How Does P2P Lending Lead to BI-Rate and Commercial Bank Income? Empirical Evidence from Indonesia

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Abstract. Technological developments have shifted the traditional financial system to digitalization by bringing joy and convenience to some parties. P2P lending comes with that excitement to debtors who do not qualify for bank lending. For this reason, this study aims to analyze the relationship of P2P lending companies to interest rates and income of commercial banks in Indonesia. Using monthly data from January 2017 to April 2022, we analyze this association with the VAR-VECM model. Through various diagnostic model tests, the regression results show that in general P2P lending companies affect interest rates, interest income, and non-interest income of commercial banks. The existence of P2P lending companies currently has a positive effect on interest rates next year. At the same time, P2P lending companies boost bank interest and non-interest income. They significantly hold down the interest and non-interest income of banks. The results record a two-way causal relationship between P2P lending companies and interest rates. The causality of P2P lending companies to non-interest income is also found, but not vice versa. This paper implies several leaps to maintain and control P2P lending risks that could potentially affect the macroeconomic and bank's financial conditions. A healthy business climate can be created when risk monitoring of P2P lending and banking can go hand in hand.

Keywords: P2P lending · interest rate · interest income · non-interest income

1 Introduction

Digital transformation has changed the system of human life in various sectors, including the financial sector [1]. Recorded in the last decade, fintech has caught the eye of researchers, not only in the fields of computer science and information systems [2] but also in economics and business sectors [3–6]. The technological paradigm is changing the traditional financial system to a digitalized system and internet. This financial digitization became known as financial technology (fintech) [7].

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With various technological facilities that cannot be obtained from traditional systems, digital financial innovations are more accepted by the general public. They offer customer-centered services and internet technology for accessibility [8]. The fintech phenomenon has also mushroomed in Indonesia after OJK (Otoritas Jasa Keuangan/Financial Services Authority) released the first licensed platform, namely Danamas. Over time, fintech lending in Indonesia grew rapidly with credit disbursement of IDR 16.40 trillion as of February 2022, an increase of 19% from the previous month [9]. In addition, Indonesia is a country with a high fintech industry development (after China) because it is used for credit penetration, especially for MSMEs and to increase financial inclusion [10]. This phenomenon seems to illustrate the enthusiasm of the Indonesian people for access to financing in fintech lending. On one side, they handle a wide range of financial services, including financing, payments, wealth management, capital markets, and insurance services [11]. On the opposite side, the existence of fintech is a threat to traditional banks' performance, especially in banks' credit income in China [3]. Banks as intermediaries play an important role in financial market shock [12], which in turn has an impact on monetary policies. One of them is using interest rates to maintain financial stability [13, 14]. For this reason, this research intends to analyze the relationship of P2P lending growth with interest rates and interest and non-interest income of commercial banks.

Theoretically, this actual phenomenon can be explained with the competition-fragility theory by Keeley [15]. This theory assumes that competition reduces market power, lowers bank performance, and encourages banks to take greater financial risks. Some recent literature also develops Keeley's [15] theory such as Kasman and Kasman [16]; Albaity et al. [17]; and Sarpong-Kumankoma et al. [18]. The existence of fintech in the loan market will create a new competitive climate and can threaten banks as credit service providers before them. Moreover, the addition of fast response facilities and few requirements allows banks to lag behind fintech lending. In the end, the bank's income decreases because they take a higher risk to catch up with their competitors.

Fintech lending or often called peer-to-peer (P2P) lending, is the practice of funding to unrelated individuals ('partners') without going through a commercial bank. P2P lending runs online with various lending platforms and uses a self-developed credit checking tool [19]. Until the end of March 2022, OJK recorded 102 registered and licensed P2P lending companies. However, from 2018 to October 2020, the Investment Alert Task Force (SWI) together with Kominfo (Ministry of Communication and Information Technology) blocked 2923 illegal fintech lending. Twenty times more than legal fintech lending platforms. According to Pohan et al. [20], this growth occurs because Indonesian P2P lending users appreciate the speed of requests that are approved as alternative financing. Although the practice of fintech lending in Indonesia has been regulated in the OJK regulation (POJK) 77/POJK.01/2016, unethical practices are like a mushroom that continues to grow. Increasingly sophisticated technology and public interest in instant loans accompanied by weak regulations have created a shadow banking practice that, if left unchecked, will increase financial risks that erode economic stability and the banking function itself [21–23]. In the recent context of Indonesia, the issue that emerged from the case of the loss of Bank Maybank customer funds amounting to Rp22 billion due to shadow banking practices became a special concern for Bank Indonesia to ensure the bank's function in monitoring money circulation.

Several recent studies have fresh discussed the role of fintech lending as alternative financing for MSMEs' development, e.g., Tambunan et al. [24]; Abbasi et al. [25]; Barkley & Schweitzer [26]; Temelkov & Samonikov [27]. However, their research did not mention the impact of fintech lending on the macroeconomy and commercial banks. In the context of Indonesia, many studies have discussed this fintech lending phenomenon. For example, Rosavina et al. [28] investigate the factors that encourage SMEs to use P2P lending platforms. They found that the loan process, interest rate, borrowing costs, loan amount, and loan flexibility were significant factors influencing SMEs to use P2P lending. Hidajat [22] highlighted the unethical practices of illegal P2P lending in Indonesia due to regulatory weaknesses. Tambunan et al. [24] and Rusadi & Benuf [29] tested the role of P2P lending on access to financing for SMEs. To the best of our knowledge, has no research that examines the causality relationship of fintech lending to interest rates and commercial banks' income.

2 Literature Review

2.1 Definition and Fintech in Indonesia

In the last decade, Fintech's success attracted the world's attention and they are growing rapidly. The effect of the existence of Fintech and its growth is becoming a global topic because of the technology they bring rather than the traditional financial system. Previously, e-commerce has succeeded in creating various startup companies such as Tokopedia, Gojek, and Alibaba. Then, Fintech emerged as a form of e-commerce efficiency. However, there is no standard definition of Fintech itself. The literature defines Fintech with various sides and scopes. For example, the World Bank defines Fintech as digitizing financial services more inclusively and efficiently.[1] More complex, Cheng & Qu [3] describes Fintech as the application of technology in banking, including artificial intelligence technology, blockchain, cloud, big data, and internet. Financial technology integrates messaging, transactions, order processing, and payment systems [30]. Kholia [31] describes Fintech as an advanced financial services innovation in technology, both in the capital market sector, blockchain, e-commerce and marketing, to banking and insurance. More specifically, Thakor [7] describes fintech as a catalyst for payment gateway innovations such as crypto, credit markets such as P2P lending, and insurance. Thus, Fintech is an efficient form of e-commerce that focuses on technology-based financial services for payments, money markets, and marketing.

In Indonesia, the first fintech platform to appear was fintech lending or P2P lending in 2016. Then microfinancing, market comparison, digital payments, and crowdfunding began to take place. In its development, P2P lending has shown extraordinary growth performance. In 2017, OJK officially announced Danamas as the first P2P lending platform to have an operating license. Data released by OJK as of January 3, 2022, recorded

[1] Quoted from the World Bank Group publication entitled Fintech and the Future of Finance, posted on 17 May 2022, accessed on 31 May 2022, https://www.worldbank.org/en/publication/fintech-and-the-future-of-finance.

103 registered and licensed fintech lenders. Until February 2022, the growth of P2P lending was rapid with credit disbursement of Rp16.40 trillion, which was an increase of 19% from the previous month (Fintech Lending Statistics for February, 2022).

2.2 Is P2P Lending a Threat?

The paradigm shift of the traditional system to digitalization by banking provides many advantages because the use of technology is intended by financial institutions for cost efficiency and achieving economies of scale with big data [7]. Especially fintech lending that offers easy and fast access to finance and money [8] to maintain customer focus [32], more specifically to those who are unbanked [33]. The reason why this gateway is so much in demand and generates a lot of fun is because it is more advanced in offering financial services than traditional banks [7]. Pohan et al. [20] make it clear that P2P lending services provide an alternative to fast credit services and users appreciate that speed. Thus, the big question arises whether the existence of P2P lending is only a new paradigm for financial services or does it have the potential to produce existential threats to banking. For this reason, empirical research needs to be carried out to answer this question. Even recently, Lee et al. [34] find that fintech lending grows more in countries with less efficient banking systems and has the potential to be a wake-up call. Banks tend to experience a decline in profitability because the growth of fintech lending creates stronger competition [35]. Bank asset quality and risk taking have deteriorated due to the development of fintech [36]. Even fintech has replaced loans from banks [37, 38].

Most of the financial literature in recent years has obtained heterogeneous results regarding the relationship between fintech and banking. The previous literature focused on exploring the opportunities and challenges of fintech for banking [39–41] and their impact on credit risk [3, 42], credit performance for SMEs [43], the negative influence of fintech companies on the bank performance [35, 44], and bank efficiency [34]. The important point that we are trying to investigate this time is that the rapid growth of P2P lending has generated excitement for borrowers, but may have affected banking income and market interest rates. Because it is known that fintech lending has succeeded in replacing traditional bank loans, while financing is closely related to the interest which is the main income of banks. Thus, it can be hypothesized as follows.

H1: P2P lending growth causes BI-rates
H2: P2P lending growth causes commercial banks' interest income
H3: P2P lending growth causes commercial banks' non-interest income.

3 Method

This study uses monthly time series data from January 2017 to April 2022. The research period was determined from January 2017 because P2P lending was first registered with the OJK, namely Danamas on February 3, 2017. The data were collected from aggregate secondary sources. For example, the growth in P2P lending is obtained from the number of fintech lending providers registered with the OJK every month during the research period. The interest rate is the monthly interest rate appointed by Bank Indonesia. Interest income and non-interest income of banks are collected from Indonesian banking statistics data from the OJK every month.

The research analysis was carried out employing the vector autoregressive (VAR) model which is popular in economic and social research for multivariate time series data analysis (e.g., 45–48]). The VAR model allows determining the causal effect between fintech lending existence, interest rates, and income of commercial banks including the mixed relationship between them. Formally, this test was introduced by Granger [49], dan Engle & Granger [50]. For example, reverse causality, whether fintech lending leads to interest rates, or vice versa. Likewise with commercial bank income, whether fintech lending leads to interest/non-interest income, or vice versa.

Second, cointegration test to evaluate long-term relationships between sets of variables in the dynamic specification framework. Furthermore, the estimation of the vector error-correction model (VECM). Using the Johansen model, the trace statistics value is compared to the critical level of 5%. Optimum lag selection is estimated by the Akaike Information Criteria (AIC) calculation. Augmented Dickey-Fuller (ADF) unit root test is performed, which is stationary if the probability is under the critical value, of 1%, 5%, or 10%. We also perform diagnostic tests to estimate the best VAR-VECM model, including the autocorrelation test (Lagrange-multiplier test) and stability test (eigenvalue stability condition).

This study estimates 6 models based on Eq. 1, where Model 1 shows the relationship between fintech lending and interest rates. Model 2 is a modification of Model 1 with involves control variables in the estimate. Model 3 shows the relationship between fintech lending and commercial bank interest income. Model 4 is Model 3 modified. Model 5 shows the relationship between fintech lending and non-interest income for commercial banks. Finally, Model 6 is a modification of Model 5 with control variables.

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X_{t-1} + \sum_{i=n}^{k} \alpha_i \Delta Y_{t-n} + \sum_{j=n}^{k} \alpha_j \Delta X_{t-n} + \sum_{z=n}^{k} \alpha_z \Delta C_{t-n} + u_t \tag{1}$$

where, Y_t represents the vector dependent variables, Y_{t-1} is lagged-1 of the dependent variable; X_{t-1} is lagged-1 of exogenous variables, n represents the amount of lag optimum, C_t represents the control variables. α_1 and α_2 are long-term coefficients, while α_i and α_j are short-term coefficients. Car, fund, bqcredit, and fqcredit variables are control variables. Car is the level of core capital adequacy of commercial banks. Fund is the distribution of funds to third parties by commercial banks in trillions. Bqcredit is the credit quality of commercial banks which is represented by the number of current loans in trillions. Lastly, fqcredit is the quality of fintech lending credit which is represented by the current loan ratio.

4 Result

4.1 Descriptive Statistics

As previously explained, the data is a time series from January 2017 to April 2022 with a total of 64 observations. A complete data description is presented in Table 1. It is

Table 1. Descriptive Statistic of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
P2P Lending	64	94.8125	53.79499	0	164
Interest Rate	64	4.542969	0.855137	3.5	6
Interest Income	64	402.0457	224.9912	61.63018	828.1974
Non-interest Income	64	195.0877	105.286	34.73684	460.0194

known that the total number of P2P lending companies registered with OJK during that period was 167. Interest rate fluctuations were seen throughout the study period, where Indonesian interest rates reached 6% at the end of 2018 until the first half of 2019 and dropped steadily to 3.5% in 2021. We noticed that interest rates were relatively high at a period when the number of P2P lending companies increased significantly. However, when the growth of P2P lending companies tends to be stable, interest rates are relatively low. In terms of banks, commercial banks' aggregate interest income reached 828 trillion in December 2019 and the lowest in January 2017 at 61 trillion. Meanwhile, the highest non-interest income in December 2021 was 460 trillion and the lowest in January 2018 was 34 trillion.

4.2 OLS Regression

We first conducted an OLS regression analysis to examine the effect of P2P lending on interest rates and bank income (see Table 2). In general, we find that interest rates and non-interest income are significant at 5% and 1%, respectively. However, these results are followed by bias problems in all three models, heterogeneity in Models 2 and 3, autocorrelation in Models 1 and 2, and an abnormal distribution in Model 1. To reduce endogeneity problems and obtain the best results, we continued the test using another approach, namely VAR model.

4.3 Unit Root Test

We check the unit root of all variables to identify whether the data is stationary or not. The term is that the ADF probability value must be higher than critical values, of 1%, 5%, or 10%. In VAR regression, stationary data is the main requisite, because VAR model specification involves lagged variables which may cause the data to be non-stationary. First of all, each variable checked the unit root at the level. If at that level the data is not stationary, then the unit root test can be continued at the first difference level. VAR estimates do not suggest stationary data in the second difference because this would be highly biased. Overall, the variables of this study are stationary at the level and first difference (see Table 3).

4.4 Optimum Lag

Because VAR involves a lagged variable in the model, the optimum lag must be known to get the best results. Optimum lag is indicated as con lowest error value. Based on the

Table 2. OLS regression results

	Model 1 (Interest Rate)			Model 2 (Interest Income)			Model 3 (Non-interest Income)		
	Coeff.	t-statistic	Prob.	Coeff.	t-statistic	Prob.	Coeff.	t-statistic	Prob.
P2P Lending	−0.004663	−2.894467	0.0053**	0.310740	0.636451	0.5269	0.836230	3.967322	0.0002*
C	5.088257	25.60061	0.0000	353.2994	5.865547	0.0000	86.84198	3.339635	0.0015
DW stat	0.039562			1.143633			1.836534		
VIF	1.000000			1.000000			1.000000		
Jarque-Bera	6.838124 (0.032743)**			3.962019 (0.137930)			0.872966 (0.646306)		
Prob. Chi-square	0.6603			0.0188**			0.0008**		
F-statistic	8.377938 (0.005316)**			0.405070 (0.526944)			15.73964(0.000199)*		
R-squared	0.124342			0.006819			0.210593		

* Significant at the 1% level
** Significant at the 5% level.

Table 3. The unit root of each research variable: ADF model

Variable	ADF - Level			ADF – First Difference		
	Z-t	Prob.	Decision	Z-t	Prob.	Decision
P2P Lending	−2.352	0.1557	Non-stationary	−6.380	0.0000	Stationary
Interest Rate	−0.172	0.9418	Non-stationary	−4.695	0.0001	Stationary
Interest Income	−4.222	0.0006	Stationary			
Non-interest Income	−3.937	0.0018	Stationary			

Table 4. Optimum lag for each estimate: AIC

Lag	Akaike Information Criteria (AIC)					
	Model 1 (Interest Rate)	Model 2 (Interest Rate + Control)	Model 3 (Interest Income)	Model 4 (Interest Income + Control)	Model 5 (Non-interest income)	Model 6 (Non-interest income + Control)
0	13.2349	20.2814	24.2468	24.9614	22.5699	23.3663
1	5.13863	7.60515	19.7747	15.3907	18.104	13.897
2	4.99012	7.47495	19.7907	15.0522	18.1054	13.5804*
3	4.90583	7.18628*	19.5538	14.8896	17.8741*	13.5923
4	4.82725*	7.37195	19.4997*	14.8306*	17.8903	13.585

* lag estimated on model

results in Table 4, shows that the optimum lags for Models 1–6 are lags 4, 3, 4, 4, 3, and 2.

4.5 Diagnostic Tests

This test is to check that the model is not autocorrelated and stable under certain time conditions. Table 5 presents the results of the Lagrange-multiplier (LM) test to detect autocorrelation. Where the probability of each estimation is more than the critical value of 5% that indicates that there is no autocorrelation. The research model is also stable in time as shown in Fig. 1, where the modulus value is not more than 1.

4.6 VAR Regression

Since the model is reported to have passed the unit root test set and the diagnostic test, VAR regression was performed to examine the effect of P2P lending on interest rates and bank income. We estimate VAR in six main models. Model 1 is the specification of the estimated interest rate dependent (bi_rate), with the control variables for Model 2. Model 3 is for the interest income dependent (interest), with the control variables for

Table 5. Autocorrelation test: LM

Lag	Chi-square Probability					
	Model 1 (Interest Rate)	Model 2 (Interest Rate + Control)	Model 3 (Interest Income)	Model 4 (Interest Income + Control)	Model 5 (Non-interest income)	Model 6 (Non-interest income + Control)
1	0.75729	0.25303	0.42911	0.34854	0.24160	0.23798
2	0.06277	0.16281	0.06003	0.45557	0.10627	0.42068

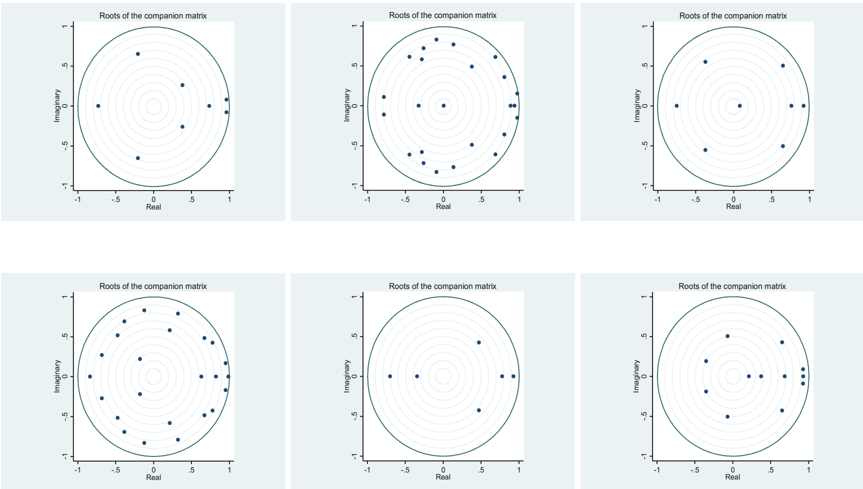

Fig. 1. Eigenvalue stability conditions for each estimation

Model 4, lastly, Model 5 is for the non-interest income dependent (non_interest) with the control variables for Model 6.

Tables 6, 7, and 8 present the results of the VAR regression for each research model. We found some evidence of these results. First, the p2p.L1 variable has a significant positive effect on interest rates (see Table 6), but its significance value decreases when the control variables are included in Model 2. These results indicate that the number of p2p lending companies in the current year has the potential to increase interest rates in the following year. However, there are differences in the effect of the p2p.L1 variable on the interest and non-interest income of commercial banks. In summary, the results report that the coefficient of the variable p2p.L1 is negative, and p2p.L2 variable is positive on commercial banks' income. p2p.L1 has a negative coefficient and is significant on commercial banks' non-interest income, but insignificant on interest income of commercial banks. After the control variables were included in Model 4, the significance of the variable p2p.L1 increased. Likewise, p2p.L2 variable becomes significant to interest

Table 6. Vector autoregressive model: Dependent of interest rate

	Model 1			Model 2		
	Coef.	z	P > |z|	Coef.	z	P > |z|
rate.L1	1.397182	11.92	0.000*	0.9706997	7.83	0.000*
rate.L2	−0.658317	−3.29	0.001*	−0.3078672	−1.75	0.079***
rate.L3	0.607439	2.99	0.003*	0.21827	1.94	0.053***
rate.L4	−0.419383	−3.52	0.000*			
p2p.L1	0.0100167	2.85	0.004*	0.0057503	1.81	0.070***
p2p.L2	−0.0071421	−1.61	0.107	−0.0029755	−0.75	0.455
p2p.L3	−0.0050178	−1.15	0.250	−0.0058272	−1.37	0.169
p2p.L4	0.0019304	0.57	0.568			
car.L1				0.0562771	1.10	0.273
car.L2				−0.0923572	−1.25	0.210
car.L3				0.0511309	0.92	0.358
fund.L1				0.6232303	1.64	0.102
fund.L2				−0.7440808	−1.76	0.078***
fund.L3				−0.1113598	−0.31	0.759
bqcredit.L1				0.0000108	0.00	0.999
bqcredit.L2				0.0151527	1.63	0.103
bqcredit.L3				−0.0059967	−0.75	0.454
fqcredit.L1				−0.8201865	−0.37	0.708
fqcredit.L2				−0.8625842	−0.32	0.748
fqcredit.L3				2.296093	1.22	0.222
C	0.3282807	2.70	0.007	0.6089159	0.33	0.742
R-square	0.9825			0.9898		
Chi-square	3373.222			4751.413		
P > Chi-square	0.0000			0.0000		

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

and non-interest income when the control variables are included in Models 4 and 6 with positive coefficient values.

We also discover that lagged interest rate variables (rate.L1, rate.L2, and rate.L3) significantly affect interest rates in different ways. We have positive coefficients on rate.L1 and rate.L3, while negative coefficients on rate.L2. We also find a lag effect in lagged dependent of the interest income (interest.L1 and interest.L4), a significant positive coefficient for interest.L1 and negative for interest.L4. Finally, the effect of the lagged

Table 7. Vector autoregressive model: Dependent of commercial banks' interest income

	Model 3			Model 4		
	Coef.	z	P > |z|	Coef.	z	P > |z|
interest.L1	0.6012754	4.71	0.000*	0.6916649	3.83	0.000*
interest.L2	−0.1353188	−0.90	0.366	−0.1516359	−0.81	0.417
interest.L3	−0.0171449	−0.12	0.907	−0.3609452	−1.70	0.089***
interest.L4	−0.2427462	−1.93	0.053***	0.252034	1.50	0.134
p2p.L1	−5.191208	−1.07	0.282	−8.166259	−1.88	0.060***
p2p.L2	8.638903	1.33	0.184	10.76702	1.85	0.065***
p2p.L3	−6.745716	−1.01	0.314	−2.912407	−0.49	0.623
p2p.L4	3.321268	0.70	0.485	1.628118	0.36	0.718
car.L1				64.89768	0.74	0.461
car.L2				−142.1101	−1.43	0.154
car.L3				193.7012	1.99	0.046**
car.L4				−148.9509	−1.83	0.067***
fund.L1				−768.378	−1.17	0.243
fund.L2				501.9889	0.75	0.451
fund.L3				673.4183	1.01	0.314
fund.L4				−709.0432	−1.20	0.229
bqcredit.L1				−18.39865	−1.88	0.060***
bqcredit.L2				−0.1134623	−0.01	0.993
bqcredit.L3				3.818517	0.28	0.777
bqcredit.L4				7.450873	0.55	0.584
fqcredit.L1				−9161.245	−2.58	0.010**
fqcredit.L2				12362.03	3.16	0.002*
fqcredit.L3				−9977.788	−2.45	0.014**
fqcredit.L4				6143.302	2.33	0.020**
C	0.6524298	0.31	0.757	3545.778	1.33	0.185
R-square		0.4124			0.7147	
Chi-square		41.41146			120.2367	
P > Chi-square		0.0000			0.0000	

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

non-interest income variable (non_interest.L1) is reported to be positive and significant. We also document the direct effect of control variables on interest rates and commercial

Table 8. Vector autoregressive model: Dependent of commercial banks' non-interest income

	Model 5			Model 6		
	Coef.	z	P > |z|	Coef.	z	P > |z|
non_interest.L1	0.5859499	4.57	0.000*	0.6295834	4.28	0.000*
non_interest.L2	−0.0764619	−0.53	0.598	−0.2346721	−1.54	0.122
non_interest.L3	−0.1322227	−1.07	0.287			
p2p.L1	−3.649302	−2.06	0.039**	−3.697778	−2.03	0.043**
p2p.L2	3.332339	1.24	0.216	3.746589	2.07	0.038**
p2p.L3	0.6706704	0.37	0.709			
car.L1				31.10704	0.93	0.351
car.L2				−38.35141	−1.11	0.267
fund.L1				−210.6571	−0.83	0.409
fund.L2				222.7365	0.85	0.394
bqcredit.L1				−7.884662	−1.64	0.100
bqcredit.L2				6.962893	1.56	0.119
fqcredit.L1				−2410.293	−1.98	0.048**
fqcredit.L2				2268.616	1.91	0.056***
C				435.2812	0.48	0.632
R-square	0.4650			0.5874		
Chi-square	52.14031			71.19515		
P > Chi-square	0.0000			0.0000		

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

bank income. Overall, only funds lagged-2 are significant to interest rates with a negative coefficient while other controls are insignificant. For the control car lagged-3 is positive and car lagged-4 is negative concerning interest income. The variable bqcredit.L1 was also found to be negative and significant to interest income. Finally, fqcredit control was reported to have varying effects on commercial bank income. Fqcredit.L1 and fqcredit.L2 have a negative and positive impact on interest income and non-interest income for commercial banks, respectively, while fqcredit.L3 and fqcredit.L4 have a negative and positive impact on interest income only.

The advantage of VAR regression is that all variables are considered endogenous, because inverse causality may occur between two variables. Although this study focuses on the impact of fintech lending on interest rates and commercial bank income, we also document an inverse causality relationship. The results are presented in Table 10, in which the p2p variable is endogenous. Overall, we find that the significance value of p2p keeps dropping as it lags behind. This means that the number of fintech lending companies has shown an increase over time. Meanwhile, interest rates and income of commercial banks also affect the growth of fintech lending. It is documented hence the negative coefficient of rate.L2 variable and non_interest.L2, as well as the positive coefficient of rate.L3 and interest.L4. In addition, we found that the variables car.L3 and fqcredit.L1 significantly caused to the development of p2p.

4.7 Long-Run Effect and Cointegration

To reduce possible endogeneity issues and strengthen our findings, VECM regression was performed for short-term relationship analysis while examining whether the models were cointegrated or not. VECM also involves "_cel" coefficient which represents the speed of adjustment of the variable back to equilibrium due to changes in each certain cointegration rank. Cointegration rank is determined with Johansen test con comparing trace statistics and its critical value. We report the cointegration rank of the six estimation models in Table 9. Sequentially, the cointegration rank for models 1–6 is 1, 1, 1, 3, 1, and 4. Thus the six models have a long-run cointegration relationship.

Table 11 is the VECM regression result for the dependent of first difference interest rate (D_rate) and differential lag of fintech lending (p2p). The results are consistent with the main finding in the VAR regression that p2p lagged-1 has a positive causality to interest rates. Models 1 and 2 also have _cel1 coefficient is negative and significant. This means that the causality relationship between both p2p and interest rate has long-term cointegration with or without the control variables. Negative causality is also shown in p2p lagged-1 to bank interest income and there is long-term cointegration because the coefficient _cel1 is negative and significant (see Table 12). However, this causality is not significant when the role of the control variables is not going down in the model. Likewise, the causality of p2p lending and non-interest income was found to be negative and there was long-term cointegration (see Table 13). In the end, the overall VECM results are the same as the main results from the VAR regression. That there is a causal relationship between fintech lending companies and interest rates and interest income of commercial banks.

To examine causality more clearly, we performed the Granger causality test. Table 14 shows that there is a causal relationship between p2p to rate, rate to p2p, and p2p to non_interest. Based on these results, it is certain that there is a two-way causal relationship between fintech lending companies and interest rates. The findings show that fintech lending companies cause non-interest income for commercial banks.

5 Discussion

Our overall empirical results show that P2P lending companies affect interest rates and commercial bank income, both interest and non-interest income. We confirm that the effect varies over time. The results of the VAR and VECM regressions provide the same information to record the relationship. By involving the lagged variables, this finding uncovers some new evidence. First, the number of P2P lending companies in the prior year affects the current interest rate differently. Its existence tends to increase interest rates. This finding can be described with market competition theory in previous

Table 9. Determination of the cointegration rank of each estimate: Johansen's test

Maximum rank	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Trace statistic	5% critical value	Trace statistic	5% critical value	Trace statistic	5% critical value	Trace statistic	5% critical value	Trace statistic	5% critical value	Trace statistic	5% critical value
0	21.3235	15.41	85.7675	68.52	31.1864	15.41	158.6034	94.15	23.4030	15.41	142.0898	94.15
1	4.1922*	3.76	51.4154*	47.21	4.5277*	3.76	109.0276	68.52	4.4988*	3.76	95.3908	68.52
2			26.5089	29.68			69.6556	47.21			63.2268	47.21
3			8.8489	15.41			34.4988*	29.68			35.8583	29.68
4			0.0203	3.76			14.1246	15.41			17.2240*	15.41
5											0.2135	3.76

* the maximum rank that applies

research, van Leuvensteijn et al. [51] explained that interest rates tend to be lower under stronger loan market competition. To be capable to exist under strong competition, funding companies may provide low-interest rates for customers. This sort of bank behavior in aggregate will affect the market interest rate. van Leuvensteijn et al. [51] also make clear in their findings that the adjustment of bank interest rates to market interest rates is faster in a more competitive loan market. Thus, competition among lending companies contributes to the transmission mechanism of monetary policy, including market interest rates. In addition, P2P lending as an alternative to loans for those who do not bank qualify [37, 38], creates a stronger competitive atmosphere. In the time series, changes in the influence of P2P lending on market interest rates have an adjustment speed of 5.43%.

Our second finding is that the existence of P2P lending companies affects the interest and non-interest income of banks. At the same time, P2P lending companies increased bank interest and non-interest income. However, in the following year, it significantly holds down the interest and non-interest income of banks. We again use the argument of van Leuvensteijn et al. [51] to stick up our findings. Banks will tend to decrease their lending rates or increase their annual interest rates when they are in strong business competition. Sequel, the bank's interest income is lower due to a higher enrollment of financial risk. Furthermore, we report that in 2 lagged years, P2P lending was found to have a positive impact on the interest and non-interest income of commercial banks. At the beginning of its emergence, online loan companies were usually affiliated with commercial banks to mobilize financial transactions. Where the bank charges handling costs for installment payments to creditors. Its fees charged can increase the bank's non-interest income. Along with their development, P2P lending created financial innovations a digital wallet with awesome marketing strategies, such as claiming discount vouchers and coins. Nevertheless, our findings strongly confirm that the effect of P2P lending leads to a tendency to decrease commercial bank income in the long term. Finally, these findings support the competition-fragility hypothesis that the existence of P2P lending in the Indonesian credit market creates a new competitive climate that can threaten commercial bank incomes.

6 Conclusion

Technological transformation has shifted the traditional financial system to a digitalized financial system. In the last decade, fintech lending or P2P lending has grown rapidly, bringing joy to debtors, especially unbanked people. Even the recent scientific literature mentions that fintech lending companies can pose a serious threat to traditional banks. However, the literature only investigates the role of fintech lending as a path substitute for the banking loan. The literature does not explain the effect of fintech lending existence on interest rates and the banking itself. For this reason, this study aims to analyze the causality of P2P lending on the interest rates and income of commercial banks in Indonesia.

In general, our findings confirm all research hypotheses that P2P lending companies affect market interest rates and commercial bank income. The effect shows a different influence. The existence of P2P lending companies currently has a positive effect on interest rates next year. The activities of lending companies (P2P lending versus banking) will create an increasingly competitive business climate. To bounce back from their defeat in technology services, traditional banks may lower lending rates or raise savings rates until interest rates are adjusted in financial markets. As a result, banks take on higher financial risks, causing the bank's interest income to decline. We also document that P2P lending companies lead to a decrease in bank income (interest and non-interest) in the long term. In addition, the two-way causality relationship between fintech lending companies and interest rates is also confirmed. Finally, the findings record that fintech lending companies determine non-interest income, but not otherwise.

Our findings imply several leaps to maintain and control P2P lending risks that could potentially affect the macroeconomic and financial conditions of banks. It would be great if the two sectors (P2P lending and banking) could go hand in hand to create a profitable business climate. In addition, this finding provides suggestions to regulators, that regulations and laws regarding full banking supervision can be socialized to P2P lending, including risk monitoring indicators. Commercial banks must also monitor and evaluate the risk of P2P lending including inspecting technology applications, developing financial systems, making emergency plans, or even cooperating with certain P2P lending platforms.

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Appendix

See Tables 10, 11, 12, 13 and 14.

Table 10. Vector autoregressive model: Dependent P2P Lending

	Model 1			Model 2		
	Coef.	z	P > |z|	Coef.	z	P > |z|
p2p.L1	0.8838043	6.94	0.000*	0.7871104	6.22	0.000*
p2p.L2	0.3859197	2.40	0.016**	0.5352714	3.38	0.001*
p2p.L3	−0.4130795	−2.61	0.009*	−0.3068602	−1.82	0.069***
p2p.L4	0.1108393	0.90	0.366			
rate. L1	5.526561	1.30	0.194	2.04886	0.41	0.678
rate.L2	−10.48084	−1.44	0.149	−11.59548	−1.66	0.097***
rate.L3	6.302484	0.86	0.392	12.39952	2.76	0.006*
rate.L4	1.824918	0.42	0.673			
interest.L1						
interest.L2						
interest.L3						
interest.L4						
non_interest.L1						
non_interest.L2						
non_interest.L3						
car.L1				3.266382	1.60	0.111
car.L2				−0.8360393	−0.28	0.776
car.L3				−3.709716	−1.68	0.094***
car.L4						
fund.L1				22.61988	1.49	0.136
fund.L2				−18.10865	−1.08	0.282
fund.L3				−3.895904	−0.27	0.788
fund.L4						
bqcredit.L1				−0.1791939	−0.53	0.594
bqcredit.L2				−0.2197374	−0.59	0.553
bqcredit.L3				−0.2480125	−0.78	0.437
bqcredit.L4						
fqcredit.L1				54.69185	0.63	0.531
fqcredit.L2				−53.67934	−0.50	0.616
fqcredit.L3				−91.63325	−1.22	0.221

(*continued*)

Table 10. (*continued*)

	Model 1			Model 2		
	Coef.	z	P > |z|	Coef.	z	P > |z|
fqcredit.L4						
C	−9.879935	−2.24	0.025	138.0904	1.87	0.061
	Model 3			Model 4		
	Coef.	z	P > |z|	Coef.	z	P > |z|
p2p.L1	0.9794655	7.73	0.000*	0.8450576	6.01	0.000*
p2p.L2	0.5055258	2.96	0.003*	0.5863958	3.11	0.002*
p2p.L3	−0.4717891	−2.68	0.007*	−0.4167327	−2.18	0.030**
p2p.L4	−0.04344	−0.35	0.728	−0.0526368	−0.36	0.718
rate. L1						
rate.L2						
rate.L3						
rate.L4						
interest.L1	0.0047536	1.42	0.156	0.007103	1.22	0.224
interest.L2	−0.0006549	−0.17	0.868	0.0008893	0.15	0.883
interest.L3	−0.0039661	−1.03	0.301	−0.007493	−1.09	0.274
interest.L4	0.0071132	2.16	0.031**	0.0110468	2.03	0.042**
non_interest.L1						
non_interest.L2						
non_interest.L3						
car.L1				4.561727	1.60	0.109
car.L2				−3.036642	−0.94	0.346
car.L3				−6.048434	−1.92	0.054***
car.L4				−0.5940974	−0.23	0.821
fund.L1				15.04586	0.71	0.480
fund.L2				−10.12268	−0.47	0.639
fund.L3				−0.8365042	−0.04	0.969
fund.L4				11.5738	0.61	0.543
bqcredit.L1				−0.1721213	−0.54	0.587
bqcredit.L2				0.1086735	0.26	0.791
bqcredit.L3				−0.0942411	−0.22	0.829
bqcredit.L4				−0.4594214	−1.04	0.297

(*continued*)

Table 10. (*continued*)

	Model 3			Model 4		
	Coef.	z	P > |z|	Coef.	z	P > |z|
fqcredit.L1				203.1491	1.77	0.076***
fqcredit.L2				−13.46109	−0.11	0.915
fqcredit.L3				−78.85759	−0.60	0.550
fqcredit.L4				−98.65299	−1.16	0.246
C	.6524298	0.31	0.757	60.47509	0.70	0.484
	Model 5			Model 6		
	Coef.	z	P > |z|	Coef.	z	P > |z|
p2p.L1	1.017617	9.34	0.000*	1.014012	7.02	0.000*
p2p.L2	0.4934288	2.97	0.003*	−0.0213504	−0.15	0.881
p2p.L3	−0.541093	−4.88	0.000*			
p2p.L4						
rate. L1						
rate.L2						
rate.L3						
rate.L4						
interest.L1						
interest.L2						
interest.L3						
interest.L4						
non_interest.L1	0.0068869	0.87	0.383	−0.0137973	−1.19	0.235
non_interest.L2	−0.0025615	−0.29	0.774	0.020722	1.73	0.085***
non_interest.L3	0.0013017	0.17	0.865			
car.L1				−0.3933415	−0.15	0.881
car.L2				−2.49793	−0.91	0.361
car.L3						
car.L4						
fund.L1				32.19469	1.60	0.110
fund.L2				−31.22544	−1.51	0.131
fund.L3						
fund.L4						
bqcredit.L1				−0.4834795	−1.28	0.202

(*continued*)

Table 10. (*continued*)

	Model 5			Model 6		
	Coef.	z	P > |z|	Coef.	z	P > |z|
bqcredit.L2				.0800787	0.23	0.821
bqcredit.L3						
bqcredit.L4						
fqcredit.L1				−31.46698	−0.33	0.744
fqcredit.L2				−32.45408	−0.35	0.729
fqcredit.L3						
fqcredit.L4						
C	2.511451	1.40	0.162	148.5912	2.07	0.039

Note(s): * significant at the 1% level; ** significant at the 5% level; *** significant at the 10% level

Table 11. Vector error-correction model: Dependent first difference interest rate (D_rate)

	Model 1			Model 2		
	Coef.	z	P > |z|	Coef.	z	P > |z|
rate.LD1	0.5082272	4.12	0.000*	0.1470412	0.96	0.338
rate.LD2	−0.1804028	−1.31	0.190	−0.2709259	−1.86	0.063***
rate.LD3	0.4390287	3.35	0.001*			
p2p.LD1	0.0104524	2.77	0.006*	0.0068277	1.97	0.049**
p2p.LD2	0.0023118	0.66	0.508	0.0037557	1.03	0.302
p2p.LD3	−0.0031222	−0.85	0.393			
car.LD1				−0.0352316	−0.52	0.601
car.LD2				−0.0918751	−1.37	0.171
fund.LD1				0.6383486	1.52	0.129
fund.LD2				0.137597	0.33	0.739
bqcredit.LD1				−0.0122244	−1.40	0.162
bqcredit.LD2				−0.0010019	−0.11	0.915
fqcredit.LD1				−3.433533	−1.40	0.160
fqcredit.LD2				−1.524234	−0.69	0.493
C	0.000565	0.03	0.976	0.1696133	2.65	0.008*
_ce11	−0.0543381	−1.92	0.055**	−0.0515834	−3.75	0.000*
R-square	0.4109			0.5425		

(*continued*)

Table 11. (*continued*)

	Model 1			Model 2		
	Coef.	z	P > |z|	Coef.	z	P > |z|
Chi-square	36.27111			41.50608		
P > Chi-square	0.0000			0.0001		

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

Table 12. Vector error-correction model: Dependent of first difference interest income (D_interest)

	Model 3			Model 4		
	Coef.	z	P > |z|	Coef.	z	P > |z|
interest.LD1	0.3952371	2.52	0.012**	0.3690522	1.74	0.082***
interest.LD2	0.2580795	1.75	0.080***	0.2088769	1.08	0.279
interest.LD3	0.2429654	1.78	0.075***	−0.3135449	−1.53	0.125
p2p.LD1	−4.397452	−0.87	0.387	−10.67159	−1.77	0.076***
p2p.LD2	4.21675	0.96	0.336	2.528713	0.50	0.618
p2p.LD3	−3.392437	−0.65	0.513	−1.331639	−0.21	0.830
car.LD1				141.6064	1.12	0.264
car.LD2				−41.82367	−0.35	0.726
car.LD3				134.6958	1.17	0.243
fund.LD1				−108.2632	−0.12	0.907
fund.LD2				156.5906	0.17	0.862
fund.LD3				754.9105	0.92	0.357
bqcredit.LD1				−2.183663	−0.14	0.887
bqcredit.LD2				−1.063639	−0.06	0.951
bqcredit.LD3				5.353785	0.32	0.749
fqcredit.LD1				−6725.586	−1.60	0.109
fqcredit.LD2				5781.537	1.30	0.194
fqcredit.LD3				−6988.698	−2.16	0.030**
C	0.0059874	0.00	1.000	−0.0001372	−0.00	1.000
_cel1	−0.7798705	−4.50	0.000*	−0.5913302	−3.10	0.002*
_cel2				4.356429	2.11	0.035**

(*continued*)

Table 12. (*continued*)

	Model 3			Model 4		
	Coef.	z	P > |z|	Coef.	z	P > |z|
_cel3				17.10017	0.34	0.737
R-square	0.3476			0.6647		
Chi-square	27.1778			49.56345		
P > Chi-square	0.0007			0.0007		

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

Table 13. Vector error-correction model: Dependent of first difference non-interest income (D_non_interest)

	Model 5			Model 6		
	Coef.	z	P > |z|	Coef.	z	P > |z|
non_interest.LD1	0.2124499	1.54	0.124	0.2274336	1.33	0.183
non_interest.LD2	0.1352763	1.03	0.302			
p2p.LD1	−3.843121	−2.14	0.032**	−4.003157	−1.95	0.052***
p2p.LD2	−0.5399393	−0.29	0.774			
car.LD1				19.31386	0.54	0.592
fund.LD1				−309.08	−1.07	0.283
bqcredit.LD1				−6.72031	−1.29	0.196
fqcredit.LD1				−2712.644	−2.28	0.023**
C	0.0050823	0.00	1.000	0.0001219	0.00	1.000
_cel1	−0.6243755	−4.33	0.000*	−0.5514356	−3.94	0.000*
_cel2				−0.1811814	−0.26	0.798
_cel3				3.274862	0.22	0.829
_cel4				−23.68483	−0.57	0.568
R-square	0.3202			0.4907		
Chi-square	25.42944			36.61535		
P > Chi-square	0.0003			0.0001		

* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

Table 14. Granger causality test

Equation	Excluded	Null Hypothesis	Chi-square	Prob > Chi-square
rate	p2p	p2p does not cause rate	11.45	0.022
interest	p2p	p2p does not cause interest	3.8249	0.430
non_interest	p2p	p2p does not cause non_interest	9.8946	0.019
p2p	rate	rate does not cause p2p	12.788	0.012
p2p	interest	interest does not cause p2p	5.8124	0.214
p2p	non_interest	non_interest does not cause p2p	0.84191	0.839

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