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Navigating the Risk-Return Spectrum: Strategic Insights into Consumptive and Productive Financing in Multifinance Companies

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Abstract
This study examines the interplay between consumptive and productive financing in multifinance companies. The results reveal that both financing types enhance ROA and ROE, with productive financing offering higher returns but greater risks—as indicated by elevated Conditional Value at Risk (CVaR) levels—compared to consumptive financing. Johansen cointegration tests confirm stable long-term equilibria among key financial indicators. Utilizing Modern Portfolio Theory (MPT), this study demonstrates that strategic diversification can optimize risk-adjusted returns. The results support regulatory mandates for a minimum productive financing allocation and highlight the necessity of robust risk management practices to sustain financial resilience in volatile economic conditions.

Keywords: Multifinance Companies, Consumptive Financing, Productive Financing, Portfolio Diversification, Risk Management.

JEL Classification: G21, G23, G28

1. Introduction

In recent years, the Indonesian Financial Services Authority (OJK) has actively encouraged multi-finance companies to increase their portion of productive financing. This policy aims to reduce dependence on consumer-based lending and foster sustainable economic growth. Productive financing, which supports business expansion and investment, is expected to generate higher economic value than consumer financing. However, a critical question arises: does increasing the proportion of productive financing enhance or weaken the financial performance of multi-finance companies? The answer has significant implications for financial institutions' strategic decisions, regulatory policies, and risk management frameworks. While productive financing offers the potential for higher returns, it also carries a distinct risk profile that could impact financial stability.

Despite the potential benefits, productive financing is more susceptible to business cycle fluctuations, affecting borrowers' ability to meet their obligations. This contrasts with consumer financing—primarily targeting salaried borrowers—which tends to exhibit greater stability. Consequently, the debate remains unresolved: does a higher allocation to productive financing improve financial performance, or does it introduce excessive risks? Prior research presents conflicting perspectives. For instance, Marsella & Ruci (2024) argue that productive financing enhances profitability by generating higher investment returns. In contrast, Wahida et al. (2023) highlight that increased exposure to credit risk, moral hazard, and adverse selection could harm financial performance, necessitating stricter monitoring mechanisms. Furthermore, Gao et al. (2021) demonstrate that productive financing, particularly for SMEs, entails significant risk due to high default probabilities, leading commercial banks to impose stricter lending conditions and increased interest rates to mitigate potential credit losses.

Consumer financing remains a significant component of multi-finance institutions, often classified as consumptive financing. Rinaldi and Sanchis-Arellano (2006) identify disposable income, unemployment, and monetary conditions as key determinants of household non-performing loans (NPL) across European countries. Similarly, Suhendri et al. (2018) find that in Indonesia, consumer financing under murabahah contracts contributes significantly to total NPL, indicating its susceptibility to macroeconomic fluctuations. While consumer financing is generally considered more stable than productive financing, it remains vulnerable to economic downturns and household financial resilience.

Despite extensive research on financing composition and financial performance, existing studies have primarily focused on Islamic banking or small and medium enterprises (SMEs), leaving a gap in understanding its impact on multi-finance companies. Priyadi et al. (2021) examine the determinants of credit risk in Sharia rural banks, emphasizing internal and external factors influencing NPL. Meanwhile, Komarudin et al. (2023) argue that productive financing in Islamic banks remains underutilized due to public misconceptions, regulatory inefficiencies, and operational constraints. These findings suggest that while productive financing holds profitability potential, its associated risks must be carefully managed to maintain financial stability.

To bridge this gap, this study analyzes the impact of productive financing on financial performance using a dataset of 147 multi-finance companies in Indonesia from June 2016 to October 2024. In the context of this study, the decision to use data from Indonesia is driven by the unique dynamics of its multi-finance sector. Indonesia's rapidly growing economy, combined with targeted regulatory initiatives by OJK, has spurred the evolution of multifinance companies into pivotal players that support both consumer and productive financing. Unlike more mature markets, the Indonesian multifinance landscape is characterized by innovative financial products, a diverse client base, and flexible risk management practices. Moreover, the decision not to use data from multifinance sectors in other countries is deliberate, as the market conditions and regulatory environment in Indonesia are uniquely dynamic and differ significantly from those in other regions. The comprehensive and representative data available domestically enable a deeper analysis of how these distinctive factors affect the balance between risk and return. Consequently, Indonesia offers a rich environment to examine these trade-offs, providing insights that are not only relevant to the domestic market but also applicable to other emerging economies with similar financial structures.

It should also be noted that the proportion of productive financing cannot be fully reflected in the financial statements for the same period. This limitation necessitates a long-term analysis to capture the dynamic influence of financing composition on financial performance. Therefore, this study employs the Johansen Cointegration Test and the Vector Error Correction Model (VECM) to examine the long-term relationships between the proportion of productive financing and key financial ratios such as Return on Assets (ROA), Return on Equity (ROE), and Non-Performing Financing (NPF). Additionally, CVaR analysis is incorporated to assess potential financial losses under extreme economic conditions, providing a comprehensive view of risk exposure in both productive and consumer financing allocations.

The findings reveal that while productive financing positively influences ROA and ROE over time, an excessive allocation without robust risk management may increase long-term credit risks. Specifically, a higher proportion of productive financing is linked to elevated Gross NPF, suggesting greater exposure to default risk. Moreover, the current financing composition between productive and consumer assets appears suboptimal, indicating significant room for improvement in balancing risk and return. By applying modern portfolio theory, multi-finance companies can optimize their financing allocation to enhance portfolio efficiency and risk-adjusted returns.

This study contributes to both academic literature and policy discussions in several ways. Unlike previous research that primarily examines the link between financing type and financial performance, this study introduces an optimization-based approach to financing allocation. By integrating modern portfolio theory and stress-testing methodologies such as CVaR, it provides a robust framework for assessing financial resilience. The findings offer valuable insights for policymakers and financial practitioners in formulating regulatory strategies that support productive financing while ensuring financial stability. Ultimately, this research aims to guide multi-finance companies toward optimal portfolio diversification, contributing to both academic discourse and practical financial strategies.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on multi-finance companies, financing risks, and portfolio optimization. Section 3 outlines the research methodology, including data collection and modelling techniques. Section 4 presents empirical results and discusses their implications. Finally, Section 5 concludes with policy recommendations and future research directions.

2. Literature Review

a. Multifinance Company Business

Multifinance companies in Indonesia are non-bank financial institutions that provide financing to support both productive and consumptive needs. Their primary revenue derives from interest income on loans, often at higher rates than banks, due to the higher cost of funding. Despite funding challenges, these companies maintain a sufficient net interest margin through effective pricing strategies and risk management practices (Satriadi et al., 2024; Hasan et al., 2023; Manurung et al., 2020).

On the cost side, the largest expense component for multifinance companies is the provision for doubtful accounts, which reflects the expected credit losses from financing disbursed (OJK Data, 2024). This expense significantly impacts the overall financial performance, emphasizing the importance of effective risk management in maintaining portfolio quality and financial sustainability.

b. Theoretical Foundations of Productive and Consumer Financing

The financial performance of multi-finance institutions is heavily influenced by their asset allocation strategies, particularly in balancing productive and consumer financing. Productive financing is often linked to higher profitability potential due to its role in supporting business expansion and investment (Marsella & Ruci, 2024). However, it is also associated with greater risk exposure, credit defaults, and higher monitoring costs (Wahid et al., 2023). This dynamic raise concerns about the trade-offs between risk and return when increasing the share of productive financing.

Previous studies have offered mixed findings on the impact of productive financing. Wahid et al. (2023) analyzed Islamic banking in Indonesia using a Markov Switching Dynamic Regression model and found that productive financing can negatively impact profitability during stable periods due to its higher credit risk. Conversely, Marsella & Ruci (2024) found that productive financing has a significant positive effect on bank income, emphasizing its role in long-term financial sustainability. These conflicting results suggest that the impact of productive financing varies based on financial institutions' ability to manage associated risks effectively.

c. Empirical Findings on Financing Composition and Financial Performance

The existing body of literature highlights the importance of optimizing financing allocation to balance profitability and risk. Wahid et al. (2023) demonstrated that excessive reliance on consumer financing during economic downturns could lead to financial instability due to an increased likelihood of restructured loans and defaults. Their findings indicate that multi-finance companies should strategically adjust their financing portfolios to mitigate potential downturn risks. Similarly, Marsella & Ruci (2024) provided empirical evidence that productive financing enhances financial performance by generating higher income margins, reinforcing the argument for a more diversified financing approach.

A key issue in previous studies is the lack of comprehensive risk assessment frameworks in analyzing the impact of financing allocation. This study addresses this gap by incorporating modern portfolio theory and Conditional Value at Risk (CVaR) analysis to optimize financing composition while accounting for extreme economic conditions. By doing so, this research contributes to a deeper understanding of how multi-finance companies can maximize profitability while mitigating financial risks.

d. Contribution to Literature and Policy Implications

This study extends previous research by providing empirical evidence on how multi-finance companies can optimize their financing portfolios. Unlike prior studies that focus solely on the profitability impact of financing types, this research incorporates risk assessment methodologies to enhance financial stability. The integration of modern portfolio theory and stress-testing models (e.g., CVaR) offers a novel approach to financing allocation that accounts for potential economic shocks.

From a policy perspective, these findings are crucial for financial regulators such as OJK in formulating policies that encourage sustainable financing practices. By ensuring a balanced approach between productive and consumer financing, multi-finance companies can enhance their long-term financial resilience while supporting economic growth. This study provides a valuable framework for policymakers and financial institutions in navigating the complexities of financing allocation, offering practical insights into maintaining financial stability amid market uncertainties.

3. Research Methodology

A. Data

The study utilizes aggregate industry data from 147 multifinance companies in Indonesia, covering the period from June 2016 to October 2024. The dataset includes information on financing receivables, interest income, provisioning, assets, equity, and non-performing financing. Financing receivables are classified according to OJK regulations.

B. Analytical Method

1) Johansen Cointegration Test

The Johansen Cointegration Test is a statistical test used to determine whether two or more time series variables have a long-term equilibrium relationship. It is commonly used in econometrics and finance when analyzing multiple time series that may be non-stationary but move together over time.

The test was developed by Søren Johansen (1988) and extends the Engle-Granger cointegration test by allowing for multiple cointegrating relationships among several time series.

Key features of the Johansen Cointegration Test:

a) Multivariate approach

The Johansen test allows for multiple cointegrating vectors within a system of variables, unlike the Engle-Granger test, which can only handle one cointegrating relationship.

b) Based on the Vector Autoregression (VAR) Model

The test is derived from the Vector Autoregressive (VAR) model, making it suitable for analyzing multiple time series that may be interdependent over time.

c) Uses Maximum Likelihood Estimation (MLE)

The Johansen test applies MLE to estimate the number of cointegrating relationships in a system.

d) Two Types of Hypothesis Tests

Trace Test: Tests whether there are at most r cointegrating vectors.

Maximum Eigenvalue Test: Tests whether the number of cointegrating vectors is exactly r compared to $r + 1$

e) Determining the Rank of the Cointegration Matrix (r)

The rank of the cointegration matrix determines how many independent long-term relationships exist among the variables.

f) Requires Non-Stationary Variables of the Same Order

The test assumes that all variables have the same order of integration, usually I(1) (non-stationary at level but stationary at first difference).

g) Considers Both Short-Run and Long-Run Relationships

Unlike standard regression models that only capture short-term relationships, the Johansen test allows for simultaneous estimation of short-run and long-run relationships through the Vector Error Correction Model (VECM).

h) Asymptotic Distribution of the Test Statistics

Since standard asymptotic distributions do not apply to processes with unit roots, the Johansen test relies on non-standard asymptotic distributions (derived from stochastic processes).

2) Vector Error Correction Model

The Vector Error Correction Model (VECM) is an econometric approach used to analyze both short-term dynamics and long-term equilibrium relationships among non-stationary but cointegrated variables. Unlike traditional time-series models, VECM incorporates an error correction term (ECT), which captures the speed of adjustment when variables deviate from their long-term equilibrium. This makes it particularly useful for examining financial indicators such as productive receivables ratio, ROA, ROE, and NPF Gross, where short-term fluctuations may occur, but underlying equilibrium relationships persist. The general form of the VECM equation is:

$$\Delta Y_t = \alpha + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \epsilon_t \quad (1)$$

$\boldsymbol{\Delta Y_t}$ represents the first-differenced dependent variables;

$\boldsymbol{\alpha}$ is the constant term;

Γ_i captures short-term dynamics;

$\boldsymbol{\Delta Y_{t-1}}$ is the error correction term that accounts for long-term equilibrium adjustments;

$\boldsymbol{\varepsilon_t}$ is the error term;

Π is cointegration matrix which indicates the strength of the long-term correction mechanism;
i is the index of observations (sample).

VECM is essential for this study because it not only identifies short-term effects but also determines whether financial variables correct toward stability over time. This model effectively handles endogeneity and bidirectional causality, making it suitable for analyzing interdependent financial indicators in multifinance companies. By distinguishing between temporary fluctuations and long-term corrections, VECM provides valuable insights for financial decision-making, risk management, and regulatory policies.

3) CVaR

The first step involved observing the returns of productive and consumptive financing to calculate VaR based on historical data. The next step involved sorting the return data for each consumptive and productive financing from the smallest to the largest value, with the value calculated based on the yield for each portfolio using the following formula:

$$\textbf{Yield}\ \% = \frac{(\textbf{(interest income from portfolio n} - \textbf{provisioning from portfolio n)} - \textbf{(interest income from portfolio n}-\textbf{1} - \textbf{provisioning from portfolio}}{\textbf{(interest income from portfolio n}-\textbf{1} - \textbf{provisioning from portfolio n}-\textbf{1)}}$$

(2)

where n represents the data for the nth month.

Subsequently, the VaR for each type of financing return was calculated at confidence levels of 95% and 99% using the Excel formula =PERCENTILE.EXC(). Once the VaR values were determined, the CVaR for each return was then calculated using the formula provided below:

CVaR = - (1 / (1 - confidence level)) * E[loss | loss > VaR] (3)

where E[loss | loss > VaR] is the expected loss given that the loss exceeds the VaR threshold.

4) MPT

The MPT is used to calculate the expected return generated by a financing portfolio consisting of consumptive financing and productive financing. In the calculation, the proportion of financing is determined using weights based on the average financing proportions derived from historical data. Subsequently, by using excel formula =NORMINV(RAND()), Monte Carlo simulation is employed to generate weights for consumptive and productive financing, resulting in variations in the expected return outcomes. Then the expected return is calculated using the formula provided below:

$$E(R_p) = \sum_i w_i E(R_i) \quad (4)$$

Where,

$E(R_p)$ is the Expected Return

R_p is the portfolio return

R_i is the return of asset i (productive financing account receivables and consumptive financing receivables)

W_i is the weighting of asset i (or the asset i proportion in the portfolio)

Lastly, the optimal portfolio composition is determined based on the highest Sharpe ratio in simulation results using the formula provided:

$$Sharpe\ Ratio = \frac{R_{p-R_f}}{\sigma_p} \quad (5)$$

Where,

R_p is the portfolio return

Risk free rate is 5,75% by referring to Bank Indonesia Rate
σ_p is a standard deviation of the portfolio's excess return

4. **Results**

a. The Effect of Consumptive and Productive Receivables Ratio on Return on Assets (ROA), Return on Equity (ROE), and Non-Performing Financing Gross (NPF)

ROA, ROE, and NPF are three key indicators commonly used to evaluate the performance and financial health of multifinance companies in the financial sector. ROA is described as a profitability ratio used to assess the return earned on a company's total assets, reflecting management's efficiency in using assets to generate earnings (Gitman & Lawrence J, 2009). ROE evaluates how well a company is managing shareholders' investments to generate profits, representing profitability relative to equity (Ross et.al, 2019). Non-Performing Financing or loans measure the financial stress on institutions, directly linked to asset quality and repayment behaviors (Kaminsky et.al, 1999).

These financial indicators—ROA, ROE, and NPF—are essential for assessing multifinance companies' stability and profitability. The Johansen Cointegration Test helps analyze their long-term relationship with the Productive Receivables Ratio, providing deeper insights into financial performance.

1) Impact of Productive and Consumptive Receivables on ROA

The stationarity test using the Augmented Dickey-Fuller (ADF) method confirms that both productive and consumptive receivables ratios are stationary, while ROA becomes stationary only after second differencing, as shown in Table 1 in the appendix.

The Vector Auto Regression (VAR) model was applied to analyze the dynamic relationship, with lag order determined using Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (BIC), Hannan-Quinn Criterion (HQIC), and Final Prediction Error (FPE):

a) For Consumptive Receivables to ROA, AIC, BIC, and FPE selected Lag 1, as shown in Table 2 in the appendix.
b) For Productive Receivables to ROA, AIC, HQIC, and FPE suggested Lag 2, while BIC indicated Lag 1 and the majority rule led to the selection of Lag 2, as shown in Table 3 in the appendix .

The shorter Lag 1 for consumptive receivables implies a faster impact on ROA, possibly due to shorter repayment periods of consumer loans. Conversely, the Lag 2 for productive receivables suggests a delayed effect typical of business financing, which requires more time for investments to generate returns.

The Johansen cointegration test proves a long-term relationship between receivables and ROA, with positive cointegration vectors, showing that increases in both productive and consumptive receivables are associated with higher ROA, as shown in Table 4 in the appendix.

However, the impact from productive receivables appears more pronounced than consumptive receivables, as evidenced by higher coefficients in the VECM model, as shown in Table 5 in the appendix.

2) Impact of Productive and Consumptive Receivables on ROE

The results for ROE mirror those of ROA, with both productive and consumptive receivables ratios stationary at level, while ROE becomes stationary after second differencing, as shown in Table 6 in the appendix.

The optimal lag for the VAR model was determined as follows:

1) For Consumptive Receivables to ROE, AIC and HQIC suggested Lag 2, while BIC suggested Lag 1, as shown in Table 7 in the appendix. Following the standard approach, Lag 2 was chosen for analysis.

2) For Productive Receivables to ROE, all criteria (AIC, BIC, HQIC, and FPE) unanimously supported Lag 2, as shown in Table 8 in the appendix.

The Johansen test establishes cointegration, indicating a positive long-run relationship between both types of receivables and ROE, as shown in Table 9 in the appendix.

However, the VECM analysis shows that consumptive receivables have a stronger impact on ROE compared to consumptive receivables, as demonstrated by a larger cointegration vector, as shown Table 10 in the appendix

3) Impact of Productive and Consumptive Receivables on NPF

The stationarity test results indicate that both productive and consumptive receivables ratios are stationary at level, while NPF Gross becomes stationary after first differencing, as shown in Table 11 in the appendix.

For both productive and consumptive receivables' impact on NPF Gross, all selection criteria (AIC, BIC, HQIC, and FPE) indicated Lag 1 as the most suitable lag, as shown in Table 12 and Table 13 in the appendix respectively. The consistent Lag 1 for NPF Gross implies that changes in receivable proportions have a rapid effect on credit risk, highlighting the sensitivity of non-performing loans to fluctuations in financing policies. This finding underscores the need for vigilant credit monitoring, especially in productive financing, which showed a positive relationship with NPF Gross, indicating higher risk exposure.

Johansen cointegration tests reveal a long-term relationship between receivables and NPF Gross, but with contrasting effects. Consumptive receivables exhibit a negative long-term relationship with NPF Gross, suggesting that an increase in consumptive receivables is associated with a decline in NPF Gross. Conversely, productive receivables show a positive long-term relationship with NPF Gross, implying that higher productive receivables are associated with increased NPF Gross as shown in Table 14 and Table 15 in the appendix respectively.

The findings indicate distinct patterns in how productive and consumptive financing impact financial performance and risk:

1. Profitability Impact (ROA and ROE): Both financing types positively influence ROA and ROE, aligning with existing literature that highlights the role of receivables management in improving profitability. However, the stronger influence of productive receivables suggests that investments in business-related financing yield higher returns compared to consumer lending.
2. Risk Impact (NPF Gross): The contrasting effects on NPF Gross reveal divergent risk profiles. The negative relationship between consumptive receivables and NPF Gross suggests that consumer loans, which are often diversified and shorter-term, contribute to lower non-performing loans. On the other hand, productive receivables, often involving larger and longer-term business loans, pose higher credit risks.
3. Long-Term Equilibrium: The Johansen cointegration tests for all relationships highlight the presence of stable long-term equilibriums, emphasizing the importance of strategic portfolio management in balancing profitability and risk.

4) Robustness Tests

The robustness test evaluates the stability of CVaR for productive and consumptive financing across varying confidence levels (90%, 95%, 97%, 99%, and 99.5%). The results confirm that CVaR remains a reliable risk measure, displaying consistent behavior and minimal sensitivity to parameter changes as shown in Table 16. The convergence of risk at higher confidence levels suggests that under extreme conditions, both financing types face comparable downside risks, validating the CVaR estimation framework for multi-finance risk management.

This finding aligns with Misankova and Spuchlakova (2017), who highlight CVaR's effectiveness in credit risk optimization, and Serraino and Uryasev (2013), who define CVaR as the average loss within the worst-case scenarios, providing a comprehensive measure of tail risk. The results indicate that productive financing carries higher risk exposure and greater potential losses under adverse scenarios, whereas consumer financing exhibits lower extreme losses, offering more stable returns under stress conditions.

These findings underscore the necessity for multi-finance companies to conduct stress testing and maintain capital buffers, particularly for productive financing, due to its higher risk exposure. This aligns with Serraino and Uryasev (2013), who emphasize CVaR as an effective internal risk management tool, enabling firms to prepare for worst-case scenarios and ensure financial resilience.

b. Portfolio Optimization

1) MPT Result Analysis

This section presents the simulation results using a Monte Carlo Simulation integrated with portfolio optimization based on MPT, as demonstrated by Shi (2024), who highlights MPT's ability to achieve diversification by adjusting the proportion of each asset to effectively manage and alter portfolio risk.

The calculation is conducted by combining the MPT and Monte Carlo Simulation. This method calculates current proportion financing to provide the optimum portfolio composition that generates optimum return relative to the risks by running 10.000 scenarios. This study evaluates three portfolio compositions—Minimum Risk Scenario, Optimum Return Scenario, and Current Composition—to determine their effectiveness in balancing risk and return. The analysis considers key metrics such as the proportion of productive and consumptive financing, expected return (E[R]), standard deviation (σ), and Sharpe Ratio to assess the performance and efficiency of each strategy. The result is as shown in appendix Table 17.

The Minimum Risk Composition is characterized by an allocation of 44.46% to productive financing and 55.54% to consumptive financing, achieving an expected return of 16.65% with a standard deviation of 28.15%. The Sharpe Ratio of 38.73% demonstrates its focus on minimizing risk while maintaining acceptable returns. This composition’s higher weight in consumptive financing reflects a conservative approach to reduce volatility, making it suitable for risk-averse multifinance companies.

The Optimum Return Composition increases the allocation to productive financing (46.89%) while reducing the proportion of consumptive financing to 53.11%. This adjustment results in the highest expected return (E[R]=16.68%) among the three portfolios, with a slightly higher standard deviation (σ=28.18%). The Sharpe Ratio of 38.79% indicates superior risk-adjusted performance, demonstrating that this composition offers the most efficient trade-off between risk and return. This portfolio aligns with Modern Portfolio Theory, as it optimizes returns relative to risk as shown in appendix Figure 1.

The Current Composition, with 43.96% allocated to productive financing and 56.04% to consumptive financing, produces an expected return (E[R]=16.65%) and standard deviation (σ=28.15%) comparable to the Minimum Risk Composition. However, its Sharpe Ratio of 38.70% is slightly lower, reflecting less efficiency in balancing risk and return. The allocation leans heavily on consumptive financing, limiting its ability to achieve optimal risk-adjusted returns.

These findings highlight that while the Minimum Risk Scenario provides stability for conservative multifinance companies, the Optimum Return Scenario delivers the most efficient performance by achieving higher returns without significantly increasing risk. In contrast, the Current Composition shows room for improvement through rebalancing to enhance efficiency. The results underscore the importance of aligning portfolio strategies with risk tolerance and financial objectives to achieve optimal performance in multifinance companies' portfolios.

2) Robustness Test

The robustness test evaluates the stability and reliability of the study's results by analyzing their sensitivity to variations in key inputs and assumptions, such as expected return, standard deviation, and the risk-free rate. By systematically adjusting these parameters by ±10%, ±20%, and ±30%, as well as testing alternative risk-free rate values (3%, 5%, and 7%) as shown in appendix table 18 and table 19 respectively, the test ensures that the findings are not overly dependent on specific conditions.

The results indicate that the Optimum Return Portfolio consistently delivers superior performance in favorable scenarios, maintaining the highest Sharpe Ratio across various risk-free rate assumptions. However, this portfolio is sensitive to negative adjustments, as extreme reductions in expected return and standard deviation significantly affect its risk-adjusted returns.

In contrast, the Minimum Risk Portfolio exhibits greater resilience, with relatively stable Sharpe Ratios and performance metrics even under adverse conditions, making it suitable for risk-averse mutlifinance companies. The Current Composition, while maintaining lower risk, demonstrates suboptimal performance and considerable sensitivity to variations, further confirming its inefficiency.

Overall, the robustness test validates the study's conclusions by showing consistent results under varying assumptions, while also highlighting the importance of portfolio optimization to withstand uncertainties in market conditions.

5. Conclusion and Recommendations

a. Conclusion

In conclusion, this study provides compelling evidence that both consumptive and productive financing positively influence key performance metrics such as ROA and ROE, while also highlighting the nuanced risk-return trade-offs inherent in each financing type. The analysis demonstrates that consumptive receivables—typically associated with diversified, shorter-term consumer loans—are linked to lower levels of non-performing loans (NPF Gross), whereas productive receivables, characterized by larger, longer-term business loans, entail higher credit risks. Notably, the conditional Value-at-Risk (CVaR) for productive financing is consistently greater than that for consumptive financing, underscoring its potential for extreme losses in adverse economic scenarios and affirming the critical role of CVaR in robust internal risk management.

The application of the Johansen cointegration tests further reveals stable long-term equilibria among the studied variables, emphasizing the importance of strategic portfolio management in achieving an optimal balance between profitability and risk. Using Modern Portfolio Theory (MPT), our findings indicate that a minimum risk portfolio—predominantly weighted towards consumptive assets—can achieve an expected return of 16.65% at a risk level of 28.15%, while a modest increase in productive financing can boost expected returns to 16.68% with only a slight uptick in risk. However, the current portfolio composition, despite maintaining the same risk level, yields a slightly lower Sharpe Ratio, suggesting room for improvement in risk-adjusted performance.

For the multifinance industry, these results underscore the necessity of a diversified financing strategy that judiciously balances productive and consumptive components. By supporting a regulatory mandate of a minimum 10% allocation for productive financing, this study not only validates the higher return potential of productive loans but also reinforces the need for comprehensive risk management strategies. Ultimately, the findings contribute to a deeper understanding of the interplay between profitability, risk, and portfolio composition, offering valuable insights for both policymakers and financial practitioners aiming to enhance financial resilience and performance.

b. Recommendation

Based on the findings of this study, the following recommendations are proposed to enhance risk management, portfolio efficiency, and financial resilience in the multifinance sector:

For OJK as regulator:

1. Preserve the minimum threshold of 10% for productive financing allocation in alignment with existing regulatory provisions, while introducing calibrated flexibility contingent upon institutional risk assessments. This adjustment is warranted by the elevated downside risk associated with productive financing—evidenced by a Conditional Value at Risk (CVaR) of –91.827%—despite its comparatively higher return potential.
2. Implement a tiered capital adequacy framework that differentiates capital reserve requirements based on the relative composition of productive versus consumptive financing. Such a framework would mandate that financial institutions with greater exposure to productive financing maintain proportionately higher capital buffers to absorb potential losses and promote systemic resilience.
3. Formulate standardized, sector-wide stress testing protocols that incorporate extreme yet plausible market scenarios to evaluate the robustness of financing portfolios. These protocols should explicitly test the sustainability of productive and consumptive financing allocations under adverse macroeconomic conditions, thereby enhancing preparedness for financial shocks.
4. Establish a forward-looking credit risk surveillance mechanism capable of detecting early indicators of financial deterioration, with particular attention to productive financing exposures. Given their inherently higher return–risk profile, these exposures warrant proactive monitoring to ensure timely intervention and risk containment.

For Multifinance companies:

1. Promote an optimal balance between productive and consumptive financing allocations to enhance risk-adjusted portfolio returns. This strategy should be grounded in the principles of Modern Portfolio Theory (MPT), enabling firms to systematically adjust asset composition in response to changing risk-return dynamics.
2. Design and implement dynamic performance monitoring systems that facilitate continuous tracking of key financial indicators such as returns, volatility, and Sharpe ratios. The integration of machine learning algorithms into Monte Carlo simulation processes is recommended to refine predictive risk modelling and improve forward-looking portfolio assessments.
3. Strengthen capital reserve frameworks for productive financing exposures, acknowledging their higher return potential alongside elevated risk. Allocating proportionally greater capital buffers to these exposures supports long-term financial resilience and aligns with prudent risk management practices.
4. Align investment and lending strategies with regulatory expectations, particularly those concerning the minimum ratio of productive receivables as stipulated by the OJK. Strategic compliance should be integrated with the firm's capital structure and broader financial objectives to ensure a cohesive and sustainable approach to risk and profitability management.

Appendix

Table 1: The stationery test result related to ROA

Variable	ADF Statistics	ADF p-value
Productive Receivables Ratio	-2.99165392560228	0.03568120393266284
ROA	-1.54657483024331	0.5103586571616999
Variable	**ADF Statistics**	**ADF p-value**
Consumptive Receivables Ratio	-2.991653925602284	0.03568120393266254
ROA	-1.5465748302433147	0.5103586571616999
Productive Variable	**ADF Statistics**	**ADF p-value**
First Differenced ROA	-2.687101374931	0.07629701387547101
Second Differenced ROA	-4.1482783266576	0.00080508646065428
Consumptive Variable	**ADF Statistics**	**ADF p-value**
First Differenced ROA	-2.687101374931	0.07629701387547101
Second Differenced ROA	-4.1482783266576	0.00080508646065428

This table shows the stationery test result related to ROA. The stationarity test shows that Productive and Consumptive Receivables Ratios are stationary at the level form, indicating their stability over time. In contrast, ROA is non-stationary at the level form and only becomes stationary after second differencing, suggesting it follows a more volatile and trend-driven process.

Table 2: The VAR for Consumptive Receivables related to ROA

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-325.45	NA	1.24e-02	47.654	48.987	48.132
1	-284.72	75.8903*	2.56e-03*	**3.8725***	**4.1123***	**3.9567***
2	-280.43	64.592	3.12e-03	39.345	42.801	40.534
3	-278.21	32.571	3.56e-03	39.762	44.287	41.309
4	-277.01	18.346	4.01e-03	40.123	45.717	42.029

This table presents the results of the VAR model selection for examining the relationship between consumptive receivables and ROA. The table compares different lag lengths from 0 to 4 using various statistical criteria such as LogL (log-likelihood), LR (likelihood ratio), FPE (Final Prediction Error), AIC (Akaike Information Criterion), SC (Schwarz Criterion), and HQ (Hannan-Quinn). The optimal lag length is determined based on the lowest values of AIC, SC, and FPE. In this case, lag 1 is identified as the most suitable, as it has the highest LR statistic and the lowest values across AIC (3.8725), SC (4.1123), HQ

(3.9567), and FPE (2.56e-03), which are marked with asterisks. This indicates that a lag length of one period provides the best balance between model fit and complexity for analyzing how past values of consumptive receivables relate to current ROA performance.

Table 3: The VAR for Productive Receivables related to ROA

Lag	AIC	BIC	HQIC	FPE
1	-27.250.537.291.744.400	-25.667.904.141.538.000	-26.610.394.827.214.100	0.0655451894939833
2	-55.254.821.928.324.100	-5.260.048.071.337.210	-54.181.536.314.645.100	**0.003984675950456413**
3	-5.490.071.991.631.250	-5.116.104.547.042.190	-533.890.823.998.032	0.0041296879932029755
4	-5.451.362.518.141.330	-4.967.470.054.469.650	-5.255.833.658.846.460	0.004295348092756013
5	-5.427.309.423.207.170	-4.832.070.218.846.110	-5.186.876.351.295.810	0.004404383231849236
6	-5.366.885.679.821.580	-4.658.847.111.843.250	-5.080.999.959.908.370	0.004685884693040501
7	-529.506.705.535.522	-4.472.744.693.274.010	-4.963.170.782.445.640	0.00504582483408222
8	-5.302.956.539.206.930	-4.364.833.207.101.730	-4.924.482.203.994.810	0.005021246754622573
9	-5.328.284.923.433.610	-4.272.809.729.294.160	-4.902.655.283.096.140	0.00491534488723305
10	-5.264.298.274.501.600	-4.089.885.605.639.240	-4.790.926.230.124.060	0.005267638190976561

Table 3 provides the lag length selection criteria for the VAR model examining the link between productive receivables and ROA. It compares lags from 1 to 10 using four different criteria: AIC, BIC, HQIC, and FPE. Lower values across these indicators generally suggest a better-fitting model. At lag 2, the model records the lowest FPE value (0.003984675950456413) and favorable AIC and HQIC scores, suggesting that this lag may offer an efficient balance between explanatory power and parsimony.

Although lag 3 has a slightly lower AIC, it does not significantly outperform lag 2 in other criteria. Therefore, based on the convergence of the indicators, lag 2 appears to be the most appropriate choice for modeling the relationship between productive receivables and ROA.

Table 4: The Johansen cointegration test result for ROA

Productive Variable	**Test Statistics**	**Critical Value 95%**
Trace Statistic	42.414510051827136	15.4943
Max Eigenvalue	42.277103645246214	14.2639
Consumptive Variable	**Test Statistics**	**Critical Value 95%**
Trace Statistic	59.489846479725536	15.4943
Max Eigenvalue	59.487312086053	14.2639

Table 4 displays the results of the Johansen cointegration test used to examine whether a long-term equilibrium relationship exists between ROA and two types of receivables: productive and consumptive. For both variables, the test statistics for the Trace and Max Eigenvalue methods are significantly higher than their respective 95% critical values. Specifically, the productive receivables show a Trace Statistic of 42.41 and Max Eigenvalue of 42.28, exceeding the thresholds of 15.49 and 14.26. Similarly, the consumptive receivables also show strong results, with a Trace Statistic of 59.49 and Max Eigenvalue of 59.49. These findings confirm the presence of cointegration, meaning that both types of receivables have a statistically significant long-run relationship with ROA, despite possible short-term fluctuations.

Table 5: VECM Result for ROA

Productive Variable	**Speed of Adjustment ($\boldsymbol{\alpha}$)**	**Cointegration Vector ($\boldsymbol{\beta}$)**
Productive Receivables Ratio	-8.88465080807581e-07	1.0
Second Differenced ROA	-6.748434199625477e-05	23298.516247436826
Consumptive Variable	**Speed of Adjustment ($\boldsymbol{\alpha}$)**	**Cointegration Vector ($\boldsymbol{\beta}$)**
Consumptive Receivables Ratio	0.08212835680769	1.9564409197735545e-05
Second Differenced ROA	-1.444095506542099	0.99999999999999

Table 5 outlines the Vector Error Correction Model (VECM) results, which help assess both the short-run dynamics and the speed at which ROA adjusts to restore equilibrium after a shock in receivables. For the productive receivables, the speed of adjustment (α) values are very close to zero, indicating a minimal and statistically insignificant adjustment process toward long-term equilibrium. The cointegration vector (β) shows that changes in productive receivables are associated with large coefficients, but again, the adjustment effect appears negligible. On the other hand, consumptive receivables show a more meaningful result. The α for consumptive receivables ratio is 0.0821, suggesting a relatively stronger speed of adjustment, while the ROA also adjusts with a negative α value (-1.444), indicating that when deviations from the long-run equilibrium occur, ROA responds in the opposite direction to correct the imbalance. The β values for consumptive variables are close to 1, which implies a stable and proportional long-run relationship. Overall, ROA tends to respond more actively to imbalances caused by consumptive receivables than to productive ones.

Table 6: The stationery test result related to ROE

Variable	**ADF Statistics**	**ADF p-value**
Productive Receivables Ratio	-2.99165392560228	0.035681203932662
ROE	-1.76956714521432	0.39567196447166064
Variable	**ADF Statistics**	**ADF p-value**
Consumptive Receivables Ratio	-2.99165392560228	0.035681203932662
ROE	-1.76956714521432	0.39567196447166064
Productive Variable	**ADF Statistics**	**ADF p-value**
First Differenced ROE	-2.72401271665049	0.06997439435992761
Second Differenced ROE	-4.0635030172358	0.0011121637507681
Consumptive Variable	**ADF Statistics**	**ADF p-value**
First Differenced ROE	-2.72401271665049	0.06997439435992761
Second Differenced ROE	-4.0635030172358	0.0011121637507681

Table 6 shows the results of the Augmented Dickey-Fuller (ADF) test to assess the stationarity of variables related to ROE. At the level form, the productive and consumptive receivables ratios have ADF statistics of -2.99 with p-values around 0.035, indicating that they are borderline stationary at the 5% significance level. In contrast, ROE in both cases is non-stationary at level, with ADF statistics of -1.77 and p-values above 0.39, suggesting a strong presence of a unit root. After first differencing, ROE remains marginally non-stationary (p-value ~0.069), but becomes clearly stationary after second differencing, with ADF statistics of -4.06 and p-values below 0.01. These results imply that while the receivables ratios may already be trend-stationary, the ROE variable requires differencing—especially twice—to achieve stationarity, which is essential for valid time-series modelling and cointegration analysis.

Table 7: The VAR for Consumptive Receivables related to ROE

Lag	**AIC**	**BIC**	**HQIC**
1	-0.35124417817970477	**-0.19298086315905755**	-0.28722993172667355
2	**-31.603.809.627.674.600**	-28.949.468.412.722.600	**-30.530.524.013.995.600**
3	-31.469.748.469.075.000	-27.730.074.023.184.400	-2.995.811.095.256.570

4	-31.075.250.624.527.700	-2.623.632.598.781.090	-2.911.996.203.157.900
5	-30.735.734.966.269.700	-24.783.342.922.659.100	-2.833.140.424.715.610
6	-30.112.004.998.961.900	-23.031.619.319.178.600	-2.725.314.779.982.980
7	-2.972.416.338.836.790	-21.500.939.767.555.800	-26.405.200.659.272.100
8	-30.340.543.328.161	-20.959.310.007.109.000	-2.655.579.997.603.980
9	-31.290.974.699.895.500	-20.736.222.758.501.000	-27.034.678.296.520.800
10	-30.407.327.388.725.500	-18.663.200.700.102.000	-2.567.360.694.495.020

The table above helps determine the optimal lag length in a VAR model by comparing three selection criteria: AIC, BIC, and HQIC. Among these, the lowest AIC value is observed at Lag 2 (-31.60), indicating this lag provides the best model fit according to the AIC. Similarly, HQIC reaches its minimum value at Lag 2 (-30.53), reinforcing the choice. However, BIC suggests Lag 1 as optimal, with the smallest value of -0.1930. In practice, AIC and HQIC are often prioritised in time-series analysis, especially when predictive accuracy is the goal, because they balance fit and complexity more effectively in dynamic models. Therefore, Lag 2 is considered the most appropriate choice, as supported by both AIC and HQIC.

Table 8: The VAR for Productive Receivables related to ROE

Lag	AIC	BIC	HQIC	FPE
1	-0.35124417817970277	-0.19298086315905555	-0.28722993172667155	0.7038388133912497
2	-31.603.809.627.674.600	-28.949.468.412.722.600	-30.530.524.013.995.600	0.04241733918452834
3	-3.146.974.846.907.500	-27.730.074.023.184.400	-2.995.811.095.256.570	0.04300425233875023
4	-3.107.525.062.452.780	-26.236.325.987.810.900	-2.911.996.203.157.900	0.04476246949702922
5	-3.073.573.496.626.970	-24.783.342.922.659.000	-2.833.140.424.715.600	0.04635532446922024
6	-30.112.004.998.961.900	-2.303.161.931.917.860	-2.725.314.779.982.980	0.04941430281796967

Lag	AIC	BIC	HQIC	FPE
7	-2.972.416.338.836.790	-2.150.093.976.755.580	-26.405.200.659.272.100	0.05148095082329341
8	-30.340.543.328.160.900	-20.959.310.007.109.000	-2.655.579.997.603.980	0.04854933351095432
9	-3.129.097.469.989.540	-2.073.622.275.850.100	-27.034.678.296.520.800	0.04432502318036455
10	-3.040.732.738.872.550	-18.663.200.700.101.900	-2.567.360.694.495.010	0.04867412801294407

In determining the optimal lag length for the VAR model, the selection is based on minimizing the values of standard information criteria. As shown in the table 8, Lag 2 yields the lowest values across all key indicators—AIC (-31.603), BIC (-28.949), HQIC (-30.530), and FPE (0.042). The convergence of all four criteria at Lag 2 strongly supports its selection as the most appropriate lag length, ensuring a model that balances goodness-of-fit with parsimony, consistent with best practices in time-series econometrics.

Table 9: The Johansen cointegration test result for ROE

Productive Variable	**Test Statistics**	**Critical Value 95%**
Trace Statistic	50.266508957734	15.4943
Max Eigenvalue	50.128591985762	14.2639
Consumptive Variable	**Test Statistics**	**Critical Value 95%**
Trace Statistic	50.266508957734	15.4943
Max Eigenvalue	50.128591985762	14.2639

Table 9 reports the Johansen cointegration test results assessing the long-run equilibrium relationship between ROE and both productive and consumptive receivables. For each variable, the Trace Statistic and Max Eigenvalue far exceed the 95% critical thresholds. Specifically, the Trace Statistic registers at 50.27, surpassing the critical value of 15.49, while the Max Eigenvalue stands at 50.13, well above its respective benchmark of 14.26. These results provide strong statistical evidence of cointegration, indicating that despite potential short-term fluctuations, ROE and both types of receivables move together in the long run.

Tabel 10: VECM Result for ROE

Productive Variable	**Speed of Adjustment (α)**	**Cointegration Vector (β)**
Productive Receivables Ratio	-2.284109042873033e-06	1.0
Second Differenced ROE	-0.000157490111203554	11443.773760352977

Consumptive Variable	Speed of Adjustment (α)	Cointegration Vector (β)
Consumptive Receivables Ratio	9.287368507111615e-07	1.0
Second Differenced ROE	-5.673695306738391e-05	31761.339153298966

Table 10 presents the Vector Error Correction Model (VECM) results assessing the short-run adjustment dynamics and long-run relationship between ROE and receivable ratios. For productive receivables, the speed of adjustment (α) for ROE is negative and small (-0.000157), indicating that deviations from the long-run equilibrium are corrected gradually over time. The cointegration coefficient (β) for second-differenced ROE is 11,443.77, reflecting the long-run proportional relationship. For consumptive receivables, the adjustment speed of ROE is slightly larger in magnitude (-0.0000567), implying a relatively quicker response to disequilibrium. Its cointegration vector is also higher, at 31,761.34, suggesting a stronger long-run association between consumptive receivables and ROE.

Table 11: The stationery test result related to NPF

Variable	ADF Statistics	ADF p-value
Productive Receivables Ratio	-2.99165392560228	0.03568120393266284
NPF	-2.64778424396039	0.08351781505061662
Variable	**ADF Statistics**	**ADF p-value**
Consumptive Receivables Ratio	-2.99165392560228	0.03568120393266284
NPF	-2.64778424396039	0.08351781505061662
Productive Variable	**ADF Statistics**	**ADF p-value**
First Differenced NPF	-6.9601489699543	9.209129992250656e-10
Consumptive Variable	**ADF Statistics**	**ADF p-value**
First Differenced NPF	-6.9601489699543	9.209129992250656e-10

Table 11 summarizes the results of the Augmented Dickey-Fuller (ADF) test used to examine the stationarity of variables related to Non-Performing Financing (NPF). At level, the ADF statistics for both productive and consumptive receivables ratios are -2.99 with p-values just below the 5% threshold, indicating marginal stationarity. However, the NPF variable itself shows ADF statistics of -2.65 with p-values exceeding 0.08, suggesting non-stationarity at level. After first differencing, NPF becomes strongly stationary in both productive and consumptive models, as indicated by a highly significant ADF statistic of -6.96 and an extremely low p-value (< 1e-9). These results confirm that while receivable ratios may already be weakly stationary, the NPF variable must be differenced once to achieve stationarity, justifying its transformation before further time-series modelling.

Table 12: The VAR for Productive Receivables related to NPF

Lag	FPE	AIC	BIC	HQIC
1	1.0000*	1.0000*	1.0000*	1.0000*
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	1	1	1
9	1	1	1	1
10	1	1	1	1

Table 12 displays the lag order selection results for the VAR model analyzing the relationship between productive receivables and non-performing financing (NPF). All criteria unanimously indicate Lag 1 as the optimal lag length, as evidenced by the lowest value marked with an asterisk (*). This consistency across all selection metrics suggests that a one-period lag provides the most appropriate model specification, balancing both explanatory power and model simplicity in capturing the dynamic interaction between productive receivables and NPF.

Table 13: The VAR for Consumptive Receivables related to NPF

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-250.12	NA	0.015623	5.7829	5.8835	5.8221
1	-140.45	205.76*	0.001125*	3.4581*	3.7593*	3.5736*
2	-138.60	3.29	0.001245	3.5128	4.0146	3.7046

Table 13 presents the lag selection criteria for the VAR model evaluating the relationship between consumptive receivables and non-performing financing (NPF). Among the options, Lag 1 consistently yields the best results: it produces the highest LR statistic (205.76), the lowest FPE (0.001125), and the lowest AIC (3.4581), SC (3.7593), and HQ (3.5736), all marked with asterisks to indicate their optimality. Although Lag 2 shows slightly lower AIC and HQ values, the improvements are marginal, while its LR value is considerably weaker. Overall, the convergence of multiple indicators at Lag 1 suggests that it offers the most efficient and parsimonious lag structure for capturing the short-run dynamics between consumptive receivables and NPF.

Table 14: The Johansen cointegration test result for NPF

Productive Variable	**Test Statistics**	**Critical Value 95%**
Trace Statistic	36.171483176794304	15.4943
Max Eigenvalue	24.6109727901202	14.2639

Consumptive Variable	Test Statistics	Critical Value 95%
Trace Statistic	36.1714831767942	15.4943
Max Eigenvalue	24.610972790120247	14.2639

Table 14 presents the results of the Johansen cointegration test to assess the presence of a long-term equilibrium relationship between non-performing financing (NPF) and both productive and consumptive receivables. For each variable, the Trace Statistic and Max Eigenvalue exceed their respective 95% critical values. Specifically, the Trace Statistic is 36.17, surpassing the critical threshold of 15.49, and the Max Eigenvalue is 24.61, higher than the critical value of 14.26. These results provide strong statistical evidence of cointegration, indicating that NPF and both types of receivables move together over the long term despite short-term fluctuations.

Table 15: VECM Result for NPF

Productive Variable	Speed of Adjustment (α)	Cointegration Vector (β)
Productive Receivables Ratio	-0.26546640871300	8.34219126406137e-05
Second Differenced ROE	-0.4812533172511072	1.0
Consumptive Variable	**Speed of Adjustment (α)**	**Cointegration Vector (β)**
Consumptive Receivables Ratio	-0.4824	-0.00001655
Second Differenced ROE	0.2503	1.0000

Table 15 displays the Vector Error Correction Model (VECM) results for examining the relationship between non-performing financing (NPF) and receivable ratios. In the productive receivables model, the speed of adjustment (α) for the receivables ratio is -0.2655, while that for second-differenced ROE is -0.4813, indicating that both variables adjust negatively toward long-run equilibrium when deviations occur. The cointegration coefficient (β) for the productive receivables is relatively small (8.34e-05), suggesting a subtle but stable long-term link. In contrast, the consumptive receivables model shows a stronger short-run correction, with α = -0.4824 for receivables and a positive adjustment of 0.2503 for ROE. The β value for consumptive receivables is negative (-0.00001655), implying an inverse long-run relationship with NPF.

Table 16: Sensitivity test for Confidence Level

Financing Category	sensitivity test for Confidence Level				
	90%	95%	97%	99%	99,50%
CVaR – Productive Financing	-79,837%	-91,328%	-91,520%	-91,827%	-91,827%
CVaR – Consumptive Financing	-71,019%	-91,330%	-91,432%	-91,546%	-91,546%

Gap (Productive-Consumptive)	-8,819%	0,002%	-0,088%	-0,281%	-0,281%

Table 17: Portfolios Compositions Evaluation Result

Information	**Minimum Risk Scenario**	**Optimum Return Scenario**	**Current Composition**
$W_{productive}$	44,46%	46,89%	43,96%
$W_{consumptive}$	55,54%	53,11%	56,04%
E[R]	16,65%	16,68%	16,65%
Standard Deviation (**σ**)	28,15%	28,18%	28,15%
Sharpe Ratio	38,73%	38,79%	38,70%

Figure 1: Optimum Return Scenario Efficient Frontier Diagram

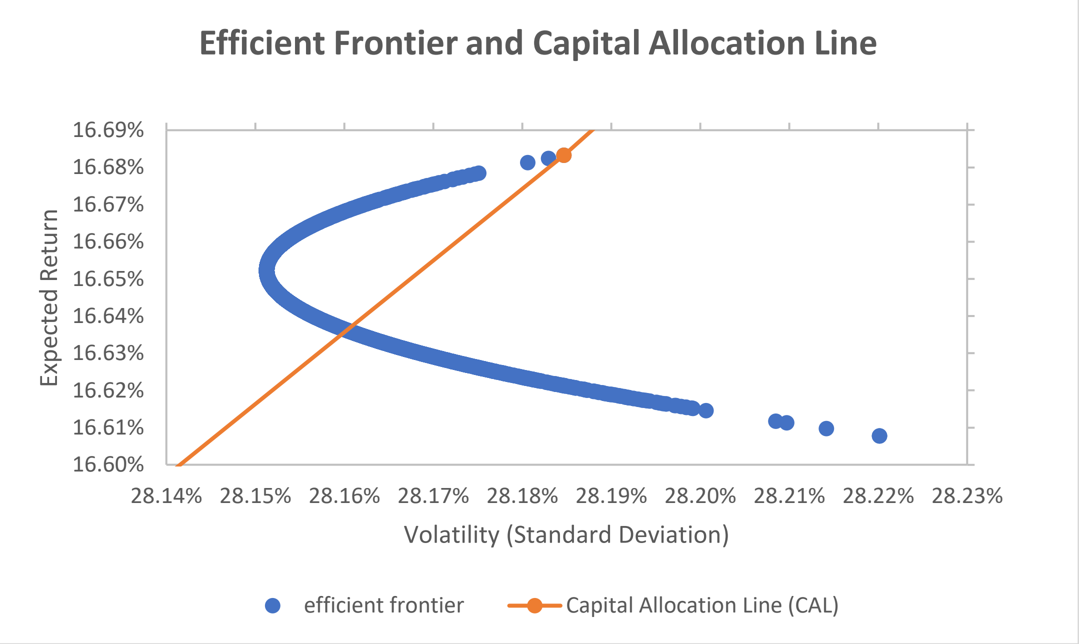

Table 18: Sensitivity Test Result for Expected Return and Standard Deviation

Information	**Sensitivity Test for Expected Return and Standard Deviation**					
	+10%	**-10%**	**+20%**	**-20%**	**+30%**	**-30%**
Optimum Return						
Highest SR	59,37%	4,42%	73,06%	-64,49%	82,83%	-270,00%
Highest E[R]p	26,68%	6,68%	36,68%	-3,32%	46,68%	-13,32%
Wprod	46,89%	46,89%	46,89%	46,89%	46,89%	46,89%
Wcons	53,11%	53,11%	53,11%	53,11%	53,11%	53,11%
E[R]p	26,68%	6,68%	36,68%	-3,32%	46,68%	-13,32%
Sharpe ratio	59,37%	4,42%	73,06%	-64,49%	82,83%	-270,00%
Minimize Risk						
Wprod	45,57%	42,64%	46,31%	40,99%	46,82%	40,99%
Wcons	54,43%	57,36%	53,69%	59,01%	53,18%	59,01%

Information	Sensitivity Test for Expected Return and Standard Deviation					
	+10%	-10%	+20%	-20%	+30%	-30%
E[R]p	35,25%	21,04%	42,34%	13,89%	49,42%	6,79%
SDp	26,67%	6,63%	36,68%	-3,39%	46,68%	-13,39%
Sharpe ratio	59,34%	4,18%	73,05%	-65,81%	82,83%	-281,84%
Current Composition						
Wprod	43,96%	43,96%	43,96%	43,96%	43,96%	43,96%
Wcons	56,04%	56,04%	56,04%	56,04%	56,04%	56,04%
E[R]p	26,65%	6,65%	36,65%	-3,35%	46,65%	-13,35%
SDp	38,15%	18,15%	48,15%	8,15%	58,15%	-1,85%
Sharpe ratio	54,77%	4,93%	64,16%	-111,67%	70,32%	1034,18%

Table 19: Sensitivity test for Risk-free rate

Sharpe Ratio	Sensitivity test for Risk-free rate		
	3%	5%	7%
Optimum Return	48,55%	41,45%	34,36%
Minimize Risk	48,50%	41,39%	34,29%
Current Composition	48,47%	41,37%	34,26%

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