# Computing
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# Value at Risk Metric

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**Abstract**

The purpose of this article is to familiarise the reader with the Value at Risk (VaR) metric, which is a commonly used statistic that gives information of potential losses resulting from an investment over a specific time frame and a given confidence level.

There are several methods to compute this metric: from more basic and standardized ones, involving simple calculations and few steps, to more advanced and complex ones, used by professional investors and traders.

In this article, we will look at 2 of these methods: we will first study a case of the Parametric Approach method, and then how we can use Monte Carlo simulations to find this quantity. After covering some basic theory and assumptions, we will dive into a couple of examples to understand how we can play around with the parameters in each of the methods to properly understand these.

# 1 First Few Concepts

Whenever we carry out an investment, it is crucial for our own financial well-being to account for the possibility that things could turn out badly for us and it was to answer this need of quantifying potential loss that VaR was introduced into the world of financial modelling.

In short, VaR is some number measured in currency units which indicates that in a large percentage of cases, you are not going to lose more than that sum of money, after keeping your investment open for some pre-established time. By "large percentage of cases", we refer to the confidence level we choose to deal with.

For example, suppose we invest £20,000 and we find the VaR over a 30-day period with a 95% confidence level to be **£5,000**. This tells us that the worst case scenario in 95% of cases is that our investment decreases by £5,000 (to £15,000), over a 30-day time frame.

# 2 The Parametric Method

This is the most commonly used method to calculate the VaR of an investment.
An important assumption that this model inherits is that the returns of a stock follow a normal distribution.
In any case, the formula is given by:

$$\mathrm{VaR} = S_A \cdot z_\alpha \cdot \sigma_A \cdot \sqrt{T},$$

where $S_A$ is the total amount of money invested in portfolio "A", $z_\alpha$ is the z-value for an $\alpha\%$ confidence level, $T$ is the amount of time we are intending on keeping our investment open and $\sigma_A$ is the standard deviation of the whole portfolio.

In order to further understand the process, we will study the following example. Suppose we would like to invest £3,000 on a portfolio consisting on 4 stocks, each of which have an equal weighting within it (25%) and they are: Tesla, Apple, Microsoft and Google.

We would like to find out what the VaR for this portfolio is over a 30-day period, with a confidence level of 95%. By using data on the internet (or by calculating it ourselves, which would be worth trying), we can see that the daily standard deviation for Apple is 0.58%, for

Google it is roughly 1.17%, for Microsoft it is roughly 0.8% and for Tesla it is 1.15%, as of mid-August 2023.

From these, we can calculate the global standard deviation of the portfolio by adding the standard deviations for each of the assets and then dividing by 4, giving us that the portfolio's daily standard deviation is approximately 0.93%. We then find the z- value of a standard normal distribution for a 95% confidence interval, which is 1.645 and now we can use the formula to find that the VaR for this investment and with the given parameters is $£3,000 * 1.645 * \sqrt{30} * 0.0093 \approx £251$.

Thus, we can be 95% sure that the worst case scenario is that we lose £251 in one month with this investment.

As a side note, VaR could alternatively be found by taking $\sigma_A$ to be the 30- day volatility of the portfolio, in which case $T = 1$ because our time frame $T$ is now measured in months, rather than days. So, what time frame should we be working with?

This depends on a broad set of factors, but the main takeout is that if we are planning to invest on high-risk, short term stocks, the ideal time frame should be the daily one.

However, doing this develops the possibility of missing the broader picture of a longer time frame, as it is quite complicated to infer a lot about an investment we want to keep open for a few months if we are just extrapolating from a model in which the daily standard deviation is being used instead.

To conclude, for longer periods of time, we might prefer to work with a monthly standard deviations.

We shall now move on to the case where we use Monte Carlo simulations to estimate the VaR. This method will prove to be quite different, but the goal is for you to think and reflect about the conceptual similarities between these two.

# 3 The Monte Carlo Approach

One of the main advantages that using Monte Carlo methods have is that we are allowed to drop the assumption that the future returns of the investment follow a normal distribution, even though it is fairly common to stick to this assumption in any case.

The process is the following: given that we would like to invest in a list of assets and after making some starting assumptions about the model, such as our significance level ($\alpha\%$), we would like to implement, we simulate several scenarios (usually more than 1000) for the value of the investment after some time, T. Afterwards, for each of the simulation we run, we subtract the investment's initial value from the value of the investment post-simulation.

We then proceed to sort these differences in ascending order and finally, we find what the threshold value is at the boundary between the top 95% and the bottom 5% of our differences.

It is now worth looking at an example by translating the previous steps to code in Python. Suppose we want to invest £1,000,000 in the same 4 stocks as in our previous example (Microsoft, Apple, Tesla and Amazon), with the same weighting for each asset in our portfolio, a time frame of 365 days and a confidence level of 95%.

To keep things simple, we will assume that our returns follow a normal distribution,

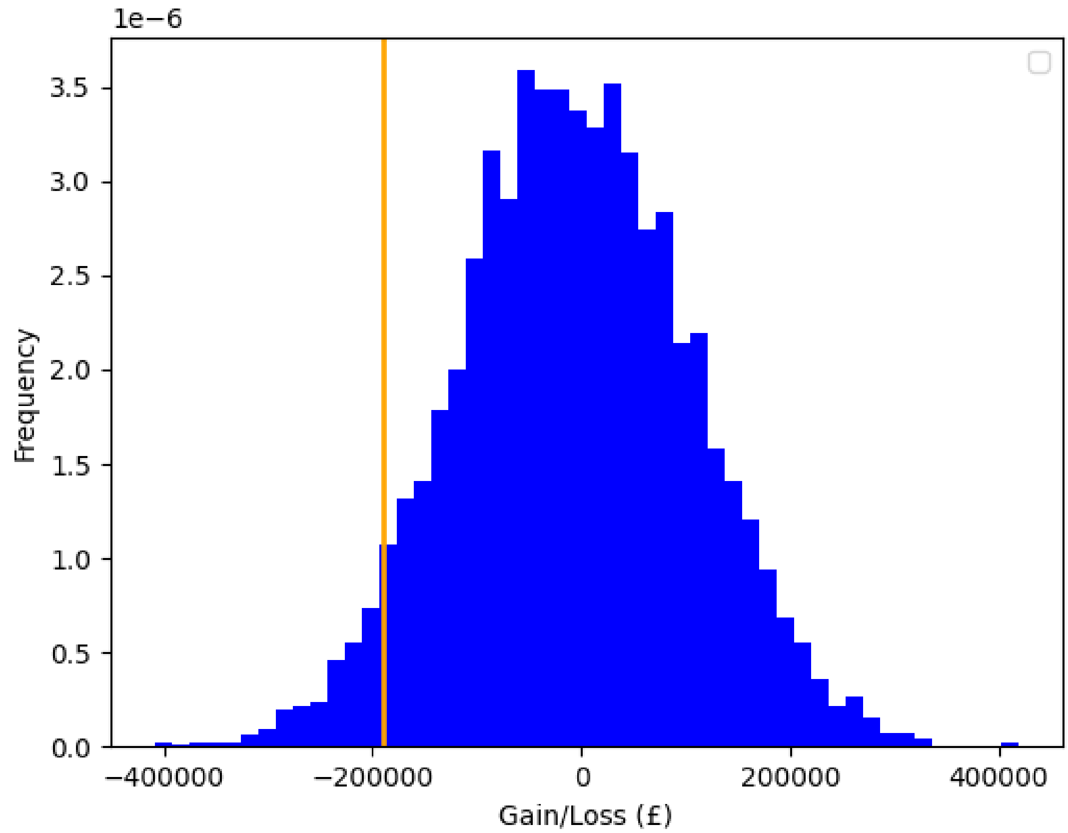


Figure 1: Distribution of Gains/Losses Over 365 days

which again, it is not a mandatory assumption. After implementing the code, we can build Figure 1's histogram, which we will analyse right now.

The orange line is the boundary between the top 95% and the bottom 5% and the projection on the x-axis of this line is approximately the value -190,000. This means that we are 95% sure that the worst case scenario of the aforementioned investment is that we lose £190,000 after a year.

In general, for complex investments, such as those involving options, non-normal distributions, among others, it is more recommended to use an MC approach, rather than a Parametric one.

If you would like to try out the code yourselves, send me an email to my Warwick account and I will be more than happy to share it with you.

# References

[1] P. Jorion, *Value at Risk: The New Benchmark for Managing Financial Risk* (2000).

[2] R. O'Connell, Computing VaR with Monte Carlo (2023).

[3] Investopedia.com, Understanding VaR (2023).