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Can Understanding Indonesian Farmers' Preferences for Crop Attributes Encourage their Adoption of High Value Crops?

By Suprehatin[1], Wendy J. Umberger[1], Dale Yi[1], Randy Stringer[1] and Nicholas Minot[2]

[1]University of Adelaide, Australia

[2]International Food Policy Research Institute, US

Abstract. *The main objective of this study is to provide insight on how Indonesian farmer preferences for crop attributes influence their adoption decisions. Results from a Latent Class (LC) cluster analysis, using the individual scores for each of the Best-Worst (BW) scaling attributes, indicate there are four clusters of farmers, each distinct in their relative preferences for crop attributes and socio-demographic characteristics. The multinomial endogenous treatment regressions show that preference cluster effect varies across models. For the binary adoption model, we find an insignificant preference cluster effect. We find a significant preference cluster effect both for the intensity of adoption and the timing of adoption models. The effects of farmers' crop preference cluster, however, are different across those models. The findings allow more targeted programming to encourage farmers to adopt high-value crops that have a high probability of offering benefits for farmers.*

1. Introduction

Indonesia, like many developing countries in Southeast Asia, is experiencing an agri-food transformation toward modern high-value commodities. Economic growth, urbanization and demographic change are among the key drivers leading to changes in Indonesian consumption patterns. Indonesian consumers' diets are becoming more diversified, and consumers are demanding more livestock products (dairy, eggs and meat) and fruits and vegetables (Reardon et al., 2014). Although production continues to expand, Indonesia's horticultural industry is still unable to meet the growing demand. For example, more than 90% of garlic consumption is met by imports (MoA, 2014).

This means that the agri-food transformation presents new market opportunities for farmers who are willing to diversify their production to include more potentially profitable non-traditional, high-value food crops (Reardon et al., 2009). Moreover, previous research demonstrates these changes present farmers with new choices about which crops to produce including the decision of whether to adopt a new horticultural crop to increase their income (Kasem & Thapa, 2011; Pingali, 1997; Reardon et al., 2009). Recent research by Sahara (2012) shows that when adopting high-value crops, such as chillies, there is an opportunity to increase income. However, the adoption of new high-value crops among Indonesian farmers remains low. These low adoption rates are puzzling considering the long history of demonstration and agricultural extension programs, as well as incentive schemes, encouraging adoption of new agricultural technologies.

Many studies on farmers' adoption in developing countries explore the factors influencing farmers' adoption of new technologies. While some studies emphasize the importance of observable variables such as farmer characteristics (e.g. education, age) and farm characteristics (e.g. farm size), others examine the role of institutional factors (e.g. credit constraint, market access) as determinants of farmers' adoption decisions (Abebaw & Haile, 2013; Doss, 2006; Feder et al., 1985; Matuschke et al., 2007; Noltze et al., 2012).

Some studies suggest that certain types of government interventions (e.g. subsidies) facilitate the adoption of new technologies by farmers (Basu & Qaim, 2007).

On the other hand, several studies show the importance of technology attributes in farmers' adoption decisions (Adesina & Zinnah, 1993; Batz et al., 1999). However, only a few studies address the role of preferences for technology attributes as factors influencing farmers' adoption behaviour (see Adesina & Zinnah, 1993; Useche et al., 2009). For example, specific attributes of some new technologies (e.g. labour-reducing or increased yield or low initial cost) may be more preferred than others. Moreover, although farmers' perceptions of attributes of technologies deserves attention in adoption studies, a research gap remains, in particular, an understanding of how farmer preferences with potential heterogeneity influence their adoption behaviour.

The effect of farmer heterogeneity on adoption has long been examined in technology adoption studies (Feder et al., 1985). Most of those studies focus on observable heterogeneity of farmer and farm characteristics. The heterogeneity in preferences for technology attributes is rarely incorporated in technology adoption studies. Heterogeneity in preferences for product attributes is extensively studied in the context of consumer choice studies (e.g Ortega et al., 2011; Loureiro & Umberger, 2007). Additionally, recent farmer preferences studies (e.g. Garrod et al., 2012; Sahara et al., 2013; Umberger et al., 2010) reveal heterogeneous farmer preferences for environmental stewardship programs and market channels; and unique segments of farmers with similar preferences for programs and market channels. There is a similar question of whether producer (farmer) preferences for certain agricultural technology products are heterogeneous. Thus, identifying groups of farmers with similar preferences for technology attributes would be useful in identifying strategies to facilitate technology adoption.

To address this knowledge gap, this study aims to understand how farmer preferences for technology attributes influence adoption behaviour. This study has three important contributions to the adoption literature. First, we consider three distinct adoption indicators recognizing that the concept of adoption is complex and has many meanings. The first is a binary adoption indicator, which is what is most commonly used in the literature to explore drivers of adoption. The other two indicators are duration of adoption and intensity of adoption. Second, we integrate a unique best-worst (BW) scaling task to elicit farmer preferences for technology attributes and to understand their adoption behaviours. Third, we perform an econometric analysis to estimate the effect of heterogeneity of preferences at the group (cluster) level (rather than at the individual level) on adoption behaviours. While some previous studies suggest the importance of technology attributes on technology adoption (e.g. Adesina & Zinnah, 1993), we are not aware of any studies that address the potential endogeneity of farmer preferences for technology attributes. To deal with this endogeneity issue, we use a multinomial endogenous treatment (selection) model.

In this study we focus on examining the adoption of "new horticultural crops" as a proxy for new technology. The preferences for crop attributes may vary among Indonesian farmers when they are considering the adoption of a new crop. For example, some farmers may prefer crops that offer high expected profit relative to other crops, while others may prefer crops that require fewer inputs (e.g. labour). Therefore, an understanding of the preferences for crop attributes and heterogeneity among farmers is important as it sheds light on what is important to farmers when considering whether or not to adopt a new crop. Moreover, this information more easily allows farmers to be targeted at the group level to encourage them to adopt high-value horticultural crops.

We conducted a survey of Indonesian farmers producing a variety of agricultural crops on Java Island, which has the largest production zone of horticultural crops in Indonesia. This study allows for including farmers that have adopted high-value horticultural crops. The remainder of this paper is structured as follows: Section 2 provides an overview of the household survey data collected in Indonesia; Section 3 describes the conceptual framework; Section 4 presents the empirical specifications and the variables used in the empirical model; this is followed by the estimated results and discussion of results in Section 5. The summary and conclusion are presented in the final section.

2. Household Survey Data

This study analyzes primary data obtained during 2012-2013 from a survey of Indonesian farmers that produce a variety of agricultural crops in both high elevation and lowland areas. A stratified random sample of 960 total farmers was drawn from 96 villages across Java. The random sample includes a significant amount of variation in production technologies employed by farm households. Eighteen experienced enumerators were recruited and trained in a six-day session during January 2013. They collected the data by interviewing selected farmers in their homes or in their fields. In addition to collecting information on farming systems and household characteristics, the survey also included a best-worst (BW) scaling task that reveal preferences for crop attributes.

2.1. Second Level Heading

This section explains the BW scaling experiment that was used to determine heterogeneity in preferences for crop attributes. BW scaling is used in consumer studies to determine the relative importance of health care and food product attributes and personal values (e.g. Auger et al., 2007; Cohen, 2009; Finn & Louviere, 1997; Flynn et al., 2007; Lagerkvist et al., 2012; Louviere et al., 2013; Mueller & Rungie, 2009). However, the literature related to producer preferences using BW scaling is still limited. Recent studies have mostly used BW scaling to analyse farmer preferences for market channel attributes (Sahara et al., 2013; Umberger et al., 2010) and policy options (Wolf & Tonsor, 2013). BW scaling is being used more frequently rather than traditional rating methods because it requires respondents to make trade-offs among sets of attributes. In other words, BW scaling requires respondents to rank attributes for the best and worst attributes only rather than ranking all attributes.

To apply a BW scaling experiment, respondents are presented with the sets of crop attributes. The crop attributes included in the BW scaling task were developed based on a review of previous studies on innovation attributes (e.g. Rogers, 2003) and crop variety preferences (e.g. Edmeades et al., 2008; Hintze et al., 2003; Wale & Yalew, 2007), as well as extensive interviews with farmers, farmer group leaders and extension officers. Originally 26 attributes were chosen and then were pre-tested with more than 30 farmers during the sample development process and again during the enumerator training sessions. The attributes were modified slightly after receiving feedback during pre-testing. This process resulted in the 11 technology attributes listed and defined in Table 1. The 11 attributes represented a wide range of categories of technology characteristics that drive adoption such as relative economic advantage (e.g. high expected profit), its cost (e.g. low initial investment costs, less labour required), its trialability (e.g. success of neighbours) and its risk or uncertainty (e.g. stable and consistent yield, stable and consistent price).

[Insert table 1]

A balanced incomplete block design (BIBD) (see Cohen, 2009) was used to develop 11 choice sets or "tasks" with five attributes each. Each attribute appeared five times across the 11 choice tasks. Respondents were asked to complete the 11 choice tasks and for each one they indicated which one of the five attributes was 'most important' ('best') and another that was 'least important' ('worst'). During the interviews with respondents, each choice task was presented on each separate card. An example of one of the BW scaling tasks is presented in Figure 1.

[Insert figure 1]

To obtain individual BW scores (B_{ij}-W_{ij}) for each of the 11 crop attributes, we summed the number of times each farmer (*i*) indicated an attribute (*j*) was 'most' (B_{ij}) and 'least' (W_{ij}) important. The sum of the 'least' in each attribute was subtracted from the sum of the 'most'. This individual BW score was used to determine preference clusters and then was integrated in the horticultural crop adoption model.

3. Conceptual Framework

To analyze the adoption of horticultural crops, we begin with a model of a household that maximizes utility by choosing a production technology and a consumption bundle while facing a number of market failures (Sadoulet & de Janvry, 1995). This is appropriate as the horticultural crops adopted for production represent a technology choice to be used in the production systems. The household maximizes utility from the consumption of goods (c) produced on-farm and purchased on the market. In addition, the utility function is conditioned on a set of household characteristics (H) to account for observable household level heterogeneity in the utility function. The objective of the household is to maximize this utility function by allocating factor inputs and a consumption bundle.

$$\max_{x,c} u(c, H)$$

The household is constrained by a number of conditions:

(i) $\sum_{i \in T} p_i(x_i + E_i - c_i) + S \geq 0$, cash constraint for tradable goods (T)

(ii) $\sum_{i \in TC} p_i(x_i + E_i - c_i) + R \geq 0$, credit constraint for tradable goods s.t. credit (TC)

(iii) $f(x, k) = 0$, a production technology

(iv) $p_i = \overline{p_i},\ i \in T$, an exogenous market price for tradable goods

(v) $c_i = x_i + E_i, i \in NT$ an equilibrium condition for non-tradables (NT)

The household maximizes utility subject to a number of constraints such as cash, credit, and production technology. We adapt the solution of the optimization problem given by Sadoulet and de Janvry (1995) and suggest that the adoption decision is modelled as a function of a set of variables measuring the farm households' incentives (p*) and the households' capacities (k). The optimal technology adoption model is as follows:

$$x^* = x(p^*, k)$$

where X_i is a variable indicating the adoption decision among farmers (e.g. adoption of high value crops) and $p*$ is a vector of decision prices, and k is a vector of fixed household assets. The decision prices p^* are a function of exogenous market prices ($\bar{p}$), the capital endowment of the household (k), household characteristics (H), exogenous transfers (S), and access to credit (R). Thus, the reduced form equation representing technology adoption is as follows, which we specify in the following estimable form:

$$X^*(\bar{p}, K, S, R, H) = X^*(Z) = Z\beta + \varepsilon$$

There is a rich literature on technology adoption among smallholder farmers analysing why some farm households adopt new technologies while others do not (Doss, 2006; Feder et al., 1985). However, the preference heterogeneity for crop (technology) attributes (e.g. reduced risk, government support), which affect how households adopt technology (Adesina & Zinnah, 1993), is seldom accounted for in cross-sectional models of technology adoption (see Useche et al., 2009).

To account for unobserved heterogeneity in household preferences for crop attributes, we utilize a latent class clustering method to account for variation across these groups. This clustering analysis used the individual scores for each of the BW scaling attributes. These were then incorporated into the adoption decision model to explore the hypothesis that differences in farmer preferences for crop attributes can affect their adoption decisions. Integrating preference heterogeneity into models of horticultural crop adoption enables more consistent estimation of parameters. By including the potential heterogeneity of preference parameters for crop attributes across farmers, the extended horticultural crop adoption model is as follows:

$$X_i^* = Z_i\beta + \alpha_j + \varepsilon_i$$

where i indexes the households and; j indexes the number of latent clusters; α is a vector representing farmer preferences for crop attributes Z is a vector of household and farm characteristics; X is a vector representing adoption (binary adoption, intensity of adoption and duration of adoption)

With this specification, we test the hypothesis that there are significant differences in farmer preferences for crop attributes at the group level that can affect the adoption decision. So, for example, a cluster which rated the perceived attributes related to costs and risks as the most important attributes, may be less likely to adopt than other clusters.

4. Empirical Specification

This section addresses our empirical strategy and discusses the key variables used in the models. Empirical studies use various methods to measure adoption behaviour such as a binary decision (e.g. Hintze et al., 2003), a continuous process (e.g. Lambrecht et al., 2014) and intensity of adoption (e.g Vignola et al., 2010). A survey of literature since the mid-1980s on conservation agriculture adoption across the world by Knowler and Bradshaw (2007) shows that about one-half of those studies used a dichotomous measure of adoption. In this study, we consider three different adoption indicators as a measure of adoption of any new horticultural crops. The main equation estimated is provided in equation (1):

$$Adoption_i = \beta\, Z_i + Cluster_j + \varepsilon_i \qquad (1)$$

Table 2 shows the descriptive statistics for the dependent and independent variables estimated in the regression model.

[Insert table 2]

In equation 1, the variable, $adoption_i$, represents the adoption decision of the respondent (farmer i). Three different specifications of $adoption_i$ are used. First, the variable takes on the value of one if the farmer household adopted a new horticultural crop in the six-year period from 2007 to 2012, and 0 otherwise. Thus, farmers who adopted any new horticultural crops in that period were identified as “new adopters” while farmers who never adopted those crops were coded as “non-adopters”. Based on that classification, 10.5% of the households adopted at least one new horticultural crop from 2007 to 2012.

Second, we generate a continuous variable to represent the intensity of adoption. This dependent variable represents the number of any new horticultural crops adopted by farmers in the six-year period from 2007 to 2012. The average number of crop adopted by 960 sample farmers was 0.14 and by 101 new adopters was 1.36.

Third, we create the timing of adoption which indicated what year farmers started to adopt any new horticultural crops. In enumerating the years of adoption by farmers, we take the value of 1 to 6 if the farmer household started to adopt a new horticultural crop in 2007 to 2012 consecutively and 0 otherwise. This variable could be used to identify which farmers are early adopters while others are laggards. On average, farmers adopted at year 0.14^{th} and new adopters at year 3.95^{th}.

The explanatory variable of interest, $Cluster_j$, is a set of dummy variables representing the preference-clusters. A detailed explanation of how this variable was generated is presented in the section 4.1. Our hypothesis is that adoption behaviour is different across clusters. However, it is important to note that the main methodological issues related to the model estimated using equation (1) is the endogeneity of α_j, the farmers’ crop preference cluster. The estimated coefficient for this variable could be biased as a result of correlation between the $Cluster_j$ variable and the error term. This correlation may be a result of reverse causation in which farmers’ adoption behaviour influences their preferences. To address this potential bias, we use multinomial endogenous selection estimation instead of ordinary least squares (OLS) estimation. The multinomial endogenous selection model is explained in the section 4.2.

The vector Z_i represents control variables, which represent the five broad categories of determinant factors frequently used in previous relevant adoption studies: farmer (household) characteristics, farm characteristics, socioeconomic, institutional factors and information (Doss, 2006; Feder et al., 1985; Knowler & Bradshaw, 2007).

Household characteristics include age of household head, years of education completed by household head, and number of people in the household more than15 years of age as proxy for household's labour endowment. Farm characteristics include farm size, land tenure, and share of irrigated land. We also include productive capital endowment which is calculated as the sum of values of three agricultural assets, namely transportation, production and storage assets. Socioeconomic factors include altitude and distance to market reflecting location and accessibility of market. We also include a variable to account for the total remittance income that a household receives as a way to control for exogenous shocks to household income. This income source may help households make the initial investments necessary when adopting a new horticultural crop.

Institutional factors include household participation in both Farmer Field School-Global Agriculture Practices/Good Handling Practices (FFS-GAP/GHP) for horticultural crops and FFS-Integrated Crop Management (FFS-ICM) for staple food crops. We also include membership in any producer organizations such as farmer groups, cooperatives, water use associations and female farmer groups. This membership variable is both a proxy for collective action, as well as an indicator of the accessibility of government programs and information related to production methods, markets and new technologies. For information factors, we also include a dummy variable indicating whether the household received information about horticultural crop production from extension officers.

In addition, to control the experience and knowledge of the farm household to grow a horticultural crop, we also generate a dummy variable "old adopters" which takes the value of one if the farmer household was engaged in horticultural crop production in 2007 and 0 otherwise. For the case of farmers who adopted any new horticultural crops in 2007 (as noted earlier as "new adopters"), the horticultural crops that were planted by them in 2007 are different from those new horticultural crops. In our data set, 62 of 101 new adopters are also old adopters.

4.1. Modelling Heterogeneity in Preferences for Crop Attributes

Based on the individual scores for each of the BW scaling attributes, we used a Latent Class (LC) cluster analysis that was conducted using LatentGold 4.5 software to model the heterogeneity of farmer preferences. LC clustering is defined as the classification of similar farmer preferences into clusters without prior information about the number of clusters or about the forms. This clustering assumes that the population consists of a certain number of latent clusters with different utility functions (Boxall & Adamowicz, 2002). LC clustering also measures heterogeneity as a discrete distribution by using a specification based on the concept of endogenous (or latent) preference segmentation. Preference parameters are relatively homogenous within clusters but differ between the clusters. The method concurrently estimates both choice probability and cluster membership (Boxall & Adamowicz, 2002; Vermunt & Magidson, 2002).

Similar to the previous studies applying LC cluster analysis to farmers' choices (e.g. Garrod et al., 2012; Sahara et al., 2013; Umberger et al., 2010; Wolf & Tonsor, 2013), we expected heterogeneity in farmer preferences for crop attributes. In this study, the 960 individual BW scores (B_{ij}-W_{ij}) for all 11 crop attributes were utilized as indicator variables. The optimal number of clusters was determined using the Akaike information criteria (AIC) and Bayesian information criteria (BIC) (i.e. smaller BIC values are preferred to higher BIC values, Vermunt & Magidson, 2002). Using the results of the LC cluster analysis, a number of unique clusters of farmers were established based on their preferences for crop attributes. To examine the heterogeneity more across clusters, we use a post-hoc Tukey Honestly Significant Difference (HSD) test to determine the differences between clusters in regard to their crop preferences and their socio-demographic characteristics. These LC clustering results are then incorporated into the horticultural crop adoption model as explanatory variables.

4.2. Multinomial Endogenous Treatment Model

After completing the LC cluster analysis to determine if Indonesian farmers have heterogeneous preferences for crop attributes, we next examine their adoption of horticultural crops. We estimate a model, which includes all control variables as explained above and the crop preference cluster variables. The estimation model is already presented in equation 1. The main methodological issues related to this estimation model lie in the endogeneity of α_j, the farmers' crop preference cluster. It seems to be a reverse causality between farmer preferences and their adoption. Farmer preferences affect their adoption behaviour, but farmers' adoption behaviour might also influence their changing preferences.

To address this endogeneity issue and given the multinomial selection variables, we use a multinomial endogenous treatment effects model (Deb & Trivedi, 2006a) to estimate the model parameters. This model, an extended model of the Heckman treatment effect method (Peel, 2014), is the most suitable method we are aware of for our case. According to Deb and Trivedi (2006a), this multinomial endogenous treatment model accommodates correlated endogenous sorting into different treatments, though neither endogenous sample selection nor endogenous participation. In this study, the treatments are the farmer preference-clusters which classified based on similar farmer preferences using LC cluster analysis. In practice, this model consisted of selection and outcome equations that estimate those equations simultaneously. Furthermore, this estimation can be used to analyse the effects of an endogenous multinomial treatment (selection) on both a binary and continuous outcome variable. As we explained before, the outcome variables in our study include both a binary variable (adoption decision, 1/0) and two continuous variables (years of adoption and numbers of crops adopted). Our selection variables, a multinomial form, are represented by the number of preference cluster variables which specified as N-1 (the base case) binary variables. More precisely, the outcome equation, an adoption equation, is written as equation (1) above and the selection equation, a multinomial logit, is provided in equation (2) as follows:

$$Cluster_i = \beta \, Z_i + \varepsilon_i \qquad (2)$$

This method controls for selection bias by allowing the error term in the selection equation (multinomial logit) to be correlated with the error term in the adoption equation. This model is estimated using maximum simulated likelihood that uses Halton draws.

To test heterogeneity across clusters, we use one cluster as the base cluster, and test if the parameters are different across clusters [H_0: $\alpha_j = 0$]. This allows the effect of the crop preference-clusters on adoption behaviour to vary across adoption models. Any significant preference-clusters ($\alpha_j \neq 0$) would indicate that crop attribute preferences are a significant source of unobserved heterogeneity in cross-sectional adoption models resulted from this study.

5. Results and Discussion

In this section we present the results from the two data analyses explained previously. First, we present the results from LC cluster followed by multinomial endogenous treatment regression.

5.1. Farmers' Heterogeneity

This study examines whether farmers are heterogeneous in their preference for crop attributes and characterizes those who are more or less likely to prefer certain crop attributes. Results from the LC cluster analysis indicate that the four-cluster model with the 11 BW indicators is the model with the best fit. The four-cluster model produces the smallest BIC value and best Wald test (the F-value was 11.15, and it was highly significant at the five per cent level of significance). We also identify the unique characteristics for each cluster using a post hoc characterization based on a comparison of means of BW indicators (Table 3), the demographic and farm characteristics across clusters (Table 4).

[Insert table 3 and 4]

Cluster 1, the largest segment or 33% of the sample, rated the perceived attributes *training and assistance on how to produce* and *government subsidies or incentives* as the most important crop attributes. Thus, we labelled this cluster as *the program dependent cluster*. Members of this cluster also consider *high expected profit*, *good quality seeds,* and *cash opportunities* as important crop attributes. The main characteristics of this group are they had the highest proportion of members who were involved in producer organizations such as a cooperative or a farmer group or a female group or a water use association (91%) and were more likely to have received production information on horticultural crops from the government (e.g. from *DINAS* and extension officers) (20%). This involvement perhaps offers opportunities for receiving more government support and consideration of government assistance programs such as training, subsidies and other technical assistance. Other main characteristics of this cluster are they have a relatively higher level education and a smaller farm size.

Farmers in cluster 2, representing 29% of the sample, placed the attribute *high expected profit* as the most important crop attribute, followed by *stable and consistent price* and *stable and consistent yield*. Compared to aggregate sample and other clusters, the attribute *high expected profit* had the highest mean BW score of any cluster. Therefore, these can be labelled as *the profit maximizer cluster*. The crop attributes of least importance to this cluster were similar to the aggregate sample and *the program dependent cluster*. The key characteristics of this cluster are they had the most dependence on agricultural activities and the lowest share of horticultural income. Members of this cluster also have the highest share of rented land (15.36%) and irrigated land (58.15%).

We labelled cluster 3, consisting of one fifth (20%) of the total sample, as *the risk-averse cluster*. Members of this cluster perceived *stable and consistent price* and *stable and consistent yield* as the most important crop attributes, followed by *high expected profit, good quality seeds* and *training and assistance on how to produce*. Interestingly, members of this cluster rated the two attributes *cash opportunities* and *success of other farmers / neighbours* as the least important attributes. On average, members in this cluster include the youngest farmers, owned more production and storage assets and higher horticultural income. They have the highest proportion of members living in lowland areas (157 m) and are located nearest to urban markets (18.97 km).

Cluster 4, 18% of the sample, ranked *high expected profit* as the most important of crop attributes. However, relative to the aggregate sample and other clusters, this cluster seems to also be more concerned about *low initial investment / start-up costs* and *less labour*. This reflects their concern about input use. Thus we labelled this cluster *the input minimizer cluster*. Interestingly, they are less concerned about *stable and consistent price* and *stable and consistent yield*, which is contrary to *the risk-averse cluster*. The main characteristics of this cluster are they are the least educated and the oldest farmers. They also had the highest share of off-farm income. Thus, this cluster seems to be less engage or was moving out to agricultural activities.

The analysis from LC clustering and post hoc Tukey HSD tests for BW indicators, socio-demographic characteristics demonstrate significant differences across clusters. The farmers are heterogeneous both in their preferences for crop attributes and their socio-demographic characteristics. In addition, their crop preferences indicate a clear differentiation in terms of the conditions they prefer to adopt a new crop. These results are similar to previous studies (e.g. Sahara et al., 2013; Umberger et al., 2010) that find unique clusters of farmers with similar preferences for certain attributes. For example, Umberger et al. (2010) identify four unique clusters of Indonesian potato producers with different utilities for marketing channel attributes. That heterogeneity in preferences for crop attributes among farmers maybe influence their adoption behaviour differently. To further validate those results, the following section presents the effect of preference heterogeneity on three types of adoption behaviour.

5.2. Multinomial Endogenous Treatment Regression Results

Results of the LC cluster analysis suggest that there is heterogeneity in crop-attribute preferences. In this section, we present the regression results of the effect of attribute preferences on adoption. We also discuss whether there are differences across clusters in the adoption of new horticultural crops. Furthermore, we also discuss the effect of other control variables on adoption patterns.

5.2.1. The Effect of Preference Cluster on Adoption

Multinomial endogenous treatment estimations are applied to test if horticultural crop adoption behaviour is uniform across preference clusters, or if adoption behaviour varies across clusters. In these estimations, we set *the profit maximizer cluster* as the reference group, and we interpret other clusters, namely *the program dependent cluster, the risk-averse cluster* and *the input minimizer cluster,* as three different groups that have differential effect on adoption behaviour. Table 5 shows the complete results of maximum simulated likelihood estimates from the multinomial endogenous treatment estimations.

[Insert table 5]

Overall, results show that the preference-cluster effect varies across models. For the binary model, we find an insignificant preference-cluster effect in this model. To validate further, we also did a post-estimation test parameter with the null hypothesis that the preference-cluster coefficients are jointly equal to zero. The results also show no difference among preference-cluster effect.

On the other hand, we find a significant preference-cluster effect on those adoption models. However, the effects of farmers' crop preference cluster are different across those models. Compared to the base cluster (*the profit maximizer cluster*), farmers in *the risk-averse cluster* are more likely to adopt at a later time. It may be because shifting to a new horticultural crop is more risky. This result is consistent with the findings of previous studies that suggest that risk and uncertainty have important roles on agricultural technology adoption including the timing of adoption (see Marra et al., 2003). Moreover, farmers in *the risk-averse cluster* are less likely to adopt new technologies that increase yield variance, especially in the early adoption process (Jack, 2011). However, at the same time, farmers in this cluster are more likely to adopt multiple new crops than other clusters. To some extent, this is an interesting result, supporting the literature on adoption studies that suggests farmers need to take up risk coping strategies to overcome the adoption constraints imposed by risk (Jack, 2011). For farmers in this cluster, by adopting multiple horticultural crops perhaps they may reduce risk through diversification: even if one new crop fails, perhaps others will not.

For farmers in *the program dependent cluster*, they are more likely to adopt at a shorter time. Their likelihood to be early adopters may be as they are more dependent to both government and non-government programs. They will consider growing a new crop if they are supported by programs that provide training or subsidies. The crops supported by government and non-government assistance are preferred by farmers in this cluster. In Indonesia, however, only certain horticultural crops are commonly supported by programs, known as *komoditas hortikultura unggulan* – competitive horticultural crops. Examples of Indonesia's competitive horticultural crops enacted by the Government of Indonesia (GoI) are chillies, shallots, potatoes, mangoes and mangosteens. Furthermore, the developments of *komoditas hortikultura unggulan* are regional or local-specific, known as *kawasan hortikultura* – horticultural regions. This may explain why farmers in this cluster are less likely to adopt a number of new horticultural crops. In addition, it may be because they are more likely to depend on the program support.

Interestingly, we find that farmers in *the input minimizer cluster* are more likely to adopt at an earlier time but less likely to adopt multiple new horticultural crops. It may be as they more concerned with the attributes *seed access, low-investment technologies* and *labour saving* as the most important crops attributes when adopting a new crop. Recognizing that the production cost of horticultural crops is relatively higher than staple food crops (Joshi et al., 2006), they perhaps not to adopt multiple new horticultural crops. These farmers also place more importance on seeing the success of neighbour growing the crop, which may cause them not to adopt multiple new horticultural crops.

Furthermore, recognizing their preferences for crop attributes, this may suggest that they have less experience and knowledge on how new horticultural crops could affect their use of inputs and labour, and then they will consider to adopt at the right time and number of crops. According to Joshi et al. (2006), relative to rice and other staple food crops, horticultural crops like vegetables are more labour intensive in activities such as planting, harvesting and post-harvest handling. Thus crop-wise labour use play an important role in deciding the production-portfolio for *the input minimizer cluster*. In addition, Joshi et al. (2006) suggest that availability of good quality seeds could be as crucial constraints faced by smallholders in horticultural adoption. Thus, farmers in *the input minimizer cluster* who favoured attribute seed access are perhaps regarded as laggards in adoption of new horticultural crops.

In addition, results also show that the endogeneity test varies across models (Table 5). For the binary model, the null hypothesis that the preference-cluster lamdas (λ) are simultaneously equal to zero is accepted which is no evidence of endogeneity (Deb & Trivedi, 2006a; Deb & Trivedi, 2006b). Conversely, for both the duration of adoption and the intensity of adoption models, we find strong evidence of endogeneity of the preference-cluster. The null hypothesis that the preference-cluster lamdas (λ) are simultaneously equal to zero is rejected in those models at one per cent level of significance. These results indicate that the traditional adoption model, ignoring potential endogeneity of preference-cluster, maybe appropriate for the binary decision model and vice versa for both intensity of adoption and timing of adoption models.

5.2.2. The Effect of Other Characteristics on Adoption

The regression results also show that government extension services had a significant positive effect on horticultural adoption across all models. In addition, farm households with younger heads of household were significantly more likely to adopt multiple new horticultural crops. This demonstrates that technical programming is effective in promoting the adoption of horticultural crops, and those younger farmers are the most suitable targets for promotion of horticultural crops.

Moreover, the effect of producer organization membership has a significant positive effect on adoption in all models. This demonstrates that producer organizations make an effective contribution to horticultural crop adoption. For the effect of FFS GAP/GHP, we find a positive response in all adoption models. This farmer field school provides knowledge to farmers regarding horticultural production possibilities (available technologies), which makes it easier for farmers to shift to desired horticultural crops. Conversely, the effect of FFS ICM is a negative to horticultural crop adoption. This is not surprising FFS ICM is aimed to farmers for staple food crops such as rice, maize and soybean.

6. Summary and Conclusions

High-value horticultural crops such as fruits and vegetables offer opportunities for Indonesian farmers to increase their income. Most previous studies on technology adoption measure adoption as a binary adoption decision and examined the factors affecting the adoption decision such as farm and farmer characteristics. This study contributes to this body of literature by examining adoption as more than binary decision and focusing on the role of heterogeneity in preferences for crop attributes,

In addition to the binary adoption indicator, we include two additional adoption measures, namely intensity of adoption and timing of adoption, that allows us to see adoption as a complex process with multiple dimensions. These indicators provide more comprehensive perspective to policy makers, extension agents and agricultural development specialists.

Second, we integrate a unique best-worst (BW) scaling task to elicit farmer preferences for technology (crop) attributes and their adoption behaviours. To do that, we utilize a LC cluster using the BW score at the individual level to address farmer heterogeneity in preferences for technology (crop) attributes at the group (segment) level. Four distinct clusters of farmers are identified: *program dependent farmers* (the largest), *profit maximizers*, *risk-averse farmers* and *input minimizers*. Each is associated with distinct socio-demographic characteristics.

Third, we add to the previous adoption studies by examining adoption behaviour as a function of preferences for technology attributes as well as farmer and farm characteristics. We test the effect of the heterogeneity of farmer preferences at the group (segment) level rather than at the individual level. In the estimation, we address the potential endogeneity of farmer preferences for technology attributes using multinomial endogenous treatment model. The multinomial endogenous treatment regressions show that preference cluster effect varies across models. We find that the product-preference cluster has no significant effect on adoption measured as a binary variable (whether or not they adopt). The product-preference cluster does have a significant effect on the intensity of adoption and the timing of adoption.

Therefore, examining the effect of farmer preferences for crop attributes is important in understanding the adoption process. Targeting farmers in *the risk-averse cluster* may be a better strategy to promote sustainable horticultural development in Indonesia. These are farmer households that are highly concerned with *stable and consistent price* and *stable and consistent yield,* followed by *high expected profit, good quality seeds* and *training and assistance on how to produce*. These households tend to be younger and have more agricultural assets. In addition, they tend to adopt multiple horticultural crops but are also relatively slow to adopt new horticultural crops. Thus, the effectiveness of horticultural development programming to induce crop and varietal shift depends on strategies to help this group of farmers adopt earlier. Targeting this clusters to diversify into horticulture is also consistent with the recommendations of IFPRI (2015) suggesting that public policy makers should support farmers in *moving up* to more profitable farming activities.

While some farmers may have the potential to successfully diversify into horticulture, others may not. That is, not all programming and policy works the same for all farm households. This implies that targeting farmers in other clusters may not the best strategy to promote sustainable horticultural development in Indonesia. For example, households in *the program dependent cluster* represent the largest proportion of farmers who consider growing a new horticultural crop if subsidies or training are provided, suggesting that they are unstable adopters. Another cluster, *the input minimizer cluster*, seems to be less engaged on agriculture activities. In other words, they could be identified as "transition group" to off-farm activities. Thus, targeting *the input minimizer cluster* to seek off-farm employment opportunities is consistent with another recommendation of IFPRI (2015) suggesting that public policy makers should support farmers in *moving out* of agriculture.

Overall, the findings suggest that knowledge about important crop attributes and heterogeneity among farmers would help policymakers, extension and agricultural development specialists attempting to encourage smallholder farmer to adopt horticultural crops. This knowledge would also help to set the priorities of crop development researchers so they can focus on the specific product-attribute preferences of farmers. These findings also allow more targeted policy and development programs by designing incentives and information on specific cropping attributes that are most likely to encourage farmers to adopt crops that have a high probability of offering benefits, resulting in improved livelihoods for smallholders.

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Appendices

Table 1. Descriptive Statistics of BW Indicators Used in the LC Cluster Analysis

Variables	Definition of Variables	Means	Std. Dev	Min	Max	Obs.
Crop Attributes						
Higher expected profit	The new crops is expected to generate higher profit / return relative to other crops	1.76	1.81	-4	5	960
Stable price	The price for the new crops is expected to be more stable and consistent and less risky with fewer fluctuations and with a guaranteed market	0.64	1.94	-5	5	960
Stable yield	The new crops is expected to produce stable and consistent yield or less variable yield (e.g. new crop is resistant to weather, pests and disease)	0.80	1.73	-4	5	960
Seed access	Good quality seeds of the new crops are accessible	0.66	1.57	-4	5	960
Less labour	Less labour is required to produce the new crops	-1.48	1.79	-5	4	960
Less water	The new crops require the use of less water than other crops	-1.94	1.88	-5	5	960
Low start-up cost	Shifting to new crops need low initial investment / start-up costs	-0.74	1.74	-5	5	960
Success of neighbour	Other farmers / neighbors have adopted the new crops and have been successful	-1.00	1.97	-5	5	960
Subsidies provided	Government should provide subsidies or incentives to plant new crops	0.66	1.81	-5	5	960
Cash opportunities	The new crops provides cash opportunities when needed (e.g. flexible harvest)	-0.01	1.84	-4	5	960
Training provided	Training and assistance on how to produce new crops is accessible (easy to reach & affordable)	0.65	2.05	-5	5	960

Table 2. Summary Statistics for Dependent and Independent Variables (N=960)

Variables	Mean	Std. Dev.
New adopters (1 if adopted any new horticultural crops in 2007-2012, 0 otherwise)	0.11	0.31
Intensity of adoption (dependent variable, number of any new horticultural crops adopted in 2007-2012)	0.14	0.48
Timing of adoption (dependent variable, 1 to 6 if farmers started to adopt a new horticultural crop in 2007 to 2012 and 0 otherwise)	0.42	1.33
Age HH (years)	51.69	11.22
Education HH (years)	7.21	3.41
Number of adult persons	2.95	1.03
Agriculture asset		
Transportation asset, e.g. motorbike, truck, cart (million Rp)	8.42	20.16
Production asset, e.g water pump, sprayer, tractor (million Rp)	1.49	3.94
Storage asset, e.g. storage house (million Rp)	2.05	18.99
Farm size (ha)	0.76	0.77
% of rented land	13.63	29.88
% of irrigated land	56.27	43.79
Remittance income (million Rp)	1.35	13.69
Distance to nearest urban market (km)	20.54	13.59
Altitude (m)	196.82	295.49
Access to extension (1 if received information about horticultural production from extension officers, 0 otherwise)	0.19	0.39
FFS GAP/GHP (1 if participated in Farmer Field School-Good Agricultural Practices/Good Handling Practices for horticultural crops, 0 otherwise)	0.09	0.29
FFS ICM (1 if participated in Farmer Field School-Integrated Crop Management for staple food crops, 0 otherwise)	0.36	0.48
Membership in producer organizations (1 if members of cooperative or farmer group or water use association or female farmer group, 0 otherwise)	0.83	0.38
Role of spouse (1 if spouse managed at least one crop, 0 otherwise)	0.39	0.49
Old adopters (1 if produced any horticultural crops in 2007, 0 otherwise)	0.40	0.49
Crop Preference-Cluster	**Freq.**	**%**
Program dependent cluster	318	33
Profit maximizer cluster	280	29
Risk-averse cluster	194	20
Input minimizer cluster	168	18

Table 3. Mean BW Indicators for Each Crop Attributes by LC Cluster

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**
Cluster Size	33%	29%	20%	18%
Crop Attribute	**Mean B-W**	**Mean B-W**	**Mean B-W**	**Mean B-W**
Higher expected profit	1.36[a,b]	3.21[a,c,d]	0.94[b,c]	1.04[d]
Stable price	0.24[a,b,c]	1.34[a,d,e]	1.80[b,d,f]	-1.09[c,e,f]
Stable yield	0.40[a,b,c]	1.59[a,d,e]	1.86[b,e]	-0.96[c,d,e]
Seed access	0.97[a]	0.17[a,b,c]	0.75[b]	0.76[c]
Less labour	-2.26[a,b]	-2.23[c,d]	-0.55[a,c,e]	0.20[b,d,e]
Less water	-2.46[a,b]	-2.85[c,d]	-0.63[a,c]	-0.93[b,d]
Low start-up cost	-1.70[a,b,c]	-0.71[a,d,e]	-0.24[b,d,f]	0.48[c,e,f]
Success of neighbour	-0.98[a,b]	-0.58[c]	-2.33[a,c,d]	-0.23[b,d]
Subsidies provided	1.67[a,b,c]	0.52[a,d]	-0.68[b,d,e]	0.50[c,e]
Cash opportunities	0.50[a,b]	-0.27[a,c,d]	-0.86[b,c,e]	0.43[d,e]
Training provided	2.26[a,b,c]	-0.18[a]	-0.06[b]	-0.18[c]

Log-Likelihood (LL) = -20810.8152; Classification errors = 0.2363; Number of parameters = 140; Degrees of freedom = 820. [a,b,c,d,e,f] Means within a row with same superscript letters are statistically different ($\alpha = 0.05$, post-hoc Tukey HSD test)

Table 4. Characteristics of LC Cluster

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	
Name of Cluster	**Program Dependence**	**Profit Maximizer**	**Risk-Averse**	**Input Minimizer**	
Size of Cluster	33%	29%	20%	18%	
Variables	**Mean**	**Mean**	**Mean**	**Mean**	**F Value**
HH Characteristics					
Age HH (years)	50.8	52.90[a]	50.01[a,b]	53.31[b]	4.41***
Age spouse (years)	41.79	42.71	40.88	42.79	0.77
Education HH (years)	7.57[a]	7.28[b]	7.25[c]	6.36[a,b,c]	4.76***
Education spouse (years)	6.97[a]	6.41	6.71	6.05[a]	2.89**
Number of adult persons	2.99	2.90	2.88	3.07	1.40
Number of children	0.79[a]	0.61	0.76	0.57[a]	4.13***
Owns mobile phone (unit)	1.98	1.79	1.81	1.67	2.43*
Farm Characteristics and Farm Assets					
Farm size (ha)	0.75	0.76	0.75	0.80	0.22
% of rented land	13.30	15.22	14.13	11.02	0.72
% of irrigated land	55.63	58.15	55.02	55.78	0.25
Spouse managed at least one crop (1/0)	0.37	0.45	0.38	0.34	2.04
Old adopters, engaged horticulture in 2007 (1/0)	0.42	0.43	0.35	0.36	1.90
Engaged any horticultural crops in 2012 (1/0)	0.45	0.46	0.41	0.39	0.94
Transportation asset (million Rp)	7.70	7.34	9.09	10.81	1.26
Production asset (million Rp)	1.55	1.32	1.63	1.50	0.27
Storage asset (million Rp)	1.57	1.35	3.64	2.30	0.65
Institutional and Information Factors					
Received to input credit (1/0)	0.13	0.10	0.10	0.09	0.64
Member of producer organizations (1/0)	0.91[a,b,c]	0.80[a]	0.78[b]	0.77[c]	7.87***
Received to extension support (1/0)	0.20	0.21	0.15	0.15	1.29
FFS GAP/GHP (1/0)	0.11	0.06	0.11	0.09	2.00
FFS ICM (1/0)	0.44[a,b,c]	0.32[a]	0.31[b]	0.30[c]	4.74***
Income Activities and Location					
Net income (million Rp)	41.40	41.67	43.29	44.42	0.08
% of off-farm income	44.70	39.91	40.04	48.32	2.54*
% of horticultural income	12.05	-20.20	17.19	11.97	1.05
% of grain (rice, maize) income	47.79	96.27	75.39	64.28	1.00
Remittance income (million Rp)	0.80	0.83	1.00	3.67	1.97
Altitude (m)	215.26	186.96	157.71	223.52	2.11*
Distance to nearest urban market (km)	21.08	20.70	18.97	21.06	1.12

Notes: ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. [a,b,c] Means within a row with same superscript letters are statistically different (α = 0.05, post-hoc Tukey HSD test).

Table 5. Multinomial Endogenous Treatment Results

Dependent Variable:	New adopters (1/0)		Intensity of Adoption		Timing of Adoption (years)	
	(1)		(2)		(3)	
Age HH (years)	-0.032**	*(0.015)*	-0.003**	*(0.001)*	-0.004	*(0.004)*
Education HH (years)	0.067	*(0.042)*	0.008	*(0.006)*	0.021	*(0.015)*
Number of adult persons	0.184	*(0.120)*	0.002	*(0.013)*	0.054	*(0.040)*
Transportation asset (million Rp)	-0.032*	*(0.019)*	-0.001	*(0.001)*	-0.002	*(0.002)*
Production asset (million Rp)	0.055*	*(0.029)*	0.004	*(0.003)*	0.010	*(0.012)*
Storage asset (million Rp)	0.009**	*(0.004)*	0.002***	*(0.001)*	0.002*	*(0.001)*
Farm size (ha)	0.014	*(0.144)*	-0.010	*(0.019)*	0.001	*(0.049)*
% of rented land	0.011**	*(0.005)*	0.002**	*(0.001)*	0.006***	*(0.002)*
% of irrigated land	-0.002	*(0.003)*	0.000	*(0.000)*	-0.002	*(0.001)*
Remittance income (million Rp)	-0.024	*(0.054)*	0.000	*(0.001)*	0.001	*(0.002)*
Distance to nearest urban market (km)	0.012	*(0.009)*	0.002	*(0.002)*	0.009*	*(0.005)*
Altitude (m)	0.001***	*(0.000)*	0.000**	*(0.000)*	0.001**	*(0.000)*
Received to extension support (1/0)	1.249***	*(0.424)*	0.162***	*(0.062)*	0.492***	*(0.191)*
FFS GAP/GHP (1/0)	0.772*	*(0.401)*	0.081	*(0.063)*	0.114	*(0.201)*
FFS ICM (1/0)	-0.547*	*(0.327)*	-0.059	*(0.036)*	-0.049	*(0.121)*
Member in producer organizations (1/0)	1.090**	*(0.485)*	0.090**	*(0.040)*	0.342***	*(0.103)*
Role of spouse (1/10)	0.123	*(0.250)*	0.039	*(0.034)*	-0.042	*(0.093)*
Old adopters (1/0)	0.514	*(0.334)*	0.019	*(0.044)*	0.059	*(0.125)*
Constant	-3.933**	*(1.197)*	0.034	*(0.133)*	-0.320	*(0.382)*
Treatment Effect:						
Profit maximizer cluster (base category)						
Program dependent cluster	0.046	*(0.417)*	-0.074	*(0.054)*	-0.249*	*(0.136)*
Risk-averse cluster	0.391	*(1.117)*	0.195***	*(0.045)*	0.815***	*(0.126)*
Input minimizer cluster	-0.283	*(0.653)*	-0.092*	*(0.048)*	-0.386**	*(0.154)*
ln sigma			-1.039***	*(0.088)*	-0.570***	*(0.102)*
λ Program dependent cluster	0.100	*(0.355)*	0.116***	*(0.035)*	0.448***	*(0.135)*
λ Risk-averse cluster	-0.839	*(1.209)*	-0.262***	*(0.035)*	-1.001***	*(0.079)*
λ Input minimizer cluster	0.316	*(0.580)*	0.119***	*(0.026)*	0.476***	*(0.129)*
Sigma			0.354	*(0.031)*	0.565	*(0.058)*
Number of obs	960		960		960	
Wald chi2(75)	160.64***		257.9***		259.13***	
Log pseudolikelihood	-1521.87		-1844.87		-2816.80	

Notes: ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors presented in parentheses. In this estimation, we used 10000 Halton sequence-based quasi random draws per observation. We used outcome density is logit for model 1 and normal for others. Standard deviation of factor density is 1.

For the following question, please tick one box in the left column to indicate the attribute that is MOST important to you and please tick one box in the right column to indicate the attribute that is LEAST important to you when considering whether to adopt a new crop. Please tick only one box per column.

Most Important (tick one box)	Of the following, which attributes are the Most and Least important to you…	Least important (tick one box)
□	1. High expected profit / return relative to other crops	□
□	4. Good quality seeds are accessible	□
□	5. Less labour is required	□
□	9. Government provides subsidies or incentives to plant	□
□	3. Stable and consistent yield (e.g. crop is resistant to weather, pests and disease)	□

Figure 1. An example of one of the BW scaling tasks