PULSE LAB JAKARTA

BANK INDONESIA

Technical Report

The Ninth Research Dive for Development on Household Vulnerability

August 2019

Executive Summary

The Asian Financial Crisis of 1997 brought on complex challenges that compelled governments across the region to rethink their approach to economic development and financial stability. In Indonesia, household-level activities were particularly important for understanding changes at the subnational and national levels, insights from which proved useful for improving long-term development planning and boosting resilience efforts. Supported by the Macroprudential Policy Department of Bank Indonesia (BI), Pulse Lab Jakarta (PLJ) brought together selected researchers from the government, academia and the public sector for its 9th Research Dive for Development to undertake further research on this topic.

This Research Dive was focused on exploring how new and emerging sources of data can be combined with traditional data sources to better enable citizens to prepare for—and respond to—financial shocks, as well as to provide critical insights to inform decisions and policy making within the Government of Indonesia. From 4-8 August 2019, the research participants worked closely with several domain experts to analyse various data sets based on these research tasks:

1. Understanding the default rate of home mortgage in Indonesia and contributing factors;
2. Identifying indicators of household indebtedness by province;
3. Using fintech data to assess customers' financial vulnerability; and
4. Evaluating the impact of natural hazards on loan-at-risk.

Household vulnerability is a broad and multidimensional topic. It is particularly important for macroprudential policy making, which is geared towards mitigating systemic risks, improving efficiencies in the financial system, and addressing challenges that may arise at the various intersections of financial institutions and markets. With Pulse Lab Jakarta's experience in advanced data analytics and Bank Indonesia's expertise in this subject area, this unique collaboration heralded a positive and strategic move to help practitioners and policymakers make data-informed decisions in a timely and cost-effective manner.

What follows here is a report that summarises the findings from the research conducted:

1. The first paper describes the list of data sets that were analysed throughout the research.
2. The second paper explores Susenas data and OLX e-commerce data in conjunction with aggregated mortgage loan data from BI to model the default rate of home mortgage at the city-level, as well as to estimate the threshold of its contributing factors.
3. The third paper combines Susenas data, lending data from fintech companies, and aggregated loan data from BI to understand the factors affecting household indebtedness.
4. The fourth paper examines the differences in loan vulnerability factors between borrowers from fintech companies and banking loan debtors, by analysing related fintech data, BI data and Susenas data.
5. The fifth paper investigates how natural hazards impact borrowers' ability to repay, by combining the International Organisation for Migration's (IOM) Displacement Tracking Matrix data and BI aggregated data on mortgage borrowers.

Pulse Lab Jakarta is grateful for the partnership with the Macroprudential Policy Department of Bank Indonesia, and the contributions from Bappenas' Directorate of Macro Planning and Statistical Analysis, Bappenas' Centre for Development of Planning Data and Information (Pusdatin), JULO, OLX Indonesia, IOM, UNDP, Statistics Indonesia, Indonesian Institute of Sciences, Politeknik Statistika STIS, Universitas Diponegoro, Institut Teknologi Bandung, Universitas Indo Global Mandiri, Universitas Pancasila, Universitas Islam Negeri Ar-Raniry, Universitas Negeri Surabaya and Pemkot Tanjung Balai Karimun. We are also thankful for the support we received from the Australian Government through its Department of Foreign Affairs and Trade.

Collaborative Research Opens Pathways to Speed Up Research Outputs

I was delighted to be one of the Research Dive advisors for this batch of participants. The event was an excellent example that demonstrates how collaborative research can offer a pathway to high-quality research and produce results in a short period of time. It also exhibited excellent collaboration between the organisers and participants, as well as the data partners.

There were great synergies between the participants that included researchers, data engineers and data scientists, which confirmed the importance of having such complementarity when working on such a diverse research. I met several young, vibrant and smart academics, data engineers, and data scientists who worked together to pull off research that usually takes weeks to get done. I hope my contribution was meaningful in helping the team to refine their ideas and research approaches.

Bagus Santoso received his bachelor's degree in economics from Universitas Gadjah Mada, and holds a master's in Social Science and a PhD in Philosophy, both from the University of Birmingham. He currently serves as an associate professor at the Department of Economics, Universitas Gadjah Mada, where his research interests include econometrics, mathematical economics, mathematics, finance and economics, and macroeconomics.

Exploring How Data Can Help Households to Rebuild Post-Disaster

As a researcher, there's always room for growth. This is my third time around participating in Pulse Lab Jakarta's Research Dive as an advisor. With each involvement, there's always something to learn (e.g. how communities come up with new coping strategies in the aftermath of natural disasters). In the humanitarian sector, sometimes we all use the same lingo, which means we don't always get to see things from alternative perspectives.

This event gave both advisors and participants an opportunity to listen and exchange ideas with people from different professional backgrounds and with diverse skill sets—this is exactly the sort of collaboration that's needed to ensure help gets to the people most affected quickly.

I was mostly involved with the team that was tasked with measuring the impact that natural hazards have on people's ability to repay a loan. It was a new area of research for me, but I was open-minded going in and left impressed with the insightful findings. Hats off to Pulse Lab Jakarta and Bank Indonesia for making sure this topic gets addressed.

Faizal Thamrin has worked at DMInnovation as a disaster management specialist, and as a data manager in the Humanitarian Data Exchange, the latter of which is focused on strengthening data collaboration across humanitarian partners, governments and academia. His professional tenure includes 10 years at the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) in Bangladesh, Indonesia, the Philippines and Pakistan in the area of geographical information and information management systems.

Diversity in Research is A Plus

Conducting research in large groups can be challenging, especially when a group consists of people from different professional backgrounds. This Research Dive, however, showed that while it may be challenging—it is possible and can yield great results. It brought together talented individuals from different professional backgrounds, who are experienced in analysing various kinds of data.

Within the span of four days, I saw how they were able to dive into the complex data sets, process them and translate them into meaningful information. Considering the amount of time, data sets and the team composition the researchers had had, it is pretty fair to say this was a great accomplishment. I'm glad to have been able to share and contribute at this event.

Muhammad Nur Aidi was awarded a bachelor's degree in Soil Science from the Bogor Agricultural Institute (IPB), and later pursued an M.Sc in Applied Statistics from the same Institute. After completing his master's degree, he went on to earn a PhD in Applied Statistics from the University of the Philippines Los Baños. At IPB, Muhammad is currently a lecturer in the Department of Statistics specialising in Statistical Modelling.

Research Dive Advisors

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Task 3 - Using fintech data to assess customers' financial vulnerability

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Task 4 - Evaluating the impact of natural hazards on loan-at-risk

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Foreword

Following the Asian financial crisis in 1997, the macroprudential approach has been set out as a part of Indonesia's strategy in economic recovery. To maintain financial stability, macroprudential policy looks at multidimensional elements that could have an impact on economic development. Household vulnerability, among other elements, becomes a crucial checkpoint that could directly affect the financial system as a result of extreme shocks to the welfare of the individuals. With that view in mind, understanding household vulnerability is essential to macroprudential policy making.

In Indonesia, it stands clear that examining household-level activities is crucial for learning changes at the subnational and national levels. Along with the rapid development of information technologies, data is produced in many ways and becomes the lifeblood of our work. This provides an opportunity to measure household vulnerability from different perspectives. Bank Indonesia acknowledges that conventional data produced by surveys still leaves many opportunities for exploration, thus complementing its insights, with non-conventional data becoming important. Considering the predictive nature of the household vulnerability measurement, the more angles used to develop the measurement, the more accurate it will be. In this case, non-conventional data sources can enrich surveys data by including insights on consumer behaviour on investing, saving, and household behaviours. With the intention of mitigating systemic risks, improving intermediary functions, and increasing financial system efficiency, non-conventional data sources can additionally help to reduce biases from conventional data, specifically on the survey's response rate and time-lag.

Earlier this year, BI recognised the opportunity to harness the use of non-conventional data in measuring household financial vulnerability by combining the analysis with banking indicators and survey results. With that being said, the Macroprudential Policy Department of Bank Indonesia collaborated with Pulse Lab Jakarta on the 9th Research Dive for Development. Researchers were brought together to dive into diverse data sets, with the purpose of developing new methods and insights into household vulnerability that could support the macroprudential policy making.

This report seeks to uncover the insights gathered from the researchers, who spent several days analysing household vulnerability. From understanding the home mortgage default rate in Indonesia and identifying indicators of household indebtedness at the provincial-level to using fintech data to assess customers' financial vulnerability and evaluating how natural hazards impact loan-at-risk, the report may serve as a useful resource to complement household vulnerability research. The initial findings can also be developed further by BI by using more data coverage, longer series, and more robust research methods.

Finally, we would like to thank all the parties involved in the 9th Research Dive for the expertise and skills they brought to make the Research Dive possible.

Jakarta, October 2019
Corporation and Household Group
Bank Indonesia

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ABSTRACT

Households make up a strategic sector that could pose potential risk to a nation s financial stability. The main reason is that households are deeply interconnected to financial institutions and non-financial corporations and are affected by the environment in which the household operates; the resources, human, physical and financial it commands; and its behavioural responses. To anticipate and to avoid such shocks towards households to occur, measuring their vulnerability becomes vital. In this era of rapid digitalisation, an abundant amount of data is being generated across Indonesia's cyberspace. This provides an opportunity to measure household vulnerability from different perspectives and complementing Bank Indonesia' s banking indicators and survey results. To support this effort, Pulse Lab Jakarta (PLJ) and the Macroprudential Policy Department of Bank Indonesia held Research Dive for Development on Household Vulnerability. Several data sets from the Macroprudential Policy Department of Bank Indonesia, Bappenas Directorate of Macro Planning and Statistical Analysis, Bappenas' Centre for Development and Planning Data and Information (Pusdatin), JULO, OLX Indonesia, International Organisation for Migration (IOM), United Nations Development Programme (UNDP) and Statistics Indonesia (BPS) were used to answer four policy-relevant research questions. This paper briefly describes the data sets utilised in the event.

KEYWORDS

household vulnerability, big data

1 INTRODUCTION

Taking on the lessons from the 1997 Indonesian financial crisis that decreased household welfare and added nation's poverty incidence [1], household turns out as a strategic sector that contributes significantly to the national economy while could also pose potential risk towards financial stability. The main reason is that households are deeply interconnected to financial institutions and non-financial corporations and are affected by the environment (macroeconomic, institutional, sociopolitical and physical environment), in which the household operates; the resources, human, physical and financial it commands; and its behavioral responses [3]. Shocks that occur in any of these aspects could threaten the household's welfare. To anticipate and to avoid such effects towards households to occur, measuring household vulnerability becomes vital.

Household vulnerability measurement itself is *ex-ante* in nature, which means this is the measurement towards risks that a household will, if currently non-poor, fall below the poverty line, or if currently poor, will remain in poverty [2]. Unlike poverty assessment that stands on the stochastic phenomenon, vulnerability assessment reflects how households prospects are in the future because today's poor might not be tomorrow's poor and *vice versa*. In this case, vulnerability to poverty can be caused by various and unexpected events such as harvest failure; layoff; an unexpected expense; an illness; and many other risks and shocks of life [3]. Therefore, household vulnerability assessment is essential to formulate policies and interventions to anticipate and mitigate such risks that will affect households' well-being, and eventually affect financial stability.

Conventionally, Bank Indonesia (BI) measures household financial vulnerability through its banking indicators and periodic survey results. The era of technological advancement and the digital revolution, however, produces an abundant amount of data from new sources. This provides an opportunity to harness big and non-conventional data to generate insights on household vulnerability. In particular, the Macroprudential Policy Department of Bank Indonesia and Pulse Lab Jakarta captured the opportunity to harness the new sources of data to measure household vulnerability, complementing the existing insights from conventional data to inform macroprudential policy making.

To support this effort, Research Dive for Development on Household Vulnerability was organised. Researchers and practitioners from the academic, government, and private sectors participated in conducting an exploratory data dive to answer four research questions, particularly: (1) understanding default rate mortgage and contributing factors, (2) identifying indicators of household indebtedness by province, (3) exploring customers vulnerability with fintech data, and (4) measuring the impact of natural hazards on loan-at-risks. The outcomes are expected to assist the Macroprudential Policy Department of Bank Indonesia in mitigating systemic risks, improving intermediary function, and increasing financial system efficiency.

2 DATA SETS

This section explains briefly the types of data used by the participants during Research Dive: Household Vulnerability.

2.1 Bank Indonesia Loan Data

In collaboration with the Macroprudential Policy Department of Bank Indonesia, PLJ team shared a view that appropriate policies could be made—in regards to household vulnerability—by harnessing conventional and non-conventional big data.

BI provided anonymised loan data customers from 2016 to 2019. The data contains information on vehicle and housing loans. However, PLJ aggregated the data on certain levels, such as Bank ID, Kabupaten/Kota ID, customer personal details, and types of loan. The aim of aggregating the loan data from BI is to protect individual's sensitive data and facilitate researchers with simple and detailed data to analyse. All fields and descriptions are shown in *Table 1*.

2.2 Susenas 2017 & 2018

The National Socioeconomic Survey (Susenas) data supports the Government of Indonesia's development agenda and is conducted by BPS. In this Research Dive, Susenas data from 2017 and 2018 and selected variables that were most related to the research were used. All provinces, regencies, and districts were classified into rural- and urban-levels. Variables from Susenas data sets encompassed: summary of family members, birth certificates, education, technology use, Internet access, employment, health, food access, social protection, financial services, goods ownership, and household source of income.

2.3 JULO Loan Data

PLJ's partnership with JULO—one of the leading fintech startups in Indonesia—provided an opportunity to enrich the research analysis by combining its non-conventional loan data with the conventional counterparts from BI. JULO provided stratified random sampling of monthly disbursement and Kabupaten/Kota. The customer loan data from JULO between August 2018 and June 2019 with over 10,000 anonymised samples were made available. The data sets included other variables such as last payment date, last balance, loan purpose, house ownership, employment status, monthly income, monthly expenses and total current debt. In addition, we added secondary data sets which contain defined Kabupaten/Kota name by JULO and by BPS as a pivot table to primary data sets.

2.4 OLX Property Advertisement

OLX collaborated with Pulse Lab Jakarta by providing advertisement data for experiments in answering various research questions and its representatives also joined as participants in a previous Research Dive in 2017. OLX provided their data from January 2016 to June 2017. In regards to the specific research question about understanding default rate of home mortgage, PLJ team decided to use

Field	**Description**
IDBANK2	Bank ID (anonymised)
BULAN	Starting-month of the loan
DEBITURKABKOT	Kabupaten/Kota ID of customers according to BPS
JENISKPRATAUKKBP	Type of loan (e.g KPR or KKBP)
JENISKREDIT	Category of loan (e.g. Konvensional and Murabahah)
TIPEPROPERTI	Type of property (e.g. Rumah Tapak 22–70, Rumah Tapak ≤ 21)
EVER_DEFAULT	Status whether loan has ever default or not (1 or 0)
PROYEKXDEBITUR	Status whether loan application location is identical to the customer's location in Kartu Tanda Penduduk (ID Card)
KOLEKTIBILITAS	Scale state of payment of loan instalments and interest (e.g. 1–smooth; 2–in particular attention, ... 5–default)
COUNT	Number of loan customers
BAKIDEBET	Remaining debt; provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
BAKIDEBETNPL	Non-performing loan (amount of debt which could not be paid as scheduled); provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
PLAFON	Ceiling (maximum permitted loan); provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
PLAFONINDUK	Total amount of ceiling that have been set for each stage; provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
UMUR	Age of loan customers; provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
DURASI	Duration of loan; provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness
SUKUBUNGA	Interest of loan at particular period; provided some statistical description such as total, maximum, minimum, mean, median, standard deviation and skewness

Table 1: Aggregated Bank Indonesia Loan Data Fields and Their Descriptions

Field	Description
year	Year of published ad
week	Week of published ad
listing_city_id	City of property's location
category_name	Category status of property (sell or rent)
property_type	Type of property (house, apartment or land area)
seller_type	Type of seller (high or low)
price	Price of property
plot_area	Area of property (in m^2)
net_area	Area of building (in m^2)
sold	Ad property status
liquid	Liquidity of property (0 or 1)
viewer	Number of ad viewers
buyer	Number of users who put the ad into their wish list

Table 2: Data Description of OLX Property Ads

ads property only and added with another table of Kabupaten/Kota name by OLX and by BPS to join with ads property data. *Table 2* shows information of variables and description of data set.

2.5 IOM's Displacement Tracking Matrix

On 28 September 2018, Indonesia was impacted by an earthquake, tsunami and liquefaction consecutively in Central Sulawesi. To respond to these disasters and gather insights on population movements, PLJ collaborated with IOM who provided us with the Displacement Tracking Matrix (DTM). DTM is a system to track and monitor the displacement and population mobility and it provides humanitarian assistance to migrants. The data contains detailed information about the location of shelters, condition of the shelters, statistical demographic in each shelter, external assistance for sanitation and electricity, etc. The data covers 942 shelters in Palu, Sigi and Donggala.

2.6 UNDP Palu Pengkajian Kebutuhan Pasca Bencana (Jitupasna) Survey Data

Jitupasna is a post-disaster needs assessment survey that was conducted by UNDP Palu for physical, financial, and psychological recovery from 2018 natural disaster. The questionnaire ranges from issues on infrastructure damage to concerns on financial and psychological disruption in households.

3 DATA AND TASK MAPPING

Loan data from BI became the main data set to all tasks which was later combined with other data sets to help researchers in answering the research questions.

Data distribution are mapped accordingly:

Task 1 used OLX ads property data, Susenas 2017 and loan data from Bank Indonesia to understand default rate of home mortgage and contributing factors.

Task 2 used Susenas 2018, loan data customer from JULO, loan data from BI and food commodity price from BI to identify indicators of household indebtedness by province.

Task 3 mapped loan data from BI with loan data from JULO and Susenas 2018 to detect customers vulnerability with fintech data.

Task 4 measured the impact of natural hazards on loans-at-risk we mapped loan data from BI with Displacement Tracking Matrix from IOM, Jitupasna survey from UNDP Palu and Susenas 2018.

In addition, the research teams were also allowed to include additional datasets, providing that they could be accessed publicly (open data) and were relevant to each task.

REFERENCES

[1] Suryahadi A. and S. Sumarto. 2001. The Chronic Poor, The Transient Poor, and The Vulnerable in Indonesia Before and After The Crisis. *Working Paper, SMERU Research Institute* (2001).

[2] Suryahadi A. and S. Sumarto. 2003. Poverty and Vulnerability in Indonesia Before and After the Economic Crisis. *Asian Economic Journal* 17, 1 (2003), 45–64. https://doi.org/10.1111/1351-3958.0016

[3] Chaudhuri S. 2003. Assessing vulnerability to poverty: Concepts, empirical methods and illustrative examples. *Columbia University* (2003).

Analysis the Default Rate of House Mortgage in Indonesia

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ABSTRACT

Household indebtedness can have macroeconomic implications because it can affect both financial system stability and real economic growth. House mortgage is playing a dominant contribution to total household debt. This paper tries to reveal the economic consequences behind higher house mortgage by investigating more deeply the default rate of house mortgage including its contributing factors. To analyze the default rate of house mortgage by districts in Indonesia, this paper employs Poisson model, Negative Binomial model, GWPR model, and Threshold regression models.

From modeling the default rate of a house mortgage, there are 3 main variables that significantly contribute to the default rate: ratio loan obligation to household per capita expenditure, interest rate, and proportion of formal workers to total workers. It can be recommended to policymakers that to minimize the default rate of house mortgage, the ratio of monthly loan obligation to household per capita expenditure should not more than 84.766% and the interest rate should not more than 11.61% per year.

KEYWORDS

Default rate, Household per capita expenditure, Interest rate, Poisson regression, Threshold regression

1 INTRODUCTION

Global financial crisis of 2007-2008 has shown how high household indebtedness can have macroeconomic implications because it can affect both financial system stability and real economic growth. From the crisis, financial health in the household sector is important because of two reasons. First, lower inability of households to pay their debt may have a negative effect on financial institution' s balance sheet like banks which in turn can generate financial instability. Second, high levels of indebtedness with lower household saving rate potentially make household more vulnerable and sensitive to economic shocks which in turn can undermine macroeconomic stability.

The global financial crisis of 2007-2008 also has shown how household debt plays a dominant role in increasing household indebtedness before the economic and financial crisis occurred. In the context of avoiding financial crisis, monitoring financial health of indebted households is being mattered. Data from Bank for International Settlements (BIS) shows that the level of household debt in Indonesia should raise concern over household vulnerability due to its large size dan growth. In Indonesia, the amount of household debt in the fourth quarter of 2018 achieved 17 % to GDP. As generally known, the number is classified as the highest record of household debt after currency crisis of 1997-1998.

Table 1: Type of Loan and Interest Rate

Type of Loan	Contribution to Total Loans	Interest Rate
Investment	24.717	10.38 %
Working Capital	47.451	10.37 %
Consumption	27.832	11.73%

Source: Bank Indonesia

At the same time, data from Bank Indonesia, that shown in Table 1, shows that although the interest rate of investment loan is relatively lower than consumption loan, the contribution of consumption credit to total loans remained higher than investment credit. The contribution of consumption credit recorded at around 28 % while investment credit contributed only at 25 %. This number indicates that household burden due to higher indebtedness as possible unless there is a higher increase in disposable income than interest rate. However, it is difficult to achieve such a condition because the interest rate of consumer credit is still above 11 %.

Furthermore, property credit still dominated household debt composition. Data from Bank Indonesia show that property credit begun to exceed non-consumption debt in the third quarter of 2013 at 51 % of total household debt. Since then, the mortgage debt relative to consumer debt consistent to increase and achieve at 58,6 % in the fourth quarter of 2017. Because of its dominant contribution to total household debt, house mortgage is supposed to be a central issue of household debt. Therefore, this paper tries to reveal the economic consequences behind higher house mortgage by investigating more deeply the default rate of house mortgage including its contributing factors.

More specifically, the purpose of this paper is to model default rate of house mortgage across the entire city/district. Also, this paper estimates the threshold of contributing factors to default rate of house mortgage. To examine the determinant factors of default rate of mortgage loan, this paper employs some statistical methods like Geographically Weighted Regression (GWR) and Threshold Regression. In addition, some key variables such as house price, expenditure per capita, aggregate interest rate were also included. The dataset for this study was collected from three main data sources such as Susenas 2017, Ads Property of OLX, and Bank Indonesia.

2 LITERATURE REVIEW

2.1 Poisson Regression and Binomial Negative Regression

Regression analysis is an analysis to model the relationship between the dependent variable and the independent variable. If the dependent variable is the count data and Poisson distribution, then the convenient model is the Poisson regression model[3]. Poisson regression model as follows as:

$$\lambda_i = exp(x^T\beta)$$

with $\mathbf{x}_i^T = [1 \quad x_1i \quad x_2i...x_ki]; \beta = [\beta_0 \quad \beta_1 \quad \beta_2...\beta_k]$ and λ : average number of events that occur in specific period

Estimation of parameters for Poisson regression using the Maximum Likelihood Estimation (MLE) method by maximizing the likelihood function. The parameter estimates for Poisson regression are as follows [6];

$$L(\beta) = \prod_{i=1}^{n} \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} = \prod_{i=1}^{n} \frac{e^{-e^{(}x_i^T\beta)}(e^{x_i{}^T}\beta)^{y_i}}{y_i!}$$

$$\frac{\partial lnL(\beta)}{\partial\beta} = -\sum_{i=1}^{n} x_i{}^T e^{x_i{}^T\beta} + \sum_{i=1}^{n} y_i x_i$$

The equation is equal to zero to get the parameter estimator. However, this method does not get precise results, so the alternative to solve the equation is Newton-Raphson's numerical iteration method. The purpose of the numerical iteration method is to maximize the log-likelihood function[6]. Simultaneous testing of the parameters of the Poisson regression model used to see the suitability of the resulting model. The concurrent testing hypothesis is as follows.

$$H_0 : \beta_1 = \beta_2 = ... = \beta_k = 0$$
$$H_1 : \text{at least one of } \beta_j \neq 0, j = 1, 2, ..., k$$

The test statistic used is obtained from the Maximum Likelihood Ratio Test (MLRT) method as follows:

$$D(\hat{\beta}) = -2ln\left|\frac{\hat{\omega}}{\hat{\Omega}}\right| = 2(ln(\hat{\Omega}) - lnL(\hat{\omega})$$

For criteria testing, reject H0 for D($\hat{\beta}$) $> x^2(v,\alpha)$. Partial parameter testing is used to determine the parameters that have a significant influence on the model. The hypothesis used in the partial test are:

$$H_0 : \beta_j = 0$$
$$H_1 : \beta_j \neq 0, \text{with} \quad j = 1, 2, ..., k$$

The testing of statistics as follows as

$$Z = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)}$$

The criteria of testing, reject $H0 for |Z| > Z_\alpha/2$.

For the Poisson regression model, one of the assumptions of the model that must be fulfilled is equidispersion, where the value of variance is equal to the mean value. The relationship between variance and mean can be expressed in terms of an equation:

$$v(\mu_i) = \phi\mu_i$$

If the value of $\phi = 1$ then the assumption of Equidispersion was fulfilled if $\phi > 1$ then it was overdispersion and if $\phi < 1$ then it was under-dispersion. In the case of overdispersion or underdispersion, one of the treatments is using Negative Binomial Regression. Similar to the Poisson regression model, the Negative Binomial regression model is written as follows:

$$\mu_i = exp(\beta_0 + \beta_i X_i 1 + ... + \beta_p X_i p)$$

$\mu_i$is the expectation value of y_i that has a negative binomial distribution. The parameter estimation of the Negative Binomial regression model uses the Maximum Likelihood Estimator method, which is then continued using Newton Raphson iteration. Simultaneous and partial testing in the Negative Binomial regression model, similar to testing the parameters in the Poisson regression model[5].

2.2 Geographically Weighted Poisson Regression (GWPR)

GWPR model is a local form of Poisson regression where location is considered which assumes that the data is Poisson distributed. The GWPR model can be written as follows[7]:

$$E(y_i) = \mu(x_i, \beta(u_i, v_i)) = exp(x_i^T\beta(u_i, v_i)); i = 1, 2, ..., n$$

y_i is dependent variable for i-th observation, while $\mu(x_i, \beta(u_i, v_i))$ is function of x_i as an independent variable and β is parameter of regression model with longitude and latitude as follow:

$x_i^T = [x_1i, X_2i, ..., X_ki]$ and $\beta = [\beta_0, \beta_1, \beta_2, ..., \beta_k]^T, (u_i, v_i)$

Estimating the parameters of the GWPR model uses the MLE method. The initial step of the method is to establish a likelihood function. Because the dependent variable is Poisson distribution ($Y_i \; Poisson(\mu(x_i, \beta))$), the likelihood function is as follows:

$$L(\beta) = \prod_{i=1}^{n} \frac{exp(-\mu(x_i, \beta))(\mu(x_i, \beta))^y i}{y_i!}$$

While testing the significance of the parameters carried out simultaneously and partially. Simultaneous testing is as follows (Fotheringham, et al., 2002):

$$H_0 = \beta_k(u_i, v_i) = \beta_k \quad ; i = 1, 2, ..., n \quad ; k = 1, 2, ..., p$$

(there is no significant difference between the Poisson regression model and the GWPR model)

$$H_1 = \text{at least one} \beta_k(u_i, v_) \neq \beta_k$$

The test of statistics,

$$D(\hat{\beta}(u_i, v_i)) = -2ln[\left[\frac{L(\hat{w})}{L(\hat{\Omega})}\right] = 2[ln \quad L(\hat{\omega} - ln \quad L(\hat{w})]$$

$D(\hat{\beta})$ also known as likelihood ratio statistics. Testing the suitability of the GWPR model using a comparison of the deviation value of the Poisson regression model and the GWPR model. Suppose the Poisson regression model is expressed with model A with degrees of freedom dfA and the model GWPR is expressed with model B with degrees of freedom dfB then:

$$F_{\text{hit}} = \frac{\text{Devians} \quad \text{Model} \quad A/df_A}{\text{Devians} \quad \text{Model} \quad B/df_B}$$

Will follow the distribution of F with free degrees df_A and df_B. The test criterion is reject H_0 if $F_{\text{hit}>F_{(a;dfA;dfB}}$.

Model parameter testing is done by testing the parameters partially. Hypothesis:

$$H_0 : \beta_k(u_i, v_i) = 0 \quad ; i - 1, 2, ...n \quad k = 1, 2, ..., p$$

$$t_{\text{hit}} = \frac{b\hat{e}ta_k(u_i, v_i)}{se(\hat{\beta}_k(u_i, v_i))}$$

The criteria of test, Reject H_0 for $|t_{\text{hit}} > t_{(a/2);n-(p+1)}$

2.3 Treshold Poisson Regression

The threshold regression model is a model regression describing structural break in the relationship between variables and popular in non-linear time series data. Thus, the threshold model assuming a priori that the relationship between variables might be non-linear [8]. The threshold model can capture cross section and time series data[1]. This model also is a valuable tool for investigating a wide variety of economic phenomena. Therefore, this model has been widely used in financial and macroeconomics studies[2].

Following Hansen' s method[1], the threshold regression model can be specified as follows:

$$Defaultdebtors = a_0 + a_1X_i(q_i \leq \gamma_1) + a_2X_i(q_i \leq \gamma_2) + u_t$$

Where $\gamma 1$ and $\gamma 2$ are the thresholds that divide the equation into three regimes with coefficients $\alpha 1$ and $\alpha 2$. Here, Xi are all independent variables such as loan to expenditure per capita, aggregate interest rate, small house price to expenditure per capita, medium house to expenditure per capita, average age of debtors and formal workers ratio.

3 DATA AND METHODOLOGY

3.1 Data and Variables

To understand the default rate of house mortgage and contributing factors, the following model may be estimated:

$$\text{Default debtors} = a_0 + a_1KX_i + a_3CX_1 + u_t$$

Where default_debtors is dependent variable, KXi is key independent variables and CXi is additional independent variables. This study used cross-section data in 2017 from Bank Indonesia, Social and Economic Survey (Susenas) and Ads Property of OLX. All the individual data from the data sources were converted to city/district data. all the individual data were processed and analyzed by using statistical software such as Phyton, R and STATA 15. The data covers 471 city/district in Indonesia.

Default rate of house mortgage in this model is defined as the number of default debtors. The data on the number of default debtors are collected from Bank Indonesia. To investigate contributing factors on the default rate of house mortgage, the model involves several key variables such as loan to expenditure per capita ratio (loan_expcap), aggregate interest rate (interest_rate), small house price to expenditure per capita ratio (hprice_small), medium house price to expenditure per capita ratio (hprice_medium). The information on loan to expenditure per capita ratio are gathered from the Indonesia Social and Economic Survey (Susenas) 2017 while the data on aggregate interest rate are obtained from Bank Indonesia.

In addition, other data such as small house price to expenditure per capita ratio, medium house price to expenditure per capita, and large house price to expenditure per capita ratio are gathered from Ads property of OLX. Two additional independent variables like average age of debtors (mean_age) and the formal workers to total workers ratio (formal_workers) are also included. The information regarding on average age of debtors are collected from Bank Indonesia while formal workers to total workers ratio are taken from Susenas 2017.The variables were obtained from various sources are described in Table 2 and are statistically summarized in Table 3.

Table 2: Variables and Data Sources

Variables	Description	Sources	Measurement Type
Dependent Variables			
Default_debtors	The number of default debtors	BI	Count
Independent Variables			
Loan_expcap	Loan to expenditure per capita ratio	BI, Susenas	%
Interest_rate	Aggregate interest rate	BI	%
Hprice_small	Small house price to expenditure per capita ratio	Ads property of OLX and Susenas	ratio
Hprice_medium	Medium house price to expenditure per capita ratio	Ads property of OLX and Susenas	ratio
Additional Independent Variables			
Mean_age	Average age of debtors	BI	Year
Formal_workers	Formal workers to total workers ratio	Susenas 2017	%

Table 3: Summary Statistics

Variables	Obs	Mean	Std.Dev.	Min	Max
Dependent Variables					
default_debtors	479	87.3591	330.0188	0	5416
Independent Variables					
loan_expcap	479	152.278	53.9398	60.8666	572.933
interest_rate	479	12.0712	1.245976	5	1.7
hprice_small	479	123.084	91.51371	0.28147	698.697
hprice_medium	479	603.028	2479.512	34.4688	51608
mean_age	479	42.8765	2.831455	28.6667	72
formal_workers	479	36.1578	16.32413	0.73376	78.0756

Table 4: Parameter Estimates of Poisson Regression Model

Variable	Estimate	Std. Error	Pr(>|z|)
(Intercept)	1.04776	0.135145	8.98e-15***
loan_expcap	0.00162	0.000131	<2e-16***
mean_age	0.01925	0.002993	1.28e-10***
interest_rate	-0.06184	0.006168	<2e-16***
hprice_medium	-0.00002	0.000006	0.000501***
formal_workers	6.98591	0.042355	<2e-16***

Signif.codes: 0'***' 0.001'**' 0.01'*'

4 RESULTS

The incidence of taking a mortgage loan from a commercial bank or cooperative for a home purchase is sharply lower in developing than industrialized countries[9]. Indonesia, one of developing countries which has more than 260 million people, the requirement for new housing is more than 800,000 units per year, meanwhile the mortgage sector only finances at the most 200,000[4]. Unfortunately, not all debtors who use bank loans for house ownership can successfully complete their obligations. So analysis regarding default rate of house mortgage is very important to ensure the success of the housing program in Indonesia.

4.1 Poisson Regression and Binomial Negative Regression

We set the default debtors, shown in Table 2 and Table 3, as the dependence variable. The type of its data is data count with Poisson distribution. Because of that, we use Poisson regression to model the default rate. We use Negative Binomial regression if the Poisson regression severe an overdispersion.

Table 4 shows the parameter estimates of Poisson regression model. All of independent variables are significantly affect the default debtors. The proportion of formal workers to total workers plays dominant role of variables that affect the default rate. Unfortunately, the assumption of equidispersion of the Poisson model is not fulfilled. So we employ Negative Binomial regression to model the default rate.

Table 5 shows the parameter estimates of Negative Binomial regression model. We obtain that only three variables (loan_expcap, interest-rate and formal_workers) are significantly affect the default debtors. Loan_expcap and interest_rate have negative sign which means that an increase of loan_expcap and interest_rate will cause the opportunity of default rate to decrease. While the formal_workers has a positive sign which means that the increase of proportion of formal workers will cause the opportunity of default rate to rise.

Table 5: Parameter Estimates of Negative Binomial Model

Variable	Estimate	Std. Error	Pr(>|z|)
(intercept)	3.9988	0.751307	0.000000***
loan_expcap	-0.0054	0.001351	0.000057***
interest_rate	-0.1170	0.05274	0.0265*
formal_workers	5.7626	0.436801	<2e-16***

Signif.codes: 0'***' 0.001'**' 0.01'*'

Table 6: Parameter Estimates of GWPR Model

Variables	Min.	1st Qu	Median	3rd Qu	Max.
Intercept	-1.133	1.440	2.524	3.106	3.910
loan_expcap	-0.004	-0.001	0.001	0.002	0.005
interest_rate	-0.177	-0.133	-0.093	-0.029	0.121
formal_workers	6.182	6.534	6.668	6.975	7.913

4.2 Geographically Weighted Poisson Regression (GWPR)

To optimize modelling the default rate, we use three variables which have significant effect obtained from Negative Binomial regression model by employing GWPR model.

$Number\ of\ data\ points$: 479
$GWDeviance$: 80441.27
$AICc$: 80453.96
$PseudoR-squarevalues$: 0.413551

Table 6 shows that the median value of loan_expcap has positive significant effect to the default rate. This is different from the result of Negative Binomial models which the loan_expcap has negative sign. Therefore we need to clarify the effect of independent variables to the default rate by using the threshold model.

Figure 1: Default rate map obtained from GWPR model

Figure 1 shows the default rate estimates obtained from GWPR models. The map shows there is spatial heterogeneity among the district in Indonesia. North Kalimantan and several provinces in north Sumatera show have high rate of default debtors. We need further studies to observe this phenomenon by utilizing more detailed data.

Table 7: Parameter Estimates of GWPR Model

Model	Deviance	df	Devians/ df	$F_t est$	$F_{;df1,df2}$
Poisson model	887.020	478	1.856	0.011	1.162
GWPR	79856.450	479	166.715		

We test the goodness of fit of GWPR model compared to Poisson model with hypothesis as follow:

$H_0 : \beta_j(u_i, v_i) = \beta_j, i = 1, 2, ..., n \quad j = 1, 2, ..., p$(Global Model)

H_1 : At least one of$\beta_j(u_i, v_i) \neq \beta_j, (GWPRModel)$

Table 7 shows that $Ftest < F; df1, df2$ so we conclude that regarding parsimony model, the Poisson model is better than GWPR model. But because of Poisson model severe overdispersion so the Negative Binomial model is more appropriate to analysis of the default rate.

4.3 Threshold Regression Model

From the results of the Negative Binomial and GWPR model we get information on the difference in effect of Loan_axcap to the default rate. To clarify this phenomenon, we employ a threshold regression model. Firstly, we estimate threshold parameter of Loan_expcap and then we estimate threshold parameter of interest_rate.

4.3.1 ***Threshold Parameter of Loan expcap.*** Table 8 shows that the threshold parameter estimate of loan_expcap is 84.766. It means that debtors will have opportunity to default if the ratio of monthly loan obligation to household per capita expenditure is more than 84.766%. In other words, if the household per capita expenditure is about IDR 1,000,000, the desired conditions that the debtors do not fail if their monthly loan obligation is not more than IDR 847,66.

Figure 2 shows the parameter estimates of Poisson model for regime 1 (loan_expcap ft 84.766), and Table 10 shows the parameter estimates of Poisson model for regime 2 (loan_expcap > 84.766).

Figure 2 shows that interest rate has positive sign of effect to default rate in regime 1. It means that an increase of interest rates will cause an increase of the risk of customers to default. For regime 1 that usually indicated a condition where household per capita expenditure is high, the financial service providers must be careful with interest rates.

Figure 3 shows that interest rate has negative sign of effect to default rate in regime 2. It means that an increase in interest rates will cause a decrease in the risk of customers to default. For regime 2 that usually indicated a condition where household per capita expenditure is low, the financial service providers must be careful with the age of debtors.

Table 8: Threshold Parameter Estimate of Loan_expcap

Threshold Estimate	84.766
Sum of Squared Errors	44736358
Residual Variance	96207.222
Joint R-Squared	0.140679198
Heteroskedasticicty Test (p-value)	0.341301432

Poisson regression — Number of obs = 18; LR chi2(6) = 1890.84; Prob > chi2 = 0.0000; Log likelihood = -1059.8683; Pseudo R2 = 0.4715

default_debtors	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
interest_rate	.1707593	.0323815	5.27	0.000	.1072927	.2342259
loan_expcap	.0250484	.0041151	6.09	0.000	.016983	.0331137
hprice_small	-.003467	.0006282	-5.52	0.000	-.0046983	-.0022358
hprice_medium	-.0019231	.000539	-3.57	0.000	-.0029796	-.0008667
mean_age	-.2909829	.0178495	-16.30	0.000	-.3259673	-.2559985
formal_workers	.0298865	.0023178	12.89	0.000	.0253437	.0344293
_cons	12.1166	.9302756	13.02	0.000	10.29329	13.93991

Figure 2: Parameter Estimates of Loan_expcap for Regime 1

Poisson regression — Number of obs = 461; LR chi2(6) = 52390.91; Prob > chi2 = 0.0000; Log likelihood = -41203.611; Pseudo R2 = 0.3887

default_debtors	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
interest_rate	-.1040036	.0065457	-15.89	0.000	-.1168329	-.0911743
loan_expcap	.0005804	.0001463	3.97	0.000	.0002936	.0008673
hprice_small	-.0007235	.0000847	-8.55	0.000	-.0008894	-.0005576
hprice_medium	-.0000225	6.37e-06	-3.53	0.000	-.0000349	-9.99e-06
mean_age	.0311543	.0030561	10.19	0.000	.0251645	.0371441
formal_workers	.0699753	.0004285	163.29	0.000	.0691354	.0708152
_cons	1.178052	.1377509	8.55	0.000	.9080648	1.448038

Figure 3: Parameter Estimates of Loan_expcap for Regime 2

Table 9: Threshold Parameter Estimate of Interest Rate

Threshold Estimate	11.6091366
Sum of Squared Errors	45303261.2
Residual Variance	97426.3638
Joint R-Squared	0.129789806
Heteroskedasticicty Test (p-value)	0.293478155

4.3.2 ***Threshold Parameter of Interest Rate.*** Table 11 shows that the threshold parameter estimate of interest rate is 11.61. It means that debtors will have opportunity to default if the interest rate is more than 11.61% per year. Table 12 shows the parameter estimates of Poisson model for regime 1 (interest rate ft 11.61), and Table 13 shows the parameter estimates of Poisson model for regime 2 (interest rate > 11.61).

Figure 4 shows that interest rate has positive sign of effect to default rate in regime 1. It means that an increase in interest rates will cause an increase of the risk of customers to default. The loan_expcap has positive sign of effect to default rate in regime 1. It means that an increase in ratio of monthly loan obligation to

Poisson regression
Number of obs = 153
LR chi2(6) = 42129.01
Prob > chi2 = 0.0000
Log likelihood = -21319.524
Pseudo R2 = 0.4970

default_debtors	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
interest_rate	1.140524	.0171477	66.51	0.000	1.106915	1.174133
loan_expcap	.0083671	.0002061	40.60	0.000	.0079632	.008771
hprice_small	-.0006947	.0001436	-4.84	0.000	-.0009761	-.0004132
hprice_medium	-.0046735	.0001021	-45.76	0.000	-.0048737	-.0044734
mean_age	.1437788	.0055382	25.96	0.000	.1329242	.1546334
formal_workers	.0874318	.0007227	120.99	0.000	.0860154	.0888482
_cons	-18.12242	.3105474	-58.36	0.000	-18.73108	-17.51375

Figure 4: Parameter Estimates of Interest Rate for Regime 1

household per capita expenditure will cause an increase in the risk of customers to default.

Poisson regression
Number of obs = 326
LR chi2(6) = 12086.10
Prob > chi2 = 0.0000
Log likelihood = -14634.852
Pseudo R2 = 0.2922

default_debtors	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
interest_rate	-.3863015	.0136167	-28.37	0.000	-.4129897	-.3596133
loan_expcap	-.0058157	.0002442	-23.82	0.000	-.0062942	-.0053372
hprice_small	.0021811	.0001151	18.95	0.000	.0019555	.0024067
hprice_medium	6.23e-07	5.07e-06	0.12	0.902	-9.31e-06	.0000106
mean_age	-.0506096	.004109	-12.32	0.000	-.0586632	-.042556
formal_workers	.039437	.0006149	64.14	0.000	.0382319	.0406421
_cons	9.914754	.2230834	44.44	0.000	9.477519	10.35199

Figure 5: Parameter Estimates of Interest Rate for Regime 2

Figure 5 shows that interest rate has negative sign of effect to default rate in regime 2. It means that an increase in interest rates will cause a decrease of the risk of customers to default. The loan_expcap has negative sign of effect to default rate in regime 2. It means that an increase in ratio of monthly loan obligation to household per capita expenditure will cause a decrease in the risk of customers to default.

5 CONCLUSIONS AND POLICY RECOMMENDATION

Modelling the default rate using Poisson regression, Negative Binomial model and GWPR model can be found that there are 3 main variables that significantly contribute to the default rate: loan_expcap, interest_rate, and formal workers. Variables loan_expcap and interest rate are used as threshold variables because those variables can be controlled by policy makers.

Threshold Poisson regression model finds that the threshold estimate for loan_expcap is 84.77. It means that debtors will have opportunity to default if the ratio of monthly loan obligation to household per capita expenditure is more than 84.766%. While the threshold estimate for interest_rate is 11.61. It means that debtors will have opportunity to default if the interest rate is more than 11.61% per year.

From this explanation, it can be recommended to policy makers that the main factors that influence the default rate of house mortgage is loan_expcap and interest rate. To minimize the default rate of house mortgage, the ratio of monthly loan obligation to household per capita expenditure should not more than 84.766% and the interest rate should not more than 11.61% per year.

6 RESEARCH LIMITATIONS

Limitations of this study include the availability of data that does not cover all districts in Indonesia. The analysis only covered 479 districts out of 514 districts in Indonesia. The variables used are also still very limited. The threshold regression that used in model to estimate parameter threshold is using normal distribution.

7 FUTURE RESEARCH

For further research, firstly, it is better to use complete data of all districts in Indonesia in order to describe the condition completely. Secondly, as this research use 2016 and 2017 datasets only, it is better to use time series data with longer time interval to gather insights from more detailed patterns of household vulnerability. The GWPR analysis also needs to be further explored with more detailed variables so that the phenomenon of diversity between districts can be more explained. Threshold models need to use assumptions that are in accordance with the distribution of data. The Bayesian approach can be used to overcome the shortcomings of this study.

REFERENCES

[1] Hansen B.E. 1999. Threshold e!ects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics* 93 (1999).

[2] Hansen B.E. 2000. Sample Splitting and Threshold Estimation. *Econometrica* 68, 3 (2000).

[3] A.C. Cameron and K.P Trivedi. [n. d.]. Regression Analysis of Count Data. *Cambridge University Press* ([n. d.]).

[4] M.C. Hoek-Smit. [n. d.]. The Housing Finance Sector in Indonesia. *World Bank* ([n. d.]).

[5] Hilbe J.M. [n. d.]. Negative Binomial Regression. *Cambridge University Press, New York* ([n. d.]).

[6] M.V. Myers. [n. d.]. Generalized Linear Model with Application in Engineering and Science 2nd Edition. *John Wiley and Sons, New Jersey* ([n. d.]).

[7] Fotheringham A.S. Brunsdon C. Nakaya, T. and M. Charlton. 2005. Geographically Weighted Poisson Regression for Disease Association Mapping. *Statistics in Medicine* 24, 17 (2005).

[8] S. Slimani. 2016. Threshold Effect of Fiscal Policy on Economic Activity in Developing Countries. *International Journal of Business and Social Research*, 6, 3 (2016).

[9] R. J. Struyk and Patel N. 2009. Which Indonesian Home Purchasers Seek Mortgage Finance? *International Real Estate Review* 12, 2 (2009).

Identifying Indicators of Household Indebtedness by Provinces

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ABSTRACT

Many indicators of financial vulnerability in households are possible. To identify the signs of household indebtedness, we analyze the information about household debt as well as demography information, loan amount request, monthly expenses, monthly housing cost, monthly income, and total current debt which are compiled from household survey data, credit data, and fintech data. The results of data processing by using logistic regression, feature selection with Boruta, Random Forest, and text mining, we obtain spatial cluster based on province. We also find compelling reasons why the debtor applies to credit market based on dominated variables. ' Renovasi rumah, modal usaha, biaya pendidikan' dominate based on the number of loans, on the other hand, 'Ongkos kerja/ Transportation fare' is dominate based on Male and Female, while ' Anak Masuk Sekolah / registration new students' dominate based on categorized married/single status.

KEYWORDS

Indicators, Indebtedness, Household, Indonesia

1 INTRODUCTION

Based on life-cycle theory, households apply to credit markets because they want to have steady living conditions over the years[4]. Since income generally increases at the beginning of a person' s life and decreases in the period following retirement, debt is the means that allows households to smooth their expenses over their lives[4]. Young families expect their future income to grow and spend more than they earn, thus accumulating debts that they will repay when they are more mature. Financial authorities in many countries improving their effort in supervising household finances. This is particularly in terms of the ability of households to fulfill their financial obligation. When many households at the same time and in large amount could not pay their debt, this will cause instability in financial system. Moreover, when households have difficulties in paying their debts, then households will try to pay the debt by reducing their expenditure from other aspect of expenditures, of by having new debts. If the expenditure that the households choose to reduce is on food, health, and education, hence this reduction due to paying the debt will have long term impact. The recent development of household credit shows that the growth of household credit is stable since 2015. The average growth of household credit on average reaching around 9 percent (Figure 1). The graph is also shown that the share of individual credit is equal compare to non-individual credit.

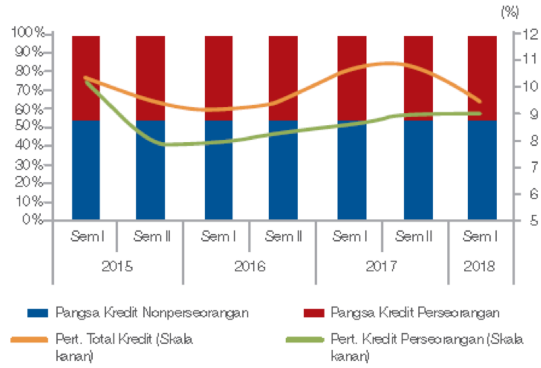

Figure 1: The Development of Household Credit, Source: Bank Indonesia

Household is exposed to various type of credit from various providers. The traditional source of credit is financial institutions, such as banks. Recently, one of the rising credit providers for households are the financial technology (fintech) company. Fintech as new technology that intended to improve and automate the delivery of the financial services. The purpose of the fintech company is to ease the access to financial products and financial transactions. In Indonesia, most of the fintech companies are start-up companies that provide services, such as payments, lending, investment, crowfunding, financial planning, and remittances. Table 1 shows that fintech lending in Indonesia has grown significantly in the pass year. The annual growth of total loan is reaching 97.68 % in June 2019. Meanwhile, the annual growth of loan outstanding reaches 68.53 %.

The purpose of the research is to find the factors that affecting the household indebtedness. Moreover, the research also tries to find the main purpose of the loan that households have. There are two types of loans that are analyzed in this research, i.e. the bank loans, which are loans that are provided by banks; and the fintech loans, which are loans that provided by the fintech companies. The unit observations are also different between these two types of loans. For the bank loan, the unit observations are the households, while for fintech lending, the unit analysis are individual lending

Table 1: The Development of Fintech Lending

Indicators	Jan 2019	Feb 2019	Mar 2019	Apr 2019	May 2019	June 2019	% June 2019 ytd
Total Loan (Rp Millions)	26.003.799	29.299.626	33.200.470	37.013.394	41.038.865	44.805.834	
Growth	14.73%	12.67%	13.31%	11.48%	10.88%	9.18%	97.68%
Loan Outstanding (Rp Millions)	5.697.890	7.050.952	7.785.150	8.221.300	8.319.030	8.500.693	
Growth	12.96%	23.75%	10.41%	5.60%	1.19%	2.18%	68.53%

Source: Otoritas Jasa Keuangan, *Statistik Fintech Lending*, June 2019

as a representation of the household loans. Moreover, due to the data availability, the provincial analysis will be conducted not for all provinces, but only for 13 provinces in Indonesia.

2 EMPIRICAL STUDIES

A lot of empirical studies have been conducted to understand the factor affecting household indebtedness. Dynan and Kohn [5] which investigating indebtedness in United States found that declines in longer-term interest rates, increases in expected incomes, increasing house prices, and financial innovation affecting the households in applying for credit. Keese [6] investigating indebtedness in Germany. The research found that the factors affecting households' indebtedness are number of children, unemployment, income shocks, and home loan. Meanwhile, based on the research of Kim [7] in Korea, the households' indebtedness are affecting by house price increases, banks' lax attitudes toward household lending, and financial institutions' favorable funding conditions. Recently, the research on household indebtedness also conducted beyond the economic aspects of households. More and more researches are also try to understand the psychological aspects of households' indebtedness. Octavioni and Vandone [1] investigating psychological aspects of indebtedness using survey data. The research found that the significant influence of individuals' impulsivity in making debt decisions. The impulsivity was able to predict unsecured debt (*i.e.* consumer credit), but it was not significantly associated with secured debt (*i.e.* mortgages).

3 DATA AND METHODOLOGY

3.1 Susenas Data Cleaning

Susenas has two types of data, *i.e.* individual data and the household data. The analysis in this research is conducted in household level, therefore, the individual data is aggregated into household data. The demography information such as age, education, and work status use in the research are the information of the head of the household. Other household information that is used are the residence ownership status, household assets, and source of income. The household is considered as the having the bank loan if the household answered Yes for the questions of having a bank loan in the past 12 months from bank (excluding the KUR loan) or from Bank Perkreditan Rakyat (BPR - People' s Credit Banks).

3.2 Fintech Data Cleaning

In fintech data, we use 5 types of independent variables: loan amount request, monthly expenses, monthly housing cost, monthly income, total current debt and dependent variable, which are the last balance. We clear the blank values using the R software.

3.3 Methods

In this study we use logistic regression[3], feature selection with Boruta[8], Random Forest[2] and Text mining. In logistics, the model is estimated using similar independent variables between the bank loan and fintech loan There are three groups of variables estimated in the model: Demographic and social indicators, and Regional financial indicators . Moreover, in Boruta the concept is same like random forest[8]. But, extended the information system and gather the Z scores computed. For a dataset *(X,Y)* with observations *x1, x2, . . . , xN* and response *y1, y2,..., yN (yi ϵ 0,1)*, bootstrap B datasets of size N. the motivation is Data sets described with far too many variables for practical model building. Usually most of these variables are irrelevant to the classification, and obviously their relevance is not known in advance

4 RESULTS

4.1 Important Variables

We use Boruta to get the best features as it follows an all-relevant feature selection method where it captures all features which are in some circumstances relevant to the outcome variable in fintech data.

Based on Figure 2 we found that only the monthly housing cost is rejected for variable selection. So the important variables are loan amount requests, monthly income, monthly expenses and load duration requests. Moreover, we perform decision tree Home status based on debtor. We can not straight forwardly classify the home status based on vehicle type 3 (do not have the vehicle) the information only 19%. But, the dependent variable information contains 81% . The complexity param=0.04311497, mean=3.02029, and MSE=0.6285738

4.2 Estimation Results - Comparing Logistic between Provinces

For the comparison between provinces, it can be seen that there are no variables that significant in all provinces. This show that

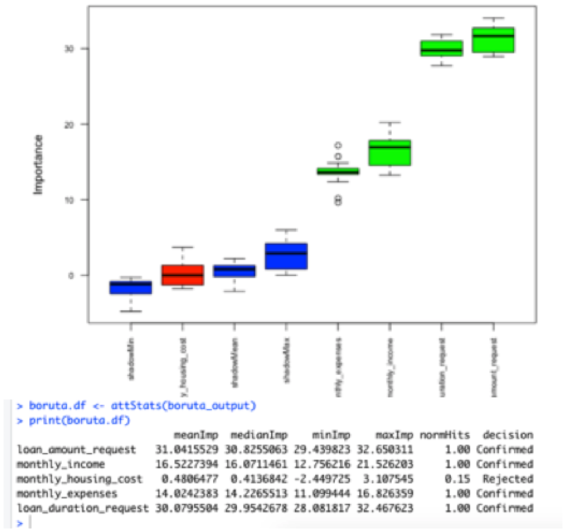

Figure 2: Variable Importance

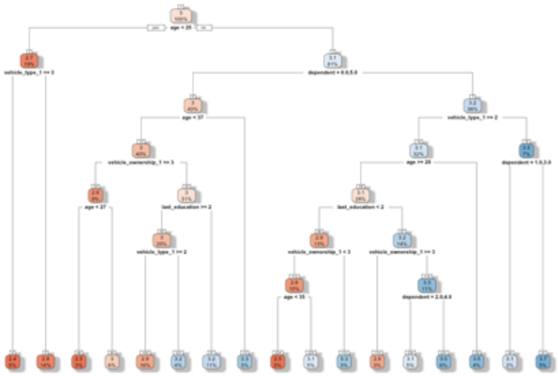

Figure 3: Random Forest

there are regional variations between provinces in household indebtedness analysis. For Banten, it can be seen that all dependent variables are not significant. Meanwhile, for West Java and Central Java, all dependent variables are significant. For DKI Jakarta, only number of dependent that are significant in affecting household bank loan. Then it will be analyzed with fintech data from Julo, it can be seen that in Table 2 and Table 3 many dependent variables are not significant in Banten, DIY, DKI, Central Java and South Sumatra. In this study we use the Wald test.

4.3 Spatial Clustering

Based on the intercept value of logistics, a cluster is formed based on provinces that have the same information. Figure 4 explains that the Susenas data for the first cluster consists of the provinces of North Sumatra, South Sumatra, West Java, Banten, Central Java, DI Yogyakarta and cluster 2 consisting of Lampung, East Kalimantan, North Sulawesi, and DKI Jakarta.

In the fintech data, cluster formation is also based on similar information and can be seen in Figure 5, in which cluster 2 is only in North Sumatra and North Sulawesi and other provinces included in the first cluster. What is interesting is that in the Susenas and Fintech data there are differences in the formation of the provincial group.

Figure 4: Spatial Clustering of Susenas Data

Figure 5: Spatial Clustering of Fintech Data

4.4 Text Mining

Our aim is to gain a deeper understanding of the main reasons for each major topic. However, we try to find borrower profiles from each sub-topics. We perform topic modelling using Latent Dirichlet Allocation (LDA) and got the most frequent of sub-topics form each top 5 major topics and We did the pre-processing and got 3813 unique words from 47217 total words.

Based on Figure 6,7 and 8 we find interesting reason the debtor based on average income, average expertise, average loan amount 'Renovasi rumah, modal usaha, biaya pendidikan' dominate based on number of loans 'Ongkos kerja/ Transportation fare' dominate based on Male and Female. 'Anak Masuk Sekolah / registration new student' is dominate based on categorized married/single.

Based on Figure 9, every customer who applies for a loan from Fintech has a relatively similar reason, namely for the business side.

5 CONCLUSIONS AND POLICY RECOMMENDATION

Overall, the variables which use to develop logmodels in fintech and bank loan is the same. We find spatial cluster based on province in terms of intercept in logistics regression based on fintech and bank loan. There is a difference between fintech and bank loan.

Table 2: Susenas Logistics

Variables	Bali	Banten	DIY	DKI	Jabar	Jateng	Jatim	Kaltim	Kepri	Lampung	Sulut	Sumut	Sumsel
Age	-0.0015	0.0022	-0.0119	-0.0057	**-0.0112**	**- 0.0074**	**-0.0075**	0.0055	-0.0165	0.0110	-0.0020	-0.0097	-0.0136
Dependent	**0.1802**	0.0568	**0.3059**	**0.3676**	**0.1368**	**0.1593**	**0.1591**	0.1298	0.1891	0.1647	0.1334	0.0895	0.0544
Last Education	**0.0878**	0.0377	**0.0653**	0.0525	**0.0548**	**0.0433**	**0.0488**	**0.0611**	**0.0650**	**0.0719**	**0.1255**	**0.0524**	**0.1015**
Vehicle Ownership	0.2870	0.6979	0.3798	0.9807	**0.6850**	**0.8913**	**0.7292**	**18.916**	1.9973	**26.359**	**0.9230**	**10.154**	**0.8818**
House Ownership	**0.4498**	0.3658	**1.0621**	0.4718	**0.6885**	**0.4607**	0.1626	**0.9055**	**11.899**	0.5833	**13.145**	0.2843	0.4805
Outstanding Loan	**0.0000**	-0.0000	0.0000	0.0000	**-0.0000**	**-0.0000**	**-0.0000**	0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
Plafon	0.0000	0.0000	-0.0000	-0.0000	**0.0000**	**0.0000**	-0.0000	0.0000	**0.0000**	0.0000	-0.0000	-0.0000	-0.0000
Constant	**-3.3425**	**-4.1528**	**-4.2502**	**-7.4771**	**-3.0209**	-3.4923*	**-29.039**	**-64.679**	**-57.628**	**-73.119**	**-56.088**	**-39.062**	**-35.860**

Table 3: Fintech Logistics

Variables	Bali	Banten	DIY	DKI	Jabar	Jateng	Jatim	Kaltim	Kepri	Lampung	Sulut	Sumut	Sumsel
Age	**-0.0015**	**0.0022**	**0.054**	**0.008**	**0.006**	**-0.16**	**0.007**	**-0.007**	**0.022**	**-2.2**	**-0.01**	**0.72**	**-0.09**
Dependent	**0.1802**	0.0568	16.2	17.18	**16.75**	16.2	**17.28**	**17.05**	**16.86**	**19.1**	**17.4**	**11.4**	**17.18**
Last Education	**-0.17**	**0.0377**	**0.14**	**-0.06**	**-0.06**	**-0.3**	**-0.09**	**-0.02**	**0.03**	**4.6**	**-0.22**	**-3.7**	**-0.09**
Vehicle Ownership	**0.2870**	**0.6979**	**1.3**	**0.01**	**-0.02**	**-0.8**	**0.11**	**0.09**	**-0.1**	**5.3**	**0**	**4.1**	**-0.14**
House Ownership	**0.4498**	**0.3658**	**-2.5**	**0.04**	**0.048**	**0.1**	**0.07**	**-0.22**	**-0.1**	**-7.4**	**0.8**	**-2.6**	**0.06**
Outstanding Loan		**-0.0000**	**0.0000**	**0.001**	**-0.0000**	**-0.0000**	**-0.0000**	**0.0000**	**-0.0000**	**-0.0000**	**0.0000**	**-0.0000**	**-0.0000**
Plafon	**0.0000**	**0.0000**	**-0.0000**	**-0.0000**	**0.0000**	**0.0000**	**-0.0000**	**0.0000**	**0.0000**	**0.0000**	**-0.0000**	**-0.0000**	**-0.0000**
Constant	**-8.2**	**-8.5**	**-9**	**-9.52**	**-9.09**	**-2**	**-9.5**	**-8.4**	**-9.2**	**79**	**-11.2**	**-31**	**-10.3**

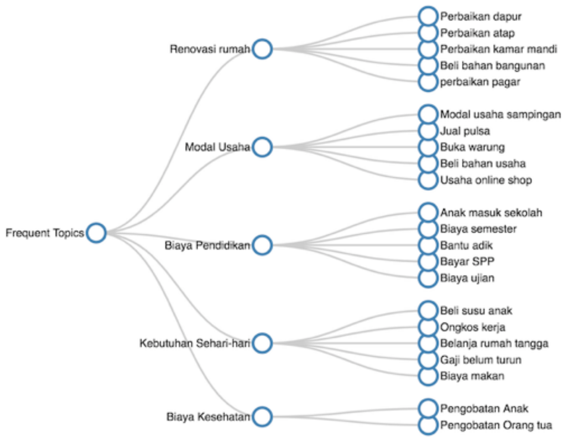

Figure 6: Major Topics

We find interesting reason the debtor based on average income, average expertise, average loan amount ’Renovasi rumah, modal usaha, biaya pendidikan’ are dominate based on number of loans ’Ongkos kerja/ Transportation fare dominate based on Male and Female ’Anak Masuk Sekolah / registration new student’ dominate based on categorized married/single. There are several suggestions and recommendations on how to improve the research or on further developing the research. The first suggestion is on expanding the Susenas data use in the research. For example, many previous empirical studies find the importance of income and consumption aspects in deciding whether a household have debt or not. Income and expenditure have not been able to be analyzed in this research because of data unavailability. Other variables in Susenas that could be explored in affecting the household indebtedness, for example, household use of information technology and the internet access, access to saving account, effort of preparing new entrepreneurship, the use of health outpatient or inpatient care of the household, and the prove of house/asset ownership.

6 FUTURE RESEARCH

Other database could also be used to further improve the research. One of the database is PODES. PODES is database on infrastructure in the village level. This database could be supplemented with Susenas database to combine the household data with the infrastructure data to have a more complete understanding on the household conditions. IFLS data could also be used to explore no-economic aspects of indebtedness, such as personality traits and risk perspectives. Moreover, other data on property will be useful since one of the main debt of household is mortgage, and data on telecommunication to sharpen the analysis on exposure to technology and information. The third suggestion is to expand the spatial analysis for eastern Indonesia region as non performing loans in that area is relatively higher than Java. The fourth suggestion is to include the Risk Factor (collectability) in analyzing the factors that affect credit both for banks and fintech. Fifth, explore beyond the current text mining analysis to understand factors affecting borrower’s reasons in applying for loan, and the relationship between reasons and the borrower’s profile, for example the factors behind the dominance of transportation fare in male - female categorization. The last suggestion is to explore the analysis not only on the indebtedness aspects of household but on household over-indebtedness to try to understand the factors that affecting households to borrow beyond their ability to repay. Other exploration that could be conducted is on household financial vulnerability. Research on household financial vulnerability is important to have a comprehensive financial

Figure 7: Borrower Profiles for Each sub-topic, measurement by averages (male/female, married/single)

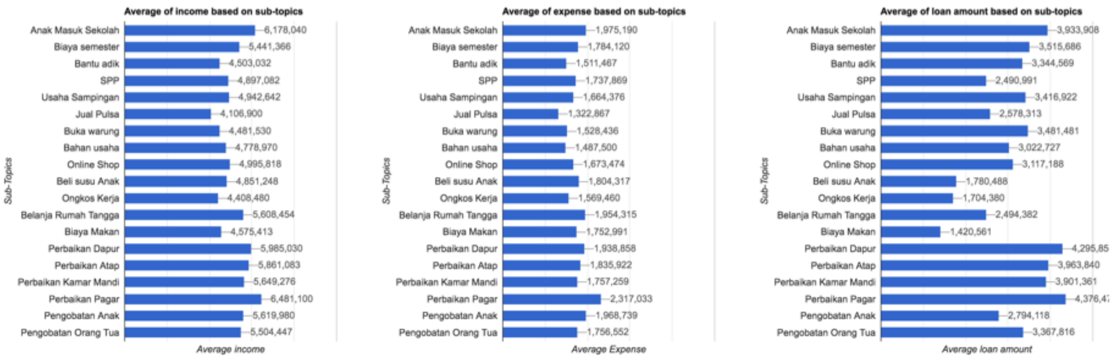

Figure 8: Borrower Profiles for Each sub-topic, measurement by averages (income, expense, loan)

Figure 9: Spatial Text Mining

understanding beyond debt on the factors that affecting household financial vulnerability.

REFERENCES

[1] Ottaviani C. and D. Vandone. 2011. Impulsivity and household indebtedness: Evidence from real life. *Journal Economic Psychology* (2011).

[2] R.E. Caraka and M. Tahmid. 2019. *Statistika Klimatologi.* Yogyakarta: Mobius Graha Ilmu.

[3] R.E. Caraka and H. Yasin. 2017. *Geographically Weighted Regression (GWR) Sebuah Pendekatan Regresi Geografis*. Yogyakarta: Mobius Graha Ilmu.
[4] G. D'Alessio and S. Iezzi. 2013. Household Over-Indebtedness: Definition and Measurement with Italian Data. *SSRN Electronic J.* (2013).
[5] K.E. Dynan and D. L. Kohn. 2011. The Rise in U.S. Household Indebtedness: Causes and Consequences. *SSRN Electronic J.* (2011).
[6] M. Keese. 2011. Triggers and Determinants of Severe Household Indebtedness in Germany. *SSRN Electronic J.* (2011).
[7] H.J. Kim, D. Lee, J.C. Son, and M.K. Son. 2014. Household indebtedness in Korea: Its causes and sustainability. *Japan World Econ.* (2014).
[8] M. B. Kursa and W. R. Rudnicki. 2010. Feature Selection with the Boruta Package. *Journal Statistical Software* (2010).

Exploring Consumer Vulnerability Using Fintech and Bank Loan Data

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ABSTRACT

Financial services play a pivotal role to improve people' s lives. Despite its importance, about 40% of Indonesian population remains financially excluded from credit. Although there have been numerous studies analyzing barriers to financial services in Indonesia, none of these focus on understanding consumer vulnerability in the context of both fintech and bank loan. This study identifies different factors contributing to consumer vulnerability for fintech and long-term bank loan customers. Age has different roles in determining the loan vulnerability, with a higher risk for fintech loan customers and lower risk for property mortgage (KPR). This paper helps fintech companies and policy makers to understand the factors contributing to consumer vulnerability both short-term and long-term credit loans.

KEYWORDS

Fintech, Consumer Vulnerability, Financial Services, Credit Delinquency

1 INTRODUCTION

Access to formal financial services has been proposed as a critical factor for poverty alleviation by providing important economic leverage for people to improve their lives [9] [10]. Financial services, such as for savings, payments and money transfer services, loans for working capital and small investments are among many services that are needed by people, particularly those who are disadvantaged [3]. Despite its importance, only about half of Indonesia' s population has access to formal financial services, with about 17% of Indonesians borrowing from banks whilst approximately 40% of the population remains financially excluded from credit[5].

Unlike other essential services in modern life, credit and loans are provided by the private sector in a competitive financial market. Lenders impose screening processes to determine the creditworthiness of loan applicants, that is whether the applicants are both capable and willing to repay their debt [1]. Lenders compute applicants' credit scores based on applicants' attribute information and make lending decisions using certain criteria [2]. This process often penalizes certain groups of consumers. For instance, imposing a requirement to provide a large deposit to qualify for a loan, excludes those who do not have property or whose incomes are low.

Consumer vulnerability within the context of financial services can be viewed as the consequences of the interplay of individuals; personal and external factors. Personal factors include individual characteristics and states that contribute to consumer vulnerability. External factors involve practices and policies in financial markets. Some people may be limited with fewer credit options due to strict requirements in credit screenings and are pushed them away toward predatory and exploitative financial services, causing a state of vulnerability [2]. Some consumers may become vulnerable after getting the loans because they cannot afford the installment payment of their loans, which may lead to delinquency and default [3]. In this sense, consumer vulnerability may be associated with loan delinquency and default.

There have been numerous studies analyzing barriers to financial services in Indonesia, but no studies focus on understanding consumer vulnerability in the context of credit and loan services [5]. This study aims at obtaining better understanding of consumer vulnerability within the context of access to credit services through comparison of factors associated with consumer vulnerability between fintech customers and banking loan debtors. The specific objectives of this study are twofold. First, using fintech customer data, our study seeks to analyze consumers′ vulnerability of short-term loans provided through an online lending platform. Second, our study seeks to analyze factors contributing to consumer vulnerability of long-term loans using credit data from Indonesia' s Central Bank (Bank Indonesia/BI) and household survey data.

2 LITERATURE REVIEW

In marketing and consumer-behavior literature, the concept of consumer vulnerability has been defined in various ways and there seems to be a lack of consensus on how it should be defined [7][6]. The difficulty to come up with a unified definition reflects the complexity that the concept of consumer vulnerability entails [6]. Rather, as Baker, Gentry, and Rittenburg pointed out, " the consumer vulnerability concept provides a unifying label for a variety of studies focusing on the social consequences of consumption for different populations in a wide range of marketing contexts" [7].

Built on Baker et al.[7], Hill and Kozup [4], and Stearn [8], we defined consumer vulnerability as a state or condition in which a consumer is exposed to greater risks of being put at a disadvantage resulting from purchasing, accessing, or using goods and services that may affect his/her welfare detrimentally. This definition implies power imbalance or a sense of powerlessness such that a consumer has little control over his or her purchasing decisions[7]. A consumer may feel compelled to purchase a good or service that he or she cannot afford or might do harms to his and her welfare. This definition treats vulnerability as a state of being, which suggests a temporal dimension of vulnerability, that is all consumers can be expected to become vulnerable at some points of their lives regardless of their individual characteristics[6].

In the context of consumer loans, consumer vulnerability may be viewed as one of the contributing factors of loan delinquency and default. Whilst a loan becomes delinquent when a debtor fails to make a payment when it is due or misses a regular installment payment, default is the eventual consequence of extended delinquency. Thus, loan delinquency can be viewed as a sign of consumer vulnerability, when a consumer becomes vulnerable due to various personal circumstances that make the consumer fails to keep up with ongoing obligations. Consumers fail to make appropriate financial decisions due to lack of information about the credit requirements (informational asymmetry)[3]. Consumers may take unneeded credits because they are under pressure to make financial decisions involuntarily (pressure vulnerability)[3]. Consumers may apply for credits that are not suitable for their needs because of the limited availability of credit options (supply vulnerability)[3]. Consumers may become vulnerable after taking the credit because they make poor financial choices but because they suffer more from making those choices (impact vulnerability) [3].

Our definition of consumer vulnerability in the context of credit services implies two vulnerability situations: the state of vulnerability prior to and after obtaining credits or loans. Our study focused on the second situation, that is the state vulnerability that consumers experience after obtaining loans.

3 DATA AND METHODOLOGY

3.1 Research Approach

We employed cross-sectional study designs. Our data did not allow for panel data or longitudinal analyses. Therefore, the estimated relationships between explanatory and outcome variables in our models between our explanatory and outcome variables do not imply causal relationships.

3.2 Data and Variables

This study used secondary data from multiple sources. Table 1 presents the description of variables used in the first analysis. The main dataset for the first analysis is JULO' s customers' loan data. JULO is an Indonesian financial technology startup that provides affordable and responsible loans to households across Indonesia. The data constitutes loan application data between August 2018 - August 2019 consisting of 14,340 loan data and is sampled randomly stratified over location and disbursement month. The data does not contain explicit loan performance data, but this could be approximated using a custom definition combining the last payment transaction and the outstanding loan amount at that date. After the data cleaning process, 14,340 observations in the dataset remained for analysis. As discussed in the previous section, loan delinquency can be viewed as a sign of which a consumer is experiencing a

Table 1: Description of Fintech Customers Variables

Variable	Description
Fintech loan customer' s vulnerability (outcome variable)	A binary variable indicating the vulnerability of a loan (1 = vulnerable; 0 = non-vulnerable)
Single	A binary variable indicating if a customer is a single (1 = unmarried, widowed, or divorced; 0 = married)
Age	Loan customerâĂŹs age (in year)
College Degree	A binary variable indicating of a customer has a college degree (1 = graduated with bachelor, master of doctoral degree, 0 = otherwise)
Productive Loan	A binary variable indicating if the purpose of the loan is for productive activities (1 = productive activity; 0 = otherwise)
Own house	A binary variable indicating if the customer owns a house (1= own a house; 0= otherwise)
Monthly Income	Customer' s reported monthly income (Rp. Million)
Private Employee	A binary variable indicating if a customer works as a private employee (1= private employee; 0=otherwise)
Number of Dependents	Number of dependents
Non-Java	A binary variable indicating if a customer resides outside Java (1= live in regions other than Java; 0 = otherwise)

Note: All variables are from JULO' s customers' data.

state of vulnerability. Therefore, we used some measures of loan or credit delinquency as our outcome variables, acting as proxies for consumer vulnerability. For the first analysis, we constructed a binary variable indicating if a customer was vulnerable if his or her loan became delinquent, which took a value of 1 if a consumer failed to complete loan payment within the due date, and a value of 0 for otherwise. For the independent variables, we included consumers' income, marital status, profession, education, age, house ownership, loan purpose, number of dependents, and geographical location.

For the second analysis, our main dataset is from BI' s credit data. Table 2 presents the description of variables used in the second analysis. We received BI' s credit data aggregated at the bank, kabupaten/kota, month and type of credit for a period of January 2018 to May 2019, comprising of 1,320,315 observations. For our research purpose, the data were further aggregated at kabupaten/kota level with the final dataset comprised of 479 observations. Additional variables were created using the National Socio-Economic Survey (SUSENAS) 2018. We also used additional data from multiple publicly available data on macroeconomic and population data.

Table 2: Description of Bank Loan Variables

Variable	Description
Loan at risk rate[1] (outcome variable)	The percentage of credit accounts with late payments at least of 1 calendar day or received payment collectability score of 2 to 5.
Percent of conventional credits[1]	Percent of credits that were categorized as using the conventional credit
Shophouse[1]	Percent of credit accounts that used shophouses as the collaterals
Landed House[1]	Percent of credit accounts that used landed houses as the collaterals
Debtors Age Average[1]	The average of debtorsâĂŹ age
Crime Rate[2]	The percentage of household that reported to experience any criminal incidents
GDP Per Capita[3]	The total of Gross Domestic Product per capita
Population Density[3]	The number of populations per km square
Employment rate[3]	The percentage of of populations who are employed.

Note: [1] Variables were created from BI' s credit data source; [2] It was created from SUSENAS 2018 data; and [3] These variables were from official publicly available data from BPS.

Our measure for consumer vulnerability for the second analysis is the loan-at-risk rate, that is the percentage of loan accounts that were classified at risk based on BI' s payment collectability status. A credit account is rated as 1 if the payment of outstanding credit is on time and no arrears that exceeds the due date, whereas a credit account with the payment of outstanding credit is yet to be between 1 to 89, 90 to 119, 120 to 179, and more than 180 calendar days after the due date are rated as 2 to 5, respectively. We considered loans at risks for all loans accounts that received the payment collectability score of 2 to 5. For the independent variables, we included percentage of conventional credits, property types as credit collateral, and average age from BI' s credit data. We also included crime rate, employment rate from SUSENAS data, and GDP per capita, and population density variables from publicly available sources.

3.3 Statistical Analysis

We employed logistic and linear regression models for our research purposes. The logistic models were employed to address the first analytical objective, to analyze consumers' vulnerability of short-term loans provided through online lending platform, considering the binary nature of our outcome variable, that is whether a customer was being vulnerable or not, indicated by the nature of the customer' s payment completion. We defined a customer as being vulnerable if he or she completed the loan payment more than the due date. In addition, we also included a Java dummy variable to minimize potential biases arising from regional differences being in Java Island compared to other islands.

Table 3: Descriptive Analysis of Fintech Customers Data

Variable	Vulnerable	Non Vulnerable
Number of accounts, n (%)	891(6.6)	13449(93.8)
Income, mean(s.d)	4.9(2.9)	5.4(3.4)
Loan amount, mean (s.d.)	2.4(1.9)	3.4(2.1)
Loan duration, mean (s.d.)	2.6(1.7)	3.8(1.9)
Education		
SD, n (%)	3(0.3)	21(0.2)
SLTP, n (%)	27(3)	316(2.4)
SLTA, n (%)	597(67)	8490(63.1)
Diploma, n (%)	96(10.8)	1478(11)
Bachelor, n (%)	161(18.1)	3050(22.7)
Master, n (%)	7(0.8)	90(0.7)
Doctoral, n (%)	-	4(0.03)
Occupation		
Civil servant, n (%)	44(4.9)	306(2.3)
Private employee, n (%)	838(94.1)	12983(96.5)
Housemaid, n (%)	1(0.1)	13(0.1)
Housewife, n (%)	8(0.9)	147(1.1)
Region		
Sumatera, n (%)	45(5.1)	508(3.8)
Java, n (%)	804(90.2)	12413(92.3)
Bali, n (%)	21(2.4)	236(1.8)
Kalimantan, n (%)	14(1.6)	179(1.3)
Sulawesi, n (%)	7(0.8)	113(0.8)

For the second analysis, we estimated a linear regression model, considering the continuous nature of the outcome variable: loan-at-risk rate. To address potential bias due to omitted variables and measurement errors, we included various explanatory variables based on our review of past literature. We estimated 2 sets of linear regression models for two types of credits: property mortgage (*Kredit Pemilikan Rumah*/KPR), and consumption credit with property collaterals (*Kredit Konsumsi Beragun Properti*/KKBP). In each set, two models were estimated: regression models with and without regional fixed-effects. Regional fixed-effects were included to account for potential regional confounders which may bias coefficient estimates.

4 RESULTS

4.1 Analysis of Consumer Vulnerability From Fintech Customers Data

For the fintech loan data, the descriptive analysis is presented in Table 3. The descriptive data provided in Table 1 shows variables that are substantially different between vulnerable and non-vulnerable customer groups. Those variables include monthly income, loan duration, education, geographical location, and occupation. Other variables are not shown in the table as the value of both groups are similar.

From the Table 3, the vulnerability of fintech consumers is about 6.6%. In addition, vulnerable customers tend to have lower income. shorter loan duration, and lower educational backgrounds compared to their counterparts. Consumers who reside outside Java, except Sulawesi, are more likely to be more vulnerable than those

Table 4: Descriptive Analysis of Fintech Customers Data

Variable	Dependent Variable	
	Odd Ratio	95% Confidence Interval
Constant	1111.3***	(444.9,2775.94)
Monthly income (log)	0.52***	(0.50,0.55)
Single	1.12***	(1.03,1.22)
Private Employee	0.58***	(0.49,0.69)
College degree	0.91	(0.81,1.04)
Age	1.02***	(1.01,1.03)
Own house	1.1***	(1.08,1.12)
Productive loans	1.06	(0.98,1.14)
Number of dependent	1.07***	(1.02,1.12)
Non-Java	1.27***	(1.11,1.46)
No.obs	14340	
Pseudo R2	0.012	

Note:

*Robust standard error; *p<0.1;**p<0.05;***p<0.01. Odds ratio value that lies between 95% confidence interval that it is significant in at least 95% level*

Table 5: Descriptive Analysis of BI Loan Customers Data

Variable	KKBP	KPR	All
Percent of loan-at-risk accounts	13.5(8.2)	9.5(5.9)	10.4(5.9)
Percent of conventional credits	88.6(17.3)	83.5(14.8)	84.9(14.7)
Percent of property collaterals by type			
Shophouse	6(14.1)	2.2(2.3)	4(9.9)
Apartment	0.5(1.4)	1.9(2.2)	1.6(2)
Landed house	63.9(26.8)	95.9(3.4)	87.5(12.1)
Average Age	43.6(2.3)	41.6(2.4)	42.3(2.1)
No. of districts	472	479	479

Note: All descriptive statistics are reported in their mean values and the standard deviation are in parentheses

who live in Java. Interestingly, civil servants tend to be more vulnerable than other occupations, though this might be due to the relatively small number of civil servants in the dataset. Civil servants account for about 2.4% of all observations.

Table 4 reports the result from logistic regression analysis of fintech costumer data. The table reports the estimated coefficients as odd ratios and their confidence intervals.

From Table 4, income, marital status, occupation, age, house ownership, number of dependents, and geographical location were significantly associated with the probability of a fintech customer of becoming vulnerable. For each 1% increase in an customer' s monthly income was associated with a decrease in the probability of being vulnerable by about 48%. The odds of being vulnerable for a single customer was about 1.12 times higher than married borrowers. A customer working as a private employee was less likely to be vulnerable than those working in other occupations. Interestingly, the odds of being vulnerable increased by about 2% for each additional year of age. Owning a house increased the likelihood of being vulnerable by about 9% than those who do not own houses. For each additional family dependent, increased the probability of being vulnerable by about 7%. Lastly, living outside Java increased the odds of being vulnerable by about three-quarter than those live in Java.

4.2 Analysis of Consumer Vulnerability From Bank Loan Customers Data

Table 5 presents the descriptive analysis. The variables shown in Table 5 are only variables from BI' s bank loan customers data. Table 5 reports summary statistics from KKBP, KPR, and all customers to highlight the baseline differences between KKBP and KPR customers.

In general, the mean of loan-at-risk rate for KKBP loans is higher than that of KPR loans. KKBP loans are dominated by conventional credits as opposed to non-conventional credits, which are based on Islamic system. Landed houses are the principal loan collaterals for both KKBP and KPR. The average age of borrowers is higher among those in KKBP group compared to KPR group.

Table 6 reports the results of linear regression analyses of loan-at-risk rate at district level. For each credit category, the results from two regression models, one without and with regional fixed-effects. The percentage of conventional credit only had a significant association with loan at risk rate in KKBP credits, with a 1%-point increase of conventional credit rate was associated with a 0.05%-point increase in the loan at risk rate of KKBP credits. The percentage of credits that used landed house as collateral was only significantly associated with the loan-at-risk rate in KKBP credits with a 1%-point increase of loans that used landed house as the collateral was associated with an increase of loan at risk rate of KKBP by about 0.12% point. The percentage of credit accounts that used shophouse as collateral had a marginal contribution to reduce the loan at risk rates in KKBP credits. In both models, crime rate might contribute to increased loan at risk rates by about 0.6% for each additional 1%-point of crime rate, though their significance were only marginal.

Other explanatory variables, GDP per capita, and employment rate were only associated with lower loan at risk rates for KKBP credits. The analysis results also show that districts in Sumatera, Kalimantan, and Sulawesi regions had higher loan-at-risk rates of KKBP credits compared to those in Java region, whereas districts in Maluku had lower loan-at-risk rates for both KKBP dan KPR credit than those in Java.

5 CONCLUSIONS AND POLICY RECOMMENDATION

Our study highlights some variables that might contribute to consumer vulnerability in the context of consumer credits. For the fintech loan, key explanatory variables include income, marital status, occupation, age, house ownership, number of dependent, and geographical location. For bank loans, we found the percentage of conventional credits, the percentage of property as collateral, debtor' s age, GDP per capita, population density, employment rate, and regions might contribute to district variation of loan at risks, with each variable plays different roles. We found age has different roles in determining the loan vulnerability. It appears age is associated with a higher risk for fintech credits. Debtors' age seems to be negatively associated with loan at-risk rates for both KKBP dan KPR credits, suggesting the potential role of financial stability among KKBP and KPR debtors.

Table 6: Linear Regression Results of BI Loan Customers Data

Variable	Dependent Variable: % Loan At Risk			
	KKBP		KPR	
Constant	41.6** (21.2)	49.2** (22.2)	29.7 (27.0)	39.6 (28.0)
Conventional loan	0.05** (0.02)	0.05** (0.02)	0.0 (0.02)	0.0 (0.02)
Shophouse (%)	-0.07*** (0.017)	-0.04* (0.019)	0.22 (0.33)	0.13 (0.34)
LandedHouse (%)	0.07*** (0.019)	0.12* (0.018)	-0.10 (0.27)	-0.08 (0.28)
Debtors Age Average	-0.59* (0.35)	-0.55 (0.37)	-0.41*** (0.13)	-0.45*** (0.13)
Crime Rate (%)	0.60 (0.38)	0.61* (0.36)	0.83*** (0.31)	0.62* (0.33)
GDP Per Capita(log)	-0.26 (0.59)	-1.67*** (0.61)	0.39 (0.41)	-0.58 (0.49)
Pop. Density	-0.0*** (0.00)	-0.004 (0.00)	-0.00** (0.00)	0.0001 (0.00)
Employment Rate (%)	-0.16** (0.07)	-0.16** (0.08)	0.01 (0.05)	-0.03 (0.05)
Sumatera	-	5.29*** (0.95)	-	2.78*** (0.73)
Kalimantan	-	2.79*** (1.06)	-	2.07*** (0.78)
Sulawesi	-	5.27*** (1.05)	-	4.28** (0.87)
Nusa Tenggara	-	-2.55 (1.57)	-	-1.43** (0.72)
Papua	-	0.83 (1.65)	-	4.84** (1.95)
Maluku	-	-4.29*** (1.64)	-	-2.72** (1.07)
No. Obs	471	471	478	478
Adj-R2	0.186	0.278	0.046	0.139

Note: Robust standard error; *p<0.1;**p<0.05;***p<0.01

6 RESEARCH LIMITATIONS

There are several caveats of our findings. Although vulnerability of fintech loan is lower than bank, it does not necessarily mean that fintech loan is less vulnerable than bank considering differences in the measurements. FinTech vulnerability measurement is relatively looser than bank loans' vulnerability. In our fintech data analysis, a loan is categorized as vulnerable when the loan payment is completed more than due date, which does not consider whether the installment (e.g. monthly or weekly) payment is late or not. In the bank loan data analysis, we used stricter criteria for determining the loan at risk rates. In our definition, all loan accounts that had late payments for at least 1 calendar day from the due date were classified as at risk. Another caveat is that the our fintech credit analysis was conducted at individual level, whereas analysis of BI' s credits was conducted at district level and used different sets of covariates. With regards of model estimations, our logistic regression models for fintech data analysis was largely unbalanced. The number of vulnerable loan data is much smaller than the number of non-vulnerable loans which might make the result not as robust as balanced data. The linear regression estimations for the second analysis may still suffer from omitted variable bias despite our efforts to control it with regional fixed effects.

7 FUTURE RESEARCH

In order to improve the study, this research can be strengthened by accommodating several aspects. First, considering that the fintech loan data is largely unbalanced, future research may employ bootstrapping technique to resample the data. The rich bank loans from BI provides some opportunities to extend the analyses to account geographical factors contributing to consumer vulnerability. Extending our regression models Geographically Weighted Regression (GWR) would provide interesting insights on variations of factors contributions to loan-at-risks across districts in Indonesia. Another possibility is to investigate the effect of loan type (conventional and Islamic based loan system) on loan-at-risk rate by applying instrumental variable approach through two stage least square (2-SLS).

REFERENCES

[1] P. Banerjee. 2005. Information Acquisition under Uncertainty in Credit Markets. *The Review of Financial Studies* 18, 4 (2005).

[2] A. I. Canhoto and S. Dibb. 2016. Unpacking the interplay between organisational factors and the economic environment in the creation of consumer vulnerability. *Journal of Marketing Management* 32 (2016).

[3] P. Cartwright. 2015. Understanding and Protecting Vulnerable Financial Consumer. *Journal of Consumer Policy* 38 (2015).

[4] R. P. Hill and J. C. Kozup. 2007. Consumer Experiences with Predatory Lending Practices. *Journal of Consumer Affairs* 41 (2007).

[5] Oxford Policy Management. 2017. Understanding people's use of financial services in Indonesia: Headline Results Report. *Jakarta: BAPPPENAS - Australian Government, Swiss Confederation, SAFIRA* (2017).

[6] P. M. Mansfield and M. B. Pinto. 2008. Consumer Vulnerability and Credit Card Knowledge Among Developmentally Disabled Citizens. *Journal of Consumer Affairs* 42 (2008).

[7] J. W. Gentry S. M. Baker and T. L. Rittenburg. 2005. Building Understanding of the Domain of Consumer Vulnerability. *Journal of Macromarketing* 25 (2005).

[8] J. Stearn. 2019. Tackling Consumer Vulnerability: An action plan for empowerment: An Action Plan for Empowerment. *Citizens Advice Citizens Advice Scotland* (2019). http://www.infohub.moneyadvicetrust.org/content_files/files/tackling_consumer_vulnerability.pdf

[9] A. Demirguc-Kunt T. Beck and R. Levine. 2005. SMEs, Growth, and Poverty: Cross-Country Evidence. *Journal of Economic Growth* 10 (2005).

[10] A. Demirguc-Kunt T. Beck and M. S. Martinez Peria. 2007. Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics* 85 (2007).

Measuring The Impact of Natural Hazard on Credit Risk

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ABSTRACT

This study aims to determine and prove the impact of natural hazards on the credit risk. This research was conducted on aggregated financial data from bank in the city of Palu, Sigi, and Donggala. The method used in this study is a quantitative method by conducting correlation and comparison tests. The comparison t-test showed that there was a difference on the bank' s collectability level of the affected areas (Palu, Sigi, Donggala) with other regions in Sulawesi that did not experience natural disasters. The bank' s collectability reflects the ability of the debtor the year before and after the disaster occurred. The results also showed that there was a difference in the level of Non-Performing Loans from areas that experienced disasters (Palu, Sigi, Donggala) with other regions in Sulawesi that did not experience disasters. Therefore, banks are advised to be able to include the risk of natural disasters in an area in the credit analysis conducted to avoid defaults due to disasters.

KEYWORDS

Natural hazards, Credit Risk, Earthquake and Tsunami, Economic, Central Sulawesi

1 INTRODUCTION

Bank is a financial institution that has an important role in an economy. Law No. 10 of 1998 concerning Banking in article 1 paragraph 2 explains that "banks are business entities that collect funds from the public in the form of deposits and distribute them to the public in the form of credit and or other forms to improve the lives of many people"[2]. Therefore, the financial performance of banks must be in good condition. The smooth level of credit payments is important for banks. This is because when bad loans occur, it is certain that bank finances will be disrupted because banks cannot return public funds that have been used for credit and do not get income from loan interest.

The smooth condition of payments in Indonesia is currently experiencing a decline. The Financial Services Authority stated that in October and November 2018 the bank' s Non-Performing Loan (NPL) level was 136,916 and 137,606 billion Rupiah. This figure increased from September 2018 which was Rp 136,061 billion. For instance, Bank Indonesia's aggregate data shows that there was an increase in banksáverage NPL in Sulawesi Tenggara from 137,7 million Rupiah in 2017 to 142,6 million Rupiah in 2018. This condition shows that there is a cause that impact an increasing level of this NPL. The increase in bank' s NPL rates in Indonesia is thought to have occurred because one of them was caused by natural hazards that happened in Palu, Sigi, and Donggala in September 2018. This is because the earthquake disaster that occurred in Palu, Sigi, and Donggala caused a quite big losses. The Head of the Center for Information and Data on Public Relations of the National Disaster Management Agency (BNPB) (2018) stated that losses and damage caused by disasters in Central Sulawesi amounted to Rp. 18.48 trillion on October 27, 2018, with details of economic losses reaching Rp. 2.89 trillion and Rp15.58 trillion for damage [5].

Based on the explanation in the previous paragraph, this research is intended in providing proof of the impact of the natural hazards that occurred in Palu, Sigi, and Donggala on the level of credit risk. The results of this study can be used as a basis for Bank Indonesia, the Financial Services Authority, and also banks as financial institutions to be able considering the natural disaster factor as a risky condition for the smooth credit payment in Indonesia.

2 LITERATURE REVIEW

2.1 Sulawesi Tengah and Natural Hazards

Sulawesi is a rich-biodiversity and unique large island shaped by the shifting of tectonic plates that led to the evolution and migration of the formation of this region due to frequent earthquakes [11]. In some previous cases, the earthquakes also generated tsunamis which often caused greater damage and loss of life.

The earthquake and tsunami that shook Palu, Sigi and Donggala, Sulawesi Tengah, on September 28, 2019, was not the first catastrophe recorded in the history of disasters of this island [16]. In addition to Sulawesi Tengah, the West Sulawesi Province including the southern right of Sulawesi (Ujung Pandang area), the western part of Sulawesi Tengah covering Toraja and Palu regions, the northern part stretches from Palu to Manado including the Tolitoli and Manado regions also impacted by this disaster [10]. The National Disaster Management Agency (BNPB) stated that Palu and Donggala have experienced earthquakes and tsunamis several times [4]. Even though the local community has already possessed a long history of experience of being exposed to disasters, but they still have low level of preparedness [12].

The history of disasters of this island recorded that on December 1, 1927, an earthquake and tsunami was occurred in Palu Bay causing 14 people died and other 50 were injured [1]. Three years later, on January 30, 1930, the similar disaster was also occurred in the West Coast of Donggala [7] with the tsunami reached a height of more than 2 meters in a duration of 2 minutes. The number of victims was unknown[1]. On August 14, 1938, the earthquake and tsunami again attacked Tambu Balaesang Bay in Donggala with the tsunami height of 8-10 meters. 200 people were reported died, 790 houses and buildings were damaged and the majority village on the west coast of Donggala was almost submerged.

After being "silent" for almost 58 years, the tsunami struck again on January 1, 1996, located in the Makassar Strait. The tsunami height was 3.4 meters and reached the land as far as 300 meters causing 9 people died and destroyed almost all buildings in Bangkir, Tonggolobibi and Donggala. Two years later, on October 11, 1998, an earthquake shook Donggala again. Hundreds of buildings were collapsed due to the earthquake. On January 25, 2015, the earthquake shook Palu and causing 100 houses damaged and 1 person died as a result of this disaster.

A decade ago, or on November 17, 2008, an earthquake shook the Sulawesi Sea and 4 people were reported died. Four years later, on August 10, 2012, the earthquake moved to Sigi and Parigi Montong Regencies causing 8 people died. The Center for Volcanology and Geological Disaster Mitigation (PVMBG) estimated that the massive earthquake of 7.4 SR was triggered by the Palu-Koro fault activity. In the mainland around the epicenter of the earthquake, specifically Donggala, it is estimated that the land were composed by pre-tertiary, tertiary and quarterly rocks. This rock has partially weathered. These Quaternary Deposits are generally decomposed, loose, soft, not compact (unconsolidated), so that strengthening the effects of earthquake shocks. The character of fracture movement tends to shift not upside fault.

2.2 Financial Service Condition Post 2018 Earthquake and Tsunami

Such the prone-to-disaster condition has had a significant impact on the development of community economic in that region, from consumption to production[5]. Post the latest earthquake that attacked the Sulawesi Tengah, on 28 September 2018, Head of the Center for Information and Public Relations Data of the National Disaster Management Agency (BNPB) (2018) stated that the losses and damages caused by the disasters amounted to IDR 18.48 trillion as of October 27, 2018, with details of economic losses reaching IDR 2.89 trillion and for damages reaching IDR 15.58 trillion.

Financial service authority (OJK) reported that gross non- performing loans (NPLs) of banks in February 2019 reached 2.59%, up from 2.56% the previous month. While the net NPL rose from 1.13% to 1.17%. Meanwhile, PT Bank Tabungan Negara (BTN) recorded bad loans or NPL (Non-Performing Loans) in the KPR (Home Ownership Credit) sector of IDR 3.5 trillion as of March 2018 in which the IDR 2.8 trillion is home loans[15].

In order to reduce the burden on the lives of the disaster victims, OJK had urged banking sectors to not collect disaster victim creditors in accordance with the regulation issued by OJK Number 45/2017 on the treatment of bank credit or financing for certain disaster affected regions in Indonesia.

OJK can request or provide policies for banks to not to collect debts from debtors affected by a disaster for a certain period of time. The total credit in the affected areas in Sulawesi Tengah is of IDR 16.2 trillion. While specifically, in the districts of Donggala and Sigi, the total loans were IDR 233 billion, only 0.3% of the total of industry loans. According to the OJK, this approach had already been implemented in Aceh, Yogyakarta, Bali and Lombok.

While BTN Tbk., in October 2018, released that they are preparing a credit restructuring scheme for debtors affected by natural disasters. BTN Tbk. will provide credit restructuring to them by taking into account the physical and psychological conditions of debtors and the future situation of Sulawesi Tengah to facilitate them rebuilding their lives. Based on data compiled by the BTN Business Continuity Management (BCM) team, there are 12,036 active consumer credit debtors in Sulawesi Tengah with a credit value of about IDR 911 billion and commercial credit debtors are 487 debtors with a credit value of about IDR 139 billion. The restructuring that will be given refers to the restructuring for earthquake victims in Lombok, Nusa Tenggara Barat.

2.3 The Influence of Natural Hazards on Economic

Natural disasters are conditions that are never expected to occur. A natural hazard is an unexpected and/or uncontrollable natural event of an unusual magnitude that might threaten people. Thus, natural disasters must always be watched and anticipated by every citizen. Natural disasters can be devastating, not only in terms of lives lost, but also for survivors livelihoods[14]. Thus, the occurrence of natural disasters will ultimately also cause the economy to be disrupted.

Although disasters are scarce events and usually occur in a fairly quick and short time, but the impact caused are often huge and able to change economic and social structure.

Many researches have been conducted to understand the influence of natural hazards on economic and social aspects. As a matter of fact, in recent years, the economists have been attracted to examine the relationship of natural hazards and economic growth. Several studies have observed the relationship and found that there is a positive influence of such natural hazards economic while others found negative correlations.

Recently natural calamities have showed the increased in number of the severity of direct impact of those events on economic with a considerable losses year by year. The disasters also deteriorate the order of social life.

Natural disasters cause banks face deposit withdrawals and experience a negative funding shock to which they respond by reducing the supply of lending and by drawing on liquid assets[2]. Moreover, natural disasters increase the likelihood of a bank' s default[6]. In addition, the impact of a natural disaster depends on the size and scope of the catastrophe, the rigorousness of financial regulation and supervision, and the level of financial and economic development of a particular country.

There are five indicators of disaster risk management[9] as explain below:

(1) Disaster Deficit Index (DDI), measures country risk from a macroeconomic and financial perspective according to possible catastrophic events;
(2) Local Disaster Index (LDI), measures social and environmental risk resulting from more recurrent lower event (subnational);

(3) Prevalent Vulnerability Index (PVI), measures social and environmental risk resulting from more recurrent lower event (sub-national);
(4) Risk Management Index (RMI), measures social and environmental risk resulting from more recurrent lower event (sub-national);
(5) Total Risk Index (RTI), measures social and environmental risk resulting from more recurrent lower event (sub-national).

There are several standard operating procedures (SOP) and policies have been issued by related government stakeholders so far, i.e.:

(1) POJK Number 45/POJK.03/2017 about Special Treatment of Credit or Bank Financing for Certain Regions in Indonesia Affected by Natural Disasters (Clause 4: Restructuring the debt after disaster);
(2) OJK Circular Letter Number 06/SE.OJK05/2017 on Premium Rates or Contribution of Private Business Insurance and Vehicle Insurance Year 2017 (How to measure the earthquake insurance contribution, included the earthquake zone);
(3) Indonesia Multi Donor Fund Facility for Disaster Recovery (IMDFF-DR). National Development Planning Agency (B appenas)/ National Development Planning - World Bank - UN in Strengthening Disaster Management Financing for Indonesia' s Resilience;
(4) BNPB Policy. What action needed before, on, and after disaster; Priority policy for each region.

3 RESEARCH METHODOLOGY

3.1 Research Data

The data in this research was collected from various resources, namely:

(1) Aggregate loan data from Bank Indonesia that consists of 17 variables and taken from the period of early 2018 to May 2019. The aggregate data is then arranged by month and idbank, by district/city and month, and by month and type of property. All the data covered up three major affected districts/cities, i.e.: Palu, Donggala and Sigi with the total observation of 2231.
(2) Data Displacement Tracking Matrix IOM Palu Earthquake. Displacement Tracking Matrix is a system to track and monitor the displacement and population mobility and it provides humanitarian assistance to migrants. The data from this system consist of 193 variables and covers 942 shelters in Palu, Sigi and Donggala.
(3) Data Survey from Post Disaster Needs Assesment/Pengkajian Kebutuhan Pasca bencana (Jitupasna) UNDP Palu. This is a needs assessment survey post disaster that conducted by UNDP Palu for recovery in physical, financial and psychological way due to disaster. The data cover up Palu, Sigi, Donggala and Parigi Moutong area.
(4) InaRisk data (BNPB) that consists of map of vulnerable and affected areas of disasters. This data allows researcher to examine the most prone and potential areas to disasters as shown in Figure 1.

Table 1: Final Dataset

No	Attributes	Explanation	Source
1	Year	Aggregate by year	BI
2	IdBank*	Aggregate by id bank	BI
3	IdKabKota	Aggregate by id of kabupaten/kota	BI
4	CreditTypes	Type of Credit	BI
5	PropertyTypes	Type of Property	BI
6	MeanBakiDebet	Mean of remaining debt	BI
7	MeanBakiDebetNPL	Mean of remaining NPL Debt	BI
8	MeanofDuration	Remaining of Duration in Days	BI
9	Collectability	Level of Debtor inability to repay the debt	BI
10	ConditionChange	Change Condition of Wage Earner	Jitupasna
11	TotalRevenue	Total Revenue of Household	Jitupasna
12	RevenueDecrease	Decreasing amount of revenue after hazards	Jitupasna
13	AccessonFPA	Access on Productive Fixed Asset	Jitupasna
14	EconomicLosses	The Amount of economic losses	Jitupasna
15	DPOrigin	Number of displacement people based on the origin city	IDM
16	IDPLocationSite	Number of displacement people based on the location site	IDM
17	RiskIndex	Risk index of the city	BNPB

**IdBank variable used in this research refers to dummy version of Bank Indonesia's IdBank that had been randomized and anonymized for research purpose*

(5) BPS data of the Palu, Sigi, Donggala populations and public servant number.

The attributes chosen in this final dataset is selected based on literature study which data can be used to answer the research questions. The results of those data selection that have been carried out in this study are presented in Table 1.

Figure 1: Disaster Risk Index

The process of analyzing the data of this research was carried out using several stages, as follows:

(1) Build a data set. Preparing and connecting dataset from 4 different data provided based on kab/kota level and idbank level.

(2) Pre-Processing. Detecting outlier data, missing values, and cutting the data off. In this stage, the data also aggregate based on the hazard time frame.
(3) Feature Selection. Determine the variables that are suitable for each data collected. This is a process of analyzing and selecting the variable from DTM and jitupasna data that have relationship to the credit-risk variable.
(4) Data Visualization and Analysis. Conduct data visualization in chart and maps also analysis using correlation testing and comparison t-test. Correlation analysis is a process of analyzing the data using Paired-Test, F-Test and Correlation Test. The last is result analysis is the last process that covers the analysis of the result and further propose Natural Hazards variable.

3.2 Research Methodology

The first three processes were conducted through three steps, i.e.: transforming and cleaning data, aggregating the data by years and selecting variables based on literature study.

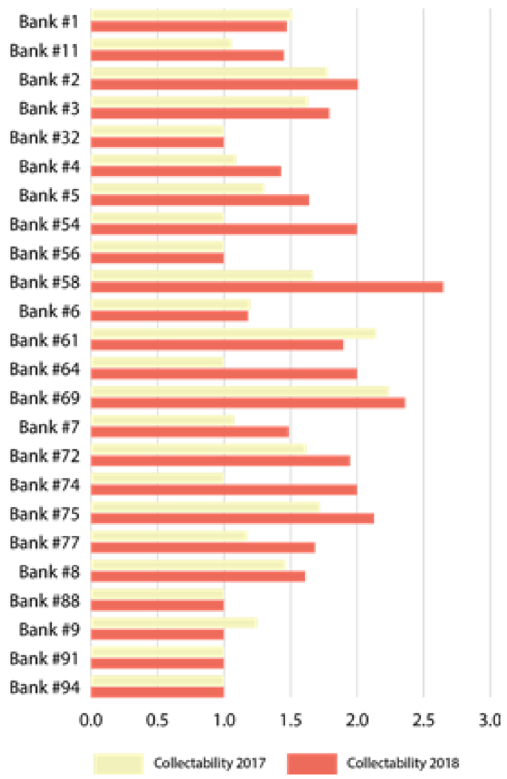

Figure 2: Collectability ID Bank

The type of collectability reflects the level of debtor's credit disability payment, the higher the more unable to pay. The figure also shows that, overall, the failure of credit payment is increasing in 2018, 20 from 30 bank.

4 RESULTS

4.1 Economic Conditions

Natural disasters that occurred in Palu, Sigi, and Donggala caused a change in the economic conditions of the people who were there. The majority of Palu, Sigi, and Donggala people earn less than 1 million per month after the disaster. These changes are presented in Figure 3.

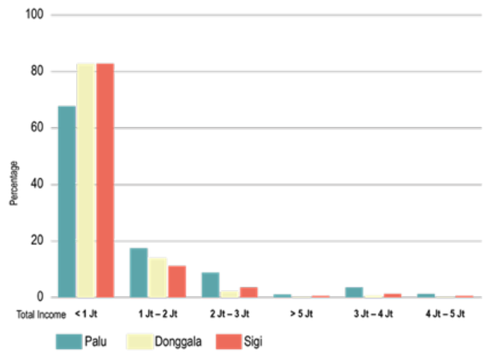

Figure 3: Economic Condition After Natural Hazards

4.2 Population Movement After Natural Hazards

Natural disasters that occurred in Palu, Sigi, and Donggala caused a population movement between the three regions. Many people from Palu and Donggala made the move to Sigi. This is because people choose areas far from the coast to avoid the possibility of tsunami. Figure 4 visualizes the displacement of household after natural disasters.

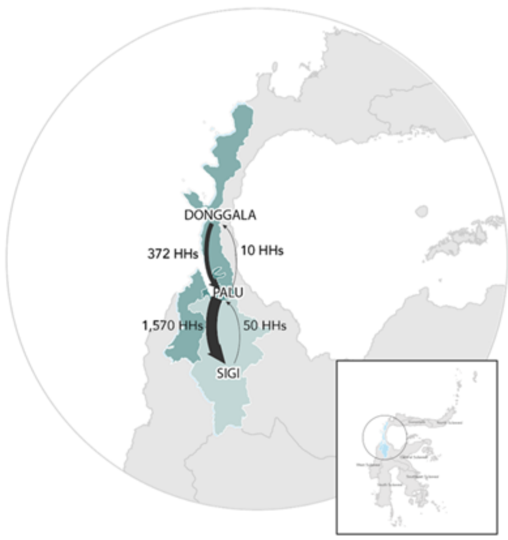

Figure 4: The Displacement of Household After Natural Disasters

4.3 The Credit Condition

Natural disasters that occurred in Palu, Sigi, and Donggala caused changes in the existing level of collectability. This level of collectability is measured in a scale from 1 (very good in repay the debt) to 5 (unable to repay or default). Overall, the collectability after natural hazards is worse than before

4.4 The Impact Of Earthquake' s Epicenter on Credit Risk

The disasters that occurred in Palu City, Sigi Regency, and Donggala Regency caused several differences in the level of bank credit collectability in the Sulawesi region. Figure 5 shows the differences of the level of collectability in Central Sulawesi. By those visualization, it can be concluded that the areas near the epicenter have lower ability to repay the debt.

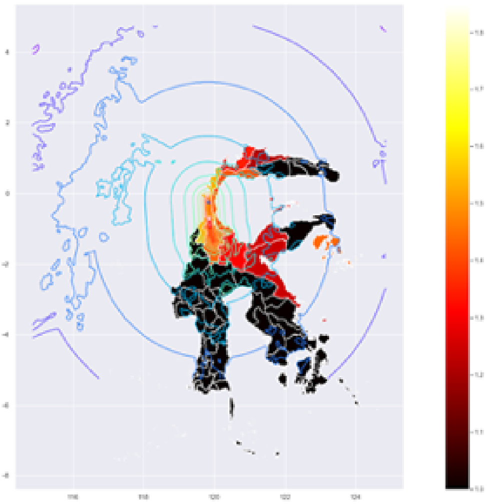

Figure 5: The Impact of Earthquake on Collectability

4.5 Correlation Test Results on DTM and Jitupasna Data

The number of IDP have correlation with collectability, risk index of locations, and the number of house damaged. On the contrary, risk index of the city did not have any correlation to the number of damaged house and the number of IDP in those cities. Details see the Table 3. The impact of natural disasters in Palu City, Sigi Regency and Donggala Regency was statistically proven by conducting correlation testing using Excel as describe in Table 4 where X1 is changes of wage earner, X2 is revenue decrease, X3 is access on productive asset, X4 is loss of financial or economic assets and the last Y is collectability.

The test results show that the level of collectability has a fairly strong negative correlation with changes of wages earners and loss of economic / financial assets. In addition, the level of collectability also has a very strong negative correlation with disorder of fixed asset productive. This implies that the greater the level of changes

Table 2: Correlation Result on Jitupasna Data

Location	X1	X2	X3	X4	Y
Palu	0.671	0.741	0.213	0.321	1.82067
Sigi	0.7101	0.9137	0.176	0.35	1.4328
Donggala	0.6556	0.8767	0.332	0.454	1.5321
Corelation	-47.5%	-99.90%	-4.56%	-46.48%	

Table 3: Comparison T-test Result of Collectability

Criteria	Number(N)	Mean Rank	Sig.
Natural Hazards	3	8.67	0.033
Normal	7	4.14	
2017	27	24.69	0.085
2018	29	32.05	

of wages earners, loss of economic / financial assets, and disorder of fixed productive assets will increasingly make the bank's level of collectability worse.

	IDP_HH	RISKINDEX	IDP_HH_ ORIGIN	HOUSE_DAMAGED_ BNPB	AFFECTED	PER_REG_ INCOME
IDP_HH						
RISKINDEX	-0,52					
IDP_HH_ORIGIN	0,98	-0,32				
HOUSE_DAMAGED_BNPB	-0,83	-0,05	-0,93			
AFFECTED	0,93	-0,16	0,99	-0,98		
PER_REG_INCOME	-0,13	-0,78	-0,35	0,66	-0,50	
COLLECTIBILITY	-1,00	0,59	-0,96	0,78	-0,89	0,054

Figure 6: Correlation in DTM Data

4.6 Comparison T-Test Result

The next test that was carried out was the comparison test (t-test) by using SPSS version 21.0. The results of these tests are presented in Table 5. There are two test that been done to measure the impact of natural hazards on credit risk. First, the comparison of before and after the natural hazards on the bank' s collectability in Palu, Sigi, and Donggala. The first test is strengthened by comparing the mean of remaining Non-Performing Loan (NPL) of those 3-region affected, either by idbank or by the region.

The t-test results show that there is a significant difference in the level of collectability and remaining debt on NPL in the affected hazards areas (Palu, Sigi, and Donggala). Thus, can be concluded that the hazards impact credit risk significantly.

Second test is intended to investigate the impact of natural disaster to the duration of remaining debt which is correlated with the restructuring debt policy. It conducted by comparing the duration of each idbank before and after the natural hazards. Table 7 shows that there are not any differences in duration, before and after the hazards happened.

4.7 Effect of Natural Hazards on The Collectability

The first hypothesis examined the relationship between natural hazards and collectability. According to the hypothesis analysis

Table 4: Comparison T-test Result of Remaining Debt of NPL

Criteria	Number(N)	Mean Rank	Sig.
Natural Hazards	3	6.33	0.067
Normal	7	4.29	
2017	27	25.41	0.14
2018	29	31.38	

Table 5: Comparison T-test Result of Duration

Criteria	Number(N)	Mean Rank	Sig.
Natural Hazards	3	6.33	0.067
Normal	7	4.29	
2017	27	25.41	0.14
2018	29	31.38	

result, the collectability in Palu, Sigi, Donggala during 2017 and 2018 is different thus the hypothesis is fully rejected. The collectability in Palu, Sigi, Donggala and other cities in Sulawesi Tengah before natural hazards also different therefore the hypothesis strongly rejected. While, the collectability in Palu, Sigi, Donggala and other city in Sulawesi Tengah after hazards is different with P-Value of 0,03, yet it is accepted with the significance 10% (see Figure 6)

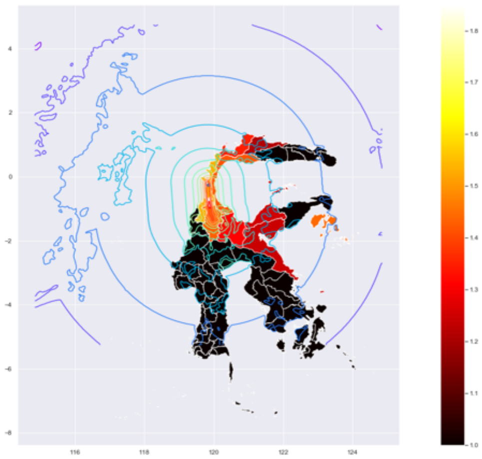

Figure 7: Impact of Earthquake to Collectability in Sulawesi Tengah 2018

Thus, it can be concluded that the collectability is influenced by the natural hazards in negative direction.

4.8 Effect of Natural Hazard on NPL' s Remain Debt

The second hypothesis investigated the effect of natural hazards on NPL' s remain debt. The analysis on the hypothesis shows that NPL Palu, Sigi, Donggala in 2017 and 2018 is different that the hypothesis is fully rejected. Next, the NPL Palu, Sigi, Donggala and other cities in Sulawesi Tengah after hazards are different thus the hypothesis is strongly rejected. Furthermore, NPL Palu, Sigi, Donggala and other city in Sulawesi Tengah after hazards is different with the P-Value of 0,053 (accepted with the significance 10%), and NPL performance of affected districts/cities is worse than others.

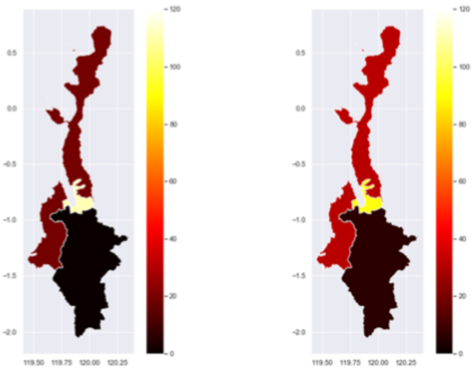

Figure 8: Comparison of Number ever Default per Kabupaten/Kota in 2017 and 2018

From the explanation above it can be concluded that the NPL is influenced by the natural hazards in negative direction.

4.9 Effect of Natural Hazard on Duration of Debt

The third hypothesis sought the relationship between natural hazards and the duration of debt. According to literature, the debtors are allowed to restructure the duration of debt based on OJK regulation. While, according to analysis result the duration of debt before and after natural disaster is difference therefore the hypothesis is rejected. The above explanation indicated that natural hazards did not affect the duration of loan in Palu, Sigi, and Donggala.

4.10 Correlation Among Variable in DTM Data

The number of IDP have a correlation with collectability, risk index of locations, and the number of house damaged. On the contrary, risk index of the affected city have a weak correlation to collectability and the number of IDP in those cities, but did not have correlation to damaged houses. Details see the figure below.

	IDP_HH	RISKINDEX	IDP_HH_ ORIGIN	HOUSE_DAMAGED_ BNPB	AFFECTED	PER_REG_ INCOME
IDP_HH						
RISKINDEX	-0,52					
IDP_HH_ORIGIN	0,98	-0,32				
HOUSE_DAMAGED_BNPB	-0,83	-0,05	-0,93			
AFFECTED	0,93	-0,16	0,99	-0,98		
PER_REG_INCOME	-0,13	-0,78	-0,35	0,66	-0,50	
COLLECTIBILITY	-1,00	0,59	-0,96	0,78	-0,89	0,054

Figure 9: Correlation Analysis

4.11 Correlation among family condition' s changes, revenue decrease, disorder on fix productive asset, lose of economic/financial asset to collectability (Jitupasna - BI)

Revenue decrease strongly correlated to collectability. Natural hazards make non-reguler-income-household (80% of IDP) loses the access of their productive land, property, or other productive assets. Natural hazards make reguler-income-household (20% of IDP) loses the additional revenue (overtime, travel funds,etc).

Change of the breadwinner in the family has a weak relationship on collectability. The main breadwinner who became the disaster victims cause the second main person in the family to take over the role.

5 CONCLUSIONS

Natural hazards have a significant impact to credit-risk, measuring by the difference of NPL and Collectability level. Natural hazards did not affect the duration of loan in Palu, Sigi, and Donggala although the debtor has rights to restructure their loan. In measuring the credit-worthiness by 6C' s score, Risk Index of the location should be included. Not in decision of appropriate or inappropriate the person is, but maybe on the additional interest rate.

Moreover, insurance is needed to protect the assets, so the bank should charge additional an insurance type of property they have, especially earthquake insurance based on location risk. Taking lessons from other cases, insurance can save households from falling into poverty and destitution and helps create a space of certainty and stability for the individual, institutions and government within which investments and planning can be undertaken [13]. However, the challenges are disaster risk insurance can be costly and cannot prevent risk and loss of lives and assets. Therefore, insurance schemes need to be complemented with other disaster-risk reduction strategies, such as integrating disaster risks into development planning, collection of data, setting up early warning systems, awareness raising, contingency planning [3][8]. Additionally, technological innovation such as satellite imaging could help lowered the costs of evaluating claims in remote and poor regions and thus of insurance products [13].

6 RESEARCH LIMITATIONS

This research has presented a research result regarding the impact of natural hazards on loan at risks. However, there are several limitations that may potentially affect the results, yet the most significant one is the limited method applied in this research to examine in detail the research variables. Some of other limitations are: the data comes at different levels (Points (DTM) and District level (BI and Jitupasna); A small sample of the area affected by natural hazards causes the analysis to have a low confidence conclusion; Credit data is aggregated data based on cities / districts so many generalizations are needed to conclude; There are totally different responses in the Jitupasna data; Additional data on Jitupasna related to income conditions before and after the disaster is not provided. Regardless of the limitation the analysis conducted towards the data had been done properly and carefully.

7 FUTURE RESEARCH

The authors call future research for different disaster affected areas and more complete research instruments and method for a more valid information and results. Research related to the impact of natural disasters on credit risk still needs to be carried out in the future. This is because research with similar themes is still very rare. Therefore, some suggestions can be done for future research, there are:

(1) Add data from other disasters that occur in Indonesia, such as Lombok and Sumbawa earthquakes, Pangandaran earthquake and tsunami, etc. So the conclusion can be drawn more objective;
(2) Add macro-economic data, such as inflation and interest rates to analyze external factors that can affect credit risk;
(3) Further study of the debt restructuring policy and link it with evidence in the field;
(4) Conduct further analysis of population movements to find out the underlying reasons and their impact on existing credit levels.

REFERENCES

[1] R.F Berry and A.E. Grady. 2005. Mesoscopic Structures Produced by Plio-Pleitocene Wrench Faulting in South Sulawesi Indonesia. *Journal of Structural Geology* 9, 5 (2005).
[2] M. Brei, P. Mohan, and E. Strobl. 2019. The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. *The Quarterly Review of Economics and Finance* 72, 2 (2019).
[3] J. David Cummins and O Mahul. 2009. Catastrophe Risk Financing in Developing Countries: Principles for Public Intervention. *World Bank* (2009).
[4] E. Gunawan, M. Kholil, and Meilano I. 2016. Splay-fault rupture during the 2014 Mw7.1 Molucca Sea, Indonesia, earthquake determined from GPS measurements. *Physics of The Earth and Planetary Interiors* 259, 1 (2016).
[5] CNN Indonesia. 2018. BNPB: Kerugian Akibat Gempa Palu Capai Rp18.4 Triliun. (2018).
[6] Klomp J. 2014. Financial Fragility and Natural Disasters: An Empirical Analysis. *Journal of Financial Stability* 14, 4 (2014).
[7] T. Mann, A. Rovere, T. Schone, A. Klicpera, P. Stocchi, M. Lukman, and H. Westphal. 2016. The magnitude of a mid-Holocene sea-level highstand in the Strait of Makassar. *Geomorphology* 257, 1 (2016). https://doi.org/10.1016/j.geomorph.2015.12.023.
[8] R. Mechler, Linnerooth-Bayer, and D. Peppiatt. 2006. Disaster Insurance for the Poor? A review of microinsurance for natural disaster risks in developing countries. *Provention Consortium* (2006).
[9] Cardona O. 2005. A System of Indicators for Disaster Risk Management in the Americas. *250th Anniversary of The 1755 Lisbon Earthquake* (2005).
[10] Maury R. C. Bellon H. Rangin C. Priadi B. Yuwono S. Atmadja R. S. Polve, M. 1997. Magmatic evolution of Sulawesi (Indonesia): constraints on the Cenozoic geodynamic history of the Sundaland active margin. *Tectonophysics* 272, 1 (1997). https://doi.org/https://doi.org/10.1016/S0040-1951(96)00276-4
[11] Ambo-Rappe R. and A. M. Moore. 2019. Chapter 25-Sulawesi Seas, Indonesia. *Sheppard* (2019).
[12] M. S. Sangkala and M. F. Gerdtz. 2018. Disaster Preparedness and Learning Needs Among Community Health Nurse Coordinators in South Sulawesi Indonesia. *Australasian Emergency Care* 21, 1 (2018). https://doi.org/10.1016/j.auec.2017.11.002
[13] UNDP. 2017. Disaster Risk Insurance. *UNDP Financing Solutions for Sustainable Development* (2017).
[14] Sawada Y. and Takasaki Y. 2017. Natural Disaster, Poverty, and Development: An Introduction. *World Development* 94 (2017).
[15] Rahayu Y.A. 2018. Kredit Macet Perumahan BTN Tembus 2.8 Triliun, Setara 45.000 rumah se-Indonesia. (2018).
[16] Chen Y. T. Zhang, Y. and W Feng. 2019. Complex multiple-segment ruptures of the 28 September 2018, Sulawesi, Indonesia, earthquake. *Science Bulletin* 64, 10 (2019).

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