FRM Part II Exam

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Questions with Answers - Market Risk Measurement and Management

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Reading 63: Estimating Market Risk Measures: An Introduction and Overview

Q.1475 If Profit/Losses (P/L) are distributed normally with a standard deviation of 18 and a mean of 12, then what is the value of the corresponding VaR using a 95% confidence interval?

A. 9.87.

B. 17.61.

C. 13.956.

D. -13.956.

The correct answer is **B.**

If P/L over some period are normally distributed with mean 12 and standard deviation 18, then the 95% VaR is given by:

$$\begin{aligned}\alpha VaR &= -\mu_{P/L} + \sigma_{P/L} Z_\alpha \\ &= -12 + 18 z_{0.95} \\ &= -12 + 18 \times 1.645 = 17.61\end{aligned}$$

Where z_α is the number of standard deviations that correspond to the desired confidence level, σ is the standard deviation of the distribution, and $\mu_{P/L}$ is the mean of the P/L distribution.

Things to Remember

When calculating Value at Risk (VaR) at a 95% confidence level, we typically use a one-tailed approach because we are only concerned with losses beyond a certain threshold (i.e., the worst 5% of outcomes). In a one-tailed setting, the z-score that captures the 5th percentile (the left tail) of a standard normal distribution is approximately -1.645. The negative sign indicates we're looking at the lower tail (losses).

In contrast, a two-tailed 95% confidence interval (common in hypothesis testing) would split the remaining 5% equally between both tails (2.5% on the left and 2.5% on the right), leading to a z-score of approximately ±1.96. This two-tailed approach is used when deviations on both sides of the mean are relevant. However, for VaR, where only extreme losses (left tail) matter, the one-tailed z-score of -1.645 is appropriate.

Q.1479 A generally coherent risk measure tends to involve increasingly sophisticated weighting functions. Which of the following is a suitable replacement for the equal weights in the 'average VaR' to estimate any risk measure?

A. Average weights.

B. Exponential weights.

C. Weights appropriate to risk measure being estimated.

D. Fixed weights regardless of risk measure being estimated.

The correct answer is **C.**

A coherent risk measure is a risk metric that satisfies a set of properties, such as subadditivity, positive homogeneity, and translation invariance. These measures typically involve increasingly sophisticated weighting functions, which means that the weights used in the calculation are determined by the underlying characteristics of the portfolio or asset under consideration. The 'average VaR' is a simple method for estimating the VaR of a portfolio or assets by averaging the VaR of each component, with equal weights assigned to each component. However, because different components may have varying levels of risk, correlation, or impact on the overall portfolio, this approach may not be appropriate for all types of risk measures. Therefore, the appropriate weights must be chosen based on the underlying component characteristics and the specific risk measure being evaluated to estimate any risk measure using a weighted approach. This is why option C, 'Weights appropriate to risk measure being estimated', is the correct choice.

Choice A is incorrect. Average weights are not an appropriate replacement for equal weights in the 'average VaR' to estimate any risk measure. This is because average weights do not take into account the specific risk characteristics of each individual asset in the portfolio, which can lead to inaccurate risk estimates.

Choice B is incorrect. Exponential weights may be used in some cases, but they are not universally applicable for all risk measures. The use of exponential weights assumes that recent data points are more relevant than older ones, which may not always be true depending on the nature of the risks being estimated.

Choice D is incorrect. Fixed weights regardless of risk measure being estimated would also be inappropriate as it does not allow for adjustments based on changes in market conditions or portfolio composition over time. This could result in a misrepresentation of potential losses and therefore an inaccurate estimation of Value at Risk (VaR).

Things to Remember

- Coherent risk measure: A risk metric that satisfies properties like subadditivity, positive homogeneity, and translation invariance.
- Subadditivity: The risk measure of a portfolio is less than or equal to the sum of the risk measures of its components.
- Positive homogeneity: Scaling the portfolio by a positive factor scales the risk measure by the same factor.

- Translation invariance: Adding a constant to the portfolio does not change the risk measure.
- Weighted risk measures: Using different weights for different components based on their risk characteristics.
- Value at Risk (VaR): A measure of the potential loss on an investment over a specific time period under normal market conditions.

Q.1480 Coherent risk measures are fundamental in the field of risk management, providing a consistent framework for assessing the risk of financial portfolios. The key to estimating coherent risk measures lies in the:

A. Ability to assign weights to assets in a portfolio accurately.

B. Ability to calculate exponential value accurately.

C. Ability to estimate quantiles.

D. Ability to approximate risk exposure.

The correct answer is **C.**

The ability to estimate quantiles is key to estimating coherent risk measures. Quantiles are values that divide a distribution into subsets of equal size. For example, the median is the value that divides a distribution in half. The Value at Risk (VaR) is a risk measure quantile that measures the maximum loss that can occur with a given probability. Estimating VaR necessitates the estimation of the appropriate quantile of the distribution of the portfolio's returns. Therefore, the ability to estimate quantiles is crucial for estimating coherent risk measures.

Choice A is incorrect. While the ability to assign weights to assets in a portfolio accurately is important in portfolio management, it is not specifically key to estimating coherent risk measures. Coherent risk measures are more concerned with the overall risk of a portfolio rather than individual asset weights.

Choice B is incorrect. The ability to calculate exponential value accurately does not directly relate to estimating coherent risk measures. Exponential values may be used in certain calculations within financial modeling, but they are not a primary factor in determining coherent risk measures.

Choice D is incorrect. Although approximating risk exposure can be part of the process when managing financial risks, it's not the key ability for estimating coherent risk measures which focus on potential losses and their probabilities.

Things to Remember

- Coherent risk measures are risk measures that satisfy certain properties such as subadditivity, homogeneity, and translational invariance.
- Quantiles are important statistical measures that help in understanding the distribution of data and estimating potential losses.
- Value at Risk (VaR) is a widely used coherent risk measure that provides an estimate of the maximum loss with a given probability over a specified time horizon.
- Coherent risk measures play a crucial role in risk management by providing a consistent and reliable framework for evaluating and comparing risks across different portfolios.

Q.1481 The precision of a risk measure estimate is evaluated using the corresponding standard error(s). On which of the following does the quantile (VaR) standard error depend?

A. f(q), Sample size n and p.

B. p, Standard error s and variance of q.

C. Sample size n, p, and the square root of the error.

D. Variance of q, sample size n and f(q).

The correct answer is **A.**

The standard error of a Value at Risk (VaR) estimate is a measure of the precision of the VaR estimate. It provides an indication of the degree of uncertainty associated with the VaR estimate. The standard error of a VaR estimate depends on three key factors: the function f(q), the sample size n, and the probability level p. The function f(q) describes the probability distribution of the returns of the investment or portfolio. The sample size n refers to the number of observations used to estimate the VaR. The probability level p represents the confidence level or the probability of the loss exceeding the VaR estimate. Therefore, the standard error of a VaR estimate is directly influenced by these three factors, making choice A the correct answer.

Choice B is incorrect. The standard error of a quantile (VaR) does not depend on the standard error s and variance of q. These are measures of dispersion and do not directly influence the precision of a risk measure estimate like VaR.

Choice C is incorrect. While sample size n and p are indeed factors, the square root of the error is not a factor that influences the standard error of a quantile (VaR). This choice incorrectly assumes that an individual observation's deviation from mean has an impact on VaR's precision.

Choice D is incorrect. Although sample size n does affect the standard error, variance of q and function value at quantile point (f(q)) do not have any direct relationship with it in this context. Variance measures how far data points spread out from their average value which doesn't directly influence VaR's precision.

Things to Remember

- Standard error is a measure of the precision of an estimate, indicating the degree of uncertainty associated with the estimate.
- The function f(q) describes the probability distribution of the returns of the investment or portfolio.
- Sample size n refers to the number of observations used to estimate the risk measure.
- The probability level p represents the confidence level or the probability of the loss exceeding the risk measure estimate.
- Variance measures how data points spread out from their average value, but it does not directly influence the precision of a risk measure estimate like VaR.

Q.1482 A portfolio has a beginning period value of \$200. The arithmetic returns follow a normal distribution with a mean of 5% and a standard deviation of 10%. Calculate VaR at both the 95% and 99% confidence levels, respectively:

A. \$23, \$36.6.

B. \$43, \$56.6.

C. \$1.65, \$2.33.

D. \$23, \$43.

The correct answer is **A.**

Using a parametric estimation approach,

$$VAR(\alpha\%) = (-\mu_r + \sigma_r \times Z_\alpha) \times P_{t-1}$$

Where:

μ_r = Mean (arithmetic) return

σ_r = Standard deviation of returns

Z_α = Normal distribution parameter

P_{t-1} = Beginning period value

$$VAR(5\%) = (-5\% + 1.65 \times 10\%) \times 200 = \$23$$
$$VAR(1\%) = (-5\% + 2.33 \times 10\%) \times 200 = \$36.6$$

Q.2628 You are assigned to calculate the monthly VaR for the stock of Apex Inc. You are provided with the following data for the ten worst returns of the stock during the last 100 months:
-12%, -7%, -32%, -26%, -24%, -20%, -19%, -17%, -15%, -14%

Which of the following is closest to the monthly VaR for Apex, using a confidence level of 95%?

A. -32%.

B. -17%.

C. -12%.

D. -14.5%.

The correct answer is **B.**

The 95% VaR can be found by finding the value that separates the 5% worst values of the returns distribution from the remaining distribution. This value will be the $[(1\text{-}95\%)100 + 1]^{th}$ observation, i.e., 6^{th} observation after rearranging all the observations in ascending order.
[-32% -26% -24% -20% -19% **-17%** -14% -15% -12% -7%]
Thus, our observation of interest is -17%

Things to Remember

- Value at Risk (VaR) is a measure used to estimate the potential loss on an investment over a specific time period under normal market conditions.
- VaR is typically used by risk managers to quantify the level of financial risk within their firm's investment portfolio.
- Confidence level in VaR represents the probability that the actual loss will not exceed the VaR estimate.
- When calculating VaR, historical data on returns is often used to estimate potential losses at different confidence levels.
- The VaR calculation involves sorting historical returns in ascending order and identifying the observation that corresponds to the desired confidence level.

Q.2632 An analyst has gathered the following information about a portfolio that has normally distributed geometric returns:

Mean	10%
Standard Deviation	40%
Portfolio	100 million

What is the 95% lognormal VAR for this portfolio?

A. $74.7 million.

B. $35.3 million.

C. $42.8 million.

D. $113.4 million.

The correct answer is **C.**

$$\begin{aligned}\text{Lognormal VaR} &= P\left(1 - e^{\mu - \sigma z}\right) \\ &= 100,000,000(1 - e^{0.1-0.4(1.645)} \\ &= 100,000,000 \times (-0.4276) = 42,764,737\end{aligned}$$

Q.2636 Jacob Watson is a risk manager for a large bank. Presently, he is estimating the VaR for the equities portfolio of the bank. He is considering estimating the VaR using normal and lognormal distribution assumptions. He has gathered the following information about the portfolio:

Value of the portfolio	USD 1 million
Mean	15%
Volatility	25%

What would be the 1-year 99% VaR for the portfolio under the two assumptions?

A. Normal distribution: \$495,000; Lognormal distribution: \$460,000.

B. Normal distribution: \$460,000; Lognormal distribution: \$495,000.

C. Normal distribution: \$432,500; Lognormal distribution: \$351,000.

D. Normal distribution: \$499,000; Lognormal distribution: \$432,500.

The correct answer is **C.**

Under normal distribution assumption:

$$VaR = -\mu + \sigma \times z$$

For a confidence level of 99%, the Z value will be 2.33.

The VaR can be calculated as:

$$VaR = -0.15 + 2.33(0.25) = 43.25\%$$

In dollar terms, this will be \$432,500.

Under the lognormal distribution assumption:

$$\text{Lognormal VaR } = 1 - e^{\mu - \sigma \times z} = 1 - e^{0.15 - 0.25(2.33)} = 35.1\%$$

In dollar terms, this will be \$351,000.

Q.2817 Assume that the P/L over a specified period is normally distributed and has a mean of 14.1 and a standard deviation of 28.2. What is the 95% VaR and the corresponding 99% VaR?

A. The 95% VaR is 32.289 and the 99% VaR is 51.4932.

B. The 95% VaR is 36.495 and the 99% VaR is 51.556.

C. The 95% VaR is 55.236 and the 99% VaR is 36.49551.

D. The 95% VaR is 36.225 and the 99% VaR is 41.586.

The correct answer is **A.**

Recall that:

$$\alpha VaR = -\mu_{P/L} + \sigma_{P/L} z_{\alpha}$$

Therefore, the 95% VaR is: $-14.1 + 28.2Z_{0.95} = -14.1 + 28.2 \times 1.645 = 32.289$

The 99% VaR is: $-14.1 + 28.2Z_{0.99} = -14.1 + 28.2 \times 2.326 = 51.4932$

Q.2818 Over time, the arithmetic returns r_t are normally distributed with a mean of 1.55 and a standard deviation of 1.07. The portfolio is currently worth 1 unit. Calculate the 95% VaR and the 99% VaR.

A. The 95% VaR is 2.3658 and the 99% VaR is 3.6588.

B. The 95% VaR is 1.4542 and the 99% VaR is 0.0652.

C. The 95% VaR is 0.6742 and the 99% VaR is 3.00896.

D. The 95% VaR is 0.21015 and the 99% VaR is 0.93882.

The correct answer is **D.**

Recall,

$$\alpha VaR = -(\mu_r - ð_r z_{\alpha})P_{t-1}$$

Therefore, the 95% VaR is: $-1.55 + 1.07 \times 1.645 = 0.21015$

The 99% VaR is: $-1.55 + 1.07 \times 2.326 = 0.93882$

Q.2819 Let&rsquo assumes that the geometric returns R_t are normally distributed with a 0.079 mean and 0.312 standard deviations. Further assumption is that the portfolio is currently worth 1 unit. Calculate the 95% and 99% lognormal VaR.

A. The 95% VaR is 0.8951 and the 99% VaR is 0.2351.

B. The 95% VaR is 0.88526 and the 99% VaR is 0.56898.

C. The 95% VaR is 0.3522 and the 99% VaR is 0.4762.

D. The 95% VaR is 0.8951 and the 99% VaR is 0.56898.

The correct answer is **C.**

From the lognormal derivation,

$$\alpha VaR = P_{t-1} - P^* = P_{t-1}(1 - \exp[\mu_R - \sigma_R Z_\alpha])$$

Applying the formula in the question we have:

$$95\%\ VaR = 1 - \exp(0.079 - 0.312 \times 1.645) = 0.3522$$

$$99\%\ VaR = 1 - \exp(0.079 - 0.312 \times 2.326) = 0.4762$$

Q.3011 Assume you are dealing with a stock " A" that displays a highly negatively skewed distribution comprised of the past 260-days returns. Suppose you have P1 = A and P2 = -A, meaning P1 is long stock A and P2 is short stock A. Which statement is most likely to be accurate about a 99% VaR?

A. |VaR (P1)| > |VaR (P2)|.

B. |VaR (P1)| < |VaR (P2)|.

C. VaR (P1) = VaR (P2).

D. Cannot be concluded from the given information.

The correct answer is **A.**

Given that the return distribution of stock A is negatively skewed, it displays a long left tail. This implies large potential losses for a long position and large potential gains for a short position. Therefore, |VaR (P1)| will be expected to be higher.

If the distribution were symmetric, a long left tail means there's a high probability of large, potentially crashing losses on the asset. If you long the asset, you are exposed to more risk. The asset price might fall considerably, triggering a major loss. If you sell short (borrow and sell in the hope of repurchasing the asset at a later date), your repurchase price is likely to be lower, which means you will record a gain. Similarly, a short position in a call option on the asset will most likely make a gain (keep the premium) because the asset will most likely fall in price, and the long position won't exercise its right to buy.

A Different Perspective

1) First, let's understand what a negatively skewed distribution means:

- It has a longer left tail

- More extreme negative returns are more likely than extreme positive returns

- The mass of the distribution is concentrated on the right

2) Now, let's consider the positions:

- P1 is long stock A: Profits when stock goes up, loses when stock goes down

- P2 is short stock A: Profits when stock goes down, loses when stock goes up

3) For a 99% VaR:

- We're looking at the loss that won't be exceeded with 99% confidence

- For a negatively skewed distribution, the left tail (negative returns) is longer

- For P1 (long position), large negative returns mean large losses

- For P2 (short position), large positive returns mean large losses

4) Key insight:

- Since the distribution is negatively skewed, extreme negative returns are more likely than extreme positive returns

- For P1, this means larger potential losses are more likely

- For P2, the extreme losses would come from positive returns, which are less likely in a negatively skewed distribution

5) Therefore:

- The VaR for P1 will capture these more extreme negative returns

- The VaR for P2 will capture less extreme positive returns

Things to Remember

1. Value at Risk (VaR) is a statistical measure that quantifies the level of financial risk within a firm or investment portfolio over a specific time frame. It is widely used in finance for quantifying the risk of loss for a portfolio of risky financial assets.

2. A negatively skewed distribution indicates that the left tail of the distribution is longer or fatter than the right side. In the context of investment returns, negative skewness implies that there are more frequent large losses and less frequent large gains.

3. In a negatively skewed distribution, a long position is exposed to larger potential losses compared to a short position. Therefore, the VaR for a long position should be higher than the VaR for a short position.

4. The skewness of a distribution can have significant implications for risk management. Understanding the skewness can help investors better manage their risk and make more informed investment decisions.

Q.3036 What would be the 95% parametric VaR of a portfolio made of two independently normally distributed stocks – A and B, with $A \sim N(0.5, 1)$ and $B \sim N(3, 15)$? Assume that $P = (A + B)$

A. 56.

B. 4.87.

C. 3.08.

D. 1.54.

The correct answer is **C.**

Assuming $P = A + B$, then $P \sim N(3.5, 16)$.

$$\begin{aligned} VaR(\alpha\%) &= [-\mu_r + \sigma_r \times Z_\alpha] \\ &= [-3.5 + 4 \times 1.645] \\ &= 3.08 \end{aligned}$$

Note. *The sum of two independent normally distributed random variables is normal. It's mean is the sum of the two means, and its variance is the sum of the two variances*

Where $\sigma_r = \sqrt{16} = 4$

Q.5289 An investment banker is evaluating the risks of a portfolio of bonds. The portfolio is valued at CAD 150 million and contains CAD 20 million in bond X. The annualized standard deviations of returns of the overall portfolio and bond X are 12% and 9%, respectively. The correlation of returns between the portfolio and bond X is 0.60. Assuming the investment banker uses a 1-year 99% VaR and the returns are normally distributed, what is the VaR of bond X?

A. CAD 1,453,879.

B. CAD 4,186,800.

C. CAD 5,813,777.

D. CAD 4,636,800.

The correct answer is **B.**

The formula for calculating the VaR of a specific asset in a portfolio is:

$$\text{VaR of Asset} = \text{Asset Value} \times \text{z-value} \times \text{Asset's Standard Deviation}$$

where the z-value for a 99% VaR is 2.33.

Plugging in the given values, we get:

$$\begin{aligned}\text{VaR of bond X} &= 20,000,000 \times 2.326 \times 0.09 \\ &= 4,186,800\end{aligned}$$

Therefore, the VaR of bond X is CAD 4,186,800

Q.5292 A data scientist is analyzing a dataset and wants to determine the distribution of his data. The scientist decides to use a QQ plot in his analysis. Which of the following statements about QQ plots is correct?

A. QQ plots are used to evaluate the precision of a statistical estimator.

B. QQ plots are useful in determining the statistical significance of a hypothesis test.

C. QQ plots should only be used when the sample size is greater than 100.

D. QQ plots are useful in determining if a dataset follows a normal distribution.

The correct answer is **D.**

QQ plots, or Quantile-Quantile plots, are indeed useful in determining if a dataset follows a normal distribution. A QQ plot is a graphical tool used in statistics to help visualize how a dataset is distributed. It plots the quantiles of the dataset against the quantiles of a standard normal distribution. If the dataset follows a normal distribution, the points on the QQ plot will approximately lie on a straight line. This is because the quantiles of the dataset will match closely with the quantiles of the standard normal distribution. Therefore, a QQ plot is a powerful tool for visually checking the assumption of normality in a dataset.

Choice A is incorrect. QQ plots are not used to evaluate the precision of a statistical estimator. They are graphical tools used primarily for assessing if a dataset follows a specific distribution, such as the normal distribution.

Choice B is incorrect. While QQ plots can help in understanding the distribution of data, they do not directly determine the statistical significance of a hypothesis test. Hypothesis testing involves comparing observed data with expected results under certain assumptions, which is different from what QQ plots are designed for.

Choice C is incorrect. The use of QQ plots does not depend on the sample size being greater than 100. They can be used with any sample size to assess if it follows a particular theoretical distribution.

Things to Remember

- QQ plots are commonly used to check the assumption of normality in a dataset.
- They compare the quantiles of the dataset with the quantiles of a theoretical distribution (e.g., normal distribution).
- If the points on the QQ plot approximately form a straight line, it indicates that the dataset follows the theoretical distribution.
- QQ plots are helpful in identifying deviations from the assumed distribution and can guide further analysis or transformations.
- Sample size does not restrict the use of QQ plots; they can be applied to datasets of any size.

Reading 64: Non-parametric Approaches

Q.1487 The non-parametric density estimation is based on the assumption that a basic historical simulation does not get the best out of the information at hand. Which of the following examples demonstrates this drawback?

A. If we have 100 P/L observations, the basic HS only permits us to estimate VaR at discrete confidence levels, say, 95%.

B. If we have 100 P/L observations, the VaR at the 95% confidence level is given by the seventh-largest loss.

C. If we have 100 P/L observations, the VaR at the 95% confidence level is given by the fourth-largest loss.

D. If we have 100 P/L observations, the VaR at the 95% confidence level is given by the ninth-largest loss.

The correct answer is **A.**

The basic historical simulation (HS) method, when applied to 100 Profit/Loss (P/L) observations, only allows us to estimate Value at Risk (VaR) at discrete confidence levels, such as 95%. This is a significant limitation of the basic HS method because it does not allow for the estimation of VaR at non-discrete intervals. For instance, with 100 P/L observations, the VaR at the 95% confidence level is given by the sixth-largest loss. However, the VaRs at 95.1%, 95.9%, and 95.5% confidence levels cannot be obtained because there are no corresponding loss observations. This limitation restricts the flexibility and precision of risk estimation, which is crucial in financial risk management. Therefore, this example accurately demonstrates the drawback of the basic HS method in non-parametric density estimation.

Choice B is incorrect. The VaR at the 95% confidence level is not given by the seventh-largest loss when we have 100 P/L observations. In fact, it should be given by the fifth largest loss because in a list of 100 observations, the top 5% (or top five) represent losses beyond the 95% confidence level.

Choice C is incorrect. Similarly to choice B, this statement incorrectly identifies that VaR at a 95% confidence level would be represented by the fourth-largest loss in a set of 100 P/L observations. This again misrepresents how VaR calculations are made as it should be represented by the fifth largest loss.

Choice D is incorrect. In a basic historical simulation with 100 observations, the 95% confidence level VaR should correspond to the sixth-largest loss, not the ninth.

Things to Remember

- Non-parametric density estimation is a method used to estimate the probability density function of a random variable without assuming a specific distribution.

- Basic historical simulation (HS) is a technique used in risk management to estimate the VaR by using historical data.

- VaR (Value at Risk) is a measure used to assess the potential loss in value of a risky asset or portfolio over a specific time period under normal market conditions at a given confidence level.

- Discrete confidence levels refer to specific confidence levels like 95%, 99%, etc., where VaR can be estimated using historical simulation.

- Non-discrete intervals refer to confidence levels that fall between the discrete levels, such as 95.1%, 95.5%, etc., which cannot be estimated using basic historical simulation.

Q.1490 Estimating historical simulation ES or VaR does not have any theoretical problems; however, it has a practical problem. Which one is it?

A. As the holding period decreases, the number of observations decreases too.

B. As the holding period increases, the number of observations decreases.

C. As the holding period decreases, the size of data decreases.

D. As the holding period increases, the size of the data decreases.

The correct answer is **B.**

As the holding period increases, the number of observations decreases. This is a practical problem encountered when estimating historical simulation ES or VaR. The reason behind this is that as we increase the holding period, we are essentially aggregating more data points into a single observation. For instance, if we have 1000 observations of daily Profit/Loss (P/L), that corresponds to four years' worth of data at 250 trading days a year. If we decide to use a weekly holding period instead of a daily one, each weekly P/L will be the sum of five daily P/Ls, reducing our total number of observations to 200. If we further increase the holding period to a month, each monthly P/L will be the sum of 20 daily P/Ls, reducing our total number of observations to just 50. Therefore, as the holding period increases, the number of effective observations rapidly falls, imposing a major constraint on how large the holding period can practically be when estimating historical simulation ES or VaR.

Choice A is incorrect. The number of observations does not decrease as the holding period decreases. In fact, it's the opposite - a shorter holding period would typically result in more observations, not less.

Choice C is incorrect. The size of data does not necessarily decrease as the holding period decreases. The size of data depends on various factors such as frequency of data collection and length of time for which data has been collected, and not solely on the holding period.

Choice D is incorrect. As explained above in choice B explanation, an increase in the holding period results in fewer observations because there are fewer periods to observe within a given timeframe. However, this doesn't imply that the size of data decreases with an increase in holding period.

Things to Remember

- Historical simulation is a method used to estimate the potential losses of a portfolio by using historical data.
- Expected Shortfall (ES) is also known as Conditional Value at Risk (CVaR) and is a risk measure that quantifies the expected loss beyond the Value at Risk (VaR) level.
- Value at Risk (VaR) is a measure used to estimate the potential loss that an investment portfolio may face over a specified time period under normal market conditions.
- When using historical simulation for estimating ES or VaR, the choice of holding period is crucial as it impacts the number of observations available for analysis.
- Increasing the holding period reduces the number of effective observations, which can limit the accuracy and reliability of the ES or VaR estimates.

Q.1492 Bootstrapping is a common technique in financial modeling and statistics, used to construct yield curves or to estimate the distribution of a statistic. Understanding its correct application is crucial for accurate analysis. Which one of the following statements is most likely correct? A bootstrapping exercise:

A. resampling from our existing data set without replacement.

B. assumes that the distribution of returns will remain the same in the past and in the future.

C. assumes that the distribution of returns in future will be markedly different from past distributions.

D. results in a VaR estimate that is a sum of sample VaRs after repeated sampling.

The correct answer is **B.**

Bootstrapping indeed assumes that the distribution of returns will remain the same in the past and in the future. This assumption is fundamental to the bootstrapping method, as it justifies the use of historical returns to forecast the Value at Risk (VaR). The underlying idea is that the past can provide valuable insights into the future, especially when it comes to financial returns. By assuming that the distribution of returns remains constant over time, bootstrapping allows us to use historical data to make informed predictions about future returns. This is particularly useful in risk management, where understanding potential future outcomes is crucial for making sound investment decisions.

Choice A is incorrect. Bootstrapping involves resampling from our existing data set, but it is done with replacement, not without. This means that the same data point can be selected more than once in the resampling process.

Choice C is incorrect. Bootstrapping does not assume that future distributions of returns will be markedly different from past distributions. In fact, it assumes that the empirical distribution of the sample represents the true underlying population distribution.

Choice D is incorrect. The VaR estimate resulting from a bootstrapping exercise is not a sum of sample VaRs after repeated sampling. Instead, it provides an estimate for VaR based on resampled data sets and their corresponding calculated VaRs.

Things to Remember

- Bootstrapping is a resampling technique where multiple samples are drawn with replacement from the original data set.
- It is commonly used in finance for estimating parameters, constructing confidence intervals, and simulating possible scenarios.
- Bootstrapping relies on the assumption that the sample data is representative of the population data.
- It is a non-parametric method, meaning it does not rely on specific distributional assumptions about the data.
- Bootstrapping can be used for various statistical measures, not just VaR, such as mean, standard deviation, and skewness.

Q.1495 Even though bootstrapping has numerous advantages, the bootstrap estimates are associated with a little bias or error. Which of the following presents an error of bootstrapping?

A. Un-sampling variability.

B. Re-sampling variability.

C. Dual-sampling variability.

D. Bootstrapping variability.

The correct answer is **B.**

In the context of bootstrapping, re-sampling variability refers to the error that arises from the fact that we take only a finite number of bootstrap re-samples (denoted by B) from our original sample, rather than an infinite number. This limitation is inherent to the bootstrapping process, as it is practically impossible to take an infinite number of re-samples. As a result, our bootstrap estimates are subject to a certain degree of variability that is directly related to the number of re-samples taken. The larger the number of re-samples, the lower the re-sampling variability, and vice versa. However, even with a large number of re-samples, the re-sampling variability can never be completely eliminated, thus contributing to the overall error in the bootstrap estimates.

Choice A is incorrect. Un-sampling variability is not a recognized term in the context of bootstrapping or statistical analysis. It does not represent any type of error associated with bootstrapping.

Choice C is incorrect. Dual-sampling variability, similar to un-sampling variability, is not a recognized term in statistics or bootstrapping methodology. It does not denote any form of error that can occur during the process of bootstrapping.

Choice D is incorrect. While it may seem plausible due to the use of the term 'bootstrapping', Bootstrapping variability isn't an identified type of error in statistical analysis or bootstrapping procedures. The errors associated with bootstrap methods are more accurately described as re-sampling errors (as stated in option B), rather than 'bootstrapping variability'.

Things to Remember

- Bootstrapping is a resampling technique used to estimate the sampling distribution of a statistic by resampling with replacement from the original sample.
- Bootstrap estimates are useful for calculating confidence intervals and assessing the variability of a statistic.
- Re-sampling variability is a key concept in understanding the limitations of bootstrapping and the potential errors in the estimates.
- The number of bootstrap re-samples (B) taken can impact the re-sampling variability, with more re-samples generally leading to lower variability.

- Bootstrapping does not eliminate all sources of bias or error, and understanding the limitations of the method is crucial for accurate interpretation of results.

Q.1496 One of the drawbacks of the historical simulation approach is that the discreteness of the data rules out estimation of VaRs between data points. For example, if there were 100 historical observations, estimation of the VaR is a straightforward process at the 95% or the 96% confidence levels, but it is impossible to incorporate a confidence level of, say 95.5%. Which of the following methods can solve this problem?

A. Applying Brute Force

B. Bootstrapping

C. Non-parametric density estimation

D. Use of a large number of re-samples

The correct answer is **C.**

Non-parametric density estimation is the correct method to solve the problem of estimating VaR between data points in the historical simulation approach. This method treats data as if they were drawings from some unspecified or unknown empirical distribution function. The existing data points can be used to 'smooth' the data points, paving the way for VaR calculation at all confidence levels. This means that non-parametric density estimation allows for the estimation of VaR at non-discrete confidence levels, such as 95.5%, which is not possible with the historical simulation approach. This flexibility makes non-parametric density estimation a powerful tool in risk management, particularly in situations where the data does not follow a known or specified distribution.

Choice A is incorrect. Applying Brute Force does not address the limitation of historical simulation in estimating VaR between data points. It refers to a method of solving problems through sheer computational power rather than through more efficient, strategic methods. In the context of VaR estimation, it would involve calculating all possible outcomes and their probabilities, which is not feasible or efficient.

Choice B is incorrect. Bootstrapping is a resampling technique used to estimate statistics on a population by sampling a dataset with replacement. It can be used to estimate the distribution of a statistic and its confidence intervals but it does not specifically address the issue of estimating VaR between discrete data points in historical simulation.

Choice D is incorrect. The use of a large number of re-samples may improve the accuracy and reliability of estimates in some statistical methods but it does not solve the problem inherent in historical simulation where we cannot estimate VaR between discrete data points due to its nature.

Things to Remember

- Historical simulation approach uses past data to simulate potential future outcomes
- Value at Risk (VaR) is a measure used to quantify the level of financial risk within a firm or portfolio
- Non-parametric density estimation is a method that does not assume a specific distribution for the data
- Bootstrapping is a resampling technique that involves repeatedly sampling data with replacement
- Brute force method involves solving problems through sheer computational power
- Estimating VaR at non-discrete confidence levels can provide more detailed risk assessment

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Q.2631 An analyst performing a historical simulation to measure the VaR of a portfolio uses a volatility-weighted approach. One month ago, the actual return of the asset was 5% and its daily volatility estimate was 2%. If the current daily volatility is 1.5%, calculate the volatility-adjusted return.

A. 0.03

B. 0.0167

C. 0.0375

D. 0.0667

The correct answer is **C.**

In a volatility-weighted approach, we adjust historical returns to account for changes in volatility over time. This method ensures that the adjusted returns reflect the current volatility environment, which is crucial for accurate risk assessment. The formula for the volatility-adjusted return is:

$$r^*_{t,i} = \left(\frac{\sigma_{T,i}}{\sigma_{t,i}}\right) r_{t,i}$$

where:

- $\mathbf{r^*_{t,i}}$ is the volatility-adjusted return.
- $\boldsymbol{\sigma_{T,i}}$ is the current volatility estimate.
- $\boldsymbol{\sigma_{t,i}}$ is the historical volatility estimate at time t.
- $\mathbf{r_{t,i}}$ is the historical return at time t.

$$\therefore r^*_{t,i} = \left(\frac{0.015}{0.020}\right) 0.05 = 0.0375$$

Q.2820 The mean return from a dataset has been pre-calculated and is given as 0.04. The standard deviation has also been given as 0.32. With 90% confidence, what will be our percentage maximum loss? Assume that from our dataset, Z = -1.28 and N(Z) = 0.10 since you are to locate the value at the $10th$ percentile.

A. 36.96%

B. 11.27%

C. 11.32%

D. 36.72%

The correct answer is **A.**

Recall that

$$Z = \frac{(X - \mu)}{\sigma}$$

From the data, we are given that: $\mu = 0.04, \sigma = 0.32$, and $Z = -1.28$

Therefore: $-1.28 = \frac{(X-0.04)}{(0.32)} \Rightarrow X = -1.28(0.32) + 0.04 = -0.3696$

$$X = -0.3696 = 36.96\% \text{ loss}$$

This means that we are 90% confident that the maximum loss will not exceed 36.96%.

Q.2822 There are 30 observations in a dataset. The worst 10 return observations (in %) are listed below:
[-20, -18, -18, -17, -15, -14, -12, -10, -7, -3]

What is the VaR at the 90% confidence?

A. 17%

B. 18%

C. 16%

D. 15%

The correct answer is **A.**

To calculate the VaR at the 90% confidence level using the given dataset, we first order the dataset VaR in the ordered dataset:

The worst 10 return observations are: [-20, -18, -18, -17, -15, -14, -12, -10, -7, -3]

Total number of observations: 30

Position = 0.10 × 30 + 1 = 3 + 1 = 4th observation

The 4th worst return in the ordered list is:

-20, -18, -18, **-17,** -15, -14, -12, -10, -7, -3

Therefore, the VaR at the 90% confidence level is **-17%**. This means that, with 90% confidence, the maximum expected loss will not exceed 17% over the specified time horizon.

Things to Remember

- VaR (Value at Risk) is a measure used to estimate the potential loss on an investment over a specific time period under normal market conditions.
- Confidence level in VaR represents the probability that the actual loss will not exceed the estimated VaR.
- When calculating VaR, the dataset is ordered from worst to best returns, and the VaR at a specific confidence level is determined based on the position in the ordered dataset.
- Percentiles are often used to calculate VaR, with the 100th percentile representing the worst possible outcome.
- It is important to understand the concept of tail risk, which refers to the risk of extreme events that are not captured by traditional risk measures like VaR.

Q.2831 Find the weight of an observation 13 days ago if the total number of days in the historical window is 300 with a 0.8 control rate of memory decay.

A. 0.014

B. 0.01099

C. 0.0205

D. 0.01374

The correct answer is **D.**

The weight of observation i-days ago is given by:

$$w(i) = \frac{\lambda^{i-1}(1-\lambda)}{1-\lambda^{n}}$$

Where n is the number of days in the historical window and θ is the control rate of the memory decay,

Therefore:

$$W(13) = \frac{0.8^{13-1}(1-0.8)}{1-0.8^{300}} \approx 0.01374$$

Q.3010 You have been hired on a popular trading floor and one of the traders comes over and asks about the impact of price changes on her VaR - made of a single long position in stock KKJL. Yesterday's closing price was USD 100.
You are using a 95% confidence historical VaR based on a 260 days moving window of historical data. In this time period, the 16 worst 1-day returns from for KKJL as of yesterday were as follows (in %): -9.5, -8, -7.6, -7.4, - 7.2, -7.18, -7.1, -6.9, -6.57, -6.56, -6.45, -6.4, -6.25, -6.05, -5.99, -5.85.

Suppose that the stock price decreased by 10% between yesterday and today following the publication of an adverse dossier on the company. The latest return to slip out of the 260-day moving window is -3%.

What will be the Historical VaR at 95% confidence in absolute terms?

A. USD 6.25

B. USD 5.445

C. USD 5.625

D. USD 6.05

The correct answer is **C.**

In general, if there are *n* ordered observations, and a confidence level *cl%*, the *cl%* VaR is given by the $[(1 - cl\%)\ n + 1]^{th}$ highest observation. This is the observation that separates the tail from the body of the distribution. Given 260 observations, we are therefore interested in the [(1 - 0.95)260 + 1]th = 14th worst observation

Before the latest 10% loss, the ordered losses are as follows:

[-9.5, -8, -7.6, -7.4, - 7.2, -7.18, -7.1, -6.9, -6.57, -6.56, -6.45, -6.4, -6.25, -6.05, -5.99, -5.85]

The 14th worst observation is -6.05. However, given that the stock decreased by 10% between yesterday and today, the arrangement changes; -10% will now be the worst return that the stock experienced over the last 260 business days. The 16 worst returns shall now be:[-10, -9.5, -8, -7.6, -7.4, - 7.2, -7.18, -7.1, -6.9, -6.57, -6.56, -6.45, -6.4, -6.25, -6.05, -5.99]

The VaR at 95% will be based on -6.25%, which is now the 14th worst return.

$$VaR = 90 \times 6.25\% = 5.625$$

Notes.

(I) 90 here is the price of the stock today (after a 10% decline yesterday)
(II) We're working with the worst returns recorded over a 260-day moving window, so we're essentially looking back and ordering the worst returns recorded during that period, and one observation slips out of the window every day. The latest return to slip out is -3%, but this is considerably higher (less negative) than -5.85% (lowest worst return on our list), so it does not affect the makeup of the worst 16 returns.

Q.3012 Simon is using the age-weighted historical simulation approach to estimate the VaR of a stock portfolio, Under age-weighted historical simulation,

A. more recent observations are weighted more and distant observations weighted less.

B. all observations are weighted equally.

C. the decay parameter takes a value of 1.

D. the historical window of observations must not exceed 250 days.

The correct answer is **A.**

The age-weighted historical simulation method assigns more weight to recent observations and less weight to distant observations. This is based on the assumption that more recent observations are more relevant to the current risk profile and therefore should have a greater influence on the simulation results. This method is often used in financial risk management to estimate potential losses, as it allows for a more accurate representation of the current risk environment. The weights assigned to the observations are typically determined using a decay factor, which can be adjusted to reflect the desired level of emphasis on recent observations.

Choice B is incorrect. The age-weighted historical simulation method does not weight all observations equally. Instead, it assigns more weight to recent observations and less weight to older ones, reflecting the belief that recent data is more relevant for estimating potential losses.

Choice C is incorrect. The decay parameter in the age-weighted historical simulation method does not necessarily take a value of 1. This parameter determines how quickly the weights decrease for older observations, and its value can vary depending on the specific model used.

Choice D is incorrect. There's no hard rule that the historical window of observations must not exceed 250 days in an age-weighted historical simulation method. The length of this window can vary depending on factors such as data availability and the nature of the risk being modeled.

Things to Remember

- Historical simulation is a method used to estimate the Value at Risk (VaR) of a portfolio by using historical data to simulate potential future outcomes.
- Weighting schemes in historical simulation include not only age-weighted, but also equally weighted, volatility weighted, and other methods.
- The decay parameter in age-weighted historical simulation determines how quickly the weights decrease for older observations, impacting the influence of past data on the simulation results.
- Choosing the appropriate historical window of observations is crucial in historical simulation to balance the trade-off between capturing enough data for accuracy and avoiding outdated information.
- Backtesting is a critical step in validating the accuracy of VaR estimates obtained through historical simulation methods.

Q.3035 Paul is using the age-weighted historical simulation approach to estimate the VaR of a stock portfolio, with a historical sample size of 100 days and a decay factor of 0.96. Over the recent past, the portfolio has registered the following returns:

Return	Periods Ago(Days)
−3.2%	109
−3.3%	75
−2.3%	66
−1.3%	22
−3.0%	45

Determine the weight on the return earned 45 days ago

A. 0.05.

B. 0.0025.

C. 0.0065.

D. 0.006751.

The correct answer is **D.**

Under age-weighted (aka Hybrid) historical simulation, the weight, w_i, given to an observation i days old is given by:

$$w_i = \frac{\lambda^{i-1}(1-\lambda)}{(1-\lambda^n)}$$

So,

$$w_{45} = \frac{0.96^{45-1}(1-0.96)}{(1-0.96^{100})} = 0.006751$$

Note. *Any return falling outside the historical window would have a weight of zero, for instance, the observation made 109 days ago.*

Q.3037 You have been hired on the trading floor, and one of the traders comes over and asks about the impact of a price change on her VaR made of a long position in stock A, whose value stood at 100 as of yesterday.
Assume you are using a 95% confidence historical VaR (based on 260 days moving window of

historical data). Further, assume that the 16 worst 1-day returns of stock as of yesterday were as follows:

-9.5, -8, -7.6, -7.4, - 7.2, -7.18, -7.1, -6.9, -6.57, -6.56, -6.45, -6.4, -6.25 -6.05, -5.99,-5.85.

Assume the price of the stock increased by 10% between yesterday and today. Further, assume that the oldest return is not among the returns given. What will the value of today's 95% VaR (in absolute value) be?

A. $6.25.

B. $6.655.

C. $10.

D. $6.05.

The correct answer is **B.**

Today's stock price is $100 × (1 + 10%) = $110
The 95% VaR is given by the 14th worst return, i.e., -6.05%,

N/B: Using 260 days moving window of historical data, the 95% VaR will be r=260(1-95%) +1 = 14th observation

The new 95% VaR will be $110 × (- 6.05/100) = -$6.655

Note. The latest return (10%) does not affect the left tail of the loss distribution. It is higher (more positive) than all the returns given and does not get a spot among the worst 16 observations. In addition, the examiner assumes that the oldest return pushed out the rolling window is not among the entries given. Therefore, today's worst 16 observations will be the same as yesterday's.

Things to Remember

- VaR (Value at Risk) is a measure used to assess the potential loss in value of a risky asset or portfolio over a specified time period with a certain level of confidence.
- Historical VaR is calculated based on historical data, while other methods like parametric VaR and Monte Carlo simulation are also used for VaR calculation.
- Confidence level in VaR represents the probability that the actual loss will not exceed the VaR estimate.
- When calculating VaR for a long position, negative returns represent losses, and the

VaR value is usually expressed as a positive number.

- The worst returns are used to calculate VaR, and the VaR value is determined based on the historical data and confidence level chosen.

Q.5295 A data analyst wishes to calculate the VaR of a credit firm using the bootstrap historical simulation approach. How is the final VaR estimate calculated using the bootstrap historical simulation approach?

A. By taking the highest VaR from all resamples.

B. By taking the lowest VaR from all resamples.

C. By averaging the VaR from all resamples.

D. By taking the median VaR from all resamples.

The correct answer is **C.**

The bootstrap historical simulation approach involves creating resamples from an original sample of data, with each resample potentially containing multiple instances of an observation or excluding some observations entirely. Each resample generates a different estimate for the VaR. The final VaR estimate is then calculated by averaging the VaR from all resamples. This approach allows for a more comprehensive and balanced estimation of the VaR, as it takes into account the full range of possible outcomes, rather than focusing solely on the best-case or worst-case scenarios.

Choice A is incorrect. The highest VaR from all resamples does not represent the final VaR estimate in the bootstrap historical simulation approach. This would only provide an extreme scenario, which is not representative of the overall risk profile.

Choice B is incorrect. Similarly, taking the lowest VaR from all resamples would also be misleading as it underestimates the potential risk and does not reflect a comprehensive view of possible outcomes.

Choice D is incorrect. While taking the median VaR from all resamples might seem like a reasonable approach, it doesn't fully utilize all available data points in generating an estimate for VaR. It may ignore significant outliers that could have substantial impact on risk estimation.

Things to Remember

- Bootstrap Historical Simulation Approach: This method involves creating resamples from an original sample of data to estimate the Value at Risk (VaR).

- Resampling: Involves generating multiple samples from the original data set, with each resample potentially containing multiple instances of an observation or excluding some observations entirely.

- Averaging: Calculating the final VaR estimate by averaging the VaR from all resamples helps in providing a more comprehensive and balanced estimation of the VaR.
- Extreme Scenarios: Choosing the highest or lowest VaR from all resamples may not provide an accurate representation of the overall risk profile and could lead to misleading conclusions.
- Outliers: Ignoring outliers in the data when estimating VaR could result in underestimating or overestimating the actual risk, highlighting the importance of using all available data points in the analysis.

Q.6431 Compared to basic (raw) historical simulation, which of the following statements correctly characterizes what occurs during bootstrapping?

A. Bootstrapping compresses the original data, leading to repeated observations.

B. It replicates the most extreme historical returns in every sample.

C. It scales each historical return by a constant factor obtained from the sample's mean.

D. It resamples (with replacement) many times, creating multiple “alternative” data sets.

The correct answer is **D.**

Bootstrapping is a resampling technique used to estimate the sampling distribution of a statistic by repeatedly resampling with replacement from the original data. "With replacement" is crucial; it means that after a data point is selected for a resampled dataset, it is put back into the original dataset, so it can be selected again. This process creates multiple "alternative" datasets, each of the same size as the original, but with potentially different combinations of the original data points (some may be repeated, others may be absent).

A is incorrect. Bootstrapping doesn't compress the data; it creates datasets of the same size as the original. While there are repeated observations within each resampled dataset, the overall amount of data across all resampled datasets is much larger than the original.

B is incorrect. Bootstrapping doesn't force the most extreme returns into every sample. The selection is random with replacement, so extreme values might appear multiple times in some resampled datasets, not at all in others, or just once.

C is incorrect. Scaling by the sample mean is not part of the bootstrapping process. Bootstrapping is about resampling the original data points, not modifying them.

Q.6432 Which statement correctly captures the essence of a correlation-weighted approach within the historical simulation framework?

A. It forces all pairwise asset correlations to zero by partitioning returns into uncorrelated blocks while leaving individual volatilities unchanged.

B. It imposes a desired set of updated correlations among assets by systematically adjusting historical returns, typically without altering each asset's overall volatility.

C. It re-weights observed co-movements to ensure the sample correlation matrix matches a diagonal matrix (i.e., only variances remain, covariances are nullified).

D. It replicates only those return paths whose correlations exceed a specified threshold, discarding paths that deviate from the target correlation profile.

The correct answer is **B.**

Correlation-weighted historical simulation aims to address a key limitation of standard historical simulation: its reliance on historical correlations, which may not be representative of current or future market conditions. This approach adjusts the historical returns in a way that preserves the individual volatilities of the assets but alters their co-movements (correlations) to reflect a desired or estimated correlation structure. This is often done using techniques like Cholesky decomposition.

A is incorrect. This describes a scenario where assets are treated as completely independent, which is the opposite of what a correlation-weighted approach aims to do (which is to incorporate specific correlations).

C is incorrect. This is similar to option A; it implies making assets uncorrelated, which is not the purpose of correlation weighting.

D is incorrect. This describes a selection or filtering process based on correlations, not a systematic adjustment of returns to impose a specific correlation structure.

Q.6433 Which of the following most closely characterizes the role of filtered historical simulation in estimating risk?

A. It fits a time-varying volatility model (e.g., GARCH) and then adjusts historical returns before resampling, reflecting evolving market conditions.

B. It reorders past returns chronologically to match any short-term volatility changes but leaves correlation unaltered.

C. It discards all returns that fall outside a user-defined confidence interval, ensuring that the final distribution is free of extreme tail events.

D. It transforms each asset's average return into a standardized zero mean but leaves the standard deviation fixed at its historical level.

The correct answer is **A.**

Filtered Historical Simulation (FHS) is designed to address a key weakness of standard historical simulation: its assumption of constant volatility. FHS uses a time-varying volatility model, such as GARCH, to capture the dynamic nature of volatility in financial markets.

The FHS process generally involves these steps:

1. **Modeling Volatility:** A time-series model (like GARCH) is fitted to historical returns to estimate the conditional volatility at each point in time. This provides a series of volatility estimates that change over time.
2. **Standardizing returns:** The historical returns are then standardized by dividing each return by its corresponding conditional volatility estimate. This creates a series of standardized residuals (or "innovations") that are approximately independent and identically distributed (i.i.d.).
3. **Resampling:** These standardized residuals are then resampled with replacement. This resampling step is similar to bootstrapping.
4. **Scaling back:** The resampled residuals are multiplied by the current (or forecasted) volatility from the GARCH model. This step is crucial because it scales the resampled data to reflect the current market volatility environment.

By adjusting historical returns based on a time-varying volatility model before resampling, FHS generates simulated future returns that are more reflective of current market conditions than those produced by standard historical simulation.

Why the other options are incorrect:
B: Simply reordering returns does not account for the magnitude of volatility changes. FHS explicitly models and adjusts for changing volatility.
C: This describes a form of censoring or truncation of the data, which is not what FHS does. FHS aims to model the entire distribution, including the tails, more accurately.
D: While standardizing returns is a step in FHS, it's not the complete picture. The key is that the standardization uses time-varying volatility estimates, and the resampled data is then scaled by the current volatility, not the historical standard deviation.

Q.6434 A small prop trading firm has only 80 days of historical returns. They want to estimate VaR at 97.5% but find the traditional historical simulation percentile approach too coarse. The head quant suggests a non-parametric density estimation method. What key benefit does this non-parametric approach offer the firm?

A. Increased sample size

B. Flexible percentile selection

C. Zero outliers

D. Constant correlation

The correct answer is **B.**

The key benefit of using a non-parametric density estimation method like Kernel Density Estimation (KDE) is that it creates a smooth, continuous distribution from the limited historical data. This allows for flexible percentile selection (B).

With only 80 data points, using a direct percentile method (like taking the 2nd smallest return for a 97.5% VaR) is very sensitive to individual data points and doesn't give a very precise estimate. KDE interpolates between the data points, creating a much smoother distribution from which you can read off any percentile you want with greater precision than the raw data would allow.

A is incorrect. KDE doesn't increase the actual number of data points. It uses the existing data to estimate a continuous density function.

C is incorrect. KDE doesn't eliminate outliers. The density estimation will still be influenced by extreme values, though their impact is smoothed out across the distribution.

D is incorrect. Correlation is not directly related to this approach. KDE focuses on the distribution of a single variable (returns in this case), not the relationship between multiple variables.

Q.6435 An analyst implements filtered historical simulation on commodity returns. She first fits a GARCH model, generates volatility forecasts, and standardizes each day's return. Then she resamples these standardized returns to estimate future risk. Which aspect best defines "filtered" in this context?

A. Zero-sum weighting

B. Conditional volatility adjustment

C. Ignoring non-positive returns

D. Age-based discard of old data

The correct answer is **B.**

The "filtered" aspect in filtered historical simulation refers to the fact that the historical returns are adjusted, or "filtered," by the conditional volatility (B) from the GARCH model.

Here's why:

1. GARCH Model: The GARCH model captures the time-varying volatility (conditional volatility) of the returns. It recognizes that volatility tends to cluster (periods of high volatility followed by more high volatility, and vice-versa).
2. Standardization: By dividing each historical return by its corresponding GARCH-estimated volatility, the analyst creates a series of standardized returns. These standardized returns have a mean of approximately zero and a standard deviation of approximately one, removing the heteroskedasticity (varying volatility) present in the original returns.
3. Resampling: The resampling is then performed on these standardized returns. This is the key "filtering" step. It ensures that when these resampled standardized returns are used to simulate future scenarios, they are scaled by future volatility forecasts from the GARCH model. This incorporates the expected changes in volatility into the risk estimation.

A is incorrect. Zero-sum weighting is not related to the filtering process in this context.

C is incorrect. Filtering does not involve discarding any returns, positive or negative.

D is incorrect. While some risk management techniques use age-based weighting or discarding of old data, this is not the defining characteristic of "filtered" historical simulation.
