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Correlation peer-to-peer lending regarding banking credit

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Abstract

This study aims to identify the correlation between peer-to-peer lending and bank credit using the pooled least squares method for the 2017-2019 period. The results show that, in the aggregate model, credit has a positive correlation with P2P lending and GDP, and a negative correlation with credit interest rates, according to the research hypothesis. Among the three main credit sectors observed in the study, P2P lending and interest rates have the greatest influence on agricultural sector credit, while GDP has the greatest influence on credit in the manufacturing sector.

Keywords: Peer to peer lending, Bank loans, Trade, Manufacture, Agriculture.

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1. Introduction

The development of information technology in the financial and banking sector has changed most patterns of financial business transactions. The World Economic Forum noted that in 2019, as many as 4.2 billion (55%) of the world's population were internet users, an increase of 4% compared to 2018, when 51% of the population used the internet. World Bank data for 2018 shows that internet users in Indonesia reached 40% of the population, an increase from 11% in 2011. Data from the Indonesian Internet Service Providers Association in the 2017 internet user behavior survey indicated that internet access is still dominated by three activities: chat applications (89.35%), social media (87.13%), and search engines (74.84%). Meanwhile, registration (16.97%), buying and selling (8.12%), and banking (7.39%) were the lowest services accessed.

World Bank Group [1] states that only 48.9% of the adult population in Indonesia has an account at a financial institution, of which 21.5% have savings and 18.4% have loans. Bappenas stated that banking access and financial literacy are still low. This is influenced by several factors from both the demand and supply sides. From the supply side, influencing factors include asymmetric information, which causes financial institutions to be selective towards customers; the perception among low-income housewives that they cannot access financial services; and the limited knowledge of banking service providers about low-income communities, resulting in financial products that do not meet their needs. Factors influencing the demand side include low household income, complicated administrative requirements, difficulty reaching financial institution offices, low financial literacy, the public's misconception that financial institutions are only for the wealthy, and sociocultural factors.

Unsal and Movassaghi [2] in their research on the impact of the Internet on the financial services industry sector, it was stated that in the future, financial service users will benefit from increased competition, and the most successful companies will be mid-level firms that offer a good combination of cost and service. Zhang et al. [3] states that technological developments in the banking industry can be seen as both opportunities and challenges, where the first change is customer behavior moving away from conventional transaction activities, leading to a redefinition of work in the banking sector. Digitalization does not mean eliminating all conventional systems but creating *equilibrium* between *online* and *offline* services because there is a market segment that must be served. The second change is the role of fintech platforms, which initially only functioned as data collectors and centers for *big data*, will switch functions like banks with economic inclusion because the data held by fintech allows them to compile credit profiles of their users. Access to banking and financial literacy are still low in Indonesia, opening up great opportunities for fintech growth.

Data from the Coordinating Ministry for the Economy in 2018 indicated that Indonesia is still predominantly characterized by payment and loan platforms. As of December 2019, there were 164 P2P business actors involved in lending, with 25 P2P business actors already licensed and 139 registered with the Financial Services Authority. Data from the Indonesian fintech association highlights a funding gap of Rp. 988 trillion in MSME needs that cannot be met by conventional banking, thereby creating opportunities for the development of P2P lending in Indonesia.

Although banking and P2P are viewed as distinct sectors in both institutional and regulatory contexts, they are interconnected because they belong to the same industry. Banks primarily function in credit distribution, whereas P2P lending also has *core business* in lending and borrowing. Tang [4] finds that P2P lending is a substitute for bank lending because it serves infra-marginal bank borrowers (substitute), but also complements bank lending for small loans (complementary). Liao et al. [5] in his research, it is state that bank loans have decreased, along with an increase in P2P credit distribution. With the growing number of P2P platforms, *lending*, whether registered and licensed or illegal fintech raises questions about whether fintech can encourage economic development or instead become a challenge with consequences.

Lending and borrowing money among neighbors, friends, or community members is perhaps the oldest and most fundamental form of financial transaction. Peer-to-peer (P2P) loans represent the development of transactions as a new and broader dimension of connections facilitated by the internet Brill [6]. Chen et al. [7] stated that in the traditional credit market, banks act as intermediaries between fund owners and debtors. However, in the last decade, *platform* loan *peer-to-peer* (P2P) has brought changes for debtors and investors to make transactions without the need for a large role from intermediaries. Debtors get the opportunity to obtain larger loans, and investors can earn *returns* that are higher than bank deposits. Einav et al. [8] in their research, they found that several benefits of using bank credit, such as reducing credit transaction costs, the ability to match various liquidity requirements of debtors and fund owners, and various methods that can be used to overcome asymmetric information, are also present in *platform* new online loan. Jagtiani and Lemieux [9] research found that in the United States, lending by LendingClub, the largest P2P platform in the country, has expanded into areas traditionally served by banks, such as markets with high concentration and regions with fewer bank branches per capita. The research also indicated that LendingClub loans increased in areas where the local economy was underperforming.

Based on data from the Fintech Association, there is a gap in financing needs that cannot be met by banks of IDR 988 billion and PricewaterhouseCoopers [10] states that 74% of MSMEs have not received financing from banks; there is still a very open opportunity for P2P to develop in Indonesia. Einav et al. [8] and Buchak et al. [11] found the reason why MSME credit distribution was not yet optimal and the high number of MSME players who are *financially illiterate*. This is due to geographical factors and still high credit interest rates. Credit distribution is still concentrated in the Wholesale and Retail Trade sector, the Processing Industry Sector, and the Agriculture, Hunting, and Forestry Sector, in line with the contribution of these three sectors to the formation of gross domestic product and the number of business actors in these sectors, which are relatively dominant compared to other sectors.

Thus, it can be concluded that the problems to be studied are: 1) Identifying the correlation between *peer-to-peer lending* with bank credit; 2) Evaluating the impact of credit distribution in *P2P lending* on the three main credit sectors.

Through this research, it is hoped that we can identify correlations between *peer-to-peer lending* on banking credit. This research is also expected to evaluate the impact of P2P credit distribution on credit in three main economic sectors. Through this research, it is hoped that a policy recommendation for Indonesia regarding P2P regulation can also be produced, *Lending* so that it can support the development of the digital economy and achieve credit targets to support economic growth.

It is hoped that this research will provide benefits for enriching knowledge regarding the correlation between P2P development in Indonesia and banking credit. The results of this research are expected to become a reference, a source of information, and additional study material for further research, as well as input for the Government of the Republic of Indonesia and related institutions, especially in terms of fintech development, so that it can formulate and plan appropriate and beneficial policies for society and the financial services industry.

In general, this research is expected to provide benefits and information to the government, the wider community, and can serve as input for the development of science.

This research focuses on third-party credit and credit in three main economic sectors based on their contribution to credit distribution and gross domestic product in the 2017-2019 period. *Peer-to-peer lending* refers to funds distributed through *platforms* for online loans that are licensed or registered with the Authority. This research uses Gross Domestic Product, Interest Rates, and *Non-Performing Loan* as control variables.

2. Research Methodology

2.1. Data Collection and Analysis Techniques

Secondary data obtained from the Financial Services Authority, Bank Indonesia, Central Bureau of Statistics, associations, and related institutions were used in conducting the research analysis. The sample period for the research was from January 2017 to December 2019, utilizing monthly data. The choice of this time period is due to limited P2P data *Lending* in Indonesia.

The variables used are converted into natural logarithms (ln), which is intended to reduce heteroscedasticity problems in estimation. *Treatment* involves different approaches on variables, *nonperforming loan* and credit interest rates, where this variable is not transformed into ln form because it is a variable with percentage units (%). This quantitative data is in the form of *time series* data from monthly observations from January 2017 to December 2019, with an aggregate model and three groups of economic sectors.

2.2. Selected Regression Model

Yusgiantoro [12] is a reference in forming a research model. This research measures the impact of P2P lending, bank characteristic variables, and macroeconomic variables on banking credit in the United States using the method of *pooled least squares* (PLS), where t represents the year of the research period, namely 2017-2019.

$$LnLoan_{it} = \alpha + \beta_1 P2PVol_{it} + \beta_2 Bank_{it} + \beta_3 Macro_{it} + \varepsilon \quad (1)$$

There are variable adjustments due to differences in P2P characteristics in Indonesia and the United States, as well as limited data available. The bank characteristic variables are represented by the credit interest rate variables and *nonperforming loans*. The macroeconomic variables are represented by gross domestic product. Data processing uses the PLS method in accordance with the reference journal.

2.3. Equations in Aggregate Model Testing and Three Main Credit Sectors:

2.3.1. Aggregate Model

Model 1 (one) is an aggregate credit model. This model explains the impact of independent variables on credit variables. The dependent variable used is the natural logarithm of third-party credit (LnLoan). The independent variable used in this model is the natural logarithm of P2P credit *lending* (LnP2PVol), while the control variables are interest rates (IR), the natural logarithm of gross domestic product (LnGDP), and *non-performing loan* (NPL).

$$LnLoan_{it} = \alpha + \beta_1 LnP2PVol_{it} + \beta_2 IR_{it} + \beta_3 NPL_{it} + \beta_4 LnGDP_{it} + \varepsilon \quad (2)$$

Table 1.
Definition and Data Sources of Research Variables.

Variable	Information	Source
LnLoan	LogNatural Third Party Credit	Indonesian Banking Statistics (SPI)
LnP2PVol	LogNatural Credit P2P *Lending*	P2P Fintech Statistics *lending*
AND	Third party credit interest rates	Basic Credit Interest Rate
NPL	Bad credit	Indonesian Banking Statistics (SPI)
LnGDP	Lognatural Product Domestic Gross	Central Bureau of Statistics
a	Constant	-
i	Economic Sector	-
t	Year	-
e	Error	-

2.3.2. Trade Sector Credit Model

Model 2 (two) is a credit model for the wholesale and retail trade sectors. The model explains the impact of independent variables on the credit variables for these sectors. The dependent variable in this model is the natural logarithm of credit in the wholesale and retail trade sector (Lntrade). The independent variable in this model is the natural logarithm of P2P credit *lending* (LnP2PVol), while the control variables are the credit interest rate for the wholesale and retail trade sector (IRtrade), the natural logarithm of gross domestic product for these sectors (LnGDPtrade), and *non-performing loans* (NPLtrade) in the wholesale and retail trade sector credit.

$$Lntrade_{it} = \alpha + \beta_1 LnP2PVol_{it} + \beta_2 IRtrade_{it} + \beta_3 NPLtrade_{it} + \beta_4 LnGDPtrade_{it} + \varepsilon \ (3)$$

Table 2.
Definition and Data Sources of Research Variables in the Wholesale and Retail Trade Sector.

Variable	Information	Source
LnTrade	LogNatural Third Party Credit wholesale and retail trade sectors	Indonesian Banking Statistics (SPI)
LnP2PVol	LogNatural credit P2P *Lending*	P2P Fintech Statistics *lending*
IRtrade	credit interest rates for the wholesale and retail trade sectors	Basic Credit Interest Rate
NPLtrade	Bad Credit in the wholesale and retail trade sectors	Indonesian Banking Statistics (SPI)
LnGDPtrade	LogNatural Gross Domestic Product, wholesale and retail trade sectors	Central Bureau of Statistics
a	Constant	-
i	Economic Sector	-
t	Year	-
e	Error	-

2.3.3. Processing Industry Sector Credit Model

Model 3 (three) is a third-party credit model for the processing industry sector. The model examines the impact of independent variables on third-party credit variables within this sector. The dependent variable in this model is the natural logarithm of third-party credit in the processing industry sector (LnInd). The independent variables include the natural logarithm of P2P credit lending (LnP2PVol), interest rates in the manufacturing industry sector (IRInd), the natural logarithm of gross domestic product in the processing industry sector (LnGDPInd), and non-performing loans (NPLInd) in the processing industry sector.

$$LnInd_{it} = \alpha + \beta_1 LnP2PVol_{it} + \beta_2 IRInd_{it} + \beta_3 NPLInd_{it} + \beta_4 LnGDPInd_{it} + \varepsilon \text{ (4)}$$

Table 3.
Definition and Data Sources of Research Variables in the Processing Industry Sector.

Variable	Information	Source
LnLoanInd	LogNatural Third Party Credit in the processing industry sector	Indonesian Banking Statistics (SPI)
LnP2PVol	LogNatural Credit P2P *Lending*	P2P Fintech Statistics *lending*
IRInd	Credit interest rates for the processing industry sector	Basic Credit Interest Rate
NPLInd	Bad Credit in the processing industry sector	Indonesian Banking Statistics (SPI)
LnGDPInd	LogNatural Gross Domestic Product processing industry sector	Central Bureau of Statistics
a	Constant	-
i	Economic Sector	-
t	Year	-
e	Error	-

2.3.4. Agricultural Sector Credit Model

Model 4 (Four) is a credit model for the agricultural, hunting, and forestry sectors. The model examines the impact of independent variables on third-party credit variables within these sectors. The dependent variable in this model is the natural logarithm of third-party credit in the agricultural, hunting, and forestry sectors (LnTani). The independent variable is the natural logarithm of P2P credit *lending* (LnP2PVol), while the control variables include the interest rate on credit for the agricultural, hunting, and forestry sectors (IRTani), the natural logarithm of gross domestic product for these sectors (LnGDPTani), and *Non-Performing Loan* (NPLTani).

$$LnTani_{it} = \alpha + \beta_1 LnP2PVol_{it} + \beta_2 IRTani_{it} + \beta_3 NPLTani_{it} + \beta_4 LnGDPTani_{it} + \varepsilon \text{ (3.5)}$$

Table 4.
Definition and Data Sources of Research Variables in the Agriculture, Hunting, and Forestry Sector.

Variable	Information	Source
LnTani	LogNatural Third Party Credit for the agricultural, hunting and forestry sectors	Indonesian Banking Statistics (SPI)
LnP2P Vol	LogNatural Credit P2P *Lending*	P2P Fintech Statistics *lending*
IRTani	Agricultural, hunting and forestry sector credit interest rates	Basic Credit Interest Rate
NPLTani	Bad Credit in the agricultural, hunting and forestry sectors	Indonesian Banking Statistics (SPI)
LnGDPTani	LogNatural Gross Domestic Product agriculture, hunting and forestry sectors	Central Bureau of Statistics
a	Constant	-
i	Economic Sector	-
t	Year	-
e	Error	-

2.4. Operational Definition of Variables and Research Hypothesis

The hypothesis in this research is based on a review of theoretical studies and empirical research from previous studies.

1. P2P loan volume uses P2P loan distribution data for the 2017-2019 period. P2P loans have a positive relationship if they are complementary and a negative relationship if they are substitutes. (Hypothesis: P2P loans are complementary to banking credit).
2. Third-party credit interest rates utilize basic credit interest rates within an aggregate model. Data are obtained from Indonesian banking statistics for credit interest rate data per sector. (Hypothesis: Credit interest rates and credit distribution have a negative relationship.)
3. *Non-Performing Loan* (NPL), using NPL data in Indonesian banking statistics for both aggregate and sector data. (Hypothesis: NPL and credit distribution have a negative relationship)
4. GDP uses Real GDP data through GDP with a base year of 2010, which is available at the Central Statistics Agency. (Hypothesis: GDP and credit have a positive relationship)

3. Results and Discussion

3.1. Descriptive Statistical Analysis

This research uses the credit variable for the 2017-2019 period as the dependent variable. Meanwhile, the independent variable that is the focus of the research is the distribution of *peer-to-peer lending*. Control variables included in the model are credit interest rates, *non-performing loans*, and gross domestic product.

Credit distribution increased in 2015-2019 (Figure 1). Credit distribution in 2019 grew by 6.08%, lower than 2018's 11.7%. The slowdown in third-party credit was caused by weakening demand for corporate credit and a decline in the performance of the mining sector. Credit slowdown also occurred in the trade, processing, and construction sectors. The decline in demand for new credit in these three sectors is noteworthy because these sectors are still the main drivers of national economic growth.

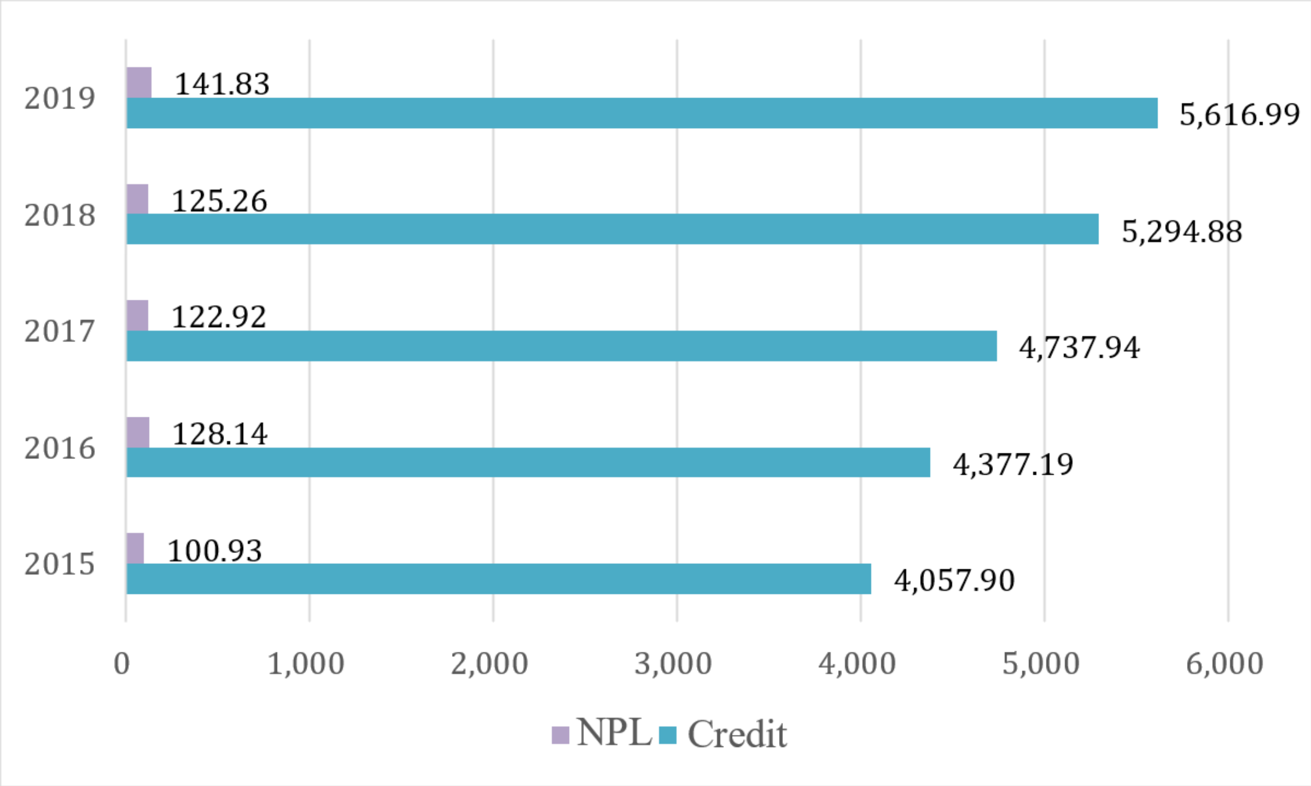

Figure 1.
Credit Distribution Trends.

The average distribution of third-party credit during the research period was IDR 4,947.42 trillion and experienced growth, with the highest distribution amounting to IDR 5,616.99 trillion in December 2019 and the lowest at IDR 4,308.08 trillion in January 2017. Credit based on the economic sector or business field is still dominated by the Trade Sector, Processing Industry Sector, and Agricultural Sector (Table 5).

Table 5.
Credit Based on Business Field (in Trillion Rupiah).

No	Business Field	Des-15	Des-16	Des-17	Des-18	Des-19
1	Wholesale and Retail Trade	793	841	885	976	1,006
2	Processing industry	760	782	824	899	932
3	Agriculture, Hunting and Forestry	255	284	317	355	370
4	Construction	173	215	259	316	362
5	Real Estate, Rental Business, Corporate Services	185	210	222	248	269
6	Financial Intermediaries	165	194	214	244	250
7	Transportation, warehousing, communications	178	172	183	217	247
8	Electricity, gas and water	99	135	146	170	198
9	Mining and Quarrying	135	126	114	138	134
10	Provision of accommodation and food and drink	86	93	98	100	110
11	Community Services, Social Culture, Entertainment	58	59	72	80	83
12	Health Services and Social Activities	21	17	19	23	34
13	Government Administration, Defense, Social Security	13	15	22	25	29
14	Education Services	8	9	10	12	14
15	Fishery	9	9	11	12	14
16	Individual Services Serving Households	3	3	3	3	3
17	International and Extra-International Bodies	0,1	0,2	0,2	0,2	0,3
18	Activities with unclear boundaries	12	11	3	2	2

Trade sector credit is the largest credit based on business field, with an average of IDR 918.91 trillion, with the highest value being IDR 1,006.07 trillion and the lowest IDR 807.95 trillion. Credit in the processing industry sector is the second largest, with an average of IDR 834.86 trillion, with the highest value being IDR 931.73 trillion and the lowest being IDR 749.53 trillion. Agricultural sector credit is the third largest, with an average of IDR 330.33 trillion, with the highest value being IDR 370.33 trillion and the lowest being IDR 278.05 trillion.

P2P loan distribution averages IDR 2.26 trillion, with the highest distribution amounting to IDR 7.59 trillion. P2P credit distribution experienced a significant increase of 259.56% in December 2019 (YTD).

During the 2015-2019 period, the average credit interest rate in rupiah based on type of credit use decreased following the decrease in the reference interest rate (Figure 3).

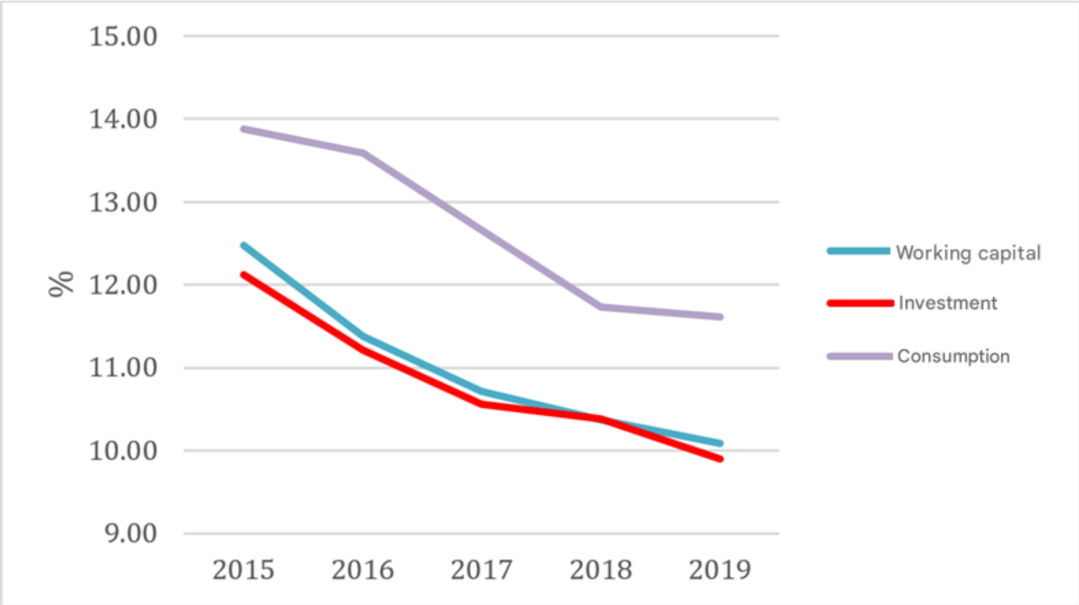

Figure 2.
Rupiah Credit Interest Rates Based on Type of Use.

The average credit interest rate is 10.69%, with the highest interest rate at 11.35% and the lowest at 10.09%. The average trade sector credit interest rate is 11.40%, with the highest at 12.23% and the lowest at 10.92%. The average agricultural sector credit interest rate is 10.31%, with the highest at 11.00% and the lowest at 9.92%. The average interest rate for loans in the processing industry sector is 9.85%, with the highest at 10.62% and the lowest at 9.09%.

Gross Domestic Product and third-party credit distribution showed a positive and unidirectional trend during the 2015-2019 period (Figure 4).

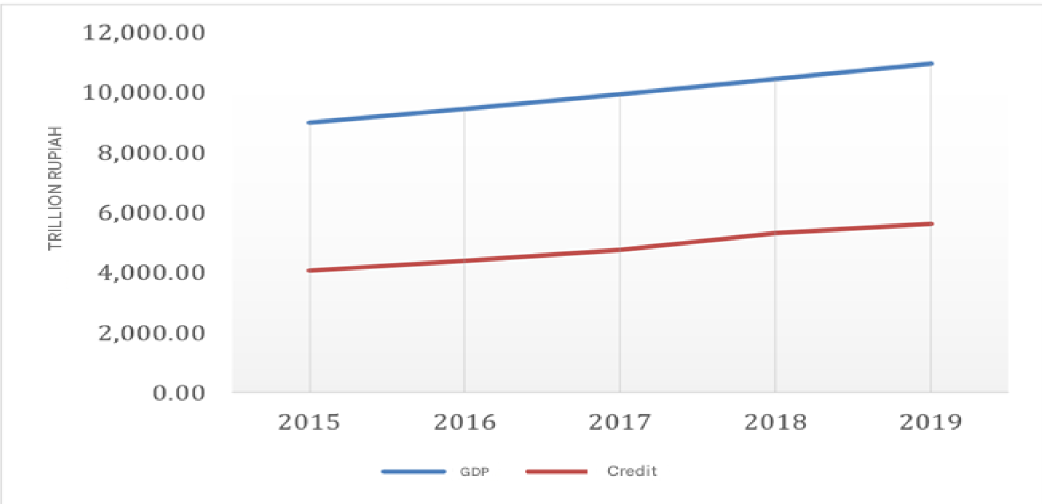

Figure 3.
Development of Indonesia's GDP and Credit.
Source: SPI and BPS, 2020.

The average Gross Domestic Product (GDP) variable is IDR 869.10 trillion, with the highest GDP at IDR 939.63 trillion and the lowest at IDR 792.72 trillion. This indicates Indonesia's economic growth during the research period. The GDP of the processing industry sector is the highest among business fields, with an average GDP of IDR 182.60 trillion. The highest GDP in this sector is IDR 194.32 trillion, and the lowest is IDR 170.38 trillion. The trade sector has the second-highest GDP among business fields, with an average of IDR 114.70 trillion. GDP in the trade sector is IDR 123.21 trillion, with a low of IDR 105.77 trillion. The agricultural sector's average GDP is IDR 108.91 trillion, with the highest at IDR 123.60 trillion and the lowest at IDR 90.74 trillion.

During the research period, the trade sector was the sector with the highest NPL until September 2019, compared to the aggregate credit NPL and the other two sectors in the research. This is in accordance with *nature*; trade credit with NPLs tends to be more sensitive to changes in people's purchasing power if there are changes in economic conditions.

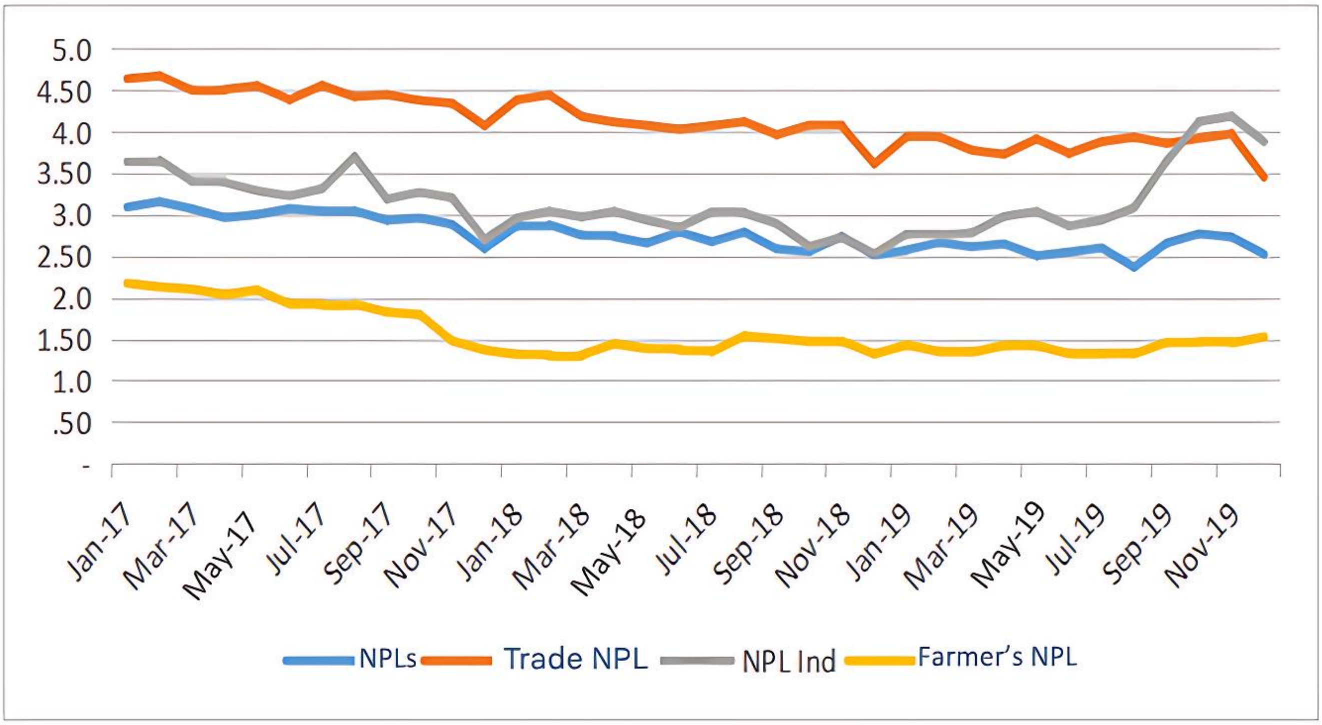

Figure 4.
NPL Trend 2017-2019.

Non-Performing Loan credit in the research period averaged 2.77%, with the lowest value being 2.36% and the highest being 3.15%. The agricultural sector has the lowest NPL compared to the other two sectors in the research. The average NPL for agricultural sector credit is 1.56%, with the highest value being 2.17% and the lowest being 1.29%. The average NPL for credit in the processing industry sector is 3.15%, with the highest value being 4.19% and the lowest being 2.53%. The average NPL for trade sector credit was 4.13%, with the highest value being 4.67% and the lowest being 3.45%.

3.2. Regression Analysis
3.2.1. Regression Analysis of Third-Party Credit Models

Table 6.
Model 1 estimation.

	Model 1: Third-Party Credit	
	Coefficient	**t-stat**
LnP2PVol	0.033	4.71*
AND	-0.075	-2.52**
LnGDP	0.254	2.67**
NPL	-0.023	-0.67

Note: * p<0.01; ** p<0.05; *** p<0.1.

In the credit aggregate model, referring to equation 3.1, the regression results show that credit is significantly positively influenced by P2P *lending* and GDP, and is significantly negatively influenced by credit interest rates. The R^2 and *adjusted* R^2 values are 95.24% and 94.62%, respectively. The LnGDP variable has the greatest positive and significant influence on the model compared to the other variables, while the NPL variable has the smallest and insignificant influence on the model.

Third-party credit is significantly positively influenced by the P2P credit distribution variable *lending*. The significance of the P2P loan variable also explains that P2P loans have been able to become a good independent variable. The LnP2PVol regression coefficient is 0.033, indicating that the relationship between LnP2PVol and LnLoan is a unidirectional/positive relationship, which aligns with the development of the hypothesis from this research in the previous chapter, where P2P loans and bank credit are considered complementary. These results also show that every 1% increase in P2P loan distribution results in an increase in credit by 0.033%. This suggests that the credit relationship with P2P is inelastic. P2P *lending* is complementary to banking credit, not competitive, because the presence of P2P *lending* expands the market share and reach of consumers who have not received banking credit, especially through collaboration between P2P and banking via sharing credit schemes distributed to consumers.

These results are consistent with reference journals and research by Buchak et al. [11] and Demirgüç-Kunt et al. [13] that P2P and banking credit have a complementary relationship. Havrylchyk et al. [14] research on the expansion of *platform* P2P to areas with low-density branch networks can also support Indonesia's conditions because, with only 29,222 bank branch offices throughout Indonesia, it still cannot reach Indonesia's geographical area. Even though, in terms of numbers, loan disbursement is still dominated by Java, P2P fintech statistical data for December 2019 shows that growth in P2P loan disbursement has increased significantly outside Java compared to Java (Figure 5). In 2019, apart from loan growth outside Java, it was 282.93%, higher than Java Island at 255.93%. Growth *borrower* outside Java was also higher than on Java Island, namely 356.51%, compared to growth *borrower* on Java Island, which was 320.16%.

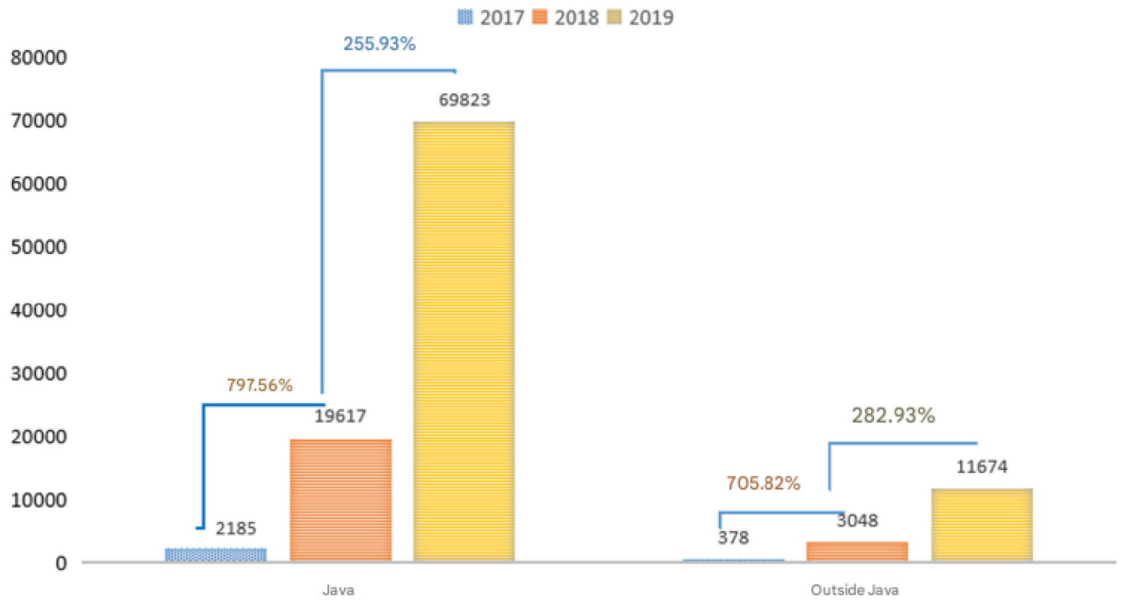

Figure 5.
P2P Loan Distribution.

The impact of P2P on the banking sector is consistent with research by International Monetary Fund [15] which states that the existence of P2P encourages banking performance through cooperation, *escrow account* and *virtual accounts*, payment and credit systems *channeling* between banking and P2P. Some banks even form venture capital to invest directly in *fintech lending*. This is demonstrated by P2P's contribution to added value in 2019 GDP, which reached IDR 60 trillion, with a contribution from the financial services sector of 93.56%. Additionally, in 2019, P2P *lending* contributed to the employment absorption of 362 thousand, an increase compared to 2018 of 215 thousand workers. In 2018, the increase in labor was dominated by the trade sector at 51%, and in 2019, the increase in labor was dominated by workers in the financial services sector at 68.68%.

Credit is significantly negatively influenced by the credit interest rate variable. The IR regression coefficient is -0.075, indicating that the relationship between interest rates and credit is a unidirectional/negative relationship, which aligns with the development of the hypothesis from this research in the previous chapter. Every 1% increase in credit interest rates will reduce credit by 0.075%. This suggests that credit and interest rates have an inelastic relationship. The results of this study are consistent with credit demand theory. Stiglitz and Greenwald [16] and research Bappenas [17] state that if interest rates are low then demand for credit distribution will increase (the slope of the curve is negative).

The GDP variable has a positive and significant effect on the model. The LnGDP regression coefficient is 0.254, indicating that the relationship between LnGDP and LnLoan is a unidirectional/positive relationship, which aligns with the development of the hypothesis from this research in the previous chapter. Every 1% increase in gross domestic product will increase credit by 0.254%. This suggests that credit has an inelastic relationship. The results are consistent with Singh et al. [18] that there is a significant positive correlation between GDP and credit distribution. Deloitte [19] stated that credit growth was triggered by the normal phase of the business cycle, liberalization of the financial sector, and capital inflows. Under normal conditions, an improvement in the domestic economy will encourage credit distribution. During the research period, credit growth was in normal conditions as part of the normal phase of the business cycle, so that GDP became the driving variable for credit growth. Apart from that, GDP contribution is the largest compared to other business fields. The contribution of the processing industry sector to GDP in 2017 was 20.16%, in 2018 it was 19.86%, and in 2019 it was 19.70%,

Credit growth in the 2017-2019 period was also supported by regulatory policies that set credit growth targets as indicators of banking sector performance, so that there could be synergy between government and banking programs in encouraging the role of credit distribution to improve the economy. In 2017, credit growth was targeted at 12-14% and was realized at 8.24%. This is because the credit growth of small and medium banks is far from the target, where Bank BUKU III recorded credit growth of 1% yoy, while Bank BUKU II's credit growth fell by 7% and BUKU I fell by 36% yoy. This decline was caused by the remaining weak demand for credit as a result of the real sector and the *supply* Bank credit is still conservative regarding credit risk. In 2018, credit growth was targeted at 10-12% and was realized at 12.45%, while in 2019, credit growth was targeted at 12-14% which was revised to 8-10%, with a realization of 6.08%. This was due to the slowdown in demand for corporate credit, which is increasingly using foreign funding, as shown by an increase in debt securities issuance of 15.8%.

Table 7.
Model 2 estimates

	Model 2: Wholesale and Retail Trade Sector	
	Coefficient	**t-stat**
LnP2PVol	0.026	4.53*
IRTrade	-0.040	-1.90***
LnGDPTrade	0.415	3.41*
NPLTrade	-0.105	-1.34

Note: * p<0.01; ** p<0.05; *** p<0.1.

In the credit model, the wholesale and retail trade sectors are significantly positively influenced by P2P *lending* and GDP, and are significantly negatively influenced by credit interest rates. The R^2 and *adjusted* R^2 values are 97.19% and 96.83%, respectively. The LnGDP variable has the greatest influence on the model in a significantly positive manner compared to the other variables, while the interest rate variable has the smallest influence on the model.

Credit in the wholesale and retail trade sectors is significantly positively influenced by the P2P distribution variable *lending*. The significance of the P2P loan variable also explains that P2P loans have been able to become a good independent variable. The LnP2PVol regression coefficient is 0.026, meaning that the relationship between LnP2PVol and LnTrade is a unidirectional/positive relationship, which is in accordance with the development of the hypothesis from this research in the previous chapter, where P2P loans and bank credit are complementary, and every 1% increase in P2P loans will have an effect on increasing 0.026% credit to the wholesale and retail trade sector. This shows that trade sector credit has an inelastic relationship with P2P. P2P *lending* is complementary to banking credit, not competitive, because of the presence of P2P *lending* expanding market share and reach of consumers who have not received banking credit, especially with collaboration between P2P and banking through sharing credit schemes distributed to consumers. P2P influence *lending* on credit in the wholesale and retail trade sector models is consistent with the influence of P2P lending on aggregate credit. The role of P2P in the trade and retail sector is consistent with research by International Monetary Fund [15] which states that P2P's contribution to GDP added value was IDR 25.97 trillion, and the trade sector contributed the most to this added value, reaching 29.4%. In 2019, from P2P contributing IDR 60 trillion to GDP, the trade sector contributed 0.27%. Apart from that, in 2018, the contribution of P2P lending to labor absorption was 215 thousand, with 51% being workers in the trade sector. However, in 2019, of the 362 thousand labor absorptions, the trade sector only contributed 3.2%. The development of platforms in the trade sector encompasses various types of businesses, such as Modalku, which provides online trade financing; Akseleran, which offers loans to SMEs that have just established businesses, including in the trade sector; and maritime funds, which finance the maritime sector, including salt and seaweed trade in eastern Indonesia, which is not yet accessible to banking credit.

Trade sector credit is significantly negatively influenced by the credit interest rate variable. The IR regression coefficient is -0.040, indicating that the relationship between IR and LnTrade is a unidirectional/negative relationship, which aligns with the development of the hypothesis of this research. Every 1% increase in interest rates will reduce credit in the wholesale and retail trade sectors by 0.040%. This demonstrates that trade sector credit has an inelastic relationship with interest rates. The influence of interest rate variables on credit in the wholesale and retail trade sector model is consistent with interest rate theory and research by PricewaterhouseCoopers [10] in Indonesia, which states that interest rates have a significant negative effect on credit in the trade sector.

The GDP variable has a positive and significant effect on the model. The LnGDPTrade regression coefficient is 0.415, indicating that the relationship between trade sector GDP and trade sector credit is unidirectional and positive, which aligns with the development of the research hypothesis. Additionally, every 1% increase in trade sector GDP will result in a 0.415% increase in trade sector credit. These results are consistent with the influence of GDP on the Aggregate Credit Model and research by Almås et al. [20] that GDP has a significant positive effect on credit in the trade sector in Indonesia. This shows that trade sector credit has an inelastic relationship with GDP.

Trade sector credit remains the cornerstone of banking credit distribution because it is supported by the rapid growth of trade businesses, and trade sector business actors have proven to be more resistant to shocks during economic turmoil or adverse market conditions. Liao et al. [5] stated that the trade sector in Indonesia is a sustainable business, has experienced debtors, and possesses good collateral. This is what causes credit distribution in the trade sector to be the largest, according to the data in the previous chapter.

Table 8.
Model 3 estimation

	Model 3: Processing Industry Sector	
	Coefficient	**t-stat**
LnP2PVol	0.030	4.79*
IRInd	-0.026	-3.22*
LnGDPInd	0.567	2.30**
NPLInd	-0.182	-1.88***

Note: * p<0.01; ** p<0.05; *** p<0.1.

In the credit model, the processing industry sector is significantly positively influenced by P2P lending and GDP, and significantly negatively influenced by interest rates and *non-performing loans*. The R^2 and *adjusted* R^2 are 95.29% and 94.68%, respectively. The LnGDPInd variable has the greatest influence on the model in a significantly positive manner compared to the other variables, while the interest rate variable has the smallest influence on the model.

Credit in the processing industry sector is significantly positively influenced by the P2P credit distribution variable *lending*. The significance of the P2P loan variable also indicates that P2P loans have become a reliable independent variable in this research. The LnP2PVol regression coefficient is 0.030, suggesting that the relationship between P2P loans and credit in the processing industry sector is a positive, unidirectional relationship, consistent with the research hypothesis where P2P loans and bank credit are complementary. This demonstrates that credit in the processing industry sector has an inelastic relationship with P2P. These results also show that every 1% increase in P2P loans results in a 0.030% increase in credit in the processing industry sector. P2P *lending* is complementary to banking credit, not competitive, because P2P *lending* expands the market share and reaches consumers who have not received banking credit, especially through collaboration between P2P and banking via shared credit schemes distributed to consumers.

P2P lending can contribute to providing financing for the processing industry, especially at the MSME scale, because the limitation of P2P financing according to statutory regulations is IDR 2 billion. During the pandemic, the distribution of P2P loans to the processing industry sector actually increased because the industrial sector was not significantly affected by Covid-19, particularly pharmaceuticals, medicines, packaged food, and food products.

Credit in the processing industry sector is significantly negatively influenced by the credit interest rate variable. The IR regression coefficient is -0.026, indicating that the relationship between credit and credit interest rates in the processing industry sector is a unidirectional/negative relationship, which aligns with the development of the research hypothesis. Every 1% increase in credit interest rates in the processing industry sector results in a 0.026% decrease in credit. This demonstrates that credit in the processing industry sector has an inelastic relationship with interest rates. The influence of interest rate variables on credit in the processing industry sector model is consistent with interest rate theory and the research results of Stiglitz and Greenwald [16] and PricewaterhouseCoopers [10] which state that credit interest rates have a significant negative effect on the processing industry sector in Indonesia.

The GDP variable has a positive and significant effect on the model. The LnGDP regression coefficient is 0.5668, indicating that the relationship between LnGDP and LnInd is a unidirectional/positive relationship, which aligns with the hypothesis development from this research in the previous chapter. This suggests that credit in the processing industry sector has an inelastic relationship with GDP. The result is consistent with the influence of GDP on the Aggregate Credit Model in Model 1 and the Trade Sector Credit Model in Model 2. This finding is in accordance with research by Gunawan (2017), which states that GDP has a significant positive effect on credit in the processing industry sector in Indonesia.

Variable *non-performing loan* has a significant negative effect on the model. The significance of the NPL variable in the processing industry sector also indicates that NPL has become a reliable independent variable in research. The NPL regression coefficient is -0.1822, suggesting that the relationship between NPL in the processing industry sector and LnInd is a unidirectional/negative relationship, which aligns with the development of the hypothesis from this research in the previous chapter. This shows that credit in the processing industry sector has an inelastic relationship with the sector Demirgüç-Kunt et al. [13] in its research on priority sector credit in Indonesia, it was stated that NPLs have a negative effect on credit in the processing industry sector in Indonesia..

The processing industry sector is a priority sector in accordance with the NAWACITA program. The processing industry sector is the economic sector that contributes the largest to GDP and is the priority sector with the widest distribution. As a priority sector, the processing industry sector receives priority credit allocation through the expansion of KUR and the provision of export-oriented KUR from national banks. The Milne and Parboteeah [21] stated that processing industry credit is not yet optimal because interest rates in the processing industry sector are still considered quite high compared to other countries, where rates are only 4-5%, and bank financing schemes are still not aligned with the types of each subsector within the processing industry sector.

Table 9.
Model 4 estimation.

	Model 4: Agriculture. Hunting and Forestry Sector	
	Coefficient	**t-stat**
LnP2PVol	0.037	5.60*
IRTani	-0.106	-2.96*
LnGDPTani	0.203	2.49**
NPLTani	-0.016	-0.50

Note: * p<0.01; ** p<0.05; *** p<0.1.

In Model 4, the agricultural, hunting, and forestry sector credit is significantly positively influenced by P2P lending and GDP, and significantly negatively influenced by interest rates and *non-performing loans*. The R^2 and *adjusted* R^2 are 97.12% and 96.75%, respectively. The LnGDPTani variable has the greatest positive and significant influence on the model compared to the other variables, while the NPL variable has the smallest and insignificant influence on the model.

Agricultural sector credit is significantly positively influenced by the P2P credit distribution variable *lending*. The significance of the P2P loan variable also indicates that P2P loans have become a reliable independent variable in this research. The LnP2PVol regression coefficient is 0.037, meaning that the relationship between P2P loans and credit in the agricultural, hunting, and forestry sectors is a unidirectional/positive relationship, which aligns with the development of the hypothesis from this research in the previous chapter, where P2P loans and bank credit are considered complementary. A 1% increase in P2P loans will result in a 0.037% increase in credit for the agricultural sector. The influence of *lending* by P2P on credit in the agricultural sector model is consistent with the influence of P2P *lending* across the three previous models. This indicates that agricultural sector credit has an inelastic relationship with P2P.

P2P *lending* is complementary to banking credit, not competitive, because of the presence of P2P *lending* expanding market share and reach of consumers who have not received banking credit, especially with collaboration between P2P and banking through sharing credit schemes distributed to consumers. The development of P2P in the agricultural sector is supported by the growing number of platforms that specialize in the agricultural sector, such as Crowde, Tanifund, Vestifarm, Igrow, and Tanijoy. These platforms not only provide financing to *borrowers* but also offer assistance to these farmers.

Agricultural sector credit is significantly negatively influenced by the credit interest rate variable. The IR regression coefficient is -0.106, indicating that the relationship between interest rates and agricultural sector credit is a unidirectional/negative relationship, which aligns with the development of this research hypothesis. A 1% increase in agricultural sector credit interest rates will result in a 0.106% decrease in agricultural sector credit. This demonstrates that the agricultural sector credit has an inelastic relationship with interest rates. The relationship between interest rate variables and credit in the agricultural sector model is consistent with previous models (1, 2, and 3). Cecilia et al. (2004) also found a significant negative relationship between the interest rate variable and agricultural sector credit.

The GDP variable has a positive and significant effect on the model. The LnGDP regression coefficient is 0.203, indicating that the relationship between LnGDP and LnTani is a unidirectional/positive relationship, which aligns with the development of the research hypothesis. A 1% increase in GDP in the agricultural sector will increase credit in the agricultural sector by 0.203%. This suggests that agricultural sector credit has an inelastic relationship with GDP. These results are consistent with the influence of GDP in Models 1, 2, and 3, and are in accordance with previous research Chen et al. [7] and Milne and Parboteeah [21] that GDP has a significant positive effect on agricultural sector credit in Indonesia.

Agricultural sector credit, which is also a priority sector credit, has expanded KUR access and optimized the network *supply* chain, such as the Food Action program in 2017, which is a collaboration between regulators, ministries, and financial services players to accelerate and increase financing in the food sector, namely agriculture, forestry, plantations, and fisheries. Through this program, 19 partner banks are targeted to be able to distribute credit amounting to IDR 260 trillion.

3.3. General Analysis

Table 10.
Summary of the Effect of P2P on Credit.

Type	Economic Sector	Coefficient	Influence	P2P on Credit
Credit	Aggregate	0.0329	Significant	Positive Correlation
	Trade	0.0263	Significant	Positive Correlation
	Processing industry	0.0299	Significant	Positive Correlation
	Agriculture	0.0371	Significant	Positive Correlation

Based on Table 10, in general, among the three sectors observed in this research, P2P loans have the greatest influence on the agricultural sector. This is indicated by the variable coefficient LnP2PVol in the agricultural sector of 0.037. This can be explained by the fact that, as of August 2019, the number of workers in the agricultural sector still dominated the workforce, accounting for 27.33%, followed by the trade sector at 18.81%, and the processing industry sector at 14.96%. Meanwhile, among the three MSME sectors observed in this research, P2P loans have the greatest influence on MSMEs in the agricultural sector. This is demonstrated by the variable coefficient LnP2PVol in the agricultural sector MSMEs of

0.058. Liao et al. [5] show that 55.33% of land-using farmers in Indonesia are smallholders with land under 500 square meters and do not possess land certificates; thus they are considered not to meet bank standards or *non-bankable*. Only 15% of farmers have access to bank credit, while 52% obtain funding from non-banks and non-programs, and 33% have credit through the PNPM program.

Apart from that, this is supported by the many P2P platforms that specialize in the agricultural sector, including Crowde, Tanifund, Vestifarm, Igrow, and Tanijoy. Crowde, which received the title as an agri-fintech startup to be reckoned with in Asia in 2020, according to Fintechnews Singapore, has distributed funds of more than IDR 100 billion to 31,831 *lenders* until 2019. Tanifund is a money lending service from Tanihub, an online shop that sells agricultural products. Tanifund has distributed IDR 126 billion with a success rate of 100%. Vestifarm has distributed funds of IDR 41 billion. Igrow is a platform with a seed purchasing system and has distributed IDR 217 billion in funds with a success rate of 96.58%. Tanijoy is *a platform* based on Sharia principles with 109 hectares of managed land and 1,820 farmers, distributing IDR 6.9 billion.

By understanding the greatest influence of P2P on the agricultural sector credit, the implication is that regulators need to provide attention and policies that support the distribution of P2P loans, especially in the agricultural sector, in order to maximize its potential. This is supported by Liao et al. [5] that the level of farmer welfare also depends on agricultural financing and national economic census data (2016), which shows that financing sources from bank credit are more prosperous for farmers compared to farmers who use non-bank and non-program credit. International Organization of Securities Commissions (IOSCO) [22] found that P2P had a positive correlation with the addition of agricultural sector workers by 1,613 people. Apart from that, P2P lending to village communities, which received the greatest benefits from P2P lending, included farmers and entrepreneurs supporting agricultural businesses. This increased farmer income by 1.29% and agricultural entrepreneurs' income by 1.34%.

The interest rate variable has the greatest influence on the agricultural sector of the three third-party credit sectors observed. This is indicated by the coefficient of the IR variable in the agricultural sector, which is -0.106. Meanwhile, for MSME credit, the interest rate variable also has the greatest influence on the agricultural sector of the three sectors observed, with a coefficient of -0.094. Research on the three sectors of third-party credit and MSME credit shows that, although interest rates have a negative effect on credit, these three sectors remain inelastic to interest rates. This may be caused by the still high dependence of the productive sector on bank credit. The research indicates that, despite the negative impact of interest rates on credit, these sectors are relatively insensitive to changes in interest rates, likely due to their ongoing reliance on bank credit.

In third-party credit, the GDP variable has the greatest influence on the processing industry sector, as indicated by the coefficient of 0.567 for the GDP variable in this sector. In accordance with the discussion regarding the reciprocal impact of GDP on credit, the government should increase credit to the processing industry sector, which can stimulate an increase in GDP, and vice versa.

Whereas *non-performing loan* only has a significant negative effect on third-party credit in the processing industry sector because non-performing loans in this sector have increased significantly since mid-2019 due to the credit of one textile company, which is currently in court for postponing its debt payment obligations, reaching IDR 22 trillion.

4. Conclusion

This research utilizes statistical monthly data from *fintech* and Indonesian banking statistics from 2017 to 2019 to estimate factors influencing credit distribution and the three main credit sectors. After conducting regression analysis and examining the results, it was concluded that:

1. The third-party credit aggregate model is positively correlated with P2P *lending* and GDP and has a negative correlation with credit interest rates. P2P *lending* is complementary to banking credit, not competitive, because of the presence of P2P *lending* expanding market share and reach of consumers who have not received banking credit, especially with collaboration between P2P and banking through sharing credit schemes distributed to consumers.
2. In general, among the three main credit sectors observed in this study, P2P loans and interest rates have the greatest influence on agricultural sector credit. This is due to employment factors, the high number of farmers who are still *non-bankable* and the development *platform* P2P, which focuses on loans in the agricultural sector.
3. GDP has the greatest influence on the processing industry sector because the contribution of the processing industry sector to GDP is the largest compared to other business fields during the research period.
4. NPLs only have a significant negative correlation in the processing industry sector. This is explained by the substantial increase in non-performing loans in this sector since mid-2019, primarily due to the credit extended to a textile company that is currently in court for postponing its debt payment obligations, which reached IDR 22 trillion.

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