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# Forecasting Analysis of the Development of Fintech Lending Financial Performance in Indonesia

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**Research article**

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**Abstract:** Fintech lending is one of the digital financial innovations that is currently popular in Indonesia. The unbankable community benefits greatly from the existence of Fintech lending, and has the potential to bring change to the financial industry. However, in the relatively new journey of fintech lending, the industry is experiencing obstacles such as compliance problems with loan repayments by borrowers and security problems. The presence of fintech lending is considered capable of contributing to financial inclusion which can provide a great opportunity for the public to more easily obtain capital loans, for example, and will indirectly affect the country's economic growth. The purpose of this research is to examine fintech lending financial performance in Indonesia. This research predicts the development of fintech lending financial performance in Indonesia using the ARIMA method.
The predicted financial performance variable is TWP90 which is a measure of the level of default or negligence in completing obligations stated in the agreement above 90 days from the due date. This research takes monthly TWP90 data from January 2018 to May 2023 and forecasts data for the next 12 months, until May 2024. The best ARIMA model for forecasting TWP90 fintech lending financial performance data is ARIMA (0,1,1). Forecasting results show that the financial performance of TWP 90 fintech lending over the next 12 months will experience an increasing trend but is still below the alert limit set by the OJK.

**Keywords:** financial; technology; fintech lending; financial performance.

## 1. Introduction

Current technological developments have made major changes in various sectors of life, including the financial services sector. One of the changes that have occurred in the financial services sector is the presence of financial technology, a digital financial innovation, which now provides various financial service facilities to the public. The ease of financial services offered includes flexibility in conducting financial transactions, accelerating the acquisition of capital loans, providing capital loans as an investment alternative, and so on. Digital innovation and technology-based business models can provide new business opportunities by changing the way they create value and offer products and services (Navaretti et al., n.d.). Digital financial innovation has changed the way people make transactions and obtain loans. In the past, people had to go to the bank, but now with easy access via smartphones and the presence of financial technology, this process is even easier.

There are many types of digital financial innovations currently available on the market such as digital banking, mobile payments, wealth management, cryptocurrencies, crowdfunding, peer-to-peer lending or fintech lending, and so on. This type of peer-to-peer

lending or fintech lending is a form of digital financial innovation that is popular in Indonesian society. Fintech lending provides a platform that directly connects lenders or investors with borrowers. Over the last decade, the emergence of fintech lending has disrupted the traditional financial industry by providing alternative digital services that allow people to have more access to get loans in a convenient and efficient way.

The development of fintech lending in Indonesia has not always experienced an upward trend in recent years. Based on statistical data from the Financial Services Authority (OJK) as an independent institution tasked with overseeing the financial services industry in Indonesia, as of January 2023 there were 102 fintech lending providers consisting of 95 conventional providers and 7 sharia-based providers. This figure decreased from the previous year, 103 fintech lending institutions. Even when compared to 2019, there are now fewer than 50 fintech lending providers registered with OJK, whereas in 2019 there were a total of 164 providers consisting of 152 conventional and 12 sharia. In addition, at its infancy, fintech lending faces many problems such as bad credit problems and data security which has made this industry a negative image in society even though it has many benefits.

Fintech lending provides great benefits to the community, especially for those who fall into the unbankable category, namely those who find it difficult to get access to traditional financial services either because they do not meet the requirements or because they are in an area that has not been touched by access to banking services. Fintech lending can even provide interest rates that can compete with traditional banking services plus the use of technology that can cut operational costs such as building maintenance costs and unnecessary employee salary costs. Asosiasi Fintech Pendanaan Bersama Indonesia (AFPI) agrees that legal fintech lending can only impose a maximum interest rate of 0.8% per day (Asosiasi Fintech Pendanaan Bersama Indonesia (AFPI), n.d.). The presence of fintech lending in Indonesia, a country with a large population and still has many remote areas, opens opportunities for many people to get access to financial services that they could not enjoy before.

The existence of fintech lending is considered to be able to accelerate financial inclusion in Indonesia so that it contributes to the country's economy. The development of fintech lending in Indonesia can be reflected in the total assets owned. Based on data from the OJK, in April 2023 total fintech lending assets in Indonesia reached IDR 6.4 trillion, this figure shows a positive increase compared to fintech lending assets at the end of 2022 which amounted to IDR 5.5 trillion. The total disbursement of fintech lending loans in May 2023 reached IDR 19.623 trillion, an increase of 13.4% from the total disbursement of loans in April, namely IDR 17.299 trillion. Unfortunately, the increase in the number of loan disbursements is in line with the large number of bad credit experienced by this industry. In May 2023, total outstanding loans rose by more than IDR 900 billion within one month to reach IDR 51.462 trillion from IDR 50.531 trillion in April.

Research on fintech lending in Indonesia has not been carried out much considering the age of this industry which is still young. Most research on fintech lending looks at the regulatory and consumer protection perspectives, as was done by Atikah, 2020; Disemadi et al., 2020; and Noor et al., 2022. Other research looks at how fintech lending influences Indonesia's economic growth, which results that fintech lending growth encourages Indonesia's economic growth (Maulana et al., 2022; Maulana & Wiharno, 2022; Wajuba et al., 2021). Therefore, this study tries to predict the financial performance of fintech lending in the next 12 months based on the level of negligence in completing obligations above 90 days by debtors variable. The results of this research are useful for fintech lending stakeholders in making decisions. This research can provide a predictive picture of the financial performance of the financial technology industry, especially fintech lending in Indonesia. This research contributes to efforts to accelerate financial inclusion in Indonesia by providing information

related to the development of the financial technology industry.

## 2. Literature Review

### 2.1. Financial Technology

Fintech is a product of the evolution of financial services in line with the development of increasingly sophisticated technology. Fintech was born from a marriage between financial services and information technology (Arner et al., n.d.), namely the use of technology to provide financial solutions. Fintech as a cross-disciplinary subject that combines finance, technology management, and innovation management (Leong, 2018). In other words, any innovation that can optimize the process of financial services by utilizing technology according to different business situations can be referred to as fintech. This innovative idea can also lead to new business models or even new businesses (Leong, 2018).

Fintech changes the business model from conventional to moderate (Bank Indonesia, 2018). The emergence of fintech has dramatically changed the way financial services are provided (Agarwal & Zhang, 2020). If in the past you had to meet face to face and carry some cash, now you can make transactions remotely by making payments that can be made in seconds. This change in business model is the result of a combination of financial services and technology. The Financial Services Authority (OJK) describes fintech as an innovation in the financial services industry that utilizes the use of technology. Generally, fintech products are in the form of systems designed to carry out certain financial transaction mechanisms. Fintech transactions include payments, lending and borrowing, digital banking, capital market, insurance (insurtech), supporting fintech services; and other digital financial innovations.

In terms of payment systems, fintech has several roles (Bank Indonesia, 2018), including:

- Providing a market for business actors
- Become a tool for payment, settlement, and clearing
- Helping the execution of investments more efficiently
- Risk mitigation from conventional payment systems
- Helping those in need to save, borrow funds and invest capital

With this role, the role of formal financial institutions such as banks can be replaced by fintech. Furthermore, the presence of fintech also provides many advantages (Bank Indonesia, 2018) such as:

1. For consumers, fintech provides benefits:
   - Get better service
   - More choices
   - Lower prices
2. For fintech players (product or service traders), fintech provides benefits:
   - Simplify the transaction chain
   - Reducing operational costs and capital costs.
   - Freezing the flow of information
3. For a country, fintech provides benefits;
   - Encouraging the transmission of economic policies
   - Increasing the speed of circulation of money thereby increasing the community's economy
   - In Indonesia, fintech has contributed to the National Financial Inclusion Strategy (SKNI)

Fintech refers to the application of new technologies in providing financial solutions to individuals and companies (Imerman & Fabozzi, 2020). According to the OJK, there are several types of fintech that are currently developing and providing financial alternatives for the

people of Indonesia, including: Crowdfunding, Microfinancing, P2P Lending Service/ Fintech Lending, Market Comparison, Digital Payment System.

### 2.2. Fintech Lending

Fintech lending is one of the most popular breakthroughs in the use of technology in the financial sector in Indonesian society. Fintech Lending, also known as Fintech Peer-to-Peer Lending or Information Technology-Based Lending and Borrowing Services (LPMUBTI), is one of the innovations in the financial sector by utilizing technology that enables lenders and borrowers to make transactions without having to meet in person (Otoritas Jasa Keuangan (OJK), n.d.). Lending and borrowing transactions are carried out through a system or platform provided by Fintech Lending providers through applications or websites and can be accessed online. Simply put, this type of fintech is fintech for borrowing money. Fintech lending is beneficial for people who need access to finance to meet various needs and allows consumers to borrow money more easily without having to go through complicated procedures as are usually encountered in traditional banks. Similar to traditional banks, the existence of fintech lending also generates real economic benefits (Balyuk et al., 2022).

Indonesia has a unique fintech lending ecosystem (PwC, 2019). In 2018, at least 70% of fintech lending users came from the "credit invisible" category, which are individuals or MSMEs that previously did not have access to credit. Fintech lending expands access to credit, potentially reduce discrimination in financial services, and encourages innovation in the financial services sector (Bruckner, 2018). PwC further stated that there is still a huge opportunity for fintech lending in Indonesia to expand and increase much-needed access to credit.

This research is needed to add insight into fintech lending so that it can contribute to accelerating financial inclusion in Indonesia and improving people's welfare. Fintech development has a strong and positive relationship with financial inclusion (Lyons et al., 2022).

### 2.3. TWP90

The financial services authority (OJK) classifies the level of completion of loan obligations by fintech lending providers into two, which are: 90-day payment success rate (TKB 90) and 90-day default rate (TWP 90). TWP90 reflects the financial performance of fintech lending as seen from the level of default or negligence in completing obligations stated in the agreement above 90 days from the due date. In other words, TWP90 is financing that is not paid by fintech lending debtors for more than 90 days from the due date. OJK calculates TWP90 from 100% minus the TKB90 value.

## 3. Research Methods

This study uses a descriptive analysis method with a quantitative approach, where the data and information obtained provide an overview of the research results and will be presented in a descriptive form. Descriptive research is a type of research that aims to provide an overview, explanation, and validation of a phenomenon being studied (Muhammad Ramdhan, 2021). Descriptive research describes the research results in detail and identifies the phenomena studied. The data used in this research is secondary data. This study takes monthly data from January 2018 to May 2023 or as many as 65 historical data points, and forecasts the data for the next 12 months, until May 2024. The data taken is the TWP90 financial performance variable from the fintech statistical reports on the Financial Services Authority (OJK) website.

This research conducts a forecasting analysis using the Box Jenkins method to see the development of fintech lending's financial performance in the coming period. The Box Jenkins method, commonly known as the Autoregressive Integrated Moving Average (ARIMA) model, is a time series forecasting method. This method uses the dependent variable, which is the past data, and ignores the independent variable (Aksan & Nurfadilah, 2020). The Autoregressive Integrated Moving Average process is generally denoted by ARIMA (p,d,q) where p indicates the ordo or degree of Autoregressive (AR), d is the level of the differencing process, and q indicates the ordo or degree of the Moving Average (MA). The accuracy of the ARIMA model is very good for non-stationary time series data at linear times and for short-term forecasting (Nofiyanto et al., 2015). In the ARIMA model, an iterative method is used to find the best model. The procedure used in the formation of the ARIMA model consists of four stages, they are the model identification stage, the model estimation stage, the diagnostic check stage, and finally the forecasting stage.

The first step in data analysis using the Box Jenkins method is model identification. Model identification begins with a data stationarity test to see whether the data is stationary or not through the ADF test. Data that has been stationary then the process can be continued to identify a temporary model. However, if the data is not stationary at the level, then the ADF test is performed at the 1st difference, and so on. This process will determine the value of d in the model. The next step is to define a temporary ARIMA model (p,d,q). For data that is stationary at the level, the value of d is 0, while for data that is stationary at the 1st difference, the value of d is 1. Then, in determining the order of p,q, it can be seen by using a correlogram and observing the patterns of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF plot is used to read moving average (q) values while the PACF plot is used to read autoreggressive values ( Aksan & Nurfadilah, 2020).

After obtaining the values of p, d, and q, the estimation of the parameters of the temporary ARIMA model is carried out. Then a diagnostic check is carried out to see if the model is good for forecasting. The best ARIMA model obtained is then used to process data forecasting for the next 12 months.

## 4. Results and Discussion

Forecasting TWP 90 fintech lending uses the Box Jenkins method or the ARIMA method. The application of this method is because it can be applied to all data patterns including non-stationary data (Aksan & Nurfadilah, 2020). The first step taken was to test the stationarity of the data. The ADF test results at level and 1st difference can be seen in the following table:

**Table 1** Augmented Dickey-Fuller (ADF) Stationarity Test Results

| | **at Level** | **at 1st Difference** |
|---|---|---|
| t-Statistic | -2.708023 | -4.642885 |
| Prob.* | 0.0783 | 0.0003 |
| Conclusion | Not Stationary | Stationary |

It can be seen in table 1 above, the ADF test results at level produce a prob value of 0.0783 where this value is more than 0.05 which indicates that the data is not stationary at level. In order for the data to be stationary, it is necessary to carry out a difference process when testing the ADF on the data. The results of the ADF test at the 1st difference show a probability value of 0.0003, where this value is less than 0.05, which indicates that the data is stationary at the 1st difference and is cyan for the next stage. If the data is stationary after the difference process

is carried out once, the d value in the model is 1.
Determination of the ARIMA model (p,d,q) uses three important parameters, namely p is the value of the autoregressive ordo, d is the differential, and q is the value of the moving average ordo (Yang et al., 2016). The determination of the ARIMA model (p,d,q) is done tentatively or by trial and error to get the best model. Determination of the value of the ordo AR(p) and MA(q) by observing the PACF and ACF plots. Following are the results of the correlogram of the data on the 1st difference:

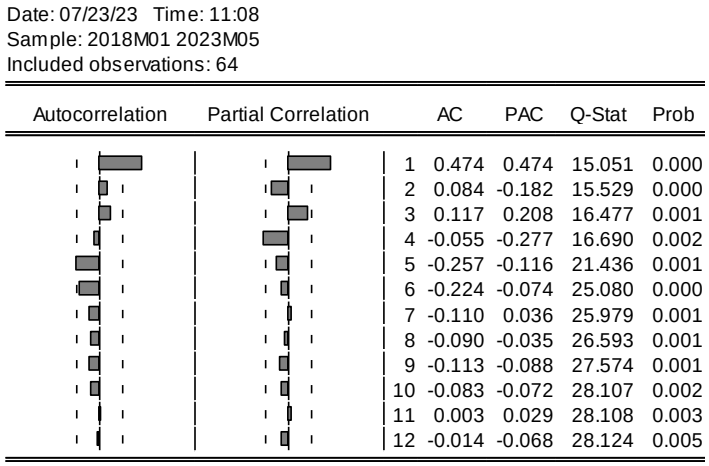


**Figure 1.** Correlogram results at 1st difference

Figure 1 shows the autocorrelation and partial correlation plots, both of which experience drastic changes beyond the dotted line at the first lag, so it can be assumed that the q and p values are 1. Apart from that, the autocorrelation plot also appears to slightly exceed the dotted line at the 5th lag. shows the order MA (q) 5 and the partial correlation plot is seen beyond the dotted line at the 4th lag which shows the order AR (p) 4. If you look at the autocorrelation and partial correlation plots, both of them have drastically changed past the dotted line at the lag First, the results of the identification of the estimated temporary model are ARIMA (1,1,1). Next, this research compares the model estimates with several model combinations using the values p=0, q=0, p=1, q=1, p=4, q=5, and d=1 to get the best model. The following is a comparison of the estimation results from several models formed:

**Table 2.** Comparison of ARIMA Model Estimation Results (p,d,q)

| Model (p,d,q) | Prob | Prob F Statistic | R-squared | Adjusted R-squared | Akaike info criterion (AIC) | Schwarz criterion (SC) | Hannan-Quinn criter. (HQC) |
|---|---|---|---|---|---|---|---|
| 1,1,0 | AR (1): 0.0000 | 0.000364 | 0,228672 | 0,203382 | 1,891415 | 1,992612 | 1,931281 |
| 1,1,1 | AR (1): 0.8518<br>MA (1): 0.0005 | 0.000042 | 0,315446 | 0,281218 | 1,809557 | 1,944487 | 1,862713 |
| 0,1,1 | MA (1): 0.0000 | 0.000010 | 0,315015 | 0,292557 | 1,778769 | 1,879967 | 1,818636 |
| 0,1,5 | MA (5): 0.0025 | 0.048531 | 0,094437 | 0,064747 | 2,057352 | 2,158550 | 2,097219 |
| 1,1,5 | AR (1): 0.0000<br>MA (5): 0.0311 | 0.000152 | 0,284275 | 0,248489 | 1,853902 | 1,988832 | 1,907058 |
| 4,1,5 | AR (4): 0.7866<br>MA (5): 0.0035 | 0.104332 | 0,096735 | 0,051572 | 2,086836 | 2,221766 | 2,139991 |
| 4,1,1 | AR (4): 0.9008 | 0.000042 | 0,315234 | 0,280995 | 1,809704 | 1,944634 | 1,862859 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | MA (1): 0.0000 | | | | | | |
| 4,1,0 | AR (4): 0.7186 | 0.909799 | 0,003095 | -0,02959 | 2,144133 | 2,245330 | 2,184000 |

The estimation stage is basically the stage of choosing which model is the best. Selection of the best model by looking at the significance of the ARIMA model and choosing among the various estimation models that have been carried out. Selection of the best model can be seen from the smallest AIC, SC, and HQC values, partial and simultaneous significance, and which model has the highest R-Squared (Afridar & Andriani, 2022). From the estimation results above, it can be seen that the smallest AIC, SC and HQC values belong to the ARIMA model (0,1,1). The ARIMA model (0,1,1) has a significant MA probability value, and a significant F-statistic probability. The largest R-squared value is owned by the ARIMA model (1,1,1), but the AR probability of this Arima model is not significant. Furthermore, the ARIMA (0,1,1) model also has the largest Adjusted R-squared value so the best model to use in this research is ARIMA (0,1,1).

The next stage is diagnostics to see whether the model can optimally produce predictions. The ARIMA model must meet the residual white noise assumptions and be normally distributed to be able to produce optimal forecasts (Cynthia et al., 2016). The selected model meets the residual white noise assumption where the residual diagnostic results show a prob value of more than 0.05. Furthermore, the model is also normally distributed where the Jarque-Bera value is more than 0.05. The following are the results of the residual diagnostic and normality test:

Date: 07/23/23 Time: 14:39
Sample: 2018M01 2023M05
Included observations: 64
Q-statistic probabilities adjusted for 1 ARMA term

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.007 | -0.007 | 0.0035 | |
| | | 2 | 0.034 | 0.034 | 0.0823 | 0.774 |
| | | 3 | 0.110 | 0.111 | 0.9247 | 0.630 |
| | | 4 | -0.020 | -0.019 | 0.9522 | 0.813 |
| | | 5 | -0.189 | -0.200 | 3.5087 | 0.477 |
| | | 6 | -0.121 | -0.143 | 4.5706 | 0.470 |
| | | 7 | -0.023 | -0.008 | 4.6089 | 0.595 |
| | | 8 | -0.072 | -0.015 | 4.9968 | 0.660 |
| | | 9 | -0.022 | 0.002 | 5.0352 | 0.754 |
| | | 10 | -0.113 | -0.160 | 6.0417 | 0.736 |
| | | 11 | 0.095 | 0.049 | 6.7550 | 0.748 |
| | | 12 | -0.083 | -0.096 | 7.3203 | 0.773 |

**Figure 2.** Residual Diagnostic- Correlogram Q-Stat

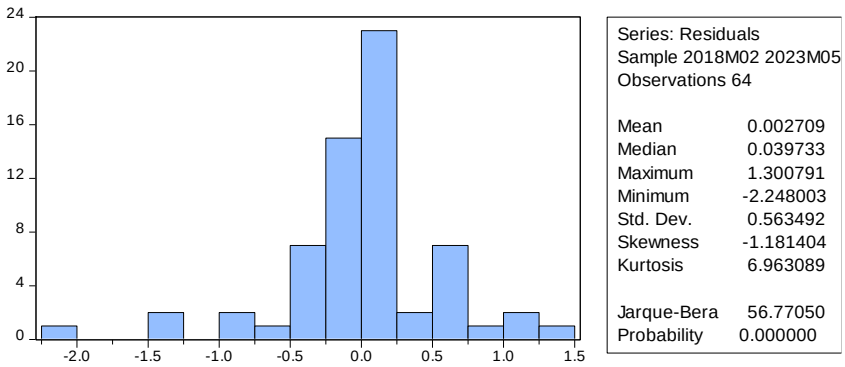


**Figure 3.** Histogram- Normality Test

Diagnostic tests are also carried out by looking at the position of the MA roots which must be

in the unit circle. The following are the ARMA Structure diagnostic results on the selected model which appear to be in a circle:

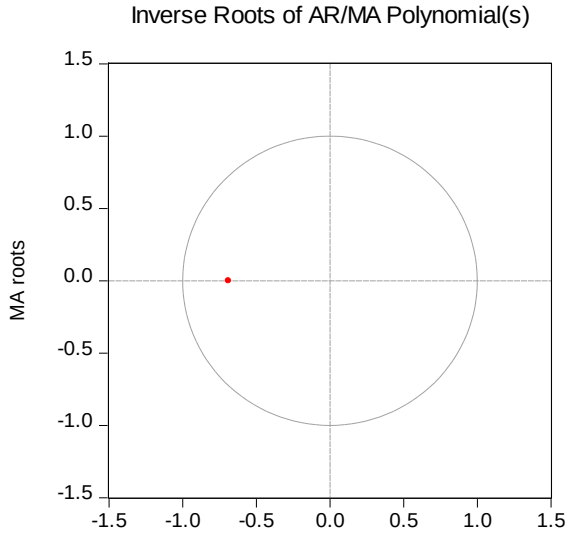


**Figure 4.** ARMA Structure Roots Diagnostic Results

The next process is using the best ARIMA model (0,1,1) to forecast TWP 90 variable. The following are the results of forecasting TWP 90 on the ARIMA model (0,1,1) for the period June 2023 to May 2024:

**Table 3** Forecasting Result

| Period | TWP 90 (%) |
|---|---|
| May-23 (actual) | 3,36 |
| Jun-23 | 3,81 |
| Jul-23 | 3,84 |
| Aug-23 | 3,88 |
| Sep-23 | 3,91 |
| Oct-23 | 3,95 |
| Nov-23 | 3,98 |
| Dec-23 | 4,02 |
| Jan-24 | 4,05 |
| Feb-24 | 4,09 |
| Mar-24 | 4,12 |
| Apr-24 | 4,16 |
| May-24 | 4,19 |

In table 3 above, you can see the prediction results for the performance of TWP 90 fintech lending in Indonesia over the next 12 months, experiencing an increasing trend. In June 2023, TWP 90 performance is estimated to increase by 0.45%, which from the actual percentage of 3.36% to 3.81%. Furthermore, from July 2023 to May 2024 the percentage of TWP 90 is estimated to increase by 0.03% each month. The estimated increase in the TWP90 percentage in the next 12 months is considered to be still within reasonable limits compared to when the Covid-19 pandemic occurred, which reached 8.88% in August 2020. The actual and forecasted TWP 90 percentage can be seen in the following graph:

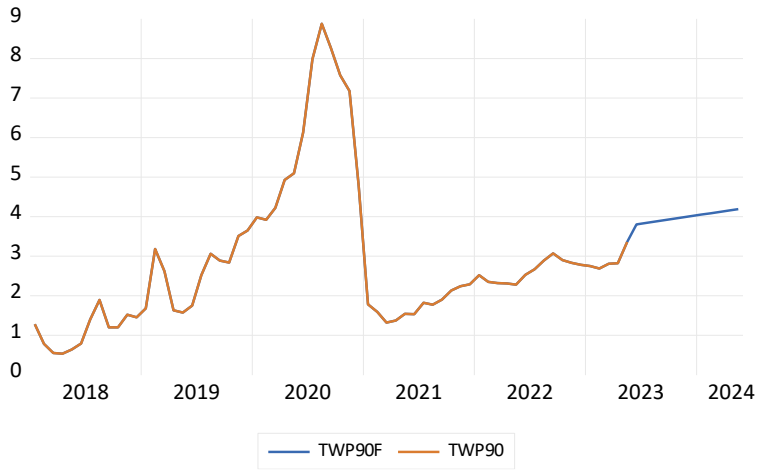


**Figure 5.** Actual and Forecast TWP90 Percentage Graph

Financial Services Authority (OJK) determines the alert number limit as a reference used for monitoring TWP 90 is 5% (OJK, 2023). The forecasting results of this research show that the percentage of TWP90 fintech lending providers from June 2023 to May 2024 does not exceed the OJK alert limit with a constant increase of 0.03% every month. This means that until May 2024, the level of default in completing obligations over 90 days by fintech lending users will remain below the reasonable limit determined by the OJK. However, predictions of a continued increase provide less positive indications, and it is possible that this percentage will continue to rise in the following months. Fintech lending industry players are expected to continue to strengthen risk management to anticipate the predicted increase in the level of bad loans.

The increase in TWP 90 or default rate is in line with the growth of fintech lending loans reaching 5.35% yoy as of May 2023, which amounted to 19.6 trillion Rupiah with total non-performing loans more than 90 days reaching 1.7 trillion Rupiah, an increase of more than 800 billion Rupiah or 88% yoy from May 2022, amounting to 917.41 billion Rupiah. This increase in loans through fintech lending reflects that the intermediation function is working well to meet people's needs for easy and fast financial access compared to banking. The results of this research can be used as a note for fintech lending providers and regulators to continue to evaluate the financial performance of fintech lending, especially TWP 90, so that it remains below the alert limit and even reaches 0%, which means there are no bad loans by debtors.

## 5. Conclusion

Forecasting the financial performance of TWP 90 fintech lending in Indonesia using the Auto-Regressive Integrated Moving Average method to get optimal results using the ARIMA model (0,1,1). Based on forecasting results, the financial performance of TWP 90 fintech lending is predicted to experience an upward trend over the next 12 months with a constant increase of 0.03% each month. The projected increase in the TWP 90 percentage in the next 12 months is still within the alert limit set by the OJK, 5%. However, predictions of a continued increase provide less positive indications, and it is possible that this percentage will continue to rise in the following months. Therefore, it is hoped that fintech lending providers can continue to strengthen risk management to anticipate the predicted increase in the level of bad loans.

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