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IBNR and RBNS Claim Reserves Modeling With Poisson Process Approach In MSE- Credit Insurance Product

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Abstract— The challenge faced by insurance companies that sell MSE credit insurance products is the lack of data related to financial/business information. While the role of insurance companies as Collateral Substitution Institution requires insurance companies to be able to carry out robust risk management and modeling. This research is focused on providing alternative risk modeling methods, especially for the calculation of claims reserves with the minimum financial/business data conditions. The use of a reduced form intensity-based model with a homogeneous poisson process approach is presented in this study to answer this challenge. Poisson linear regression will be used to estimate the intensity rate λ so that the probability of default of each policy/group policy can be determined. Thus the claim reserves will be estimated using the individual loss model. Quantitative analysis is carried out on empirical data in the form of PT ABC credit insurance claims for a period of 5 years, from 2014 to 2018. The results of this study indicate that the credit period and the amount of credit initial limit greatly influence the level of risk of each credit insurance policy. Because modeling risk policies individually so that this model can accurately model the type of IBNR Claim and RBNS with estimated results with good accuracy.

Index Terms — Insurance Risk Management, Reduce Form Intensity Based Model, Poisson Process, Poisson Regression Model, Credit Insurance.

1 Introduction

As an industry that deals with guarantees and losses, reliable risk management is essential for insurance companies. Especially since the onset of the global crisis in the financial industry which also affected insurance companies, regulators have pushed for and issued several policies that require insurance companies to be able to manage risks according to their risk profile. One form of risk management is the management of liabilities in the form of claim reserves, where companies are required to be able to form claims reserves to anticipate possible payment obligations, which consist of claims reserves of IBNR- Incurred but Not Reported, Claim RBNS- reported but Not Settled and reserves of Claims Payable, for claims that have been approved but have not been paid in whole or in part (the possibility of a gradual claim payment).

One of the classic problems that often occur related to this risk management effort is an obstacle related to the adequacy of sufficient information/data to carry out risk modeling. This obstacle will especially be very evident for credit insurance products for the micro and small business (MSE) credit segment. The characteristics of MSEs, which are mostly in the form of individual businesses and managed in a traditional and familial manner, have not been touched by modern business management, causing the majority of MSEs to not have good accounting, there is no separation between family finance and business. Such business characteristics cause financial institutions, both insurance and financing institutions such as banks, to face difficulties in carrying out the risk assessment process. The majority of banks view MSEs as a less attractive and even high-risk sector to be financed. The inability of MSEs to meet the requirements demanded by banks for the financing process has caused banks to categorize MSEs as not-bankable businesses, even though there are so many business potentials that are feasible to be financed, having promising business prospects.

On the other hand, MSEs are the main business actors and the backbone of the Indonesian economy. The Ministry of Cooperatives and SMEs in their presentation in January 2018 stated that the number of MSMEs was recorded at 59.69 million units, which was 99.9% of the total business operators in Indonesia. In addition, based on the MSME Business Profile issued by the Indonesian Banking Development Institute (LPPI) and Bank Indonesia (BI) in 2015, MSMEs have contributed 57-60% of Gross Domestic Product (GDP) and employment rates of around 97% all national labor. MSMEs have also proven to be unaffected by the crisis when the crisis hit Indonesia in the 1997-1998 period, only MSMEs were able to remain firmly established.

Seeing the enormous potential and role of MSEs in the Indonesian economy, the government has issued various regulations to support the growth of MSEs, one of which is in the

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International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
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capital sector. To overcome the capital constraints of UMK, the government through Bank Indonesia has issued Bank Indonesia Regulation (PBI) No. 17/12 / PBI / 2015 dated June 25, 2015. In the PBI, banks are required to allocate credit/financing to MSMEs gradually starting from 5% in 2015 to 20% by the end of 2018. Through the PBI, banks are encouraged to play a role in developing MSEs, which of course for banks is a business opportunity as well as a challenge in terms of risk management, given the characteristics of MSE businesses that are less bankable in terms of bank financing requirements. For this reason, the government encourages banks to synergize with guarantee companies such as insurance companies to manage the risk of financing MSEs. In this agreement, insurance companies carry out their roles and functions as Collateral Substitution Institutions, namely guarantor institutions that bridge the gap between decent MSMEs but do not have enough collateral to obtain credit from financial institutions, both banks, and non-bank institutions (feasible but not bankable).

As a risk guarantor institution, of course, it must be balanced with reliable risk management as well, especially the guaranteed risk is MSE credit risk. As stated earlier, the problem that arises when conducting a risk assessment for the MSE sector is the limited information and data, especially related to business capacity data and other quantitative data related to the MSE business. In general, historical data owned by banks and especially insurance companies is only limited to qualitative data related to business administration, credit structure and credit quality or historical data for filing claims from policyholders. This condition will be the first problem that will be discussed in this study, namely;

<u>How to assess risk with the limitations of the data, what factors or variables will affect risk and how do they relate to the level of credit insurance risk?</u>

To answer the research question above, in this study we will present the use of the credit risk assessment theory "reduced form intensity-based model" approach. The choice of this model is based on the limited or even the absence of relevant data/information related to the assets and liabilities of MSE companies to be assessed, so that the credit default events are not modeled directly on the company's assets and liabilities, but as poisson type events, which occur entirely randomly with the probability determined by a certain intensity or hazard function. The default model with the Poisson process approach is based on the pattern of Non-Performing Loans (NPL) for MSE loans which can be seen in figure 1.1 below. The NPL figure for MSE loans over the past six years ranges from 3% - 5%, so the determination of the Poisson process approach to model the occurrence of credit defaults on MSE loans is theoretically reasonable.

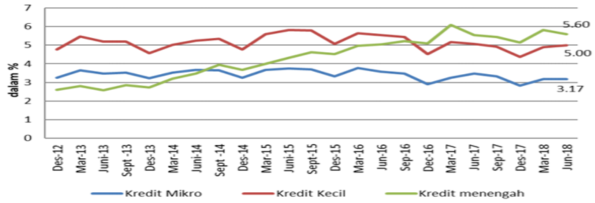

Figure 1.1 NPL Pattern of UMKM Loans as of June 2018

Source: Bank Indonesia (2018)

The use of Poisson linear regression will be presented in this study to analyze what factors or variables influence the level of risk, in this case, the probability of default (PD), which will be expressed in the parameter intensity rate λ. An interesting thing from the use of the Poisson process approach to modeling default events is the fact that in credit insurance the trigger for claims is the occurrence of credit default, and the maximum claim is once in one insurance coverage period, assuming the claim is submitted immediately after credit default, default events can be assumed to be the same as claim arrival time, so modeling the default with the Poisson process approach is also modeling the arrival of the claim itself. In other words, the modeling for calculating the severity of the claim will be the same or done together with the modeling to determine the frequency of occurrence of claims. So in this research, the parameter λ has two meanings, namely the intensity of the default (to calculate PD) and is the average number of claims in one time period for a particular group of policies.

After the risk level of each policy/group of policy is determined, the next problem to be discussed in this study are:

<u>How to estimate the total claim reserves in accordance with regulatory provisions, which include claims reserves for IBNR, RBNS and Claims Payable, which correspond to the risk profile of the credit insurance product?</u>

The common claim reserve calculation method in the general insurance industry is the method of the collective-chain ladder group, which is based on the aggregate concept of claims assuming each policy has the same period of a claim so that individual risk modeling cannot be done. Meanwhile, for credit insurance, each policy has a different submission period according to the credit period, each policy will automatically have a different level of risk, so the use of collective methods is not possible. Therefore in this study, the claim reserve estimate will be estimated using the individual loss model method, by modeling the frequency and severity separately. The severity of the claim will be calculated with the expected loss concept, while the arrival frequency of claims is calculated by the Poisson process approach. The estimation of total claim reserves is calculated by the concept of total aggregate loss "S" which is the sum of each individual/group of policies with a relatively equal level of risk. The expectation value and vari-

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
ISSN 2229-5518

ance of the total claim reserves will be calculated by compound poisson distribution.

The next problem that will be discussed in this study is to answer the research question;
How accurate are the estimation results compared to actual claim liabilities?
For this reason, in this study, backtesting of the results of the calculation of claim reserves will be carried out with data from the out-sample study and then compared the results with the actual claims that occur in the corresponding year. The best estimate of the expected total claim reserves will be presented assuming the compound poisson distribution produced will follow a normal and log-normal distribution.

Thus the research objectives to be achieved in this study are:
1. Analyzing factors or variables that affect the level of risk of credit insurance products, especially for MSE credit insurance based on data available at PT ABC.
2. Calculating the estimated total claim reserves required using an individual loss model with a Poisson process approach, including claims reserves for IBNR, RBNS and Claims Payable for PT ABC's MSE credit insurance products.
3. Doing backtesting to assess the accuracy of the estimation results of the total claims reserves compared to the actual data of PT ABC's MSE credit insurance product claim obligations.

In this study, there are several limitations and assumptions used in the calculation and analysis of the estimated total reserves of claims. The limitations and assumptions can be described as follows:
1. Credit insurance products that are subject to research are non-KUR Micro and Small Business (MSE) credit insurance products at PT ABC with a credit period of 12 months to 60 months and the initial credit limit of Rp 5 million to Rp 500 million.
2. Data is taken from samples of observational data on credit insurance policies with the criteria as above, with the observation period July 2013 to July 2018. Observations are made on the waiting time until the first claim occurs, assuming the waiting time for the claim is the same as the waiting time of the credit default.
3. The length of waiting time is calculated assuming a discrete time with a monthly unit of time, assuming all debts will be due at the beginning of each month or the 1st of each month. In the observation, the right sensor is applied so that the maximum length of waiting time is equal to the maximum coverage time or equal to the maximum credit period.
4. The amount of the claim is calculated based on the expected loss of credit assets that are the object of insurance, assuming there is no recovery factor so that the LGD value (Loss Given Default) is constant, thus expected loss is the product of probability of default (PD) with exposure at default (EAD).
5. Exposure at default (EAD) is the outstanding loan at the time of default, which is calculated using the loan annuity formula with fixed monthly installments, assuming the loan interest rate uses a commercial bank counter rate for MSE credit products with a constant interest rate throughout the credit period.

2. Theoretical Review

2.1 Reduce Form-Intensity Based Model.

In the finance science literature, modern methods of measuring credit risk can be divided into two different branches of methodology, namely the options-theoretic structural approach pioneered by Merton (1974) and the reduced form approach using intensity-based models to estimate stochastic hazard rates, following the literature pioneered by Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997), and Duffie and Singleton (1998, 1999). Both schools of thought offer different methodologies to solve one of the same main tasks in measuring credit risk, namely to estimate the probability of default (PD) (Allen, 2002).
The philosophy of a structural approach is to consider the company's obligations as contingent claims on company assets so that in this case the total market value of the company's assets is a fundamental variable. While the reduced form approach, the default is not modeled directly on company assets and liabilities, but as poisson type events that occur entirely randomly with probabilities determined by intensity or certain hazard function. The probability of default (PD) is modeled as a Poisson process with intensity λ, so PD during the next short period of time, "Δ", will approach $\Delta\lambda$, and the waiting time until the default is $1 / \lambda$. (Allen, 2002).
The basic assumption of the intensity-based reduce form approach consists of setting a default time equal to the first jump time of the N Poisson process with a constant intensity λ so that the default time of T will be exponentially distributed, and probability of default (PD) is given with an exponential CDF $F(T) = P[t \leq T] = 1 - e^{-\lambda T}$ (Giesecke, 2002).

2.2 Expected loss

The expected loss is an expectation of the amount of all losses that might occur. Mathematically expected loss (EL) is a multiplication of probability of default (PD), loss given default (LGD) and exposure at default (EAD), EL = PD * LGD * EAD. Where LGD is usually stated at a certain rate, LGD = 1-recovery, and EAD is the amount of outstanding loan at default time outside the recovery value. So that if the recovery

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
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factor is assumed to not exist then LGD will be equal to 1 and EL = PD x EAD.

2.3 Poisson Distribution and Poisson Process

This distribution is sometimes referred to as the law of small numbers because it is a probability distribution of the number of events of an event that is rare but has many opportunities to occur. According to Denuit et al. (2007), random variable poisson is generally used to model the number of events that occur in certain time or spatial intervals, such as the number of claims submitted to insurance companies in a certain period. The characteristic that is related to the Poisson distribution is that the variance and mean have the same value, this condition is called equidispersion.

The characteristics of events that have a Poisson distribution (also called poisson postulates or poisson processes) are as follows.

1. The probability of occurrence of one event at a very short interval is very small.
2. The probability of occurrence of two or more occurrences at very short intervals is zero.
3. The number of events at intervals that are not mutually exclusive is independent.

Poisson process is an example of the arrival process, with the interarrival time giving the most convenient description because the interarrival time is defined as independent and identical distribution (i.i.d). So poisson process is a renewal process with interarrival intervals having an exponential distribution function, so for all $\lambda > 0$, every X_i will have a density function $f_X(x) = \lambda \exp(-\lambda x)$ for all $x \geq 0$. Which makes poisson a unique process among other renewal processes is the memoryless property of the exponential distribution. Any random variable X is said to have a memoryless property if Pr {X> 0} = 1, so for X which is a positive random variable and for all $x \geq 0$ and $t \geq 0$, then Pr {X> t + x} = Pr {X> x} * Pr {X> t}, because memoryless random variable X is an exponential distribution, then Pr {X> t}> 0 for each t > 0, this means Pr {X> t + x | X> t} = Pr {X> x}.

By utilizing the memoryless property of the exponential random variable, the distribution of the waiting time of the first arrival at any time t > 0 in the Poisson process can be determined. So the provisions for Poisson process apply with the rate λ, where for any time t > 0, the length of the time interval from t to the first arrival after t is a variable non-negative Z with a distribution function 1- exp $(-\lambda z)$ for $z \geq 0$. The random variable is independent of all t arrival times and is also independent of a collection of random variables $\{N(\tau); \tau \leq t\}$. (MIT OpenCourseWare, 2011)

2.4 Aggregate Loss Model

According to Klugman at al. (2012), there are two ways to model total claims from several insurance products that occur and are paid in a certain period;

a. The collective risk model. In this model, the total claim S is the sum of the number of claims from N individual claims in a given period. Collective risk model is defined as a model that has a formula $S = X_1 + X_2 + \text{---} + X_n$, with X_js being an independent and identical random variable (i.i.d).
b. The second model is to determine the random variable for each insurance contract, formally this model can be defined as follows; The Individual Risk Model represents the aggregate loss as a sum, $S = X_1 + X_2 + \text{---} + X_n$ from the specified number of n insurance contracts. The amount of loss/claim for contracts n, namely $X_1, X_2, \ldots, X_n$, with X_js is assumed to be a mutually independent distribution but not necessarily identical. Distribution from X_js generally has a Null probability associated with the occurrence of no claims or losses in certain insurance contracts. In special cases when the X_js distribution is an identical distribution, the individual risk model will be a special case of the collective risk model.

2.5 Previous Research

Related research using the concept of individual loss models for the calculation of claims reserves in general insurance products can be traced from research conducted by Karlson and Jan Erick (1973) who modeled the reserve claims of IBNR and RBNS with the Poisson process approach, another study conducted by Arjas (1989) who uses the point process theory to estimate claims reserves in non-life insurance and research conducted by Ragnar (1993) which uses the marked Poisson process approach to model claims individually.

The most recent research is research conducted by Nichi and Vallois (2015) and Ahn at al. (2017). Geoffrey Nichi and Pierre Vallois (2015) developed individual stochastic models by considering the characteristics of each individual borrower (credit holder/debtor) as a trigger/main factor in the emergence of claims, namely the existence of a "borrower default"/credit default. In this study, the occurrence of defaults is described as an event with Poisson distribution, so that the estimated default occurrences in the future can be modeled using a Poisson point process. Thus the claim reserve can be calculated as the sum of individual claims. While research conducted by Ahn at al. (2017), modeling claim reserves for general insurance, especially vehicle insurance, to calculate claims reserves of IBNR and RBNS, by modeling the occurrence of accidents as Poisson distribution so that they can be determined using the Poisson process method. What distinguishes this research from before is the possibility of multiple claims, so that the model is developed with marked poisson arrivals which consist of the time of claim reporting, claim settlement and the possibility of multiple payments in a given period.

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
ISSN 2229-5518

3. Research Methods

3.1 Data and Research Data Grouping

Observation data consists of 41,037 credit insurance policies that meet the observation criteria with a composition of 1706 data for policyholders who submit claims during the insurance period, or claim submission time less than the maximum insurance period, and 39,331 policy data that up to the maximum deadline does not claim, so that the waiting time is the same as the maximum credit guarantee time. The data is divided into two categories, namely data in samples for claims data from 2013 to 2016, and out-sample data for claims data from 2017 to July 2018. Data in samples will be used in the modeling process, while data out samples will be used for backtesting.

In this study the waiting time is assumed to be Poisson distribution and follows a homogeneous poisson process with constant intensity/poisson rate-λ, so to fulfill this assumption the data used will be grouped according to the risk level. The research data is taken from the qualitative data of the existing credit structure, which is based on the time period and the amount of the initial credit limit. The selection of this categorical variable is not only due to data limitations as previously stated, but also based on the assumption that the relevant risk assessment process based on credit risk assessment has been carried out under the underwriting process, so it can be assumed that the agreed credit contract with the same credit structure, for the term the same credit time and initial credit limit will have relatively the same level of risk. Based on these categories, 16 groups of policies were obtained which were a combination of time period and initial credit limit categories. The results of grouping data can be seen in table 3.1 below.

Table. 3.1 Research Data Groups

Data category	Total of Data		Information (CP=Credit period , CL=credit initial Limit)
	No- claim	claim	
A1	18,867	327	CP ≤ 24 month, and CL ≤ Rp 25million
A2	2,819	143	CP ≤24 month, and CL > Rp 25 - ≤ Rp50 million
A3	1,363	29	CP≤24 month, and CL > Rp 50 - ≤ Rp100 million
A4	548	11	CP ≤ 24 month,and CL > Rp 100 million
B1	7,219	181	CP > 24 - ≤ 36 mont, and CL ≤ Rp 25 million
B2	2,044	315	CP > 24 - ≤ 36 month, and CL > Rp 25 - ≤ Rp 50 million
B3	753	94	CP > 24 - ≤ 36 month, and CL > Rp 50 - ≤ Rp100 million
B4	361	107	CP > 24 - ≤ 36 month, and CL > Rp100 million
C1	1,201	11	CP > 36 - ≤48 month, and CL ≤ Rp 25 million
C2	425	34	CP> 36 - ≤48 month, and CL l > Rp 25 - ≤ Rp 50 million
C3	339	54	CP > 36 - ≤48 month, and CL > Rp 50 - ≤ Rp 100 million
C4	274	28	CP > 36 - ≤48 month, and CL > Rp 100 million
D1	2,298	40	CP > 48 - ≤60 month, and CL ≤ Rp 25 million
D2	486	86	CP > 48 - ≤60 month, and CL > Rp 25 - ≤ Rp50 million
D3	241	171	CP > 48 - ≤60 month, and CL > Rp 50 - ≤ Rp 100 million
D4	93	75	CP > 48 - ≤60 month, and CL > Rp 100 million
Total	39,331	1,706	41,037

Source: Data of PT. ABC, processed with Excel software

3.2 Linear Poisson Regression

The method that will be used to determine the poisson rate and intensity rate is the same, namely by poisson linear regression, or often also called the log-linear model. In Poisson regression, it is assumed that the response-y variable (dependent variable) has a Poisson distribution so that the expected value of that variable can be modeled as a linear combination of several unknown parameters. In this study the response variable assumed to be Poisson distribution is the waiting time until the default occurs. De Jong and Heller (2008) state that if the response variable –y specified is the number of events at a certain interval of time, poisson can be used as a distribution of responses, with expectation values μ, i.e. the average waiting time can be explained in explanatory variables x through the appropriate link function. The Poisson regression model is $y \sim (\mu)$, with $(\mu) = x'\beta$. The link (μ) function for poisson generally log link $\ln \mu = x'\beta$. With log link, $\hat{\mu} = \exp(x'\hat{\beta})$ is positive. So for a model with a categorical single explanatory variable with number of levels r, it is assumed that the level r-th as the base level, then the number of variables is replaced by r - 1 variables, $x_1, \ldots, x_{r-1}$ and $g(\mu) = \beta_0 + \beta_1 x_1 + \cdots + \beta_{r-1} x_{r-1}$. With the log link, it is obtained $\mu = e^{\beta_0 + \beta_1 x_1 + \cdots + \beta_{r-1} x_{r-1}}$, with variables on the baseline level, $\mu = e^{\beta_0}$ and at the level j, $\mu = e^{\beta_0 + \beta_j x_j}$. So that in this study the form of poisson linear regression equation used is the log-linear model with the following equation:

$$\ln(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8$$

Where x_1 to x_4 are categorical explanatory variables for the credit period and x_5 to x_8 are categorical explanatory variables for the initial credit amount. Determination of the parameters β_0 to β_8 is calculated by the maximum likelihood method using statistical software for regression analysis. Parameter significance testing is based on statistical tests with t and P value, with a significance level of $\alpha = 0.05$.

3.3 IBNR Claim Calculation Method

The amount of IBNR - X_{ibnr} Total Claim is the sum of all losses that may occur from a number of insurance contracts which are still active at time T, can be written $X_{ibnr} = {}_{ibnr}Y_1 + {}_{ibnr}Y_2 + \ldots + {}_{ibnr}Y_{n(t)}$, with ${}_{ibnr}Y_j$ is the claim amount for each j insurance contract/policy, which is the amount of loss that may occur from the loan product guaranteed in the insurance contract. $n(t)$ is a poisson counting process that calculates the number of claims that have a Poisson distribution with the rate λt.

Thus X_{ibnr} will have a compound poisson distribution, the expectation of the total claims of IBNR, $E[X_{ibnr}] = E[n(t)]\, E[{}_{ibnr}Y]$, because n (t) is a poisson counting process with a poisson distribution with rate λ, $E[n(t)] = \lambda t$. Assuming there is no recovery so LGD is equal to one, then the loss expectation is multiplication between PD at time -T and EAD, PD can be calculated with CDF from exponential distribution with probability function $\Pr(t \le T) = F_t(T) = 1 - \exp(-\lambda T)$, and the EAD value is the same as the outstanding loan at the time of default multiplied by the insurance coverage, which is between 70% and 80% of the loss. Using the compound poisson distribution property, then $E[X_{ibnr}] = \lambda t \sum_{j=1}^{n} PD_j\, EAD_{ibnr\text{-}j}$ and $Var[X_{ibnr}] = \lambda t\, E[(EAD_{ibnr})^2] = \lambda t \sum_{j=1}^{n} PD_J\, (EAD_{ibnr\text{-}j})^2$.

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
ISSN 2229-5518

3.4 Calculation Method for RBNS Claims and Claims Payable

The emergence of RBNS claims is based on the fact that the claim settlement process generally cannot be completed in one process, generally there is a lag time, usually called the delay time, starting from the beginning of the claim submitted until the claim paid to the insured/policyholder. The delay time will be approached by the Poisson distribution approach, the occurrence of the approved claim is assumed to be Poisson type, so that the claim approved for a certain period of time is assumed to be a Poisson event divided into events according to the length of the period of time delay, where each sub -the event will have a different probability, P_i, because it is a probability $\sum Pi = 1$. In accordance with the decomposition property of the Poisson distribution as a counting process, if the events enumerated by Poisson process N (t) can be classified into different types of k, the counting process of type *i* is a counting process $Ni\ (t)$ with the rate $\lambda i = \lambda Pi$, where Pi is the probability of types *i* and $Ni\ (t)$ mutually independent, so that $N\ (t) = {}_k\sum_{i=1} N_i(t)$ and $\lambda = {}_k\sum_{i=1} \lambda_i$, since $\sum P_i = 1$, assumed the probability of the occurrence of type *i (Pi)* is constant over time (Cunningham at al., 2006). For example, for a claim that has a delay of two months, it means i = 2, because this delay time is an event with consecutive time intervals, then $\lambda_2 = \lambda\ (P_0 + P_1 + P_2)$ can be interpreted as the probability of the number of claims approved in the period 0 to with 2 months [0.2].

Because it is a claim that has already occurred and has been reported, in accordance with the nature of credit insurance which only allows for one claim for each insurance contract, the expectation of the number of claims, $E\ [n\ (t)] = 1$, and the claim amount of the RBNS are $EAD_{rbns\text{-}j}$, namely outstanding loan at the default time T multiplied by the guarantee coverage. So that the expectation of the total claim of the RBNS, X_{rbns} is $E\ [X_{rbns}] = {}_n\sum_{j=1} [1\text{-}Pr\ (R \le r_j)]\ EAD_{rbns\text{-}j}$ and Variance $[X_{rbns}] = {}_n\sum_{j=1} [1\text{-}Pr\ (R \le r_j)]\ [EAD_{rbns\text{-}j}]^2$, with the value of $Pr\ (R \le rj) = P_0 + P_1 + ... + P_{rj}$. While the rest is in the category of Claims Payable.

Like RBNS claims, Claims Payable is a claim that has already occurred and is approved already, then the expectation of the number of claims is also one, and the amount of the claim is the same as the amount of the claim that was previously approved. So that Total Claims Payable is the sum of all claims payable for policy j (HKj) plus the portion of RBNS claims that are likely to be approved in the reserve period. So the expectation of total claims payable, $E\ [X_{HK}] = {}_n\sum_{j=1} \{[Pr\ (R \le {}_{rj})]\ EAD_{rbns\text{-}j} + HK_j\}$ and variance $[X_{HK}] = {}_n\sum_{j=1} \{[Pr\ (R \le r_j)]\ [EAD_{rbns\text{-}j}]^2 + [HK_j]^2\}$, with the values of $Pr\ (R \le r_j) = P_0 + P_1 + ... + P_{rj}$.

3.5 Method of Calculation of Total Claim Reserves

The total of Claim Reserves, S, are sums of Total Claim Reserves of IBNR, RBNS and Claims Payables (HK), $S = X_{ibnr} + X_{rbns} + X_{HK}$, because of the total claim reserves of IBNR, RBNS and HK have compound poisson distributions, assuming that each claim is independent, then according to the property of the Poisson distribution, S is the sum of the compound poisson which will also be a compound poisson distribution with $\lambda = \lambda_{ibnr} + \lambda_{rbns} + \lambda_{HK}$ (additivity properties of the Poisson distribution). E [S] and Variance [S] can be calculated by the formula $E\ [S] = \lambda\ E\ [X]$, and $Var\ [S] = \lambda\ E\ [X^2]$. Because X is not assumed to be certain parametric distribution, then the amount of E [X] and E $[X^2]$ are calculated empirically based on the observational data in this study, by calculating the expectation of the number of total claim reserves of each type of claim.

3.6 Backtesting and Analysis of Total Claim Reserves

Backtesting is done by using data in samples (claims data from 2013 to 2016) as a model, then calculating the estimated total claim reserves that must be formed for the position of December 31, 2016, to anticipate liability claims that may occur in the next year, during 2017. The backtesting process is carried out in two scenarios, first with data for the end of 2016 position to calculate 2017 reserves and data per position December 31, 2017, to calculate claims reserves 2018.

Statistical analysis will be carried out using the normal and log-normal distribution approach. Approach with standard normal distribution using central limit theorem can be done and will give a fairly good approach if E [N] is large and for N which has a Poisson distribution means λ is close to infinity, then the distribution of Total Claims S will be normally distributed. However, if λ is not large enough so that the S distribution will tend to be asymmetrical (skewed), the approach using log-normal distribution can be used and can provide good results even though there is no theory that supports that choice (Klugman, Panjer and Willmot, 2012).

4. Research Results

4.1 Results of Poisson Linear Regression

From the regression results, the regression equation is obtained as follows

$Ln\ (\mu) = 3.176 + 0\ x_1 + 0.355\ x_2 + 0.603\ x_3 + 0.745\ x_4 + 0\ x_5 - 0.072\ x_6 - 0.088\ x_7 - 0.17\ x_8$

From the above equation, the value of β_0 is 3.176, which is intercept, so that the baseline intensity rate can be calculated by the formula $\mu_0 = e^{\beta 0} = 23.9508$, and $\lambda_0 = 1 / \mu_0 = 0.042$, then the average waiting time and intensity rate for each group of data can be calculated, eg for data categories A1, $\mu_{A1} = e^{\beta 0 + \beta 1 + \beta 5} = 23{,}9508$ and intensity rate-λ_{A1} or the number of claims that occur for one unit time interval t, in this case monthly, for group A1 data can be calculated at $\lambda_{AE} = 1 / \mu_{AE} = 0.042$. Values μ and λ for each data category can be calculated as in Table 4.1 below.

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
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Table: 4.1 Determination of λ - 16 Data Groups

	μ	λt
base line	23.9508	0.0417523
A1	23.9508	0.0417523
A2	22.2869	0.0448694
A3	21.9332	0.045593
A4	20.2064	0.0494892
B1	34.1581	0.0292756
B2	31.7852	0.0314612
B3	31.2807	0.0319686
B4	28.818	0.0347005
C1	43.7722	0.0228455
C2	40.7314	0.0245511
C3	40.0849	0.024947
C4	36.9291	0.0270789
D1	50.4509	0.0198213
D2	46.9461	0.021301
D3	46.2009	0.0216446
D4	42.5636	0.0234942

Source: Research Results

From the regression results, it can be concluded that the credit period and credit initial limit have a significant influence on the level of credit risk, with the relationship directly proportional to the increase in credit risk. It can be seen from the relationship, the longer the credit period and the greater the credit initial limit, the waiting time for the default (μ) to be shorter, it means that the risk level of the loan is higher.

4.2 Determination of Probability of Default and Expected Loss

PD can be calculated using an exponential distribution with the parameter λ, then it is used to calculate the expected loss, or in this study the expected amount of claims, where Expected Loss = PD * EAD. EAD is calculated using the annuity formula for loans with monthly installments and fixed interest rates. Illustration of the use of the parameter intensity rate λ in one credit asset can be seen in table 4.2, assuming a credit limit of Rp. 100 million, a credit period of 24 months, with a constant counter rate of 1.25% per month during the credit period, and no credit recovery process, with guarantee coverage of a maximum of 80% of the outstanding loan at the time of default and the insured (bank) only can submit a claim after the debt is minimal in the condition of Collectibility 4 (doubtful with 121-180 days in arrears). There is an extension of the time period up to T = 30, to accommodate the expiration period of the claim submission period.

Table 4.2 Illustration of Calculation of Claim Amount/Expected Loss
(For A3 groups, 24 month credit period and initial limit of Rp 100 million)

Group A3(Credit Period < =24 month and credit initial limit <= 100 million			
μ_{A3}	21.9331677	Credit initial Limit	100,000,000
λ_{A3}	0.04559305	Installments	4,848,665
Time t=T	Prob. Of Default	Exposure at Default (EAD)	Expected Loss (Claim Amount)
1	0.0445693	96,401,335.20	-
2	0.08715218	92,757,687.08	-
3	0.12783718	89,068,493.36	-
4	0.16670887	85,333,184.73	11,380,638.78
5	0.20384807	81,551,184.73	13,299,241.41
6	0.23933201	77,721,909.74	14,881,072.64
7	0.27323445	73,844,768.80	16,141,547.94
8	0.30562589	69,919,163.61	17,095,285.08
9	0.33657366	65,944,488.35	17,756,142.09
10	0.36614211	61,920,129.65	18,137,253.41
11	0.39439271	57,845,466.46	18,251,064.33
12	0.42138421	53,719,869.99	18,109,363.88
13	0.44717271	49,542,703.56	17,723,316.03
14	0.47181184	45,313,322.55	17,103,489.60
15	0.49535282	41,031,074.28	16,259,886.57
16	0.51784459	36,695,297.90	15,201,969.20
17	0.53933392	32,305,324.32	13,938,685.79
18	0.55986549	27,860,476.07	12,478,495.22
19	0.57948198	23,360,067.22	10,829,390.34
20	0.59822417	18,803,403.25	8,998,920.27
21	0.61613104	14,189,780.99	6,994,211.62
22	0.63323981	9,518,488.44	4,821,988.68
23	0.64958606	4,788,804.75	2,488,592.64
24	0.66520376	0.00	-
25	0.6801254	expiration time of insurance period	-
26	0.69438199		-
27	0.70800317		-
28	0.72101727		-
29	0.73345133		-
30	0.74533122		-

Source: Research Results

4.3 Determination of Probability per Delay Period

From the results of the analysis of the delay time in the research sample data obtained a model and the calculation of the probability of delay time as shown in table 4.3 below.

Table 4.3 Time Delay Modeling Result

time of delay-r (month)	Cummulative Probability Pr (R≤ r)
0	0.1055
1	0.4115
2	0.5797
3	0.6530
4	0.7040
5	0.7479
6	0.7978
7	0.8288
8	0.8429
9	0.8611
10	0.8904
11	0.9285
12	0.9478
13	0.9713
14	0.9883
15	0.9906
16	0.9930
17	0.9936
18	0.9971
19	0.9977
20	0.9977
21	0.9982
22	1.0000

Source: Research Results

The illustration of the use of Table 4.3 above can be explained as follows, for example, a policy with a credit structure with category A3 as in the illustration illustrated in table 4.2, submits a claim in October 2016 which coincides with the 20th installment of the loan, so that the EAD is Rp. , 8 million, because it is a claim that has been submitted, then PD = 1, with a guaranteed coverage of 80% of the loss, so the expected loss = 0.8 EAD = Rp. 15.04 million. With the assumption that until the end of 2016 the claim has not been resolved so that it falls into the category of claims in the process of completion or RBNS Claim. So at the end of the 2016 financial year, when an estimated reserve claim is made for 2017, the RBNS claim will be 2 months old. Then the development of the RBNS claim next year can be estimated as follows; with data on the position of December 31, 2016, the probability that the claim will be settled is 0.57972 from the outstanding claim of Rp. 15.04 million, that is to say, estimated at Rp. 15.04 X 0.579972 = Rp. 8.72 million of the portion of the RBNS claim will change to Claim payables or will be approved next year, and the remaining IDR 15.04 - IDR 8.72 million = IDR 6.32 million will remain as an RBNS claim.

4.4 Backtesting Results and Analysis of Total Claim Reserves

Table. 4.4 Comparison of Calculation of Total Claim Reserves with Actual Claims

Comparison of -Individual Methods vs. Actual Claims	Estimated Reserve Claims 2017 as per 12/31/2016	Estimated Reserve Claims 2018 as per 12/31/2017
Model-Indv. Loss (poisson)		
Expectation of Total Claim Reserves - E[S]	4,368,202,353	10,214,907,437
Actual Claim	4,206,521,803	10,366,915,788
Ratio-Estimasi /Actual	103.84%	98.53%

Source: Research Results

From the comparison table of the estimation of the total claims reserves above, the estimation results are quite accurate compared to the actual claims that occur. The estimation results of total claim reserves using this method are able to cover claims liabilities in 2017 and 2018, with a ratio of 103.84% and 98.53%

International Journal of Scientific & Engineering Research, Volume 10, Issue 1, January-2019
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to actual claims, or can be said to have an error of ± 1.5 to 3.5% compared to actual claims occurs in the corresponding year. Table 4.5 presents the best estimation results from the expectation of total claim reserves, using individual loss models with the Poisson process approach discussed in this study.

Table 4.5 Best Estimates of the Calculation Result of Total Claim Reserves

Summary of Calculation of Total Claims Reserves Expectations	Estimated Reserve Claims 2017 as per 12/31/2016	Estimated Reserve Claims 2018 as per 12/31/2017
IBNR - E[Xibnr]	2,198,132,074	958,747,690
RBNS - E[Xrbns]	291,959,732	3,212,458,154
Claim Payables- E[HK]	1,878,110,547	6,043,701,593
Total Claim Reserves- E[S]	4,368,202,353	10,214,907,437
Variance [S]	110,483,020,405,146,000	720,705,684,480,490,000
Standard Deviation	332,389,862	848,943,864
Parameter Estimation - Dist Log-Normal		
Mean - μ	22.19473	23.04367
Standart Deviasi - σ	0.07598	0.08297
N (number of Data/polis)	26,148	13,736
number of claim- E[N]= λ	958	675
claim ratio -(N/λ)	0.0366	0.0491
Best estimate with α=0.05		
Dist. Normal Approach	4,914,935,024	11,611,295,831
Dist. Log-Normal- Approach	4,935,461,397	11,668,260,818
Best estimate with α=0.01		
Dist. Normal Approach	5,141,456,802	12,189,846,190
Dist. Log-Normal- Approach	5,091,209,151	12,346,996,269

Source: Research Results

5. Conclusion

From the analysis and discussion of the results of the study can be concluded several things, as follows:

1. From this study it can be concluded that the credit period and the amount of the initial credit limit are variables that influence the risk level of credit assets, the longer the credit period and the greater the initial credit limit, the higher the level of credit risk, and so vice versa.
2. The method of calculating claims reserves based on individual loss models with the Poisson process approach can be used as an alternative method for calculating the estimated reserves of claims for insurance products that have varying levels of risk such as credit insurance products. The results of this study indicate that based on the results of backtesting, the estimated total claim reserves generated by this method provide estimates that are quite accurate compared to actual claims. This method is also able to estimate claims reserves of IBNR, RBNS, and Claim payables more specifically with the best estimation at a statistical confidence level of 95% and 99% with normal and log-normal distribution approaches.
3. The accuracy of the estimation results of the total claim reserves in this method is very dependent on the adequacy of the sample data used as models and assumptions used in estimating the parameters needed in the process of calculating claims reserves. Like claims ratio, assumptions related to credit interest rates that can affect the number of claims and other information that can affect the level of risk of the insurance coverage object.

6. Suggestions

For further research, readers can develop further by applying time-varying intensity rate $-\lambda$, so that it can model risk more accurately. In addition, the reader can also develop further related to the poison regression model used, for example by adding other categorical independent variables such as industry type, geographical location, length of business and other relevant factors. Including interest rate assumptions and recovery factors which in this study were considered constant and nonexistent. Further researchers can develop research using the assumption that interest rates are not constant and recovery factors are taken into account.

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