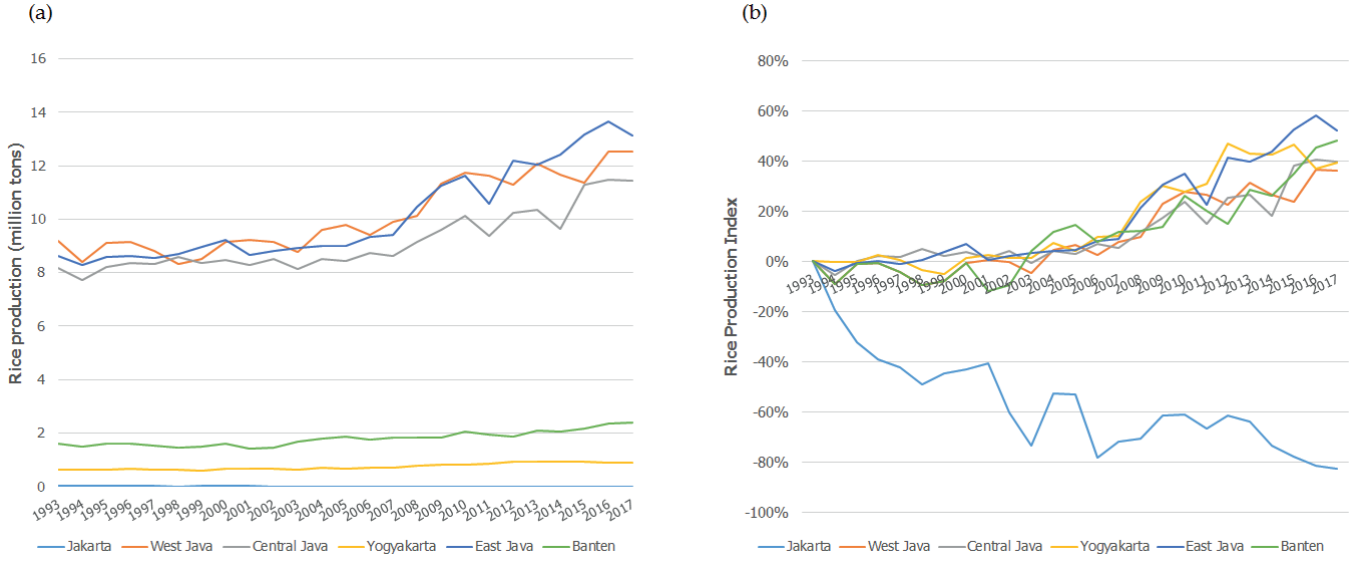
the 1993 median. As areas have been largely constant, the most feasible way to increase rice production in West Java is to bring the productivity growth back to its levels before 2010 (see the bold-dashed line in Figure 5.4).

Figure 5.4 clearly indicates that productivity of the districts of West Java has grown substantially more heterogeneous in recent years in comparison with 1993. While maximum and minimum productivity in 1993 amounted to 10% more and 10% less than the 1993 median, this difference has risen to 33% more and 7% less than the 1993 median in 2014. This difference indicates that the productivity growth of the least productive districts has been relatively slower and even stagnated since 2011 in comparison to the most highly productive districts, which is visible in the almost constant growth rate of maximum productivity after 2010.

The bold-dashed line in Figure 5.4 marks the hypothetical continuation of the linear growth the least productive district showed until 2010. Thus, Figure 5.4 indicates a substantial productivity gap (the fat black vertical double-arrow) because the growth of average productivity in the 20 least productive districts (the lower three quartiles) has virtually stagnated since 2010. This gap represents a substantial loss of rice productivity leading to a loss of rice production. Based on extrapolation of the bold dashed line[17], we find that the total loss of rice production in West Java due to this stagnation amounts to 768,808 tons. This corresponds to 2.2% of the total actual rice production of West Java between 2011 and 2015 or the annual consumption of 9 million inhabitants of West Java[18].

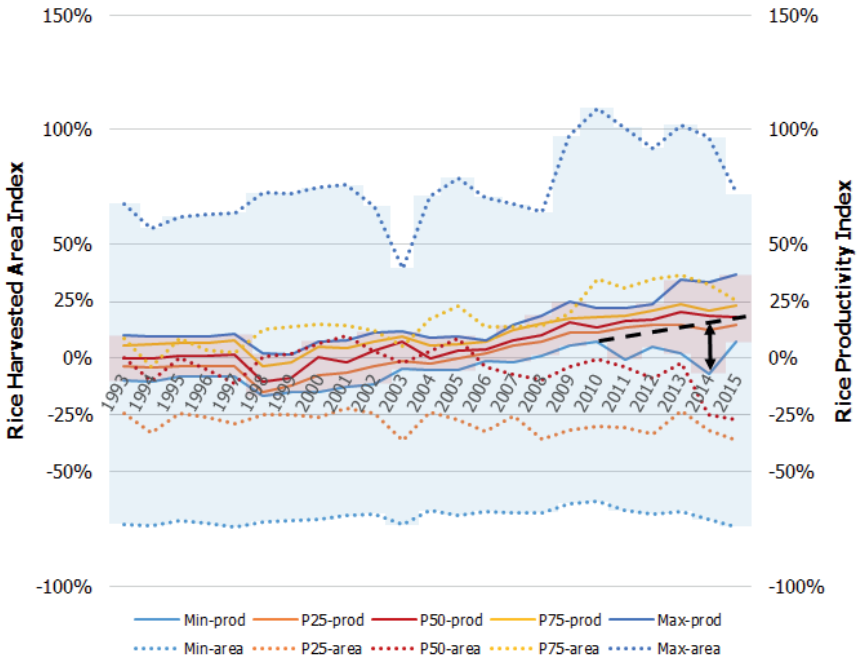
[17]The extrapolation calculates the hypothetical annual productivity growth of each percentile variable, except the maximum productivity, of the year 2011 to 2015. The total hypothetical rice production is the summation of the hypothetical production of each district resulted from the product of the results of the extrapolation and the observed harvested area of each sub-district belonging to the percentile of each year. Difference between the observed and hypothetical production indicates the loss of rice production.

[18] BPS (2014) reports that annual rice consumption in West Java was 86.23 kg per capita and year in 2014.



Source: Authors based on BPS (1990, ..., 2017).
Note: All variables signifying each province of Java Island in panel (b) are indexed, that is, the rice production in year 1993 is set to equal zero and the values of them for the following years are each divided by the rice production in 1993 of the corresponding variable, and one is subtracted from the resulting quotient. The province of Banten has been autonomously established since 2000 from the province of West Java. We, therefore, do extrapolation to quantify Banten's rice production in the years before this proliferation. This extrapolation is the multiplication of the total rice production of West Java before this proliferation with the average share of Banten in the total rice production of West Java and Banten after the proliferation.

Figure 5.3. Rice production in the five provinces of Java island.



Source: Authors based on BPS (1998, ..., 2016).
Note: The variables Min-prod (Max-prod) and Min-area (Max-area) denote the minimum (maximum) value of rice productivity and harvested area within 27 districts of West Java. The remaining variables are the 25%, 50%, and 75% percentiles of rice productivity and area, respectively. These variables are indexed based on their percentage deviation from the median of productivity and area in 1993, respectively. Their observed values are divided by P50 of 1993 of the corresponding variable and one is subtracted. Data of the year 2016 and 2017 are yet not available. For example, the harvested area of the district with the maximum rice area in 1993 was about 60% larger than in the district with the median rice area. Due to regional proliferation in 2007 and 2013, there was a change in the number of West Java's districts, and thus data distribution of rice productivity and the harvested area is analysed according to the new number for the period after the year of the proliferation. For example, the West Bandung district was established in 2007 so that after this year this district is included in the following analysis.

Figure 5.4. Growth of Rice Productivity and Harvested Areas in West Java

Figure 5.5 panel (a) describes the spatial distribution of the productivity across sub-districts. Nearly 52% of all sub-districts have a rice productivity of between 5.82 and 6.42 tons/hectare, and located far from

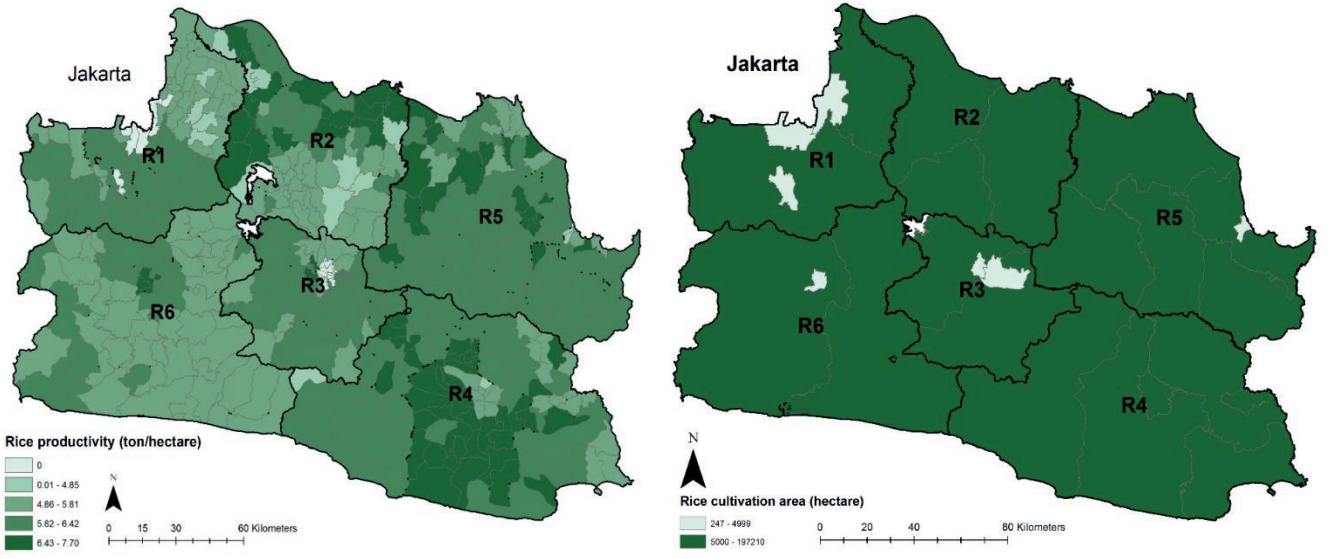
Jakarta. About 15% of all sub-districts located in regions R2, R4 and R5 show the highest productivity, ranging from 6.43 to 7.70 tons/hectare, and 3% of them are included in the lowest productivity located in region R1 and R2.

This wide spatial variation of rice productivity was caused by the variation of production technologies applied by farmers across Indonesian regions, such as seed technologies (Simatupang & Timmer, 2008; Mariyono, 2014). Simatupang and Timmer (2008) moreover, emphasise that this variation of the technology application occurs because agricultural technology delivery systems are in disarray. Thus, dissemination of the new technologies is slow to reach all farmers at the same time. Many village cooperatives which had been established to spread inputs and technologies have closed down and regional governments seem less capable of ensuring extension services to reach all villages (Simatupang and Timmer, 2008). Furthermore, physical irrigation infrastructure as crucial public good for rise production is not sufficiently maintained leading to low productivity (Panuju et al., 2013; Mariyono, 2014). Panuju et al. (2013) find that about 48% of canals in Indonesia are damaged. Simatupang and Timmer (2008) point to the decline in government's investment in irrigation infrastructure maintenance.

BPS (2013) reports that the 2.2 million rice farmers dominate West Java's agricultural sector accounting for 59% of all farmers of West Java. These farmers are mostly concentrated in regions where favourable agricultural resources for rice cultivation exist. For policy reasons, MoA (2016d) identifies regions which have at least 5,000 hectares of rice cultivation as rice clusters as being strategic for national rice production. According to MoA (2016d), the province of West Java has been identified as one of these rice clusters, located in almost all districts of this province, excluding urbanised regions. Figure 5.5 panel (b) illustrates the geographical distribution of these governmentally declared rice clusters shown by the dark green shading.

(a) Regional Rice Productivity

(b) Rice Clusters across 27 Districts of West Java



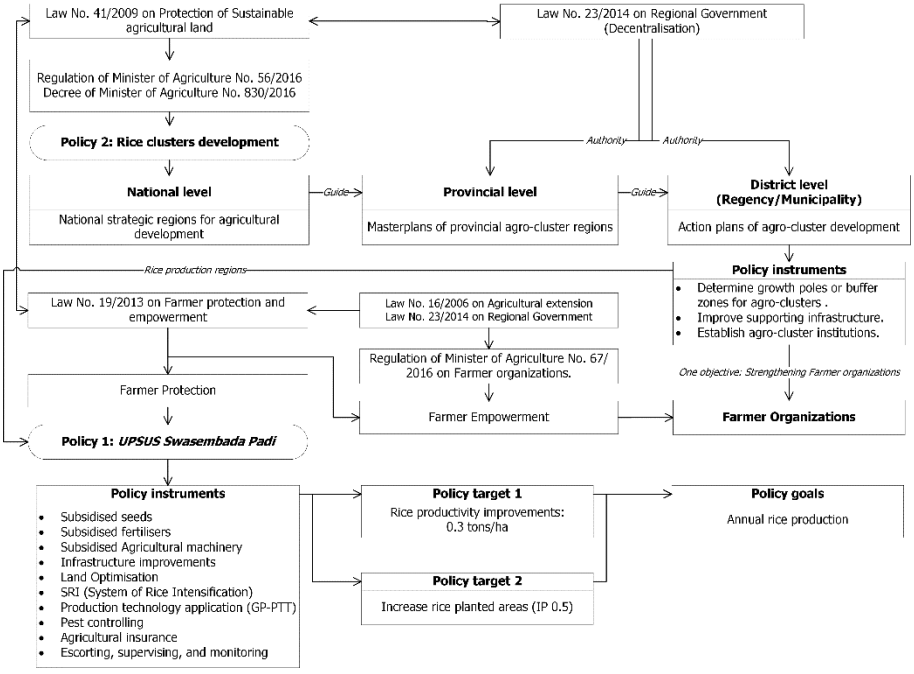
Source: Authors.

Note: Regional rice productivity is based on BPS (2015b). The category of rice clusters is based on MoA (2016c). The following regions are a group of districts based on GoWJ (2010): R1 denotes districts close to Jakarta, such as Bekasi, Depok and Cianjur. R2 refers to Karawang, Purwakarta and Subang. R3 is Bandung Metropolitan. R4 comprises Tasikmalaya, Ciamis, Banjar, Garut and Pangandaran. R5 represents Kuningan, Indramayu, Cirebon, and Sumedang. R6 comprises Sukabumi and its surrounds.

Figure 5.5. Rice Productivity and Rice Clusters in West Java

5.4. Current Policies for The Improvement of Rice Productivity

Currently, various policies are implemented at national and regional levels of Indonesia for accelerating the increase of rice productivity. Figure 5.6 shows the governance structure and regulatory bases of the two current policies designed to ensure Indonesia's rice self-sufficiency. *UPSUS swasembada padi* (the *rice self-sufficiency policy*) as the prioritised policy for increasing rice production is based on Law No. 19 (MoLHR, 2013) and MoA regulations (MoA, 2015b, 2015c). The second major policy is *kawasan strategis nasional* (the *national strategic areas policy*) which relates to the development of rice clusters under Law No. 41 (MoLHR, 2009) and MoA Regulation No. 56 (MoA, 2016d). Unlike the first policy, this policy aims not only to increase productivity but also to raise farmers' income.



Source: Authors.

Figure 5.6. Indonesian Policy Framework for Rice Productivity

Both policies are expected to be coordinated at the three major administrative levels of Indonesian governance. Decentralisation Law No. 23 (MoLHR, 2014) emphasises that regional governments at provincial and district levels have full authority to stimulate the growth of the agricultural sector within their regions. Figure 6 indicates that this law has also been the single regulatory base for designing both policies at both provincial and district levels including planning, staffing, and budgeting.

5.4.1. Status of Current Policies

UPSUS Swasembada Padi

After the short-lived success of rice self-sufficiency in the early 1980s (McCulloch & Timmer, 2008), Indonesian rice production growth has stagnated. During the current Jokowi cabinet, expectations of the government towards *UPSUS swasembada padi* were high to re-establish this success. MoA in collabouration with the provincial and district levels is responsible for bringing this policy to success. This policy also involves other institutions, such as universities, other research institutions and Indonesian National Armed Forces (Tentara Nasional Indonesia, TNI) which take a role in supervision, monitoring, and evaluation (MoA, 2015c).

Figure 5.6 shows ten of the 17 policy instruments implemented in total by these two polices. All of them aim at achieving a total annual production of dried unhusked rice (GKG) of about 78 million tons in 2017 by increasing productivity by 0.3 tons/hectare per year and widening planted areas by 0.5 of rice cropping intensity index[19] per annum (MoA, 2015b). West Java, therefore, is expected to reach 6.7 ton/hectare or around 13 million tons GKG in 2018 (AoAFCH, 2013). In 2015, MoA allocated about 11.8 trillion Indonesian Rupiah (IDR, 874 m USD) (MoA, 2015a) for these instruments

[19] Rice cropping intensity index is a ratio between rice planted areas and existing rice fields.

reducing this amount to 9.3 trillion IDR (689 m USD) in 2016 and to 7 trillion IDR (518 m USD) in 2017 (MoA, 2016c, 2017). In 2015, MoA also heavily invests in subsidising agricultural machinery (25% of the total expenses), improving irrigation infrastructure (23% of the total expense), subsidising seeds and fertilisers (12%) (MoA, 2015a). One trillion IDR (76 m USD) is allocated to production technology dissemination (GP-PTT), such as *Jajar legowo super* or superior seeds. Moreover, in collaboration with financial institutions, this program offers insurance for farmers to handle failures with subsidies of 146 billion IDR (11 m USD).

This setup results in several challenges of *UPSUS swasembada padi* at the national level. Firstly, the regulatory fundament underpinning this policy is complex, based on overlapping regulations as shown in Figure 5.6. This overlap can lead to problems in policy consistency such as contradictions and misinterpretations. Secondly, since involving various stakeholders, this policy requires the strong commitment of all involved actors to collaborate. If this commitment is not given, the program's success is at risk. Thirdly, it tends to neglect farmer empowerment as illustrated in Figure 5.6. The policy does not encourage farmers to develop initiative and self-motivation to create innovations. As a consequence, benefits of the policy have been reported to be distributed among wealthiest farmers and managers of farmer organisations (Hamyana, 2017). The Indonesian farmer union even suggests that farmers are treated as labourers who are forced to produce rice under the commands of the TNI, academics, and regional governments (SPI, 2017).

Regional governments at provincial and district levels are vital actors of *UPSUS swasembada padi*. Instead of being in charge of the full authority according to the decentralisation law, they have less power in practice for designing their own policies in terms of rice self-sufficiency given that the development of this policy is centralised by the national government.

Regional governments only execute the national policy instruments. According to (MoA, 2015c), the provincial government of West Java has responsibilities for technically supervising the policy of *UPSUS swasembada padi* while district governments act as technical executors. The national government allocates nearly 6% of the total agricultural national budget for West Java to the implementation of this program (DJTP, 2016).

Furthermore, both regional governments are given the power to develop additional instruments in the framework of their mandate and as long as these support the attainment of the nationally defined policy. Their responsibilities are (a) identifying, verifying, and validating targeted rice farmer groups; (b) supervising, coordinating, monitoring, and evaluating all activities of the program; and (c) ensuring the availability of extension services (MoA, 2015b). For example, West Java spends nearly 41% of its total expenditure on agriculture on the instruments of *UPSUS swasembada padi*, such as extension services or irrigation (AoAFCH, 2013). District governments spend various amounts of their own district budgets depending on their local needs. For instance, Indramayu district spends around 66 billion IDR (5 m USD) for improvements in irrigation infrastructure.

UPSUS swasembada padi encounters challenges at regional level as well. First, in some cases district governments could not arrange the provision of rice seeds and agricultural machinery by themselves, as the national government controlled this procurement (Nugroho et al., 2017). Accordingly, farmers may delay rice planting because the national government conducted late seed distribution, or it provided machinery not suitable for farmers' specific localities. Second, the design of this policy explicitly elaborates potential policy instruments and the distribution of responsibility on each governmental level, but this is not followed by its planned costs (MoA, 2016c). Up to 2017, the provincial and district

governments of West Java, however, do not have their local policies as the interpretation of the national policy. Third, extension services which are crucial in the implementation of this policy tend to be less prioritised so far at both national and regional levels: The provincial government of West Java, for instance, only allocates less than 6% of total agricultural expenditure for training extension officers and farmers as well as strengthening farmer organisations (AoAFCH, 2013).

Rice Cluster Development

Unlike *UPSUS swasembada padi*, the rice cluster development policy is expected not only to subsidise inputs and improve agricultural infrastructure, but also to strengthen collaboration between farmers and other stakeholders. Its main aim is supporting the spatial concentration of farming activities. This policy is targeted at farmer organisations to increase their productivity and income. Figure 5.6 depicts its governance structure across national, provincial, as well as district levels. The provincial governments are instructed by the national technical guidelines for designing a rice cluster masterplan, and district governments are responsible for translating this masterplan into action plans.

The national Indonesian as well as regional governments of West Java pay less attention to the implementation of the rice cluster program as they have no specific budgets allocated for it. The national government has only defined 20 out of the 28 districts of West Java as being national strategic areas for rice clusters (MoA, 2016b). Regardless of the clear authority distribution, both provincial and district governments did not have a masterplan or action plans for rice cluster development until 2017.

5.4.2. Evaluation of Policy Quality

In the following, we evaluate both ongoing policies based on OECD (2007, p. 26) which defines five desirable characteristics of well-defined policy instruments. First, policies should be transparent, meaning that they should have explicitly identifiable goals, budgets, staff and beneficiaries. Second, policies should be targeted implying that they are designed to reach specific, clearly defined outcomes and only the beneficiaries in need not influencing producers' decisions on factor allocation (decoupling). For instance, improving irrigation infrastructure is targeted at regions categorised by low rice productivity due to damaged irrigation channels. Third, policies need to be tailored. This means that they reach identified outcomes without wasting public resources but only provide the minimum necessary support for reaching the goals. Fourth, policies should be flexible, meaning that they should be able to adapt to changes in targets and priorities over time due to, for example, shifts in the Indonesian political landscape. Last, the policies should be equitable, meaning that they should aim at reducing wealth or income disparities among farmers and regions. Given the context of the goal to achieve rice self-sufficiency, an equitable policy should prioritize poor regions of low rice productivity.

Table 5.1 summarises the evaluation of all 17 instruments of the two policies based on these OECD criteria. None of the ten instruments of *UPSUS swasembada padi* meets all five criteria of OECD (2007). While most of them are targeted, tailored and flexible, almost none is transparent or equitable. Although total budgets of each instrument are transparently identified, budget allocations for instrument 10 (supervision and monitor involving universities and TNI) are not made public. The policy is not equitable because none of its instruments prioritises regions for reducing the productivity disparity across districts. For instance, Purwakarta district, which has the lowest productivity (see Figure 5.5), was allocated only 2% of

total budget for West Java, while the Cianjur district, realising the highest productivity, obtained 13% (DGoB, 2015).

Policy instruments 1 and 3 are not tailored to farmers' specific local needs. DJTP (2016) reports that the budget for providing seeds is not exhausted because farmers argue that the subsidised varieties do not meet their expectations. Nugroho et al. (2017) find that tractors and transplanters do not fit the characteristics of the regions in which they are distributed to farmers. The quality of periodic evaluation reports on this policy is barely monitored; consequently, its data management is poor (SPI, 2017). Policy instrument 9 (Table 5.1) is an example of one of the instruments best designed in the sense of OECD (2007) because it is targeted, tailored and flexible. According to DJPSP (2017), the intended beneficiaries are farmers who operate rice fields less than 2 hectares. These farmers will earn 6 m IDR (460 US dollar) per hectare per season if more than 75% of their rice planting was damaged. Regarding the flexibility, there is no indication in the policy documents that this instrument will change over time, despite, for instance, the changes of cabinet leaders.

According to FAO (2011), the two major factors in the success of Indonesia's previous policy of rice self-sufficiency were developing human resources and increasing knowledge. However, explicit policy instruments on building farmer cooperation and increasing farmers' capabilities are not existing within *UPSUS swasembada padi*. Farmers only act as passive recipients of subsidies. The beneficiaries of this policy are farmers who join farmer groups as MoA (2015b, pp. 7-10) explicitly mandates provincial and district governments to identify farmer groups willing to implement the program. This mandate implies that individual farmers have no access to obtain the benefits of this program. As a consequence, farmer cooperation becomes crucial in distributing the benefits of the program to all farmers in need.

Table 5.1. Evaluation of Instruments of *UPSUS Swasembada Padi* and Rice Cluster Development in West Java

Policy Instruments	OECD's Evaluation Criteria				
	Transparent	Targeted	Tailored	Flexible	Equitable
UPSUS swasembada padi					
1. Subsidising seeds	Yes	Yes	No	No	No
2. Subsidising fertilisers	No	Yes	Yes	No	No
3. Subsidising agricultural machinery	No	Yes	No	No	No
4. Improving irrigation infrastructure	No	Yes	Yes	Yes	No
5. Optimising land	No	Yes	Yes	Yes	No
6. Applying SRI	No	Yes	Yes	Yes	No
7. Applying GP-PTT	No	Yes	Yes	Yes	No
8. Controlling pests and climate changes	No	No	No	No	No
9. Adopting agricultural insurance	No	Yes	Yes	Yes	No
10. Supervision and monitoring	No	No	No	No	No
Rice cluster development					
1. Mapping cluster regions	Yes	Yes	Yes	Yes	Yes
2. Strengthening cooperation and collaboration	No	No	No	No	No
3. Facilitating supporting infrastructure	No	No	No	No	No
4. Improving the capability of involved actors	No	No	No	No	No
5. Strengthening institutions	No	No	No	No	No
6. Creating and disseminating new technology	No	No	No	No	No
7. Developing off-farm industries	No	No	No	No	No

Source: Authors based on Indonesia's 2015-2017 regulations (MoA, 2015b, 2015c, 2015a, 2016d, 2017).
Note: the evaluation is based on OECD's criteria

Table 5.1 also evaluates the rice cluster development program. All except its first instrument do not meet any OECD criteria. While the instruments of *UPSUS swasembada padi* fulfil 22 of the 50 criteria evaluations, the instruments of the rice cluster development program meet only 5 of 35. The instruments of *UPSUS swasembada padi* are therefore much better designed than the ones of the cluster development program in the sense of OECD (2007). MoA (2016d) clearly explains the design of the cluster development program and explicitly determines regions of West Java targeted. On the implementation of instruments 2 to 7, no details such as budget allocations, staffing or technical guidelines are specified in policy documents of the national and regional governments.

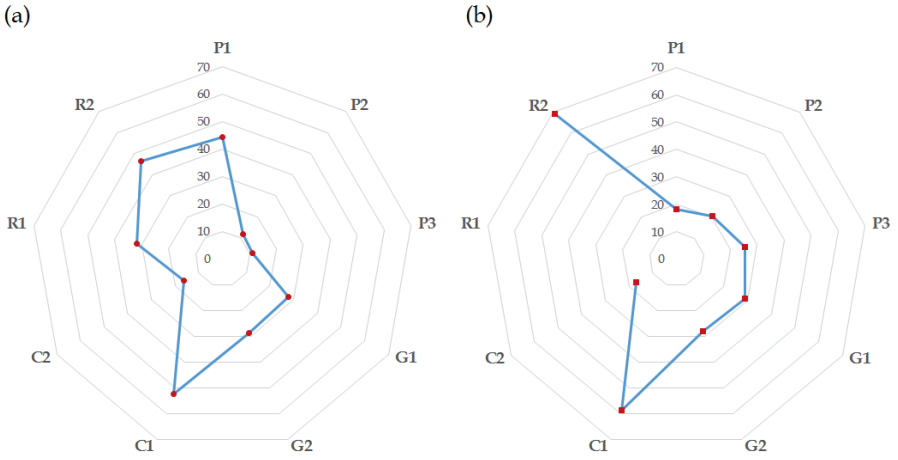
5.5. Alternative Policy Options for Increasing Productivity

As discussed in Sub-section5.4.1, farmer organisations could be an alternative to enhance farmers' access to the benefits of *UPSUS swasembada padi;* yet, this policy is not at all concerned with strengthening the benefits of these organisations within rice clusters for raising rice productivity. According to Law no. 19 on farmer organisations (MoLHR, 2013) and Decree no. 67 of the Minister of Agriculture (MoA, 2016a), farmer organisations (FOs) in Indonesia are defined as farmer groups (FGs), federations of farmer groups, crop associations or national agricultural commodity boards (MoA, 2016a). West Javanese farmers have been reported to be less interested in joining FGs (BPS, 2013c; SoAE, 2015). SoAE (2015) reports that until 2015 the number of rice farmer groups of West Java was about 19 thousand. On average, only one-fourth of total West Javanese rice farmers joined at least one FG. The highest participation rate exists in region R5 with the rate of about 39% of total rice farmers, followed by regions R4 and R6 with the ratio of 29% and 26%, respectively. Such low participation creates a challenge for

regional governments of West Java to spread the benefits of the two above-mentioned policy programs.

OECD (2012) emphasises that although the number of FOs in Indonesia is increasing, they have managerial problems, are highly dependent upon the support of other institutions and have no clear targets for their activities. FOs are commonly established for the purpose of attaining access to governments' support, and governments at the national and regional levels heavily intervene in their activities. Members' participation in the FO's activities is low, e.g., less than 50% of total members attend routinely group meetings because they argue that the FOs often fail to deliver benefits (Hermanto & Swastika, 2011). Third, cooperation between members and managers is poorly developed and social conflicts frequently occur.

This point is shown by Figure 5.7 which is based on the results of our own survey showing the frequency of determinants for joining FOs mentioned by farmers. Panels (a) and (b) of Figure 5.7 highlight the perception of member and non-member farmers, respectively. On one side, 51% of member farmers consider that social conflicts will occur during cooperation. Despite such conflicts, they also believe that reciprocal relationships are the reason why they are willing to cooperate with their neighbours. On the other side, 70% of non-member farmers are worried about unethical behaviour from other farmers. For example, about 20% of them have been cheated and have had a bad experience in cooperation. In addition, even more than one third of non-member farmers do not benefit from the organisations, for example in terms of high selling prices or low production costs.



Source: Authors based on authors' survey data.
Note: Panels (a) and (b) illustrate the frequency of perceived determinants influencing member farmers or non-member farmers, respectively, on building cooperation. P1 is reciprocal relationship. P2 denotes prospective partners. P3 is support for personal life. G1 is expected gains related to easy access to production inputs, markets, and government supports. G2 indicates expected benefits related to easy access to information. C1 is social conflicts. C2 denotes possible expenditure due to cooperation. R1 is estimated risk about unclear organisation management and R2 signifies unethical behaviour from others.

Figure 5.7. Factors Influencing Member and Non-member Farmers towards Cooperation.

5.5.1. Potential Benefits of Farmer Organisations for Rice Productivity

Kumar et al. (2018) suggest that the organisation of dairy smallholders increase their milk yields and net returns. We too find strong evidence for the benefits of FO membership for increasing rice farmers' productivity. Using propensity score matching (PSM) and OLS, we estimate model (5.1):

$$prod_i = f(D\_member_i, X_i). \quad (5.1)$$

Thus, we model productivity $prod_i$ of farmer i in tons of rice per hectare and year as a function of the membership D_member_i (D_member_i=1 signals membership). The vector of control variables X_i includes characteristics of the farmer and the farm as well as agro-cluster density.

Using PSM, we assess the treatment effect of membership on rice productivity by comparing member and non-member farmers who have similar observed attributes. This procedure can handle selection bias in observable covariates (Heckman et al., 1997). Thus, the membership effect is estimated as:

$$\begin{aligned} ATT &= E(\Delta | D\_member_i = 1) \\ &= E(prod_{i1} | D\_member_i = 1) - E(prod_{i0} | D\_member_i = 0) \end{aligned} \tag{5.2}$$

where ATT is the average treatment effect on the treated. $E(prod_{i1} | D\_member_i = 1)$ and $E(prod_{i0} | D\_member_i = 0)$ are the expected productivity of members and non-members, respectively.

The results in Table 5.2 show that members have a significantly higher rice productivity than non-members of about half a ton/ hectare. The result is robust for both matching approaches used[20]. This outcome is in line with Figure 5.2, which hypothesizes the positive effects of agro-clusters on rice productivity in the first phase of the production curve. This rise due to membership may be caused - as discussed in section 2 - by the fact that farmers' ability to increase scale efficiency and to mutually exchange technologies in regions of high agro-cluster density.

[20] An OLS estimation of (1) in Table C.1 finds also this positive impact of membership on rice productivity inside regions of higher agro-cluster density to be significant at the 5% level. The effect is with 0.19 tons/hectare smaller than the PSM result.

Table 5.2. PSM Results of the Effect of Membership on Rice Productivity

	Nearest neighbour		Kernel	
	Coefficient	**p-value**	**Coefficient**	**p-value**
ATT				
Membership dummy				
Member vs. non-member	0.72*** (0.28)	0.00	0.51*** (0.21)	0.00
Observations	858			
No. members	639			
No. non-members	219			

Source: Authors' calculation based on authors' survey data.
Note: The distribution of the propensity score is [0.18, 0.99]. Standard errors in parenthesis.

The potential of the positive role of FOs can also be seen from the case study of the FG "*Sarinah Organik*" located in the Bandung district of West Java (AoA, 2013). Initially, this farmer group faced poor irrigation infrastructure and polluted rice fields due to nearby textile factories. In 2007, its eight members set up an initiative to apply an integrated farming system to overcome these constraints. The governments of the province of West Java and of the Bandung district supported this initiative.

As a result, the FG's operated land increased by ten times, its rice productivity doubled to 8 tons/hectare, and its membership reached 138 farmers in 2013. Recently, this FG has succeeded to get its rice products organically certified based on USDA and European Union standards, which enabled exportation to Singapore. This remarkable success was made possible by three main factors. First, the farmer group showed independent activity facilitated by strong management and clearly identified purposes. Its leaders and members benefitted from the mutual cooperation. Second, the government was able to identify the actual needs of the beneficiaries and consistently supported growth of the activities. Third, solid collaboration

with other supporting institutions, such as universities or research institutions, helped to create such innovation.

5.5.2. Feasible Policy Improvements

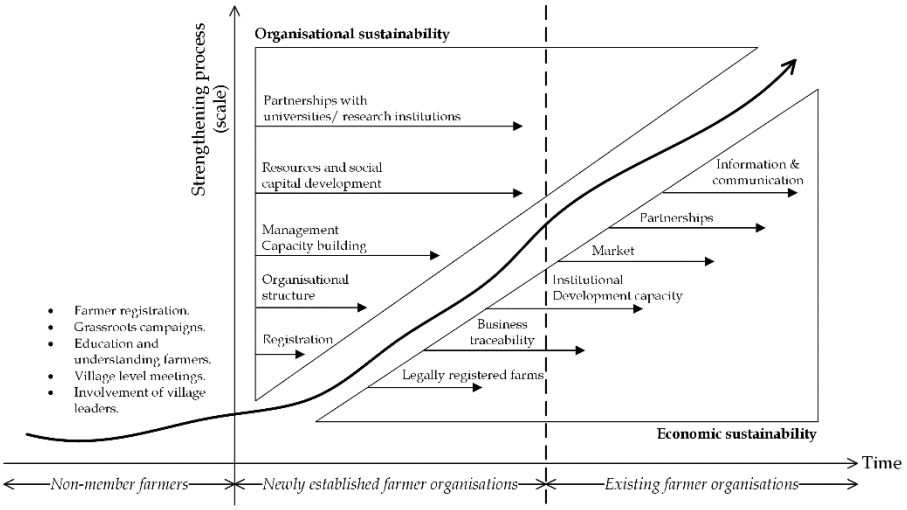
Strengthening the Role of Farmer Organisations

As discussed in the Sub-section 5.5.1, farmer organisations within agro-clusters allow member farmers to increase rice productivity. World Bank (2005) actually recommended the Indonesian government to reinforce the dissemination of production technology to all farmers for reaching increased crop productivity. However, the opportunity to utilise the potential of farmer organisations (FOs) for strengthening such organisations is not fully exploited by the two currently implemented policy programs for achieving rice self-sufficiency. Table 5.1 shows that the two polices are barely tailored, flexible and equitable. Additionally, farmers commonly act as passive recipients.

We thus suggest that strengthening farmer organisations as feasible and effective first policy improvement for addressing the weaknesses of the rice self-sufficiency current policies. This improvement primarily focuses on achieving organisational and economic sustainability of such organisations. Organisational sustainability is related to the aspects of organisational management and leadership. FAO (2014) points out that a strong farmer organisation is institutionally characterised as an active and self-motivated institution, collective planning and specific own purposes, shared responsibility and transparent management. Economic sustainability refers to the business stability of the FOs related to rice production and marketing. That is, FOs should ideally be able to generate profits sustainably in the sense of Doane and MacGillivray (2001) who define economic sustainability as the process of allocating and protecting scarce resources for increasing

incomes in the long-term. Figure 5.8 depicts the goal of this policy improvement: strengthened farmer organisations satisfying these two aspects of sustainability.

We suggest that the policy program of *UPSUS swasembada padi*, in particular, should be augmented to facilitate direct investment in FOs for improving farmers' capacities. Based on Figure 5.8, this improvement can be directed towards three possible groups of the FOs: non-member farmers, newly established FOs or existing FOs. Table C.2 elaborates possible instruments which involve all three governance levels to reach this goal.



Source: Authors.
Note: The y-axis denotes the scale of strengthening process, and x-axis represents the temporal order.

Figure 5.8. Strengthened Farmer Organisations

For the group of non-member farmers, the new policy instruments should be targeted to increase the attractiveness of FOs towards them. As an initial step, registration of all farmers is necessary to identify their current status and preferences. District governments collaborating with

stakeholders, such as Statistics Agency of Indonesia (BPS) or NGOs, and financially supported by national and provincial governments, should carry out this registration (Table B.2). As emphasised in Figure 8, consistent grassroots campaigns and routine trainings appear to be an effective and cost-efficient policy instrument for improving farmers awareness of FOs. As social interactions of neighbouring farmers have been shown to increase positive beliefs in cooperation (Braguinsky & Rose, 2009), organising regular meetings involving local community leaders and village institutions could be another effective policy instrument.

As newly established or "young" FOs[21] may suffer from poor management and weak relationships among members, , the new policy instruments should be directed to prioritising the achievement of organisational sustainability as stressed by FAO (2014). Figure 8 highlights five policy instruments for achieving this sustainability. Similar to the suggestion of Staber (2007a) and FAO (2014), the instruments aim at building social capital such as trust or reciprocity among members. Improving the management capacity of the organisational and financial administration are a crucial aspect to reinforce FOs. Enhancing the ability of leadership – developing vision, setting priorities, and improving the communication among members – is required to raise organisational sustainability as suggested by FAO (2014). Universities or research institutions could also help the government to implement these five policy instruments, for instance, by carrying out regular trainings on such skills or objective progress monitoring. Table B.2 summarises the role of each governmental level in West Java needed to implement this improvement.

[21]According to Regulation of Minister of Agriculture No. 67 (MoA, 2016a), Indonesian farmer organisations are categorised into 4 classes based on their competence level: *Kelas Pemula*, *Kelas Lanjut*, *Kelas Madya*, and *Kelas Utama* (Bahasa Indonesia for: beginner, intermediate, upper intermediate, and advanced classes, respectively) – thus, we regard the first three classes as young FOs.

For the group of the existing FOs, we suggest that policy instruments should be adopted which help to transform them from interest groups into business-oriented entities, that is, being targeted to achieve the economic sustainability of the FOs. They would not only help FOs to raise rice productivity, but also contribute to enhance members' incomes. Developing innovation and creating business networks should be prioritised to reach such economic sustainability. The "*Sarinah Organik*" could be one example. Figure 8 and Table B.2 explain six alternative policy instruments for reaching this aim: institutional legalisation, business traceability (the ability to identify and trace crucial requirements throughout rice business cycle), institutional capacity improvement, and market and partnership development. Regional governments should support FOs for improving the capacity of business-cycle management, such as production and inventory control.

Coordination Across Different Administrative Levels

The second policy improvement we would like to suggest is strengthening coordination across different governance levels. Niaounakis and Blank (2017) highlight that intensive coordination among different governmental levels is a crucial factor for policy success. Table 5.1, however, illustrates that the currently implemented policy programs are barely transparent and flexible. Two major issues cause are responsible for that. First, complex regulatory governance as applied by Indonesia in the form of a multi-regulatory system leading to numerous overlapping regulations (OECD, 2015) is likely to challenge or even impede the implementation of policies. Second, the centralisation style of the policy implementation may weaken coordination between governance levels. Section 5.4 stresses that multi-stakeholder involvement in *UPSUS swasembada padi* results in the need

for strong coordination among them. Naidoo (2013) emphasises that a rigid coordination style with centralised operating protocols and performance standards provokes problems with coordination. As a consequence, governments at provincial and district levels face constraints to design their own tailored policies as flexibility of policy development is severely restrained (Nasution, 2016).

Table C.2 offers several alternative policy instruments. At the national level, the government should develop a clear and comprehensive guidance for growth of rice productivity. Furthermore, it should provide a flexible coordination system by reducing the complexity of the regulatory base. This guideline can take the form of a single strategic planning document incorporating all existing regulations, for example in the way regulatory complexity was reduced in the European Union with the introduction of the single Common Market Organisation in the year 2007 (Silvis & Lapperre, 2011, p. 182). Such an approach would reduce regulatory conflicts and misinterpretations. This over-arching policy document could give freedom to regional governments in well-defined institutional ranges. This could, for example, resemble the approach adopted by the Common Agricultural Policy of the European Union regarding the freedom it grants to national governments in terms of maintaining voluntarily coupled support despite of the general decoupling of support (Ihle et al., 2017, p. 46). Such an architecture would allow regional governments to develop their own tailored and targeted policy instruments.

5.6. Summary and Conclusions

Rice self-sufficiency has been a central long-term policy goal of Indonesia. However, West Java experienced a decrease of average rice productivity of up to 11% in least productive districts of lowest rice productivity percentile since 2011. This productivity decline prevented the

production of about 800 thousand tons of rice corresponding to the annual consumption of about 9 million West Javanese people. Simatupang and Timmer (2008) stresses that importing rice for dealing with rice shortage in the domestic market is not well-perceived by the Indonesian government. The policies of *UPSUS swasembada padi* ("special efforts for rice self-sufficiency") and of rice cluster development have thus been set up to close the production gap. For analysing the quality of these policies, we focus on West Java because it is the province with the highest share of Indonesian population (about 18%) and it contributes about 15% to the national annual rice production.

This paper investigates the quality of these two policy programs at all three levels of governance. We apply the policy evaluation framework of (OECD, 2007) for ex ante assessment. The quality of *UPSUS swasembada padi* in the sense of OECD (2007) is mixed. While most of its ten instruments are targeted, tailored and flexible, barely any is transparent or equitable. This implies that the design of the instruments of *UPSUS swasembada padi* needs to be improved especially concerning the latter two properties in order to meet internationally accepted OECD standards. The picture is worse, and therefore the need for improvement is larger, for the rice cluster development program as none of its seven instruments except of the first one meets the OECD criteria. The main reason is that national as well as regional governments pay little attention to it and barely have own budgets for it. This finding stresses the need for improvement of the design of these two policy programs to reach rice self-sufficiency of Indonesia. We argue that strengthening farmer organisations is an effective and cost-efficient way to do so. Utilising propensity score matching and OLS estimation, we can show that farmers being members in such groups have a significantly higher per hectare rice yield of about half a ton than non-members. Farmers located

in agro-clusters of higher density produce about 0.2 tons per hectare more when they join at least one farmer organisation.

To reach this policy goal, we suggest two feasible improvements of the existing policies. These policies are putting virtually no emphasis on facilitating farmer cooperation for increasing productivity and are barely tailored, flexible, and equitable. Therefore, strengthening farmer cooperation through farmer organisations is very likely to raise productivity as farmers will gain easier access to existing support programs. Instruments for achieving this goal should be tailored to the degree of experience of farmer organisations and to non-members. Options can involve routine grassroots campaigns targeting non-members, improving the management and governance capacity for inexperienced organisations or establishing business partnerships with supply chain stakeholders for creating innovation for experienced organisations.

We also recommend to strengthen coordination between the three governance levels as second feasible policy improvement. Current policies suffer from a complex regulatory system and centralisation by the national government impeding the transparency and tailoring of existing support. The national government should develop an over-arching policy document which incorporates and combines all relevant existing regulations. Such a document would reduce regulatory complexity and allow regional governments to tailor it to local needs. Governments should ensure a consistent policy framework regardless of leadership changes.

The feasibility of the implementation of these two improvements can be threatened by low quality of extension service provision. As agricultural extension services are a crucial determinant for successful implementation, sufficient budget should be allocated for the recruitment, training and salaries of new and existing staff. However, AoAFCH (2013) reports a current lack of extension officers in West Java having only one quarter of

total extension positions staffed. Hence, the governments at all three governance levels should commit to prioritise the improvement of these services and to set time frames for completing it which can be accompanied by collaborating with local communities and educational institutions to set up service centres at village level.

Appendix C

C.1. Data Collection

We conducted a survey from 1,250 farmers located in 15 districts of West Java, from May to September 2016. For this survey, we designed a questionnaire consisting of four lists of question items related to the expected characteristics of prospective partners, expected benefits, as well as estimated costs and risk from being a member of cooperation. In order to select our respondents, we apply two selection stages. At first, we chose targeted districts by considering the combination of three aspects: agro-cluster density, poverty rate, and whether the properties of districts are mainly urban or mainly rural. We measure the agro-cluster density rd_s by applying the model of Fingleton et al. (2004).

$$rd_s = e_s - \left(\frac{e}{E}\right) E_s$$

Variables e_s and e denote the observed number of farmers in sub-district s and in West Java, respectively. Variables E_s and E are the total employee number of that sub-district and of West Java, respectively. From this measure, the higher the value of rd_s in a sub-district, the higher the density of the agro-cluster in that given region is. Last, we randomly selected farmers located in the targeted regions. Since focusing on rice

farming, we exclude farmers who cultivate other crops. Accordingly, we have 858 rice farmers in our data.

Prior to analysing our data, we utilise component principal procedure with varimax rotation to group the lists of questions. Streiner (1994) suggests that question items which have factor loadings larger than 0.4 are accepted.

Table C.1. OLS Estimation Result of the Effects of Membership on Rice Productivity

	Dependent variable: rice productivity	
Variable	**Coefficient**	**Standard error**
Membership dummy	1.09***	0.10
Interaction:		
D_Member * Agro-cluster density	0.19***	0.02
Farmer Characteristics		
Male dummy	0.04	0.11
Age	-0.01***	<0.01
Year of schooling	0.02	0.01
Job dummy	0.38*	0.21
Household size	0.05	0.03
Asset	0.001***	<0.01
Farm size	-0.26***	0.08
Regional Properties		
Rural dummy	-0.22**	0.10
Constant	4.59***	
Observations	858	
R-squared	0.24	

Source: Authors' calculation.
Note: one, two, three asterisks denotes significance at 10%, 5%, and 1%, respectively.

Table C.2. Alternative Policy Options of Rice Self-sufficiency for Strengthening Farmer Groups inside Agro-clusters

National Government	Provincial Government	District Government
Non-member farmers		
1. Facilitate regional governments to create their own policy measures, either finance or legal procedures. 2. Provide extension services.	1. Facilitate district governments to innovate their own policy measures. 2. Provide extension services at district and village levels. 3. Routine grassroots campaigns.	1. Register all farmers, including attitudes, skills, resources and expectations. 2. Routine grassroots campaigns on the role of farmer groups and all their activities. 3. Extension services for educations at villages. 4. Approach local leaders of community to establish routine meetings at village levels. 5. Involve village institutions to attract farmers to join in the groups.
Newly Established Farmer Groups		
1. Facilitate regional governments to create their own policy measures, either finance or legal procedures. 2. Provide extension services.	1. Facilitate district governments to innovate their own policy measures. 2. Provide extension services at district and village levels. **3.** Create partnerships with research institutions/universities.	1. Registration and institutional legalisation on newly established farmer groups. 2. Organisational sustainability: (1) Design organisational structure: leadership, membership rules, purposes. (2) Build management capacity (FAO, 2014). • Organisational management and leadership. • Financial management. (3) Establish routine meetings facilitated by extension officers or village facilitators. 3. Economic sustainability: business traceability.
Advanced Farmer Groups		
1. Facilitate regional governments to create their own policy measures, either finance or legal procedures.	1. Facilitate district governments to innovate their own policy measures. 2. Create partnerships: • Research institutions/universities.	1. Registration and institutional legalisation on existing farmer organisations. 2. Organisational sustainability: (1) Build management capacity (FAO, 2014).

Table C.2. (Continued)

National Government	Provincial Government	District Government
1. Create partnerships with exporters, national-scale companies, and international institutions.	1. Buyers and food industries. 2. Develop ICT.	• Organisational management. • Financial management. (1) Networking and advocacy. (2) Establish routine meetings facilitated by extension officers or village facilitators. 1. Economic sustainability: (1) Improve institutional development capacity (FAO, 2014). • Business-cycle management. • Process and product improvements. (2) Build partnerships with buyers and food industries. (3) Develop ICT system.
Policy and Legal Frameworks		
1. Establish one formal guideline for policy measures, which include current policy measures of rice self-sufficiency, farmer cooperation, and agro-clusters based on existing regulations.	1. Establish legal frameworks on food self-sufficiency, farmer cooperation, and agro-clusters which explain national regulations. 2. Establish one formal guideline for policy measures at the provincial level.	1. Establish legal frameworks on food self-sufficiency, farmer cooperation, and agro-clusters which explain national and provincial regulations. 2. Establish one formal guideline for policy measures at the district level.
Regional Settings (MoA, 2016c)		
1. Determine national strategic regions for rice production. 2. Improve supporting infrastructures inside rice clusters.	1. Determine strategic districts for rice production. 2. Develop rice clusters. 3. Improve supporting infrastructures in rice clusters, such as road and irrigation, connecting with between districts.	1. Determine strategic villages for rice production. 2. Improve supporting infrastructures inside rice clusters, such as road and irrigation, connecting between villages.

Source: Author

CHAPTER 6
Synthesis

6.1. General Discussion

The Association Southeast Asian Nation (ASEAN, 2012)states that all member countries have experienced significant reduction of agricultural food production. This organisation also points out that farmers of member countries have been facing an unfavourable environment which made many of them uncompetitive and unprofitable when they engaged with liberalised markets. Nonetheless, ASEAN (2012) still insists that agriculture remains a crucial component in rural development for reducing rural poverty across Southeast Asian countries. It, therefore, has established a framework for rural development and poverty eradication for the period 2016 – 2020. This framework promotes regional specialisation via the One Village One Product (OVOP) programme and rural community driven development (ASEAN, 2017, p. 4). Although this thesis studies only one region of Indonesia, insights of this research on the role of regional specialisation for agricultural growth can be valuable for other regions in Indonesia as well as other Southeast Asian countries. These insights may offer alternative pathways to advance agro-clusters because these countries often have similar farming characteristics in terms of topography, climate or the importance of smallholder farming (ASEAN, 2012).

The literature on agglomeration economies remains inconclusive and rare in the empirical analysis of agglomeration effects in the agricultural sector. Contrary to the insight of Jacobs externalities (De Groot et al., 2009),

this thesis assesses to what extent specialisation in agriculture increases agricultural productivity and thus reduces rural poverty. As defined in Subsection 1.3.1, Chapter 2 confirms that Marshall-Arrow-Romer (MAR) externalities within geographically concentrated farming activities are one predominant factor reducing poverty. Chapter 2 also adds to the literature on rural development, proving that the agricultural sector is a crucial determinant for reducing rural poverty in West Java. Whether agriculture has a similar role in other regions of ASEAN countries needs to be clarified by future research.

Schmitz (1999) argues that, along with the advantages of such externalities, cooperation between farmers within agro-clusters allows them to enhance income. OECD (2001b, p. 15) states '[...] each area has a specific capital – its "territorial capital" […].' Camagni (2009) suggests that such capital may include tangible aspects (e.g. natural resources, infrastructure, capital stock) and intangible aspects (e.g. human capital, social capital, agglomeration economies). Together, they play a crucial role in defining the economic performance of farmers and of the regions in which they are located. Whether intangible aspects can affect the performance of farming activities is questionable. According to Camagni (2009), localised externalities and proximity relationships in a specific region constitute a capital of psychological and political nature. This capital may affect farmer institutions within agro-clusters. Taking West Javanese farmers as the study focus, Chapters 3 and 4 clarify these aspects by investigating the socio-economic interactions between proximate farmers.

Every chapter of this thesis contributes to the understanding of one aspect of the role of agro-clusters for rural development. Chapter 2 provides empirical evidence that agriculture remains an important activity for reducing rural poverty. Through analysing spatial dependence at the sub-district level, the geographical concentration of specialised farming activities

leads to lower poverty rates. Chapter 3 and 4 analyse the determinants of farmer cooperation and the effects of competitive pressure between proximate farmers on farmer's behaviour at the micro-economic level. Cooperation between proximate farmers is found to evolve within the higher density of agro-clusters (Chapter 3). However, the competitive pressure, which also arises within these agro-clusters, reduces the level of cooperative behaviour of farmers and increases their level of selfishness (Chapter 4). The findings of Chapters 3 and 4 emphasise the need to balance between cooperation and competition, e.g., by strengthening collective action within agro-clusters. Chapter 5 elaborates on the role of the government in reinforcing these institutions facilitating collective action by looking at effects of farmer groups on improvements in rice productivity. Sections 6.2 to 6.5 synthesise the main insights gained in each chapter, answering the research questions formulated in section 1.2.

6.2. Agro-clusters and Rural Poverty

Chapter 2 examines the links between agro-clusters and poverty rates. ASEAN (2012) finds uneven wealth distribution across regions in member countries: rural regions show structurally higher poverty rates than urban regions. For this purpose, a spatial econometric analysis is used, which accounts for spatial interactions between neighbouring sub-districts of West Java since farming activities tend to be spatially concentrated. According to Anselin & Bera (1998), such models can capture spatial-spillover effects among neighbouring regions neglected in OLS models. Six econometric specifications model the sub-district poverty rate as a function of various agro-clusters characteristics - input- and output-based indexes of concentration and specialisation of farming – as key explanatory variables. The input-based index is quantified by horizontal clustering (Fingleton et al.,

2004) and the output-based index is measured by the relative Krugman specialisation (Krugman, 1991).

The core insights of this chapter are that, first, the higher the agro-cluster density of a sub-district is, the lower its poverty rate. Second, sub-districts with higher specialisation in crop production are found to have lower poverty rates. Similar to the finding of Barkley and Henry (1997) highlighted in page 5, agro-clusters thus play a significant role in poverty reduction. Thereby, both findings empirically prove the study of McCulloch et al. (2007) that agriculture is an essential sector to accelerate the reduction of poverty in Indonesian rural regions as targeted by UN's SDGs framework in 2030, as mentioned in Section 1.1.

In line with the study of Capello (2002) discussed in Sub-section 1.3.1, Chapter 2 finds that the effect of agro-clusters on poverty reduction is found to barely result in spill-over effects to neighbouring regions. Travel time to the nearest big city and the capital-city – measured by the ratio between population size of Jakarta and distance to this city – are found to have a smaller impact on poverty reduction in regions where farming activities are spatially concentrated. This finding indicates that localisation externalities of the MAR type are more pronounced in the context of agricultural growth. Proximate farmers share inputs, knowledge, information, and labourers with each other. Thereby, agricultural innovation and efficiency gains in production can be created and transmitted inside agro-clusters. However, the finding of Chapter 2 also highlights the presence of negative externalities within agro-clusters due to the high number of farmers as suggested by Duranton et al. (2010). Farmers facing such negative-externalities will be less flexible when sourcing production inputs and marketing products (Deichmann et al., 2008).

6.3. Farmer Institutions within Agro-clusters

As elaborated in Sub-section 1.3.2, Huggins and Thompson (2017) point out that interpersonal networks are based upon the interactions and relationships among involved actors to access knowledge beyond their boundaries. Hence, Chapters 3 and 4 closely examine farmer institutions by assessing how farmers build cooperation and react to competitive pressure from their peers. Building on Porter (1990), farmer institutions involving cooperation and competition are two crucial attributes of agro-clusters (see Figure 1.1). When farmers express trust towards their neighbours inside an organisation, that expression strengthens a network within that organisation. Confirming the findings of Braguinsky and Rose (2009) as discussed in Sub-section 1.3.2, this thesis finds in Chapters 3 and 4 that both cooperation and competition amplify within agro-clusters. Sub-section 1.3.2 elaborates that farmers may strategically decide to cooperate or to compete with neighbours for achieving income improvements. Therefore, it is necessary for policy makers to find the right balance between cooperation and competition inside such clusters as discussed in Sub-section 1.3.2. The following sub-section elaborates on the core insights gained concerning each of the two forces.

6.3.1. Farmer Cooperation

Chapter 3 assesses determinants of individual farmers' decisions for or against establishing cooperation with other farmers when they are located spatially close to each other. Building on the theory of behavioural interactions, farmer cooperation is modelled through a two-stage decision process: the "willingness" stage and the "actual cooperation" stage. The Heckman selection model is utilised to estimate this two-stage model. Bolwig et al. (2009) argue that this selection specification is able to model a

dichotomous dependent variable in order to obviate sample selection bias. The dependent variable is binary: whether or not farmers have the willingness to build cooperation and whether or not they actually cooperate with their neighbours in the case that they show a positive attitude. The dependent variable takes unity if farmers have the willingness to cooperate or actual cooperation, and zero otherwise.

The core insights of Chapter 3 are that farmers located in agro-clusters are likely to actually cooperate with their neighbours by sharing production inputs and technology as well as crop marketing. Such cooperation enhances their income level. These findings imply that cooperation could allow West Javanese farmers to deal with crucial constraints related to farming practices for productivity improvements as highlighted by McCulloch et al. (2007) in page 1. Regarding the factors driving farmer decisions on cooperation, Chapter 3 also finds that the "willingness" towards cooperation is most strongly influenced by personal characteristics of farmers such as whether they cultivate rice or not, gender and assets. Psychological aspects play a significant role in shaping a farmer's attitudes towards cooperation (Dowling & Chin-Fang, 2007). In the second stage, farmers who have a positive attitude may not actually engage in cooperation. This decision relies upon external environments, such as social interactions, the density of agro-clusters, distance, regional poverty rates, and whether or not the region farmers live in are rural or urban. Prospect theory of Kahneman (2011), as discussed in page 6, implies that farmers decide to work together with their neighbours when they believe that the advantages of such cooperation exceed its costs.

The benefits of farmer cooperation inside agro-clusters are in line with Li and Geng (2012) and Geldes et al. (2015) (see Sub-section 1.3.2). They claim that individuals easily build cooperation as they could frequently interact one another within such clusters. Spatial proximity reduces barriers

to establishing networks over regional administrative boundaries (Boschma, 2005). Since proximity is an advantage, adjacent farmers can interact with one another more intensively. The finding confirms Hanslaet al. (2008) and Tsusaka et al. (2015) who find that from the Southeast Asian context, individual decisions towards cooperation are influenced by personal characteristics, economic factors, and social interactions between neighbours.

6.3.2. Farmer Competition

Chapter 4 analyses the effects of peer pressure farmers perceive within agro-clusters on their behaviour towards neighbouring farmers. Building on the theories of planned behaviour and behavioural interactions, two different models are developed for assessing the impacts of peer pressure on farmers' cooperative behaviour and their self-interest behaviour. The theoretical framework serves to deduce and econometrically test several explicit hypotheses. The dependent variables of the OLS models are behavioural variables measuring cooperative and self-interest behaviour quantified by factors constructed based upon a 5-point Likert scale from a set of question items. Peer pressure as the key explanatory variable is measured by two variables: the degree of pressure and the comprehensiveness of pressure. The former quantifies the extent farmers generally feel pressure from their peers on a scale between 0 and 10. The latter captures farmers' behavioural responses to other farmers' actions quantified by six factors of specific farming practices based on a 5-point Likert scale.

The main insights of Chapter 4 are that the marginal effect of the degree of pressure is not constant on both cooperative and self-interest behaviour. Farmers located in sub-districts of higher agro-cluster density show the highest level of cooperative behaviour when they perceive low

degrees of pressure from their peers. This behaviour decreases and shifts towards more self-interest behaviour as the degree of peer pressure rises. Several reasons why farmers tend to adopt selfishness are identified based on the variable measuring the comprehensiveness of the pressure. First, farmers attain less information on new seeds and production technologies relative to others. Similar to the points highlighted in page 1, farmers often face limited access to crucial production inputs and crop marketing. They report to be satisfied with the yields they earned. Third, they envy the change of income opportunities of others.

In line with the arguments in Sub-section 1.3.2, all findings of Chapter 4 augment the literature on competitive pressure within the agglomeration economies (Staber, 2007a; Braguinsky & Rose, 2009). Staber (2007a) claims that spatial proximity may not be necessarily associated with a strong cognitive and organisational proximity. Farmers under pressure due to high density of farming clusters may conceal crucial information from their neighbours when they expect that this behaviour may offer gains. Likewise, James and Hendrickson(2008, p. 352) argue that "an increase in the perceived economic pressure a farmer feels will result in a lowering of that farmer's ethics".

6.4. Agro-clusters and Government Policy

ASEAN (2012, p. 8) emphasizes that "For years, agriculture received less public investments, with weak domestic markets, poor rural infrastructure, inaccessible financial services, inadequate agricultural extension services and deteriorating natural resource base [...]". Dorward et al. (2004) highlight that government policies have been playing an active role in the agricultural growth in Asia over the last four decades. Porter (1990) sees this role as an essential attribute of geographically concentrated economic activities (see Figure 1.1). Hence, Chapter 5 investigates the role of

the government in increasing farm productivity within agro-clusters. The analysis of this chapter is complementary to the findings of Chapters 3 and 4. Analysing the case of rice clusters in West Java, Chapter 5 is divided into two parts: evaluating the quality of existing policies for achieving Indonesian rice self-sufficiency – *UPSUS swasembada padi* and rice cluster development – and suggesting and analysing the effect of rice farmer organisations as a complementary policy tool for raising rice productivity. In the first part, the policy evaluation utilises five criteria defined by OECD (2007). OECD (2007) suggests that these criteria could help policy-makers to allocate scarce resources and budgets in efficient ways, and thus achieving specific desired outcomes. The second part uses propensity score matching and an OLS model for empirical analysis. The results of this second part are used as a justification for policy improvements for rice self-sufficiency in Indonesia.

The main insights of Chapter 5 are that both existing policies can potentially be improved since they largely do not meet the OECD criteria. Farmer organisations appear to be a promising tool for this policy improvement as shown to allow farmers to increase rice productivity on average if joining these organisations. Pingali and Xuan (1992) find that Viet Nam became the largest rice exporter among all Southeast Asian countries because it shifted production in the 1980s to collective farms. Section 1.1 shows that Indonesia has lower rice productivity than other Southeast Asian countries; hence, the policy improvement could allow Indonesia to increase productivity at least at the same pace as other countries in the long-term.

These findings add to the literature on the benefits of agglomeration economics on firms' productivity (Torre & Rallett, 2005; Geldes et al., 2015) through providing empirical evidence that agro-clusters allow farmers to increase productivity when farmers work together with their neighbours. Despite the large investments to be taken for implementing the existing

policy instruments, rice productivity in Indonesia has not been able to keep up at the pace of population growth. In Chapter 5, a yield gap of rice production from 1993 to 2015 for West Java alone has been estimated. In line with the ASEAN framework discussed in Section 6.1, the results of Chapter 5 suggest that the Indonesian government should not undertake large investments in subsidised inputs and agricultural infrastructure in the absence of strong farmer organisations, but should strengthen these organisations instead.

6.5. Critical Reflection

This thesis fills the research gap of the effects of agro-clusters on rural poverty in the literature on agglomeration economics and rural development. Most current studies focus on urban settings and theoretically analyse why firms are geographically concentrating in a certain region instead of other regions (Krugman, 1991; Henderson, 1995). Through the lens of the analysis of farmers' individual behaviour and of aggregated socio-economic properties at the regional level, this thesis augments the empirical evidence on the interactions of agglomeration economics and regional development with a special focus on geographically concentrated farming activities.

The analysis in this thesis is subject to a number of limitations, several of them related to challenges in the measurement of core economic concepts. Chapter 2 quantifies agro-clusters as the output-based measure by Krugman relative to specialisation. Palan (2010) suggests that this index cannot decompose large interregional or inter-sectoral disparities across regions. Hence, we are not able, for instance, to distinguish regional competitiveness among sub-districts within West Java. The attitude measurements adopted in Chapter 3 do not comprehensively measure the psychological characteristics of farmers which might be decisive for influencing their

decision in favour of cooperation. As a consequence, we miss explaining why farmers have different attitudes towards cooperation; this difference is based on their individual rationality (Binmore, 2009). This rationality might vary between different scenarios of gains and losses in relation to cooperation for income improvements (Kahneman, 2011). We measure peer pressure in chapter 4 by quantifying the comprehensiveness and the degree of such pressure. The comprehensiveness measure may not distinguish peer pressure from different impact channels on, for example, learning strategies, output and input markets, and economics of scale in marketing. Individual farmers may react differently to these different channels. Some farmers may get too much pressure when they have no access to superior seeds or cheaper fertilisers, but some others may be worried about getting buyers. We therefore cannot elaborate individual perceptions on these different channels separately. Chapter 5 suffers from limited data availability for the analysis of policy evaluation. I evaluate the policies of Indonesian rice self-sufficiency only based on accessible policy documents. Such evaluation lacks the viewpoints of other stakeholders such as farmers, NGOs or extension officers.

In all chapters, econometric methods are applied. Kennedy (2003) points out that these methods empirically analyse economic relationships between variables intended to capture economic phenomena. However, I would like to reflect now on several caveats related to the research methods used. The spatial econometric models as used in Chapter 2 are estimated using cross-section data and therefore do not take time into consideration, although this might be important for the economic analysis of the development of poverty. Therefore, inference about the spatial-temporal association of agro-clusters and poverty rates was not possible. In Chapter 3, reversed causality or endogeneity could be a critical issue, especially between cooperation and income as farmers may also cooperate with their

neighbours for the sake of income improvements. This problem may also exist in Chapter 4, between farmer behaviour and income. Farmers might exhibit selfishness or cooperative behaviour because they intend to increase income. Because of this problem, we are not sure about the causal relationships between dependent and explanatory variables. Furthermore, the limited data available only from the national and regional governments for Chapter 5 could threaten the objectivity and reliability of the data and thus of the policy analysis.

A number of alternative approaches may be useful to overcome these limitations. Palan (2010) recommends that despite the significance of the Krugman specialisation index, the Theil index could be an alternative for future research. A spatial-dynamic analysis could be an insightful option to capture dynamic responses over time through spatial econometric specifications with panels of data in Chapter 2. To address the issue of endogeneity in Chapters 3 and 4, alternative econometric models could be applied for further research, such as IV instruments or truncated regression models (Verbeek, 2012). In addition, the complexity of human behaviour might be addressed by a dynamic analysis based on a panel dataset (Hsiao, 2007). The analyses in Chapters 3 and 4, however, use a cross-section dataset so that the analyses cannot deal with the dynamic effects of agro-clusters on cooperation, competitive behaviour and income. For further research, it might be relevant to apply panel models. Experimental methods (Crawford, 1997) or agent-based modelling (Jackson et al., 2017) could be an alternative to investigate the interactions between proximate farmers in the perception of individual farmers, thus extending the findings of Chapters 3 and 4. Future research could empirically analyse the impact of the policy from an ex-post perspective, extending Chapter 5. Such an analysis should consider the perception of all involved actors, which include farmers as the beneficiaries, government institutions, politicians, and other stakeholders.

I would also like to highlight the main challenge in applying these alternative approaches, which is the availability of suitable data. Indonesia has a ten-year data collection policy for poverty measurement or agricultural censuses. As a consequence, dynamic spatial econometric specifications could not be feasibly applied because the necessary panel datasets are unavailable, particularly at sub-district level. Although providing such data is costly, the Indonesian government needs to prioritise data collection in the shorter periods. Also econometric models based on panel datasets to analyse cooperation and competition between neighbouring farmers becomes problematic due to the requirement of time-series datasets. Hence, agent-based modelling could be an alternative to handle the limited data available. This approach is computationally intensive to observe the behaviour of any number of agents and their interactions over time (Jackson et al., 2017). A few survey rounds are also required to conduct the ex-post evaluation for the analysis of Chapter 5. The data related to the perception of other related actors are not publicly available and not all variables of interest in this thesis are included in current agricultural databases.

According to Martin and Sunley (2003), the phenomenon of economic clusters is a complex system including geographical scale, internal and external socio-economic dynamics, business strategy, knowledge and innovation concepts. Consequently, efforts to investigate this phenomenon should embrace multidimensional aspects. As this thesis only focuses on the attributes of cooperation and competition between neighbouring farmers within agro-clusters in response to income improvements, there is still a lot to be understood about the remaining attributes of agro-clusters (as illustrated in Figure 1.1). For instance, the vertical relationships between West Javanese horticultural farmers and food or retail industries is barely understood. To what extent do these farmers benefit from established farming contracts with retailers, given the rapid rise of Indonesian retailers?

To what extent do horticultural farmers associations influence their bargaining power towards retailer industries? Does their location within agro-clusters make any difference?

Even though all the evidence generated by this thesis comes from the Indonesian province of West Java, the results could potentially also hold for other Indonesian regions, for entire Indonesia and other Southeast Asian countries. However, this generalisation needs to be empirically confirmed. Regardless of this pending generalisation, this thesis has helped to enrich the scientific debate and the literature on the role of agriculture in poverty reduction in rural regions, and the role of social capital inside agro-clusters.

List of References

ADB. (2015). *Asian Development Outlook 2015: Financing Asia's Future Growth*. Manila: ADB (Asian Development bank).

AIAT. (2016). *Guidance for Rice Cultivation using Jajar Legowo Super [Indonesian version]*. Indonesian Agency for Agricultural Research, Ministry of Agriculture: Jakarta.

Adriani, F., and S. Sonderegger. 2015. Trust, trustworthiness and the consensus effect: An evolutionary approach. *Review of. European Economic Review* 77:102-16.

Ahmed, M. H., & Mesfin, H. M. (2017). The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. *Review of. Agricultural and Food Economics* 5 (1):6.

Ainembabazi, J. H., van Asten, P., Vanlauwe, B., Ouma, E., Blomme, G., Birachi, E. A., . . . Manyong, V. M. (2017). Improving the speed of adoption of agricultural technologies and farm performance through farmer groups: evidence from the Great Lakes region of Africa. *Agricultural Economics*, 48(2), 241-259.

Alcacer, J. (2006). Location choices across the value chain: How activity and capability influence collocation. Management Science, 52(10), 1457-1471. doi:10.1287/mnsc.1060.0658

Alkire, S., & Robles, G. (2015). Multidimensional Poverty Index—*Winter 2015/16*: *Brief Methodological Note and Results*. from Oxford Department of International Development, University of Oxford.

Alpmann, J., & Bitsch, V. (2015). Exit, Voice, and Loyalty in the Case of Farmer Associations: Decision-Making of Dairy Farmers during the German Milk Conflict. *International Food and Agribusiness Management Review, 18*(4), 61-84.

Ajzen, I. (1991). The Theory of Planned Behaviour. *Organisational Behaviour and Human Decision Processes*, 50(2), 179-211.

Amiti, M., & Cameron, L. (2007). Economic Geography and Wages. *Review of Economics and Statistics*, 89(1), 15-29.

An, J., Cho, S. H., & Tang, C. S. (2015). Aggregating Smallholder Farmers in Emerging Economies. *Production and Operations Management*, 24(9), 1414-1429.

Anríquez, G., & Stamoulis, K. (2007). Rural development and poverty reduction: is agriculture still the key?

Anselin, L., & Bera, A. K. (1998). Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In A. Ullah & D. E. A. Giles (Eds.), *Handbook of Applied Economic Statistics* (pp. 237-289). New York: Marcel Dekker.

AoA. (2013). *Profil Kelompok Tani Sarinah Organik* [*Profile of 'Sarinah Organik' Farmer Group*]. Bandung: Agency for Agriculture, Bandung Regency.

AoAFCH. (2013). *Medium-term Strategic Plans for Agriculture, 2013-2018*. Bandung: Agency of Agriculture Food Crops and Horticulture, West Java Province.

ASEAN. (2012). *ASEAN Framework Action Plan on Rural Development and PovertyReduction 2011 - 2015*. Jakarta: Secretariat of the Association of Southeast Asian Nation.

ASEAN. (2017). *ASEAN Framework Action Plan on Rural Development and Poverty Reduction 2016-2020*. Jakarta: Secretariat of the Association of Southeast Asian Natio.

Aydogan, N., & Lyon, T. P. (2004). Spatial proximity and complementarities in the trading of tacit knowledge. *International Journal of Industrial Organisation*, 22(8-9), 1115-1135.

Balland, P. A. (2012). Proximity and the Evolution of Collabouration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies, 46*(6), 741-756.

Ballard, T. J., Kepple, A. W., & Cafiero, C. (2013). *The Food Insecurity Experience Scale: Development of a Global Standard for Monitoring Hunger Worldwide*.

Bardhan, P. (1993). Analytics of the institutions of informal cooperation in rural development. *World Development*, 21(4), 633-639.

Barkley, D. L., & Henry, M. S. (1997). Rural Industrial Development: To Cluster or Not to Cluster? *Review of Agricultural Economics*, 19(2), 308-325.

Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy*, 38(2), 318-337.

Bergstrom, T. C. (2002). Evolution of social behaviour: Individual and group selection. *Journal of Economic Perspectives, 16*(2), 67-88.

Binmore, Ken. 2009. *Rational Decision*. Edited by Richard Blundell, The Gorman Lectures in Economics. New Jersey: Princeton University Press.

Board of Agricultural Extensions of West Java of Indonesia. (2015). *Information System on Agricultural Extensions* [Indonesian version]. Bandung, Indonesia.

Boari, C., Odorici, V., & Zamarian, M. (2003). Clusters and rivalry: does localization really matter? *Review of. Scandinavian Journal of Management*, 19 (4):467-89.

Bolwig, S., Gibbon, P., & Jones, S. (2009). The Economics of Smallholder Organic Contract Farming in Tropical Africa. *World Development*, 37(6), 1094-1104.

Bommer, M., Gratto, C., Gravander, J., & Tuttle, M. (1987). A Behavioural-Model of Ethical and Unethical Decision-Making. *Journal of Business Ethics, 6*(4), 265-280.

Boschma, R. A., & Lambooy, J. G. (2002). Knowledge, market structure, and economic coordination: Dynamics of industrial districts. *Growth and Change, 33*(3), 291-311. doi:Doi 10.1111/1468-2257.00192

Boschma, R.A. (2005). Role of proximity in interaction and performance: Conceptual and empirical challenges. *Regional Studies*, 39(1), 41-45.

BPS. (1990, ..., 2017).*West Java in Figure 1990, ..., 2017*. Statistics Agency of West Java. Bandung: BPS.

BPS. (2010). *Peraturan kepala BPS 37/2010 tentang klasifikasi perkotaan dan perdesaan (Decree of head of the Statistics Indonesia 37/2010 on the classification of rural and urban regions)*. Jakarta: Statistics Agency of Indonesia.

BPS. (2011). *Pendataan Program Perlindungan Sosial (Data Collection for Social Protection Programs)*. Jakarta: Statistics Agency of Indonesia.

BPS. (2013a). *Jakarta dalam angka 2013 (Jakarta in figures 2013)*. Statistics Agency of Jakarta. Jakarta: BPS.

BPS. (2013b). *Jawa Barat dalam angka 2013 (West Java in figures 2013)*. Statistics Agency of West Java. Bandung: BPS.

BPS. (2013c). *Sensus Pertanian (Agricultural Census)*. Statistics Agency of Indonesia. Jakarta: BPS.

BPS. (2015a). *West Java in Figure 2015*. Statistics Agency of West Java. Bandung: BPS.

BPS. (2015b). *Statistics for Food Crop Production of West Java, 2011 - 2015*. Bandung: Agency for West Java Statistics.

BPS. (2017). *Profile of Indonesian Poverty September 2017*. News on Official Statistics No. 05/01/Th. XXI, 2nd of January 2018. Statistics Agency of Indonesia: Jakarta: BPS.

Besley, T., Burgess, R., & Esteve-Volart, B. (2007). *The policy origins of poverty and growth in India.*

Braguinsky, S., & Rose, D. C. (2009). Competition, cooperation, and the neighbouring farmer effect. *Journal of Economic Behaviour & Organisation*, 72(1), 361-376.

Brañas-Garza, P. (2006). Poverty in dictator games: Awakening solidarity. *Journal of Economic Behaviour & Organisation, 60*(3), 306-320.

Brasier, K. J., Goetz, S., Smith, L. A., Ames, M., Green, J., Kelsey, T., . . . Whitmer, W. (2007). Small Farm Clusters and Pathways to Rural Community Sustainability. *Community Development*, 38(3), 8-22.

Breschi, S., & Lissoni, F. (2001). Localised knowledge spillovers vs. innovative milieux: Knowledge "tacitness" reconsidered. *Papers in Regional Science, 80*(3), 255-273.

Burger, K., Kameo, D., & Sandee, H. (2001). Clustering of Small Agro-processing Firms in Indonesia. *International Food and Agribusiness Management Review*, 2(3/4), 289-299.

Cali, M., & Menon, C. (2013). Does Urbanization Affect Rural Poverty? Evidence from Indian Districts. *World Bank Economic Review*, 27(2), 171-201.

Camagni, R. (2009). Territorial Capital and Regional Development. In R. Capello & P. Nijkamp (Eds.), *Handbook of regional growth and development theories* (pp. 118-132). Cheltenham, UK: Edward Elgar Publishing Limited.

Capello, R. (2002). Entrepreneurship and Spatial Externalities: Theory and Measurement. *Annals of Regional Science*, 36(3), 387-402.

Cassi, L., & Plunket, A. (2014). Proximity, network formation and inventive performance: in search of the proximity paradox. *Annals of Regional Science, 53*(2), 395-422. doi:10.1007/s00168-014-0612-6

Chaserant, C. (2003). Cooperation, contracts and social networks: From a bounded to a procedural rationality approach. *Journal of Management and Governance*,7(2),163-186.

Coad, A., & Teruel, M. (2013). Inter-firm rivalry and firm growth: is there any evidence of direct competition between firms? *Industrial and Corporate Change*, 22(2), 397-425.

Combes, P.-P., & Gobillon, L. (2015). The Empirics of Agglomeration Economies. In G. Duranton, J. V. Henderson, & W. Strange (Eds.), *Handbook of Regional and Urban Economics* (Vol. 5A, pp. 247-347). Amsterdam, North-Holland.

Cravo, T. A., & Resende, G. M. (2013). Economic Growth in Brazil: A Spatial Filtering Approach. *Annals of Regional Science*, 50(2), 555-575.

Crawford, V. P. (1997). Theory and experiment in the analysis of strategic interaction. In D. M. Kreps & K. F. Wallis (Eds.), *Advances in Economics and Econometrics: Theory and Applications: Seventh World Congress* (Vol. 1, pp. 206-242). Cambridge: Cambridge University Press.

Crozet, M., Mayer, T., & Mucchielli, J.-L. (2004). How Do Firms Agglomerate? A Study of FDI in France. *Regional Science and Urban Economics*, 34(1), 27-54.

Curran-Cournane, F., Cain, T., Greenhalgh, S., & Samarsinghe, O. (2016). Attitudes of a farming community towards urban growth and rural fragmentation-An Auckland case study. *Land Use Policy*, 58, 241-250.

Darwis, V. (2009). *The Performance of Land Ownership as Main Factor to Determine Farmer's Income'. [Indonesian Version]*. Center for Socio-Economic Analysis and Agricultural Policy, Republic of Indonesia.

Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing*, 18(3), 301-331.

Day, J., & Ellis, P. (2014). Urbanization for Everyone: Benefits of Urbanization in Indonesia's Rural Regions. *Journal of Urban Planning and Development*, 140(3).

Day, J., & Lewis, B. (2013). Beyond univariate measurement of spatial autocorrelation: disaggregated spillover effects for Indonesia. *Annals of GIS*, 19(3), 169-185.

De Groot, H. L., Poot, J., & Smit, M. J. (2009). Agglomeration externalities, innovation and regional growth: theoretical perspectives and meta-analysis. *Handbook of regional growth and development theories*, 256.

Deaton, A. (1992). Household Saving in Ldcs - Credit Markets, Insurance and Welfare. *Scandinavian Journal of Economics*, 94(2), 253-273.

Deichmann, U., Lall, S. V., Redding, S. J., & Venables, A. J. (2008). Industrial location in developing countries. *World Bank Research Observer*, 23(2), 219-246.

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, Convergence, and Economic Performance. *Research Policy*, 43(10), 1785.

DGoB. (2015). *Budget List of Directorate General of Food Crops Ministry of Agriculture Year of 2015*. Jakarta: Directorate General of Budget, Ministry of Finance, Republic of Indonesia.

Dijk, M. P., & Sverrisson, A. (2003). Enterprise clusters in developing countries: mechanisms of transition and stagnation. *Review of. Entrepreneurship & Regional Development* 15 (3):183-206.

DJPSP. (2017). *Minister of Agriculture Decree No. 15/Kpts/SR.230/B/05/2017 on Guidelines for Agricultural Insurance in Rice Farming*. Jakarta: Directorate General for Agricultural Infrastructure, Ministry of Agriculture, Republic of Indonesia.

DJTP. (2016). *Performance Report, 2016*. Jakarta: Directorate General of Food Crops, Ministry of Agriculture, Republic of Indonesia.

Doane, D., & MacGillivray, A. (2001). Economic Sustainability The business of staying in business. *New Economics Foundation*, 1-52.

Dorward, A., Kydd, J., Morrison, J., & Urey, I. (2004). A Policy Agenda for Pro-Poor Agricultural Growth. *World Development*, 32(1), 73-89.

Dowling, J.m., & Chin-Fang, Y. (2007). *Modern Developments in Behavioural Economics: Social Science Perspective on Choice and Decision Making* (1 ed.). Singapore: World Scientific Publishing Co. Pte. Ltd.

Duranton, G., Martin, P., Mayer, T., & Mayneris, F. (2010). *The Economics of Clusters: Lessons from the French Experience* (1st ed.). New York: Oxford University Press.

El-Osta, H. S., & Morehart, M. J. (2008). Determinants of Poverty among U.S. Farm Households. *Journal of Agricultural and Applied Economics*, 40(1), 1-20.

Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*, 5(1), 9-28.

Ellison, G., & Glaeser, E. L. (1999). The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? *American Economic Review*, 89(2), 311-316.

Estudillo, J. P., & Otsuka, K. (2010). Rural Poverty and Income Dynamics in Southeast Asia. In P. L. Pingali & R. E. Evenson (Eds.), *Handbook of Agricultural Economics* (Vol. 4, pp. 3435-3468). Amsterdam, North-Holland.

Fan, S. G., & Chan-Kang, C. (2005). Is small beautiful? Farm size, productivity, and poverty in Asian agriculture. *Agricultural Economics*, 32, 135-146.

FAO. (2011). *Indonesia and FAO Achievements and Success Stories*. Jakarta: FAO Representation in Indonesia.

FAO. (2014). *Farmers' Organisations in Bangladesh: A Mapping and Capacity Assessment (Bangladesh Integrated Agricultural Productivity Project, Technical Assistance Component)*. Rome: Food and Agriculture Organisation of the United Nations.

FAO. (2015). *Statistical Pocketbook 2015: World Food and Agriculture*. Rome: Food and Agriculture Organisation of the Unted Nations.

Fehr, E., & Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *Quarterly Journal of Economics, 114*(3), 817-868.

Fingleton, B., Igliori, D. C., & Moore, B. (2004). Employment growth of small high-technology firms and the role of horizontal clustering: Evidence from computing services and R&D in Great Britain, 1991-2000. *Urban Studies*, 41(4), 773-799.

Fischer, E., & Qaim, M. (2012a). Gender, agricultural commercialization, and collective action in Kenya. *Food Security*, 4(3), 441-453.

Fischer, E., & Qaim, M. (2012b). Linking Smallholders to Markets: Determinants and Impacts of Farmer Collective Action in Kenya. *World Development*, 40(6), 1255-1268.

Fishbein, M., & Ajzen, I. (2010). *Predicting and Changing behaviour: the reasoned action approach*. New York: Psychology Press: Taylor & Francis Group.

Fitzroy, F.R., & Kraft, K. (1987). Cooperation, Productivity, and Profit Sharing. *Quarterly Journal of Economics*, 102(1), 23-35.

Folta, T. B., Cooper, A. C., & Baik, Y. (2006). Geographic cluster size and firm performance. *Journal of Business Venturing*, 21(2), 217-242.

Fowler, C. S., & Kleit, R. G. (2014). The Effects of Industrial Clusters on the Poverty Rate. *Economic Geography*, 90(2), 129-154.

Fujita, M., & Thisse, J.-F. (2002). *Economics of Agglomeration: Cities, Industrial Location, and Regional Growth* (1st ed.). Cambridge, UK: Cambrisge University Press.

Galves-Nogales. (2010). *Agro-based clusters in developing countries: staying competitive in a globalized economy*. Rome: FAO.

Geldes, C., Felzensztein, C., Turkina, E., & Durand, A. (2015). How does proximity affect interfirm marketing cooperation? A study of an agribusiness cluster. *Journal of Business Research*, 68(2), 263-272.

Giang, L. T., Nguyen, C. V., & Tran, T. Q. (2016). Firm Agglomeration and Local Poverty Reduction: Evidence from an Economy in Transition. *Asian-Pacific Economic Literature*, 30(1), 80-98.

Gino, F., Krupka, E. L., & Weber, R. A. (2013). License to Cheat: Voluntary Regulation and Ethical Behaviour. *Management Science, 59*(10), 2187-2203.

Glaeser, E. L., Kallal, H. D., Scheinkman, J., xe, A, & Shleifer, A. (1992). Growth in Cities. *Journal of Political Economy*, 100(6), 1126-1152.

Government of Indonesia. (2013). *Law No. 19 year of 2013 on the Protection and Empowerment of Farmers* . In edited by Ministry of Law and Human Rights. Jakarta.

GoWJ. (2010). *Regional Regulation No. 22 on Spatial Planning of West Java Regions the year of 2009-2029* 22 C.F.R. Government of West Java: Republic of Indonesia.

GoWJ. (2014). *Medium-term Strategic Plans of West Java Province, 2013 – 2018.* Bandung: Agency for Development Planning, Government of West Java Province.

Graafland, J. J. (2002). Modelling the trade-off between profits and principles. *Economist-Netherlands, 150*(2), 129-154.

Graham, S. (2014). A new perspective on the trust power nexus from rural Australia. *Journal of Rural Studies*, 36, 87-98.

Greve, A., & Salaff, J.W. (2003). Social networks and entrepreneurship. *Entrepreneurship-Theory and Practice*, 28(1), 1-22.

Grice, J. W. (2001). Computing and evaluating factor scores. *Psychological Methods, 6*(4), 430-450.

Groot, J. C. J., Rossing, W. A. H., & Lantinga, E. A. (2006). Evolution of farm management, nitrogen efficiency and economic performance on Dutch dairy farms reducing external inputs. *Livestock Science*, 100(2-3), 99-110.

Hakelius, K., & Hansson, H. (2016). Measuring Changes in Farmers' Attitudes to Agricultural Cooperatives: Evidence from Swedish Agriculture 1993-2013. *Agribusiness*, 32(4), 531-546.

Hamyana, U. R. (2017). Development and Social Conflict in the Village Community (Ethnographic Study of Implementation of UPSUS Swasembada Pajale in Bondowoso, East Java). *Agriekonomika*, 6(2).

Hansla, A., Gamble, A., Jullusson, A., & Garling, T. (2008). Psychological determinants of attitude towards and willingness to pay for green electricity. *Energy Policy*, 36(2), 768-774.

Harbaugh, R., & To, T. (2014). Opportunistic discrimination. *European Economic Review, 66*.

Hazell, P. B. R., & Rahman, A. (2014). *New directions for smallholder agriculture* (1st ed.). Oxford: Oxford University Press.

Heckman, J.J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1), 153-161.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64(4), 605-654.

Henderson, V. J. (1995). Innovation and agglomeration: Two parables suggested by city-size distributions: Comment. *Japan and the World Economy*, 7(4), 391-393.

Henderson, V. J., & Kuncoro, A. (1996). Industrial Centralization in Indonesia. *World Bank Economic Review*, 10(3), 513-540.

Hendrickson, M., & James, H. S. (2005). The ethics of constrained choice: How the industrialization of agriculture impacts farming and farmer behaviour. *Journal of Agricultural & Environmental Ethics, 18*(3), 269-291.

Hendrickson, M. K., & James, H. S. (2016). Power, Fairness and Constrained Choice in Agricultural Markets: A Synthesizing Framework. *Journal of Agricultural & Environmental Ethics, 29*(6), 945-967.

Hermanto, & Swastika, D. K. S. (2011). Penguatan Kelompok Tani: Langkah Awal Peningkatn Kesejateraan Petani [Farmers' Groups Empowerment as an Initial Step to Farmers' Welfare Improvement] *Analisis Kebijakan Pertanian*, 9(4), 371 - 390.

Holm, H. J., Opper, S., & Nee, V. (2013). Entrepreneurs Under Uncertainty: An Economic Experiment in China. *Review of. Management Science* 59 (7):1671-87.

Hsiao, C. (2007). Panel data analysis - advantages and challenges. *Test*, 16(1), 1-22.

Huggins, R., & Thompson, P. (2017). The behavioural foundations of urban and regional development: culture, psychology and agency. *Journal of Economic Geography*.

Humphrey, J., & Schmitz, H. (2001). Governance in global value chains. *Ids Bulletin-Institute of Development Studies*, 32(3), 19-+.

Humphrey, J., & Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters? *Regional Studies*, 36(9), 1017-1027.

IFAD. (2013). *Smallholders, Food Security, and the Environment*. Report of IFAD and the United Nations Environment Programme. Rome: IFAD.

Ihle, R., Dries, L., Jongeneel, R., venus, T., & Wesseler, J. (2017). *The EU Cattle Sector: Challenges and Opportunities - Milk and Meat* (Vol. IP/B/AGRI/IC/2016-014). Brussel: the European Parliament.

Isaksen, A. (2016). Cluster emergence: combining pre-existing conditions and triggering factors. *Entrepreneurship and Regional Development*, 28(9-10), 704-723.

Jackson, J. C., Rand, D., Lewis, K., Norton, M. I., & Gray, K. (2017). Agent-Based Modeling:A Guide for Social Psychologists. *Social Psychological and Personality Science*, 8(4), 387-395.

James, H. S., & Hendrickson, M. K. (2008). Perceived economic pressures and farmer ethics. *Agricultural Economics*, 38(3), 349-361.

Jr, H.S.J., & Sykuta, M.E. (2006). Farmer trust in producer- and investor-owned firms: Evidence from Missouri corn and soybean producers. *Agribusiness*, 22(1), 135-153.

Kandel, E., & Lazear, E.P. (1992). Peer Pressure and Partnerships. *Journal of Political Economy*, 100(4), 801-817.

Kahneman, D., & Tversky, A. (1979). Prospect Theory - Analysis of Decision under Risk. *Econometrica, 47*(2), 263-291.

Kahneman, D. (2011). *Thinking, fast and slow*: Macmillan.

Kennedy, P. (2003). *A guide to econometrics*: MIT press.

Kibler, E. (2013). Formation of entrepreneurial intentions in a regional context. *Review of. Entrepreneurship and Regional Development* 25 (3-4):293-323.

Kim, Y., Barkley, D. L., & Henry, M. S. (2000). Industry characteristics linked to establishment concentrations in nonmetropolitan areas. *Journal of Regional Science, 40*(2), 231-259.

Kiminami, L., & Kiminami, A. (2009). *Agricultural Clusters in China*. Paper presented at the International Association of Agricultural Economists, 16-22 August, Beijing.

Knorringa, P., & Nadvi, K. (2016). Rising Power Clusters and the Challenges of Local and Global Standards. *Journal of Business Ethics*, 133(1), 55-72.

Krugman, P. (1991). *Geography and Trade*. USA: The MIT Press.

Krugman, P. (1995). *Peddling Prosperity: Economic Sense and Nonsense in an Age of Diminished Expectations*. New York: W. W. Norton.

Kumar, A., Saroj, S., Joshi, P. K., & Takeshima, H. (2018). Does cooperative membership improve household welfare? Evidence from a panel data analysis of smallholder dairy farmers in Bihar, India. *Food Policy*, 75, 24-36.

Lajili, K., Barry, P.J., Sonka, S.T., & Mahoney, J.T. (1997). Farmers' preferences for crop contracts. *Journal of Agricultural and Resource Economics*, 22(2), 264-280.

Lazzeretti, L., & Capone, F. (2016). How proximity matters in innovation networks dynamics along the cluster evolution. A study of the high technology applied to cultural goods. *Journal of Business Research*, 69(12), 5855-5865.

Lee, D.Y., & Tsang, E.W.K. (2001). The effects of entrepreneurial personality, background and network activities on venture growth. *Journal of Management Studies*, 38(4), 583-602.

Li, J., & Geng, S. (2012). Industrial clusters, shared resources and firm performance. *Entrepreneurship and Regional Development*, 24(5-6), 357-381.

Lissoni, F. (2001). Knowledge codification and the geography of innovation: the case of Brescia mechanical cluster. *Research Policy, 30*(9), 1479-1500.

Mani, Ankur, Rahwan, I., & Pentland, A. (2013). Inducing Peer Pressure to Promote Cooperation. *Review of. Scientific Reports* 3:1735.

Mariyono, J. (2014). Rice production in Indonesia: policy and performance. *Asia Pacific Journal of Public Administration*, 36(2), 123-134.

Markelova, H., Meinzen-Dick, R., Hellin, J., & Dohrn, S. (2009). Collective action for smallholder market access. *Food Policy*, 34(1), 1-7.

Marsden, P.V., & Campbell, K.E. (1984). Measuring Tie Strength. Social Forces, 63(2), 482-501

Martin, R., & Sunley, P. (2003). Deconstructing clusters: chaotic concept or policy panacea? *Journal of Economic Geography*, 3(1), 5-35.

McCulloch, N., Timmer, C. P., & Weisbrod, J. (2007). Pathways out of Poverty during and Economic Crisis: An empirical assessment of rural Indonesia: *World Bank Publications*.

McCulloch, N., & Sjahrir, B. S. (2008). Endowments, Location or Luck? Evaluating the Determinants of Sub-national Growth in Decentralized Indonesia Policy Research *Working Paper* (Vol. 4769). Washington, DC: World Bank.

McCulloch, N., & Timmer, C. P. (2008). Rice Policy in Indonesia: A Special Issue. *Bulletin of Indonesian Economic Studies*, 44(1), 33-44.

Meyer-Stamer, J. (1998). Path dependence in regional development: Persistence and change in three industrial clusters in Santa Catarina, Brazil. *World Development, 26*(8), 1495-1511.

Miron, J. R. (2010). What the Firm Does On-Site: Agglomeration, Insurance, and the Organisation of the Firm.*The Geography of Competition: Firms, Prices, and Localization* (pp. 177-199). New York: Springer.

Miyata, S., Minot, N., & Hu, D. H. (2009). Impact of Contract Farming on Income: Linking Small Farmers, Packers, and Supermarkets in China. *World Development*, 37(11), 1781-1790.

MoA. (2014). *Statistics of Agricultural Land 2009 - 2013*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2015a). *Performance Report, 2015*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2015b). *Regulation of Minister of Agriculture No. 03/permentan/OT.140/2/2015 on Guidance for "UPSUS Swasembada padi, jagung, kedelai" through the program of irrigation improvement, 2015*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2015c). *Regulation of Minister of Agriculture No. 14/Permentan/OT.140/3/2015 on Guidance for Integrated Supervision of Agricultural Extension Officiers, University Students, and Military Officers in Increasing the Production of Rice, Corn, and Soybean*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2016a*). Minister Decree No. 67 on Technical Guidance for Farmer Organisations*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2016b). *Minister of Agriculture Decree No. 830/kpts/RC.040/12/2016 on National Strategic Regions for Agricultural Development*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2016c). *Performance Report, 2016*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoA. (2016d). *Regulation of Minister of Agriculture No. 56/PERMENTAN/RC.040/11/2016 on Guidance for Agro-cluster Development*. Jakarta: Directorate General of Laws, Ministry of Laws and Human Rights

MoA. (2017). *Performance Report, 2017*. Jakarta: Ministry of Agriculture, Republic of Indonesia.

MoLHR. (2009). *Law No. 41 on Protection of Agricultural Sustainable Land*. Jakarta: Ministry of Laws and Human Rights,Republic of Indonesia.

MoLHR. (2013). *Law No. 19 on The Protection and Empowerment of Farmers*. Jakarta: Ministry of Law and Human Rights, Republic of Indonesia.

MoLHR. (2014). *Law No. 23 on Regional Government*. Jakarta: Ministry of Law and Human Rights, Republic of Indonesia.

Morosini, P. (2004). Industrial clusters, knowledge integration and performance. *World Development, 32*(2), 305-326.

Morris, K.S., Mendez, V.E., & Olson, M.B. (2013). "Los meses flacos': seasonal food insecurity in a Salvadoran organic coffee cooperative. *Journal of Peasant Studies*, 40(2), 423-446.

Mukai, K., & Fujikura, R. (2015). One village one product: evaluations and lessons learnt from OVOP aid projects. *Development in Practice*, 25(3), 389-400.

Mundlak, Y. (1992). *Agricultural Productivity and Economic Policies*: OECD Publishing.

Mur, J., & Angulo, A. (2006). The Spatial Durbin Model and the Common Factor Tests. *Spatial Economic Analysis*, 1(2), 207-226.

Naidoo, V. (2013). The challenges of policy coordination at a programme level: Why joining-up is hard to do. *Development Southern Africa*, 30(3), 386-400.

Najib, M., & Kiminami, A. (2011). Innovation, cooperation and business performance: Some evidence from Indonesian small food processing cluster. *Journal of Agribusiness in Developing and Emerging Economies*, 1(1), 75-96.

Nasution, A. (2016). *Government Decentralization Program in Indonesia*. ADBI Working Paper, 601.

Niaounakis, T., & Blank, J. (2017). Inter-municipal cooperation, economies of scale and cost efficiency: an application of stochastic frontier analysis to Dutch municipal tax departments. *Local Government Studies*, 43(4), 533-554.

Nooteboom, A. (2006). Innovation, learning and cluster dynamics. In B. Asheim, P. Cooke, & R. Martin (Eds.), *Clusters and Regional Development: Critical Reflections and Explorations Clusters and Regional Development* (pp. 137 - 163). New York: Routledge.

Nugroho, A. D., Utami, S. N. H., Yuslianti, Y., Nurrokhmah, L., & Huda, M. A. A. (2017). Implementation UPSUS Swasembada Pangan in

Wonosobo District, Central Java Province [Indonesian version]. *Jurnal Pengabdian kepada Masyarakat*, 3(1).

OECD. (1998). *Agricultural Policy Reform and the Rural Economy in OECD Countries*. France: OECD.

OECD. (2001a). *Measuring Productivity - OECD Manual*: OECD Publishing.

OECD. (2001b). *OECD Territorial Outlook*.

OECD. (2007). *Agricultural Policies in Non-OECD Countries: Monitoring and Evaluation*. Paris: OECD Publishing.

OECD. (2011). *Fostering Productivity and Competitiveness in Agriculture*: OECD Publishing.

OECD. (2012). *OECD Review of Agricultural Policies*: Indonesia OECD Publishing.

OECD. (2014). *OECD Framework for Regulatory Policy Evaluation*. OECD Publishing.

OECD. (2015). *Indonesia Policy Briefs*. OECD Publishing.

OECD. (2016). *OECD Regional Outlook 2016*.

Opper, S., & Nee, V. (2015). Network effects, cooperation and entrepreneurial innovation in China. *Asian Business & Management*, 14(4), 283-302.

Osterberg, P., & Nilsson, J. (2009). Members' Perception of Their Participation in the Governance of Cooperatives: The Key to Trust and Commitment in Agricultural Cooperatives. *Agribusiness*, 25(2), 181-197.

Ostrom, E. (2007). *A diagnostic approach for going beyond panaceas*. Proceedings of the National Academy of Sciences of the United States of America, 104(39), 15181-15187.

Ostrom, E. (2010). Analyzing collective action. *Agricultural Economics*, 41, 155-166.

Otsuka, K., Liu, Y., & Yamauchi, F. (2016). The Future of Small Farms in Asia. *Development Policy Review*, 34(3), 441-461.

Pacheco, J.M., Traulsen, A., Ohtsuki, H., & Nowak, M.A. (2008). Repeated games and direct reciprocity under active linking. *Journal of Theoretical Biology*, 250(4), 723-731.

Padmore, T., & Gibson, H. (1998). Modelling Systems of Innovation: II. A Framework for Industrial Cluster Analysis in Regions. *Research Policy*, 26(6), 625-641.

Palan, N. (2010). *Measurement of Specilisation - The Choice of Indices*. FIW Working paper, 62.

Panuju, D. R., Mizuno, K., & Trisasongko, B. H. (2013). The dynamics of rice production in Indonesia 1961–2009. *Journal of the Saudi Society of Agricultural Sciences*, 12(1), 27-37.

Parrilli, M. D. (2009). Collective efficiency, policy inducement and social embeddedness: Drivers for the development of industrial districts. *Review of. Entrepreneurship & Regional Development*, 21 (1):1-24.

Parto, S. (2008). Innovation and Economic Activity: An Institutional Analysis of the Role of Clusters in Industrializing Economies. *Journal of Economic Issues*, 42(4), 1005-1030.

Partridge, M. D., & Rickman, D. S. (2008). Distance from Urban Agglomeration Economies and Rural Poverty. *Journal of Regional Science*, 48(2), 285.

Paul, M., & wa Gĩthĩnji, M. (2017). Small farms, smaller plots: land size, fragmentation, and productivity in Ethiopia. *The Journal of Peasant Studies*, 1-19.

Pingali, P. L., & Xuan, V.-T. (1992). Vietnam: Decollectivization and Rice Productivity Growth. *Economic Development and Cultural Change*, 40(4), 697-718.

Porac, J. F., Thomas, H., Wilson, F., Paton, D., & Kanfer, A. (1995). Rivalry and the Industry Model of Scottish Knitwear Producers. *Administrative Science Quarterly, 40*(2), 203-227.

Porter, M. E. (1990). *The Competitive Advantage of Nations: With A New Introduction* (1 ed.). New York: The Free Press.

Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review*, 76(6), 77-+.

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, 14(1), 15-34.

Pouder, R., & StJohn, C. H. (1996). Hot spots and blind spots: Geographical clusters of firms and innovation. *Academy of Management Review, 21*(4), 1192-1225.

Qin, Y., & Zhang, X. (2016). The Road to Specialization in Agricultural Production: Evidence from Rural China. *World Development*, 77, 1-16.

Quincieu, E. (2015). *Summary of Indonesia's Agriculture, Natural Resources, and Environment Sector Assessment*. ADB Papers on Indonesia, 8(October).

Rabbie, J. M. (1991). Determinants of Instrumental Intra-group Cooperation. In R. A. Hinde & J. Groebel (Eds.), *Cooperation and Prosocial Behaviour* (pp. 238 - 262). Cambridge: Cambridge University Press.

Raya, A. B., 2014. Farmer Group Performance of Collective Chili Marketing on Sandy Land Area of Yogyakarta Province Indonesia. *Asian Social Science*, 10(10).

Reardon, T., Berdegué, J., & Escobar, G. (2001). Rural Nonfarm Employment and Incomes in Latin America: Overview and Policy Implications. *World Development*, 29(3), 395-409.

Rosairo, H.S.R., Lyne, M.C., Martin, S.K., & Moore, K. (2012). Factors Affecting the Performance of Farmer Companies in Sri Lanka: Lessons for Farmer-Owned Marketing Firms. *Agribusiness*, 28(4), 505-517.

Rotemberg, J.J. (1994). Human-Relations in the Workplace. *Journal of Political Economy*, 102(4), 684-717.

Sato, Y. (2000). Linkage Formation by Small Firms: The Case of a Rural Cluster in Indonesia. *Bulletin of Indonesian Economic Studies*, 36(1), 137-166.

Satterthwaite, D., McGranahan, G., & Tacoli, C. (2010). Urbanization and its implications for food and farming. *Philosophical Transactions of the Royal Society B: Biological Sciences, 365*(1554), 2809-2820.

Schmit, T.M., & Hall, J.S. (2013). Implications of Agglomeration Economies and Market Access for Firm Growth in Food Manufacturing. *Agribusiness*, 29(3), 306-324.

Schmitz, H. (1995). Collective Efficiency - Growth Path for Small-Scale Industry. *Journal of Development Studies*, 31(4), 529-566.

Schmitz, H. (1999). Collective efficiency and increasing returns. *Cambridge Journal of Economics*, 23(4), 465-483.

Schmitz, H., & Nadvi, K. (1999). Clustering and Industrialization: Introduction. *World Development*, 27(9), 1503-1514.

Schoenefeld, J., & Jordan, A. (2017). Governing policy evaluation? Towards a new typology. *Evaluation*, 23(3), 274-293.

Schubert, R., Brown, M., Gysler, M., & Brachinger, H.W. (1999). Financial decision-making: Are women really more risk-averse? *American Economic Review*, 89(2), 381-385.

Shleifer, A. (2004). Does competition destroy ethical behaviour? *American Economic Review, 94*(2), 414-418.

Silvis, H., & Lapperre, R. (2011). Market, Proce, and Quota Policy: from Price Support to Safety Net. In A. Oskam, G. Meester, & H. Silvis (Eds.), *EU Policy for Agriculture, Food, and Rural Areas* (pp. 182). Wageningen: Wageningen Academic Publishers.

Simatupang, P., & Timmer, P. C. (2008). Indonesian Rice Production: Policies and Realities. *Bulletin of Indonesian Economic Studies*, 44(1), 65-80.

SoAE. (2015). *Information System of Agricultural Extension of West Java Province*. Bandung: Secretariat of Agricultural Extension of West Java Province

Songsermsawas, T., Baylis, K., Chhatre, A., & Michelson, H. (2016). Can Peers Improve Agricultural Revenue? *World Development*, 83, 163-178.

SPI. (2017). *Report 2017*. Jakarta: Serikat Petani Indonesia.

Staber, U. (2007a). Contextualizing research on social capital in regional clusters. *International Journal of Urban and Regional Research*, 31(3), 505-521.

Staber, U. (2007b). A matter of distrust: Explaining the persistence of dysfunctional beliefs in regional clusters. *Growth and Change*, 38(3), 341-363.

Staber, U. (2009). Collective learning in clusters: Mechanisms and biases. *Review of. Entrepreneurship and Regional Development* 21 (5-6):553-73.

Stallman, H.R., & James, H.S. (2015). Determinants affecting farmers' willingness to cooperate to control pests. *Ecological Economics*, 117, 182-192.

Streiner, D. L. (1994). Figuring out Factors - the Use and Misuse of Factor-Analysis. *Canadian Journal of Psychiatry-Revue Canadienne De Psychiatrie, 39*(3), 135-140.

Stuart, T. & Sorenson, O. 2003. 'The Geography of Opportunity: Spatial Heterogeneity in Founding Rates and the Performance of Biotechnology Firms'. *Research Policy*,32(2): 229–53.

Stucke, M. E. (2013). Is Competition Always Good? *Journal of Antitrust Enforcement*, 1(1), 162-197.

Suire, R., & Vicente, J. (2009). Why do some places succeed when others decline? A social interaction model of cluster viability. *Journal of Economic Geography, 9*(3), 381-404.

Tambunan, T. (2005). Promoting small and medium enterprises with a clustering approach: A policy experience from Indonesia. *Journal of Small Business Management*, 43(2), 138-154.

Tian, L., Wang, H. H., & Chen, Y. (2010). Spatial Externalities in China Regional Economic Growth. *China Economic Review*, 21(S1), S21-S31.

Torre, A., & Rallett, A. (2005). Proximity and localization. *Regional Studies*, 39(1), 47-59.

Tsusaka, T.W., Kajisa, K., Pede, V.O., & Aoyagi, K. (2015). Neighborhood effects and social behaviour: The case of irrigated and rainfed farmers in Bohol, the Philippines. *Journal of Economic Behaviour & Organisation*, 118, 227-246.

Umberger, W. J., Reardon, T., Stringer, R., & Loose, S. M. (2015). Market-Channel Choices of Indonesian Potato Farmers: A Best-Worst Scaling Experiment. *Bulletin of Indonesian Economic Studies*, 51(3), 461-477.

UN. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. United Nations.

UNEP. (2005). *Integrated Assessment of the Impact of Trade Liberalization: A Country Study on the Indonesian Rice Sector*. Nairobi: United Nations Environment Programme

USDA. (2017). *International Agricultural Productivity*. United States Department of Agriculture.

Van der Panne, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics*, 14(5), 593-604.

Vaske, J. J., Beaman, J., & Sponarski, C. C. (2017). Rethinking Internal Consistency in Cronbach's Alpha. *Leisure Sciences, 39*(2), 163-173.

Verbeek, M. (2012). *A guide to modern econometrics* (fourth ed.): John Wiley & Sons.

Verhofstadt, E., & Maertens, M. (2014). Can agricultural cooperatives reduce poverty? Heterogeneous impact of cooperative membership on farmers' welfare in Rwanda. *Appl Econ Perspect Policy, 37*.

Vissers, G., & Dankbaar, B. (2013). Knowledge and Proximity. *European Planning Studies*, 21(5), 700-721.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica, 48*(4), 817-838.

Wiggins, S., & Proctor, S. (2001). How Special Are Rural Areas? The Economic Implications of Location for Rural Development. *Development Policy Review*, 19(4), 427-436.

Wood, G. A., & Parr, J. B. (2005). Transaction Costs, Agglomeration Economies, and Industrial Location. *Growth and Change*, 36(1), 1-15.

World Bank. (2005). *Feeding Indonesia*. the World Bank, East Asia Pasific Region.

World Bank. (2008). *World Development Report 2009: Reshaping Economic Geography*. Washington DC: The World Bank.

World Bank. (2015). *Indonesia Database for Policy and Economic Research*. In W. B. Group (Ed.), Annual.

Ye, H., Chen, S., Luo, J., Tan, F., Jia, Y. M., & Chen, Y. F. (2016). Increasing returns to scale: The solution to the second-order social dilemma. *Scientific Reports*, 6.

Yesuf, M., & Bluffstone, R.A. (2009). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics*, 91(4), 1022-1037.

Zheng, S., Wang, Z.G., & Song, S.F. (2011). Farmers' behaviours and performance in cooperatives in Jilin Province of China: A case study. *Social Science Journal*, 48(3), 449-457.

Appendix D. Questionnaire

District	:	
Sub-district	:	
Village	:	
GPS Coordinates	:	1. Farm 2. Closest partner 3. Closest selling point 4. Most important centre of economic activity 5. Closest city centre

Section I. Socio-economic profile

Personal Information of Respondent

I.1 Gender: : 1. Male ☐ 0. Female ☐

I.2 Age: : .....

I.3 How many years did you attend schools for education? : ……. Years

I.4 Which of this subsequent occupation do you spend most of your working time? (Choose one)

No	The Type of Occupation	Tick one
1.	Government Employment	
2.	Private employment	
3.	Paid labour in Government Agriculture (full time)	
4.	Paid labour in private agriculture (full time)	
5.	Seasonal worker (agriculture/livestock)	
6.	Occasional jobs – please fill in which:	
7.	Own agriculture/farm management	
8.	Own livestock breeding, animal products	
9.	Self employed	
10.	Education	
11.	Health	
12.	Transport	
13.	Mechanics and services	
14.	Construction	
15.	Security	
16.	Other:	

I.5 How much do you spend your time on farming a day? : .....

Household Information

I.6 Are you the head of your household? : 1. Yes 0. No

I.7 How many people living in your household? : .....

I.8 What is your current average monthly income from agriculture? : ..... IDR

I.9 What is your current average monthly income from non-agriculture? : ..... IDR

I.10 On average what is the proportion of your household income for providing the food of the household? : ……..… %

I.11 Please state your experience related to your meals in the last 12 months.

Activity	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I am worried that my household would not have enough food.					
Any household members or I have to eat fewer meals in a day because there was not enough food.					
My household members or I have to eat a smaller meal then you felt you needed because of no food.					
There was ever no food to eat of any kind in my household because of a lack of resources to get food.					
Any household members and I go to sleep at night hungry because of no food.					
Any household or me go a whole day and night without eating because of no food.					

Household Assets

I.12 How many of the following assets in Table "Asset Ownership" does your household possess?

(Write the quantity, Column 3)

Table. Asset Ownership

No.	Items	Quantity	Estimated Values (IDR) per unit
1.	Permanent house		
2.	Semi-permanent house		
3.	Car		
4.	Motorcycle		
5.	Land		
6.	Cattle		
7.	Goats and sheep		
8.	Chicken and duck		
9.	Horse		
10.	Buffalo		
11.	Rabbit		
12.	Fish Pond		
13.	Smartphone		
14.	Jewellery		
15.	Rice milling units		

Farm Information

I.13 How many total area of do you operate for agriculture? : ……. ha

I.14a Which of the following crops did you mainly cultivate in the last 12 months?

No	Crop
1.	Rice
2.	Corn
3.	Cassava
4.	Potato
5.	Tomato
6.	Cabbage
7.	Onion
8.	Pepper
9.	Avocado
10.	Mango

No	Crop
11.	Strawberry
12.	Ornamental plant
13.	Coffee
14.	Tea
15.	Tabaco
16.	Mushroom
17.	Eggplants
18.	Nuts

Choose the 3 most important crops in last 12 months (Tick one per column)

Crop	From which most revenue in last year?	Which needed most labour?	For which did they have most costs?

Crop	How much revenue in last season?	How much cost in last season?	What share did this contribute to your household income?

I.14b How much did you produce in the last season? How much did you sell and get for the product?

Crop	Seasons per year	Area cropped in last season (ha)	Production in last season (ton)	Quantity sold after last season (ton)	Selling price in last season (IDR/kg)

Production Costs

I.15 You stated that the crop from which you get most income is …. (fill in from I.21)
How much did you spend on cultivating this crop in the last season?

No	Expense	Total cost in last season (The 1st most important) (IDR)	Total cost in last season (The 2nd most important) (IDR)	Total cost in last season (The 3rd most important) (IDR)
1.	Seeds			
2.	Fertilizer			
3.	Pesticides			
4.	Nutrients			
5.	Hired labour			
6.	Machinery			
7.	Handling and processing			
8.	Marketing			
9.	Leasing land			

I.16 How satisfied were you with this crop in the last season?

Indicator	Much less than normal	Less than normal	Normal	Higher than normal	Much higher than normal
The area which I used for this crop					
The costs for this crop were					
The yield of this crop was					
The selling price of this crop was					
The selling quantity of this crop was					

Section II. Attitudes towards cooperation

In this section, we are interested in your expectations and wishes about cooperation with other farmers. By 'cooperation', we mean working together with one or more than one other farmers with that payment is taking place. For example, if you sell some of your work time as day labourer to other farmers, this would not be considered cooperation

II.1 Do you wish to cooperate with other farmers : 1. Yes 0. No

II.2a What would you expect from farmers with whom you would like to cooperate?

Perception	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
They are credible to work with.					
I am willing to share information about good selling prices.					
I am willing to share information about cheap input prices.					
I am willing to lend money to them.					
I am willing to offer the seeds that I applied to them.					
I want to give fertilisers and pesticides that I applied to them because I know they need these also.					
I am willing to lend my agricultural machinery and tools to them.					
I am willing to work with them on their farms.					
I am willing to give storage for them if they need it.					
I wish other farmers do not control my activities					

Perception	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
If they have big accident, I am willing to support their family on the farms.					
They are willing to lend their agricultural machinery and tools to me.					
They are willing to lend their money to me.					
They are willing to share the seeds that they have with me.					
They are willing to offer their used fertilisers and pesticides when I severely need.					
I would expect that they help me in my farm works.					
If I have big accident, I would expect that they support my family on the farms.					

II.2b How secure would you have from other farmers if you work together with them?

Statement	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I am concerned that they do not share their knowledge with me, as I do with them.					
I am afraid that they damage my agricultural machinery and will not tell me.					
I am afraid that they will not pay me back all the money I have lent to them.					

Statement	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I am concerned that I do not know precisely my jobs in the cooperation.					
I am concerned that they might not know precisely their jobs in the cooperation.					
I am afraid that they will not listen to my advice.					
I am concerned that they will not return the favour I did to them.					
I am afraid that they profit from me more than I profit from them.					
I am afraid that I cannot count on them when I am in severe need.					
I am afraid that they want to control my decisions.					
I am afraid that they will act selfishly.					
I am concerned that they will take advantage of me.					

II.3 What gains do you expect to have when cooperating with other farmers:

Benefits	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I have opportunities to get easier and cheaper seeds.					
I have opportunities to buy easier and cheaper fertilisers and pesticides.					

Benefits	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I have opportunities to get someone lending me money with low interest rate.					
I have opportunities to use and lend agricultural machinery to make my jobs easier.					
I will get training from government or universities to implement new technology.					
I can more easily obtain government's subsidies.					
I can improve my crop productivity.					
I would expect that I get better information about price opportunities.					
I will be able to sell my products with higher prices.					
I would expect that It is easier to find buyers for my products.					
I can sell my products to markets beyond my village.					
I would expect that I have to make less effort and costs to sell my products.					

II.4 What costs do you estimate to incur when working together with other farmers?

Costs	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I need to spend more time and energy for meeting with them.					

Costs	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I need to spend some money to travel to meeting places.					
I may have conflicts with them.					
I need to give a part of my harvest to them for free.					
I need to share fertilisers and pesticides with them for free.					
I need to compete against them for buyers.					
My technology use depends on the decisions of my partners.					
I will lose my independence as a farmer.					
I will lose my creativity and ability.					
I will take higher risks in my farming decisions.					
My power to decide to whom I want to sell my products will be reduced.					

II.5 What are distance and cost from your farm to the following destinations? How long do you travel (one way)? The number of partners?

No	Item	Destination			
		Most important partner	Centre of economic activity	Selling point	City centre
1	Distance (km)				
2	Travel time (Minutes)				
3	Travel cost (IDR)				

Section III. Actual Cooperation

In this section, we are interested in your actual experiences with cooperation with other farmers. By 'cooperation', we mean working together with one or more than one other farmers with that payment is taking place. For example, if you sell some of your work time as day labourer to other farmers, this would not be considered cooperation.

III.1 Are you currently working together with other farmers? : 1. Yes 0. No

If No, Go to question IV.4

III.2a Of which of the following associations or groups of?
(*Please write 1 = member or 0 = not*)

III.2b Are you currently a member of cooperative?

	Membership
Farmer Group	
Rice Group	
Corn group	
Vegetable group, specify: ……...……......	
Fruit group, specify: ……	
Coffee group	
Tea group	
Ornamental plant group	
Female farmer group	
Other: ……	
Farmer association	
Cooperative	
Other: ……	

III.3 How many times in the last 12 months, did you participate in the meetings of the group? : ..... times

III.4 Think of the cooperation with other farmers, which you had during the last 12 months. How did you perceive this cooperation? How do you think your partners perceived this cooperation?

Statement	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I am satisfied when cooperating.					

Statement	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
There was written agreement when I worked with them.					
I implemented all points written in agreement documents					
When cooperating with them, I knew my jobs and rights.					
I am loyal in this cooperation.					
I attended the regular meetings.					
All my expectations from this cooperation were fulfilled.					
I found easy to communicate with the partners during this cooperation.					
These partners were part of my extended family.					
Most of my partners live also in my village.					
We shared our responsibility equally.					
They were satisfied with this cooperation.					
When cooperating, they knew their jobs and rights.					
They implemented all points written in agreement documents.					
They are loyal in this cooperation.					
My partners attended the regular meetings we planned.					
All their expectations from this cooperation were fulfilled.					

III.5 Imagine you could get any amount of help from cooperation in the production process. For which your farm activities would be helped most beneficial?

Table. The frequency of the cooperation you had in the following activity in the last 12 months (**Tick one**)

Activity	Never	Once in a year	Once in a season	Once in a month	Once in a week
Purchasing inputs					
Preparing land					
Sowing					
Weeding					
Harvesting					
Storage					
Handling					
Processing					
Marketing					
Machinery maintenance					
Irrigation					

Table. The number of farmers whom I helped and who helped me in the last 12 months

Activity	Inside own village		Beyond own village	
	Family	Non family	Family	Non family
Purchasing inputs				
Preparing land				
Sowing				
Weeding				
Harvesting				
Storage				
Handling				
Processing				
Marketing				
Machinery maintenance				
Irrigation				

Section IV. Cooperating and Non-cooperating Farmers

In this section, we are interested in your motivation, benefits, and costs you incurred in cooperation with other farmers or when you do not work with them.

Cooperating Farmers

IV.1 Why did you work you together with other farmers?

Motivation	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
They are credible to work with.					
I shared information about good selling prices.					
I shared information about cheap input prices.					
I lent money to them.					
I offered the seeds that I applied to them.					
I gave fertilisers and pesticides that I applied to them because I know they need these also.					
I lent my agricultural machinery and tools to them.					
I worked with them on their farms.					
I gave storage for them if they need it.					
They do not control my activities					
If they have big accident, I supported their family on the farms.					
They lent their agricultural machinery and tools.					
They lent their money to me.					
They shared the seeds that they have with me.					

Motivation	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
They offered their used fertilisers and pesticides when I severely need.					
They helped me in my farm works.					
If I have big accident, they supported my family on the farms.					

IV.2 What are the benefits you earned when cooperating with the other farmers?

Benefits	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I found easier and cheaper seeds.					
I brought easier and cheaper fertilisers and pesticides.					
I had someone lending me money with low interest rate.					
I used and lent agricultural machinery to make my jobs easier.					
I got training from government or universities to implement new technology.					
I easily obtained government's subsidies.					
My crop productivity rises.					
I got information about good selling prices.					
I got good prices for my products.					
It is easier to find buyers for my products.					

Benefits	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I sold my products to markets beyond my village.					
I have to make less effort and costs to sell my products.					

IV.3 What are the costs you incurred when working with other farmers?

Costs	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I spent more time and energy for meetings with them.					
I spent some money to travel to meeting places.					
I had conflicts with them.					
I gave a part of my harvest to them free.					
I shared fertilisers and pesticides with them free.					
I competed against them for buyers.					
My technology use depends on the decisions of my partners.					
I loosed my independence as a farmer.					
I loosed my creativity and ability.					
I took higher risks in my farming decisions.					
My power to decide to whom I want to sell my products was reduced.					

Non-cooperating farmers

IV.4 Why do you not work together with the other farmers?

Motivation	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
They are not credible to work with.					
I do not have the time to spend to work together with them.					
I have to spend too much energy to work together with them.					
I cannot freely decide the way of production processes.					
It will cost me too much time to travel to the meetings.					
It will cost me too much money to travel to the meetings.					
I feel that the cooperation would be too risky.					
I refuse to work together due to too much administrative burdens.					
I am more confident when working alone.					
I do not feel comfort when sharing information with other farmers.					
I do not think that I can get better selling prices from cooperating with other farmers.					
I do not think that I can reduce my costs of farming by cooperating with other farmers.					
I do think that I can improve my marketing opportunities by cooperating with other farmers.					

Motivation	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I do not expect that they would help me in my farm works.					
I have bad experience in cooperation.					
People are too much cheating.					

IV.5 What are the constraints you have when you do not work together with the other farmers?

Constraints	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
My family members suggested me not to cooperate with them					
I do not have any contact them.					
I have no opportunity to meet them due to distance.					
I have no opportunity to cooperate with them due to my financial problems.					

Section V. Economic Pressure from Other Farmers

In this section, we are interested in how much economic pressure you think other farmers are putting on you because they are competing with you for cheapest input and best output prices etc. We are interested in knowing to what extent this is the case for you, in which respect you are most impacted, and what you do to deal with that. So please only consider for answering the following questions only the crop you produce from which you get most income.

V.1 What is the number of farmers in your village who produce the same main product as you? : ..... persons

V.2 Do you feel high pressure to keep up with other farmers?

Not at all ——————————————— Completely

V.3a How does economic pressure from other farmers impact your farming practices?

Perception	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I am using new varieties of seeds because other farmers use them too.					
I have to use new fertilisers because many other farmers do so too.					
I don't have enough land to enlarge because other farmers are already using it.					
I must purchase the inputs as soon as possible otherwise I could not buy because other farmers also.					
I have to use new technology because other farmers use it.					

Perception	Strongly disagree	Disagree	I do not agree nor disagree	Agree	Strongly agree
I have to sell at low prices because other farmers sell also at this price.					
I have difficulties to find hired workers because other farmers have a high demand for them.					
I do not have enough water for irrigation because many other farmers are also using it.					
I have to use new technologies for processing and handling the product because many other farmers this use too.					
I have to improve the quality of my products because many other farmers are selling such high quality.					
I prefer to store my product because I could get higher prices later on.					
It is difficult to find buyers of my product because there are so many suppliers.					

V.3b How did the economic pressure on you change your farming practices in the last 5 years? Please tell us your perception of the general development during the last 5 years.

Statement	--	-	0	+	++
Seeds costs					
Fertilizer costs					
Pesticides costs					
Hired labour costs					
Machinery					
Leasing land					

Note: -- decreasing strongly; - decreasing; 0 neither decreasing nor increasing; + increasing; ++ increasing strongly.

V.3c How did the economic pressure on you change your income opportunities in the last 5 years? Please tell us your perception of the general development during the last 5 years.

Indicator	--	-	0	+	++
The area which I used for this crop has been					
The selling price of this crop which I obtained has been					
The quantity of this crop I was able to sell has been					

Note: -- decreasing strongly; - decreasing; 0 neither decreasing nor increasing; + increasing; ++ increasing strongly.

V.4a How do you share information and technology with other farmers under economic pressure? (Cooperative behaviour)

Statement	Strongly disagree	Disagree	Neither disagrees nor agree	Agree	Strongly agree
I shared increasingly information and technology with farmers who belong to my family.					
I shared increasingly information and technology with farmers living in the same village as me.					
I shared increasingly the information and technology to other farmers in the same group.					
I shared increasingly the information to farmers from different groups.					
I shared all these information for free.					

V.4b How do you get access to information and technology with other farmers under economic pressure?

Statement	Strongly disagree	Disagree	Neither disagrees nor agree	Agree	Strongly agree
I have limited access to technology and information compared to other farmers.					

Statement	Strongly disagree	Disagree	Neither disagrees nor agree	Agree	Strongly agree
I have limited access to market information compared to other farmers.					
I have limited access to production input information compared to other farmers.					
I have limited access to government's subsidies compared to other farmers.					

V.4c How frequently did you use the following types of interactions to share information in the last 12 months?

Type of interactions	Never	Once in a year	Once in a season	Once in a month	Once in a week
Face-to-face meeting					
Postal mail					
Phone					
Training					
Workshop					
Documents					
Group discussions					

V.5 Based on your experience, how do you perceive the influence of cheating on your farming practices? (Self-interest behaviour)

Statement	Strongly disagree	Disagree	Neither disagrees nor agree	Agree	Strongly agree
I do not tell them all the benefits I have from new cultivation technologies.					
I do not tell them all the benefits I have from new processing technology.					
I do not tell them all the benefits I have from new seeds.					
I do not tell them to whom I sold my products.					
I do not tell them the selling price I got from my buyers.					
I do not tell them the quality of my sold products.					
I do not inform them about the governments' subsidies.					

Summary

This thesis intends to make a contribution to the existing literature of agglomeration effects of farming activities on rural development by providing theory-based empirical evidence on crucial determinants of such effects. Its main findings are that an agro-cluster could be a policy strategy for rural regions to reduce the poverty rate of those regions. Chapter 1 defines the core of this thesis through explaining the concepts of agro-clusters and their attributes for rural development. It also presents an overview of the methodologies and research questions. In the following paragraphs, the core analyses and findings corresponding to each research question are explained.

Chapter 2 attempts to explain to what extent that agro-clusters reduce rural poverty. The spatial analysis is utilised to address this aim by introducing spatial dependence between neighbouring sub-districts of the Indonesian province of West Java, where farming activities are geographically concentrated. The finding is that agro-clusters in a certain sub-district positively impact poverty reduction of that region. It implies that localisation externalities within the agro-clusters increase agricultural productivity. However, this effect declines as the density of agro-clusters increases after regions have certain farmer numbers. This shift occurs due to the presence of negative externalities within agro-clusters with this high density.

Chapters 3 and 4 elaborates the interactions between proximate farmers with respect to the benefits of localisation externalities for strengthening farmer institutions. Chapter 3 focuses on farmer cooperation within agro-clusters and its determinants based on a two-stage decision process of individual farmers. The results indicate that farmers with a

positive attitude located in the higher density of agro-clusters are most likely to cooperate with their neighbours. Such an attitude is influenced by psychological aspects and individual characteristics. External factors, such as the number of neighbouring farmers and peer meeting frequency, and farm characteristics, such as crop diversity and farm size, increase the likelihood of farmers actually working together. Hence, the cooperating farmers have an opportunity to raise their income.

The agro-clusters also foster competitive pressure, which farmers perceive from their neighbours, enlarging their individual benefit vis-à-vis competing farmers. Chapter 4 highlights such pressure. The main result in this chapter confirms that farmers located in regions with a high agro-cluster density show cooperative behaviour if they perceive low pressure from peers, while they show the lowest levels of cooperation in environments of low density and high pressure. In contrast, farmers exhibit the highest levels of self-interest in regions of high agro-cluster density and high pressure. Competition for seed application exerts the most relevant effect on raising self-interest, followed by the competition for production technology.

Chapter 5 examines West Java's rice farming as a case to elaborate the role of governmental institutions in strengthening farmer organisations inside rice clusters. In this chapter, the Indonesian existing policies of rice self-sufficiency are also evaluated. It is found that the membership of the farmer organisations has a positive impact on rice productivity, and farmers located in a more dense agro-cluster enjoy higher rice productivity when they join such organisations. This finding implies that policies towards Indonesian rice self-sufficiency, therefore, should not undertake large investments in subsidised inputs and agricultural infrastructure in the absence of strong farmer organisations in order to attain sustainable improvements in rice productivity.

Authorship Statement
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PhD candidate's name	:	Dadan Wardhana
Promotor	:	Prof. Dr W.J.M. Heijman
Title of PhD thesis	:	Agro-clusters for Rural Development in the Indonesian Province of West Java
Date of public defence	:	9 October 2018

Chapter 1 Introduction. I discussed the chapter's structure with my promotor and co-promotor. I developed a framework linking four main research questions of this thesis and connecting them with the existing literature. I then wrote the first draft and revised it incorporating feedback from my promotor and co-promotor.

Chapter 2 Agro-clusters and Rural Poverty: A Spatial Perspective for West Java. Based on the existing literature, I developed the research questions in collaboration with my promotor and co-promotor. In order to address these questions, I jointly worked with my promotor and co-promotor to design specifications of the spatial econometric models. I collected the data and carried out the empirical analysis. I drafted this chapter and revised it according to the comments of my promotor and co-promotor. After finishing this chapter, I submitted it to Bulletin of Indonesian Economic Studies. It was finally published online in this journal on 7 November 2017.

Chapter 3 Farmer Cooperation in Agro-clusters. Collaborating with my promotor and co-promotor, I developed the research questions. We designed the questionnaire and developed the strategy for empirical analysis. I conducted a survey, analysed the data, wrote the first draft of this

chapter elaborating the link between these questions and the existing literature, revised the draft. Finally, I submitted this chapter as a separate manuscript to Agribusiness: an International Journal, and I am currently working on the revision incorporating comments of the referees.

Chapter 4 Farmer Performance under Peer Pressure in Agro-clusters. Collaborating with my promotor and co-promotor, I defined research questions. As for chapter 3, we designed the questionnaire and set up the data analysis plan. I carried out the survey, analysed the data, wrote the first draft of this chapter describing the link between these questions and the existing literature and revised it. I submitted the final version of this chapter as a separate manuscript to Wageningen Journal of Life Sciences.

Chapter 5 The Potentials of Agro-cluster Policies for improving Productivity of Rice Farming in the Indonesian Region of West Java. Working with my promotor and co-promotor, I defined research questions, and described how it fits in the existing literature. My co-promotor proposed the method for the first part of the analysis, and my promotor and I suggested the method for the second part. I collected the data and analysed them. I wrote the draft of the chapter and revised it incorporating feedback from my promotor and co-promotor. After finishing this chapter, I submitted it as a separate manuscript to Food Security.

Chapter 6 Synthesis. I wrote the draft of this chapter after discussing its structure and argumentation with my promotor and co-promotor and revised it incorporating feedback from my promotor and co-promotor.

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Completion of this Ph.D. thesis has become the huge milestone of my professional life. It has been a long dialectical process that leverages my curiosity about regional economics, agricultural economics, and rural development. This process, thus, expands the way of my thinking not only from the perspective of policymakers but also of researchers. This increase may be valuable for dealing with a current approach of policy development, that is, towards evidence-based policies. I acknowledge that this thesis could not have been realised without the support of remarkable individuals.

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can be implemented to help them to develop rural regions in West Java where agriculture is mainly located.

Wageningen has been a wonderful city where I have created a lot of good memories. I am grateful to all of those with whom I have made these memories in the middle of happiness, sadness, excitement, homesickness, independence, and loneliness. This gratitude especially goes to all Indonesian PhDs and their families: Teh Novi and Kang Indra, Pak Eko, Pak Erry, Pak Iman, Pak Dikky, Pak Fajar, Yuda, Pak Yohanes, Mbak Nani, Mbak Nurmi, Mbak Atiek, Mbak Vivi, Mbak Hikmah, Mbak Aviv, Neng Windi, and OBS Tarthorst Family. I believe that we will still see each other and remain friends for a long time.

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Wageningen, 9th October 2018

Dadan Wardhana

About Author

Personal Background

Dadan Wardhana completed his Bachelor study in 2003 from Padjadjaran University, majoring on agricultural technology. He has been working for Regional Government of Bandung Regency, Indonesian province of West Java since 2005 on planning and policy development at Agency for Agriculture. In 2007, he received grant from Indonesian Ministry of National Development Planning for the double degrees of master study. Because of this grant, He holds two master degrees from two universities including National Graduate Institute for Policy Studies (GRIPS), Tokyo, Japan and Institute of Technology Bandung (ITB), Bandung, Indonesia. At GRIPS, his specialisation was on economics, planning and public policy; meanwhile, at ITB he took specialisation on regional planning and development. After finishing his masters in 2010, he returned to Indonesia and continued working for Agency of Agriculture and Forestry, Bandung Regency as Head of Planning Sub-division.

In 2013, he joined the program of 300-doctor initiated by Government of West Java Province. This program supported his English and research proposal preparation. He received Ph.D scholarship from the Indonesian Endowment Fund for Education (LPDP) in 2014, and started his Ph.D in September 2014 at the Agricultural Economics and Rural Policy Group in Wageningen University, the Netherlands. His areas of research interests mainly include regional and spatial economics, agricultural economics, and rural development in developing countries. He has a special interest in the spatial concentrations of agricultural production and agribusiness for rural economic development. Final results of the total Ph.D project are included in this thesis.

Overview of Publications

1. Scientific Publication

Wardhana, D., Ihle, R., & Heijman, W. (2017). Agro-clusters and Rural Poverty: A Spatial Perspective for West Java. Bulletin of Indonesian Economic Studies, 53(2), 161-186.

2. Conference

Wardhana, D., Ihle, R., & Heijman, W. (2015). The Effects of Agro-clusters on Rural Poverty: A Spatial Perspective for West Java of Indonesia. Presented at the 150th European Association of Agricultural Economists Seminar: 'The spatial dimension in analysing the linkages between agriculture, rural development, and the environment', Edinburgh, UK, October 22-23, 2015.

Wardhana, D., Ihle, R., & Heijman, W. (2017). Farmer Cooperation in the Context of Agro-clusters. Proceeding in the 9th Asian Society of Agricultural Economists International Conference: 'Transformation in agricultural and food economy in Asia', Bangkok, Thailand, January 11-13, 2017.

Wardhana, D., Ihle, R., & Heijman, W. (2017). Farmer Performance under Competitive Pressure in Agro-cluster Regions. Proceeding in the 9th Asian Society of Agricultural Economists International Conference: 'Transformation in agricultural and food economy in Asia', Bangkok, Thailand, January 11-13, 2017.

Wardhana, D., Ihle, R., & Heijman, W. (2017). The Effects of Agro-clusters on Rural Poverty: A Spatial Perspective for West Java of Indonesia. Presented at the 1st Wageningen Indonesia Scientific Expose in Wageningen, the Netherlands, March, 8-9, 2017.

Wardhana, D., Ihle, R., & Heijman, W. (2017). Farmer Cooperation in Agro-clusters. Presented at the WASS PhD Day in Wageningen, the Netherlands, May, 18, 2017.

Wardhana, D., Ihle, R., & Heijman, W. (2018). Farmer Performance under Peer Pressure in Agro-clusters. Presented at the 14th Indonesian Regional Sciences Association Conference: 'Strengthening Regional and Local Economy', July 23-24, 2018 in Surakarta, Central Java Indonesia.

Wardhana, D., Ihle, R., & Heijman, W. (2018). The Potentials of Agro-cluster Policies for improving Productivity of Rice Farming in the Indonesian Region of West Java. Abstract in the 14th Indonesian Regional Sciences Association Conference: 'Strengthening Regional and Local Economy', July 23-24, 2018 in Surakarta, Central Java Indonesia.

3. Publications for Social Relevance

Wardhana, D., Ihle, R., & Heijman, W. (2016). How regions can enhance nutrition and food security. The Jakarta Post, June 24.

Wardhana, D. (2017). West Java's Poverty in A Spatial Perspective [in Indonesian: Kemiskinan Jawa Barat dalam Perspektif Keruangan]. Pikiran Rakyat, February 22.

Dadan Wardhana
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Organisation of Agribusiness, BEC 31306	WUR	2014	6
Advanced Econometrics, YSS 34306	WUR	2015	6
New perspectives on the urban and the rural: spatial thinking in the social sciences	WASS	2015	4
Spatial and Regional Economics, AEP 22806	WUR	2015	6
B) General research related competences			
Introduction course	WASS	2014	1
Research Methodology: From Topic to Proposal	WASS	2014	4
Writing Research Proposal	WUR	2016	6
'*The Effects of Agro-clusters on Rural Poverty: A Spatial Perspective for West Java of Indonesia*'	The 150th Seminar of the European Association of Agricultural Economists, Edinburgh UK	2015	1
'*Farmer Cooperation in Agro-clusters*'	The 9th Asian Society of Agricultural Economist International Conference, Bangkok, Thailand	2017	1
'*Farmer Cooperation in Agro-clusters*'	WASS PhD Day, Wageningen, the Netherlands	2017	0.5
'*Farmer Performance under Competitive Pressure in Agro-clusters*'	The 9th Asian Society of Agricultural Economist International Conference, Bangkok, Thailand	2017	1
'How regions can enhance nutrition and food security'	The Jakarta Post, 24 June 2016	2016	1
'West Java's Poverty in A Spatial Perspective [in Indonesian: Kemiskinan Jawa Barat dalam Perspektif Keruangan]'	Pikiran Rakyat, 22 February 2017	2017	1
C) Career related competences/personal development			
Efficient Writing Strategies	WGS	2015	1.3
Project and Time Management	WGS	2015	1.5
Scientific Writing	WGS	2015	1.8
Speaking skills	Into' Language	2017	1.5
Total			**44.6**

*One credit according to ECTS is on average equivalent to 28 hours of study load.

Colophon

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