**PRMIA 3.A.3 Advanced VaR Models**

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Market shock is likely to be followed by a large return (in either direction) for some time.  
  
By failing to take account of volatility clustering a form would potentially take unduly large risks, or will hold insufficient capital, in periods of market crisis.  
  
In addition they would hold on to too much expensive capital at other times.

## 3.A.3.2 Standard Distributional Assumptions

## Stylised Facts

* The mean of the daily returns is close to zero
* Risk is expressed in two ways: standard deviation per day and volatility ( annualised standard deviation)
* Skewness is often negative
* Excess kurtosis is often positive, indicating that the distribution has heavy tails relative to the normal distribution.

**Volatility Clustering**

* Volatility clustering is also known as the “heat wave effect”
* Volatility Clustering is arguably the most important empirical characteristic of financial data.

3.A.3.3 Models of Volatility Clustering

3.A.3.3.1 Exponentially Weighted Moving Average (EWMA) model

EWMA can be thought of as a very simple GARCH Model.

3.A.3.3.2 GARCH models

Focuses on volatilityclustering  
Addresses issues raised by heteroskedascity  
All GARCH models share a positive correlation between risk yesterday and risk today (an "autoregressive" structure)  
  
The simplest GARCH model consist of 2 equation which can be estimated together  
  
conditional mean equations  
  
conditional variance equations  
  
In the absence of a market shock, the variance will tend towards its steady state variance , defined by

3.A.3.4 Volatility Clustering and VaR

3.A.3.4.1 VaR using EWMA

Volatility can be incorporated into VaR using the "exponentially weighted moving average" (EWMA) approach.

1. Historical simulation using volatility weighted data
2. MC simulation using EWMA
3. Analytical VaR using EWMA

Once the covariance matrix has been defined, it can be used for VaR calculations using either:

1. The analytical method
2. MC simulation

3.A.3.4.2 VaR and GARCH

3.A.3.5 Alternatives to Non-Normality

1. Student’s t distribution
2. Extreme Value Theory
3. Normal Mixtures

3.A.3.6 Decomposition of VaR

VaR models form the basis for internal economic capital allocation and limit setting.

Disaggregation of Risk is used to set limits, assess new investments, for hedging and for performance measurement.

1. Stand-alone capital
2. Incremental VaR
3. Marginal Capital

3.A.3.7 Principal Component Analysis

Principal Component Analysis is a statistical tool that decomposes a positive semi-definite matrix into its principal components.

The first principal component explains the largest part of the variation in the system.

The nth principal component explains the least variation.

PCA applied to a covariance matrix or a correlation matrix has many applications for financial risk management. It is particularly effective in highly correlated systems such as term structures.

PCA is useful in reducing dimensions. By retaining only the first few principal components, enough to cover 95% of the variation, it simplifies subsequent analysis.

Principal Components are uncorrelated with each other.

3.A.3.8 Summary hold on