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Value at Risk Evaluation of Defined Contribution and Defined Benefit Pension Plans

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ABSTRACT

Pension funds such as the Defined Benefit Pension Program (DBPP) and the Defined Contribution Pension Program (DCPP) have risks that need to be managed carefully. Previous research has looked at VaR in other contexts, but no one has specifically discussed VaR in pension funds, especially DBPP and DCPP. The main objective of this research is to determine the VaR value for the two pension programs and analyze the risk differences between DBPP and DCPP. The method used is VaR measurement with Monte Carlo simulation based on data from January 2015 to July 2023. The research results obtained from these measurements show that DBPP provides the largest potential maximum loss (VaR) value for the next one-month period compared to DCPP.

Keywords : **Pension Funds; Defined Benefit Pension Program; Defined Contribution Pension Program; VaR; Monte Carlo Simulation**

ABSTRAK

Dana pensiun seperti Program Pensiun Manfaat Pasti (DPMP) dan Program Pensiun Iuran Pasti (PPIP) memiliki risiko yang harus dikelola dengan hati-hati. Penelitian sebelumnya telah banyak yang membahas VaR dalam konteks lain, namun belum ada yang secara khusus membahas VaR pada dana pensiun, khususnya DBPP dan DCPP. Tujuan utama dari penelitian ini adalah untuk mengetahui nilai VaR untuk kedua program pensiun tersebut dan menganalisis perbedaan risiko antara DBPP dan DCPP. Metode yang digunakan adalah pengukuran VaR dengan simulasi Monte Carlo berdasarkan data dari Januari 2015 sampai dengan Juli 2023. Hasil penelitian yang diperoleh dari pengukuran tersebut menunjukkan bahwa DBPP memberikan nilai potential maximum loss (VaR) terbesar untuk periode 1 bulan ke depan dibandingkan dengan DCPP.

Kata Kunci : ***Dana Pensiun; Program Pensiun Manfaat Pasti; Program Pensiun Iuran Pasti; VaR; Simulasi Monte Carlo***

INTRODUCTION

The importance of maintaining a sustainable income for citizens who have entered retirement requires more effective attention and action, one of which is by providing a pension fund program. Pension funds are pools of savings accumulated during the working life of individuals. At any given point in time, they are the sum of the flow of the employer and employee contributions, investment income, and eventual benefits paid (Impavido, 2013). Pension funds collect money from employers and employees to fund employee retirement obligations. Pension fund providers look to long-term growth of capital to support the needs of future retirees as the cost of living increases over their working lives. This makes pension funds similar to insurance companies in the desired composition of their investment portfolios (Glickman, 2014). Pension funds are established by employers to facilitate and organize the investment of employees' retirement funds. Defined benefit plans specify payments that employees will receive when they retire and defined contribution plans define employer and employee contributions, but actual benefits depend on fund investment performance (Teall, 2018).

As a legal entity that manages assets and runs a pension program intending to offer pension benefits to maintain the stability of participants' income after retirement, pension funds are very vulnerable to risk. Risk generally refers to the potential for loss, both in material and non-material form, which can arise directly or indirectly and have an impact on the company's financial situation, both now and in the future. In the context of pension fund management, the risk faced is the potential for a lack of funds, which could ultimately hinder the ability of pension funds to fulfill their obligations in paying pension benefits to participants (Lestari, 2013).

Pension program funding is an effort to provide funds carried out by companies and employees so that the funds collected are sufficient to pay benefits (Kusnandar & Satyahadewi INTISARI, 2014). On funding defined benefit pension programs, the amount of pension benefits that participants receive at the time pension is first determined based on a pension benefit formula following fund regulations applicable to pension (Yopi et al., 2021). In calculating pension funds, an actuary must be consistent using calculation methods and actuarial assumptions (Rahmawati Z & Rosita, 2022). A Defined Benefit Pension Program is a pension program that uses a certain formula for the pension benefits received by participants which has been determined by pension fund regulations. The benefit an employee receives upon retirement is linked to the employee's salary and is set upfront, i.e., defined (Dyachenko et al., 2022). DB pension plans have also helped pool some of the risks associated with long-term saving for retirement. Not only are some of these risks transferred to the employer in a DB pension plan but also can be pooled between members (International Actuarial Association, 2018). By contrast, in a defined contribution (DC) scheme, a sponsoring company contributes a certain percentage of the employee's salary, so how much the employee gets when she retires depends on the market return of the investment strategy(Dyachenko et al., 2022).

Pension funds provide the necessary risk management solutions that can protect a person from these risks. This research will focus on the maximum possible loss that occurs during a certain period. Risk management is carried out using Value at Risk (VaR). VaR is a measuring tool that can be used to assess the worst loss that may occur for an investor or business entity for its investment in securities or assets, either individually or in a portfolio at a certain time, at a predetermined level of opportunity. In VaR, the probability of loss is calculated from the probability of a loss event being worse than a specified percentage (Stuart A. Klugman, 2012).

Several studies are relevant to this research. Research conducted by Suhandi (Suhadi, 2012) entitled Evaluation of Value at Risk Calculations using Monte Carlo Simulation and Historical Simulation on three State-Owned Enterprise Banks (BUMN) aims to explain how Value at Risk is measured in portfolios and to determine potential losses in the three research stock assets . In this research, a method using secondary data was used and the test used was Monte Carlo and historical VaR analysis. The results of this research show that at a historical alpha level of 5% there were 10 deviations while in Monte Carlo there were 11 deviations. Research conducted by Sofiana (Sofiana, 2011), Measurement of Value at Risk in Portfolios using Monte Carlo Simulation, aims to explain how Value at Risk measurement in portfolios is conducted using Monte Carlo simulation. This study utilized secondary data, and the test employed was VaR analysis with Monte Carlo. Research conducted by Islamiah (Islamiah, 2018), Market Ratio Analysis to Predict Changes in Company Profits Using the Value at Risk (VaR) Method with Monte Carlo Simulation, aims to determine changes in company profits using market ratio analysis and the Value at Risk method with Monte Carlo simulation. Then, research conducted by Tariq M (Thariq M, 2020), Measuring Risk Value at Risk (Var) in Stock Investments Using the Monte Carlo Simulation Method (Case Study: Pt. Bank Pembangunan Daerah Jawa Timur Tbk), this study aims to determine risk measurement share investment in PT. East Java Regional Development Bank Tbk for the last year using the Value at Risk method using Monte Carlo simulation. The Value at Risk method is used to measure the maximum risk of loss in a company's stock investment performance. In the Monte Carlo method, random numbers are generated with a norming distribution, and then the Value at Risk calculation is carried out using the results of random number generation. Also, research conducted by R Taruna (R Taruna, 2022), Analysis of Financing Risk Measurement Using the Value At Risk (VAR) Method in BPRS in Indonesia for the 2015-2021 Period, aims to measure potential risks in Mudharabah, Musyarakah, and Murabahah financing and measure potential risks of BPRS financing in each province in Indonesia. This research uses a quantitative approach with data sources from secondary data. The data in this research was taken from the Financial Services Authority. This research uses the Value at Risk Monte Carlo approach to measure potential losses.

Another previous research about pension funds conducted by Anggraeni (Anggraeni et al., 2023) aims to calculate Indonesian pension funds using the GSA method, Rokhim (Rokhim et al., 2022) about the Indonesian pension system, and Huda (Huda & Kurnia, 2022) admins to constructing a business model for an Islamic digital pension fund. Previous research has not focused on discussing VaR in pension funds and comparing VaR in Defined Benefit Pension Program (DBPP) and Defined Contribution Pension Program (DCPP) funds.

Therefore, the novelty of this research is calculating VaR in DBPP and DCPP pension funds. The method to be used involves finding VaR through Monte Carlo simulation. The case study will utilize data from the Defined Benefit Pension Program (DBPP) and Defined Contribution Pension Program (DCPP) for the period January 2015 – July 2023. The main objective of this research is to determine the VaR value for the two pension programs and analyze the risk differences between the two. The method used is VaR measurement with Monte Carlo simulation based on data from January 2015 to July 2023.

RESEARCH METHOD

The method used is measuring VaR through Monte Carlo simulation based on data from January 2015 to July 2023. The data used in this study are secondary data sourced from the Financial Services Authority (OJK), which consists of data from the Defined

Benefit Pension Program (DBPP) and Defined Contribution Pension Program (DCPP) from January 2015 to July 2023. The variables used in this study are the Total liabilities outside the present value of actuarial liabilities/benefit liabilities of the Defined Benefit Pension Program (DBPP) and the Total liabilities outside the present value of actuarial liabilities or benefit liabilities of the Defined Contribution Pension Program (DCPP).

The research approach chosen for this study is a quantitative approach, which is characterized by reliance on numerical data (numbers) to test hypotheses. The population in this study is the monthly finances of pension fund companies in Indonesia. In this research, the author used a sample of Indonesian pension fund company liabilities published January 2015 – June 2023 with a sample size of 103.

In managing the data, the author uses Autoregressive Integrated Moving Average (ARIMA) using Minitab statistical software 21 to forecast the results of the values of the data. VaR will be carried out using the Monte Carlo simulation method to measure the maximum potential loss limit that can be borne by the company using Microsoft Excel. The steps for measuring VaR on DBPP and DCPP using Monte Carlo simulation are: Forecasting liabilities using ARIMA, calculating UCF to find unexpected cash flow by looking for the difference between expected data and actual data, Monte Carlo simulation, VaR calculation (See Formula 1), calculating mean VaR, and comparison of mean VaR DBPP and DCPP.

$$\boldsymbol{VaR_{(1-\alpha)}(t) = W_0 R^* \sqrt{t}} \quad \textbf{(1)}$$

Based on Formula 1, $VaR_{(1-\alpha)}(t)$ is Maximum loss potential, W_0 for initial investment funds, R^* is mean the 1-α quantile value of the unexpected cash flow distribution, and $\sqrt{t}$ is for period.

RESULTS AND DISCUSSION

Data

The data in Table 1 from the OJK website concerning pension funds, namely the Defined Benefit Pension Program (DBPP) and Defined Contribution Pension Program (DCPP), for the period January 2015 to July 2023 consists of 103 data points each.

Table 1. DBPP and DCPP Actual Data

Month	DBPP Actual Data	DCPP Actual Data
Jan-15	1151	179
Feb-15	974	227
Mar-15	1009	215
Apr-15	1379	273
May-15	1270	168
Jun-15	1241	162
Jul-15	1010	143
Aug-15	884	144
Sep-15	972	140
⋮	⋮	⋮
Jan-23	1198.91808	261.6345022
Feb-23	1448.084266	329.535819
Mar-23	1729.125066	287.1858886
Apr-23	1432.897822	253.0441546
May-23	1355.266166	313.5165839
Jun-23	1198.446644	474.2625539
Jul-23	1252.878778	253.973701

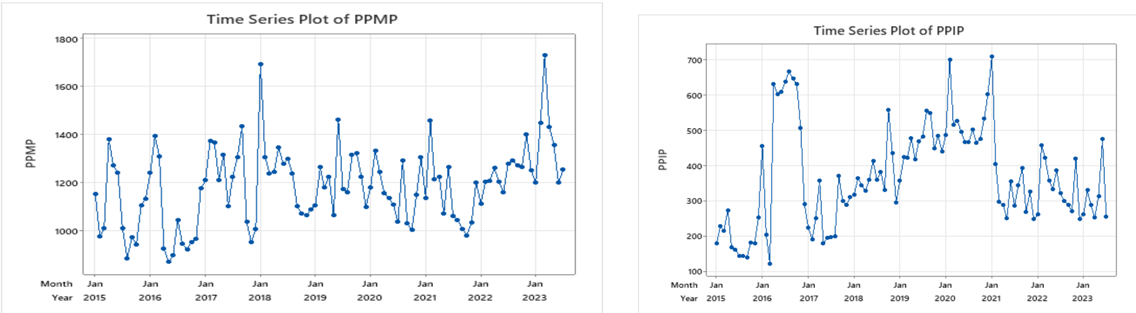
Source: Statistics and pension funds on the website, 2023

Forecasting Using ARIMA

Forecasting data using Autoregressive Integrated Moving Average (ARIMA). To create a forecasting model, there are 4 stages: model identification, parameter estimation, diagnostic checking, selection of the best model, and prediction.

In the initial stage of data analysis, the focus is on identifying the characteristics of the available data. This involves determining whether the data shows an upward trend, is seasonal, or is random. To assess trends in a time series, a graphical representation of the time series data is created. Additionally, this step is crucial to meet the basic assumptions of using the ARIMA model, which requires the time series data used in the model to be stationary. If the existing data is non-stationary, differencing is needed to ensure that the resulting model accurately represents the overall data conditions. Data processing is done using statistical software, particularly Minitab 21. Figure 1 is the time series data plot illustrating the Defined Benefit Pension Program and Defined Contribution Pension Program from January 2015 to July 2023.

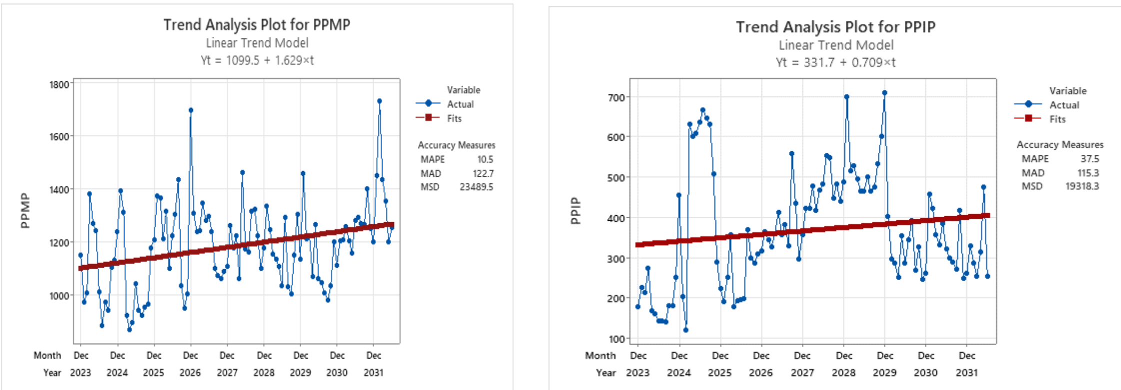
The first step in forecasting is to examine the plot of the time series data to assess its stationarity. Stationarity of data can be in terms of variance or mean.



Source: Processed Minitab output results, 2023

Figure 1. DBPP and DCPP Time Series Data Plot

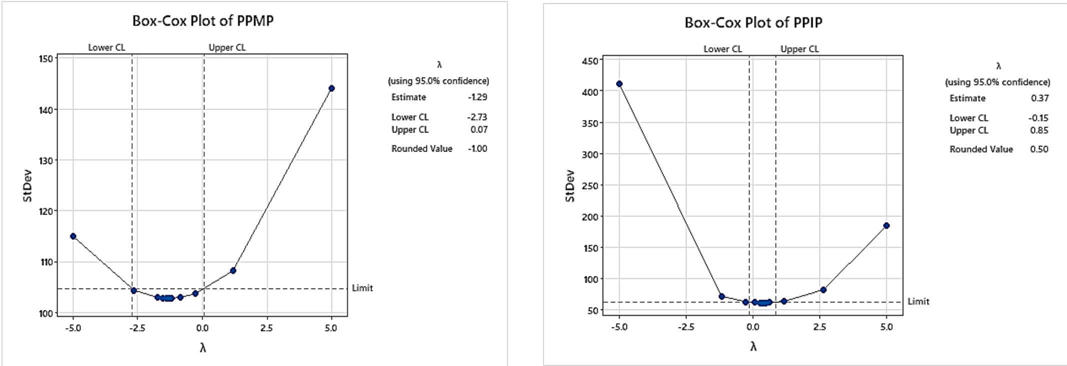
Based on Figure 1, it can be observed that the data pattern formed by DBPP and DCPP data is a non-stationary data pattern. To confirm the non-stationarity of the data, several steps were taken with the results in Figure 2.



Source: Processed Minitab output results, 2023

Figure 2. Trend Analysis Plot of DBPP and DCPP Data

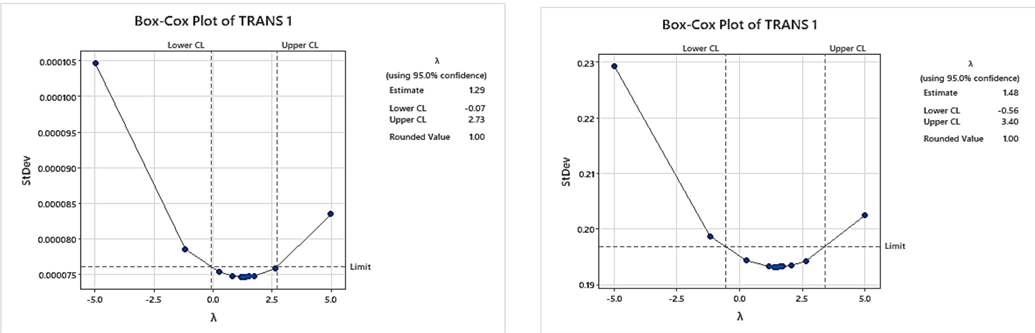
In figure 2, it is evident that the DBPP and DCPP data are non-stationary with respect to the mean because the line representing the mean is not horizontal, indicating that the data exhibits a linear trend that tends to increase.



Source: Processed Minitab output results, 2023

Figure 3. Box-cox Plot of DBPP and DCPP Data

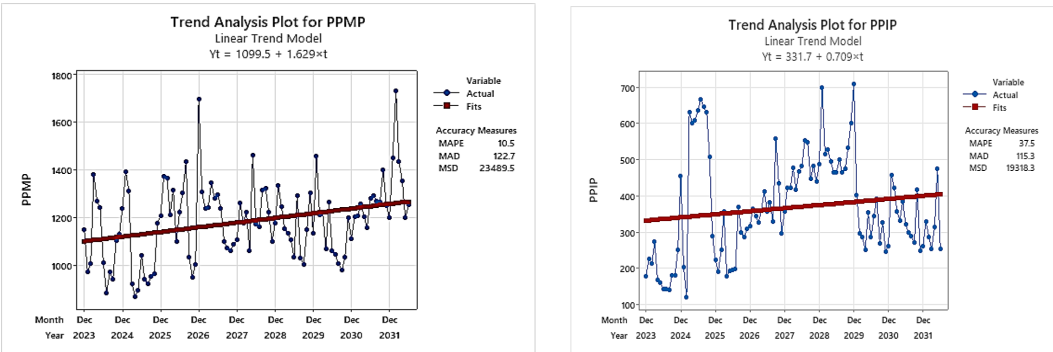
In Figure 3, it is evident that the DBPP and DCPP data are non-stationary to the variance because the rounded values are not equal to 1, namely -1.00 and 0.50. Therefore, transformations and differencing are necessary to make the data stationary.



Source: Processed Minitab output results, 2023

Figure 4. Box-cox Plot of DBPP and DCPP Data Resulting from Transformation 1

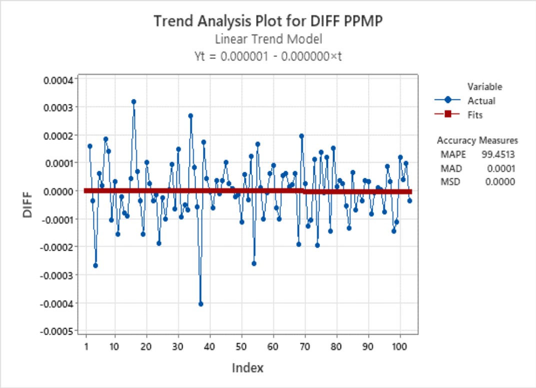
In Figure 4, it is evident that the DBPP and DCPP data, after undergoing transformation 1, meet the stationary condition with respect to variance because the rounded values are equal to 1. Next, trend analysis is conducted on each data resulting from the transformation.



Source: Processed Minitab output results, 2023

Figure 5. Trend Analysis Plot of DBPP and DCPP Data Resulting From Transformation 1

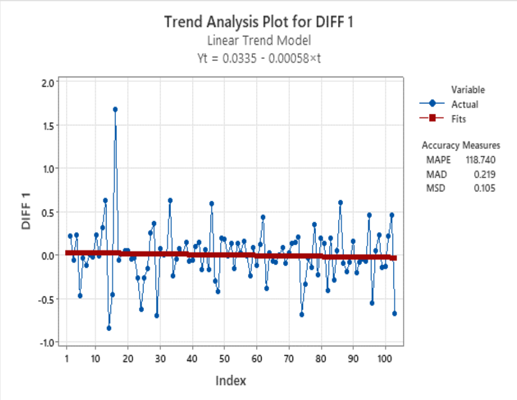
In Figure 5, it is evident that the DBPP and DCPP data resulting from transformation 1 are not stationary with respect to the mean because the line is not horizontal. Therefore, differencing is needed for the data and the results are in Figure 6.



Source: Processed Minitab output results, 2023

Figure 6. Trend Analysis Plot After Differencing 1 From DBPP Data

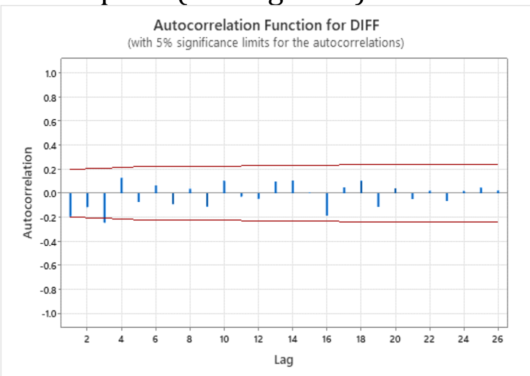
In Figure 6, the trend analysis results from differencing the DBPP data show a change, as the line is more horizontal compared to before.



Source: Processed Minitab output results, 2023

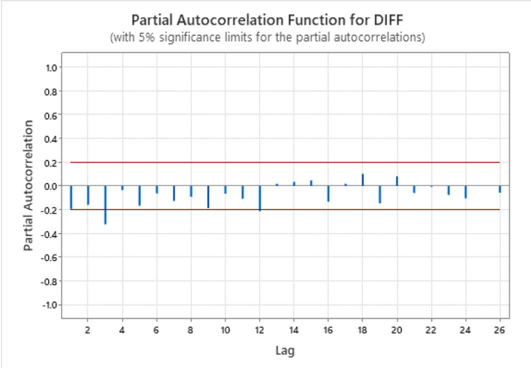
Figure 7. Trend Analysis Plot After Differencing 1 From DCPP Data

In Figure 7, the trend analysis results from differencing the DBPP data show a change, as the line is more horizontal compared to before. After making the data stationary with respect to variance and mean, the next step is to identify the potential ARIMA model by examining the ACF and PACF plots (See Figure 8).



Source: Processed Minitab output results, 2023

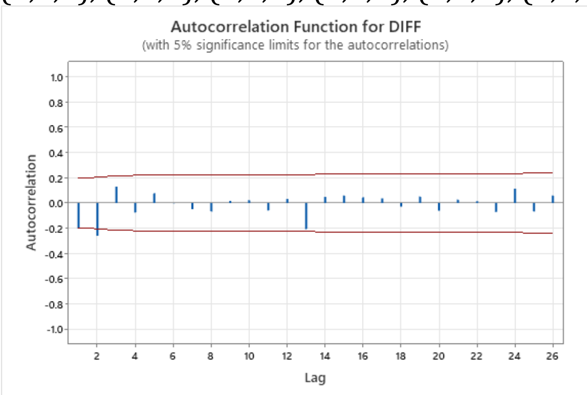
Figure 8. ACF Plot of 1 DBPP Differencing Data



Source: Processed Minitab output results, 2023

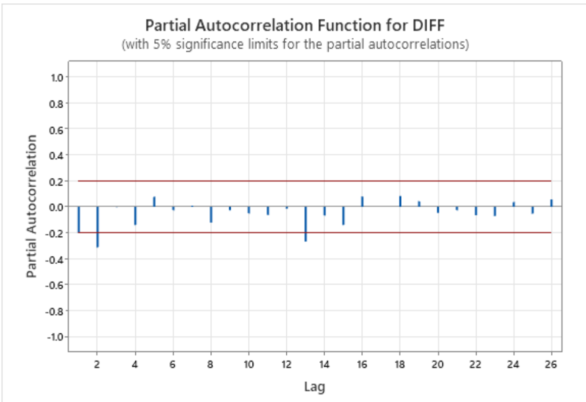
Figure 9. PACF Plot of 1 DBPP Differencing Data

In Figures 8 and 9, it can be determined that the order of AR=2 (based on the PACF plot) and the order of MA=1 (based on the ACF plot) by observing the number of lags (blue lines) passing through the interval lines (red lines). Thus, a tentative model with the maximum order is obtained, which is ARIMA (2,1,1). With 10 possible ARIMA models: (0,0,1), (1,0,0), (1,0,1), (2,0,0), (2,0,1), (1,1,0), (2,1,0), (0,1,1), (1,1,1), and (2,1,1).



Source: Processed Minitab output results, 2023

Figure 10. ACF Plot of First DCPP Differencing Data



Source: Processed Minitab output results, 2023

Figure 11. PACF Plot of 1 DCPP Differencing Data

In Figures 10 and 11, it can be determined that the order of AR=2 (based on the PACF plot) and the order of MA=1 (based on the ACF plot) by observing the number of lags (blue lines) passing through the interval lines (red lines). Thus, a tentative model with the maximum order is obtained, which is ARIMA (2,1,). With 10 possible ARIMA models: (0,0,1), (1,0,0), (1,0,1), (2,0,0), (2,0,1), (1,1,0), (2,1,0), (0,1,1), (1,1,1), and (2,1,1).

After obtaining several tentative models, the next step is to test whether the parameters are significant (p-value < α) or not (p-value > α). Based on the p-value estimates that will be attached below, the conclusion drawn by the author is that ARIMA (0,01), (1,0,0), (1,1,0), (0,1,1), (1,1,1) for the DBPP data and ARIMA (0,0,1), (0,1,1), (1,1,1), (1,1,0) for the DCPP data are significant, while ARIMA (1,0,1), (2,0,0), (2,0,1), (2,1,0), (2,1,1) for the DBPP data and ARIMA (1,0,0), (1,0,1), (2,0,0), (2,0,1), (2,1,0), (2,1,1) for the DCPP data are not significant.

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
AR 1	0.4175	0.0967	4.32	0.000
MA 1	0.9819	0.0337	29.13	0.000
Constant	0.947	0.770	1.23	0.222

Residual Sums of Squares

DF	SS	MS
99	2025312	20457.7

Back forecasts excluded

Source: Processed Minitab output results, 2023

Figure 12. Parameter Estimates from ARIMA (1,1,1) DBPP Data

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
AR 1	0.6874	0.0874	7.87	0.000
MA 1	0.9687	0.0476	20.36	0.000
Constant	0.00105	0.00114	0.92	0.359

Residual Sums of Squares

DF	SS	MS
99	9.29592	0.0938982

Back forecasts excluded

Source: Processed Minitab output results, 2023

Figure 13. Parameter Estimates from ARIMA (1,1,1) DCPP Data

In Figures 12 and 13, based on the MSE, it can be concluded that the best model is ARIMA (1,1,1) with an MSE of 20457.7 for the DBPP data and ARIMA (1,1,1) with an MSE of 0.0938982 for the DCPP data.

After selecting the best model, which is ARIMA (1,1,1) for the DBPP data and ARIMA (1,1,1) for the DCPP data, the final step of the ARIMA method is to make predictions based on the chosen model. Table 2 is the predicted results for the DBPP and DCPP data for the period January 2015 to July 2023.

Table 2. DBPP and DCPP Forecast Data Results

Month	Data Forecast DBPP	Data Forecast DCPP
Jan-15	1261.932079	290.7223919
Feb-15	1266.6588	316.876678
Mar-15	1269.579001	335.5515531
Apr-15	1271.744907	348.9461323
May-15	1273.595864	358.6129416
Jun-15	1275.315318	365.6480294
Jul-15	1276.979863	370.8251809
Aug-15	1278.621482	374.6906714
Sep-15	1280.253529	377.6301587
Oct-15	1281.881578	379.9159085
May-23	1429.77539	448.8464412
Jun-23	1431.400574	449.5625022
July-23	1433.025758	450.2785632

Source: Processed Minitab output results, 2023

Unexpected Cash Flow

It is the difference between the forecasted data and the actual data, where the resulting difference data will be used to find the Value at Risk (VaR) value. The Results of Differences Between DBPP Forecast Data and Actual DCPP Data are displayed in Table 3.

Table 3. Results of Differences Between DBPP Forecast Data and Actual DCPP Data

Month	Data Forecast DBPP	Data actual DBPP	UCF DBPP
Jan-15	1261.932079	1151	110.9320787
Feb-15	1266.6588	974	292.6588004
Mar-15	1269.579001	1009	260.5790013
Apr-15	1271.744907	1379	-107.2550929
May-15	1273.595864	1270	3.595864283
Jun-15	1275.315318	1241	34.31531776
Jul-15	1276.979863	1010	266.9798632
Aug-15	1278.621482	884	394.6214822
Sep-15	1280.253529	972	308.2535286
Oct-15	1281.881578	942	339.881578
Apr-23	1429.77539	1432.897822	74.50922429
May-23	1431.400574	1355.266166	232.9539302
Jun-23	1433.025758	1198.446644	180.1469805

Source: Processed Minitab output results, 2023

Table 4. Results of Differences Between DCPP Forecast Data and Actual DCPP Data

Month	Data Forecast DCPP	Data actual DCPP	UCF DCPP
Jan-15	290.7223919	179	111.7223919
Feb-15	316.876678	227	89.87667805
Mar-15	335.5515531	215	120.5515531
Apr-15	348.9461323	273	75.94613232
May-15	358.6129416	168	190.6129416
Jun-15	365.6480294	162	203.6480294
Jul-15	370.8251809	143	227.8251809
Aug-15	374.6906714	144	230.6906714
Sep-15	377.6301587	140	237.6301587
Oct-15	379.9159085	182	197.9159085
Apr-23	448.8464412	253.0441546	195.0862256
May-23	449.5625022	313.5165839	135.3298572
Jun-23	450.2785632	474.2625539	-24.70005171

Source: Processed excel output results, 2023

Value at Risk Calculation Using Monte Carlo Simulation

Determining the parameters of Unexpected Cash Flow (UCF), where Unexpected Cash Flow is assumed to have a mean and variance.

Table 5. Parameters of Unexpected Cash Flow (UCF).

	Mean	Standard Deviation
DBPP	165.9136226	154.0150132
DCPP	42.3293559	137.4527057

Source: Processed Excel output results, 2023

Simulating Unexpected Cash Flow. Simulate the value of Unexpected Cash Flow by generating n random Unexpected Cash Flow data using parameters obtained from step (1) to produce an empirical distribution of Unexpected Cash Flow data.

The step to generate data uses the function =RAND(), which generates random numbers greater than 0 and less than 1. This function is commonly used to generate random numbers. Simulate and reach 10,000 units to strengthen the research model. In Microsoft Excel, use the function =NORM.INV(probability, mean, standard deviation). By using the mean and standard deviation parameters, the values of each Unexpected Cash Flow number will appear randomly.

Finding the maximum loss estimate at the confidence level (1-α), which is the α-quantile value from the empirical distribution of Unexpected Cash Flow data obtained in step (2) denoted by R*.

At this stage, use the formula =PERCENTILE(array, k), where the array is the simulated value of Unexpected Cash Flow with mean and standard deviation in the NORM.INV formula. The results of the quantile calculation can be seen in Table 6 using confidence levels of 99%, 95%, and 90%.

Table 6. Percentile of DBPP and DCPP

Level of Confidence	Percentile DBPP	Percentile DCPP
99%	-189.6165032	-279.8186382
95%	-82.54373932	-182.1112755
90%	-31.44268329	-132.5962508

Source: Processed excel output results, 2023

Table 7. DBPP and DCPP VaR Calculation Results

	DBPP	DCPP
$VaR_{(0,01)}$	-189.6165032	-279.8186382
$VaR_{(0,05)}$	-82.54373932	-182.1112755
$VaR_{(0,1)}$	-31.44268329	-132.5962508

Source: Processed excel output results, 2023

In Table 7, the VaR values for DBPP and DCPP are -189.6165032 for DBPP and -279.8186382 for DCPP (negative sign indicates loss) with a 99% confidence level over a one-month period and beyond. This means that the maximum loss to be incurred will not exceed Rp. 1,896,165,032.00 for DBPP and Rp. 2,798,186,382.00 for DCPP, within one month after July and beyond. The higher the confidence level, the greater the risk incurred, and vice versa. As the risk values may fluctuate, it is necessary to store the data and perform iterations.

The simulated risk values will continue to change, so it is necessary to calculate the optimal value at risk by performing 10,000 iterations on the value at risk with confidence levels of 99%, 95%, and 90%, by generating random data for these values.

Calculate the mean VaR from the data of 10,000 iterations for each confidence level using the function =AVERAGE(input data of 10,000 iterations for each confidence level) to stabilize the VaR values because of the results generated by each simulation. (See Table 8).

Table 8. Results of Calculating Mean VaR DBPP and DCPP

	Mean VaR DBPP	Mean VaR DCPP
$VaR_{(0,01)}$	-183.9534048	-279.5528646
$VaR_{(0,05)}$	-87.04800376	-183.4321183
$VaR_{(0,1)}$	-31.36593224	-132.008041

Source: Processed excel output results, 2023

In Table 8, the Mean VaR values for DBPP and DCPP are -183.9534048 for DBPP and -279.5528646 for DCPP (negative sign indicates loss) with a 99% confidence level over one month and beyond. This means that the maximum loss to be incurred will not exceed Rp. 1,839,534,048.00 for DBPP and Rp. 2,795,528,646.00 for DCPP, within one month after July and beyond.

CONCLUSION

The implementation of VaR measurement in pension funds using Monte Carlo simulation resulted in average VaR values for DBPP and DCPP of -183.9534048 and -279.5528646 with a 99% confidence level, -87.04800376 and -183.4321183 with a 95% confidence level, -31.36593224 and -132.008041 with a 90% confidence level (negative sign indicates loss) over one month. This means that the maximum loss to be incurred will not exceed Rp. 1,839,534,048.00 and Rp. 2,795,528,646.00 at a 99% confidence level, Rp. 8,704,800,376.00 and Rp. 1,834,321,183.00 at a 95% confidence level, Rp. 3,136,593,224.00 and Rp. 132,008,041.00 at a 90% confidence level within one month after July 2023 and beyond.

Based on the VaR calculation results using the Monte Carlo Simulation method at confidence levels of 99%, 95%, and 90%, it can be concluded that the confidence level is directly proportional to the risk. This means that the higher the confidence level used, the higher the likelihood of maximum loss incurred, and vice versa.

RECOMMENDATION

As for suggestions related to the conducted research, for future research with similar themes, it is recommended to use VaR with both Variance-Covariance and Historical methods to enable comparison. Expanding the discussion on VaR to other securities such as deposits, bonds, real estate, or foreign securities would also be beneficial.

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