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How Does Optimize Peer to Peer Lending Investment

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Abstract

This research uses general data about loans in 5 Credit Grades A, B, C, D and E which can be obtained from the KoinWorks P2PL factsheet platform. The research results show that there are 4 combinations of funding assets in the calculation of the optimal portfolio of the Markowitz Model with the lowest risk preferences consisting of funding assets in Credit Grades A, B, D and E with an expected portfolio return of 24.29% for the year and 2.02. % for monthly and the best risk level in a year of 1.39% for annual and 0.11% for monthly. Meanwhile, in the optimal portfolio planning of the Markowitz model with sharpe ratio, there are 3 combinations of funding assets consisting of Credit Grades A, B and D which obtain an expected portfolio return of 18.29% in the current year and 1.52% in that month. and the level of risk. best in a year of 1.39% for this year and 0.48% for this month, and portfolio performance of 13.1.

Keywords: peer to peer lending, portfolio, Markowitz model, sharp ratio

Introduction

The development of information technology means that the financial industry must be ready to change and transform (Omarini, 2017). Now information technology has entered the era of financial industrial revolution 4.0. This era is increasingly embedded in changing people's lifestyles in Indonesia, changes in consumption patterns and people's desires for something easy and fast (Muljani & Ellitan, 2019). The change in behavioral patterns in the financial sector has been followed by the proliferation of financial technology (fintech) for both payments and funding or better known as peer-to-peer lending (P2PL). Along with advances in information technology, it is not balanced with the public's understanding of investing in peer to peer lending fintech platforms (Setiawan et al., 2020).

The lack of knowledge regarding investment instruments, especially those related to the capital market, is the factor that most influences the low investment interest of the Indonesian people (Prayudha & Kuswanto, 2019). Regarding the importance of investment and the types of investment instruments available in making it easier for people to choose suitable investments, both in terms of profits and risks, therefore the public needs to receive basic education about investing. These transactions are mostly carried out by specialized platforms, where financial institutions only serve as intermediaries (Havrylchyk & Verdier, 2018). P2PL lending platforms create a new market environment for borrowers and investors (lenders). Borrowers generally explain

their reasons and objectives for applying for a loan and include various information about their financial status (income, credit history, home ownership, debt, etc.)

On the other hand, a low rate of return on people's deposits and savings can change overall investment behavior (Dolan et al., 2012). This creates a new environment that is very profitable for P2PL platforms which provide new alternatives for people in investing compared to traditional methods such as opening savings or deposits in banking. People want to be independent in their investment decisions and not depend on financial institutions. P2PL platforms provide a suitable marketplace where borrowers and lenders make their own decisions without financial institutions as financial intermediaries (Slavin, 2007). Apart from that, low interest rates on savings and deposits after the Covid-19 pandemic have forced people to look for new forms of investment to provide more attractive returns. For a comparison, the rate of return on investing in the form of savings and deposits is around 2% to 6%. It will be more attractive for people to invest using a P2PL platform that claims a rate of return of 15% or higher.

In 2016, the new Koinworks P2PL platform was launched in Indonesia, on this platform investors or lenders can find out information about their borrowers in forming interest rates in a fact sheet which contains information in the form of: loan amount, term, loan purpose, type of payment, type of loan and form of business. All the information contained in the factsheet is then entered into a credit grade form ranging from Grade A to Grade E, so that investors can know the returns they will get and the risks they may face later.

By using this information, investors or lenders who want to invest should have the ability to diversify in forming an optimal investment portfolio regarding the expected returns and possible risks that will be faced in the investment process, but the data used in this research is past data whether the portfolio which is formed by minimizing risk and can maintain investment value nominally and in real terms (Suryono et al., 2021).

The Koinworks P2PL platform provides borrowers with information about the level of risk and rate of return which is described in interest rates which are then classified into Credit Grade A, B, C, D and E, which will be However, investors on the P2PL platform, especially Koinworks products, do not yet understand and realize that risks such as the risk of default that will arise as a result of investing can be mitigated in the form of optimal portfolio diversification. As a result of this lack of understanding, many investors who are risk averse only invest in Koinworks products which have a low level of risk but the returns given are small, such as investing in products or borrowers that are classified as Credit Grade A and B and vice versa, if investors are risk-taking and want high returns, they will tend to invest in products or borrowers in Credit Grades C and D, even though if investors understand how to invest in a portfolio by paying attention to the risk-return combination for each product offered by the platform P2PL Koinworks can be on the efficient frontier of optimal portfolios. However, the data used in this research is past data on whether the portfolio formed by

minimizing risk can maintain investment value in nominal and real terms (Campbell et al., 2001).

Method

This research was conducted in February 2019-December 2023. The data in this research consists of secondary data totaling 7876 borrowers which can be obtained on the KoinWorks P2PL platform factsheet. The quantitative data that will be used includes historical data in the form of borrower or borrower information, starting from Grade A which has the lowest returns but low risk to Class E which has high returns but also has high risks. KoinWorks P2PL Platform 2019-2023. The object of the research is the KoinWorks P2PL platform which has information on borrowers or borrowers in credit ratings from Grade A to Grade E in the 2019-2023 period. The population of this study is information on borrowers or borrowers available on the KoinWorks P2PL platform starting from Grade A to Grade E. Sampling uses a non-probability sampling technique with a census method, namely a sampling technique if all members of the population are used as samples or examples.

This portfolio analysis uses two methods as a tool in forming an optimal portfolio, namely the Mean-Variance method and the Sharp Ratio method. The Markowitz Model portfolio analysis relies on parameters in the form of return, variance and covariance for each funding in credit grading. The assumption used in using this method is that investors ignore funding in risk-free funding assets. The Mean-Variance portfolio optimization model is formulated with the following stages:

Calculating the Expected Return

$$E(R)=\Sigma_{i=1}^{n} R_i pr_i \quad (1)$$

In where : E(R) = expected return, Ri = I-th return that may occur, pri = probability of the I-th return, n = number of possible returns

Calculating Risk

$$\text{varians return} = s^2 = [\, Ri\text{-}E(R)]^2 \; pri. \quad (2)$$

And

$$\text{Standar deviasi} = s = (s)^{\frac{1}{2}} \quad (3)$$

In where : s^2 = variance of return, s = standard deviation, E(R) = expected return, Ri = possible I-th return, pri = probability of the i-th return

Calculating the Correlation Coefficient

$$\rho = \frac{n\sum(RA)(RB) - \sum RA \sum RB}{\sqrt{\{[n\sum RA^2 - (\sum RA)^2][n\sum RB^2 - (\sum RB)^2]\}}} \quad (4)$$

In where ; = Correlation coefficient, n = number of funding results in grades that may occur, RA = funding returns in Grade A, RB = funding returns in Grade B

Calculating the Expected Return of the Portfolio

$$E(Rp) = \Sigma\_(i=n)\text{^}nWiE(Ri) \quad (5)$$

In where: E(Rp) = expected return from the portfolio, Wi = weight of the I-th portfolio, E(Ri) = expected return of the I-th, n = total amount of funding on the grade in the portfolio

Calculating Portfolio Risk

$$sp = [W^2A\, s^2A + W^2B\, s^2B + 2(W_A)(W_B)(r_{AB})s_A s_B]^{\frac{1}{2}} \quad (6)$$

In where: s_p = standar deviasi portfolio, W_A = portfolio weight on grade A r_{AB} = correlation coefficient grade A and B

Sharp Index Method

$$R/V_s = \frac{(\bar{R}p - \bar{R}f)}{s_p} \quad (7)$$

In where : R/V_s = Indeks Sharpe (*reward to variability ratio*), $\bar{R}p$ = Average portfolio return, $\bar{R}f$ = risk-free investment interest, s_p = Standard deviation of portfolio return.

Results and Discussion

Company Profile PT. Lunaria Annua Technology (KoinWorks)

PT. Lunaria Annua Teknologi or better known as KoinWorks is a provider of Financial Technology (Fintech) based money lending and borrowing services using the peer to peer lending (P2PL) method, where borrowers who need funding are connected with potential investors or lenders. Koinworks offers a payment system, loan assessment system and technology that provides a better experience for investors and borrowers. Koinworks is the first information technology-based money lending and borrowing service provider that has been officially registered and supervised by the Financial Services Authority (OJK) since May 4 2017 with registered letter S1862/NB.111/2017.

KoinWorks is here as a Super Financial App, which is the solution to all personal and business financial needs. KoinWorks wants to make all the financial

dreams of lenders and borrowers come true in the future with just one dashboard. PT Sejahtera Lunaria Annua (PT SLA), which collaborates with PT. Lunaria Annua Teknologi as an affiliate in organizing the KoinWorks Super Financial App, has been registered as a Digital Financial Innovation Organizer in the Aggregator Cluster at the Financial Services Authority (OJK), with registration letter number No. S-87/MS.72/2020 dated 10 February 2020. KoinWorks also has Electronic System Operator Registration Certificate (PSE) No. 00257/DJAI.PSE/02/2020 and has been registered as a member of the Indonesian Fintech Association (AFTECH),

Data Characteristics of KoinWorks Peer to Peer Lending Platform

Credit grade is a system usually used by financing or banking institutions to determine whether or not it is appropriate to receive a loan. Credit grade is done by analyzing all borrower data which is collected through the filling they have done previously for the loan application. So, it could be said that transaction history, such as paying bills correctly or not or how much credit you have, can also be used as a determinant of credit grade.

Credit grade really helps banks or other financial institutions in analyzing credit applications in addition to other factors (Min & Lee, 2008). Currently debtor credit report data or now better known as the Financial Information Services System (SLIK), which replaces BI Checking, can only be viewed directly by the Financial Services Authority (OJK). In this credit assessment, there are also many factors that can be taken into consideration, such as age, marital status, residence status, education, type of work, length of work and others. Apart from banks which usually implement a credit grading system, Peer-to-Peer Lending (P2PL) financial technology (fintech) companies, especially KoinWorks, also implement the same thing.

KoinWorks uses credit grading in selecting potential borrowers. Each P2PL platform, including KoinWorks, has its own credit grade model, such as analyzing Cashflow or cash flow from prospective borrowers, analyzing the collateral provided (which can be in the form of bills from Invoices and inventory), as well as analyzing Credit Behavior. CoinWorks credit grade results will have an impact on the amount of expected return or interest rate charged to prospective borrowers. As a reference, the following is a credit grade table based on interest rates and risks on the KoinWorks P2PL platform:

Table 1 Credit Grade Grouping Based on Interest Rates and Risk

Credit Grade	Expected Return/ Interest Rate	Protection Fund
A (Lowest Risk/Return)	15-19%	100%
B	19-24%	80%
C D	24-29%	60%
E (Highest Risk/Return)	29-34%	40%
	34-38%	20%

Source: Processed data (2023)

Based on the data above, peer-to-peer lending (P2PL) fintech startup KoinWorks is the only platform that provides protection initiatives in the form of Protection Funds. Protection funds aim to minimize investor capital losses if a borrower fails to pay. The loan will be categorized as failed if the borrower does not pay the installments within 90 days and does not provide information regarding the delay. Within 30 days of the announcement of the loan as default, KoinWorks will take protection funds to be paid to investors to reduce capital losses. Capital loss is the difference between the initial capital amount and the total payments received from loan installments. In the same time frame, KoinWorks will immediately write off the loan after the announcement of default.

The existence of the Protection Fund is a pure KoinWorks initiative to protect investment funds up to 100%. KoinWorks defines five levels compensation for reducing investment fund losses, in different loan categories through Credit Grade A to E. Credit Grade is determined based on the results of the borrower's risk level analyzed by KoinWorks. By considering the amount of the Protection Fund, the range of compensation given to investors varies, starting from 20% for investors who provide grade E, to 100% for grade A investors.

Table 1 presents the grouping of funding assets in credit grade based on loan amount. On the KoinWorks P2PL platform there are 5 grades, namely A to E, and each grade consists of five different levels, such as A1 to A5, where A1 is the most considered capable. to pay loans and E5 is the lowest grade in this case. At a safe point, for example A1, the interest rate charged is the lowest while at E5 it is the highest. For investors, investing in E5 will provide greater profits but has higher risks, while in A1, investor funds will be much safer but the profits will be minimal. This is where it is useful for investors to diversify while understanding interest rates and credit scoring, so that they can form an optimal portfolio by calculating the returns and risks that will be obtained.

Formation of an Optimal Portfolio with the Markowitz Model

Markowitz shows how portfolio diversification can minimize risk. Portfolio risk is not just a weighted average of each funding asset at credit grade in the portfolio, but must also consider the relationship between these funding assets. The statistical concepts that are important here are correlation and covariance (Sun & Weckwerth, 2012). Correlation is a measure that describes the level of closeness of the return relationship between two funding assets in the portfolio. Meanwhile, covariance is a measure that shows the extent to which the returns from two funding assets in a portfolio tend to move together. According to Markowitz (1952), portfolios are based on the assumption that investment decisions only depend on the values of E(Rp) and Op^2 of the total return of the portfolio. With the Markowitz model, investors can form an optimal portfolio where the portfolio is able to minimize variance or risk with a certain expected return value

Based on the explanation in the research method section, the procedure that must be carried out first is to calculate the expected return and individual variance for each funding asset at credit grade

Calculate the expected rate of return (E(Ri)) which is in the form of daily data. Calculated using the following formula equation:

$$E(Ri) = \frac{\sum Ri}{n} \quad (8)$$

The risk level of funding assets at credit grade is calculated using the variance (you can also use the formula from Ms. Excel, namely with STDEVA first to get the standard deviation) of the rate of return for each share. Or with the following formula:

$$\sigma_i^2 = \sum_{i=1}^{n} \frac{(R_i - E(R_i))^2}{n-1} \quad (9)$$

The following is the calculated data that will be included in the Markowitz model portfolio presented in Table 2:

Table 2 Calculation Results of Expected Return, Risk and Risk Free Rate

No	*Credit Grade*	Annual			Monthly		
		E(Ri)	*SD*	*Rf*	*E(Ri)*	*SD*	*Rf*
1	A	0.1580	0.0136	0.06	0.0132	0.0011	0.005
2	B	0.1923	0.0152	0.06	0.0160	0.0013	0.005
3	C	0.2419	0.0162	0.06	0.0202	0.0014	0.005
4	D	0.2982	0.0158	0.06	0.0248	0.0013	0.005
5	E	0.3246	0.0160	0.06	0.0271	0.0013	0.005

Source: Processed data (2023)

Based on the data in Table 2 above, the largest funding asset risk is in Credit Grade C, namely for an annual amount of 0.0162 and a monthly amount of 0.014. Then the smallest expected return is found in funding assets in Credit Grade A, namely 0.1580 for annual expected return and 0.0132 for monthly expected return. Meanwhile, the largest expected return is on funding assets in Credit Grade E, namely 0.3246 for annual expected return and 0.0271 for monthly expected return.

The next step is to calculate the covariance and correlation values of the returns between shares. Correlation calculations are carried out using 'Data Analysis' contained in the MS program. Excel. Table 3 below shows the covariance values:

Table 3 Annual Markowitz Model Optimal Portfolio Covariance Matrix Values

Credit Grade	A	B	C	D	E
A	0.0001862	0.0001926	0.0002116	0.0000928	0.0000419
B	0.0001926	0.0002299	0.0002306	0.0000927	0.0001176
C	0.0002116	0.0002306	0.0002638	0.0001474	0.0000463

D	0.0000928	0.0000927	0.0001474	0.0002481	-0,0000984
E	0.0000419	0.0001176	0.0000463	-0,0000984	0.0002537

Source: Processed data (2023)

Table 4 Monthly Markowitz Model Optimal Portfolio Covariance Matrix Values

Credit Grade	A	B	C	D	E
A	0.0000013	0.0000013	0.0000015	0.0000006	0.0000003
B	0.0000013	0.0000016	0.0000016	0.0000006	0.0000008
C	0.0000015	0.0000016	0.0000018	0.0000010	0.0000003
D	0.0000006	0.0000006	0.0000010	0.0000017	-0,0000007
E	0.0000003	0.0000008	0.0000003	-0,0000007	0.0000018

Source: Processed data (2023)

Before calculating the proportion of funding assets in credit grades A to E, the inverse covariance matrix of returns on funding assets in Credit Grades A to E is calculated using Ms. Excel as follows

Table 5 Inverse Value of the Optimal Portfolio Covariance Matrix for the Annual Markowitz Model

Credit Grade	A	B	C	D	E
A	79131	-13181	30976	21279	50622
B	-13181	21958	-51601	-35447	-84327
C	30976	-51601	12126	83299	19816
D	21279	-35447	83299	57221	13612
E	50622	-84327	19816	13612	32384

Source: Processed data (2023)

Table 6 Inverse Value of the Optimal Portfolio Covariance Matrix Monthly Markowitz Model

Credit Grade	A	B	C	D	E
A	-29560	49089	-11642	-7805	18958
B	49089	-81519	19334	12961	3148
C	-11642	19334	-45857	-3074	-7466
D	-7805	12961	-3074	20608	-50056
E	-18958	3148	-74669	50056	12158

Source: Processed data (2023)

After the inverse matrix value of the covariance matrix for annual and monthly returns on funding assets at Credit Grade A to E is obtained, the proportion for each funding asset in the portfolio will be calculated by solving the algebraic equation. From this algebraic equation, the proportion of each funding asset in Credit Grade A to E is obtained as follows.

Table 7 Optimal Portfolio Proportions Markowitz Model

Credit Grade	Annual Proportion	Monthly Proportion
A B C D	0.128331108	0.13466709
E	2.700686156	2.688443212
	-3.788860267	-3.773033587
	1.831383333	1.822331605
	0.12845967	0.127591681

Source: Processed data (2023)

Based on the data in Table 7 above, there is a proportion of funding assets that have a negative value, namely at annual and monthly Credit Grade C. The proportion or weight in forming a portfolio using the Markowitz Model method has several constraint functions, namely the first constraint function is the total proportion invested in each funding asset for the whole is equal to 1 or 100% and the second constraint function is the proportion of each Each funding asset cannot have a negative value. Where, the Markowitz Model portfolio does not allow negative proportions in each funding asset. Therefore, funding assets in annual and monthly Credit Grade C must be removed or eliminated from the optimal portfolio of the Markowitz Model. So that means we have to repeat the weighting process from starting to calculate the covariance as before.

Table 8 Optimal Portfolio Covariance Matrix Values Annual Markowitz Model without Credit Grade C

Credit Grade	A	B	D	E
A	0.0001862	0.0001926	0.0000928	0.0000419
B	0.0001926	0.0002299	0.0000927	0.0001176
D	0.0000928	0.0000927	0.0002481	-0,0000984
E	0.0000419	0.0001176	-0,0000984	0.0002537

Source: Processed data (2023)

Table 9 Optimal Portfolio Covariance Matrix Values Monthly Markowitz Model without Credit Grade C

Credit Grade	A	B	D	E
A	0.0000013	0.0000013	0.0000006	0.0000003
B	0.0000013	0.0000016	0.0000006	0.0000008
D	0.0000006	0.0000006	0.0000017	-0,0000007
E	0.0000003	0.0000008	-0,0000007	0.0000018

Source: Processed data (2023)

The optimal portfolio covariance matrix of the Markowitz model without funding assets in Credit Grade C that has been obtained will then be used to calculate the weight value of each funding asset in Credit Grades A, B, D and E

Before calculating the proportion of funding assets in credit grades A, B, D and E, the inverse covariance matrix of returns on funding assets in Credit Grades A, B, D and E is calculated using Ms. Excel as follows:

Table 10 Inverse Value of the Optimal Portfolio Covariance Matrix for the Markowitz Model without Annual Credit Grade C

Credit Grade	A	B	D	E
A	77100	-52697	-19380	-2059
B	-52697	42582	9264	1099
D	-19380	9264	12581	960
E	-2059	1099	960	121

Source: Processed data (2023)

Table 11 Inverse Value of the Optimal Portfolio Covariance Matrix for the Markowitz Model without Monthly Credit Grade C

Credit Grade	A	B	D	E
A	11064	-7463	-2840	-2958
B	-7463	5979	1342	1551
D	-2840	1342	1839	1396
E	-295	155	139	174

Source: Processed data (2023)

After the inverse matrix value of the covariance matrix for annual and monthly returns on funding assets in Credit Grades A, B, D and E is obtained, then the proportion for each funding asset in the portfolio will be calculated by solving the algebraic equation. From this algebraic equation, the proportion of each funding asset in Credit Grade A, B, D and E is obtained as follows :

Table 12 Proportions and Combinations of the Markowitz Model portfolio based on the smallest risk preference with Solver

Credit Grade	Annual Proportion	Monthly Proportion
A B D E	0.438705506	0.476210072
	0.036744026	0.014305177
	0.506758089	0.492803934
	0.017792379	0.016680817
∑	1.000000000	1.00000000

Source: Processed data (2023)

Based on Table 12, the Markowitz Model with the smallest risk preference produces 4 combinations of Credit Grade A, B, C and D funding assets. The largest fund allocation is in Credit Grade D, amounting to 50.67% annually and 49.28% monthly. The

smallest fund location is Credit Grade E at 1.78% annually and 1.67% monthly. The combination and proportion of these fund allocations produces the following expected levels of return and risk.

Table 13 Formation of returns, risk and portfolio performance in the Markowitz Model based on the smallest risk preference

	Annual	Monthly
Return Portofolio	0.2429943	0.0202483
Standard Deviasi Risk	0.0239642	0.001164
Free	0.06	0.0048676
Sharp Ratio	13.10461	13.2137474

Source: Processed data (2023)

If investors want to invest their funds in 4 combinations of funding assets, the resulting portfolio performance will be 24.29% annually and 2.02% monthly. A portfolio with this combination is a portfolio which can be used by investors who also consider the risk and performance of their portfolio (risk taker).

Formation of an Optimal Portfolio with the Sharpe Ratio

The next portfolio formation is by optimizing portfolio performance which is measured using the Sharpe Ratio and processed using Solver in Microsoft Excel. The following are the stock combinations and their proportions that form the Markowitz Model portfolio based on the optimal Sharpe Ratio.

Table 14 Combination and allocation of portfolio funds based on the Markowitz Model Optimal Sharpe Ratio.

Credit Grade	**Annual Proportion**	**Monthly Proportion**
A B D	0.762505506	0.730506055
	0.013944026	0.015394626
	0.224458089	0.264459808
∑	1.000000000	10000000000

Source: Processed data (2023)

Based on Table 14, the formation of the Markowitz Model portfolio using the Sharpe Ratio produces 3 combinations of funding assets. The largest fund allocation is in Credit Grade A funding assets at 76.25% and the smallest fund allocation is in Credit Grade B funding assets at 1.39%. A portfolio with this combination is a portfolio that can be used by investors who also consider the risk and performance of their portfolio (risk averse). The combination and proportion of these fund allocations produces the following expected levels of return and risk.

Table 15 Formation of returns, risk and portfolio performance for the Markowitz Model based on the Sharp Rasio

	Annual	**Monthly**

Return Portofolio	0.1829943	0.0152483
Standard Deviasi Risk	0.0139641	0.001164
Free	0.06	0.0048676
Sharp Ratio	13.10461	13.2137474

Source: Processed data (2023)

If investors want to invest their funds in the products listed in Table 15, they are expected to provide an overall return on investment of 18.29% monthly and 1.53% monthly. This combination is an efficient portfolio combination based on the preferences of investors who tend to avoid risk (risk averse)

Conclusion

Investors or lenders need to implement strategies in investing to avoid potential losses that may occur when investing their capital, one of the right strategies is to invest funds in funding assets that have the best performance that can be obtained through optimal portfolio calculations. The combination of funding assets that have the best performance is obtained using the Markowitz Model with an optimal Sharpe Ratio, namely investment in Credit Grade A, B and D funding

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