Productivity and Technical Inefficiency of Alternative Pest Management Compliant and Non-Compliant Farmers: The Case of Shallot Growers in Java

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Abstracts

In response to (a) growing demand for high safety and quality fresh food products; (b) increasingly stringent standards on chemical residues, and (c) concern regarding the sustainability of chemical input intensive agriculture, the adoption of sustainable production systems (IPM, Pesticide-Free, organic) in agriculture is rapidly expanding. This study uses data from 2011 Shallots Growers Survey in Indonesia to compare the productivity, technical efficiency of APM-adopter and conventional (non-adopter) shallots farmers. We also measure yield loss that may associate with technology adoption. Self-selectivity may cause the frontier production function to differ between the adopters and non-adopters. Propensity Score Matching (PSM) method is used to address self-selectivity before we continue the analysis with Stochastic Production Frontier (SPF). We reject the homogenous technology hypothesis and interestingly the result indicates that on average yield loss that associated with adopting APM farming practices only 1.5%. The yield loss itself can be gradually improved by implementing a proper training and extension methods and empowering the role of farmers' group among shallot farmers.

Key words Alternative Pest Management, Shallots, Technical Inefficiency, Propensity Score Matching, Indonesia

JEL Code Q12, Q16

1. Introduction

Recent studies have indicated that many consumers in emerging markets such as Malaysia, Thailand and Vietnam have become highly concerned with the safety and quality of their food products especially fresh produce (Ahmad & Juhdi 2010; Mergenthaler, Weinberger & Qaim 2009; Posri, Shankar & Chadbunchachai 2006). Grunert (2005) also found that the increasingly concerned for these attributes have been triggered by several factors such as a variety of food scares; consumer criticism for food production and processing.

Meanwhile, major economies in Asia have been experiencing with the growth of modern retail market development in their food retail chain. Moreover, retailers in Asia have indicated that chemical residues and microbe contamination and spoilage are the common threats in Asian market (McKinsey 2009) These conditions lead to the stringent standards on procurement systems for fresh food product. Food safety standards become crucial and in some cases this condition may limit the involvement of smallholder farmers.

Moreover, since the early 1970s, the Indonesian agricultural sector has experienced serious soil degradation as a result of excessive use of chemical inputs (fertilizers, pesticides) and over-intensive land-use . The diffusion of modern rice varieties was accompanied by a substantial increase in the use of chemical inputs which may have contributed to long-term negative impacts on soil quality (Simatupang & Timmer, 2008).

Given these increasing concerns over high quality and safety products, stringent standards of fresh food products and chemical input intensive technology in agriculture, the use of sustainable production systems (organic, pesticide-free and Integrated Pest Management) in agriculture is rapidly expanding. Sustainable agriculture aims to provide sufficient, accessible, nutritious food without decreasing the quality of natural resources on the farms (Garnett, 2013). In relation to these phenomena, this study has been argued that Indonesia should considering sustainable agriculture production systems in their agricultural policies to balance the current policies which are highly dominated with either intensification or extensification farming systems. Restructure the agricultural policies is very important for Indonesia, in particular to provide the availability of food for nearly 273 million people in the 2025 (projection data from the World Bank) without increasing the damage of natural resources on farms.

However, a significant source of uncertainty is constraining the diffusion of sustainable production systems may be the lack of knowledge regarding the yields of these technologies. Pretty (2008) indicated many factors that may also limit the technology adoption such as risks for reducing the existing use of fertilizer or pesticide, yield loss that may associated with reducing external input use and time constraint to achieve the efficiency in production. Moreover, González-Flores et al. (2014) also found that the adoption of new techniques and practices are not always implemented in an efficient manner. These conditions highlighted the exact problems that are faced by farmers in the field, in particular to measure the foregone yield if they implemented any sustainable agriculture-type technology.

As a result, it is important to examine the reasons for yield loss when adopting resource - conserving technology. At the same time, exploring the source of difference in yield loss is necessary since it will help the policy maker to design a better technology for smallholder farmers. Kumbhakar, Tsionas and Sipiläinen (2009) started the discussion by examining the source of productivity differential between alternative production systems. These authors explained that the differential appeared as a result of technology changes or differences in technical efficiency or both.

These studies are drawn the analysis to measure yield loss that may have resulted from: (a) technical inefficiency in using a novel production system; (b) self-selection bias which may indicated that the higher likelihood that the more educated, wealthier, more diversified farmers adopt this new technology may be skewing beliefs on the magnitude of the yield loss.

To date this study is known as the first study who measures the impact of technology adoption in horticulture sectors (shallots farming) and in the same time addressing self-selection problems which almost appeared in many technology adoption studies. The primary objective of this study was to measure the loss in productivity due to two components involved in the adoption of Alternative Pest Managements production systems: (1) the innate nature of the production technology, and (2) the farmer's technical inefficiency in using an unfamiliar production system. The idea to contract the loss in productivity into these components was critical, in particular when we tried to identify the reasons for the yield loss. As a result of this definition, researchers are able to examine how much of the decline in yield can be addressed by improving farmers' productive efficiency variables such as extension and training.

Previous study by Mayen, Balagtas and Alexander (2010) used the Propensity Score Matching (PSM) before Stochastic Production Frontier method to quantify the yield loss on dairy farming. However, these methods have not been applied to horticultural crops, which tend to be much more depend on chemical inputs and more likely to gain higher price-premium for either organic or pesticide-free products. This study is a good case to highlight the above phenomena in high-value agricultural sector in Indonesia.

Among vegetables products in Indonesia, shallots are known as the most heavily sprayed with pesticides (Shepard et al, 2009). Shallots also known as the essential commodity for Indonesian cuisine and many farmers refer this commodity as a cash crop (high-value agriculture), therefore shallots farmers tend to over- sprayed their farm to avoid pests and diseases that highly associate with the foregone of money during the harvesting time

In this study, we focus our analysis on the adoption of Alternative Pest Management or APM farming practices on shallots. APM means the implementation of farming systems that are based on pest management technology such as Integrated Pest Management and the application of pesticide-free principles. In this study, we differentiate the conventional and APM farming systems in shallots industry based on the application of pesticides.

Conventional farming system applies pesticides on timely basis, while in APM farming system the application of pesticides is based on the necessary condition of pest problems, which means this has to consider the condition of threat from pest and the population of natural enemies on shallots farms.

In this study we investigated the losses by implementing Stochastic Production Frontier (SPF) analysis. SPF is simply specified as a Cobb-Douglas production function with two types of error terms: the first error is a normally distributed term representing statistical noise and the second one is a non-negative term representing inefficiency. However, the measurement of SPF is complicated by the fact that this is not an experimental study. In our study, the farmers being surveyed made a decision on technology adoption based on a non-random process. This consequently creates the so called self-selection bias (Minot et al. 2013). As a consequence, in our study, these two groups of farmers (adopter and conventional) may have systematic differences in their characteristics which may have affected the yields. As a result, the farmer's decision on adopting APM farming systems has been determined by a set of covariates. Having similarities with Wu et al. (2010), we defined this condition as farmers' self-selectivity. This endogenous self-selection results in biased parameter estimates for both the technology and technical inefficiency.

2. Theoretical Model

2.1. Stochastic Production Frontier

Existing studies which have combined Stochastic Production Frontier analysis to measure productivity and efficiency at the same time as also addressing the self-selectivity problem are under-represented. Sipilainen and Lansink (2005) started to address both issues in their research which estimated the technical efficiency of organic dairy farming and used Heckman's two step procedure to address the selectivity bias. These authors used a probit model to estimate the choice between organic and conventional dairy farming from pooled data. Inverse Mill's Ratio (IMR) from the basis of the probit model was used in the frontier models. IMR estimation was used to address the self-selectivity bias in the organic and conventional models. Kumbhakar, Tsionas and Sipiläinen (2009) continued the process by confirming that technology choice may cause an endogeneity problem. Thus, according to these authors, it is important to distinguish the difference in the technology from the beginning. Based on this claim, they argued that a two-step procedure was not appropriate and they introduced a single-step maximum likelihood method. In the first estimation, they analysed the parameters (inputs) by ignoring the endogeneity of the technology, while in the second-stage of estimation, the analysis was based on three different distributions of the noise term in the adoption equations.

At last, Mayen, Balagtas and Alexander (2010) extended the analysis by addressing the gap in the previous studies. These authors claimed that a formal test of the homogenous technology was missing from both studies and they expanded the analysis by highlighting two important methodological issues. First, Propensity Score Matching was used to address the potential self-selection bias in the first stage of analysis. Second, they continued by conducting a formal test of the homogenous assumption of the technology choice before progressing the analysis to the Stochastic Production Frontier.

Just recently, a similar approach was used by Rao, Brummer and Qaim (2012) to measure the impact of farmer participation in a supermarket channel. González-Flores et al. (2014)) used a similar approach in their analysis to measure the impact of a national program (Plataformas de Concertación) on productivity growth. This program was introduced to help smallholder farmers participate in high-value producer chains by introducing new technologies, providing organizational skill training, and linking them to final markets. Abdoulaye and Sanders (2013) also followed similar methods to analyse the impact of new agricultural technologies in Niger.

In this research, we adopted earlier study by Mayen, Balagtas and Alexander (2010) and used Stochastic Production Frontier analysis to estimate the shallot production functions of farmers who were using Alternative Pest Management farming practices (defined as adopters), as compared with farmers who never used this technology and were classified as non-adopters or conventional farmers. The stochastic production frontier model is specified as a Cobb-Douglas production function

$$\ln y_i = x_i\beta + v_i - u_i \qquad (1)$$

where y_i denotes the yield (value of shallots production per hectare) for the *i*th farmer (i = 1,2,….,N), x_i is a vector of production inputs per hectare, $\boldsymbol{\beta}$ is a vector of the parameter to be estimated, v_i is a two-sided stochastic term that accounts for statistical noise, and u_i is a nonnegative stochastic term representing inefficiency.

In the next stage, we estimated the output-oriented measurement known as Technical Efficiency. TE indicates the magnitude of the shallot production as an output of the i-th farmer relative to the output that could be produced in a frontier (fully-efficient) farm using the same input bundles (Coelli 1995).

$$TE_i = \frac{y_i}{\exp\ (x_i\beta + v_i)} = \frac{\exp\ (x_i\beta + v_i - u_i)}{\exp\ (x_i\beta + v_i)} = \exp\ (-u_i) \qquad (2)$$

2.2. Self-selection

As in other social research, sample selection always occurs as a generic problem when the researcher is not able to draw a random sample from the population of interest (Winship & Mare 1992Self-selection has appeared as a major methodological problem due to the nature of the definition of adopter, in which the farmers' decision whether or not to adopt the technology was endogenously determined by the farmers themselves (Crost et al. 2007). These authors demonstrated that, if a correlation between the technology (in this case Bt Cotton) and high yields is observed, this positive result may be caused by the technology or it may have happened as a self-selection effect. It may occur since farmers who are already very efficient with their farming adopt the technology more rigorously. As a consequence, many recently published literatures have been focusing on the development of new methodologies that are able to solve the problem of endogeneity and the simultaneity of farmers' decisions (Doss 2006).

The nature of the data set that was used in our model also contains a similar self-selection problem, in particular when we observed the sampling selection for the APM's adopter or treatment group. We found that technology choice at household level was not a random assignment, and that assignment was based on observable characteristics such as age, education, income, assets, being a member of farmer group and othersIn this study, the selection problem itself occurred during the selection process in two ways, first, during the selection of farmers within a farmer group, and second, during the selection of the farmer group. In many cases, the leader, who was normally found to be the smartest and most progressive of the farmers, was chosen to represent the farmer group. In this method it was expected that the trained FFS farmer would be able to lead the diffusion process within the group.

Other earlier studies also found similar problems, for example that the researchers or extension workers aimed to target progressive farmers first (Diagne 2006). Also Feder, Murgai and Quizon (2004) investigated the self-selection occurring during the establishment of the FFS program in communities and found that the selected farmers were most likely to be different from other farmers in the group. This is not surprising when Röling and van de Fliert (1994) indicated that the approach of FFS recruitment in the IPM program had not been tested in isolated villages. Thus it became obvious that the majority of the program recruited the better informed and more affluent farmers. Noting this condition, our own study used a matching method to control for potential endogeneity issues.

2.3. Matching Methods

Propensity Score Matching (PSM) is known as an alternative method to estimate treatment effects when random assignment of treatments to subjects is not feasible. This method is the pairing of treatment and control units with similar values on the propensity scores and possibly other covariates, and the discarding of all unmatched units (Rubin 2001). The basic idea of the propensity score method is to replace the collection of confounding covariates with only one function that summarizes the confounding covariates or determinants (Rubin 1997). This factor is called the propensity score and in our study the propensity is to adopt APM technology (treated). As a result, the collection of confounding covariates is collapsed into a single factor (predictor). In this study, each APM farmer is matched with an equivalent conventional farmer to serve as a synthetic control for comparison.

Heckman and Navarro-Lozano (2004) explained that the reasons for using matching models are considered if the conditioning on observable variables is able to replace the sample selection bias. Moreover, Caliendo and Kopeignig (2008) also remained the users of this model that the aim in using the propensity score matching method has to meet the underlying assumption which is known as un-confoundedness or selection based on observables or conditional independence. The researcher has to be confident that 1) the underlying identifying assumptions can develop from the information in the data set, and 2) where the sample selection takes place is well defined during the set-up of the sampling design.

We utilize propensity score matching to measure the effect of two activities, the adoption of APM technology and the difference in technical efficiency between the APM-adopter farmers and conventional farmers. In our analysis, matching criteria are selected from the variables that normally are used to model technology adoption. Learning from the previous literatures, in our probit model, we included variables that represent the characteristic of farm, farmer and household, and farm management as determinant variables. Nevertheless, in our study we found that the decision to adopt is strongly influenced by attitudinal variables such as the importance of certification for producing fewer pesticide-treated shallots and concern over soil fertility and health risks' awareness, therefore we also included these variables in the estimation.

2.4. Data

In this study we use data that were generated by the Shallot Grower Survey which was implemented by the Indonesian Center for Agriculture Socio Economic and Policy Studies (ICASEPS) in collaboration with the International Food Policy Research Institute (IFPRI), and the University of Adelaide. This survey was part of the Australian Centre for International Agricultural Research (ACIAR) funded project "Markets for high-value commodities: Promoting competitiveness and inclusiveness". The data collection process involved 18 trained enumerators and was conducted in Brebes, Central Java, which is known as a major producing area of chillies and shallots in Indonesia. The interview process with selected farmers ran from June to July 2011.

A sample of 687 shallot growers was drawn from two different sampling selection methods. Systematic random sampling was applied to draw 531 traditional or conventional shallot growers, while the remaining samples were drawn from the list of organic fertilizer users that purchased their products from local organic fertilizer suppliers. We started our sampling frame processes based on annual chilies and shallots production data over the previous five years (2005 – 2009). We used this information as a bench mark to select the sub-district, village and household randomly.

We designed the selection process of villages at sub-districts with replacement and followed the proportional value of the means of production. As a result, any sub-district which had higher production of chilies and shallots was more likely to be selected. Following the serial process we are able to select 47 villages randomly and these selected villages are located in 10 sub-districts (Kecamatan). In every selected village, we collected a list of shallot farmers who also a land-tax payers. In the final process, we used the Excel program to select the household from the list to be interviewed randomly. By applying these stages of sampling selection process, we were able to draw around 12-17 household samples in every village. Then, using this list, the trained-enumerators worked in a group and interviewed the selected household or respondent face to face using a 24-page structured questionnaire.

Meanwhile, a sampling selection approach for non-conventional shallot farmers was started by interviewing the local organic fertilizer supplier (with the local brand "NASA"). The aim of selecting this type of farmer was to explore whether or not the farmer had been exposed to the introduction of Alternative Pest Management practices such as Integrated Pest Management and Pesticide Free. From the provided lists, we visited each farmer and asked whether or not they had cultivated shallots over the last five years. Any farmer who indicated "a yes" answer was included into a list of non-conventional shallot farmers. For the next step, we randomly selected the shallot growers from the list by using the same method that was applied for selecting conventional shallot farmers. Finally we were able to draw 156 non-conventional shallot growers who were located in 32 villages. Interestingly, in some cases we could find both types of shallot farmers in the same village.

During the interview process we asked all the questions in the questionnaire to all of samples. In the analysis, we generated a definition of APM-adopter farmers based on respondents' responses to serial questions in the technology adoption section in the questionnaire. Serial questions of technology adoption that were covered in the questionnaire were whether or not they had been heard, trained, and adopted APM farming practices. For any respondent who indicated "a yes" answer to the last question, then we included this respondent as an adopter. From this selection process, we obtained 214 APM adopter-farmers (120 farmers from the non-conventional group and 94 from the conventional group) while conventional or general farmers were about 473 farmers (36 from the non-conventional group and 437 from the conventional or general farmer group). However, because not all APM-adopter farmers were included in the analysis during the process of extracting and generating the variables, we were able to generate variables from 187 treated-samples and 420 samples as untreated (control or conventional) samples. We discarded all the remaining samples which had missing data.

2.5. Empirical Model

Based on the nature of APM's diffusion, we assumed that the production function for APM farming systems was different from conventional. The production functions in the log form were:

$$y_i = x_i\beta + v_i - u_i \qquad 3)$$

where y_i is yield (shallot production per hectare) and x is a vector of inputs. The parameter vector to be estimated is β, v_i is a two sided stochastic term that accounts for statistical noise and u_i is a non-negative stochastic term, which represents inefficiency. The vector of inputs in the SPF models were land size, seed, fertilizer, pesticide, insect trap, labor, irrigation costs, assets of production capital and the number of adults in the household.

To achieve the aims of this study by decomposing the potential yield loss that might appear from inefficiency in using APM farming practices, we define inefficiency variables as a function of education and being a member of the farmer group. APM farming practices is considered as knowledge-intensive task technology, our hypothesis indicates that level of education helps farmers to understand the content of technology adoption. Winarto (2004) explained that the main message of pest management technology adoption was to balance the numbers of natural enemies in the farms. Therefore, farmers needed to learn and be able to distinguish the difference between the good and the bad insects through a daily monitoring of pests in their farms. At the same time, since the nature of diffusion is delivered as a collective action, we hypothesize that being a member of a farmer group may able to help farmers to get a better access to information on production and receive a proper training such as in a Farmer Field School.

As mentioned earlier, it is important to distinguish difference in technology at the early stage of the analysis. The aim of this differentiation is to examine whether there are any indications that may appear from the different groups (treated and control). Rao, Brummer and Qaim (2012) considered difference in technology at the beginning of their analysis. These authors ignored the hypothesis of homogenous assumption by redefining their hypothesis. They assumed that, by participating in supermarket channels, the adopter farmers may adopt advance farming systems. However, in many technology adoption studies, the contribution to the methodological gap could be acknowledged by examining the differences between the new technology and conventional ones. For example, Kumbhakar, Tsionas & Sipiläinen (2009) estimated a separate production frontier without conducting any test of the homogenous technology assumption. The hypothesis to do the separation was strongly influenced by self-selection problems. Moreover, Sipilainen and Lansink (2005) checked the validity of the assumption by including interaction dummy variables for organic. However, in their analysis the interaction variables caused a potential endogeneity problem due to self-selection when the dairy farmers claimed themselves as organic producers. Both of these studies failed in addressing this problem. Later Mayen, Balagtas and Alexander (2010) extended the analysis to address the methodological issues. The organic farmers in the US have to meet the requirements from their organic standards; therefore these authors assumed that technological difference may exist. In their study, they used Propensity Score Matching to compare the organic farms with similar conventional farms. They continued the process by analysing the production frontier of each farm and used the stochastic production frontier approach which was applied under different assumptions (homogenous and heterogeneous). The result from the formal test proved that the technology was different between the organic and conventional farmers. However, Mayen, Balagtas and Alexander (2010) failed to address the bias for unobserved factors (Bravo-Ureta, Greene & Solís 2012).

In our study, we ignored the homogenous assumptions of the technology based on this following condition. Alternative Pest Management farming practices might require skills and knowledge before the farmers are able to adopt and apply the systems on their farm. For example, farmers were trained to understand the basic elements and technology components through the farmer field school of IPM (Martono 2009). Through this process the author assumed that IPM farmers had improved their knowledge and increased their confidence in producing agricultural commodities with fewer chemical inputs. As being trained, adopter farmers had been taught to monitor the existence of natural enemies on their farm. This helped them to justify the economic threshold of the pests and diseases, before they decided to apply the pesticides (Martono 2009).

The propensity score matching method is estimated before we analyse the production function. We estimate the probit model to obtain the propensity scores:

$$\Pr\ (APMi = 1) = w_i'\alpha + \ e_i \qquad 4)$$

Where w_i is a vector of farm, farm management, farmer and household characteristics, and α is a vector of the parameter to be estimated. The propensity score estimates the probability of being an Alternative Pest Management adopter for each farmer.

We specify the probability of being an APM adopter as a function of farm, farm management, farmer and household characteristics. We hypothesize that farm characteristics may influence the propensity to adopt APM technology. The variables of farm characteristics that are included in the estimation are the share of the irrigated area that has been used for shallot farming and land-tenure systems. We define land tenure systems in shallot farming as total rented land and own-farmed land. We also include farm management variables in the estimation, such as a marketing decision to sell the shallot. In this case we use a dummy variable to distinguish whether or not the farmer has sold their product under a trader-harvester contract (tebasan). Access to extension workers as the main source of production information is also included as a determinant factor of farm management in the probit model. Moreover, we also include farmer and household characteristics such as the age and level of education of the respondents, the total value of production assets, ownership of internet and mobile phone, and household size as a proxy of family labor. In measuring the total value of production assets we included the value of a motor-cart, cart, water-pump, sprayer, tractor, hand-tractor and grain mill. Interestingly we also include attitudinal variables in the estimation. Both these variables measure farmers' attitudes towards technology adoption in relation to matters such as: 1) the importance of food certification systems for producing less-pesticides shallots; 2) the importance of farming systems that reduce health risks from chemical exposure; and 3) the importance of the declining of soil fertility on the farm.

Natural log transformation was used for all continuous variables in both frontier and probit models.

Table 1 presents summary statistics and the statistical significance of tests of equality of means for continuous variables and equality of proportions for the binary variables of adopters, non-adopters and matched conventional *(Table 1 attached here).*

On average, APM and conventional farmers operate in the same size of land. The average land size is 0.25 hectares for APM-adopter farmers and 0.21 hectares per cycle for conventional farmers. Farmers who have adopted APM farming practices tend to use fewer inputs compared with the conventional. Descriptive statistics indicate that the APM technology requires less seeds, fertilizer, chemical pesticides and hired labour. Nevertheless, this farming practice is also able to reduce costs for irrigation. On average the differences are highly significant between these two group of farmers. Insect traps are known as one of the alternative solutions for controlling pests. Therefore adopter farmers are more likely to use insect traps to minimize pests and nearly one-third of APM-adopters use insect traps. However, only 15% of conventional farmers use insect traps and the differences are highly significant.

Many farmers in Brebes have been farming their shallots in irrigated areas and the summary statistics indicate that the differences are statistically significant between the adopters and the conventional farmers. Irrigated areas that have been used by APM-adopter farmers for shallot farming reach almost 93.7 % from their total land use while the conventional farmers have a lower proportion (83.3 per cent). In this study we also measure average land use for shallot farming based on land tenure systems such as rented and own-farmed land. Although the differences are not statistically significant, APM-adopter farmers occupy a larger proportion of own-farmed land than rented-land.

Moreover, in our study many adopters or conventional farmers, consider a trade-harvester (tebasan) contract as their most efficient option in selling their shallot. In relation to the source of information in production systems, the summary statistic indicates that APM-adopter farmers are more likely to use an extension officer to obtain the information. On average, almost 27% of APM- adopter farmers obtain the information from an extension officer to improve their shallot farming, while only 10% of conventional farmers depend on this source of information.

Furthermore, there are significant differences in farmer and household characteristics between APM-adopter farmers and conventional farmers. Summary statistic indicate that APM-adopter farmers are more educated and wealthy compared to the conventional. On the other hand, with a lower level of education, conventional farmers own production capital assets to the value of only one-fifth of the adopters or equal to 2.8 million rupiah over the same period of time. APM-adopters farmers are also considered to be younger and more likely to join a farmer group. In relation to collective action performances, the adopters are more likely to use a farmer group as a place to learn and maximize the information either from the leader, from members of a farmer group or from the extension officer to improve their farming practices. Moreover, the differences between these two groups are significant. Nearly 90% of farmers in the adopter group become a member of a farmer group while only 52% of conventional farmers join this organization.

In this research we are also able to include attitudinal variables in the analysis. The summary statistics indicate that both groups have significant differences in relation to their perceptions on the importance of certification, health risks and soil fertility. These two attitudinal variables demonstrate that APM-adopter farmers are more concerned to obtain a certification that is able to guarantee the quality and safety of their shallots (in this case less-pesticide shallots). At the same time, this group of farmers is also more concerned about the impacts of chemical exposure, and about their health risks and the declining trend in soil fertility on their farm. Finally, we see that income from shallot contributes almost fifty per cent of total household income and the differences are statistically not significant between the APM-adopter farmers and conventional farmers.

3. Results and Discussion

3.1. Propensity Score Matching Analysis

This study uses Propensity Score Matching approach in this case probit model to generate propensity scores that can be translated as the predicted probability of every farmer to adopt APM farming practices. These scores are used to match the APM adopter with conventional farmers. The estimation results from probit model are presented in Table 2 with The chi-squared statistics from a Wald test is 203.94 with 16 degrees of freedom (ρ-value = 0.0000). The result shows that farmer and household characteristics variables are contributed significantly to the decision of shallot farmer to adopt the technology. Probit model indicates that older farmers are more likely to adopt APM farming practices. Interestingly, earlier study in the US indicated that younger farmers were more likely to adopt organic dairy farming (Mayen, Balagtas and Alexander (2010). Meanwhile, another study which conducted in Southern Malawi (Dey et al. 2010) found that older farmers were more likely to adopt the integrated aquaculture-agriculture farming. The estimation shows that farmers who have higher level of education (years of schooling) are more likely become APM-adopters. As we may note, this practices are characterized as knowledge-intensive type of technology. Farmers who have higher years of schooling are able to translate the content of the technology much more easily. In other words, farmers need to visualize the information on the package of the technology into a concept that they can easily understand before they apply the methods on the farm. However, while previous studies indicated a mix of results, they all delivered similar messages: that level of education was not significantly influenced the decision of the farmers to adopt the technology (Abebaw & Haile 2013; Dey et al. 2010; Mayen, Balagtas & Alexander 2010). *(Table 2 attached here)*

Moreover, the total value of production assets also significantly influences willingness to adopt APM farming practices. Farmers who own higher value of production assets are more likely to adopt the technology. Adopting a technology is not always means reducing the cost of inputs, and during the period of adaptation, farmer may require a certain amount of capital to apply this new technology in their farm. Earlier study in Bangladesh showed a similar result, although the result was not significant, but the sign indicated that production capital increased the possibility to adopt new technology and reduced the poverty incidents (Mendola, 2007).

Although living in rural areas, many smallholder shallot farmers in our study location have been exposed with internet connection. We use this variable as an indicator of modern living habit. The estimation result shows that farmers who have an internet connection at home are more likely to become APM adopters.

We include farmers' attitudinal variables which are related to the adoption of APM farming practices in the estimation. Farmers who are highly concerned about the importance of food certification as an assurance for producing less-pesticides shallot are more likely to be APM-adopters. In the same time, farmers who are concerned with health risks from the chemical exposure and the decreasing trend of soil fertility are more likely to adopt APM farming practices. Previous studies who examined the determinants of technology adoption never included any attitudinal variables in their estimation. To date, our probit estimation shows that these two variables are able to explain farmers' likelihood to adopt the technology.

Farmers who used higher proportion of irrigated land for their shallot farming are strongly associated with the adoption of APM farming practices. Previous finding also indicated that farmers who had higher proportion of cultivated land under irrigation system in Bangladesh were more likely to cultivate modern rice varieties (Rahman 2009). Majority of shallot farming in Indonesia use irrigated land as their cultivated area. Majority of irrigated land in Brebes normally are constructed as part of the large irrigation systems. Shallot requires significant amount of water in their life cycle in particular at the early stages of production. Therefore, farmers tend to use water from secondary or tertiary canals to irrigate their farms. However, if water scarcity exists or water availability from gravity systems is not available, o many shallot farmers build a canal along the farm and use ground water as the main source of water supply, or sometime they use buckets to bring water from the canals.

Majority of shallot farmers who owned also farmed the land tend to be a risk aversion. The probit estimation result indicates that farmers who have higher proportion of own-farmed land are less likely to adopt the APM-technology. Other studies also included land tenancy issues as the covariates in the probit model. Mayen, Balagtas and Alexander (2010) and Mendola (2007) indicated that farmers with higher proportion of rented-in land were more likely to adopt the new technology. Although have similar sign, this variable is not significant in influencing farmers decision to adopt.

We also included farm management variables in the probit estimation. Farmers who have joined a farmer group are strongly associated with APM-adopters. In the same time, farmers who are considered extension officer as their main sources of production information are more likely to adopt APM farming practices. As mentioned earlier, the diffusion process of any agricultural technology or farming systems in Indonesia used farmer group as a place to introduce new technology and in many cases an extension officer was selected as the trainer. Both variables indicate a strong relationship and able to increase the propensity to adopt APM farming practices.

To illustrate this process, these following figures show the Kernel Density estimates of the distribution of propensity score for APM adopter farmers (treated) and conventional farmers (untreated) before the matching as presented in Figure 2. The matching process results a new group called as conventional-matched, this group is the conventional farmers who have similarity in propensity scores that are represented by the collection of significant confounding covariates in probit model.

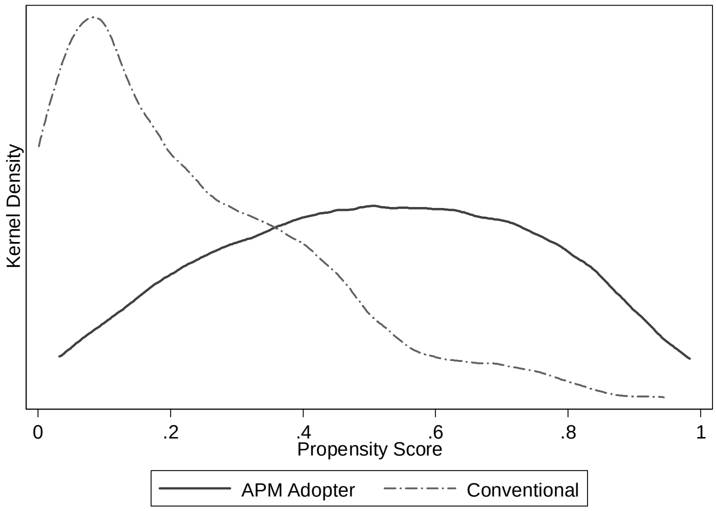

Figure 2. Kernel densities for propensity scores before matching

The resulting subsample of this group consists of 187 farmers. It is approximately half the size (44.5 per cents) of the original conventional farmers. Ideally, the matched conventional farmers do not have a significant difference with APM adopters. The descriptive statistics (Table 1) shows that majority of the covariates are not significantly different from zero between the adopters (treated) and the matched-conventional (matched-untreated). However, some differences still exist such as on average the level of education of matched-untreated farmers are lower than APM-adopter farmers. Moreover, matched-conventional farmers also own less production assets, have less exposed to internet connection, and have different responses to attitudinal variables. The differences in attitudinal variables are highly significant for farmers' attitudes towards health risks and the decreasing trend towards soil fertility while attitudinal responses to the importance of food certification for producing fewer pesticide shallots are less significant. Interestingly, only 18 per cents of farmers in matched-conventional group use extension officer as their main sources of production information. Thus, this condition indicates that APM-adopter farmers are more exposed to the extension officer compare to matched-conventional farmers.

3.2. Stochastic Production Frontier Analysis

Having similarities with previous technology adoption studies, we also considered whether there are any differences in technology to produce APM and conventional shallots. We test the restrictions in this case APM technology over yield as the dependent variable with every input variable. The aim of this test is to test whether APM intercept and slope shifters are jointly equal to zero. The chi-squared statistics from a Wald test is 31.18 with 10 degrees of freedom (ρ-value = 0.0005). The result shows that we reject the null hypothesis of the homogenous technology assumption. It shows that at least one of the APM intercepts and slopes shifter is not equal to zero. Thus, we can conclude that the technology between APM and conventional farming practices are different.

The result from Stochastic Production Frontier models estimation of APM and matched conventional shallot farmers are presented in Table 3. The results show that the input elasticity for seed, fertilizer, pesticide, insect traps, labor, irrigation and the value of production assets are positive and statistically significant in affecting the productivity of shallot for conventional farmers. However, land size and number of adults in the household are negative and significant in determining yield levels. The results also indicate that insect traps have the largest influence and positive effect on yield. Interestingly, the results also proof that the conventional farming is highly dependent on pesticides. The results indicate that the elasticity of pesticide is positive and highly significant in explaining the productivity of conventional shallot.

As a comparison of the technology, the results also indicate that the intercept shifter of the adoption variables (APM technology) has the largest effect on yield and it is highly significant in determining yield levels in the frontier. However, the inputs such as pesticide, insect trap and irrigation indicate a lower productivity for APM-adopter farmers and the elasticities are less significant. Meanwhile, the most important indicator in these results is the level of education of the adopter and the member of farmer groups. Both variables indicate that these variables are highly significant in reducing inefficiency level for APM-adopter farmers. *(Table 3 attached here)*

In the next analysis, we estimate technical efficiency for each farmer based on the estimation of stochastic production frontiers between APM-adopter and conventional farmers. We use bar diagram to illustrate the distribution of technical efficiency level of each farmer as presented in Figure 4. In details this study presents the difference of means and standard errors of the technical efficiencies under different technology regime in Table 4. The data indicate, there is not much difference in technical efficiency between this two group of farmers under PSM Subsample or all farms. *(Table 4 attached here)*

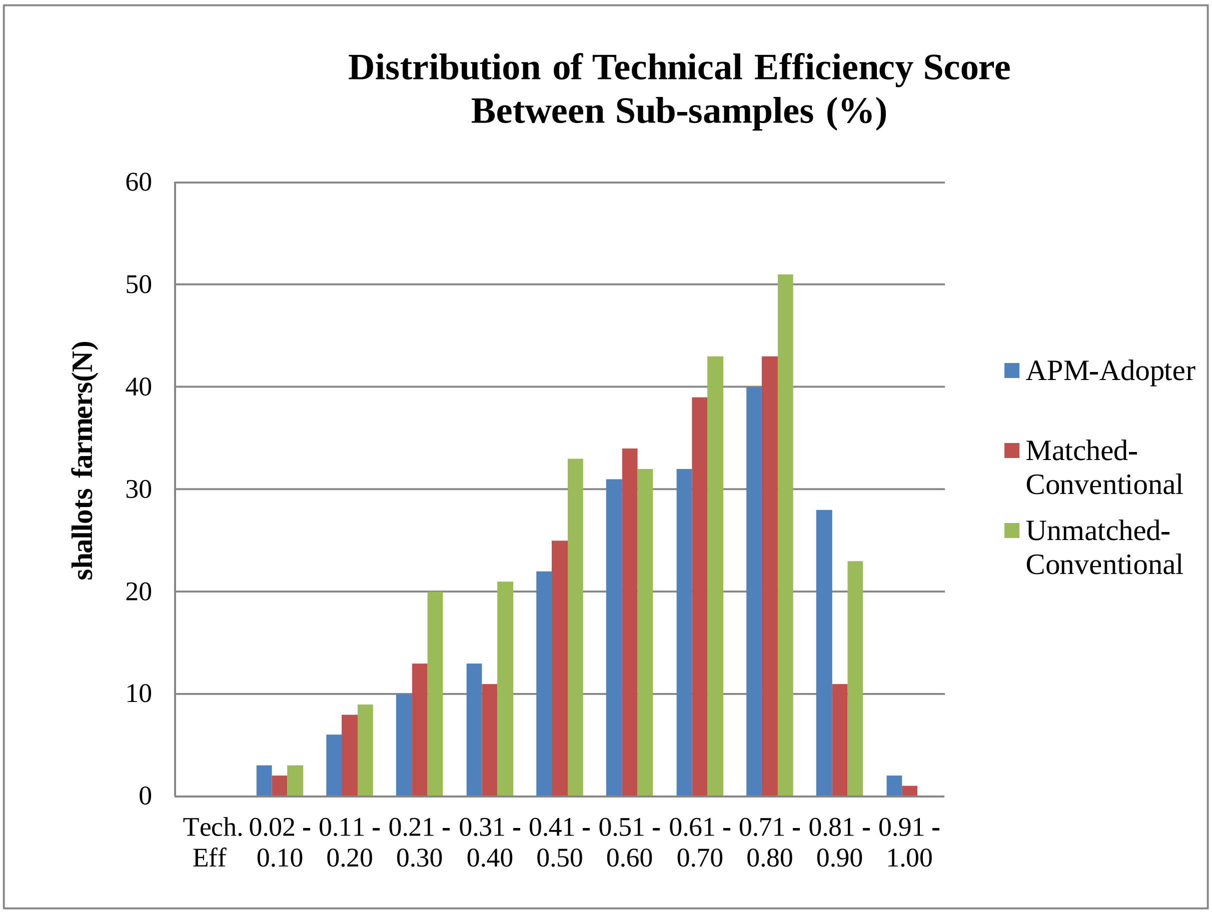

Figure 5. The Distribution of Technical Efficiency Score between PSM Sub-samples

Bar diagram is presented to illustrate the distribution of technical efficiency score between adopter, untreated-matched and untreated-unmatched group of farmers. Having addresses self-selection bias we are able to compare APM-adopter with matched-conventional farmers. Bar diagram indicates that matched-conventional farmers are slightly efficient compare to the adopter in particular in the range of TE score between 0.41- 0.80. However, we also find that APM-adopter group has higher number of farmers who are able to reach the frontier (0.81-0.90). This result indicates that adopter farmers are able to reach the efficiency level as the matched-conventional although APM-adopter farmers are required to reduce the amount of pesticides application on their shallots farming. The next section illustrates more detail result in particular measuring on average how much yield loss that may associate with technology adoption. Technical efficiency score from the SPF approach proofs that APM-adopter farmers have a competence to reach the efficiency level as the conventional.

3.3. Decomposing the yield loss

In this study we also examine yield loss which is associated with the differences in technology. The results from SPF models indicate that farmers who have been adopting APM farming practices are less efficient than the conventional. Therefore, it is important to examine whether or not the APM farmers may experience with the yield loss as an impact of the technology adoption. The main objective of this study is to decompose the yield loss that may cause by: 1) the nature of the production technology and 2) the farmer's technical inefficiency. As illustrated in Figure 5, we build the estimation of yield loss under two different input bundles as presented in horizontal axis and two different production functions. Under assumption of the different technology in production systems, the analysis continue to examine the predicted total productivity of shallots under two conditions of input bundles (adopter and conventional) over two types of technology production (APM and conventional). The results from Table 5 indicate that APM-adopter farmers experience with yield loss. Over two different input bundles, on average APM farmers are less efficient compare with matched-conventional farmers. The yield loss from the SPF results is the difference between the average of yield on APM input bundles for using different technology APM technology (11304.4 kg/ha) and (11479.6) for conventional using bundles and between (11623.7) and (11493.5) using conventional input bundles. Yield loss that associated with adopting APM farming practices on average around 175.18 kg/ha (1.5%). Interestingly, these results also inform the importance of addressing self-selectivity that might result from the data, without matching process the differences between this two groups of farmers are very small (13.24 kg/ha or 0.12%). Although very small, ignoring a self-selection bias might result upward bias information.

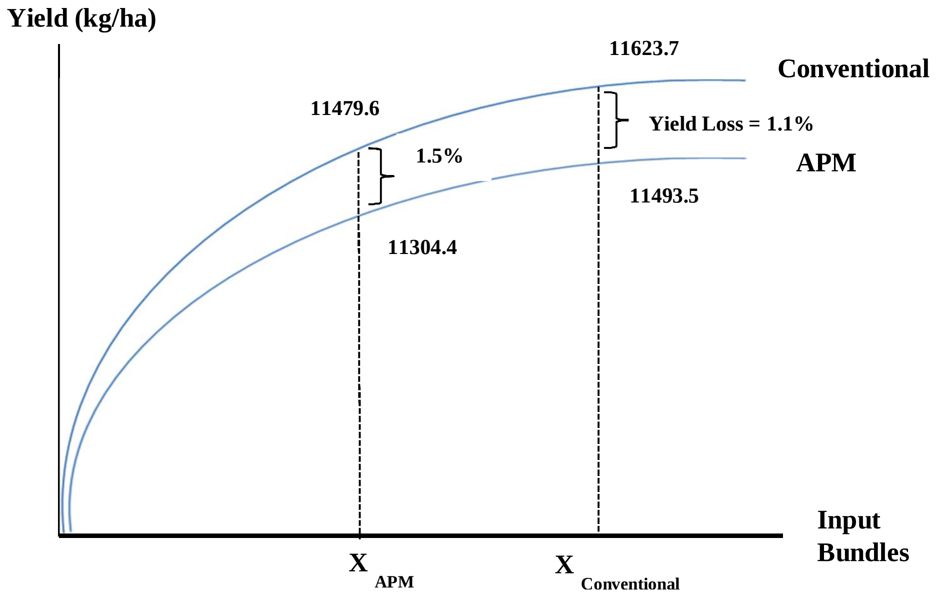

Figure 5. Measuring Yield Loss between APM adopter – Conventional Farmers

4. Conclusion

Differ from previous green-technology adoption studies; this paper contributes to the literature by analysing yield loss that associated with technology adoption. The measurement of yield loss is generated by estimating technical efficiency between Alternative Pest Management (APM) versus conventional farming systems. APM in this study refers to pest-management based production systems such as Integrated Pest Management and Pesticide-Free. APM allows farmers to reduce the application of chemical pesticides and to increase the amount of natural enemies on farms.

This study finds that yield loss that is associated with APM farming practices is very small (less than 1.5 % of total production (11479.6 kg) or 175 kg). We also find that the choice of econometric models impact on these estimates. If we ignore self-selection problems in production, the result indicate that APM farming practices produces slightly higher (0.1 %) amount of yield if farmer use the adopter input bundle or higher 1.4 % if farmer use the conventional input bundle.

The yield loss itself can be gradually improved by implementing a proper training and extension methods and empowering the role of farmers' group among shallot farmers. This paper also indicates that APM farming practices are able to improve the quality of shallots and to meet the expectation of consumer demand for higher safety and quality fresh produce in Indonesia. Nevertheless, a better market structure is needed to guarantee the traceability of minimum-pesticide residue shallots from farm to table.

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Table 1. Summary Statistics and Units for Determinant Variables in the Study

VARIABLES	Adopters	Non-adopters	Matched-conventional [a]
Age (years)	46.82	47.50	47.09
	(0.788)	(0.536)	(0.824)
Education (years)	7.80	5.24***	6.71***
	(0.285)	(0.192)	(0.291)
Number of adults in the HH (person)	3.16	3.25	3.25
	(0.083)	(0.065)	(0.102)
Assets of production capital (million IDR)	10.82	2.81***	4.87*
	(2.789)	(0.697)	(1.548)
Internet (1/0)	0.37	0.20***	0.26**
	(0.035)	(0.020)	(0.032)
Mobile Phone (1/0)	0.86	0.76***	0.81
	(0.025)	(0.021)	(0.029)
Distance (km)	0.01	0.01	0.01
	(0.002)	(0.002)	(0.003)
Share of Irrigated Land (%)	93.72	83.29***	91.43
	(1.407)	(1.653)	(1.806)
Share of Rented Land (%)	28.21	25.30	26.99
	(2.852)	(1.845)	(2.794)
Share of Own-farmed Land (%)	36.30	40.25	36.63
	(2.855)	(2.024)	(2.941)
Sold in contract (1/0)	0.52	0.50	0.49
	(0.037)	(0.024)	(0.037)
Farmer group (1/0)	0.89	0.52***	0.87
	(0.023)	(0.024)	(0.025)
Share of shallot income to total household income (%)	51.28	48.87	50.26
	(1.998)	(1.425)	(2.087)
Factor Certification	0.31	-0.10***	0.11*
	(0.077)	(0.047)	(0.069)
Factor Risks	0.21	-0.10***	-0.08***
	(0.080)	(0.048)	(0.070)
Extension (1/0)	0.27	0.10***	0.18**
	(0.033)	(0.014)	(0.028)
Area planted (ha)	0.25	0.21*	0.23
	(0.024)	(0.009)	(0.014)
Seed (kg)	1,185.95	1,219.71	1,203.47
	(30.638)	(33.653)	(41.870)
Fertilizer used in cycle (Kg)	2,445.59	2,799.76	2,922.27*
	(159.273)	(145.494)	(230.516)
Chemical pesticide used in cycle (million IDR)	5.50	6.55	6.66
	(0.355)	(0.396)	(0.740)
Insect trap used in cycle (1/0)	0.29	0.15***	0.15
	(0.033)	(0.017)	(0.026)
Labor used in cycle (days)	507.36	513.53	561.45
	(23.648)	(25.974)	(35.383)
Irrigation fee in cycle (milion IDR)	7.16	12.24***	10.48
	(0.914)	(0. 858)	(1.195)
(sum) yield	6,938.98	6,773.73	7,447.12
	(257.36)	(405.21)	(845.41)
Observations	187	420	187

Note: Asterisks denote a statistically significant difference with the APM mean at the 10 percent (*), 5 percent

Table 2. Probit Estimation of the Propensity to Adopt APM-Farming Practices

	Coefficient	SE
Constant	-2.589	0.468***
Age	0.014	0.006***
Education	0.062	0.017***
Number of adults in the HH	-0.114	0.163
Assets of production capital	0.209	0.039***
Internet	0.344	0.137***
Mobile phone	-0.210	0.167
Distance	1.123	1.679
Share of Irrigated Land	0.005	0.002**
Share of Rented Land	0.000	0.002
Share of Own-farmed Land	-0.005	0.002***
Sold in contract	0.083	0.118
Farmer group	0.895	0.136***
Share of income from shallot	0.003	0.002*
Food certification concern	0.140	0.061**
Heatlh Risk and Soil Fertility Concern	0.129	0.058**
Access to extension officer	2.482	0.158***
McFadden Pseudo R^2	0.246	
Log likelihood chi^2 (16)	203.94	
No. of observation	667	

Note: Asteriks denote statistical significance at the10% (*), 5% (**) and 1% (***) levels

Table 3. Estimation of Stochastic Production Frontier of APM Adopters and Matched Conventional Farmers (Different Technology)

	Coefficients	S.E.
Constant	3.386	0.841***
Area planted	-0.160	0.064***
Seed	0.123	0.070*
Fertilizer	0.135	0.079*
Chemical pesticides	0.185	0.065***
Insect traps	0.324	0.133***
Labour	0.162	0.053***
Irrigation costs	0.010	0.005**
Assets of production capital	0.063	0.031**
Number of adults in the household	-0.227	0.104**
APM	2.847	1.111***
APM x area planted	0.128	0.081*
APM x seed	0.055	0.082
APM x fertilizer	-0.019	0.100
APM x chemical pesticides	-0.145	0.084*
APM x insect traps	-0.290	0.153*
APM x labour	-0.095	0.064*
APM x irrigation costs	-0.011	0.007*
APM x assets of production capital	-0.051	0.038
APM x no of adults in the household	0.121	0.149
Variance of *v*		
Constant/Intercept	-2.212	0.319***
APM	-0.619	0.462
Variance of *u*		
Constant/Intercept	-0.256	0.470
APM	1.192	0.604**
Education	0.015	0.032
APM x education	-0.082	0.044*
Farmer group	-0.213	0.357
APM x farmer group	-0.761	0.506*
Wald $chi^2(19)$	180.97	
Prob > chi^2	0.000	
Log likelihood	-307.487	
No. of observations	374	

Note: Asterisks denote statistical significance at the 10% (*), 5% (**) and 1% (***) level.

Table 4. Means and Standard Deviation of Technical Efficiency for Shallot Farmers

	Alternative Pest Management (APM)		Conventional		Difference in Means
	Mean	SD	Mean	SD	
PSM Subsample	0.596	0.198	0.576	0.190	0.020
All farms	0.596	0.198	0.570	0.194	0.026

Table 5. Differences on Yield (kg/ha) Between PSM Sub-samples and All Farms

Input	Technology/Frontiers		Differences	
Bundles	APM	Conventional	Value	Percentage
	With Matching (PSM Sub-Samples)			
APM-adopter (N=187)	11304.43	11479.61	-175.18	-1.53
Matched-conventional (N=187)	11493.49	11623.67	-130.18	-1.12
	Without Matching (All Samples)			
APM-adopter (N=187)	11304.43	11291.19	13.24	0.12
Conventional (N=422)	11493.49	11331.03	162.46	1.41