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Risk aversion level influence on farmer's decision to participate in crop insurance: A review

Rizky Yanuarti, Joni Murti Mulyo Aji, Mohammad Rondhi*

Department of Agribusiness, Faculty of Agriculture, University of Jember, Jember, Indonesia
**Corresponding author: joni.faperta@unej.ac.id*

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Abstract: Agricultural insurance in Indonesia is focused specifically on rice farming and is locally known as Asuransi Usahatani Padi (AUTP). To encourage farmer participation, the government subsidises farmers' cost of insurance (premium) by 80%. Despite high subsidy, AUTP is still unable to reach the coverage target. The objectives of this study are to investigate farmers' Risk Aversion Level (RAL), its influence on farmers' decision to participate in AUTP, and the effect of farmers' participation in AUTP on their income. The result of this study can contribute to enriching agriculture insurance literature from the point of view of developing countries and catalyse other studies on this matter especially in Indonesia. The analysis methods used in this study were multiple pricelist designs and propensity score matching with a logistic regression model. 130 farmers were interviewed. The results showed that farmers tend to have a high level of risk aversion (82.3% of farmers insure almost all of their land). RAL has a significant effect on farmers' decision to purchase AUTP (< 0.01). A positive value of Average Treatment on the Treated (ATT) indicated that participation in AUTP has a positive impact on farmers' income. AUTP is able to absorb production risks and encourage use of high input in farming.

Keywords: agricultural insurance; propensity score matching; rice farming; risk aversion

Agricultural farming is a risky business since weather, pests, diseases, and other factors may affect crop yields. Long production cycle makes farmers particularly vulnerable to natural disasters which causes uncertainty in production profits, livelihoods, and sometimes leads to harvest failure. As a result, yield variability is one of the top two risks feared by producers of major field crops (Harwood et al. 1999). One way to reduce farmers' risk is by agricultural insurance (Afroz et al. 2017).

Indonesia, known as one of the agrarian countries in Southeast Asia, has been concerned about and thus actively supporting the implementation of national agricultural insurance since 2015. The agricultural insurance support is currently still focused on Rice Farming Insurance, locally called Asuransi Usaha Tani Padi (AUTP). The implementation of AUTP is still rather new, and in order to encourage farmer participation, the government subsidises premium payments by 80% while the rest is paid independently by farmers. The government has selected Perseroan Terbatas (PT) Jasindo as the insurance company to handle AUTP.

Government has an important role in maintaining the implementation of agricultural insurance. Coble et al. (1997) state that government interventions can also give incentives to farmers, prompting them to manage risk privately. Frequently, the reason for subsidising crop insurance is closely linked to potential market failures due to combination of farmer risk aversion, farm-specific risks, and information problems.

Research of Zhao et al. (2017) on subsidised farmers in China confirms that farmers who choose to participate in insurance programs generally have a risk-averse attitude or a certain Risk Aversion Level (RAL). Farmers with a high perception of risk generally take part in an insurance program. Lyu and Barré (2017) analyse farmer risk aversion levels by using a ball-game experiment. The experimental design was modified so it would easily be understood by farmers. A similar study was also conducted by Vassalos and Li (2016)

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using the question with assumptions method adapted from Binswanger (1980). RAL influence on farmers' decision can be analysed using logistic regression by adding complementary factors such as farmers' demography. It was found that RAL has an important role to play in farmer decision to purchase crop insurance and in their participation in agricultural contracts (Vassalos and Li 2016). In addition, farmers' decision to buy insurance is influenced by insurance experience, farming experience, age, cropland area, harvest failure experience (Zhao et al. 2016).

Theoretically, the existence of rice farming insurance will have a positive impact on farmer income. Because if a farmer's land is affected by a disaster, that farmer can still get income from insurance compensation to be paid by PT Jasindo. The compensation can be used by farmers as capital for farming in the following season. Zhao et al. (2016) used Propensity Score Matching (PSM) to assess the impact of farmer participation in crop insurance on farmer income in China. PSM involves an analysis of factors that influence farmer decision to participate in crop insurance by using a logistic regression model. Nearest Neighbourhood Matching (NNM), Radius Matching (RM) and Kernel Matching (KM) algorithms indicate that the matching process already appropriates between participants and non-participants in an insurance scheme. It was found that participation in insurance had no significant effect on increasing farmers' income in China. This is partly due to high premium subsidies provided by China government that urge producers, who tend to be neutral towards risk, to participate. This makes crop insurance attractive both for high-risk and low-risk farmers.

Nevertheless, since it was implemented in 2015, rice farming insurance in Indonesia has not been able to reach the target. Based on data from Indonesian Ministry of Agriculture (2018), in 2015 the AUTP target was set at 1 million ha, but AUTP was only implemented on 0.23 million ha (23.35%). In 2016, the target was only 0.5 million ha because of a budget cuts policy, with the realisation of 0.49 million ha (99.9%). In 2017, AUTP target was 1 million ha, with the realisation of 0.99 million ha (99.99%). The latest data from 2018 show that AUTP realisation was around 0.806 million ha, at 80.62% of the 1 million ha target. The realisation of AUTP for the past four years (2015–2018) shows a positive trend with total insured paddy fields reaching 2.5 million ha from the target of 3.5 million ha (72.50%). However, the coverage ratio is still low. Despite an 80% subsidy, AUTP is still not able to reach the coverage target. The question is, then, why even with the high subsidy, AUTP coverage is still low. From this description, the objective of our study is to determine the farmer RAL, its influence in farmer decision, and agricultural insurance impact on farmer income.

MATERIAL AND METHODS

According to the Government of Indonesia Law No. 19 2013, the implementation of AUTP will be consistent in all regions across the country. The government is focusing on AUTP implementation in rice barns area, one of which is East Java. Jember is one of the largest rice producing areas in East Java, thus we selected Jember as our research area. Based on data from PT Jasindo in 2018, 130 farmers were selected from the total of 367 farmers using Slovin formula. The sample was divided into two groups, namely treatment and control groups. The treatment group consisted of 65 farmers who followed AUTP (taken from the insurer list). Control group consisted of farmers who did not follow AUTP and were randomly selected.

Risk aversion level measurement

This research used a multiple price list design to obtain farmer risk aversion level. The model used was a modification of Vassalos and Li (2016). Modifications were made to fit the characteristics of rice farmers' decision to purchase AUTP. In detail, farmers were asked to choose between two conditions, i.e. to insure or not to insure their rice farming. Farmers were asked to consider their choice on the basis of possibility of disasters (floods, pest attacks, drought), and on different economic returns (Binswanger 1980; Vassalos and Li 2016).

In order to measure RAL, farmers in this study were asked the following, each in a tailored manner: e.g. you have 5 plots of rice fields, each plot having an area of 0.25 ha. You can freely choose to insure the land or not. If you choose to join insurance, there is a premium to be paid in the amount of 2.54 USD/ha/planting season, but your land is guaranteed from losses due to disasters (floods, droughts, pest attacks). "Guaranteed" means that the insured land will receive compensation of 424.03 USD/ha. Conversely, if you do not take insurance, you do not need to pay premiums but your land is not guaranteed from losses due to disasters. If there is no disaster (with a 50% probability), each plot will generate a profit

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of 70.67 USD, so the total profit that can be obtained (from five plots) is 353.37 USD. However, if a disaster occurs, then the profit is 0 USD, i.e. there is no profit.

Table 1 shows the questions used to find out farmers' perception of risk, ranging from A (extreme), B (severe), C (intermediate), D (moderate), E (slight to neutral), to F (neutral to negative). The advantage of this method is that it can be used even though the respondent does not have knowledge about probability. Then the value is analysed using logistic regression to determine its effect on farmers' decisions in following AUTP. Options A to F were given an ordinal value from 1 to 6 respectively, and before being analysed the value was changed to interval value by using the Method of Successive Intervals (MSI).

Effect of crop insurance on farmer income

In general, econometric techniques for identifying unbiased estimates of the impact of treatment rely on the use of a control group as a means of accounting for potentially confounding factors. The success of this procedure depends crucially on the assumption that, conditional on observable factors, the treatment and control groups differ only in treatment status. PSM is an analysis using the propensity score from treatment and control groups to measure the effect of treatment on the outcome by comparing across observations in each identified group (Rosenbaum and Rubin 1983).

The propensity score is the conditional probability of being treated; in our case, receiving crop insurance. Specifically:

$$p(X) = \Pr(Y = 1 \mid X) = E(Y \mid X) \quad (1)$$

where Y is a binary variable indicating whether a farmer participates in AUTP (1 = yes; or 0 = no), X is the multidimensional vector of pre-treatment characteristics of a farmer, Pr is the probability of being treated, E is the mean outcome and $p(X)$ is the propensity score. Standard probit or logit regression models are commonly deployed to estimate $p(X)$. Following the estimation of the propensity score, one must estimate the average effect of treatment. Estimation of the treatment effect is done using matching methods. The difference between groups of treated farmers and selected control group farmers is used to estimate the effect of treatment. Common methods include NNM, RM, and KM (Becker and Ichino 2002). In what follows, we explore treatment effect estimates based on each approach for comparison and assurance that our estimates are robust. Table 2 describes the variables used in logistic regression analysis.

After that, the matching method was selected. This research used three matching methods, NNM, KM, and RM. NNM selects the closest score from the control group covariates to be matched with the treatment group. The weakness of the NNM method is that the matching process produces poor results if the value of the closest neighbour propensity score is distant. In the Kernel method, each individual in the treatment group was matched with the weighted average of individuals who had the same propensity score, where greater weight was given to subjects with a closer score. The radius matching method uses a tolerance level at maximum propensity score distance between subjects in the treatment group and all individuals in the control group at that distance. If the radius used is small, it is possible that some individuals in the treatment group did not get a suitable partner because the nearest neighbour did not have the appropriate propensity score (Pan 2014).

We point out that in the PSM case, a distinction must be made between Average Treatment Effect (ATE) which is the average treatment effect on all observations, regardless of treatment, and the Average

Table 1. Risk preferences elicitation question

Choices (choose one)	Insured plots (number)	Uninsured plots (number)	If disaster does not happen (probability 50%; USD)	If disaster happens (probability 50%; USD)	Risk aversion class
A	5	0	350.22	530.09	extreme
B	4	1	350.90	424.03	severe
C	3	2	351.47	318.05	intermediate
D	2	3	352.11	212.01	moderate
E	1	4	352.74	106.01	slight to neutral
F	0	5	353.37	0.00	neutral to negative

Source: Alternative Combination Model (Vassalos and Li 2016)

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Table 2. Description of logistic regression variable on farmer decision to purchase AUTP in Jember, 2018

Factors		Description	Units	Measure
Y	option to buy insurance	farmers' decision whether or not purchase crop insurance; 1 means purchase rice farming insurance AUTP and 0 means do not purchase AUTP	–	nominal
X_1	Risk Aversion Level (RAL)	RAL is obtained by using the question method with assumptions, according to the research conducted by Vassalos and Li (2016); there are six answers that can be chosen by farmers, each of which has a value ranging from 1 to 6	Method of Successive Interval (MSI)	scale
X_2	age	farmers' age in the year when the research was conducted	year	scale
X_3	farming experience	farmers' experience in the year when the research was conducted	year	scale
X_4	cropland area	paddy farming area	ha	scale
X_5	harvest failure experience due to pest attack	farmers' harvest failure to represent farmers understanding towards risk where 1 means farmers have experienced loss and 0 means farmers never experienced loss	–	nominal

AUTP – rice farming insurance, locally called as Asuransi Usaha Tani Padi in Indonesia

Source: own elaboration, 2018

Treatment on the Treated (ATT), which is the average effect of treatment only on the treated observations. ATE is identical to ATT; however, in more complex models, the ATE and ATT are calculated separately – see Becker and Ichino (2002) for further technical details and computational implementation using Stata. In this research, the ATT value was used to determine the effect of agriculture insurance on farmer income. ATT is estimated as follows:

$$ATT = E[E\{Y_{1i} \mid D_i = 1, p(X_i)\} - \\ -E\{Y_{0i} \mid D_i = 0, p(X_i)\} \mid D_i = 1] \quad (2)$$

where the expectation is over the distribution of $(X_i)|D_i = 1$; i denotes the household, with $1i$ and $0i$ as the potential outcomes in the two counterfactual situations of treatment and non-treatment respectively, and D as the treatment group indicator. The hypothesis is as follow:

H_0: AUTP does not affect farmers' income;

H_1: AUTP affects farmers' income.

Decision criteria:

H_0 rejected and H_1 accepted if value of ATT is positive;
H_0 accepted and H_1 rejected if value of ATT is negative or zero.

RESULTS AND DISCUSSION

Based on the result of primary data collection it can be stated that farmers who perform rice cultivation are predominantly male farmers. The age range of respondents was between 22 and 74 years with an average family of 4 members. Respondents mostly got education up to high school but there were some respondents who had reached a bachelor degree. On average, the farmers have experience in rice farming of 22 years with the area of land used between 0.2 and 3 ha. Meanwhile, farmers who follow AUTP or participate in agricultural insurance generally are of lower age with an average of 51 years, have more farming experience (23 years), and have more land (0.78 ha).

Risk aversion level

The results of RAL measurement of farmers in this study are described in Table 3.

Table 3 shows that farmers tend to have a relatively high level of risk aversion. 36.92% of farmers prefer to insure the entire land they have (choice A), 27.69 and 17.69% choose to insure most of their land (choices B and C, respectively), while only 2.31% prefer not to insure their land at all (choice E). Vassalos and Li (2016) also found that more than half of their sample can be classified as risk averse. Farmers tend to have an attitude to avoid risk and that attitude affects their decision to participate in agricultural insurance. Farmers tend to use agricultural insurance at the end of farming season due to high input expenses that are spent from the beginning to the

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Table 3. Result of risk aversion level classification in Jember, 2019

Choices	Risk aversion class	Insured plots (number)	Uninsured plots (number)	MSI value	Number of choices	Percentage (%)
A	extreme	5	0	1.00	48	36.92
B	severe	4	1	2.04	36	27.69
C	intermediate	3	2	2.66	23	17.69
D	moderate	2	3	3.27	17	13.08
E	slight to neutral	1	4	3.85	3	2.31
F	neutral to negative	0	5	4.39	3	2.31
Total	–	–	–	–	130	100.00

MSI – Method of Successive Interval

Source: primary data, 20 19

end of the farming season. In this situation, farmers generally perceive that anticipatory actions are needed to overcome the possibility of harvest failure, one of them being by participating in agricultural insurance. Accordingly, farmers who have experienced harvest failure also tend to participate in insurance. This can be seen from the results of the logistic regression analysis as follows. The influence of farmers RAL towards their decision was analysed with logistic regression in Statistical Package for the Social Sciences (SPSS). The results of logistic regression analysis can be seen in Table 4.

Table 4 indicates that RAL, age, farming experience, cropland area, and harvest failure experience have a significant influence on farmers' decision to participate in AUTP (significance column). RAL has a regression coefficient of –1.531, meaning that if farmers' risk aversion level experiences a change of 1 unit, this will reduce the chances of farmers to follow AUTP by 1.531. The odds ratio has a value of 0.216, indicating that farmers with a lower level of risk aversion have a tendency to participate in AUTP 0.216-times smaller than farmers who have a higher level of risk aversion. RAL has a significant influence on farmers' decisions to purchase AUTP with 0.000 significance value.

These results are consistent with Lyu and Barré (2017) research which states that farmers with high risk aversion and large planting areas will be willing to participate in agricultural insurance. Conversely, farmers with low risk aversion and small cropland areas will refuse to participate. In other words, farmers who do not like risk will tend to participate in insurance. Based on the analysis it can be concluded that farmer RAL has a significant effect on the decision to purchase AUTP. These results indicate that the first hypothesis is accepted. Other factors that were found to be significant were age, farming experience, cropland area, and experience of crop failure due to pests.

Effect of agricultural insurance on farmer income

Propensity Score Matching Analysis (PSM) begins with preparing the regression model. This research used logistic regression as described in the previous

Table 4. Result of logistic regression analysis on farmers decision to participate AUTP in Jember, 2019

Variables	Variable name	*B*	Standard error	Wald value	Significance	Exp(*B*)
X_1	risk aversion level	–1.531	0.308	24.777	0.000**	0.216
X_2	age	–0.048	0.029	2.739	0.098*	0.954
X_3	farming experience	0.096	0.042	5.271	0.022**	1.101
X_4	cropland area	1.738	0.566	9.419	0.002**	5.687
X_5	harvest failure due to pest attack	1.270	0.562	5.109	0.024**	3.562

*90% confidence level; **95 and 99% confidence levels; AUTP – rice farming insurance, locally called as Asuransi Usaha Tani Padi in Indonesia; *B* – coefficient of variable; Exp(*B*) – odds ratio

Source: primary data, 2019

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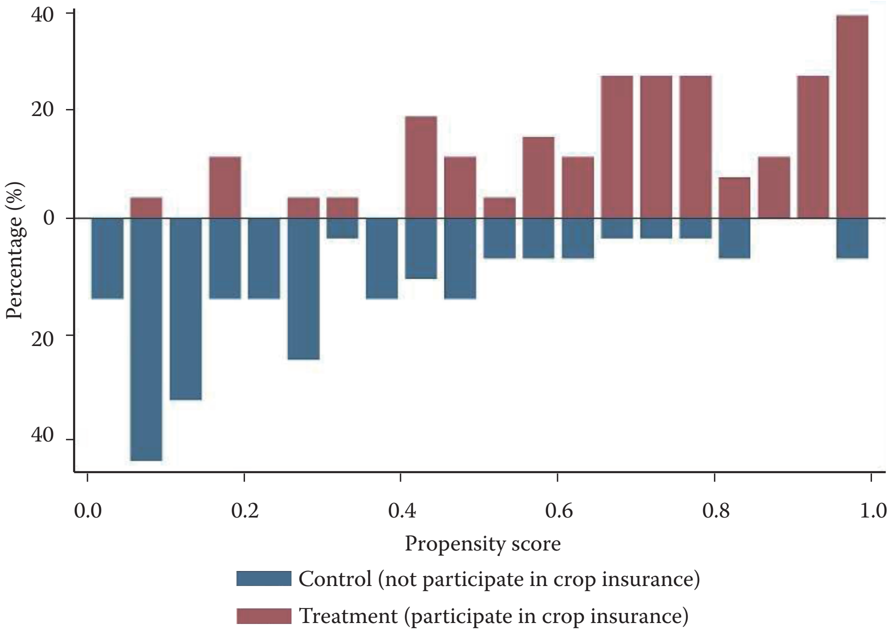

Figure 1. Distribution of propensity score in common support area

Source: primary data, 2019

sub-chapter. The next step is estimating propensity score of treatment group (farmers who purchased insurance) and control group (farmers who did not purchase insurance). The analysis was carried out with the help of Stata software. There are five independent variables that influenced farmers' decisions to purchase AUTP and those variables form a propensity score.

Common support analysis was done to match characteristics of the treatment and control groups through propensity score. The following is an image presenting the estimation of propensity score and common support area for treatment and control groups.

The top and bottom of Figure 1 show propensity score distribution for treatment and control groups. Y-axis represents the value of the proportions of the two groups. In accordance with the figure, the result of this study shows that propensity score distribution of the two groups is entirely in the common support area, which is between 0 and 1 or between the minimum and maximum values obtained. It can be concluded that each respondent has a positive and good probability to be both a participant and non-participant in AUTP. This result is consistent with Caliendo and Kopeinig (2008) research stating that implementation of the common support condition ensures that any combination of characteristics observed in the treatment group can also be observed in the control group. The next step was matching followed by balancing test. The main purpose of estimating propensity scores was to balance covariates between treatment and control groups (Rosenbaum and Rubin 1983). Therefore, after the matching process, a balance test is needed. This is done to find out whether the differences in covariates between the two groups have been eliminated in the matching process (Pan 2014). These are the results of covariates covariate balance test using NNM, KM, and RM.

Table 5 shows that there is bias reduction as a result of the matching process. There was no significant difference between treatment and control groups after the matching process (p-value > 0.05). Robustness of results can be seen from insignificance of the p-value and bias reduction after the matching process. Before matching, there will be differences between the two groups, but after matching the covariate must be balanced which indicates there are no significant differences (Caliendo and Kopeinig 2008).

The standardised mean bias, median bias, and pseudo-R^2 values as matching indicators are described in Table 6.

A decrease in mean bias and the median bias from 52.10 and 53.50 before matching to 16.10, 18.50, 20.10 and 14.30, 20.60, 11.00 after matching using NNM, RM, and KM respectively in sequence implies a good match. The distribution of covariates is balanced if mean bias and median bias between treatment and control groups are below 20% (Rosenbaum and Rubin 1985). In this study, the mean bias and median bias values after matching are each below and

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Table 5. Balance test results for propensity score using NNM, RM, KM methods

Variable matched	NNM		RM		KM	
	bias reduction (%) |bias|	t-test $p > \|t\|$	bias reduction (%) |bias|	t-test $p > \|t\|$	bias reduction (%) |bias|	t-test $p > \|t\|$
X_1	96.5	0.80	89.6	0.49	90.7	0.52
X_2	–875.0	0.02	–551.0	0.11	–893.0	0.01
X_3	46.1	0.17	470.0	0.19	20.6	0.04
X_4	91.9	0.82	89.7	0.78	80.9	0.59
X_5	73.3	0.47	43.7	0.11	79.5	0.57

X_1 – risk aversion level; X_2 – age; X_3 – farming experience; X_4 – cropland area; X_5 – harvest failure due to pest attack; NNM – Nearest Neighbourhood Matching; RM – Radius Matching, KM – Kernel Matching

Source: primary data, 2019

Table 6. Summary of statistical analysis result for testing matching quality using NNM, RM and KM methods

Matching algorithm	Pseudo-R^2		P > Chi^2		Mean bias		Median bias	
	before	after	before	after	before	after	before	after
NNM	0.32	0.03	0.0	0.27	52.1	16.1	53.5	14.3
RM	0.32	0.03	0.0	0.38	52.2	18.5	53.5	20.6
KM	0.32	0.04	0.0	0.24	52.2	20.1	53.5	11.0

NNM – Nearest Neighbourhood Matching; RM – Radius Matching, KM – Kernel Matching

Source: primary data, 2019

close to 20%, which means that after matching there were no observable differences in the characteristics of participants and non-participants.

Pseudo-R^2 value describes how well the covariate is able to explain the possibility of farmers to participate in AUTP. Sianesi (2002) stated that after the matching process, the pseudo-R^2 value must be lower because this means there are no differences in covariate distribution between treatment and control groups. So, from the results of covariate analysis it can be seen that the matching process succeeded in balancing covariate distribution between the two groups. This can be interpreted as proving that the differences that occurred in farmers' income were caused by the existence of treatment, namely farmers' participation in AUTP as explained below.

Each stage of finding out the effect of AUTP on farmers' income using propensity score analysis has been carried out. The following was Average Treatment on the Treated (ATT) value that was used as the indicator of treatment impact. Treatment, in this case, was participation in AUTP.

Table 7 shows that the ATT value obtained from the three matching processes is positive. This means that farmers' participation in AUTP has a positive impact on farmers' income. Positive ATT values are consistent with the results of Varadan and Kumar (2012) research, which found that agricultural insurance absorbed production risk and encouraged use of high inputs in farming. Nahvi et al. (2014) found a significant and positive relationship between income and agricultural insurance in Iran. Ali (2013) states that farmers were satisfied with agricultural insurance system and wish to continue purchasing agricultural insurance. Based on this explanation it can be con-

Table 7. Impact of AUTP participation on farmers' income in Jember, 2019

Matching algorithm	Variable outcome: farmer's income		
	ATT	standard error	t-value
NNM	1341329.86	1509044.44	0.89
RM	985656.73	1265196.32	0.78
KM	1376918.49	1389255.49	0.99

AUTP – rice farming insurance, locally called as Asuransi Usaha Tani Padi in Indonesia; NNM – Nearest Neighbourhood Matching; RM – Radius Matching, KM – Kernel Matching; ATT – Average Treatment on the Treated

Source: primary data, 2019

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cluded that the participation of farmers in AUTP has a positive impact on farmers' income. AUTP and claim guarantees can absorb the risk of production and encourage the use of high inputs (such as fertilisers) in the implementation of farming, so that rice production can be expected to be higher and have a positive impact on farmers' income.

CONCLUSION

Farmers tend to show a relatively high level of risk aversion, with 36.92, 27.69, and 17.69% of rice farmers choosing A, B, and C, respectively; 82.3% of the sample chose to insure almost all of their land. It is proven statistically that farmers' RAL has a significant effect on the decision to participate in AUTP (< 0.01). Farmers' participation in AUTP had a positive impact on farmers' income. AUTP is able to absorb production risks and encourage high input use in the implementation of farming so that rice production is expected to be higher and directly influence the farmers' income.

This study contributes to the literature in the field of implementation of agricultural insurance for developing countries, specifically for those who have just implemented it like Indonesia. Government subsidy for insurance premium is still needed in order to encourage farmer participation and prevent market failures of agricultural insurance.

There is a limitation in this study. This study discusses RAL but has not linked it to the possibility of adverse selection. In order to do that, it would be necessary to add new variables, such as the existence of irrigation, and to expand the study area. Further studies need to be carried out in this field, in particular with reference to the possibility of adverse selection or even moral hazards in agricultural insurance in developing countries.

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