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An Estimated Analysis of Willingness to Wait Time to Pay Rice Agricultural Insurance Premiums Using Cox's Proportional Hazards Model

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Abstract: In this paper, we determined the factors that affect the waiting time of rice farmers' willingness to pay the premium for the Rice Farming Insurance Program (RFIP) using survival analysis. The survival analysis method was carried out using the Cox proportional hazard model with the Efron approach. The case study in this research is rice farmers in Cibungur Village, Parungponteng District, Tasikmalaya Regency. The results of the analysis show that the predictor variables that are significant to the waiting time of rice farmers' willingness to pay the insurance premium for RFIP are their last education, other occupations, rice production, and farming costs. The results of the research are expected to produce additional information for the government and implementers of rice farming insurance regarding the condition of farmers in the field, so that it can be improved in the future.

Keywords: rice farming insurance; Cox proportional hazard model; survival analysis

MSC: 91G70; 62N02; 90B50; 91G80

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1. Introduction

Business activities in the rice farming sector are faced with quite high risks because they are highly dependent on natural conditions [1,2]. The increase in climate variability over the last decade has made the agricultural environment in many developing countries more uncertain, thereby increasing risk exposure when producing crops [3,4]. In addition, attacks by plant-disturbing organisms such as pests, weeds, and disease vectors are also the cause of losses in farming [5]. This uncertainty and the high risk allow farmers to switch to other commodities that have high economic value with a smaller risk of failure. If this is allowed to continue, it is feared that it will have an impact on the stability of national food security, especially the production and availability of the staple food of rice [6,7].

In responding to this problem, the government cooperates with incorporated PT. Asuransi Jasa Indonesia (Jasindo) helps protect rice farming in the form of RFIP, which is implemented as an agreement between farmers and insurance companies to bind themselves to the risk coverage of rice farming [8–10]. Through RFIP, guarantees can be provided against losses due to plant damage caused by floods, droughts, and plant-disturbing organisms. The main objective is to protect the loss of the economic value of rice farming due to crop failure, so that farmers have working capital for the next crop [11–14].

There are many factors that can affect the time of rice farmers' willingness to pay the RFIP premium, and to find out what factors influence it, survival analysis can be used.

Survival analysis is a collection of statistical methods for analyzing data with the outcome variable being considered as the time until an event occurs [15]. One of the models used to solve the problem of survival time is the Cox proportional hazard model [16,17]. In addition, many other methods are used in discussions about influencing factor analysis such as decision tree-based integration methods [18], random forest [19], XGBoost [20], and LightGBM [21].

Survival analysis using the Cox proportional hazard model has become a hot topic of research. Wang et al. [22] explored the suitability of survival analysis models for agricultural insurance design for rice, maize, and sorghum in various yield coverage areas in Panjin City, Liaoning Province, China. Yu and Cheng [23] applied the Cox proportional hazard model and probit analysis to explain the factors influencing the value of willingness to pay and participation rates under different insurance protection levels. The results showed that factors including years of farming, planting areas, degree of specialization, family income, the greatest loss of rice production, awareness of policy-oriented insurance, and risk preferences have significant influences on rice farmers' willingness to pay for insurance policies. Jinzheng et al. [24] investigated whether residents in rural China are willing to insure their property against flood damage and what kind of factors influence their willingness to seek insurance protection using a logit model, ordered logit model (OLM), and Cox proportional hazard model (CPHM). They found that the there exists a strong need for flood insurance in rural China, and factors including flood experience in the past 30 years, the elapsed time since the latest serious flood, income, and insurance experience influence rural residents' willingness to participate in flood insurance.

Furthermore, Ren and Wang [25] investigated rural residents' willingness to buy insurance according to a national survey using logit, ordered logit, and Cox proportional hazard models. The results showed that there exists a strong need for flood insurance in rural China, and the influencing factors in the insurance demand include the recent frequency of floods, income, and past experience with lack of flood insurance. Fajarini and Fatekurohman [26] discussed gender, age, sum assured, occupation, method of payment of premiums, premiums, and types of products that can affect the level of customers' ability to pay life insurance premiums. Kim et al. [27] investigated the impact of crop insurance on farm disinvestment and exit decisions using the KFMA farm-level panel dataset. They showed that the Cox proportional hazard model and Kaplan–Meier survival curve indicate that crop insurance has a negative and significant impact on farm exit. We find similar effects of crop insurance on farm disinvestment. Ofori et al. [28] examined the factors influencing farmers' time-to-adoption decisions as the duration between the year of commercialization of precision agriculture (PA) technologies and year of adoption, at the farm level using the Cox proportional hazard model. The findings indicated that time-to-adoption for embodied-knowledge technologies such as automated guidance and section control were statistically shorter than for information-intensive technologies such as yield monitors, precision soil sampling, and variable rate fertility. Zheng et al. [29] developed a novel hybrid repair–replacement model in the proportional hazards model with a stochastically increasing Markovian covariate process. They found that the comparison with two heuristic policies confirms the superiority of the proposed policy in reducing maintenance costs. They also developed a novel recursive method to approximately assess the health indices of the proportional hazards model with a Markovian covariate process [30]. The main findings showed that the proposed method can produce accurate assessment results with higher efficiency and less memory compared to existing approximation methods [30]. However, some issues about the factors that affect the waiting time of rice farmers' willingness to pay the premium for the Rice Farming Insurance Program are not discussion in the abovementioned literature.

The main contribution and novelty of this paper is the investigation of the factors that affect the waiting time of rice farmers' willingness to pay the premium of the RFIP using the Cox proportional hazard model with the Efron maximum partial likelihood method. In

addition, we interpret the Cox proportional hazard model for a case study of the waiting time of rice farmers' willingness to pay the premium of the RFIP in Cibungur Village.

The paper is organized as follows. Section 2 presents the objective of the research, research methods, and the analysis of the factors that affect the waiting time of willingness to pay the premium of the RFIP using the Cox proportional hazard model. Section 3 briefly describes the discussion and analysis of the factors that affect the waiting time for willingness to pay the premium of the RFIP. Finally, the conclusion is presented in Section 4.

2. Methodology

2.1. Proportional Hazard

In this work, the proportional hazard assumption is a situation where the hazard ratio is constant with time. The assumption test used in this study is goodness-of-fit (GOF) using the Schoenfeld residual test. After obtaining the Schoenfeld residual with Equation (1) [31,32],

$$RS_{ij} = x_{ij} - E\left(x_{ij}\middle|R\left(t_j\right)\right) \tag{1}$$

with

$$E\left(x_{ij}\middle|R\left(t_j\right)\right) = \frac{\sum_{l\in Rt_j} x_{il}\exp\left(\hat{\beta}x_l\right)}{\sum_{l\in Rt_j}\exp\left(\hat{\beta}x_l\right)} \tag{2}$$

where RS_{ij} is the residual Schoenfeld of the i-th predictor variable that experienced the event at time t_j, and x_{ij} is the value of the i-th predictor variable that occurs at time t_j. $E\left(x_{ij}\middle|R\left(t_j\right)\right)$ is the conditional expectation of x_{ij} and $R\left(t_j\right)$ is the set of individuals who experience the event at time t_j. Next, we tested the correlation between the residual Schoenfeld variables with the survival time rank; the correlation coefficient value can be obtained using Equation (3) [33,34].

$$r_{RT,RS_i} = \frac{n\sum_{j=1}^{n} RT_j RS_{ij} - \left(\sum_{j-1}^{n} RT_j\right)\left(\sum_{j-1}^{n} RS_{ij}\right)}{\sqrt{n\sum_{j=1}^{n} RT_j^2 - \left(\sum_{j=1}^{n} RT_j\right)^2}\sqrt{n\sum_{j=1}^{n} RS_{ij}^2 - \left(\sum_{j=1}^{n} RS_{ij}\right)^2}} \tag{3}$$

where RS is the Schoenfeld residual for each variable and RT is the survival time rank. Furthermore, we estimated the parameters with Cox proportional hazard regression using the Efron partial likelihood method with the equation using Equation (4)

$$L\left(\beta_{Efron}\right) = \prod_{i=1}^{r} \frac{e^{\left(\sum_{j=1}^{p}\beta_j s_j\right)}}{\prod_{k=1}^{d_j}\left[\sum_{l\in R(t_j)} e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)} - \frac{k-1}{d_j}\sum_{l\in D(t_j)} e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}\right]} \tag{4}$$

where $L\left(\beta_{Efron}\right)$ is the maximum likelihood function of parameter β using the Efron partial likelihood method, β is the parameters of the regression model to be estimated, s_j is the sum of each p predictor variable of the individual experiencing the event at time t_j, $D\left(t_j\right)$ is the set of individuals who get the event at time t_j, d_j is number of cases of co-occurrence

at time t_j, and $R(t_j)$ is the set of individuals who have the risk of failing at time j. From Equation (4), the ln partial likelihood function is obtained as Equation (5), as follows [35,36]:

$$\begin{aligned} lnL\left(\beta_{Efron}\right) &= ln\left[\prod_{i=1}^{r}\frac{e^{\left(\sum_{j=1}^{p}\beta_j s_j\right)}}{\prod_{k=1}^{d_i}\left[\sum_{l\in R\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j x_{lj}\right)}-\frac{k-1}{d_j}\sum_{l\in D\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}\right]}\right] \\ lnL\left(\beta_{Efron}\right) &= \sum_{j=1}^{r} ln\left[\frac{e^{\left(\sum_{j=1}^{p}\beta_j s_j\right)}}{\prod_{k=1}^{d_i}\left[\sum_{l\in R\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}-\frac{k-1}{d_j}\sum_{l\in D\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}\right]}\right] \\ lnL\left(\beta_{Efron}\right) &= \sum_{j=1}^{r}\left(\sum_{j=1}^{p}\beta_j s_j\right. \\ &\quad \left.-\sum_{k=1}^{d_i} ln\left(\sum_{l\in R\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}-\frac{k-1}{d_j}\sum_{l\in D\left(t_j\right)}e^{\left(\sum_{j=1}^{p}\beta_j X_{lj}\right)}\right)\right). \end{aligned} \quad (5)$$

To estimate the parameter β_j in the model, find the first derivative of the ln likelihood function with respect to the parameter β_j and equate it with zero. Thus, we obtained:

$$\frac{\partial\left(\sum_{j=1}^{r}\left(\sum_{j=1}^{p}\beta_j s_j-\sum_{k=1}^{d_i} ln\left(\sum_{l\in R(t_j)}e^{(\sum_{j=1}^{9}\beta_j X_{lj})}-\frac{k-1}{d_j}\sum_{l\in D(t_j)}e^{(\sum_{j=1}^{p}\beta_j X_{lj})}\right)\right)\right)}{\partial\beta_j}=0 \quad (6)$$

Furthermore, it is solved by the Newton–Raphson iteration, and then the general form of the parameter estimation is obtained using the Newton–Raphson iteration method:

$$\begin{bmatrix}\hat{\beta}_1\\ \hat{\beta}_2\\ \vdots\\ \hat{\beta}_p\end{bmatrix}=\begin{bmatrix}\hat{\beta}_0\\ \hat{\beta}_1\\ \vdots\\ \hat{\beta}_p\end{bmatrix}-\begin{bmatrix}\frac{\partial^2 lnL(\beta)}{(\partial\beta_1)^2} & \frac{\partial^2 lnL(\beta)}{\partial\beta_1\beta_2} & \cdots & \frac{\partial^2 lnL(\beta)}{\partial\beta_1\beta_p}\\ \frac{\partial^2 lnL(\beta)}{\partial\beta_2\beta_1} & \frac{\partial^2 lnL(\beta)}{(\partial\beta_2)^2} & \cdots & \frac{\partial^2 lnL(\beta)}{\partial\beta_2\beta_p}\\ \vdots & \vdots & \ddots & \vdots\\ \frac{\partial^2 lnL(\beta)}{\partial\beta_p\beta_1} & \frac{\partial^2 lnL(\beta)}{\partial\beta_p\beta_2} & \cdots & \frac{\partial^2 lnL(\beta)}{\partial\left(\beta_p\right)^2}\end{bmatrix}^{-1}\begin{bmatrix}\frac{\partial lnL(\beta)}{\partial\beta_1}\\ \frac{\partial lnL(\beta)}{\partial\beta_2}\\ \vdots\\ \frac{\partial lnL(\beta)}{\partial\beta_p}\end{bmatrix} \quad (7)$$

Furthermore, the parameter significance test was carried out as a whole with the likelihood ratio test and partially with the Wald test.

$$G^2=-2ln\frac{L(\hat{\omega})}{L(\hat{\Omega})}=-2\left[lnL(\hat{\omega})-lnL(\hat{\Omega})\right] \quad (8)$$

where $L(\hat{\omega})$ is likelihood function of the regression model before all X variables are included, and $L(\hat{\Omega})$ is the likelihood function of the regression model after all X variables are included. The Wald test can be seen in Equation (9), as follows [37]:

$$W^2=\left(\frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}\right)^2 \quad (9)$$

where W^2 is the Wald test, $\hat{\beta}_k$ is the covariate coefficient k, and $SE(\hat{\beta}_k)$ is the standard error of $\hat{\beta}_k$. Furthermore, the selection of the best Cox proportional hazard model is done by forward selection with the likelihood ratio test using Equation (10) [38,39].

$$G^{(m)}(i)=-2\left[lnL^{(m-1)}(\hat{\omega})-lnL^{(m)}(\hat{\Omega})\right] \quad (10)$$

where $L(\hat{\omega})$ is the likelihood function of the regression model before all X variables are included, and $L(\hat{\Omega})$ is the likelihood function of the regression model after all X variables are included [40].

Finally, we present the calculation of the hazard ratio of the variables that significantly affect the waiting time of farmers' willingness to pay the RFIP premium. In interpreting the Cox proportional hazard model, there are three kinds of provisions regarding the increase or decrease in the hazard value:

a. If $\beta_j > 0$, then every increase in the value of X_j will increase the hazard value, or the greater the risk of an individual to experience the event.
b. If $\beta_j < 0$, then every increase in the value of X_j will reduce the hazard value, or the risk of an individual experiencing an event will be smaller.
c. If $\beta_j = 0$, then the risk of an individual to experience the event is the same as the risk of an individual to fail.

2.2. Object of Research

The data used in this study are primary data, namely, data from rice farmers in Cibungur Village, Parungponteng District, Tasikmalaya Regency, West Java, which include name, gender, age, marital status, last education, years of farming, other occupations, land area owned, the amount of rice production, and the cost of farming per growing season.

The variables in this study consisted of response variables and predictor variables. The response variable used was the waiting time for rice farmers in Cibungur Village with the following conditions: (a) the initial time in this study was 4 weeks before the planting period began and the final time was 4 weeks after planting; (b) the incidence in this study is the willingness of farmers to pay RFIP premiums within 8 weeks of the registration period, namely, 4 weeks before the planting period begins and 4 weeks after planting; and (c) the unit of time used is weeks. This means that if a rice farmer has the willingness to pay the RFIP premium within 8 weeks of the registration period, then it is declared as observed data. If a rice farmer is not willing to pay the RFIP premium within 8 weeks, then it is declared as censored data. Meanwhile, the predictor variables used in this study are as follows: gender (X_1), age (X_2), marital status (X_3), last education (X_4), length of time farming (X_5), other work (X_6), land area (X_7), rice production (X_8), and farming costs (X_9).

3. Results and Discussion

The data used in this study are data from rice farmers in Cibungur Village, Parungponteng District, Tasikmalaya Regency, from 2021. These data were collected through questionnaires and direct interviews with respondent farmers, as shown in Table 1.

Table 1. Data relating to rice farmers in Cibungur Village.

Farmer Name	WKM	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Amin	5	1	73	1	2	40	2	0.5600	4.8	10.8
Ida	8	2	64	1	2	14	2	0.5600	6.4	10.6
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Uum	8	1	60	1	2	15	2	0.1450	1.6	2.9
Aroh	8	2	68	2	3	17	1	0.0560	0.5	1.02

The data are said to be uncensored (observed) if the rice farmers are willing to pay the RFIP premium within 8 weeks of the registration period, while the data are said to be censored if, until the 8th week, the farmers are not willing to pay the RFIP premium. Table 2 below shows the percentage of observed and censored data.

Table 2. Willingness of respondent farmers to pay RFIP premium.

		Frequency	Percentage
Status	Observed	45	45%
	Censored	55	55%
Total		100	100%

From Table 2, it can be seen that out of 100 rice farmers, 45% of rice farmers in Cibungur Village were observed; in other words, this number is the number of rice farmers who are willing to participate in the RFIP program and pay a premium within 8 weeks of the registration period. Meanwhile, 55% of the rice farmers in Cibungur Village are not willing to pay the RFIP premium until the 8th week of the registration period, and are declared censored data.

In this work, we used validity tests to measure the validity of the questionnaire. A questionnaire is said to be valid if the questions can reveal something that is being measured. Next, the question items are measured using the Pearson product–moment correlation coefficient using Equation (11):

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{n}(x_i - x)^2}\sqrt{\sum_{i=1}^{n}(y_i - y)^2}} \tag{11}$$

where n is the sample size and x_i and y_i are the values of the i-th individual sample. We tested the validity and reliability using SPSS v25 software (See Table 3). The results of the questionnaire validity test are presented as follows:

Table 3. Questionnaire validity test.

		Land_Area	Rice_Production	Farming_Fee	Status	Time	Total
Land_area	Pearson Correlation	1	0.959 **	0.991 **	0.415 **	−0.320 **	0.603 **
	Sig. (two-tailed)		0.000	0.000	0.000	0.001	0.000
	N	30	30	30	30	30	30
Rice_production	Pearson Correlation	0.959 **	1	0.951 **	0.340 **	−0.259 **	0.638 **
	Sig. (2-tailed)	0.000		0.000	0.001	0.009	0.000
	N	100	100	100	100	100	100
Farming_fee	Pearson Correlation	0.991 **	0.951 **	1	0.431 **	−0.339 **	0.589 **
	Sig. (two-tailed)	0.000	0.000		0.000	0.001	0.000
	N	30	30	30	30	30	30
Status	Pearson Correlation	0.415 **	0.340 **	0.431 **	1	−0.819 **	−0.260 **
	Sig. (two-tailed)	0.000	0.001	0.000		0.000	0.009
	N	30	30	30	30	30	30
Time	Pearson Correlation	−0.320 **	−0.259 **	−0.339 **	−0.819 **	1	0.549 **
	Sig. (two-tailed)	0.001	0.009	0.001	0.000		0.000
	N	30	30	30	30	30	30
Total	Pearson Correlation	0.603 **	0.638 **	0.589 **	−0.260 **	0.549 **	1
	Sig. (two-tailed)	0.000	0.000	0.000	0.009	0.000	
	N	30	30	30	30	30	30

**. Correlation is significant at the 0.01 level (two-tailed).

H_0 is accepted if $r_{count} > r_{table}$ or $p - value < \alpha$;
H_1 is rejected if $r_{count} \leq r_{table}$ or $p - value \geq \alpha$.

Table 3 shows that the p-value < 0.05, meaning that H_0 is accepted and all questionnaire items used in this study are valid for use.

A reliability test is used to determine the consistency of a questionnaire item in measuring the intended research object. In this study, Cronbach's alpha was used to measure the reliability of the questionnaire used. Cronbach's alpha is calculated using Equation (12):

$$r_{11} = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_b^2}{\sigma_t^2}\right) \quad (12)$$

where r_{11} is the instrument reliability coefficient, k is the number of valid questionnaire items, $\sum \sigma_b^2$ is the total variance of each questionnaire item, and σ_t^2 is the variance of the total score. A questionnaire is said to be reliable when the value of $r_{count} > r_{table}$. The results of the reliability test can be seen in Table 4.

Table 4. Results of the reliability test.

Case-Processing Summary			
		N	**%**
Cases	Valid	30	100.0
	Excluded	0	0.0
	Total	30	100.0

Listwise deletion based on all variables in the procedure.

In Table 4, the percentage of 100% indicates that all respondents in the pilot survey are valid and no respondents are excluded from this study. To find out whether the questionnaire data can be trusted and are consistent or reliable, the findings can be seen in Table 5.

Table 5. Results of the Cronbach's alpha value test.

Reliability Statistics	
Cronbach's Alpha	N of Items
0.635	6

Based on Table 5, it was found that the r_{count} = 0.635. This value is greater than r_{table}, which is 0.361. This shows that the questionnaire used in this study is reliable and consistent.

3.1. Descriptive Analysis

Descriptive analysis for categorical variables is done by compiling the frequency distribution. The frequency distribution of the data from each categorical variable used in this study is shown in Table 6.

Table 6. Frequency distribution of categorical variables in rice farmers' data.

Variable	**Category**	**Frequency**	
		Observed	**Censored**
Gender	1 = Male	28	28
	2 = Female	17	27
Marital status	1 = Married	39	35
	2 = Not Married	6	20

Table 6. *Cont.*

Variable	Category	Frequency	
		Observed	Censored
Last education	1 = No School	0	4
	2 = Graduated from Elementary School Equivalent	29	42
	3 = Graduated from Junior High School Equivalent	4	7
	4 = Graduated from Senior High School Equivalent	6	2
	5 = Graduated College	6	0
Other Jobs	1 = Have Another Job	28	14
	2 = Do Not Have Another Job	17	41

Furthermore, to find out the initial description of each numerical variable, the minimum value, maximum value, mean, and median are calculated. The data description of each numerical variable used in this study is presented in Table 7.

Table 7. Descriptive statistics of numerical variables.

Variable	Minimum	Maximum	Mean	Median
Time to Pay	1.00	8.00	6.24	8.00
Age	24.00	84.00	61.15	62.00
Length of Time Farming	2.00	50.00	22.92	22.50
Land Area	0.0426	0.7000	0.1704	0.1400
Rice Production	0.2000	4.5000	0.7823	0.6000
Farming Costs	0.390	6.400	1.528	1.128

Table 7 shows that the minimum value of the waiting time for willingness to pay is 1 week and the maximum value is 8 weeks, with an average of 6.24 weeks and a median of 8 weeks. The average age of the rice farmers in Cibungur Village is 61.15 years, with the youngest age being 24 years and the oldest 84 years. For the length of time farming variable, the minimum value is 2 years and the maximum value is 50 years, with an average of 22.92 years of farming and a median of 22.50 years. The average area of rice planting area owned by farmers in Cibungur Village is 0.1704 Ha, with the widest planting area being 0.7000 Ha and the smallest 0.0426 Ha. The largest rice production is 4.5000 tons and the lowest is 0.2000 tons, with an average rice production of 0.7823. In terms of the farming costs incurred by rice farmers in Cibungur Village for one growing season, the lowest is IDR 390,000.00 and the largest is IDR 6,400,000.00, with the average cost of farming incurred by farmers being IDR 1,528,000.00 for one growing season.

3.2. Cox Proportional Hazard Assumption Test

The Cox proportional hazard assumption test used is the goodness-of-fit test with the Schoenfeld residual test. The goodness-of-fit test results were obtained with the help of R 4.1.1 software, as shown in Table 8. The following is an example of calculating the goodness-of-fit test for the gender variable (X_1) using hypotheses [32,41].

a. H_0: $\rho = 0$ (there is no correlation between survival time rank and the residual Schoenfeld gender variable).
b. H_1: $\rho \neq 0$ (there is a correlation between survival time rank and the residual Schoenfeld gender variable).

Table 8. Cox proportional hazard assumption test results.

Variable	$\lvert t_{Count} \rvert$	$p-Value$	Information
X_1	0.209671	0.8349	Accept H_0
X_2	0.750504	0.4570	Accept H_0
X_3	0.469346	0.6412	Accept H_0
X_4	1.083211	0.2848	Accept H_0
X_5	0.091425	0.9276	Accept H_0.
X_6	0.108048	0.9145	Accept H_0
X_7	1.376480	0.1758	Accept H_0
X_8	0.715343	0.4783	Accept H_0
X_9	1.387547	0.1724	Accept H_0

The calculation using Equation (3) obtained $r_{RT,RS_1} = -0.031958$. Furthermore, statistical tests were carried out using Equation (13), and the following results were obtained:

$$\begin{aligned} t_{Count} &= \frac{r_{RT,RS_1}\sqrt{45-2}}{\sqrt{1-r^2_{RT,RS_1}}} \\ t_{hit} &= \frac{-0.031958\sqrt{45-2}}{\sqrt{1-(-0.031958)^2}} \\ t_{hit} &= -0.20967 \end{aligned} \tag{13}$$

Reject H_0 if $|t_{Count}| > \left|t_{(0.025;43)}\right| = 2.01669$ or $p - value < \alpha = 0.05$.

Based on the calculation obtained, i.e., $|t_{hit}| = 0.20967 < 2.01669$, then the decision is to accept H_0. This means that there is no correlation between the Schoenfeld residuals from the gender variable (X_1) and the survival time rank variable, so for the gender variable (X_1), the proportional hazard assumption is met.

In Table 8, it can be seen that for all predictor variables, the value of $|t_{hit}| < t_{(0.025;43)} = 2.01669$ and the value of $p - value > 0.05$, and thus the decision is to accept H_0. This means that there is no correlation between the Schoenfeld residuals and the survival time rank variable, so for X_1, $X_2, \ldots, X_9$, the proportional hazard assumption is complete.

3.3. Initial Model Parameter Estimation

Parameter β_j is estimated using maximum partial likelihood estimation with the Efron method using Equation (14).

$$\hat{\beta}_{l+1} = \hat{\beta}_l - I(\hat{\beta}_l)^{-1} u(\hat{\beta}_l) \tag{14}$$

The estimation results of the Cox proportional hazard model parameters are based on calculations with the help of R 4.1.1 software and are presented in Table 9.

Based on the estimation results in Table 9, it is assumed that all predictor variables have a significant effect on the model, so that with the Efron method, Equation (15) is obtained, which is the initial model of the Cox proportional hazard.

$$\begin{aligned} \hat{h}(t, X) = h_0(t) \exp(&0.50790X_1 + 0.03325X_2 - 1.12705X_3 + 0.70783X_4 + 0.01336X_5 \\ &+1.12742X_6 + 1.32673X_7 - 0.90992X_8 + 0.79996X_9) \end{aligned} \tag{15}$$

Table 9. Parameter estimation of Cox proportional hazard model with Efron method.

Variable	β_j	$\exp(\beta_j)$	$SE(\beta_j)$	$\Pr(>\|z\|)$	Significance Level 95%	
					Lower Limit	Upper Limit
X_1	0.50790	1.66180	0.41133	0.21691	0.7421	3.7210
X_2	0.03325	1.03381	0.02268	0.14255	0.9889	1.0810
X_3	−1.12705	0.32399	0.55354	0.04174	0.1095	0.9587
X_4	0.70783	2.02959	0.24607	0.00402	1.2530	3.2870
X_5	0.01336	1.01345	0.01973	0.49832	0.9750	1.0530
X_6	1.12742	3.08769	0.39992	0.00482	1.4100	6.7620
X_7	1.32673	3.76872	9.83225	0.88060	0.0000	0.0000
X_8	−0.90992	0.40256	0.73162	0.21361	0.0960	1.2×10^{-8}
X_9	0.79996	2.22545	0.89981	0.37399	0.3815	12.980

3.4. Overall Parameter Significance Test

The overall significance test is carried out using the likelihood ratio test as follows:

a. H_0: $\beta_1 = \beta_2 = \ldots = \beta_p = 0$ (no predictor variables contribute to the change in the response variable).
b. H_1: $\rho \neq 0$ (there is at least one predictor variable ($\beta_k \neq 0$, $k = 1, 2, \ldots, p$) that contributes to changes in the response variable).

If $lnL(\hat{\omega}) = -195.4119$ and $lnL(\hat{\Omega}) = -168.8938$, then the likelihood ratio value is obtained as follows:

$$G^2 = -2ln\frac{L(\hat{\omega})}{L(\hat{\Omega})}$$
$$G^2 = -2[lnL(\hat{\omega}) - lnL(\hat{\Omega})]$$
$$G^2 = -2[-195.4119 - (-168.8938)]$$
$$= 53.0362.$$

Then we get $G^2_{hit} = 53.0362 > \chi^2_{(9;0,05)} = 16.919$ and $p - value = 3 \times 10^{-8} < 0.05$, so the decision is to reject H_0. This means that there is at least one predictor variable ($\beta_k \neq 0, k = 1, 2, \ldots, p$) that contributes to changes in the waiting time for willingness to pay premiums [42].

3.5. Parameter Significance Test Partially

The results of the partial parameter significance test using the Wald test with the help of R 4.1.1 software are shown in Table 10. The following is a partial parameter significance test procedure using the Wald test for the gender variable (X_1):

a. H_0: $\beta_1 = 0$ (the gender variable does not contribute to changes in the time of willingness to pay premiums).
b. H_1: $\beta_1 \neq 0$ (the gender variable contributes to changes in the time of willingness to pay premiums).

Using Equation (9), the following is the Wald's test of the gender variable:

$$W^2 = \left(\frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}\right)^2 = \left(\frac{-0.3374}{0.3078}\right)^2 = 1.2$$

Table 10. Partial significance test results with Wald test.

Variable	β_p	$Wald(W^2)$	$p-Value$	Decision
X_1	−0.3374	1.2	0.3	Accept H_0
X_2	−0.0129	1.37	0.2	Accept H_0
X_3	−1.0525	5.74	0.02	Reject H_0
X_4	0.6363	18.94	0.00001	Reject H_0
X_5	−0.0108	0.74	0.4	Accept H_0
X_6	1.1795	14.56	0.0001	Reject H_0
X_7	3.2901	16.18	0.00006	Reject H_0
X_8	0.4891	11.24	0.0005	Reject H_0
X_9	0.3634	17.94	0.00002	Reject H_0

Then we get $W^2 = 1.2 < \chi^2_{(0,05,1)} = 3.841$ and $p - value = 0.3 > 0.05$, so H_0 is accepted. This means that the gender variable does not contribute to changes in the waiting time for willingness to pay the RFIP premium.

Based on the Wald test in Table 10, the following conclusions are obtained:

- Variable X_1 obtained $W^2 = 1,2 < \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.3 > 0.05$, thus H_0 is accepted. This means that the gender variable does not contribute to changes in the waiting time of willingness to pay premiums.
- For the variable X_2, $W^2 = 1.37 < \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.2 > 0.05$, so H_0 is accepted. This means that the age variable does not contribute to changes in the waiting time for willingness to pay premiums.
- For the X_3 variable, $W^2 = 5.74 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.02 < 0.05$, thus H_0 is rejected. This means that the marital status variable contributes to changes in the waiting time for willingness to pay premiums.
- For the X_4 variable, $W^2 = 18.94 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.00001 < 0.05$, so H_0 is rejected. This means that the last education variable contributes to changes in the waiting time for willingness to pay premiums.
- For the X_5 variable, $W^2 = 0.74 < \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.4 > 0.05$, so H_0 is accepted. This means that the length of time farming variable does not contribute to changes in the waiting time for willingness to pay premiums.
- For the X_6 variable, $W^2 = 14.56 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.0001 < 0.05$, and thus H_0 is rejected. This means that other job variables contribute to changes in the waiting time for willingness to pay premiums.
- For the X_7 variable, $W^2 = 16.18 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.00006 < 0.05$, so H_0 is rejected. This means that the land area variable contributes to changes in the waiting time for willingness to pay premiums.
- For the X_8 variable, $W^2 = 11.24 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.0005 < 0.05$, and thus H_0 is rejected. This means that the rice production variable contributes to changes in the waiting time for willingness to pay premiums.
- For the X_9 variable, $W^2 = 17.94 > \chi^2_{(0.05,1)} = 3.841$ and $p - value = 0.00002 < 0.05$, so H_0 is rejected. This means that the variable farm costs contribute to changes in the waiting time of willingness to pay premiums.

3.6. Selection of Best Cox Proportional Hazard Model

In this study, forward selection is used to obtain the best Cox proportional hazard model, so that at each stage it will be decided which variable is the best predictor to be included in the model. Forward selection was stopped when the new predictors had no significant effect ($\alpha > 0.05$) on the response variable [43,44]. The calculation results for

the best modeling of Cox proportional hazards using the forward selection method are presented in full in Table 11.

Table 11. Results of selection of the best Cox proportional hazard model.

Stage	Model	ln $L(\beta)$	$G(i)$	$p-Value$
0	0	−195.4119		
	X_3	−191.7522	7.3194	0.0068209
	X_4	**−187.4746**	**15.8746**	**0.0000676**
	X_6	−187.8388	15.1462	0.0000994
	X_7	−188.9954	12.833	0.0003405
	X_8	−191.0960	8.6318	0.0033033
	X_9	−188.3238	14.1762	0.0001665
1	$X_4 + X_3$	−185.0029	4.9434	0.0261918
	$X_4 + X_6$	−183.3299	8.2894	0.0039877
	$X_4 + X_7$	−179.3460	16.2572	0.0000553
	$X_4 + X_8$	−181.4746	12.0000	0.0005320
	X_4+X_9	**−179.0222**	**16.9048**	**0.0000393**
2	$X_4 + X_9 + X_3$	−176.2846	5.4752	0.0192900
	X_4+X_9+X_6	**−174.9610**	**8.1224**	**0.0043725**
	$X_4 + X_9 + X_7$	−178.8973	0.2498	0.6172952
	$X_4 + X_9 + X_8$	−177.3867	3.2710	0.0705225
3	$X_4 + X_9 + X_6 + X_3$	−174.0217	1.8786	0.1704989
	$X_4 + X_9 + X_6 + X_7$	−174.8912	0.1396	0.7086120
	X_4+X_9+X_6+X_8	**−172.5745**	**4.7730**	**0.0289077**
4	$X_4 + X_9 + X_6 + X_8 + X_3$	−171.7279	1.6932	0.1931794
	$X_4 + X_9 + X_6 + X_8 + X_7$	−172.4699	0.2092	0.6474581

Based on the results of the forward selection in Table 11, four predictor variables that entered the best Cox proportional hazard model are obtained, namely last education (X_4), other occupations (X_6), rice production (X_8), and farming costs (X_9). Furthermore, the parameter estimation of the best Cox proportional hazard model is carried out using Equation (12) with the help of R 4.1.1 software, and the results can be seen in Table 12.

Table 12. Parameter estimation of the best Cox proportional hazard model.

Variable	β_j	$\exp(\beta_j)$	$SE(\beta_j)$	$\Pr(>\|z\|)$	Significance Level 95%	
					Lower Limit	Upper Limit
X_4	0.3751	1.4551	0.1643	0.022434	1.0545	2.0079
X_6	1.0680	2.9095	0.3455	0.001991	1.4783	5.7262
X_8	−1.4001	0.2466	0.6431	0.029484	0.0699	0.8697
X_9	1.2196	3.3859	0.3653	0.000843	1.6546	6.9285

Based on Table 12, the Cox proportional hazard model is obtained for modeling the waiting time for the willingness of rice farmers in Jayaraksa Village to pay the RFIP premium in Equation (16).

$$\hat{h}(t, X) = h_0(t) \exp(0.3751X_4 + 1.0680X_6 - 1.4001X_8 + 1.2196X_9) \quad (16)$$

3.7. Interpretation of Cox Proportional Hazard Model

The interpretation of the Cox proportional hazard model is done by looking at the hazard ratio, which is a value that indicates the risk of an individual experiencing an event. The hazard ratio can be determined by looking at the exponential value of the parameter β estimation for each response variable.

For the last education variable (X_4), the hazard ratio obtained for X_4 is $e^{0.3751} = 1.4551$. Because $0.3751 > 0$ and $1.4551 > 1$, it can be interpreted that the higher the last education level of the rice farmers in Cibungur Village, the more likely the rice farmers in Cibungur Village are willing to pay the RFIP premium [45].

For other work variables (X_6), the hazard ratio obtained for X_6 is $e^{1.0680} = 2.9095$. Because $11.0680 > 0$ and $2.9095 > 1$, it can be interpreted that the waiting time for the willingness to pay the RFIP premium from rice farmers who have jobs other than farming is 2.9095 times faster than rice farmers who do not have other jobs. In other words, rice farmers who have other jobs are 2.9095 times more likely to be willing to pay the RFIP premium [46].

For the rice production variable (X_8), the hazard ratio obtained for X_8 is $e^{-1.4001} = 0.2466$. Because $-1.4001 < 0$ and $0.2466 < 1$, every increase in the amount of rice production will reduce the possibility that rice farmers in Cibungur Village are willing to pay the RFIP premium.

In this study, if we compare the amount of rice production that is more than 2.0 tons (A) with the amount of rice production that is less than 1.0 tons (B), the following comparison is obtained:

$$\begin{aligned} HR &= \frac{h_A(t,X^*)}{h_B(t,X)} \\ HR &= \frac{\exp\left(\beta x_8^*\right)}{\exp(\beta x_8)} \\ &= \frac{\exp(-1.4001(2.0))}{\exp(-1.4001(1.0))} = 0.246 \end{aligned} \tag{17}$$

Based on the results of the above calculation, $h_A(t, X^*) = 0.246 h_B(t, X)$ is obtained, so it can be said that the waiting time for willingness to pay the RFIP premium from rice farmers who obtain a total rice production of more than 2 tons for one growing season is 0.246 times slower than farmers who obtain the amount of rice production of less than 1 ton.

For the variable cost of farming (X_9), the hazard ratio obtained for X_9 is $e^{1.2196} = 3.3859$. Because $1.2196 > 0$ and $3.3859 > 1$, then any increase in the cost of rice farming will increase the possibility that rice farmers in Cibungur Village are willing to pay the RFIP premium [47,48].

In this work, if we compare the cost of farming of more than IDR 3,000,000.00 (A) with the cost of farming of less than IDR 2,500,000.00 (B), the comparison is obtained as follows:

$$\begin{aligned} HR &= \frac{h_A(t,X^*)}{h_B(t,X)} \\ HR &= \frac{\exp\left(\beta x_9^*\right)}{\exp(\beta x_9)} \\ HR &= \frac{\exp(1{,}2196(3{,}0))}{\exp(1{,}2196(2{,}5))} \\ HR &= 1.840 \end{aligned} \tag{18}$$

Based on the calculation results above, $h_A(t, X^*) = 1,2\, h_B(t, X)$, so it can be said that the waiting time for the willingness to pay the RFIP premium from rice farmers whose farming costs are more than IDR 3,000,000.00 for one planting season is 1,840 times faster than for farmers whose costs are less than IDR 2,500,000.00 [49].

4. Conclusions

In this paper, we determined the factors that affect the waiting time of rice farmers' willingness to pay the premium for the Rice Farming Insurance Program (RFIP) using survival analysis. The survival analysis method was carried out using the Cox proportional

hazard model with the Efron approach. The case study in this research is rice farmers in Cibungur Village, Parungponteng District, Tasikmalaya Regency. The results show that the Efron method obtained a Cox proportional hazard regression model estimator of the factors that affect the waiting time of rice farmers' willingness to pay the RFIP premium, which is significantly influenced by the last education variable (X_4), other occupations (X_6), rice production (X_8), and farming costs (X_9). Furthermore, the hazard ratio of each predictor variable that has the most influence on changes in the waiting time for the willingness of rice farmers in Cibungur Village to pay the RFIP premium is the last education variable at 1.4551, other occupations at 2.9095, the rice production variable at 0.2466, and the cost of rice farming at 3.3859. In this study, the Efron approach was used to estimate the model, so for further research in this area, this can be compared with other approaches, namely the exact approach and the Breslow approach.

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Nomenclature

Symbol	Description
RS_{ij}	Residual Schoenfeld of the i-th predictor variable that experienced the event at time t_j
x_{ij}	Value of the i-th predictor variable that occurs at time t_j
$R\left(t_j\right)$	Set of individuals who experience the event at time t_j
$E\left(x_{ij}\middle\|R\left(t_j\right)\right)$	Conditional expectation of x_{ij}
RS	Schoenfeld residual for each variable
RT	Survival time rank
$L\left(\beta_{Efron}\right)$	Maximum likelihood function of parameter β by Efron partial likelihood method
β	Parameters of the regression model to be estimated
s_j	Sum of each p predictor variable of the individual experiencing the event at time t_j
$D\left(t_j\right)$	Set of individuals who get the event at time t_j
d_j	Number of cases of co-occurrence at time t_j
$L(\hat{\omega})$	Likelihood function of the regression model before all X variables
$L(\hat{\Omega})$	Likelihood function of the regression model after all X variables
W^2	Wald test
$\hat{\beta}_k$	Covariate coefficient k
$SE(\hat{\beta}_k)$	Standard error of $\hat{\beta}_k$
r_{11}	Instrument reliability coefficient
k	Number of valid questionnaire items
$\sum \sigma_b^2$	Total variance of each questionnaire item
σ_t^2	Variance of the total score

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