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Market risk in UST securities and futures: How much did volatility increase in March of 2020 through the lens of filtered historical simulation value-at-risk models?

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1. Introduction

Market volatility increased substantially in March of 2020 as the financial market participants reacted to the risk of Covid-19. Even the market for US Treasury securities, long considered a safe haven and one of the most liquid debt instruments in the world, experienced large swings in volatility. In this Policy Discussion Paper, I demonstrate that as volatility increased, model estimates of the market risk increased as well. First, I will explain the background on filtered historic simulations Value-at-Risk (VaR) modeling. This is followed by an overview of the assessment methodology, and analysis on the impact to US Treasury exchange traded funds (ETFs) and futures during March of 2020. Lastly, I provide a historical comparison of market volatility. The findings are that market risk during March of 2020 increased quickly in both the treasury securities and futures markets, and market risk was higher in the treasury securities market in comparison to the treasury futures market.

2. What is a VaR Model?

The origins of VaR based risk modeling date back to the 1920's (Holton, 2002).[1] The adoption of VaR dramatically increased in the 1990s with firm-wide VaR calculations based on a JP Morgan developed approach in the 1980s.[2] The approach essentially allowed firms to know, with a 95%[3] degree of confidence, how much they could lose in one day – in other words 95% of the time their risk of financial loss based on changes in market prices would be equal to or less than the calculated VaR value.

Over the decades, with increases in computational power and financial engineering expertise in both the academic and private sectors, the VaR models have evolved. One notable change was an approach of scaling the estimated risk of loss estimate to account for recent changes in market volatility. So as market volatility increased so did the estimated risk of loss in VaR, and vice versa as volatility decreased. This approach was published by Alan White and John C. Hull in 1998 in volume 1 of the Journal of Risk and titled "Incorporating volatility updating into the

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[1] See http://stat.wharton.upenn.edu/~steele/Courses/434/434Context/RiskManagement/VaRHistlory.pdf

[2] See https://www.value-at-risk.net/riskmetrics/

[3] The confidence could be different than 95%, but 95% was widely used in 1990s since executives viewed 95% as a proxy for 1 in 20 which in turn was viewed that 1 day a month the loss would be higher.

historical simulation method for Value-at-Risk".[4] The novel approach was dubbed Filtered Historic Simulation Value-at-Risk FHS VaR.

FHS VaR models are still widely used by financial market participants, including central counter parties (CCPs)[5], to estimate market risk.[6] Since CCPs guarantee contracts, they institute risk management measures to help ensure that both parties in the contract meet their obligations. One of the most important measures is the calculation of the appropriate level of collateral. CCPs require that both parties in a contract post collateral in the form of initial margin. If one party defaults on their side of the contract, their initial margin is used to cover any resulting losses, including mark-to-market or costs incurred to replace the counterparty that defaulted. Accordingly, the CCP sets initial margin to cover such market risk based on their quantitative modeling along with any relevant expert judgement.

The calibration of the model is typically tailored for the given products and markets involved in the portfolio being risk assessed. The calibration typically requires back-testing to ensure the results of the model meet regulatory requirements and aligns with applicable risk appetites and/or accounts for stakeholder feedback.[7] Additionally, the models may be supplemented with other risk modeling techniques when setting collateral requirements for an expected level of market risk for a given portfolio. The supplemental techniques may be employed to mitigate model risk and/or meet regulatory requirements e.g., anti-procyclicality (APC) requirements where CCPs "….should appropriately address procyclicality in margin arrangement. In this context, procyclicality refers to changes in risk management practices that are positively correlated market, business or credit cycles."[8] Table 1 provides a summary of FHS model parameters for CCPs which disclose employing FHS VaR based models. The table also includes information on any supplemental risk modeling techniques based on public disclosures and regulatory rule filings.

[4] https://www.risk.net/journal-of-risk/2161156/incorporating-volatility-updating-into-the-historical-simulation-method-for-value-at-risk

[5] CCPs guarantee transactions on a post-trade basis. They provide each participant with a guarantee that the other participant will fulfill commitments until settlement of contract see https://www.chicagofed.org/publications/policy-discussion-papers/2017/pdp-1 and https://ccp12.org/clearing/ for additional information

[6] See https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2015/filtered-historical-simulation-value-at-risk-models-and-their-competitors.pdf and https://ccp12.org/wp-content/uploads/2018/12/CCP12_White_Paper_Primer_on_Initial_Margin.pdf

[7] https://ccp12.org/wp-content/uploads/2018/12/CCP12_White_Paper_Primer_on_Initial_Margin.pdf

[8] CPSS-IOSCO (2012), paragraph 3.6.10, p 53 https://www.bis.org/cpmi/publ/d101a.pdf

Table 1: FHS parameters and supplemental risk modeling techniques

CCP FHS VaR and Risk modeling techniques

CCP	Eurex	ICE Clear U.S. and Europe	HKEX OTC Clear	JSCC	CME Clearing	LCH
Model Type	FHS	FHS	FHS	FHS	FHS	FHS
Lookback	3 Years	1, 2, & 4 in U.S. and 10 Years in Europe	5 Years	5 Years	5 Years	10 Years
Lambda	Not Disclosed	Not Disclosed	Not Disclosed	Not Disclosed	97*	
Asset Class/Products	OTC Interest Rate Swaps "IRS", Fixed Income Derivatives and Foreign Exchange "F/X"	Financial Futures and Soft Commodities in U.S. and Energy Futures in Europe	OTC IRS and F/X	OTC IRS	OTC IRS, Interest Rate Futures and OTC F/X	
VaR or ETL**	VaR		ETL	ETL	VaR	ETL
Additional modeling or APC techniques	250 Stress days***		Stress Scenarios	Stress Periods	Stress Periods*	

*https://www.cftc.gov/sites/default/files/stellent/groups/public/@rulesandproducts/documents/ifdocs/rul033012cme001.pdf and https://www.cmegroup.com/education/files/cleared-otc-irs-margin-methodology.pdf

**ETL is expected tail loss. VaR is a specific point in the tail for risk loss calculation while ETL averages the tail e.g. for a 99% confidence level Var would use the 99% loss data point while ETL would average all the loss data points above 99%. ETL is synonymous with Expected Shortfall or Conditional VaR "CVaR"

***Eurex uses FHS models with different stress periods with its PRISMA framework for other products e.g., equities

Sources: Public Disclosures by the CCPs

3. Analysis

As mentioned previously, a FHS VaR model was employed to gauge how market risk estimates change as market volatility increased in 2020 (see the outline of the calculation steps in Appendix 1). While some of the publicly disclosed information on FHS VaR parameters is either limited or lacks consensus across CCPs, I have utilized the following:

- FHS VaR model rely on historic data as input. For the analysis in this paper, I used a rolling data history (or lookback window) of four years which is within the range of values that CCPs use based on table 1. Moreover, as evidenced in an industry paper,[9] the lookback window is not that critical in FHS based models for assessing simple portfolios of a single product or risk factor. Rather, longer lookbacks are more useful for more complex portfolio as a richer dataset of correlation changes can be modeled.

- For FHS VaR models, a lambda is required in order to derive an exponentially weighted moving average, and lambda of 97 is a common calibration level for FHS VaR models.[10] Also, the value is within the range of other research papers on CCP margin models.

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[9] "Procyclicality of CCP margin models: systemic problems need systemic approaches" https://www.world-exchanges.org/storage/app/media/Procyclicality_cut7.pdf

[10] Author also understands this his prior experience in CCP risk management

- Confidence Level of 99% in line with regulatory requirements for CCPs as codified in the Principle for Financial Market Infrastructures[11].

- Risk models, including FHS VaR, will have a time horizon for which the model forecasts risk. For the analysis in this paper, I used a risk time horizon of one day which is consistent with the input data of one day price changes.

In order to gauge the changes in volatility and market risk expectations in the Treasury related securities and futures market, I use a benchmark futures and ETFs.[12] For the ETFs, I used iShares 7-10 Year Treasury Bond Fund (symbol IEF) and the iShares 20+ Treasury Bond (symbol TLT). Both are listed on NASDAQ while DTCC serves as the CCP in the US. The ETFs are also part of the first fixed income ETFs to be introduced in the US[13] and two of the larger UST related ETFs in terms of asset under management.[14] The price data for the ETFs are from Yahoo Finance.

For UST future products, I chose the 10 Year Note future and the Ultra T-Bond future. Both have maturity profiles comparable to the ETFs. The 10 Year is one of the oldest UST future products dating back to the 1970s. The Ultra T-Bond contract was launched in 2010. Both are listed on the Chicago Board of Trade (CBOT) and cleared through CME Clearing. The price data were sourced from Bloomberg using rolling front month as TY1 and WN1, 10 Year note and Ultra T-Bond respectively.

4. What were the results for the March 2020 Covid related market stress?

Using the FHS VaR model parameters outlined above, the results show that the ETF products were more volatile than the comparable future products, which in turn, would have led to higher market risk estimates for ETFs relative to futures in 2020. Summary statistics are set out below in Table 2.

[11] See 3.6.6 in https://www.bis.org/cpmi/publ/d101a.pdf

[12] The author also chose UST ETF since changes in maturity of underlying UST securities creates practical issues of not having enough price data for a multiyear lookback. Alternatively, continuously rolling data for on-the-run securities would have created larger price swings with the on-the-run issue changes. The issues are less of a concern with the chosen ETFs as they contain multiple UST securities.

[13] https://www.etf.com/publications/etfr/15-years-bond-etf-history-nutshell

[14] https://etfdb.com/etfs/bond/treasuries/

Table 2 - Summary statistics of FHS VaR results as percentage of market value for long and short positions

	FHS VaR on 10 Year Note Future		**FHS VaR on ETF IEF**		**FHS VaR on Ultra T-Bond**		**FHS VaR on ETF TLT**	
	Long	Short	Long	Short	Long	Short	Long	Short
Feb 28th	0.7%	0.8%	0.8%	0.9%	1.9%	2.2%	1.8%	2.1%
March 31st	1.5%	1.7%	2.2%	2.6%	6.1%	6.7%	6.3%	7.9%
Increase Pct	118.4%	122.3%	168.8%	190.7%	215.5%	204.2%	241.6%	269.7%

Source: Author's calculations based on data from Bloomberg Finance L.P. and Yahoo Finance.

The market volatility was heightened during March of 2020 which led to substantial increases in the market risk estimates in my FHS VaR calculations as shown in Table 2. Given the significant changes in a relatively short period of time, results from prior periods of heightened market volatility could be used to compare and determine if the changes in FHS VaR were higher or lower in previous events.

5. How did results compare for prior stress periods?

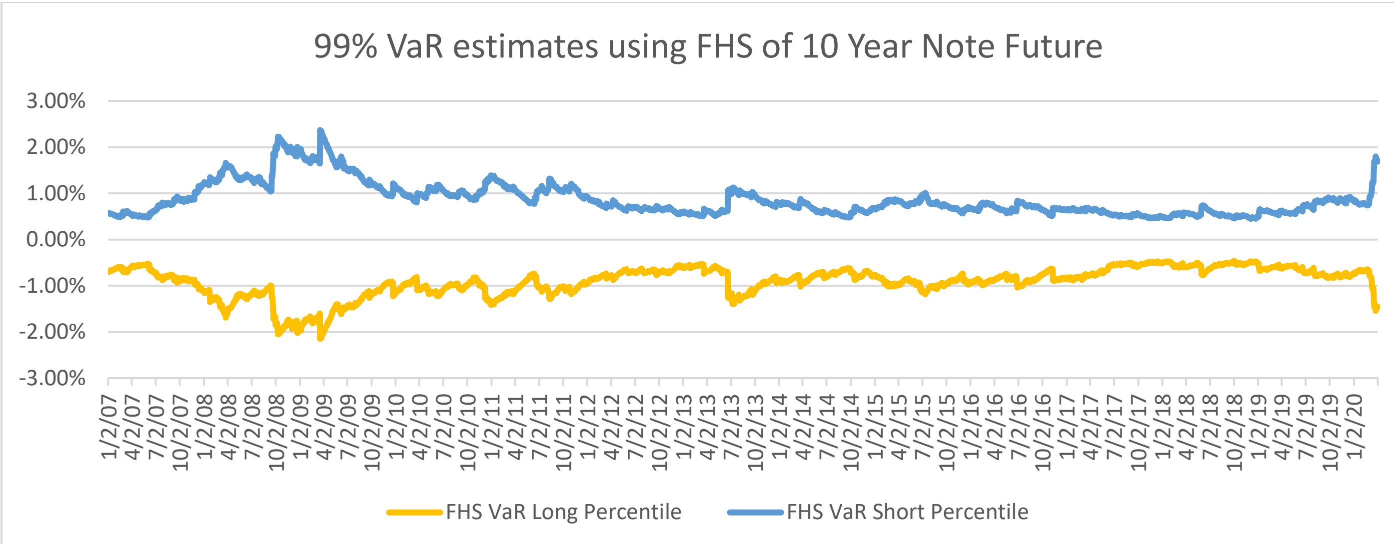
To get a sense of FHS VaR on Treasury products during prior events, I used the same parameters stated in section 3. The FHS VaR modeling was applied back to January of 2007 in order to capture a time period before and through the Global Financial Crisis (GFC) of 2008-09.

I focused on medium maturity products since the 10 year note futures have a longer price history. Figures 1 and 3 show the FHS VaR change for the 10 Year Note future and the IEF ETF, respectively. Figures 2 and 4 show the percentage rate of change on a rolling 22-day basis for FHS VaR value i.e., month on month change in market risk estimates plotted daily. While the FHS VaR values in March of 2020 in Figure 1 nearly approached levels of the GFC, the rate of change depicted in Figure 2 was larger in March of 2020 relative to the change observed during the GFC.

These results imply that:

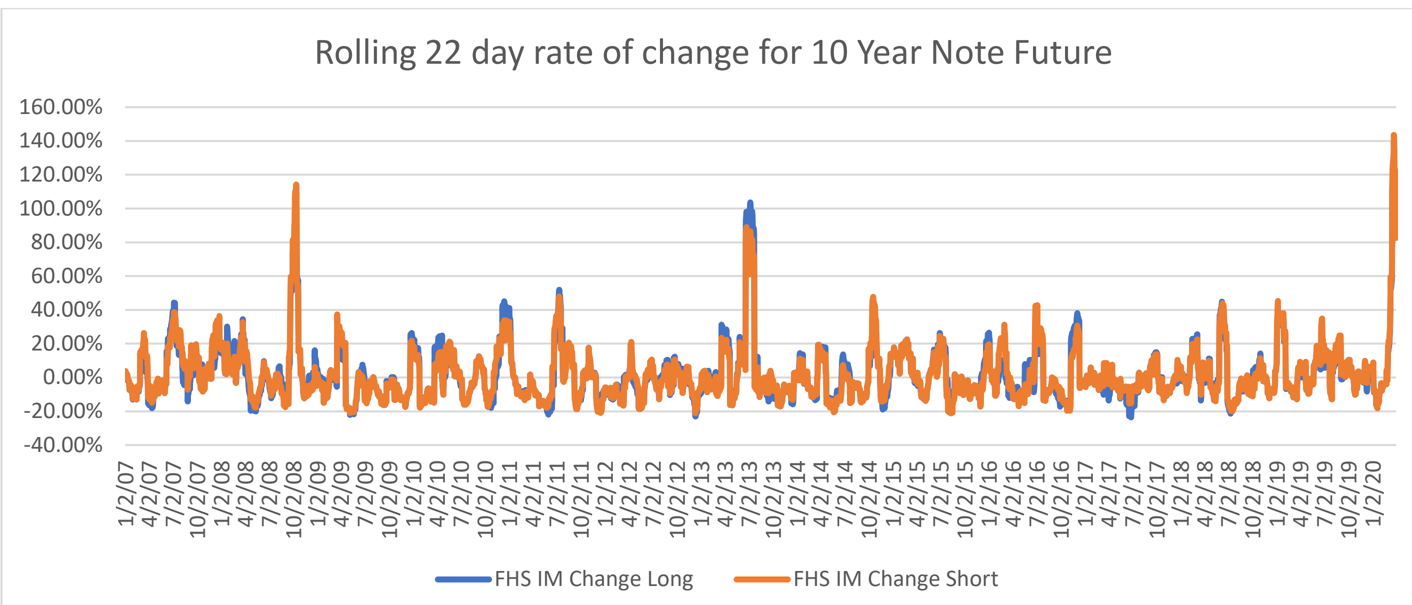
- market risk during March of 2020 increased quickly in both the treasury securities and futures markets at a rate faster than the rate of change during the GFC; and
- market risk was higher in the treasury securities market in comparison to the treasury futures market with the market risk of the securities being above levels observed in the GFC.

Figure 1 - FHS VaR for 10 Year Note Future as percentage of market value



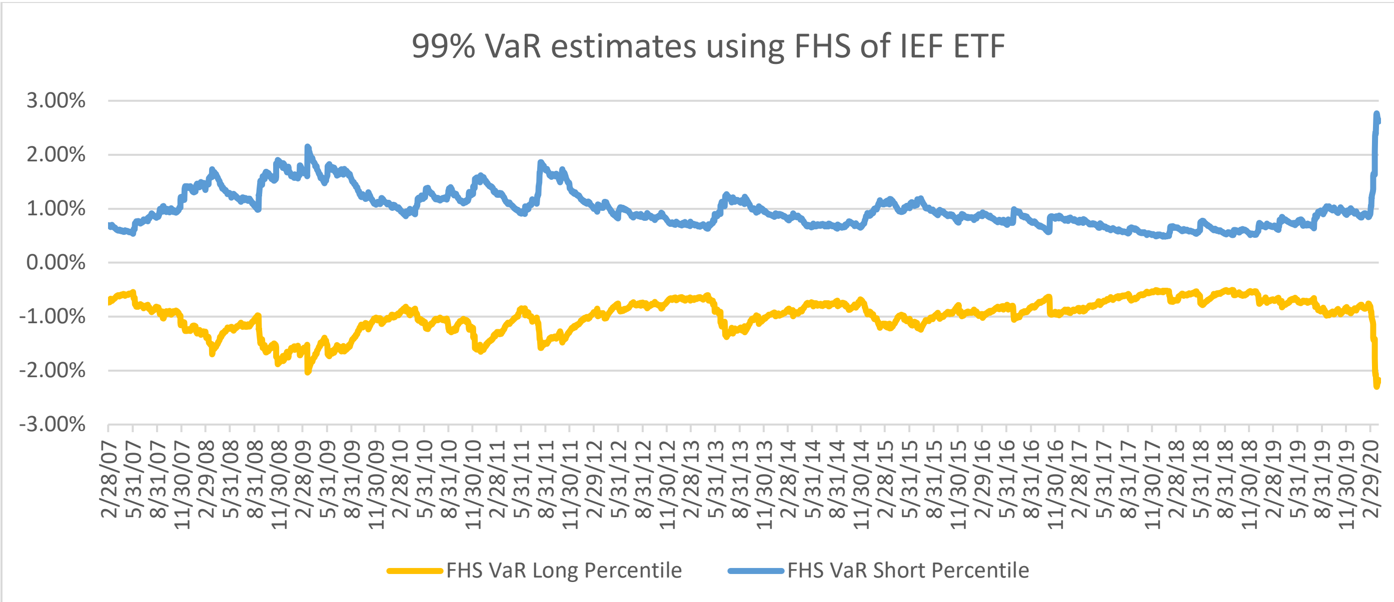
Source: Author's calculations based on data from Bloomberg Finance L.P. and Yahoo Finance.

Figure 2 - Percentage change in FHS VaR of 10 Year Note Future for rolling 22 days



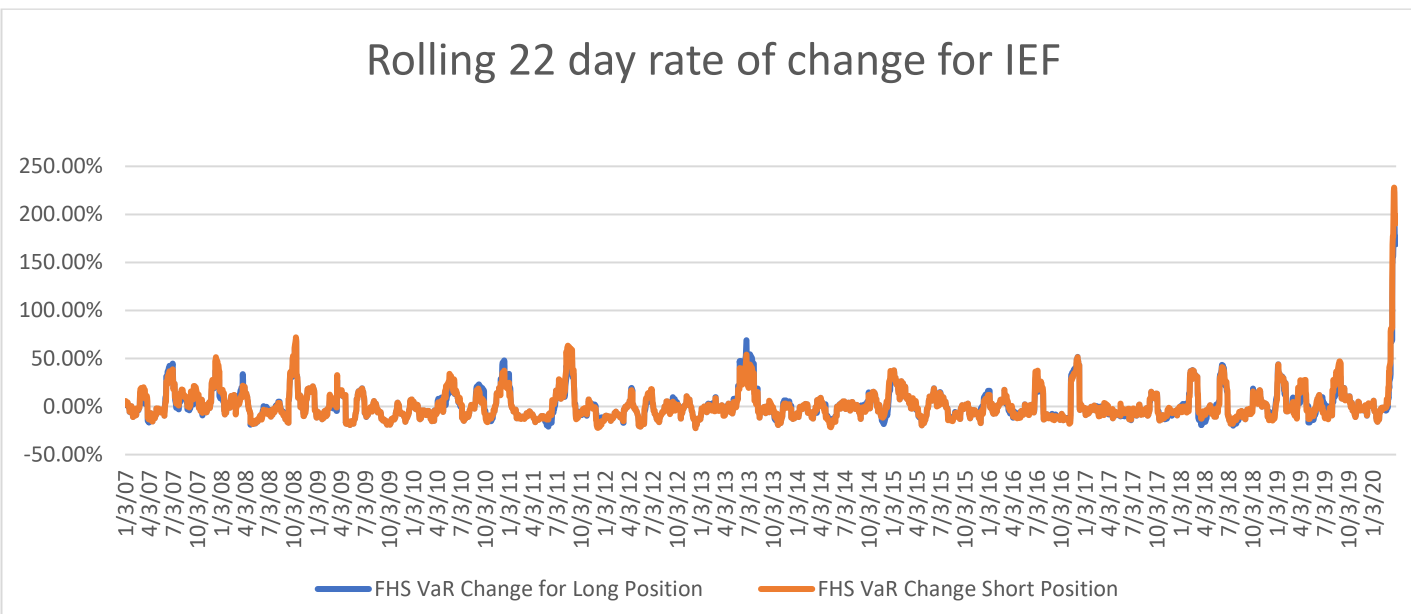
Source: Author's calculations based on data from Bloomberg Finance L.P. and Yahoo Finance.

Figure 3 - FHS VaR for IEF ETF as percentage of market value



Source: Author’s calculations based on data from Bloomberg Finance L.P. and Yahoo Finance.

Figure 4 - Percentage change in FHS VaR of IEF ETF for rolling 22 days



Source: Author’s calculations based on data from Bloomberg Finance L.P. and Yahoo Finance.

6. Conclusion/Summary

In this paper, I have calibrated a FHS VaR model in line with academic papers and CCP calibrations. While the FHS VaR results support the notion that market risk increased sharply during the March 2020 stress, the market risk was more pronounced in the ETF securities market relative to the futures market for US Treasury. In reviewing the longer-term results, it appears that a pure FHS model, which automatically increases risk estimates as volatility increases (and vice versa as volatility decreases) , is cyclical and may lead to large swings in market risk estimates.

Such swings are likely a reason that most of the CCPs in Table 1 use additional modeling techniques rather than a pure FHS VaR to establish IM requirements. Moreover, since the CCPs must provide a single market estimate for a given portfolio, it would make sense for the CCP to calibrate the FHS VaR parameters holistically with consideration to the other risk modeling techniques to ensure the model is "fit for purpose" for the given markets cleared and participants involved.[15] Such calibration would need careful consideration to balance the cost efficiency with resiliency in order to calculate an appropriate level of collateral.

*Thanks to Jahru McCulley for his data assistance. Thanks to Nahiomy Alvarez, Michael Gordon, Michael O'Connell of the Federal Reserve Bank of Chicago for their helpful comments.

[15] https://www.fia.org/articles/next-generation-risk-management /

Appendix 1 – Overview of the FHS VaR calculations

Step 1: Obtain the historic closing prices each security or financial instrument for the time horizon. In this case, a set of 1001 days are required to generate 1,000 returns. 1000 is used since it approximates 4 years of history. The actual set of trading days for a given market will vary since trading holidays are different

Step 2: For each security or financial instrument, calculate a return on each historical date. The return can be as a percentage change[16] between the closing price on any trading day relative to the immediately preceding trading day. Based on 1,001 closing prices obtained in step 1, a return matrix of 1-day percentage returns (1-day rolling percentage changes based on closing price) for a total of 1,000 returns is calculated.

$$r_{\mathrm{t}} = \frac{S_{\mathrm{t}}}{S_{\mathrm{t\text{-}1}}} - 1$$

where

t is each of the rolling trading days

r is the 1-day percentage on trading day *t*

S_{t} is the closing price on trading day *t*

Step 3: For each security or financial instrument, calculate the exponentially weighted moving average (EWMA) volatility on each trading day *t* from respective 1-day returns from step 2

For each historical time snapshot, use EWMA to compute a forecast of volatility

$$\sigma_t^2 = (1 - \lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2$$

where

t is each of the rolling trading days

σ is the EWMA volatility forecasted at time *t*

r is the return from step 2

λ is the coefficient (i.e., 97)

[16] Log return or absolute change are alternative approaches for computing returns.

Step 4: For each historical return, use the forecasted volatility (both the current day's forecast and the EWMA forecast as of the sampling date) to compute a scaling coefficient

$$c_{T-t} = \sigma_T / \sigma_t$$

where

c_{T-t} is the scaling coefficient for each of the trading days

t is each of the rolling trading days

σ_T is EWMA volatility for the current trading date T

σ_t is the EWMA volatility forecasted at time t

λ is the coefficient (i.e., 97)

Step 5: For each return, multiply the coefficients from step 4 to the return matrix obtained from step 2. This step is often referred to as rescaling volatility as the historic returns are scaled up or down based on the most recent EWMA volatility.

$$R_t = c_{T-t} * r_t$$

where

t is each of the rolling trading days

R is the scaled return for each security or financial instrument

r is the original return for each security or financial instrument

Step 6: Compute the profit and loss vector for each security or financial instrument from the rescaled returns (i.e., the R return values from step 5) and take the X^{th} percentile (i.e., 99%) on loss side as the VaR loss value. For this paper, the 99% loss value using the percentile function in Microsoft Office.[17]

[17] https://support.microsoft.com/en-us/topic/91b43a53-543c-4708-93de-d626debdddca