TOOLS AND TECHNIQUES FOR FINANCIAL STABILITY ANALYSIS

COMPLETE VOLUMES ON THEORY AND PRACTICE OF FINANCIAL STABILITY

Volume 1: Understanding Financial Stability

Volume 2: The Banking Sector under Financial Stability

Volume 3: The Corporate, Real Estate, Household, Government and Non-Bank Financial Sectors under Financial Stability

Volume 4: Economic Areas under Financial Stability

Volume 5: Tools and Techniques for Financial Stability Analysis

Praise for *The Theory and Practice of Financial Stability*

Indranarain Ramlall's proposal is a great attempt at giving a comprehensive view of financial stability from a theoretical, practical and policy perspective. It aims at providing future students with the tools to understand the framework in which financial stability is assessed and understood today by international organisations and central banks across the world. To my knowledge, this is the only book that covers such a wide range of topics related to financial stability. It, therefore, has the potential to become a good reference book on the topic. I believe that Indranarain Ramlall has made a great proposal to provide a 'big picture view' on financial stability. I look forward to reading the textbook!

Celine Tcheng, Central Bank of France

Financial stability has become a major concern for central banks, after the 2008 global financial crisis. More and more research is tackling topics regarding the role of the financial system in macroeconomic models and the implementation of macroprudential policy. Therefore, a comprehensive overlook of financial stability issues, such as the one offered by *The Theory and Practice of Financial Stability* can prove particularly useful for experts working in the financial system, central bankers included. The textbook covers a diverse set of topics from policy matters to risk assessment analysis.

Elena Banu, Central Bank of Romania

This book is a comprehensive work on one of the most actual topics in the aftermath of the Great Recession. It covers a wide range of topics on financial stability complementing theoretical frameworks with practical examples.

Starting with a conceptual description on financial stability, the book overviews a history of the major financial crises and Basel regulation rules. Particularly useful is an inquiry of the financial stability perspectives across different asset classes and economy sectors. Another beneficial feature of this book is a complete oversight of stress testing methodologies.

The book is a thorough compilation of topics on financial stability and definitely deserves a place on the bookshelves of central bankers, government and private institutions' officials.

Vaidotas Sumskis, Bank of Lithuania

Dr Indranarain's book is an actual textbook for interpreting interrelations between all aspects and sectors of the international economy and will surely be a highly useful tool for credit institutions, investors, practitioners as well as academics. From a Central Bank's point of view, this book provides an integrated approach to macroeconomic environment and the interactions between the various factors and an actual tool for assessing and measuring leading circumstances and indicators that affect financial stability and may cause vulnerabilities.

Vasiliki Vlachostergiou, Central Bank of Greece

This is a monumental work! I didn't find anything missing. I think it will be useful for students, economic and finance professionals and policymakers.

Christophe Andre, OECD

Financial stability was always a priority for financial sector regulators, and it has surpassed other objectives since the global financial crisis. Given various complexities associated with the financial stability and rapid developments over time, existing literature tends to deal with specific aspects of financial stability. It is very difficult to get a comprehensive book dealing with the wide range of concepts, different segments of financial sector, ever increasing variety of financial instruments and regulations associated with financial stability. The current book is a very good attempt to fill this gap through its comprehensive coverage of almost the entire gamut of financial stability-related topics. This book should be useful for financial sector regulators, related ministries in the governments, researchers, multilateral institutions, other financial sector stakeholders and general public who are interested to know the complexities of the financial sector and financial stability.

Ajay Prakash-an expert in Financial Stability

THE THEORY AND PRACTICE OF FINANCIAL STABILITY, VOLUME 5

TOOLS AND TECHNIQUES FOR FINANCIAL STABILITY ANALYSIS

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INVESTOR IN PEOPLE

Dedicated to God for making me an instrument of his own

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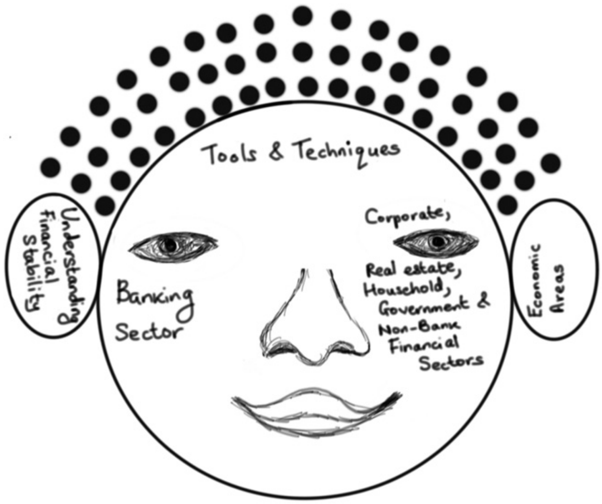
Preface

The last volume of this series of five books on financial stability covers all key aspects of tools and techniques useful for sound financial stability assessments. Comprehensive coverage is made on value at risk, stress testing, graphical tools on financial stability, financial system stress index and ratios/metrics of financial stability assessment with the last chapter being dedicated to challenges of financial stability.

The author expects the book to be particularly useful to economists, policy-makers, researchers and students in the sphere of financial stability in the banking sector. As at date, there is no textbook on financial stability which weaves through all aspects of financial stability from theory to practice. This series of five books on financial stability attempts to fill in such a vacuum. Comments and suggestions can be made to i.ramlall@uom.ac.mu/iiramii3@gmail.com.

The author seizes this opportunity to thank an anonymous referee from the London School of Economics for his suggestions and reviews made by professionals from central banks and reputable organisations.

Dr Indranarain Ramlall
June 2018



Financial Stability as a field of its own.
Dr. I. Ramlall 20/09/18

Chapter 1

Value at Risk

1.1. Definition of Value at Risk

Value at risk (VaR) can be succinctly defined as the maximum level of loss which can be borne by an institution at a given time period over a specified confidence level. Compared to other forms of risk management metrics, the VaR risk indicator represents a form of downside risk. Technically speaking, the VaR for t days is calculated as the VaR for one day multiplied by the square root of time. The statistical value for 95%, 99% and 99.5% in the case of VaR is 1.645, 2.326 and 2.58, respectively. Choosing a high probability, say 99%, signifies that losses higher than the VaR can be tolerated only infrequently. The main assumption of VaR is that the data used are normally distributed which is unlikely to hold true in practice. For instance, financial returns are leptokurtic in nature with exhibition of fat tails. The VaR was particularly useful for the banking sector as it helped in computing the level of capital required to absorb feasible unexpected losses. The selection of the time horizon and the significance level will be a function of the organisation's ability and willingness to bear the risk.

1.2. Benefits of VaR

The VaR is widely used in financial institutions for risk assessment, risk-based capital controls and risk-adjusted performance measurement. The VaR aggregates risk into a single component. VaR can be applied to different types of risks to thereby constitute a metric which enables comparative assessments of the distinct types of risks which buffet any institution. VaR gained prominence in the world on the back of being easy to apply and to understand. VaR is able to capture the level of risk aversion through the confidence level. As a matter of fact, the choice of the confidence level in VaR should sieve out the risk aversion level of the company. Thus, a higher level of risk aversion is reflected through a higher confidence level or a lower significance level which is also same as a higher statistical value of VaR.

1.3. Limitations of VaR

No metric of risk assessment is fully perfect and so is the case for VaR. The VaR has certain limitations such as overlooking of the upside potential, being good only to the extent that the inputs used are good and relying on normality assumptions.

In relation to financial stability, VaR has not been a good student. This can best be captured by Choudhry (2013) who comments that VaR underestimates risks during the Great Recession, a time when it was most needed, belittling the robustness of VaR as a reliable risk management tool. This induced the Basel Committee on Banking Supervision to scrap VaR in favour of Expected Shortfall (ES). In contrast to VaR which gauges on 'How bad can things get?', ES asks the question 'If things get bad, what is our expected loss?'. In essence, ES calculates the expected value of losses beyond a stated confidence level.

The VaR suffers from non-additive principle, that is, the VaR of a portfolio of two assets is not the same as the combined sum of VaRs of these two assets individually, signifying the need to give due consideration to correlation whenever focusing on portfolio VaR.

The VaR fails to sieve out the true value of loss in the case that strong fat tails permeate the data-generating process of the asset under scrutiny which thereby infringes the assumption of normality. Recourse can be made to the Student *t*-distribution of the generalised hyperbolic distribution (GHD) to deal with such a problem. In a parallel manner, the non-stationarity principle represents a statistical warning that the past is not necessarily a guide to the future. Under extreme economic situations, historical relationships easily break apart.

Illiquidity: if securities do not trade in highly liquid markets, reliable prices are not available to compute rates of return. Alarmingly, if there are large adverse price movements, portfolio managers may not be able to dispose of large quantities of the security without unleashing a fall in the share price, particularly if other portfolio managers are doing the same. The VaR will underestimate the severity of bad outcomes unless markets are highly liquid.

Non-linearity: standard VaR calculations do not allow for non-linear relationships. For example, a 2% change in the security price may cause the portfolio to lose US$1million but a 4% change may generate it to lose US$10million. Non-linearities can be accommodated but only at the expense of more risk in the economic model.

Whether the variance-covariance, historical or Monte Carlo approaches are used, all of them assume that the future will repeat itself. This explains the rationale as to why stress testing is deemed to be better than VaR as it is more flexible in incorporating more realistic scenarios. In fact, based on the shortcomings of VaR, it should be complemented with other risk management tools such as stress testing. This is supported by the notion that VaR tends to be rigid in nature because it is based on normal conditions, let alone the fact that it does not factor in what-if conditions.

Despite the abovementioned limitations, yet, VaR is important for risk management. The VaR is often accompanied by stress testing and scenario analysis because VaR is seldom used in isolation.

1.4. Framework under VaR

1.4.1. Distinction between CDF and PDF

Prior to gaining insight on the framework embedded in VaR, it is of paramount significance to master two key tools in statistics, namely the probability density function (PDF) and the cumulative density function (CDF).

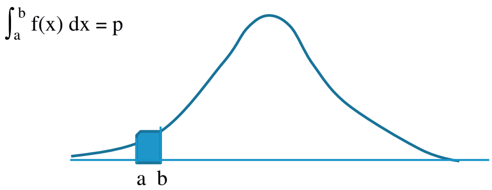


Figure 1.1. Probability and Cumulative Density Functions. *Source*: Author's illustration, x-axis: x; y-axis: $f(x)$.

1.4.2. Probability Density Function

For a continuous random variable X, the PDF can be defined as the probability of outcomes manifesting between any two points. Given a random variable X, the PDF $f(x)$ can be defined as the probability p that X lies in between point a and point b (Figure 1.1).

1.4.3. Cumulative Density Function

The CDF tells us the probability of a random variable being less than a specific value. Technically speaking, the CDF can be ejected out by integrating the PDF. Hence, differentiating the CDF leads to the PDF. Hence, CDF is read on the same PDF graph but taken as the integral of PDF or area under the curve. In that respect, since probability can never exceed one and never be negative, the value of CDF ranges from zero to one.

Conventionally, the CDF is denoted by capital letters. Hence, for a random variable X with a PDF $f(x)$, the CDF is $F(x)$.

$$F(a) = \int_{\infty}^{a} f(x)\mathrm{d}x = P[X \leq a]$$

1.5. The Generalised Hyperbolic Distribution

Returns from financial variables like stock prices, interest rates and exchange rates are usually characterised by more peakedness and heavy tails than normal distribution. The GHD was introduced by Barndorff-Nielsen (1977) who introduced GHDs in the study of grains of sand. Since its development, the GHD has been applied in diverse fields like physics, biology and finance. The presence of non-normality, fat-tails, skewness and kurtosis in the distribution of the returns necessitates the fitting of distributions that account for this phenomenon. In that respect, it becomes considerate to fit the GHD and the normal inverse Gaussian (NIG) to the daily returns of African stock exchanges. In essence, GHD contains five main parameters. Technically speaking, the GHD is a superset as it contains other types of functions such as Gaussian, Student-t, variance-gamma and NIG distributions. Consequently, GHD is anticipated to fare well relative to any other type of distribution function but this comes with significant complexity. The GHD is derived by estimating its five parameters. If random variable X follows a GHD, then X may be written as follows:

$$X \sim \text{GH}\ (\lambda, \alpha, \beta, \delta, \mu)$$

where

X: a random variable.
λ: impacts on the kurtosis and characterises the specific type of the GHD, can be labelled as a class-defining parameter.
α: influences the shape.
β: skewness parameter.
δ: scale parameter (in lieu of gamma).
μ: location parameter.

The PDF of the GHD is specified as follows:

$$\rho_{\text{GH}}(X : \lambda, \alpha, \beta, \delta, \mu) = a(\lambda, \alpha, \beta, \delta, \mu)\left(\delta^2 + (x-\mu)^2\right)^{(\lambda-1/2)2} K(\lambda, \alpha, \beta, \delta, \mu)$$

$$K(\lambda, \alpha, \beta, \delta, \mu) = K_{\lambda-1/2}(\alpha\sqrt{\delta^2 + (x-\mu)^2}\exp\ (\beta(x-\mu))$$

$$a(\lambda, \alpha, \beta, \delta) = (\alpha^2 - \beta^2)^{\lambda/2} \div \sqrt{2\Pi}\alpha^{(\lambda-1/2)}\delta^{\lambda}\ K_{\lambda}(\delta\sqrt{\alpha^2 + \beta^2})$$

$K\ (\lambda)$ denotes the modified Bessel function of the third kind with index λ.

Two prevalent forms of generalised hyperbolic functions permeate the finance theory. First, there is the case where $\lambda = 1$ which generates the simple hyperbolic function H(α, β, δ, μ) where the PDF is spelt down as follows:

$$\rho_{\text{GH}}(X : \alpha, \beta, \delta, \mu) = a\ (\alpha, \beta, \delta, \mu)\left(\delta^2 + (x-\mu)^2\right)^{(1/2)2} K\ (\alpha, \beta, \delta, \mu)$$

$$K(\lambda, \alpha, \beta, \delta, \mu) = K_{1/2}(\alpha\sqrt{\delta^2 + (x-\mu)^2}\exp\ (\beta(x-\mu))$$

$$a(\lambda, \alpha, \beta, \delta) = (\alpha^2 - \beta^2)^{1/2} \div \sqrt{2\Pi}\alpha^{(1/2)}\delta^{1}\ K_{1}(\delta\sqrt{\alpha^2 - \beta^2})$$

$$\begin{aligned}\rho_{\text{GH}}(X : \alpha, \beta, \delta, \mu) \quad &= \left\{(\alpha^2 - \beta^2)^{1/2} \div \sqrt{2\Pi}\ \alpha^{(1/2)}\delta^1 K^1\left(\delta\sqrt{\alpha^2 + \beta^2}\right)\right\} \\ &\left(\delta^2 + (x-\mu)^2\right)^{(1/2)2}\left\{K_{1/2}\ (\alpha\sqrt{\delta^2 + (x-\mu)^2}\exp\ (\beta(x-\mu))\right\}\end{aligned}$$

When $\lambda = ½$, this generates the NIG distribution.

The VaR risk assessment metric focuses on the maximum permissible loss with a given level of confidence (95% or 99%) over a specified time period such as one day, one week or one month. The VaR constitutes a direct function of the probability distribution at the left tail which shows negative returns.

1.6. Three Approaches in VaR Computations

Three different methods exist to compute VaR, namely the variance-covariance approach, the historical approach and the Monte Carlo approach. Each of these three approaches has its own specificities. For instance, the variance-covariance approach is purely parametric in nature because it relies heavily on variances/standard deviations with the VaR being computed as the products of standard deviation, the value of the normal distribution at the specified significance level (corresponding z-value of one-tailed test under chosen significance level) and the portfolio value. The historical approach requires the ranking of the data to then apply a filter hinging on the chosen significance level to the left tail of the data (focus on the losses). Thus, no parametric distribution is needed under the historical approach — reason as to why it is also called a non-parametric approach.

Table 1.1 captures the differences which prevail between the three main approaches to VaR computation.

1.7. Questions-based Insights on VaR

The best way to master a subject is to start learning from questions—answers. This section is anticipated to leverage on the knowledge of the readers on VaR.

(1) A US$100 million portfolio has a 2% VaR at the 5% probability over one week. Interpret the loss.

The portfolio could lose (2% of US$100 million) US$2 million over one week. Most importantly, there is 5% chance that more than US$2 million will be lost over one week and 95% chance that less than US$2 million will be lost over one week.

What would be the impact if the 5% probability were to be adjusted to 1% probability?

The 1% probability would signify higher risk, that is, the VaR value in % would exceed the 2% VaR leading to a higher loss amount.

(2) A portfolio, worth US$200,000, generates a yearly return of 5% with a standard deviation of 10%. You are required to compute the VaR at the 5% level. How would the results change if the focus were laid on monthly and weekly computations?

[Hint: 5% significance level under one-tailed test is 1.645]

$$\mathrm{VaR} = \left[R_p - z_\alpha \sigma\right] \times V_p$$

where

R_p: return on portfolio over one year.
z_α: corresponding z-value of one tail test under chosen significance level α.
σ: standard deviation of returns.

Table 1.1: Differences between Approaches in VaR Computation.

	Analytical (Variance−covariance Approach)	**Historical**	**Monte Carlo**
Distribution	Normal	No distribution imposed	Computer-generated results based on specified distribution
Confidence level	One-tailed	One-tailed	One-tailed
Benefits	• Easy to understand and to apply • Can be adjusted to any time period under focus	• Easy to understand and to apply • Can be adjusted to any time period under focus	• Can be adjusted to any time period under focus
Drawbacks	• Assumes normal distribution while most returns are leptokurtic (fat tails) so that VaR underestimates the loss • Difficult to compute standard deviations in large portfolios, computed from asset correlations and covariances	• Presumes that historical returns will repeat themselves in the future	• Need computer software; expensive and difficult • GIGO output is only as good as the input
Computation	$\text{VaR} = \left[R_p - z_\alpha \sigma\right] \times V_p$	Ranked returns from highest to lowest to then look for the closest rounded return to sieve out the VaR value 5% significance level = look at 5% of total observations consisting of lowest returns Similar to Monte Carlo then	Ranked returns from highest to lowest to then look for the closest rounded return to sieve out the VaR value 5% significance level = look at 5% of total observations consisting of lowest returns Similar to historical then

Source: Author's illustration.

V_p: value of the portfolio.

= (5% − 1.645 × 10%) × US$200,000
= (5% − 16.45%) × US$200,000
= −US$22,900

In the case of monthly computations, divide the returns by 12 and the standard deviation by the square root of 12. In the case of monthly computations, divide the returns by 52 and the standard deviation by the square root of 52.

(3) A portfolio, worth US$200,000, generates monthly returns as follows:
−1%, 3%, −4%, −0.5%, 3%, −2%, −2.5%, −1%, 2%, 1%, 2%, −1.5%

You are required to compute the monthly VaR at 5% significance level using the historical VaR approach.

First, rank the returns from highest to lowest:

3%, 3%, 2%, 2%, 1%, −0.5%, −1%, −1%, −1.5%, −2%, −2.5%, −4%

5% of total number of monthly returns = 5% × 12 = 0.6th observation, rounded to closest = first lowest observation = −4%.

This implies that there is 5% chance of a monthly loss exceeding −4%.

Hence, the monthly VaR is (−4% × US$200,000) = −US$8,000.

(4) What are the three major elements that define VaR?

Amount of loss in value, time period over which risk is assessed and level of confidence.

'*How much can I lose with x% probability over a set horizon?*'

(5) What are the three main approaches to VaR estimation?

Historical simulation, Parametric modelling and Monte Carlo simulation.

(6) Is the VaR derived from the normal distribution too conservative? Fully explain.

Yes, in practice, financial data returns are leptokurtic, exhibiting fat tails and negative skewness so that the use of the first two moments is not enough to properly capture the essence of the distribution under focus. Consequently, in the case that VaR is applied to the normal distribution, it will be underestimated. However, such underestimation is weakened as the data frequency level is being lowered – that is, lower frequency data tend to drift closer to normal distribution relative to high-frequency data.

(7) What is the major shortcoming of parametric VaR?

Parametric VaR is typically computed as the product of the value of a given confidence level and the standard deviation of the return distribution. In that respect, the parametric VaR is a realistic risk management metric when the return distribution takes after a normal distribution.

$$\text{VaR}_{\alpha}^{\%} = Z_{\alpha}\sigma$$

(8) Distinguish between the CDF and the PDF.

Table 1.2: Two-assets Portfolio.

	Asset A	Asset B
Standard deviation weekly	1.5%	
Standard deviation quarterly		2%
Nominal value	Rs 200,000	Rs 150,000

Source: Author's illustration.

The CDF tells us the probability of a random variable being less than a specific value. Technically speaking, CDF is generated by integrating the PDF. Hence, differentiating the CDF leads to the PDF. Hence, CDF is read on the same PDF graph but taken as the integral of PDF or area under the curve. In that respect, since probability can never exceed one and never be negative, the value of CDF ranges from zero to one (Table 1.2).

(9) Table 1.2 shows information on two different assets.

You are required to calculate the VaR at the 1% significance level for both assets on a yearly basis to sieve out the riskier asset.

For 95% confidence, VaR is 1.645 standard deviations from the mean.

For 99% confidence, VaR is 2.326 standard deviations from the mean.

Annualised Standard Deviation = Standard Deviation of Weekly Returns × Sqrt(52)

Annualised Standard Deviation = Standard Deviation of Quarterly Returns × Sqrt(4)

$VaR = SD \times 2.326 \times$ *asset value*

$VaR_A = (0.015) \times sqrt(52) \times 2.326 \times 200{,}000 = 50{,}319$

$VaR_B = (0.02) \times sqrt(4) \times 2.326 \times 150{,}000 = 13{,}956$

So, asset A is the riskier asset.

(10) Calculate the portfolio VaR at the 1% significance level in the previous case if it is assumed that the correlation coefficient between asset *A* and asset *B* is 0.2. Show all your workings.

Weight for asset A = (200,000)/350,000 = 0.57

Weight for asset B = (1 – 0.57) = 0.43

$$\sigma_P^2 = (w_A\sigma_A + w_B\sigma_B)^2 = {w_A}^2{\sigma_A}^2 + {w_B}^2{\sigma_B}^2 + 2w_Aw_B\rho_{AB}\sigma_A\sigma_B$$

Compute portfolio variance based on the above equation.

Then, calculate portfolio VaR.

VaR_P = *SD of portfolio(0.0672) × 2.326 × 350,000 = 54,740*

(11) Based on your answers from questions (9) and (10), is the VaR of a portfolio equal to the sum of the VaR for the two assets? Explain.

No

(12) What are the three major elements that define VaR?

Amount of loss in value, time period over which risk is assessed and level of confidence.

'How much can I lose with x% probability over a set horizon?'