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Our company
Founded in 1994 with the mission of creating innovative software for quantitative financial analysis.

Well established in northern Europe, Algorithmica has an extensive client list including top tier financial institutions.

Algorithmica successfully combines leading edge competence in quantitative finance and software development.

We are committed to academic work on all levels, and actively sponsor research, student activities and courses in quantitative finance.

Value-at-Risk assessment in a year with COVID-19 distress

The financial industry uses value-at-risk models for many different purposes.

It is commonly used for measurement of capital, fund exposures, and limiting trading risk. Backtesting analysis show the (non)performance of the various models during the last year.

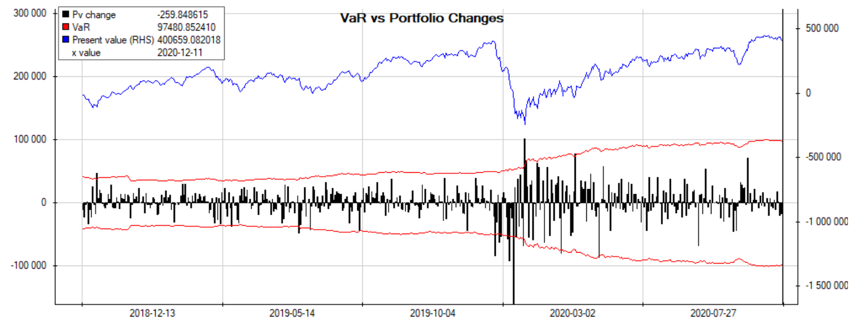
The question is; are all models equally good and how should we interpret the failed backtesting results of some of them?

We show stylised facts of three different models, for holdings of stocks and bonds.

Benchmarking three models for a Future Contract on OMXS30

(comparing theoretical PnL with VaR prognosis over 500 days)

Model: UW Historical Sim
Rolling window: 250 days
Conf level: 99% VaR



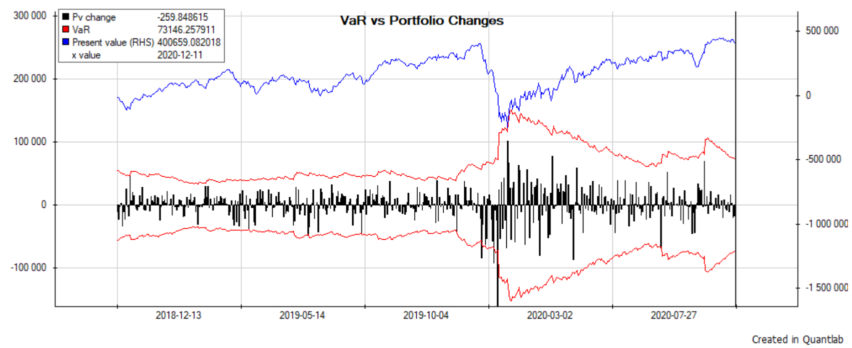
Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
12,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	4,92	T < 3.84
Conditional Coverage Test	13,89	T < 5.99

Model: Filtered Hist Sim
Vol-time-decay: 0,94
Rolling window: 250 days
Conf level: 99% VaR



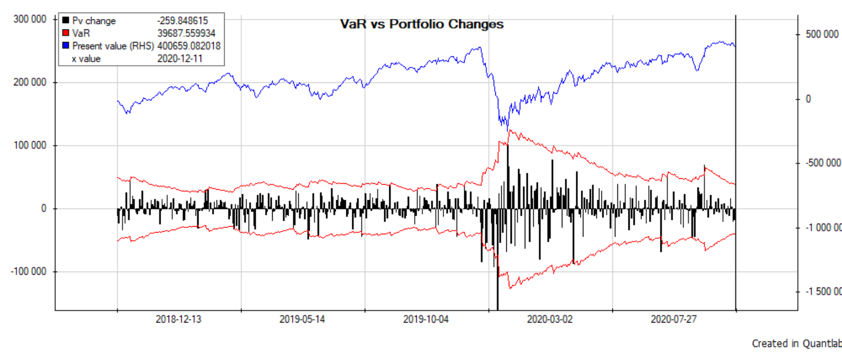
Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
5,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	0,28	T < 3.84
Conditional Coverage Test	0,47	T < 5.99

Model: Delta Analytical
Covar-time-decay: 0,94
Rolling window: 250 days
Conf level: 99% VaR



Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
15,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	0,99	T < 3.84
Conditional Coverage Test	16,46	T < 5.99

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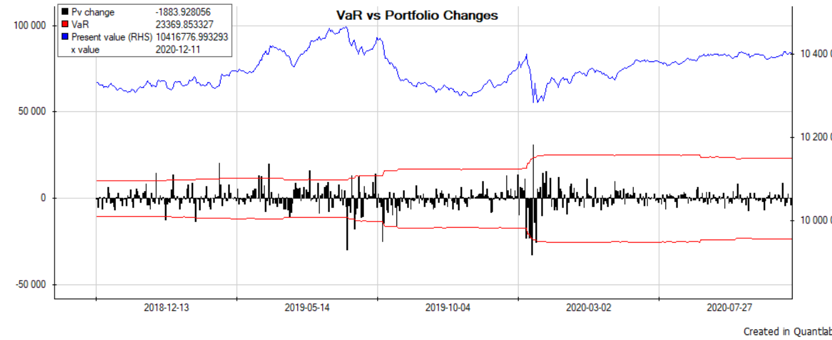
Benchmarking three models for SEK Mortgage Bond (Swedhyp193)

(comparing theoretical PnL with VaR prognosis over 500 days)

Model: UW Historical Sim
Rolling window: 250 days
Conf level: 99% VaR



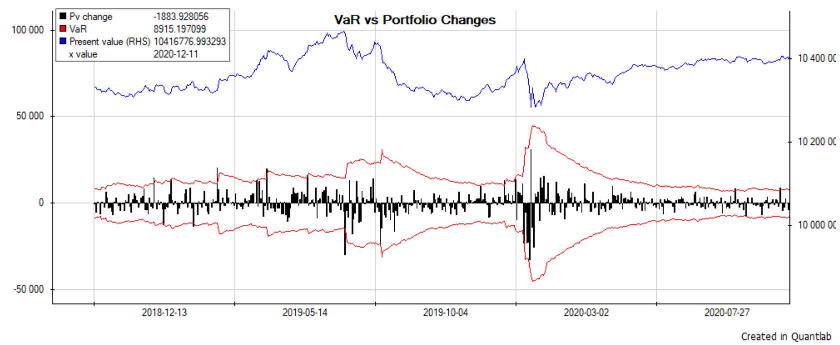
Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
10,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	0,50	T < 3.84
Conditional Coverage Test	5,92	T < 5.99

Model: Filtered Hist Sim
Vol-time-decay: 0,94
Rolling window: 250 days
Conf level: 99% VaR



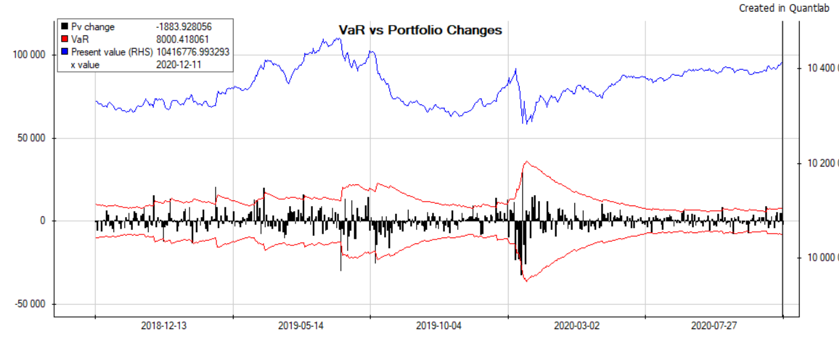
Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
4,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	0,28	T < 3.84
Conditional Coverage Test	0,28	T < 5.99

Model: DG Analytical
Covar-time-decay: 0,94
Rolling window: 250 days
Conf level: 99% VaR



Kupiec Test - 95% Level Test Coinfidence

Number of exceptions	Nonrejection region for number exceptions N.
10,00	0.6 < N < 9.4

Christoffersen Test - 95% Level Test Coinfidence

Test name	Test statistic	Nonrejection region for test statistic T
Independence Test	6,39	T < 3.84
Conditional Coverage Test	11,80	T < 5.99

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Results and discussion

In both the equity and bond case, the only model to pass the statistical tests for number of exceptions and clustering independence was the Filtered Historical Simulation. This model combines two desired features of a risk model, making no assumption about statistical distribution and adaptiveness to current volatility regime.

As can be expected, the Filtered HS has a somewhat higher VaR when averaging over the whole period. However, it is only about 16% higher on average than the analytical delta model, and actually 17% lower than the non-weighed HS. The non-weighted HS model obviously will estimate high VaR numbers for a long period after the stressed event and thus present the worst of all worlds type model. On average too high, too many breaches as it will not adapt and then prescribing too high a risk when markets settle down.

When measuring financial risks, there is no go-to model to handle every aspect. That is why proper risk management involves traditional greek sensitivities, at least two complementing value-at-risk models, and scenario modeling. Risk models must also be adapted to handling of non-linear effects coming from option positions and bonds.

Value-at-risk, properly used and interpreted, is a valuable tool in the risk managers toolbox and should be evaluated to be correctly calibrated in times of stress. One must also remember that VaR is a statistical measure and we should expect to have a certain number of breaches for the model to be valid. Value-at-risk is a statistical speed gauge for risk taking, it is not a crystal ball to predict the next black swan.