Does Value at Risk provide an accurate and reliable measure of risk exposure, as a stand - alone risk management tool for a financial institution in periods of economic uncertainty?

By

Declan J. Harvey
Masters (of Arts) in Finance
The National College of Ireland

Research Advisor

Mr. Joe Naughton

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Declaration

I hereby certify that this material, which I now submit for the assessment of the programme of study leading to the award of the Masters of Arts in Finance is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

Signature: __________________________

Declan Harvey

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Student Number: **08876258**

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Abstract

This dissertation seeks to investigate whether Value at Risk, as a stand - alone risk management tool, provides an accurate, credible and reliable measure of risk exposure for a financial institution in periods of economic uncertainty.

In order to achieve an answer to this question, I propose to create a hypothetical currency fund, with a portfolio value of €100,000,000 equally weighted over 10 major liquid currencies and invested 100% in cash and ascertain how the actual Evolving Rolling monthly VaR measure, calculated from daily pricing data over the 2005 -2008 period performed compared to the VaR estimates, during the period of September 2008 – September 2010.

The many disagreements surrounding previous research projects into VaR and the various approaches to modelling market risk, coupled with the numerous advantages / disadvantages of using a VaR model to estimate an adequate amount of capital to hold on reserve to cover estimated risk from normal operations, has lead me to the conclusion that a further research project into this area is justified.

Also, in the light of the recent financial crisis of 2008, risk management and prediction of market losses have begun to play a crucial role in the world of finance.

This thesis seeks to prove that, through analysing the actual fluctuations of the above mentioned currency fund against VaR estimates, over the period of 2008 – 2010, Value at Risk models do not provide a satisfactory stand alone risk measure and must be supplemented with stress testing.

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1.0 An introduction to Risk Management.

1.1 Background to Risk Management

"The essence of risk management lies in maximizing the areas where we have some control over the outcome, while minimizing the areas where we have absolutely no control over the outcome and linkage between effect and cause is hidden from us."[1]

Sampling is an essential element to risk taking and samples of the present and of the past are consistently being taken to make estimates about the future. We all have to make decisions on the basis of limited data, so the question arises, how accurate is the sample data we refer to?

In his book 'Against the Gods, the Remarkable Story of Risk' Peter L. Bernstein draws references to the fact that almost all critical decisions would not be possible if it were not for sampling. For example, one sip of wine can determine whether or not the whole bottle is drinkable, how a courtship with a future spouse is much shorter than the lifetime that lies ahead and how the Dow Jones Industrial Average consists of just 30 stocks, yet we use it to measure daily changes in trillions of dollars worth of wealth.

Managing risk has always been at the centre of every financial institution's activities as their ability to survive adverse economic cycles and phases of high volatility is highly correlated to both the quality of its risk selection and its capital endowment.[2]

The word 'risk' is derived from the early Italian word 'risicare', which means 'to dare'. In this sense, risk is a choice and not a fate. The actions we dare to take, which depends upon how free we are to make choices, are what the story of risk is all about.[3]

Many people regard risk as a negative element in financial investments, but managed prudently and measured accurately higher levels of risk exposure usually result in higher levels of portfolio return.

The term 'model risk' is commonly applied to include various sources of uncertainty in statistical models. Following Cairns (2000) it is possible to distinguish two sources of model risk;

(a) Model choice which includes inappropriate assumptions about the form of the statistical model for the random variable and,
(b) Parameter uncertainty or estimation error in the parameters of the chosen model. This includes sampling error and optimization error. [4]

The origins of portfolio theory can be traced to non-mathematical discussions of portfolio construction. Authors such as Hardy (1923) and Hicks (1935) discussed in depth, the advantages to a portfolio of diversified assets while Leavens (1945) while not explicitly identifying a VaR metric, nonetheless he put forward the idea of possible gains and losses based on the standard deviation of portfolio returns and offered a quantitative example, which may well have been the first VaR measure ever published.[5]

Then in 1952, both Markowitz and Roy independently published different types of VaR measures that attempted to develop a method of portfolio selection which incorporated covariance between risk factors based on optimizing rewards for a given level of risk. Both measures proved to be remarkably similar from a mathematically point of view, however Markowitz used a variance of simple return metric while Roy used a metric of shortfall risk.[6]

1.2 The Rise of the Risk Management Profession

The last decade has seen the rise of risk management as a distinctive discipline and the growth of the risk management profession. There has also been growing awareness amongst senior management of financial institutions of the need to understand the risks faced by their companies and to understand the ways in which such risks can be managed. One important aspect of risk management is risk disclosure, and there is a good argument that appropriate risk disclosure can help investors and other interested parties make more informed decisions.[7]

Risk management, even if flawlessly executed can never guarantee that excessive losses will not occur, as many losses can be the result of bad business decisions or just a result of bad luck. Moving forward from the recent financial crisis, risk models will need to improve and also place a greater emphasis on stress tests and scenario analysis. In practice this can only be based on position based risk measures that are the basis for modern risk measurement architecture.[8]

Overall, the financial crisis of 2008 has reinforced the importance of risk management. As Philippe Jorion notes, financial risk management refers to the design and implementation of procedures for identifying, measuring, and managing financial risks.[9]

The 1970's and 1980's witnessed sweeping changes in how financial markets operated due, in no small part to the advancement of technology which would ultimately alter how financial organisations would view and measure the appropriate level of risk to be undertaken.

When the Bretton Woods agreement collapsed in 1971, exchange rates were allowed to float, and an active foreign exchange forward market soon emerged. This marked the beginning of the modern era in foreign exchange and shortly after, led to the publication of the Black – Scholes option pricing formula, which provided the conceptual framework and basic tools for risk management and measurement.[10]

One of the most important consequences of these innovations and technological advances throughout the 1970's and 1980's was the proliferation of leverage and the advent of financial products such as derivatives markets. As these products were developed further and higher levels of leverage became common place, financial institutions sought new ways to calculate and manage their risk exposures as traditional risk metric's of financial accounting were becoming inefficient and outdated, especially when applied to derivatives as they failed to consider components such as correlations, duration, convexity, delta, gamma or vega. [11]

Then, the 1990's saw the rise of specialised financial data firms such as Bloomberg and Reuters who began to compile databases of historical financial prices, providing the raw data needed to feed more complex Value at Risk methodologies.

The resources needed to implement VaR systems were now readily available and regulators began laying the ground work for them to be incorporated as the recognised industry standard for risk management.[12]

As a result, many firms are now reporting financial risk information in their annual reports with an increased emphasis on both, the development of, and reporting of, quantitative risk measures.

The most notable of these is the Value at Risk (VaR) measure, which is a statistical risk measure of potential losses combining the price yield relationship with the probability of an adverse market movement and traces its roots back to the infamous financial disasters of the early 1990's.

1.3 Regulation & Early Risk Management Measures

Early VaR measures developed along two parallel lines. One was portfolio theory, and the other was capital adequacy computations.

US securities markets were largely self-regulated up until 1933 and the New York Stock Exchange (NYSE) imposed its own '10% of assets comprising proprietary positions and customer receivables' capital requirements on member firms.[13]

The SEC modified its capital requirements rule in 1944 to subtract from net capital 10% of the market value of most proprietary securities positions held by a firm. This haircut afforded a margin of safety against market losses that might arise during the time it would take to liquidate such positions.
Then in 1965, the haircut for equity securities was increased to 30%.[14]

Later, in 1974, in response to the fallout over the forced liquidation of the troubled German Bank Herstatt, the Group of 10 formed a committee under the supervision of the Bank of International Settlements, called the Basle Committee on Banking Supervision. The main function of the Basle committee was to define the roles of regulators in cross-jurisdictions and promote uniform capital requirements so banks from different countries may compete with one another on a "level playing field."[15]

In 1988, The Basel Committee published 'The 1988 BIS Accord' which was an agreement between the regulators on how the capital a bank is required to hold for credit risk purposes should be calculated.

Several years later, in 1996, the Basel committee published 'The Amendment' which required banks to hold capital for both credit risk and market risk. The amended also requires banks and other financial institutions to hold in reserve enough capital to cover 10 days of potential losses based on the 99% 10-day VaR. [16]

The capital that the banks are ultimately required to hold, is k times the VaR measure, with an adjustment for what are termed as specific risks. The multiplier k, is chosen on a bank by bank basis by the regulators and must be a multiple of at least 3.[17]

The Basle Committee's new proposal was incorporated into an amendment to the 1988 accord, which was adopted in 1996. It went into effect in 1998.[18]

2.0 Literature Review

2.1 A History of Financial Risk Mismanagement...

When we talk about financial risk, we can break it down into four broad categories, namely (a) market risk, (b) liquidity risk, (c) credit risk and (d) operational risk.

(A) Market Risk

Market Risk is the risk of losing money due to adverse movements in the volatility of market prices and can be described in the form of either absolute risk, which is a measure of the volatility of total returns, given in dollar amounts or relative risk, which is a measure of the deviation of the portfolio compared to a benchmark or index and measures risk in terms of tracking error.

Market risk includes all factors that directly affect firm or portfolio values including interest rates, exchange rates, equity prices, commodity prices etc and Value at Risk measures can be used, in part to help control market risk.[19]

In order to outline an example of uncontrolled exposure to market risk, I have chosen to look at the financial disaster that engulfed Orange County, a prosperous district in California in the United States, who, on December 6th 1994 declared bankruptcy with losses of over $1.6 billion, which resulted from a wrong way bet on interest rates in one of its principal investment pools.

Orange County treasurer, Bob Citron was entrusted with a $7.5 billion portfolio belonging to county schools, cities, special districts and the county itself. In order to generate more income, Citron borrowed $12.5 billion through reverse purchase agreements, for a total of $20 billion, which was, in turn invested in agency notes with an average maturity of four years.

This highly leveraged strategy was initially very successful due to falling interest rates, resulting in short term funding costs being lower than medium term yields, however, as every financial institution know, borrowing short term and investing long term leads to liquidity risk. In February 1994, interest rates began to increase and the fund began to receive margin calls due to the losses it was incurring.

Citron ignored the shift in interest rates and the mounting "paper losses" his portfolio was suffering and by the end of 1994, as panic started to grow, investors

began to pull their investment from the fund, creating a liquidity gap until finally, the fund defaulted on margin payments and in December of that year, Orange County were declared bankrupt with a realised loss of over $1.8 billion.
County officials blamed Citron for undertaking risky investments and not being forthcoming about his highly leveraged, highly risky strategy. However, the losses were allowed to grow so large due to the fact that government accounting standards do not require municipal investment pools to report paper gains and losses, and as a result investors claim they were misled by the fund. As a result, Orange County was the victim of both market risk and liquidity risk. [20]

Christopher L. Culp states in his article entitled ' Value at Risk: Uses and abuses', that had Orange County been using a Value at Risk measurement system, it almost certainly would have terminated its investment program once it was made aware of the $1 billion risk estimate, for fear of the public outcry of the exposure.[21]

The Orange County example in turn, highlights one of the major potential abuses of a VaR measurement system in how the information is conveyed, by highlighting large potential losses over a long time horizon without conveying any information about the corresponding expected return. I agree with Christopher L. Culp's conclusion on the Orange County case study, in that VaR measures of risk are only meaningful when interpreted alongside estimates of corresponding potential gains.[22]

(B) Liquidity risk

Liquidity risk refers to the possibility of sustaining significant losses due to the realisation of a random variable which is not consistent with the expectation of the economic agent and can be broken down into two main categories:

- Market liquidity risk, which is defined as the ability to trade an asset at short notice, at a low cost and with little impact on its price, and

- Funding liquidity risk, which is defined by the Basel Committee of Banking as the ability of a financial institution to meet their liabilities, unwind or settle their positions as they fall due. [23]

Standard & Poor's defines liquidity risk as the risk that a trading operation's need for cash collateral may exceed its total liquidity resources.

In order to outline an example of uncontrolled exposure to liquidity risk, I have chosen to examine the 1998 financial meltdown of Long Term Capital Management (LTCM).

LTCM was a large private hedge fund set up by a highly profitable group of ex Solomon Brothers bond arbitrage traders and academics, operating a highly leveraged strategy seeking to take advantage of relative value or convergence arbitrage trades by betting on differences in prices, differences in spreads or differences in closely related securities.
These strategies tend to provide only tiny profits, so LTCM exploited intrinsic weaknesses in their risk management system by using a *leverage ratio* of 25:1 to magnify returns.

By December 1997, LTCM's balance sheet showed a position of $125 billion, while the funds equity capital was only $5 billion. The off balance sheet position, which included swaps, options and other derivatives combined to give an astonishing notional position of $1.25 trillion.

The funds positions had now grown to a level where, by trying to liquidate or manoeuvre them would result in large market movements and they were so highly leveraged that relatively small market moves against them, could wipe out their equity base. [24]

The fund was using the same covariance matrix both to measure risk and to optimise positions and their spectacular failure has been largely ascribed to its use of Value of Risk. However, the primary reason that VaR was developed was to measure and, in turn to control an organisations exposure to risk and as Long Term Capital Management experienced, optimizing a portfolio risk/return profile and using the resultant VaR to measure leads to serious optimization biases.

LTCM severely underestimated its risk exposure due to an over reliance of short term historical data and risk concentration.[25] Their problems began in 1997 with convergence in Europe in anticipation of the single currency, introduced in January 1999. Credit spreads shrank to their lowest level for almost a decade and convergence trades become less profitable. As a result, the fund's performance suffered and returned only 17% in 1997, compared to 40% the previous year.

Next, in May 1998 the funds equity suffered a 16% loss in value, and capital dropped to $4 billion, due to a downturn in the mortgage backed securities market.

Later, on August 17th 1998, Russia announced that it was defaulting on its debt and restructuring its bond obligations. The news caused markets to panic with credit spreads jumping sharply and stock markets diving. LTCM were long interest rate swap rates and short stock market volatility and as a result of these two bets, the fund lost over $550 million in one day alone. The funds equity had dropped faster that its assets and as a result, the leverage ratio had now increased to 50:1. [26]

The fund's losses continued through September of that year, and on 21st September 1998, lost a further $550 million due to an increase in volatility in equity markets. LTCM's prime broker, Bear Stearns faced a large margin call from a losing LTCM T-Bond futures position and required increased collateral, which in turn reduced the funds liquid resources even further.

At this point counterparties began to fear that LTCM would not be able to meet further margin calls, and would have to liquidate their repo collateral. [27]

The potential effect on financial markets across the globe was such that the New York Federal Reserve felt compelled to act, and on the 23rd September 1998, organised a bailout of LTCM encouraging 14 of Wall Street's biggest banks to invest $3.6 billion in return for a 90% stake in the firm.[28]

LTCM were ultimately the victim of uncontrolled liquidity risk, which in turn is positively correlated with volatility and the fund failed as a result of its unsuccessful bid to manage their financial risks through portfolio optimization.[29] There was little diversification across risk factors and, ultimately, when they needed to liquidate positions, the very size of the fund made it almost impossible to organise an orderly portfolio liquidation.

One of the major questions that needs to be addressed through the LTCM experience, is how traditional VaR models can be used to account for the cost of liquidation. Liquidity effects are quite predictable in normal markets, however, more difficult to predict in stressed markets.

(C) Credit Risk

Credit risk arises from the uncertainty due to the counterparty's potential inability or unwillingness to perform their contractual obligations, can occur before an actual default and often does not occur in isolation.

The two major components of credit risk include sovereign risk and settlement risk. While default risk is generally company specific, sovereign risk is country specific.

Credit risks can be controlled by placing limits on notional, current and potential exposures and requiring collateral for marking to market. [30]

(D) Operational Risk

The Basel II capital accord requires large financial institutions to use an Advanced Measurement Approach (AMA) to model their operational risk exposure, which refers to the potential for loss owing to inadequate internal processes, people and systems and from external events. Break downs in the flow of information, legal issues and rogue trades can all be classified under operational risk.

In order to outline an example of uncontrolled exposure to operational risk, I have chosen to look at the bankruptcy case that engulfed The Barings Bank, one of the largest and oldest banks in the United Kingdom.

With over 233 years of banking history Barings was declared bankrupt on the 26th February 1995, after accumulating losses of more that €1.3 billion. These losses were achieved through large derivative positions giving exposure to the Japanese stock market and were attributed to one rouge trader, Nicholas Leeson.

Officially Nick Leeson was arbitraging the Nikkei 225 futures contracts on the different exchanges, the Singapore International Monetary Exchange (SIMEX) and the Osaka Stock Exchange (OSE), buying the same futures at a low price in one exchange and selling simultaneously at a higher price on the other exchange.[31]

Barings total notional position on both exchanges added up to over $7 billion and they started to suffer huge losses in January of 1995 as the market fell more than 15%. The losses were compounded due to options Leeson had sold, betting on the market to remain stable. Then Leeson increased the size of his positions in the belief that the market would turn around. Finally, the bank were unable to make the margin payments to the exchange and were declared bankrupt.

Barings bank, it was revealed was the victim of fraud and had a huge, uncontrolled exposure to operational risk. Leeson had control over both the trading desk and the back office, two functions that should be kept separate for legal reasons and to avoid a conflict of interests.

Leeson was able to take unauthorised derivative positions as his limits were unsupervised and he was given an unlimited amount of capital to invest. In addition, the bank did not have a separate risk management desk to ensure that all the trading activity was within the guidelines set out in the banks prospectus. [32]

Christopher L. Culp states in his article entitled ' Value at Risk: Uses and abuses', that if Barings Bank had a Value at Risk model in operation, it would have aided senior management in measuring their overall risk exposure, enabled them to take corrective action and shut down Leeson's trading operating in time to save the firm.

However, Barings failure was not simply due to the fact that they did not have a Value at Risk measurement system in place, but also because their internal management and control systems were weak, in that the same individual who was making the trades, was also the person recording those trades, which violates one of the key principles of best practice.[33]

2.2 A Definition of Value at Risk

Value at Risk was initially developed to measure financial risk exposure and communicate this data in a simplistic form to the stakeholders and was later upgraded to provide a common benchmark to control and compare total risk across risk taking units. Moving forward form its initial purpose, it has been used to calculate the optimal level of capital to be held in reserve by a financial institution.[34]

During the late 1980's, JP Morgan developed an early firm-wide VaR system, based on a covariance matrix of historical data modeling hundreds of different risk factors. Each trading desk would report their positions delta against each of the risk factors on a daily basis, and this data would then be combined and used to calculate the standard deviation of the portfolio value.[35]

Value at risk can be defined as the worst loss that can happen under normal conditions, over a specified time horizon and at a specified confidence level.[36] It is an attempt to provide a single number to summarize the total risk in a portfolio of financial assets that is capable of producing an aggregate view of a portfolios total risk after considering leverage, correlations and total positions, which more traditional risk measures cannot achieve. (See Appendix - Exhibit 2).

While being based on firm scientific foundations, it is very easily understood and has become widely used by corporate treasurers and fund managers as well as by financial institutions however there is no general consensus on how to actually calculate it (Thompson & McCarthy, 2008).

Bank regulators also use VaR in determining the capital a bank is required to keep for the risks it is bearing.[37] In other words, VaR summaries the worst loss over a target horizon that will not be exceeded with a given level of confidence by measuring the shortfall from the quantile of the distribution of trading revenues.

When using the Value at Risk measure, an analyst is interested in making a statement of the following form:

"I am X percent certain that there will not be a loss of more than V dollars in the next N days."

The variable V, is the VaR of the portfolio and it is a function of two parameters, the time horizon (N days) and the confidence level (X percent). When X days is the time horizon and X% is the confidence level, VaR is the loss corresponding to the (100 – X)th percentile of the distribution of the change in the value of the portfolio over the next N days. [38]

VaR measures are based on two quantitative parameters; the confidence level and the time horizon and if it is used to report and compare risk, the parameters can be arbitrarily chosen, as long as they are consistent.

However, if VaR is used as the basis for setting the amount of equity capital, the confidence level must be high enough, so that the probability of exceeding VaR is very low.

The Basel committee have chosen a confidence level of 99% and a 10 day time horizon to determine the minimum capital level for commercial banks and the resulting VaR must be multiplied by a factor of at least 3 to account for non normalities or model errors.

The time horizon must be related to (a) the time required to cover an orderly liquidation or (b) the time necessary to raise additional funds for corrective action.[39]

Whether the Var of a firm's portfolio is a relevant measure of the risk of financial distress over a short period of time depends in part on the liquidity of the portfolio of positions and the risk of adverse extreme net cash outflows, or on severe disruptions in market liquidity.[40]

As Darrell Duffie and Jun Pan point out in their 'An overview of Value at Risk' article, that in the event of the firm suffering some degree of extreme adverse scenarios, they may suffer margin calls on derivative positions and other short term financing needs coupled with the additional costs involved in liquidating trades at highly unfavourable spreads, resulting in balance sheet reductions.

So, in this type of environment, Value at Risk is relevant, only if it is supplemented by an additional measure of cash flow at risk as VaR will only capture one aspect of the market risk and is thus, too narrowly defined to be used as a sufficient stand alone measure of capital adequacy.[41]

2.3 Previous Research in VaR

Due to the many disagreements surrounding VaR and the various approaches to modelling market risk, coupled with the different advantages / disadvantages of using a VaR model to estimate the amount of capital to hold on reserve, in my opinion, these differences merit a further research project into this area.

There has been extensive research done and literature written about Value at Risk, however there are only a few studies available that directly compare a portfolios actual results against that which was expected.

In an 1995 study, Beder(1995,pp.12-24) applies eight common VaR methodologies to three hypothetical portfolios. The results show the differences among these methods can be very large, with VaR estimates varying by more than 14 times for the same portfolio. Clearly, there is a need for a statistical approach to estimation and model selection.[42]

In another study undertaken in 2006, Bao, Lee & Saltoglu evaluated the predictive power of VaR models in emerging markets. Through their research, they applied traditional VaR models, conditional autoregressive VaR models and also applied their models to extreme value theory.

Their results showed that their benchmark, the RiskMetrics model developed by J.P. Morgan, produced good results in tranquil periods, whereas in crisis periods VaR approaches based on extreme value theory produced better results. The authors also discovered that while filtering can improve the predictive results using Extreme Value Theory, it can make the other models less useful.[43]

In 2006 Kuesters, Mittnik & Paolella applied both a conditional and an unconditional VaR model to NASDAQ-composite data and concluded that most of the models were unable to produce accurate results due to a tendency to underestimate market risk.

However, they did find that although the conditional VaR models do produce an increased level of volatility in their estimates, if heteroskedasticity is factored into the calculation, then the model will provide a satisfactory output. The authors final conclusion, was that mixed normal GARCH, extreme value theory and filtered historical stimulation models usually provide the most accurate forecasts.[44]

In summarizing the literature I have researched, it is my conclusion that there is no universally agreed upon VaR model that can be relied upon to provide an accurate forecast for any sample dataset. The more advanced models, which allow for heteroskedasticity and other conditional parameters should provide a more accurate forecast than the more traditional models.

2.4 The Phenomenon that is… Fat Tails

One of the key assumptions underpinning most financial models, including the Capital Asset Pricing Model and the Black – Scholes Option Pricing Model, is that an asset's returns are normally distributed, as in the bell shaped curve. However, in reality this assumption does not always prove to be true.

The normal distribution forms the core of most systems of risk management and can be used to provide more important information than just a measure of samples.
However, a normal distribution is most unlikely when the probability of one event is determined upon the preceding event, as the observations will fail to distribute themselves symmetrically around the mean.

Under the normal distribution assumption, a divergence from the mean of five standard deviations are rare and known as a five sigma event. A ten sigma event is considered to be almost impossible. However, despite the statistical improbability of such extreme events taking place, the more recent history has shown that radical market movements have been occurring in ever greater frequency.

The term that is used to describe this undesirable phenomenon is known as 'Fat Tails' which are a property of some probability distribution and are described as statistical irregularities, in which extremely large kurtosis, or extreme swings in value (both positive and negative) occur on a more frequent basis that the normal distribution of returns would predict (See Appendix - Exhibit 3).

A standard measure of tail fatness is kurtosis whose estimates are highly sensitive to extremely large returns and similar to volatility, tail fatness measured by kurtosis has a term structure according to the time horizon over which the total return is calculated.

VaR has tail risk when it fails to summarise the relative choice between portfolios as a result of its underestimation of the risk of portfolios with fat-tailed properties and a high potential for large losses. The tail risk of VaR emerges since it measures only a single quartile of the profit/loss distributions and disregards any loss beyond the VaR level. This may lead one to think that securities with a higher potential for large losses are less risky than securities with a lower potential for large losses.[45]

Fat Tails and the shortcomings of the normal distribution have been identified by many mathematicians and economists, most notably Benoît Mandelbrot and Nassim Nicholas Taleb.

In the world of portfolio management, the existence of fat tails can, in part, be linked to behavioural finance due to excessive optimism or pessimism from the investor, causing large market movements and ultimately leads to additional risk exposure.

Under the normal distribution, the tails to the extreme left and extreme right become smaller and smaller until, ultimately they reach zero occurrences. Fat tails are a result of the interdependence and illogical decision making during periods of extreme market movements and are an extremely important concept when modelling an assets expected return and demonstrating the risk exposure.[46]

"Tail-Risk" hedging was a very popular topic of debate on Wall Street throughout the year 2008 after global financial markets crashed, causing investors to try and understand how they could protect themselves from extreme events, which are well outside the ordinary distribution of outcomes, but still have the potential to cause massive losses[47]

Tail risk is technically defined as a higher-than-expected risk of an investment moving more than three standard deviations away from the portfolio's mean distribution.

In other words it has come to signify any big downward move in a portfolio's value. There are different ways to hedge tail risk, but a popular one is to create a basket of derivatives that will perform poorly during normal market conditions but soar when markets plunge. These include options on a variety of asset classes, such as equity indices and credit-default-swap indices.

Through the use of VaR as a measurement tool and tail risk hedging, it appeared possible to measure every financial risk and to adjust expected returns as necessary. However, the more risks that could be standardized, the easier it was to package up debt and turn it into securities to be sold, or to be held on the balance sheet, which in turn could be used as collateral for higher levels of leverage.[48]

Christopher M. Turner (2009) is critical of the manner in which VaR models have been applied and Nassim Nicholas Taleb (2007) even questions the very idea of using statistical models for risk assessment. Despite the warnings of Turner, Taleb and other critics of VaR models, most financial institutions continue to employ them as their primary tool for market risk assessment and economic capital allocation.[49]

2.5 Shortfall Risk

Shortfall risk measures are alternatives to VaR that allow a risk manager to define a specific target value below which the organisations assets must never fall and they measure risk accordingly.[50]

VaR models are usually based on normal asset returns and do not work under extreme price fluctuations. This point is emphasised through the financial market crisis of 2008. Concerning this crisis a large amount of occurrences were found to be in the tails of the distributions and as a result VaR models were useless for measuring and monitoring market risk.[51]

For some organisations, asymmetric distributions pose a problem that VaR on its own cannot address and may consider it more useful not to examine the loss associated with a chosen probability level but rather to examine the risk associated with a given loss.

In their paper entitled 'Comparative analyses of expected shortfall and value-at-risk under market stress' authors Yasuhiro Yamai and Toshinao Yoshiba concluded that VaR and expected shortfall may underestimate the risk of securities with fat-tailed properties and a high potential for large losses.

They also found VaR and expected shortfall may both disregard the tail dependence of asset returns. Finally, they conclude expected shortfall has less of a problem in disregarding the fat tails and the tail dependence than VaR does.[52]

2.6 Attractions & Limitations of VaR

One of the main reasons VaR has become so popular as the risk managers tool of choice in the financial industry is due to its sheer simplicity, however, it still remains only a benchmark for relative judgement, such as:

- The risk of one desk relative to another,
- The risk of one portfolio relative to another or
- The modelled risk relative to the historical experience of mark to marking and
- The risk of one volatility environment relative to another and so on. [53]

VaR is capable of measuring risk across all types of positions, including derivatives, and risk factors, also outside of purely market risk and it provides a monetary and probabilistic expression of loss amounts allowing for the measure to be utilized in the following ways:

- Management can set overall risk targets and from that determine the corresponding risk position.
- VaR can be used to determine capital requirements
- VaR is useful for reporting and disclosing purposes
- VaR can measure other risks such as credit, liquidity and operational risks.[54]

Despite the many benefits to using a Value at Risk measurement system to calculate total risk exposure, when used in isolation it is not very useful at keeping the firms risk exposures in line with their chosen risk tolerances, even when appropriately calculated.

Although VaR provides a first line defence against financial risk, users must still understand it limitations and drawbacks the most obvious being the fact that as VaR only provides an estimate of losses at some specified confidence level, it does not provide a measure of the absolute worst loss and this is the principal reason why back testing has become an essential component of the system, to serve as a reminder that exceptions do occur.

The Value at Risk system still has many critics, the most noted being Nassim Nicholas Taleb who has lobbied for the immediate suspension of VaR in financial risk management due to the following perceived shortcomings;

- It involves principal-agent issues and is often not realistic in real world scenarios, as the model can only be made sub-additive when imposing normality assumptions on return distributions, and this is in contradiction to the reality of financial time series.
- An over-reliance on VaR can lead to bigger losses as the ultimate Var figure can be used as a target to maximize the portfolio risk.
- VaR models based on historical data assume that the recent past is a good projection of future randomness which underestimates the change in risk exposure caused when historical patterns change abruptly.
- VaR does not consider losses beyond the stated confidence level and as a result may actually impede sound risk management practices. [55]

This last point is of particular significance when considering the role the financial institutions played out during the financial market crisis of 2008. For example, when VaR is used as a means to measure adequate capital requirements to be held in order to cover expected market risks from normal operations, then it is imperative that the underlying risks are being correctly estimated, otherwise it will result in organisations maintaining excessively high or low levels of capital on reserve.

VaR also assumes that the position is fixed over the time horizon, ignoring the possibility that trading positions may change over time in response to changing market conditions.

Another shortfall when considering VaR is the vast number of different ways it can be calculated, leaving comparison of results almost futile in many cases.

3.0 Methodology - Calculation of an evolving Variance Covariance Rolling VaR

3.1 Measuring VaR

In order for VaR to be measured, a model of random changes in the prices of the underlying instruments, such as equity indices, interest rates, foreign exchange rates must be assembled and also, a model for computing the sensitivities of derivative prices to the underlying prices.

One approach used to measure these key elements is to integrate the two models across the trading desks, and then add the additional elements necessary for measuring risks of various kinds. However, considering the many complexities involved in implementing different systems from different trading environments, such as data collection, theoretical and empirical models and computational methods, a more common approach is to develop a unified and independent risk management system.[56]

There are three approaches to calculate a VaR:

- Variance-covariance-approach

This is an analytical estimation of the volatility of asset returns and of the correlations between these movements in the assets price. The method assumes that stock returns are normally distributed and requires only two factors to be estimated, expected (or average) return and standard deviation, which in turn will allow a normal distribution curve to be plotted (See Appendix - Exhibit 1).

Using this assumption it is possible to determine the distribution of mark – to – market portfolio profits and losses. The advantage of the normal curve is that we automatically know where the worst 5% and 1% lie on the curve. They are a function of our desired confidence and the standard deviation (σ): [57]

- Monte Carlo simulation

The monte Carlo Simulation involves developing a model for future stock price returns and running multiple hypothetical trials through the model. A Monte Carlo simulation refers to any method that randomly generates trials, but by itself does not tell us anything about the underlying methodology.[58]

- Historical simulation

Under the Historical Simulation method the actual historical returns of the portfolio are simply reorganised in order of worst to best. The assumption, from a risk perspective, is simplt that history will repeat itself.[59]

3.2 Assumptions, basis for Variance Covariance & Data collection

My monthly VaR estimates are based on the variance-covariance approach and on historical simulations.

Under this method, the normal distribution of portfolio returns is assumed and requires the expected return and standard deviation of returns for each currency to be determined.

The advantage of this method is its simplicity. The disadvantage is that the assumption of a normal return distribution can be unrealistic.

The basis for the Variance Covariance value at risk methodology is to take a portfolio whose value depends linearly on a single factor.

The Change in value $\Delta\Pi = w_1 \Delta f_1$ where w1 is the sensitivity of the portfolio to factor 1 (f1)

The variance of the changes in the value of the portfolio σ_Π^2 is given as:

$$\sigma_\Pi^2 = w_1 \sigma_{f_1}^2$$

Where $\sigma_{f_1}^2$ is the variance in the changes in factor 1.

Next, if we extend this to a two factor portfolio we see:

Change in Value $\Delta\Pi = w_1 \Delta f_1 + w_2 \Delta f_2$

Now, the variance of the changes in the value of the portfolio σ_{Π}^2 is given as:

$$\sigma_{\Pi}^2 = w_1^2\sigma_{f_1}^2 + w_2^2\sigma_{f_2}^2 + 2w_1w_2\rho\sigma_{f_1}\sigma_{f_2}$$

We can represent this in matrix form as follows:

$$\sigma_{\Pi}^2 = \begin{pmatrix} w_1\sigma_{f_1} & w_2\sigma_{f_2} \end{pmatrix}\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\begin{pmatrix} w_1\sigma_{f_1} \\ w_2\sigma_{f_2} \end{pmatrix}$$

And this in turn, allows us to calculate the standard deviation of the portfolio:

$$\sigma_{\Pi} = \sqrt{\begin{pmatrix} w_1\sigma_{f_1} & w_2\sigma_{f_2} \end{pmatrix}\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\begin{pmatrix} w_1\sigma_{f_1} \\ w_2\sigma_{f_2} \end{pmatrix}}$$

This can easily be extended to a multi factor risk model using Excels built in matrix algebra capabilities. (See Appendix – Exhibit's 4,5,6 &7).

3.3 Calculation of a Variance Covariance Evolving VaR in Excel

The starting point for my VaR calculation was to extract 6 years of daily pricing data, from 2005 – 2011, for 10 currencies, all valued against the Euro and with no cross currencies included in the hypothetical portfolio.

This data was taken from Bloomberg and the assumption is that funds are equally weighted across the currencies, ie 10% capital allocated to each.

1. The first step was to calculate the variance of the portfolio in excel.

- The variance is a measure of how far each individual member of a data set is from the mean of the set.
- In practice, the variance is calculated by subtracting the mean from each individual member of the data set.
- Next, square each distance, in order for all results to be positive, and then sum all the squares together.
- Then, divide the sum of the squares by the number of members in the data set.
- I achieved this result by computing the log returns for each currency on a continuous compounding basis. The advantage of using log returns is that they are much more adaptable when considering standard deviations and correlations. (See Excel data – Column V – Out of Sample Test)
- The variability of the portfolio is the daily standard deviation of the log returns.

2. The second step in the process was to calculate the standard deviations of the selected currencies. (See Appendix - Exhibit 6 for Jan 2008 Sample Data).

   The Standard deviation is the square root of the variance, which was calculated in the previous step.

3. The next step was to choose a sample set of data, and develop a correlation matrix (See Appendix – Exhibit 4 for Jan 2008 sample data) in order to calculate the standard deviation of the daily returns.

   The correlation of returns helps to identify the currencies that move together in the same direction resulting in a less diversified portfolio.

I have chosen the data from 2005 – 2008 as my sample. Once I have the standard deviation of the sample set, I can conduct an 'out of sample' test to determine the accuracy of our model (See Appendix – Exhibit's 8 & 9).

The correlation is calculated by multiplying the standard deviation (calculated in the previous step) by the weight of the portfolio in each currency. For this project, I have chosen an asset allocation of 10% to each currency. (See Appendix – Exhibit 5)

In excel the correlations can be calculated by using Tools/Data Analysis/Correlation/ Correlation Matrix. This Matrix will form the basis for calculating VaR.

4. The matrix algebra is a twostep process;

- I take the correlation matrix from above, and multiply it by the standard deviation. The result will be the overall matrix product.
- Next, I take the overall matrix product, from above, and calculate the square root. The result will represent the Ex-Ante VaR (i.e the VaR before I undertake any testing). See Appendix – Exhibit 8 for all Evolving VaR calculations.
- See table from Appendix – Exhibit 6 for this result.
- At the 95% confidence level, our VaR result is €482,715.

This figure reflects that, at a 95% level of confidence our portfolio will not lose any more than €482,715 in any one day on a continuously compounded basis.

5. Next, I take the next 3 years of pricing data (from step 1 above) representing the period from 2008 -2011 and calculate the actual P&L results achieved against this VaR figure. (See the 'Out of Sample Test Results' in Appendix – Exhibit 9 & 10)

6. Comparing the results of the actual performance against the expected Evolving VaR at the 95% confidence level, we can observe that while we were expecting the actual P & L figures to exceed the VaR estimate 5% of the time, in actual fact, the model was exceeded 8.15% of the time (3.15 % worse that what was expected). Also, from this data I calculate the performance ratio as 1.63 while we were expecting a ratio of 1.

7. As I continue to test the out of sample data, and go to a higher confidence level of 99% I see that the model performs even worse, with VaR being exceeded 28 times, which represents a failure rate of 3.26% when I was expecting a rate of 1%. Again, when I calculate the performance ratio, I observe it to be 3.26 while I was expecting a ratio of 1.

8. Finally, if I go to an extremely high confidence level of 99.999%, again I observe the model does not perform satisfactorily.

   This time VaR is exceeded 10 times when the satisfactory number is only .001. The observed frequency is 1.16% again, while I was expecting to see a figure of .01%. Again the performance ratio shows the model to be severely flawed with a ratio of 116.41 while the number should be 1.

4.0 The need for Back-Testing

4.1 Testing the Validity of a Model

When calculating VaR, regardless of which method is used, it is imperative to back test the model.

Back-testing compares the daily VaR model results against the daily variation in the portfolio's value and is an extremely important function to validate the accuracy and reliability of a VaR model, not only from the perspective of best practice, but also to concur with the regulatory framework.

With this in mind, each financial organisation should have in place a structure in which all deficiencies and volatile risk exposures should be captured.

Back-tests in their simplest form investigate how the VaR estimates would have performed in the past and must be calculated using hypothetical variations in the value of the portfolio over the time horizon, t, by keeping the positions in the portfolio constant. A breach occurs when the hypothetical portfolio variation is greater than the VaR estimate and in order for the model to be approved, it must produce no more that 4 breaches over a 250 working day period, as laid down under the regulatory guidelines.

It is the industry best practice to perform a back-test using a long period of historical data, as the longer the period under review, the more trustworthy the results and back-tests are usually performed on a daily basis, but must be carried out at least once a week.

The starting point for any back-test is to fix the estimation period, which will define the sample data used to estimate the VaR parameters.

The need for back-testing is also outlined under UCITS, through which regulators oversee the reliability and efficiency of the VaR model. The Commission encourages the UCITS to implement back testing checks, basing themselves either on the effective fluctuations ("dirty back-testing") or the hypothetical fluctuations ("clean back-testing") of the portfolio's value and to undertake appropriate measures to improve their back-testing program where necessary.[60]

Clean back-testing refers to the practice of comparing the VaR estimates with the hypothetical P&L value of the portfolio at the end of the time horizon, t, having kept the composition unchanged.

Dirty back-testing compares the VaR estimates with the actual mark – to – market P&L values at the end of the time horizon, t.

The quality of the forecasts produced by the VaR model must be demonstrated through a comparison of the potential market volatility, calculated by the model and the actual change in the value of the portfolio, calculated by the back-test. If the actual change in the value of the portfolio exceeds the potential market risk amount calculated by the back test, on more occasions than would be predicted using the stated confidence level, then immediate action need to be undertaken. [61]

A common starting point for this procedure is referred to as the indicator function, in which a value of 1 is assigned to the model in the case where the return at time t exceeds the VaR at time t. If the VaR limit at time t is not exceeded by the return at time t, then the function takes a value of zero. [62]

The indicator function must contain the following two characteristics in order for it to be classified as being reliable, according to Christoffersen (1998).

- Unconditional Coverage Property in which the VaR model cannot be too conservative, and
- Independence Property, which states the manner in which violations may occur. According to Campbell in 20005, if the two properties of the indicator function are not independent of each other, then this indicates that the model is not responsive enough capture market volatility.

4.2 Empirical results from the sample data

After I calculated the Evolving VaR figures (See Appendix – Exhibit 8) based on the daily pricing data from 2005-2008 for my currency fund, I back tested the model by taking the next 3 years of pricing data, representing the period from 2008 -2011 and calculated the actual P&L results achieved against these VaR figures.

When I compared the results of the actual performance against the expected VaR, I discovered that the model failed more often that what was expected at each of the given confidence levels, leading to the conclusion that the VaR methodology may be suspect and gives a false sense of security to the users, especially at the higher levels of confidence resulting from the activity in the tails of the distribution.

Tail events are defined as the largest percentage of losses measured relative to the respective value-at-risk estimate—the largest 5 percent in the case of 95th percentile risk measures and the largest 1 percent in the case of 99th percentile risk measures. However, the average tail event is almost always a larger multiple of the risk measure than is predicted by the normal distribution.[63]

The empirical results achieved from my sample data show this conclusion to be true.

Another observation I made from my VaR calculations is that by the time I got to calculating the VaR figure of €800,704 for January 2011, the figure has almost doubled from €482,715 in Jan 2008. This is to be expected, due to the fact I am calculating data based on historical simulation.

5.0 The Need for Stress Testing

5.1 Extreme Market Movements

The tendency for market returns to exhibit volatility clusters has always been a crucial issue for analysts attempting to understand large market movements. As a result of these clusters, it is imperative to supplement the VaR calculation with a stress test in order for VaR measures to be credible.

A stress test is a risk management tool used to evaluate the potential impact on portfolio values of unlikely, although plausible, events or movements in a set of financial variables (Lopez, 2005). In other words, the process involves examining how the portfolio would have performed under a scenario of more extreme market conditions, both positive and negative.

Stress tests are designed to explore the tails of the distribution of losses beyond the threshold (typically 99%) used in Value-at-Risk analysis and they provide two vital pieces of information:

- The extent of potential losses in catastrophic circumstances and
- The scenarios in which such losses might occur.

Such information is a vital input to the decision making process concerning, the need (if any) to hedge, the level for limit setting, portfolio allocations and capital adequacy decisions.[64]

Stress testing the portfolio will take into account extreme events that do occur from time to time but are virtually impossible according to the probability distributions assumed for market variables.

For example, a five standard deviation daily move in a market variable would be an example of one such extreme event. In theory under the assumption of a normal distribution, such an event is likely to occur one out of every 7,000 years.

However, in practice a five standard deviation daily move can be observed once or even twice in a 10 year period![65]

5.2 A new emphasis on stress tests

In the wake of the financial crisis of 2008, leading industry practitioners have called on the Basel Committee on Supervision to re-examine stress testing methodologies and as a result there has been a very definite shift in both attitude and regulatory policy towards a more defined emphasis on the area of stress testing. Since 1996, financial institutions using VaR models to measure risk exposure have been required to implement stress tests, however, there is now a much more direct link to provide cover for the results of the stress test from a capital adequacy perspective.

Stress tests are developed through analysing a selection of the risks that are perceived to be the most pressing in the current environment and can be designed around historical or hypothetical events, or a combination of both. They can be broken down into a two stage process: first specifying the initial shock event and then, specifying the subsequent response to that shock event.

Historically, only the initial impact to the portfolio of shock events was considered by stress testing, but more recently the ability to analyse the after effects of these extreme events, in particular, taking into account the implications to market liquidity, and the ability to close out of positions at a fair price has grown in importance.[66]

Stress tests have been the subject much criticism in the past, with Berkowitz (1999) and Greenspan (2000) being the most noticeable. The main arguments presented against stress tests relate to the fact that often they are conducted outside the context of a risk model, making it difficult to evaluate the probability of each scenario occurring and difficult to put a weight of importance on each variable which ultimately results in a severe lack of rigour.

In addition there is also the argument that many stress tests fail to incorporate the characteristics that markets are known to exhibit in crisis periods, such as the increased probability of further large movements, increased co-movements between different markets, greater implied volatility and reduced liquidity resulting in the possibility of many extreme, yet plausible scenarios are not even considered in the calculation.[67]

In evaluating how well the stress test performed, it is important to consider

- The size of the first extreme event
- The definition of 'worse case loss' and
- The holding period for the test, as the basic parameters.

The choice of stress test horizon should account for the reduced level of market liquidity, the size of the position relative to the market and any potential delays in managerial reaction to a shock event.[68]

6.0 Conclusions & Recommendations

6.1 The Conclusion

This thesis set out to examine whether or not the Variance Covariance Value at Risk methodology was sufficient, as a credible, accurate and reliable basis as a stand-alone risk management tool for a financial institution.

By creating a hypothetical currency fund, with a notional total asset value of €100,000,000 equally weighted and invested in 10 liquid currencies and calculating the adaptive evolving VaR over the period 2005 – 2008, then back testing the data and analysing the results, I have come to the conclusion that during periods of high volatility and financial uncertainty, Value at Risk does not provide financial institutions with an suitable measure of risk exposure.

The process of calculating VaR in this way highlights one of the major flaws with VaR models, in that as we go to a higher confidence level (i.e 99.99%), the perceived notion of safety and reliability is increased but the model performs even worse that at a lower level of confidence (i.e 95%). This phenomenon is described in Extreme Value Theory, which looks at predicting what happens in the (fat) tails of the distribution when extreme events occur and goes beyond the scope of this project.

However, papers dealing with VaR with the help of extreme value theory jointly share the opinion that traditional parametric models for VaR estimation are unsuitable for events with an extremely low probability of occurrence. This follows from the fact that financial return distributions have heavy tails and fitting the distribution into the return series leads to underestimation of tails as the majority of observation lies in the centre, which is accommodated by the distribution. Hence, these models tend to fail, when they are needed most; i.e. when low-probability event occurs, and can lead to huge losses. Extreme value theorists handle this problem by extracting as much information as possible straight from the tail.[69]

In November of 1998, in an article entitled 'Risk Management: Too Clever by a Half' published by The Economist magazine, the authors put forward an argument that, attempts to measure risk in financial markets actually may be making them even more risky! For example, Persaud (2000) advanced the 'vicious circle hypothesis' whereby he noted that in August of 1998, before the Russian default, the market experienced falling prices and increased volatility which in turn increased the VaR and capital requirements. As a result financial institutions were forced into either pumping in fresh capital if possible or placing large sell orders to unwind their positions in falling bear markets, regardless of the levels of liquidity available, which in turn pushed prices down even further and volatility higher, feeding further into the VaR calculation.

By facilitating the consistent measurement of risk across distinct assets and activities, VAR allows firms to monitor, report, and control their risks in a manner that efficiently relates risk control to the desired and actual economic exposures. At the same time, reliance on VAR can result in serious problems when improperly used.[70]

Dangerous misinterpretations of the risk facing a firm can result when VAR is wrongly applied and is only appropriate as a measurement tool for firms engaged in total value risk management.

In conclusion, I would like to point out that no form of risk measurement—including VAR—is a substitute for good management. Risk management as a process encompasses much more than just risk measurement and in my conclusion, I recommend that VaR models need to be supplemented with stringent back testing procedures in order to maintain a realistic level of confidence in the model.[71]

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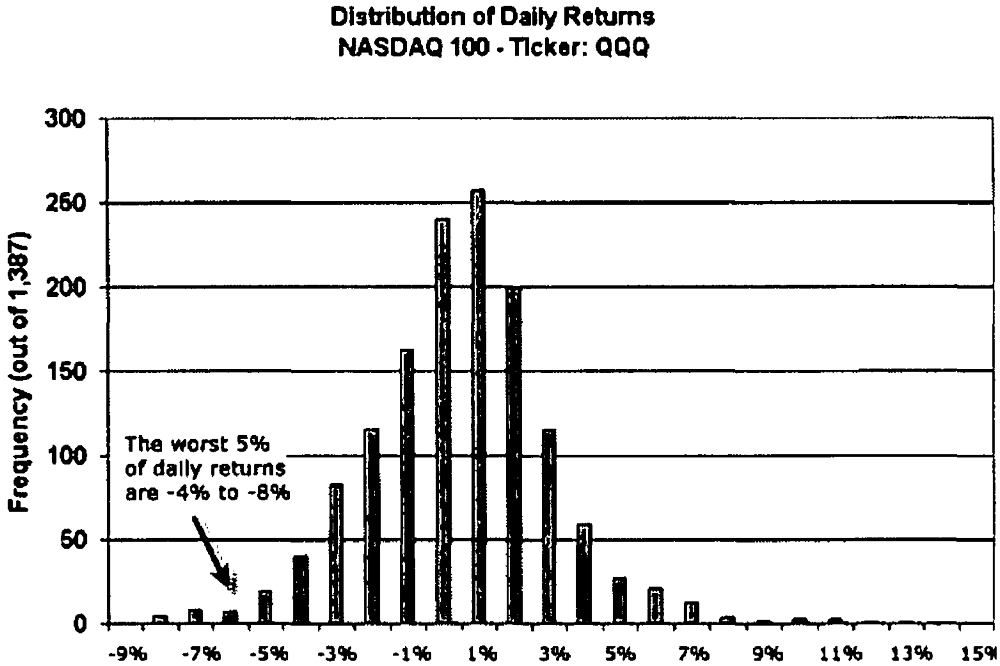
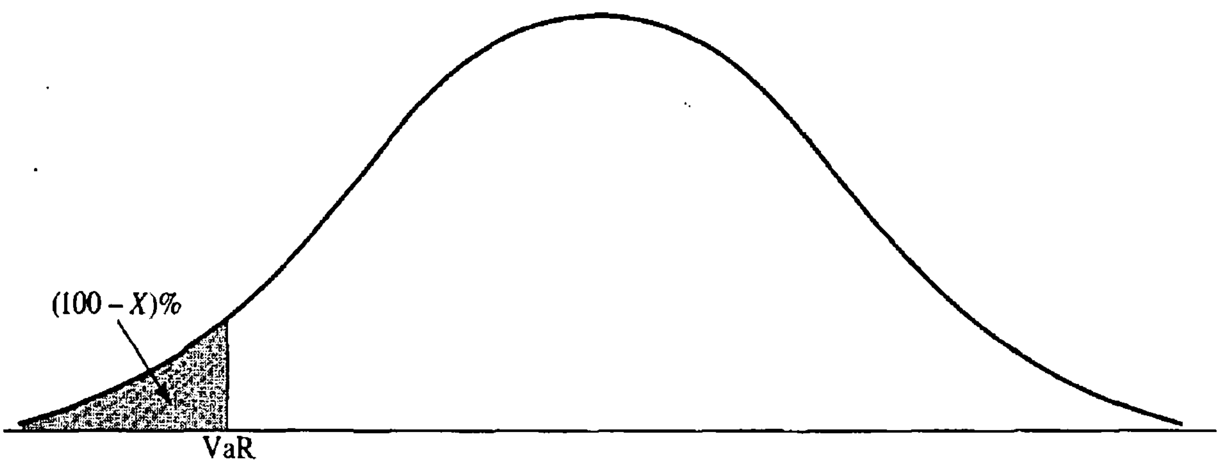
Appendix

Exhibit 1.



Distribution of Daily Returns from the NASDAQ 100.

Exhibit 2.



Calculation of VaR from the probability distribution of changes in portfolio value; confidence level is X%

Exhibit 3.

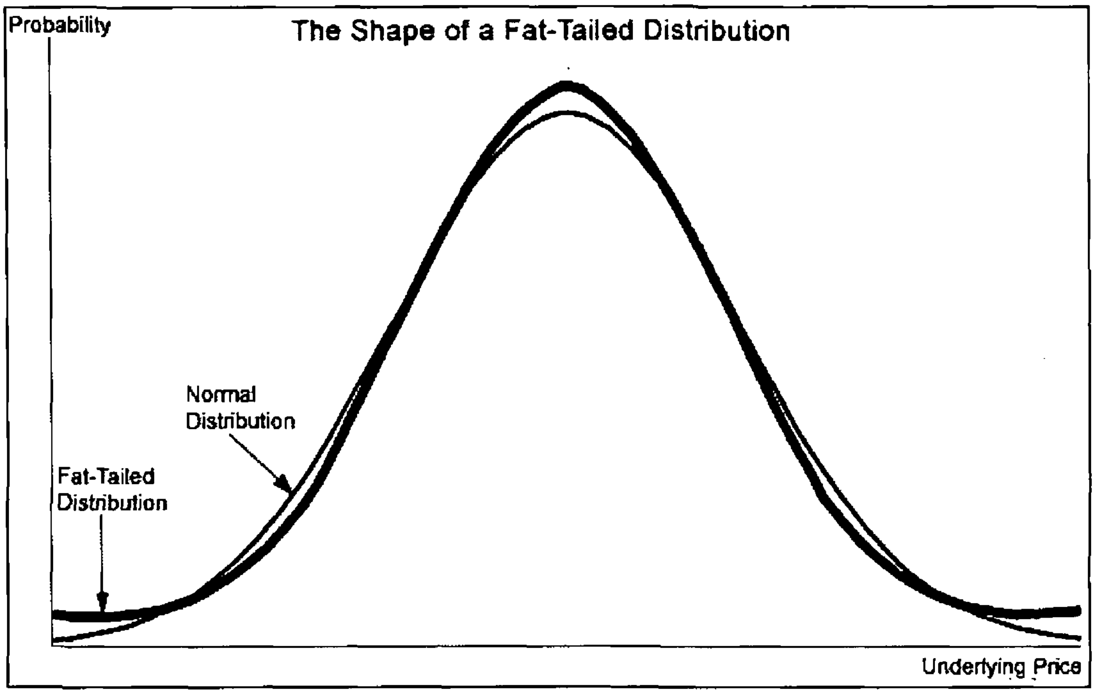

Probability
The Shape of a Fat-Tailed Distribution
Normal
Distribution
Fat-Tailed
Distribution
Underlying Price

Exhibit 4.

	EURINR	EURNZD	EURCNY	EURBRL	EURCHF	EURCAD	EURAUD	EURJPY	EURGBP	EURUSD
EURUSD	0.56636	0.15468	0.97442	0.34009	-0.06095	0.48753	0.18536	0.41553	0.33886	1.00000
EURGBP	0.18545	0.28836	0.34661	0.09514	0.05611	0.26788	0.33098	0.15981	1.00000	0.33886
EURJPY	0.22965	-0.21067	0.42164	-0.03097	0.41092	0.03893	-0.14873	1.00000	0.15981	0.41553
EURAUD	0.11783	0.71631	0.19510	0.34230	-0.28388	0.45190	1.00000	-0.14873	0.33098	0.18536
EURCAD	0.28796	0.35230	0.47111	0.34004	-0.20276	1.00000	0.45190	0.03893	0.26788	0.48753
EURCHF	-0.07776	-0.27743	-0.05974	-0.28620	1.00000	-0.20276	-0.28388	0.41092	0.05611	-0.06095
EURBRL	0.16651	0.29716	0.32671	1.00000	-0.28620	0.34004	0.34230	-0.03097	0.09514	0.34009
EURCNY	0.54477	0.15905	1.00000	0.32671	-0.05974	0.47111	0.19510	0.42164	0.34661	0.97442
EURNZD	0.08839	1.00000	0.15905	0.29716	-0.27743	0.35230	0.71631	-0.21067	0.28836	0.15468
EURINR	1.00000	0.08839	0.54477	0.16651	-0.07776	0.28796	0.11783	0.22965	0.18545	0.56636

Correlation Matrix (Jan 2008)

Exhibit 5.

Standard Deviation Table (Jan 2008) - Data for Jan 2008 – As example

Currency	Weights	Standard Deviations	Weight * Standard Deviation
EURUSD	**0.1**	**0.00477**	**0.000477**
EURGBP	**0.1**	**0.00316**	**0.000316**
EURJPY	**0.1**	**0.00541**	**0.000541**
EURAUD	**0.1**	**0.00516**	**0.000516**
EURCAD	**0.1**	**0.00535**	**0.000535**
EURCHF	**0.1**	**0.00204**	**0.000204**
EURBRL	**0.1**	**0.00926**	**0.000926**
EURCNY	**0.1**	**0.00482**	**0.000482**
EURNZD	**0.1**	**0.00657**	**0.000657**
EURINR	**0.1**	**0.00487**	**0.000487**

Exhibit 6.

Matrix Algebra

Correlation Matrix * Standard Deviation Vector	
	0.00231
	0.00142
	0.00097
	0.00175
	0.00198
	- 0.00035
	0.00184
	0.00230
	0.00160
	0.00161

Exhibit 7.

Overall Matrix Product	8.61246E-06
Square Root Square Root = Portfolio standard Deviation	**0.00293**
Portfolio Value	100,000,000
Confidence Interval	95.0000000%
Number of s.d.'s	1.645
VaR Jan 2008	**482,715.00**

Evolving VaR Calculation (For Jan 2008)

Exhibit 8.

Back Testing Data for Evolving VaR

Monthly VaR Figures.

Month	Value at Risk	Month	Value at Risk
Jan-08	482,715	Jan-10	711,989
Feb-08	481,260	Feb-10	713,246
Mar-08	484,431	Mar-10	714,562
Apr-08	487,158	Apr-10	721,035
May-08	494,493	May-10	728,001
Jun-08	495,554	Jun-10	746,425
Jul-08	499,868	Jul-10	764,176
Aug-08	503,644	Aug-10	772,428
Sep-08	505,244	Sep-10	781,895
Oct-08	506,066	Oct-10	790,609
Nov-08	487,790	Nov-10	795,788
Dec-08	556,079	Dec-10	798,820
Jan-09	602,603	Jan-11	800,704
Feb-09	642,039	Feb-11	809,058
Mar-09	670,135	Mar-11	814,460
Apr-09	685,759		
May-09	698,555		
Jun-09	701,544		
Jul-09	704,087		
Aug-09	708,815		
Sep-09	710,309		
Oct-09	712,087		
Nov-09	709,450		
Dec-09	710,820		

Exhibit 9.

Out of Sample Test Data Results at confidence levels – Evolving VaR

VaR Exceeded	Obsvd. Frequency	Exp. Frequency	Ratio	Conf. Level	90.00%
111	12.92%	10.00%	1.29		

VaR Exceeded	Obsvd. Frequency	Exp. Frequency	Ratio	Conf. Level	95.00%
70	8.15%	5.00%	1.63		

VaR Exceeded	Obsvd. Frequency	Exp. Frequency	Ratio	Conf. Level	97.50%
50	5.82%	2.50%	2.33		

VaR Exceeded	Obsvd. Frequency	Exp. Frequency	Ratio	Conf. Level	99.00%
28	3.26%	1.00%	3.26		

VaR Exceeded	Obsvd. Frequency	Exp. Frequency	Ratio	Conf. Level	99.90%
13	1.51%	0.10%	15.13		

(Ratio Column Should be equal to 1)

Exhibit 10.

Evolving VaR Performance Evaluation Table

Confidence Level	Observed Exceedences	Expected Exceedences	Performance Ratio
90.00%	12.92%	10.00%	1.29
95.00%	8.15%	5.00%	1.63
97.50%	5.82%	2.50%	2.33
99.00%	3.26%	1.00%	3.26
99.90%	1.51%	0.10%	15.13

Evolving VaR Performance Evaluation Table