

A portfolio approach to improving market and credit risk management

BY

Marius Botha

*Thesis submitted in fulfilment of the requirements for
the degree of Philosophiae Doctor at the School of Management,
University of the Free State, Bloemfontein, South Africa.*

PROMOTER: DR GARY VAN VUUREN

CO-PROMOTER: PROF HELENA VAN ZYL

LONDON, ENGLAND
2009

To

GARY VAN VUUREN

AND

LIZL BOTHA

Preface

Much of the theoretical work described in this thesis was carried out whilst in the employ of Threadneedle Asset Management (London, UK). Some theoretical and practical work was carried out in collaboration with the School of Management, University of the Free State (South Africa) under the supervision of Dr Gary van Vuuren and Prof Helena van Zyl.

These studies represent the original work of the author and have not been submitted in any form to another university. Where use was made of the work of others, this has been duly acknowledged in the text. Unless otherwise stated, all data were obtained from Bloomberg™ and the internal, non-proprietary financial databases of Threadneedle Asset Managers, London, UK. Discussions with personnel from this institution also provided invaluable insight into current investment trends and challenges faced in the risk management arena.

The literature study which embraces all market and credit risk management aspects of the thesis, presented in Chapter 2, has been submitted to the *South African Journal of Economics and Management Sciences*. The work involving the Omega ratio, now widely considered to be a superior measure of portfolio performance than the more familiar Sharpe and Sortino ratios, was applied to South African hedge fund returns and the results published in the *South African Journal of Economics* (Chapter 3). The liquidity value at risk research in market portfolios, which has provided valuable insight into both the origins and consequences of the 2008-9 'credit crisis', was published in the *South African Journal of Economics and Management Sciences* (Chapter 4). The investigation into increased discrimination of the probability of default in credit portfolios uncovered a potential problem with the Basel II Accord's treatment thereof. For some loan types, *increased* discrimination led to *amplified* capital charges – a violation of a core principle of the Accord (rewarding improved risk measurement through reduced capital charges). The analysis and results of this work were published in *Risk Management in Financial Institutions* (Chapter 5). The finding that implied asset correlations in empirical loss data of several retail loan portfolios were considerably lower than those imposed by the Basel II Accord – even after taking into account the severity of the credit crisis – demonstrated the punitive conservatism embedded in the accord. The work relating to this study (Chapter 6) has been accepted for publication in *Risk Management in Financial Institutions*.

MARIUS BOTHA 15 February 2010

Acknowledgements

I acknowledge an enormous debt of gratitude to all that have contributed in some way or another to the completion of this thesis. In particular, I draw special attention to my appreciation for the assistance provided – in whatever form – by the people mentioned below:

- My good friend Gary for inspiration, motivation, guidance and patience, but – most importantly – for his enduring friendship. He has proved to be a great motivational supervisor and an inspired cultivator of profound ideas,
- My wife Lizl for her motivation, patience, love and understanding (not just during the many hours of work, but always) and for suggesting the whole idea in the first place,
- my parents for their profound guidance through laudable example, for encouraging me to think and without whom neither I – nor this thesis – would have been written.
- Prof. Helena van Zyl for overseeing, assembling and installing the necessary framework for this project and for her valuable feedback and enthusiasm. Despite a heavy workload of her own, she has guided me comfortably through this degree and I am grateful indeed for her dependable tutelage,
- Prof. Philippe Burger for his thorough proofreading and valuable comments on many of the papers addressed herein,
- My examiners and anonymous referees for their valuable comments and helpful suggestions.

Abstract

The credit crisis (which began in August 2008) has affected almost every segment of the international financial system. Credit has been severely curtailed as banks struggle to contain further losses caused by reckless lending practices that characterised the last two decades. Asset prices have tumbled as fearful investors flee to safer havens, abandoning traditional investments and hedge funds with resolute consistency. Governments – in an attempt to stave off stagflation and kick-start failing economies – have reduced interest rates to historic lows, initiated stimulus packages and instigated bank bailouts, but the efforts have (as yet) had minimal to no effect on markets. The dire economic environment characterised by diminishing industrial production, falling house (and other asset) prices and rising unemployment, has only discouraged spending and investing and promoted capital hoarding. In the ensuing crisis, the regulatory economic environment (dominated by the Basel Committee for Banking Supervision's (BCBS) Basel II Accord) has proved inadequate. Potential solutions have not yet presented themselves and the crisis looks likely to continue for the foreseeable future.

In the light of these events and contemporary failings of finance in general, the need to continuously augment existing and invent new techniques to measure and manage financial risks are paramount. This thesis explores four significant problems facing modern risk management in a portfolio context.

The first problem examines the assumption of normally distributed portfolio returns. Compelling evidence for the consistent failure of this assumption is provided. A measure for ranking portfolio performance is discussed and explained with reference to several South African hedge fund portfolios.

The second of these problems explores the assumption of unlimited liquidity in market risk measurement models. This assumption has been shown to be utterly fallacious and indeed, is now believed to be the principal component of the credit crisis. A new portfolio market risk model, which incorporates the effect of severely diminished liquidity, is introduced and applied to several South African market portfolios. The results indicate a substantially improved model of market risk.

The third problem probes the effect of obligor default quality discrimination to address a subtle discrepancy in the BCBS's formulation for credit portfolio capital charges. The cause of this discrepancy is located and its effects discussed with far reaching consequences for retail loan portfolios.

Finally, the lack of a robust technique to extract retail asset correlations from empirical loan loss data is investigated. A methodology is devised using the underlying BCBS formulation for credit risk and the results obtained are compared with retail asset correlations stipulated by the BCBS. The empirical correlations (and the associated capital charges) were found to be considerably lower than the BCBS correlations (and capital charges), even during the elevated losses currently (2009) being experienced. The accuracy of these punitive impositions in a portfolio context is assessed and suggestions are made for further empirical study.

Opsomming

Die kredietkrisis wat besig is om te ontvou (in 2008 'n aanvang geneem), het omtrent elke segment van die internasionale finansiële stelsel beïnvloed. Krediet is ernstig ingekort soos wat banke worstel om verdere verliese, veroorsaak deur roekelose uitleenpraktyke wat die afgelope 20 jaar gekenmerk het, in toom te hou.

Batepryse het getuimel soos wat angstige beleggers na veiliger toevlugsoorde vlug, en tradisionele beleggings en verskansingsfondse laat vaar. Regerings, in 'n poging om stagflasië te voorkom en sukkelende ekonomieë aan die gang te kry, het rentekoerse tot historiese laagtepunte verminder, aansporingspakkette geïnisieer en reddingspogings vir banke aangevoer, maar die pogings het (tot op hede) 'n minimale tot geen effek op markte gehad. Die knellende ekonomiese omgewing, gekenmerk deur laer bedryfsproduksie, huis- (en ander bate-) pryse wat daal en stygende werkloosheid, het besteding en investering ontmoedig en kapitaalopgaring bevorder. In die daaropvolgende krisis, is die regulerende ekonomiese omgewing (gedomineer deur die Basel II Akkoord van die Basel Komitee vir Bank Toesighouding (BKBT)) as ontoereikend bewys. Moontlike oplossings het hulle nog nie voorgedoen nie en dit lyk waarskynlik dat die krisis vir die afsienbare toekoms sal voortduur.

In die lig van hierdie gebeure en die hedendaagse tekortkominge van die finansiële omgewing oor die algemeen is die behoefte om voortdurend bestaande tegnieke om finansiële risiko te meet en te bestuur, uit te brei, asook om nuwe tegnieke te vind. Hierdie proefskrif verken vier belangrike probleme wat deur moderne risikobestuur in portefeulje verband in die gesig gestaar word.

Die eerste probleem ondersoek die aanname van 'n normaalverspreide portefeulje-opbrengs. Onomstootlike bewys vir die deurlopende mislukking van hierdie aanname word gelewer. 'n Maatstaf wat portefeulje-prestasie in rangorde plaas, word bespreek en verduidelik met verwysing na verskeie Suid-Afrikaanse verskansingsfondsportefeuljes.

Die tweede van hierdie probleme verken die aanname van onbeperkte likwiditeit in markrisiko metingsmodelle. Hierdie aanname word as misleidend bewys en daar word inderdaad geglo dat dit die hoofkomponent van die kredietkrisis is. 'n Nuwe portefeulje markrisiko model, wat die effek van wesenlik verminderde likwiditeit inkorporeer, word bekendgestel en op verskeie Suid-Afrikaanse portefeuljes toegepas. Die resultate dui op 'n substansieel verbeterde model van markrisiko.

Die derde probleem peil die effek van skuldenaar wanbetalingskwaliteit diskriminasie om 'n subtiële teenstrydigheid in die BKBT se formulering van kredietportefeulje kapitaalkostes aan te spreek. Die oorsaak van hierdie teenstrydigheid is vasgestel en die effekte daarvan bespreek met verreikende gevolge vir alle kleinhandel leningsportefeuljes.

Ten slotte is die gebrek aan 'n robuuste tegniek om kleinhandel batekorrelasies uit empiriese leningsverlies data te ekstraheer, ondersoek. 'n Metodologie wat die onderliggende BKBT formulering vir

kredietrisiko gebruik, is bepaal en die resultate verkry word vergelyk met kleinhandel batekorrelasies soos gestipuleer deur die BKBT. Die empiriese korrelasies (en geassosieerde kapitaalkostes is as aansienlik laer as die BKBT korrelasies (en kostes) bevind, selfs tydens die verhoogde verliese wat tans (2009) ondervind word. Die akkuraatheid van hierdie belemmerende beperkings in portefeulje verband is geassesseer en voorstelle vir verdere empiriese studie word aan die hand gedoen.

Table of Contents

DEDICATION	ii
PREFACE	iii
ACKNOWLEDGEMENTS	iv
ABSTRACT	v
OPSOMMING	vi
TABLE OF CONTENTS	viii
1. INTRODUCTION	1
1.1 INTRODUCTION AND BACKGROUND	1
1.2 PROBLEM STATEMENT AND OBJECTIVES	4
1.3 OVERVIEW	4
1.3.1 <i>The Omega ratio</i>	5
1.3.2 <i>Liquidity value at risk</i>	6
1.3.3 <i>Capital charge optimisation in retail loan portfolios</i>	6
1.3.4 <i>Implied asset correlation in retail loan portfolios</i>	6
1.4 THESIS OUTLINE.....	7
1.5 RESEARCH DESIGN AND PROCEDURE	8
1.6 CONCLUSION	10
2. MARKET AND CREDIT PORTFOLIO RISK MANAGEMENT: A LITERATURE STUDY	12
3. A COMPARISON OF SOUTH AFRICAN HEDGE FUND PERFORMANCE MEASURES	49
4. PORTFOLIO LIQUIDITY-ADJUSTED VALUE AT RISK	70
5. CREDIT CAPITAL CHARGE OPTIMISATION AND THE NEW BASEL ACCORD	90
6. IMPLIED ASSET CORRELATION IN RETAIL LOAN PORTFOLIOS	112
7. CONCLUSIONS AND RECOMMENDATIONS.....	135
7.1 SUMMARY AND CONCLUSIONS	135
7.1.1 <i>The Omega ratio</i>	135
7.1.2 <i>Liquidity adjusted VaR</i>	136
7.1.3 <i>PD discrimination</i>	137
7.1.4 <i>Extraction of empirical asset correlations from retail loan losses</i>	137
7.2 RECOMMENDATIONS.....	138
7.2.1 <i>Omega ratio</i>	138
7.2.2 <i>Liquidity VaR</i>	138
7.2.3 <i>PD discrimination</i>	139
7.2.4 <i>Empirical asset correlations</i>	139
7.3 CONTRIBUTION	139
7.4 FINAL STATEMENT	141
8. REFERENCES	143
9. SUMMARY	151
10. OPSOMMING	153

Chapter 1

Introduction

1.1 Introduction and background

Financial markets have been rocked and disrupted by several calamities in the last few decades. Perhaps the most severe was the 1987 market crash (also known as Black Monday) when the US market lost almost a quarter of its value within a few hours due to ageing computer systems unable to deal with a sudden, inordinate increase in trades (Carlson, 2006: 3). Reckless lending and currency manipulation in the late 1990s resulted in the Asian crisis: aftershocks of this event led to a derivative trading strategy failure of the US hedge fund Long Term Capital Management in 1998. The dotcom crash then resulted in a mini-recession in the early 2000s when the Millennium Bug did not materialise as predicted and expensive systems and personnel became redundant (Spiegel, 2000).

Between early 2003 and mid-2007, hedge and private equity funds, collateralised debt obligations and structured products all enjoyed explosive growth, permeating inextricably into the marketplace (Hay, 2004). Asset prices – including residential and commercial property – inflated in this era of excess, awash with liquidity and bolstered by low interest rates. Global markets enjoyed high returns with little downside. Risks were dutifully measured and stress tests obediently performed, but the results indicated considerable risk dilution as record numbers of trades flooded the market and advanced quantitative models assigned ever more negligible probabilities to severe events (Fender and Kiff, 2004).

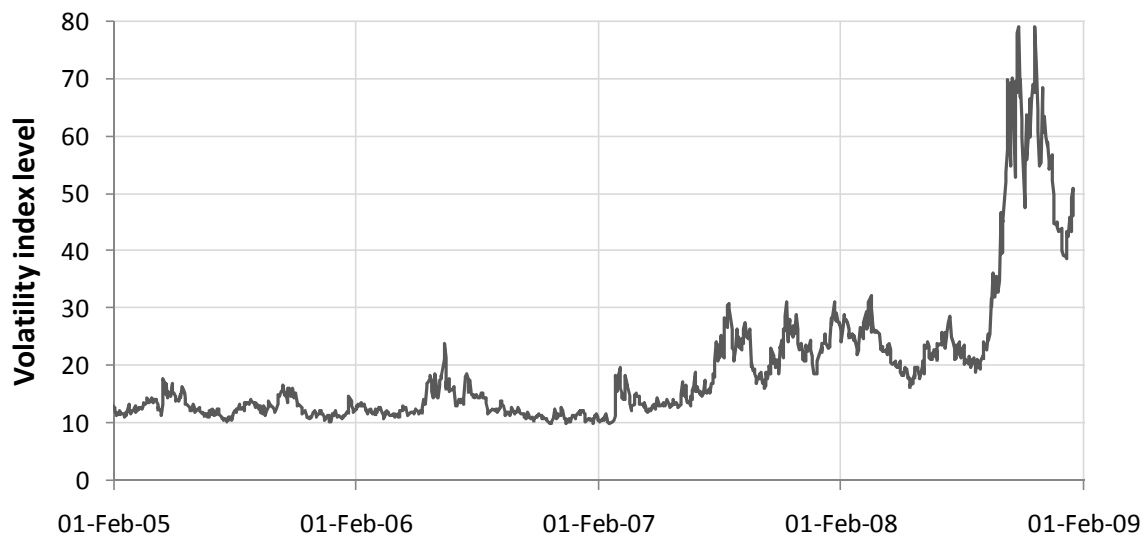
Pessimists that did not join the fray and chose (in hindsight, justifiably) not to participate in the frenzy were punished by investors who simply sought higher returns elsewhere. These and other factors resulted in the 2008-9 credit crisis, due largely to the evaporation of liquidity in securitisation markets¹ as well as significantly increased correlation between constituent assets. Traditionally, hedge funds provided liquidity to these markets through active trading, but rising risk levels have reduced trading activity and diminished risk budgets due to amplified risk aversion. Hedge fund assets declined by about 20% to \$1.5 trillion over the course of 2008, a loss of some \$350 billion (Yamazaki, 2009). Many market participants have expressed surprise and concern that the products designed to *mitigate* threats (via risk dispersion and risk dilution) have emerged as one of the culprits responsible for the reces-

¹ The drying up of market liquidity has spread to *all* asset classes (June 2009).

sionary conditions in 2009. Measured risks and results from stress tests fell far short of the severe losses ultimately experienced in the market, but this was not due to risks being ignored: some were underestimated, some misevaluated and others, due to their novelty, were missed completely.

The credit crisis is directly responsible for the bleak forecasts (2009 and beyond) faced by the global economy. The measure of global volatility, the VIX trebled (see Figure 1.1) in the third quarter of 2008 (CBOE, 2009),² interest rate spreads between government fixed income securities and interbank rates widened to unprecedented levels (Reuters, 2009), global inflation threatened an already fragile, volatile marketplace (Saied, 2009),³ corporate and retail loan default rates rose (Lagorio, 2009) and downgrades of large financial institutions (such as US monoline bond insurers) and many corporates were experienced by major rating agencies during the first quarter of 2009 (Fitch, 2009 and Moody's, 2009).

Figure 1.1: The Chicago Board Options Exchange volatility index, the VIX.



Source: Chicago Board Options Exchange, Feb 2009.

The malaise which stalked world finance emphasised that the field of risk management is constantly evolving, driven by two principal, connected factors, namely:

1. the *adaptation of existing risk frameworks* (if and when these become invalid) to accommodate the unremitting proliferation of innovative – and often more complex – financial products, and

² In January 2009, the VIX fell by half from its December 2008 high of 80, but remained highly volatile for months thereafter (CBOE, 2009).

³ The threat of deflation coupled with diminished growth, stagflation haunts global economies (Stiglitz, 2008: 68).

2. the *origination of entirely new risk measures* designed to probe composite financial instruments when the adaptation of old risk models proves inadequate.

History is replete with tales of the co-evolution of financial innovation and risk management. As new products emerge and market participants rush for a share of profits, risk measurement techniques must adapt quickly to address fears of potential catastrophic losses (which may stem from new, unfamiliar sources). The invention of ever more complex financial products (such as derivatives and structured financial products) to spread risk and smooth earnings, however, often coincides with spectacular market 'corrections'. These new financial instruments precipitate newer, more complicated risks that ultimately result in the very events they were designed to prevent. Risk management's failure to adapt sufficiently quickly to the rapidly-changing environment sometimes gives rise to accusations of incompetence or malpractice. This is unfortunate because institutions require better and more adept risk measures to deal with these crises, not distrust and suspicion.

Achieving the goal of improved risk management requires far more research into the nature and manifestation of financial risks. Methods to manage and mitigate these risks can only be developed when the ways in which risks develop and magnify are sufficiently understood. The major concepts of risk management are all well-researched, reported in depth and then firmly established in mainstream 'best practice'. For the sake of simplicity and implementation ease, however, many generalisations abound (Dash, 2004: 213). A few (seemingly) inconsequential details are generalised, glossed over or ignored completely – yet it is precisely here that calamities often reside (Dash, 2004: 216). What is unclear is *where* more detailed investigation is required before events conspire to cause significant losses. *Which* model parameters are flawed? *What* model assumptions proved inadequate? *Why* were certain aspects of the financial instrument's pricing ignored? It is the role of the modern risk manager to understand and anticipate not only where risks arise, but also how they may arise and how severely they may affect the financial system when they do.

Universities and some research departments of major financial institutions perform the valuable function of education in the fundamental principles of risk management, but it is the *practitioner* that adds significant value via market experience and familiarity with the subtleties of financial pricing and risk management, the vagaries of market sentiment and the curious impulses of market participants (Jorion, 2003: 32).

1.2 Problem statement and objectives

Contemporary financial markets are in constant flux, changing and adapting as novel instruments are invented or augmented. The search for profit opportunities requires knowledge and experience, but accelerated computing speeds make ever increasing demands on practitioners to understand the market as a coherent whole, not in segmented components. Increasing innovation and augmentation is inevitably accompanied by significantly enhanced risks.

The credit crisis has revealed severe flaws in modern risk management techniques. Risk has been too narrowly measured – broad portfolio effects have been largely ignored or aggregated only in simple ways. Risk types have also been too stringently segmented: it is now accepted that market portfolios suffer from substantial credit risk (in addition to market risk) and loan portfolios prone to default risk are also subject to extensive risks emanating from market conditions. It is imperative that future risk management co-evolves with the financial products it measures, for example by adapting existing risk measures, inventing new risk measurement techniques and merging previously partitioned risk types. These can all be achieved by embracing a broad portfolio risk framework – much broader than has been employed in the past.

The primary objectives of this thesis are to introduce, discuss and critically evaluate several new portfolio approaches to the measurement and management of financial market and credit risks present in traditional and novel asset classes. This will be accomplished through the modification of existing risk measurement techniques and, in some cases, through the development of new techniques when older risk models prove to be inadequate.

The testing of these methodologies – in real-world contexts – to ascertain their reliability and robustness is a principal secondary objective as is adapting the methodologies in the light of new empirical evidence. Important secondary objectives are the invention of novel approaches (if research results require) and the introduction of practical ways to use results. Some portfolios tested employ simulated data, others comprise entirely empirical data.

1.3 Overview

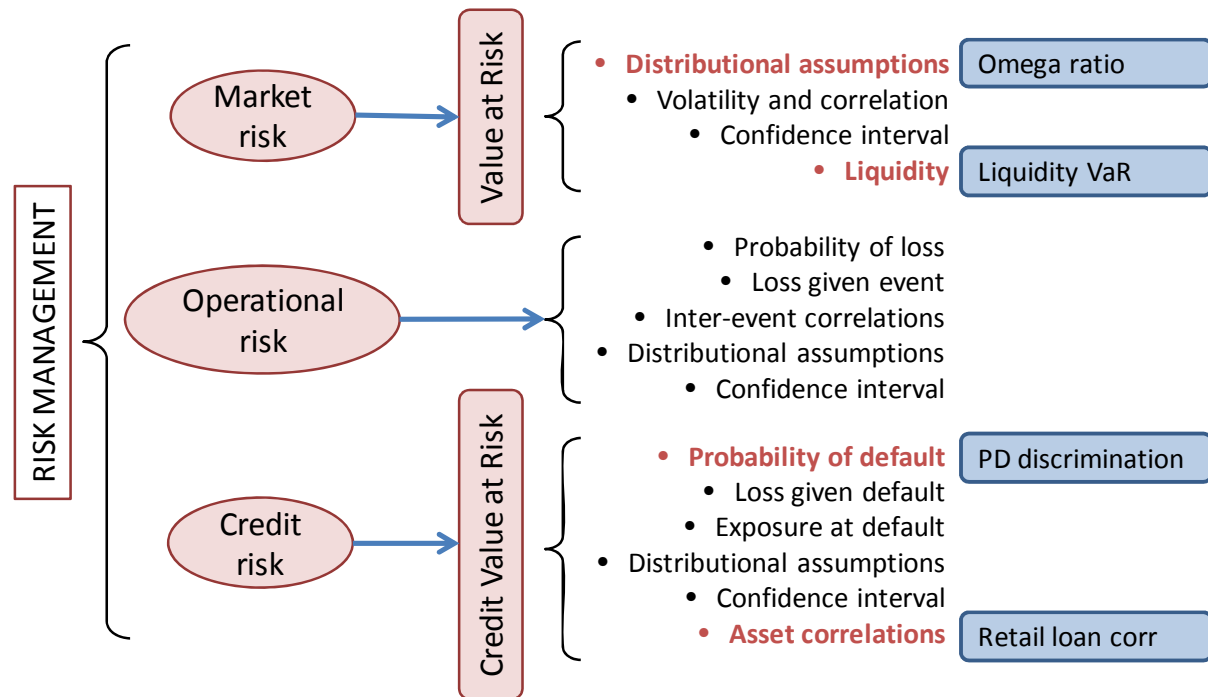
Since the field of financial risk measurement and management is broad and deep, this thesis focuses on connected aspects of market and credit risk via several topics.⁴ Together, these projects (which constitute and unify different aspects of risk measurement and management

⁴ Operational risk has been deliberately ignored in these studies as the field is too new and unexplored for a detailed analysis at this stage (2009).

and are described in more detail in Sections 1.3.1 through 1.3.4) are components of the main risk types as classified by the BCBS's Basel accords (Martin, 2003).

The unifying theme linking the main concepts of the thesis is illustrated in Figure 1.2 below.

Figure 1.2: Schematic representation of thesis.



The problems investigated are summarised in the sections below.

1.3.1 The Omega ratio

Since their inception in the early 1990s, hedge funds promised high returns with relatively low accompanying risk. The very definition of 'hedge fund' is rooted in the implication that risks associated with these (opaque) investment strategies are mitigated via appropriate hedging and that, therefore, the high return/low risk combination they promised was not necessarily contradictory. After the dotcom crash of early 2000, low interest rates, above-average economic growth and reduced arbitrage opportunities began to threaten the dominance of hedge funds over traditional asset management. Almost all assets generated above-average profits (Spiegel, 2000): investors did not appear to need complex hedging strategies to protect portfolios, nor were they willing to pay the accompanying large hedge fund management fees. Distinguishing between hedge funds – an onerous task with notoriously opaque investment strategies – thus became paramount in the search for optimal, risk-adjusted returns. Simple risk and return performance measures cannot cope with the demands of an increasingly complex financial milieu, so investors have focussed on more effective and

more discriminatory portfolio performance measures. The Omega ratio is just such a measure, embracing portfolios' empirical return distributions rather than relying on (often fallacious) distributional assumptions.

1.3.2 Liquidity value at risk

An important, yet neglected, aspect of market risk management is liquidity risk – namely changes in asset value due to reduced availability of traded financial instruments. This ubiquitous risk has emerged as one of the key drivers of the credit crisis with global financial liquidity plummeting since the crisis began in 2008. Despite massive cash injections by governments, the crisis continues (2009). Contemporary research has focussed on liquidity components of single instruments' value at risk (VaR), but the need for an extension of this work to embrace a *portfolio* approach is long overdue. A technique is developed which integrates individual instruments' liquidity-adjusted VaR into a portfolio environment without a commensurate increase of statistical assumptions.

1.3.3 Capital charge optimisation in retail loan portfolios

The BCBS's new Basel Accord (introduced in 2008) and accompanying credit risk capital equations are designed to encourage the improvement of risk management practices. However, over a range of loan quality for some loan types, these improvements (through enhanced borrower discrimination) *increase* regulatory capital charges despite the employment of expensive resources for no empirical reason. The effect is due entirely to the mathematics underlying the new Basel Accord's treatment of portfolio credit risk and could discourage financial institutions from improving risk management for retail loans, thereby violating the spirit of the Basel II Accord and contravening the aims of the BCBS. The source of the problem is located and investigated and its effect on regulatory capital illustrated.

1.3.4 Implied asset correlation in retail loan portfolios

Credit risk arises from the interaction of multiple connected factors, but the most frequently-used models designed to measure it assume only one. These models fit, *inter alia*, distributions to loss data and are heavily influenced by the common correlation between loan values and the single factor (commonly assumed to be some gauge of economic health, usually the local gross domestic product). Scarce and shoddy loss data for retail loan portfolios hampers the estimation of this correlation. A technique is proposed to calculate asset correlations embedded in empirical loss data and these values are compared with those stipulated by the Basel II Accord for minimum capital requirements.

1.4 Thesis outline

Risk management techniques that appeared robust and accurate in the early part of the new millennium (characterised by low interest rates, steady economic growth and rising asset prices), with deep, unrelenting liquidity and credit crises stunting growth and eroding asset values, seem inadequate and naïve. For risk management to remain relevant in a turbulent financial milieu, constant vigilance is required. The accompanying literature augmentation, on which these studies are based, is vigorous and relentless. Chapter 2 presents a comprehensive literature review for the Omega ratio and liquidity VaR studies (from a market risk perspective) and establishes the context of these studies in the broader theme of improved portfolio risk management. In addition, Chapter 2 provides a broad background of the relevant literature regarding probability of default discrimination in credit portfolios and empirical asset correlation extraction from retail loan portfolios.

Chapter 3 addresses the common problem of faulty assumptions of return distributions in a market risk framework. Large and abrupt movements in portfolio returns are of great concern to all market participants. Assuming that these returns are always distributed normally is severely flawed and potentially damaging to both manager reputations as well as fund values.⁵ Depending upon the investment strategy employed, hedge fund returns in particular can have large outliers in both tails of their distributions (an indication of large risky bets that often succeed, but occasionally fail) which are often also severely skewed and leptokurtic. The relatively new Omega ratio is explored in this chapter. The application of the Omega ratio to hedge fund portfolio ranking is detailed and the results contrasted with those obtained using the traditional Sharpe ratio (which assumes normally distributed returns).

The severe consequences of ignoring liquidity effects in market risk portfolios are explored in Chapter 4. Many of the damaging outcomes precipitated by the ongoing (2009) credit crisis have been blamed directly on a lack of liquidity in the market. Traditional measures of market risk, most notably VaR models, do not take this effect into account other than cursorily via the 'square root of time' rule. This statistical tenet applies well to normally distributed returns and in normal market conditions, but in times of stress is inadequate and limiting. Existing work on single instrument VaR is expanded in this chapter to embrace a portfolio approach and the new formulation is back-tested on portfolio data.

⁵ Despite this, the assumption of distributional normality is widespread.

Problematic aspects of risk assessment of retail credit portfolios are then examined in Chapter 5. The BCBS methodology for the measurement of credit risk provides equations which are purported to govern credit risk losses accurately. Major inputs into the model are user-specified, such as the probability of default (PD) of the underlying obligors. The way in which these PDs may be allocated into ranges, or 'buckets', is not specified by the BCBS. Examination of the way in which this is achieved yield surprising results: increased PD discrimination (through improved risk management) does, in most cases, tend to reduce regulatory capital charges, but over a certain range of PDs, increased discrimination leads to higher capital charges thereby reducing any incentive to improve credit discrimination (and, by association, credit risk management) for these loans. This effect is explored in detail, located and potential mitigants discussed.

Chapter 6 explores the extraction of empirical asset correlations from retail loan portfolios. These correlations are required for use in most credit risk models: they are essentially the drivers of the loss distribution shapes. Retail loan loss data, however, are notoriously difficult to obtain due to their relative scarcity and the lack of common reporting standards. Using US Federal Reserve retail portfolio loan loss data, a method was devised to extract empirical asset correlations. These values were then compared with correlations specified by the BCBS to ascertain whether or not the latter are fairly allocated. The procurement and subsequent evaluation of these correlations should allow portfolio managers to decide which values are more appropriate for use in internal economic capital models.

Chapter 7 then provides concluding thoughts on the studies detailed in this thesis and gives some suggestions for further work that is required in this constantly evolving field of portfolio risk management.

1.5 Research design and procedure

The research design of this thesis followed the outline below:

Pose research questions: Broad questions were first posed about how to address inadequate portfolio risk management in the current (2009) financial environment. Even before the credit crisis, gaps in risk management theory and practice were becoming increasingly obvious and more difficult to ignore. With the goal of portfolio risk management uppermost, and the fields of credit and market risk in need of much further investigation, four topics were decided upon.

Critical literature review: A critical literature review ensued in which existing work by practitioners in the field was consulted. Often, adjustments were only required to *existing* risk management procedures, i.e. no new techniques were needed to solve particular problems. The existing literature is copious in such cases. Where an entirely new approach to risk practices was required, the literature was less obliging. Nevertheless, popular, well-established mathematical techniques are almost always available for such endeavours and again, abundant literature exists to address these models.

Theory building/adapting/testing: Augmenting existing risk management ideas for practical implementation into market or credit portfolios usually enjoys rich precedent. In these cases, pursuing existing, well-established methodologies allows subtle, but significant, improvements to be made to risk measurement practice. Developing new ideas requires much back-testing, validation and endorsement from other practitioners. Ultimately, the bulk of the results reported in this thesis were from empirical analyses of real return (or other) data.

Action research/data collection: Data used were from original sources where possible (e.g. the US Federal Reserve for loan loss data, South African hedge funds for hedge fund return data, etc.), usually directly from the market. This by-passed third party vendors and helped minimise errors which occur when accessing multiple, unchecked sources. In most cases, data were plentiful (sample error was minimised) and in all cases, relevant.⁶

Conceptual development: This research is intended to provide accurate, but highly practical, solutions for use by risk analysts and risk managers. As a direct result, the primary source of analytical work was Microsoft ExcelTM since this is the tool of choice for almost all financial institutions.⁷ While clearly not designed to perform the most advanced statistical or algebraic analysis, Microsoft ExcelTM nevertheless performs adequately. These spreadsheet-based models use visual basic programming language (a flexible, functional and highly valuable desktop tool available to all quantitative analysts and risk managers alike) to develop macros for undertaking onerous and repetitive computing tasks. The use of macros involves much further testing with dummy data, back-testing and model validation. Results were compared to and calibrated with more sophisticated software output and found to agree extremely well.

⁶ Where publicly available data (such as asset return series) were required, these were obtained from third party data sources such as ReutersTM or BloombergTM. If such data were not disclosed to market participants, but available to the author, these were suitably generically employed as to disguise the source. Some hedge fund data, for example, are proprietary and not permitted for public consumption. Permission to present analytical results without data source disclosure was sought from data owners where necessary.

⁷ Standard statistical software was used in cases where Excel proved inadequate.

Reflection/theory extension: Results obtained from these models are then critically assessed, analysed and the findings are meaningfully displayed. The analysis sometimes involved further, more detailed investigation, using different – or 'cleaned' – data (e.g. real versus nominal gross domestic product values). If the results indicated inconsistencies or contradictions with theory, further theory was developed and implemented.

State/disseminate findings: Having analysed the data, obtained meaningful results and displayed these appropriately, the findings were written up into article-style reports for peer review and publication.

Further work: To complement major findings of and ensure the continuation of work not addressed (or that could not be undertaken due to lack of data or theory) in this thesis, future work was then proposed for risk theorists and practitioners.

1.6 Conclusion

The field of risk management is undergoing an upheaval and, possibly, a revolution (Engle, 2009). The severe credit crisis which began in mid-2008 has been blamed on central banks (for not managing interest rates more effectively during boom times), regulators (for lax risk management monitoring procedures), rating agencies (for incorrectly assessing the risks associated with the exotic credit products available in abundance pre-2008), investment and commercial banks (for encouraging profligate risk-taking with little regard for – or complete disregard for – the potential risks involved) (Gilbert, 2008). Most governments, central banks, institutional investors, practitioners and regulators now realise that the state of risk measurement and management is in jeopardy: urgent issues remain unsolved in the recognition of the conceptual and technological limitations of the models, systems and policies. The results presented in this thesis concur with this view: serious problems were ignored or glossed over in pursuit of higher returns and in an environment of perceived diminished risk. A central tenet of this thesis is that, (to assign yet another culprit to the list above) the often naïve treatment of risks on an individual asset class basis, as opposed to a portfolio view of risk, is also to blame for the risk management inadequacies experienced. A portfolio outlook embraces the risks associated with individual components of the portfolio as well as the collective whole and leads to an enhancement of risk measurement, management and ultimately risk practice itself.

The next chapter provides a comprehensive literature review of the constantly changing field of portfolio risk measurement. In particular, it addresses the specific and widespread

assumption of the normal distribution of asset returns as well as the serious omission of liquidity risk from standard market risk measurement metrics. Literature which addressed the management of portfolio credit risk is also detailed in the next chapter.

Chapter 2

Market and credit portfolio risk management: A literature study

Market and credit portfolio risk management – A literature study

MARIUS BOTHA*

Abstract

Although hedge funds have enjoyed unrivalled dominance after years of stellar returns, a combination of low interest rates, sustained economic growth and diminished arbitrage opportunities now threaten them. Distinguishing between funds – an onerous task with notoriously opaque investment strategies – has become paramount in the search for optimal returns. Simple risk and return performance measures cannot cope with the demands of an increasingly complex financial milieu. Interest has thus focussed on more effective discriminatory performance measures. The innovative Omega ratio is calculated for South African hedge funds and compared with both Sharpe and Sortino ratios.

An important aspect of risk management is liquidity risk; changes in value due to reduced availability of traded financial instruments. This ubiquitous risk has emerged as one of the key drivers of the developing “credit crunch” with global financial liquidity plummeting since the crisis began. Contemporary research has focussed on the liquidity component of single instruments’ value at risk (VaR). This work is extended to measure portfolio VaR, employing a technique which integrates individual instruments’ liquidity-adjusted VaR into a portfolio environment without a commensurate increase of statistical assumptions.

The Basel Committee for Banking Supervision's new Basel Accord and accompanying credit risk capital equations are designed to encourage the improvement of risk management practices. However, over a range of loan quality for some loan types, these improvements increase regulatory capital charges despite the employment of resources for this Committee-endorsed aim for no empirical reason. The effect could discourage banks from improving risk management for such loans, thereby contravening the Committee’s aims. The source of the problem is investigated and located and its effect on regulatory capital illustrated.

Credit risk arises from the interaction of multiple connected factors, but the most frequently-used models designed to measure it assume only one. These models are heavily influenced by the common correlation between loan values and the single factor (some gauge of economic health). Scarce and shoddy loss data for retail loan classes hampers the estimation of this correlation. A technique is proposed to calculate asset correlations embedded in empirical loss

*Visiting professor, School of Management, University of the Free State, PO Box 339, Bloemfontein, 9300, South Africa.

data. These values are then compared with those stipulated by the Basel II Accord for minimum capital requirements.

JEL classification: C5, L5, C53, C134, G21, G32

Keywords: Omega ratio, risk measurement, risk management, liquidity, Value at risk, Basel.

1. INTRODUCTION

The field of risk measurement and management has produced abundant research yet the 'credit crisis' of 2008-09 – which felled global markets – encouraged a profusion of new analysis and fresh investigations. From the onset of the crisis it was clear that traditional risk models were either wholly incorrect or at best inadequate: new risk paradigms were required and prevalent model assumptions, although popular, required substantial revision.

Although much of the research presented in this paper was undertaken and published prior to the onset of the crisis, the work has subsequently attained particular relevance. The risks associated with the vast, interconnected tangle of instruments and transactions that characterised the financial milieu prior to the meltdown, were not adequately explored from a holistic viewpoint. Risk functions were allocated to segregated departments with little communication and interaction between them. When problems arose in one area, they spread rapidly and unhindered to others. Credit risk, for example, transformed into liquidity risk as the market for commercial paper dried up amidst fears of amplified defaults. In banks' trading books, capital cushions were quickly overwhelmed when market risks (widely believed to be dominant in the trading book) were dwarfed by hidden – but now soaring – credit risks. The failure by the financial establishment to examine and mitigate risk from a comprehensive, portfolio perspective has been hailed as one of the key malfunctions which precipitated the crisis and has prompted a swift re-examination of prevailing risk dogma.

The assumption of normality (in the statistical sense) of market returns is widespread and hugely popular, despite its obvious falsehood. This shortcoming has prompted much new research activity free from such restrictive assumptions. The Omega ratio avoids the normality assumption completely. Indeed, the Omega ratio ignores all distributional assumptions and instead opts for the empirical underlying distribution of market returns and offers rich potential avenues for exploration. At present popular only amongst hedge fund aficionados (who acknowledge the clear non-normality present in their returns), the Omega ratio is nevertheless gaining support from more traditional quarters as the ramifications of the credit crisis unfold.

Prior to the crisis, the industry largely ignored liquidity risk as a potentially devastating risk class. Indeed, the assumption of infinite liquidity is widespread in financial theory including the popular Black and Scholes' analysis of derivative pricing, credit default swap analysis and portfolio theory. Whilst the new Basel Accord does mention liquidity risk, before the crisis it drew little attention to the potential scale of liquidity risk, nor did it quantify or delineate ways to measure and manage it. This has now altered. The origins of the credit crisis have been ascribed to a misunderstood liquidity crisis (rather than a credit crisis) and the Basel Committee for Banking Supervision (BCBS) has scrambled to include this risk type in amendments to the fledgling Basel II Accord. Standard value at risk (VaR) models for market risk include liquidity considerations, but only through the 'square root of time rule' which simply scales the volatility with time. Many studies have indicated the inadequacy of this assumption, yet it remains popular and widespread.

Credit risk models are currently (2009) enjoying explosive proliferation. The BCBS's Basel II Accord introduces and encourages the use of several credit risk approaches, some – such as the advanced internal ratings based approach – fairly complex. The BCBS acknowledge that one of the accord's chief aims is to persuade financial institutions to adopt more risk-sensitive approaches to credit risk management. Regulatory recognition for this implementation could involve diminished capital charges (depending on application outcomes). It is arguably such incentives that have led to the widespread acceptance and implementation of the new accord. The accord is, however, not without its flaws: it has been shown to be demonstrably inadequate following the causalities and fallout from the credit crisis. The failings of the accord, however, are not attributable purely to a lack of conservatism on behalf of the BCBS. Indeed, some aspects of the accord have been found to be internally inconsistent and in some cases even self-contradictory. For some loan types, for example, improved risk discrimination leads to diminished capital requirement benefits, while for others reduced risk discrimination produces the same effect. Considering the time and resource effort banks will no doubt dedicate to renewed and improved risk measurement and management, it is unacceptable that such inconsistencies have not yet been addressed (nor, it seems, widely reported).

Other facets of the accord are highly punitive in a manner which does not benefit banks (from a capital cushion point of view) when the financial environment becomes malignant. One of these is the asset correlation parameter imposed (it is not user-defined) by the BCBS. Retail asset correlations were measured empirically using global loan loss data and found to be significantly lower than those enforced by the BCBS, even in times of elevated defaults and

losses. These restrictions are of considerable import to financial institutions attempting to measure and maintain capital at an appropriate level. Comparison with economic capital reserves highlights these differences.

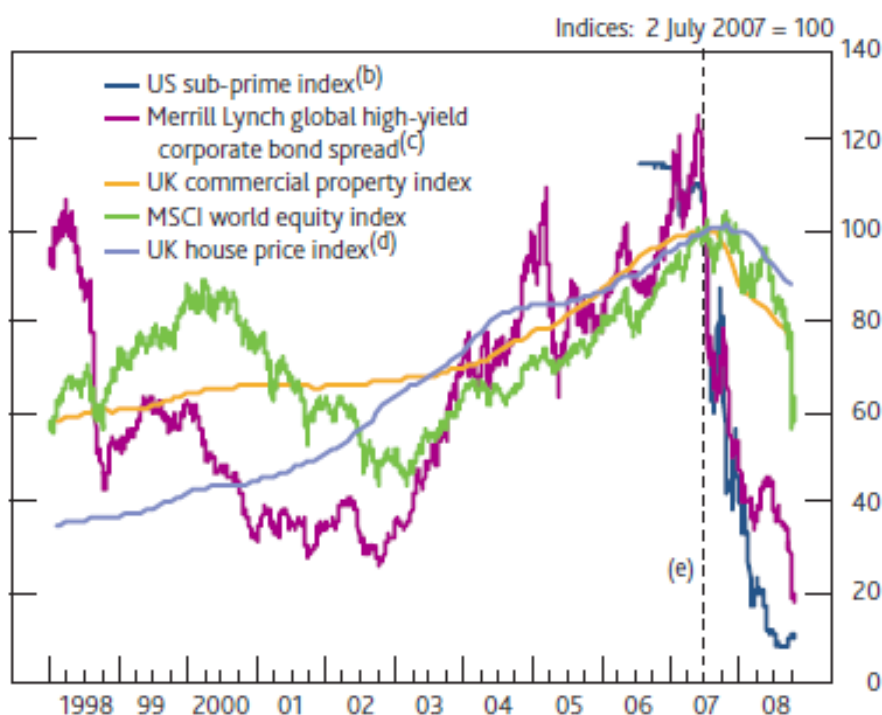
2. THE OMEGA RATIO

Hedge funds are portfolios of assets which aim to reduce risk by transferring it to other investors using various techniques. Hedge funds have historically taken investment positions that are relatively uncorrelated with broader financial markets or that may be in opposition to broader markets. Academics, regulatory authorities and industry professionals argue that hedge funds benefit the economy by assuming risks that others will not, mitigating price downturns, making securities more liquid and seeking out inefficiencies (Cheng, 2002: 5). Those benefits are possible because hedge funds are subject to less regulation than most investment vehicles. Compared to unit trusts, for example, hedge funds are less restricted in their use of derivatives and leverage, and have greater incentives to do so because they are not (yet) required to publicly disclose their investment strategies or holdings. The hedge fund industry in South Africa has expanded rapidly since 2000 and shows no signs of abating (Botha, 2005).

A benign global interest rate environment¹ (combined with indifferent regulatory scrutiny and a lack of viable investment alternatives) for many years encouraged the explosive growth of the hedge fund business (HFRX, 2006). This situation has now begun to be challenged. The hedge fund industry posted a record outflow of USD149bn in December 2008 (see Figure 1) and some USD270bn over the full year of 2008 (Hedgeweek, January 6, 2009).

¹ For the many hedge fund strategies that rely on borrowed funds to leverage investment positions, a benign interest rate environment is highly favoured. The global low-interest rate environment which – despite several recent interest rate increases – remains well below the long-run average, is widely considered as one of the prime drivers in the explosive growth of the industry (see Fiford, 2004).

Figure 1: Growth and decline of selected indices since 1998.



Sources: Halifax, IPD, JPMorgan Chase & Co., Merrill Lynch, Nationwide, Thomson Datastream and Bank calculations (January 2009).

Notes:

(a) Data to close of business on 20 October 2008.

(b) Sub-prime series is the A-rated 2006, H2 vintage ABX.HE index.

(c) Series inverted.

(d) Average of Halifax and Nationwide house price indices.

(e) Dashed line shows start of July 2007.

The ongoing education of the investment community has also allowed investors to become far more able to discriminate between market returns (*b*) and manager out-performance (*a*), with investors increasingly expecting to pay only for the latter. Hedge funds have historically charged a (high) basic fee plus a percentage of profits, but the rise of exchange traded funds² (ETFs) and the recent (2008) performance of hedge funds has called these fees into question. Over 130 ETFs were launched internationally in the first half of 2006 – more than in the entire previous year. These quoted securities track pre-specified indices and enable investors to acquire portfolios comprising a wide range of assets at relatively small fees compared to

² ETFs are part-fund, part stock. Like unit trusts, they track baskets of assets, such as stock market indices or commodities, but unlike standard funds they can be bought and sold throughout the trading day, so investors can make (or reverse) broad bets quickly, without having to buy many separate shares. Portfolios are rebalanced throughout the day so ETFs trade at or close to the net value of their assets, unlike many unit trust funds. ETFs have been embraced enthusiastically by hedge funds, lured not only by the combination of diversification and trading convenience, but also by rules that allow ETFs to be sold short as their prices fall. Retail investors are also keen purchasers of ETFs. Large providers of ETFs such as Barclays Global Investors and State Street estimate that retail investors now account for 2/3 of capital inflows – double the share since 2002. Retail investors are attracted by low fees (about 0.25% on average), efficient pricing and generous tax advantages (*The Economist*, 2007).

hedge funds. Some US\$500 billion of assets are now controlled by ETFs, and it is estimated that they will control over US\$2 trillion by 2011 (The Economist, 2006b). Private equity³ and large property portfolios (so-called 'alternative asset investments'), which grew by 20% in 2005, now have assets in excess of US\$1.25 trillion and enjoy enormous popularity for their flexibility and low fees.

Also, the relatively unrestricted and unregulated milieu – so enjoyed by hedge funds – is coming under increased scrutiny. Legislators, regulators and a nervous public are beginning to demand the imposition of investment controls and restrictive policy rules on hedge funds (The Economist, 2006b, Financial Times, July 4 2006). This is unlikely to diminish, despite the overwhelming opposition of financial markets to these measures. It has been argued that, in this age of electronic trading and highly complex automated searches for market value, arbitrage gaps in foreign exchange, equity and other markets have shrunk considerably (Ammann and Moerth, 2005). The quest for investment returns has become ever more frenetic (Bank of Japan, 2006). Hedge funds have provided a new vehicle for experimentation and improvisation: the highest returns since 2002 have been from these funds. Hedge fund assets currently total some US\$1 trillion from a global total of 12 000 funds (Géhin, 2005 and updated values in Fung et al. 2006, The Economist, 2006a, Financial Times, July 10 2006 and Hennessee Group LLC, 2007). The innovations that distinguish one hedge fund from another are necessarily covert: forced disclosure is likely to stifle originality.⁴

Increased regulatory activity (Sarbanes Oxley, Basel II, IFRS standards) have loaded the market with onerous, costly (and some argue, unnecessary. See, for example, Lemke et al. 2006 and articles therein) scrutiny. Wary investors have shrunk from previously well-tested markets in an effort to forestall or forego regulatory penalties. This has drained the system of liquidity: the lubricant which ensures efficient, reduced-friction functioning (Song, 2006). Historically, hedge funds have proved remarkably adept at pumping in liquidity to a thirsty market where and when such is lacking and mopping it up in times of critical over-supply. Free from regulatory scrutiny, hedge funds have proved to be efficient resource-allocators in

³ Private equities are equity securities of unlisted companies and the term private equity is a broad term that refers to any type of equity investment in an asset in which the equity is not freely tradeable on a public stock market. Private equity investments are not subject to the same high level of government regulation as stock offerings to the general public and they are also far less liquid than publicly traded stock. Categories of private equity investment include leveraged buy-out, venture capital, growth capital, angel investing, mezzanine capital and others. Private equity funds typically control management of the companies in which they invest, and often bring in new management teams that focus on making the company more valuable. Funds raised through private equity can be used to develop new products and technologies, to expand working capital, to make acquisitions, or to strengthen a company's balance sheet (FSA, 2006).

⁴ A brief history of the market's objections to increased regulatory pressure on hedge funds is available from Shadab (2007). Shadab argues persuasively that increased regulation will do far more harm than good to the global hedge fund industry.

recent years, surviving and indeed thriving in the recent lengthy benign credit environment which has flooded the market with cheap money. Defenders of this view claim that:

"...by exploiting (and thereby eliminating) pricing anomalies and by being less encumbered by prudential controls than most other financial institutions, hedge funds promote efficiency in the allocation of capital by searching out returns more effectively than others. On the assumption, moreover, that those who put money into hedge funds know what risks they are taking...people might take the view that what investors do with their money is their own business." (Stevens, 2006).

Hedge funds, however, are still highly risky investments: stellar returns cannot be achieved without spectacular risks. Critics claim that hedge funds

"...can overwhelm and distort small markets. A tendency for herd behaviour, and application of leverage,⁵ amplifies the problem, in the view of these critics. When hedge funds decide simultaneously to get into or out of a position, they can disrupt market functioning." (Stevens, 2006).

If no justification for high fees is forthcoming, it is unlikely hedge funds will continue to enjoy their vaunted status in the alternative investment arena. Hence the ongoing need for new measures to assess and manage hedge fund risk. The better the knowledge of the relative riskiness of a fund, the more efficient the allocation of investment capital and the fairer the apportionment of fees charged. In this regard, the recently introduced Omega ratio (Shadwick and Keating, 2002, and later adaptations thereof) has been met with cautious optimism (see, for example, Kazemi, 2003 and du Toit, 2005). While research in this field is still in its relative infancy, ongoing exploration has yielded innovations which highlight aspects of traditional performance ratios as well as explored limiting assumptions.

Arguably the most widely used of the traditional risk-adjusted performance measures is the Sharpe ratio (Sharpe, 1966), defined as the quotient of the excess portfolio return over a risk-free rate and the portfolio standard deviation – in essence it is the price of excess return per unit of risk.

The traditional Sharpe ratio has enjoyed much success in the modelling of empirical financial data. It distinguishes reliably between two or more alternative investments, provided the returns to the assets in question are normally distributed and uncorrelated with the returns to the existing portfolio of a fund. The fund with the higher Sharpe ratio is chosen as the superior

⁵ The term "hedge fund" is misleading in this context. Not all hedge fund strategies make use of leverage in order to boost returns. Thus, discussions regarding funds likely to be directly affected by increasing interest rates refer only to those hedge fund strategies which employ leverage as a principal driver of performance.

performer. In effect, the Sharpe ratio is taken as a proxy for the risk-adjusted return and the investment whose risk-adjusted return is highest is chosen. However, the traditional Sharpe ratio presupposes that the return of each prospective investment is uncorrelated with the return of the existing portfolio of the institution. Sharpe himself acknowledged that the Sharpe ratio may not give a reliable ranking if one or more of the assets involved are correlated with the rest of the portfolio (Sharpe, 1994). The Sharpe ratio has many desirable properties and it is relatively straightforward to comprehend and implement. This is evidenced by its use in the assessment of investment returns for over 40 years. However, the Sharpe ratio is a far from a perfect risk-adjusted performance measure.

The limitations inherent in the Sharpe ratio obscure some risks, particularly when considered against the background of the fundamental economic theory of decision making under uncertainty of Von Neumann and Morgenstern (1947). This theory is only consistent with the mean-variance portfolio approach under the following severely limiting conditions:

- investment returns are normally distributed
- the investor's utility function is quadratic (i.e. higher moments of the statistical distribution are ignored, which implies (unlikely) increasing absolute risk aversion) and
- investment risk is 'small', i.e. second order Taylor approximation to the utility function is sufficient.

The common assumption that investment returns are normally distributed has been challenged repeatedly and vigorously (Mandelbrot and Hudson, 2005, and sources therein). The assumption of normality truncates the right tail of the returns distribution (profits) at the expense of fat left tails – i.e. the market crashes (Sharma, 2005). The Sharpe ratio is thus incapable of handling large risks concealed in higher statistical moments.

In addition, the Sharpe ratio is leverage invariant, while it also does not account for correlations. The market has recently expressed concern regarding the "increasingly high levels of correlation between supposedly diverse strategies, reduced liquidity in the financial system and excessive bullishness" (Financial Times, July 10, 2006). Merrill Lynch claim that the correlation between hedge funds and the S&P500 index is 0.96, up from 0.32 measured in 2000 (Birger, 2006). Emerging market correlations are similarly implicated.

McLeod and Van Vuuren (2004) demonstrated that the fund with the maximum Sharpe ratio in declining markets is the fund with the highest probability of outperforming a risk-free in-

vestment. This contrasts with the standard interpretation that it is the fund with the largest excess return per unit of risk that has the maximum Sharpe ratio.

In order to address these shortcomings, Treynor (1966) extended the work of Sharpe and proposed his Treynor ratio. This ratio replaces the volatility of the portfolio with a measure of systematic risk. In addition, it makes use of the CAPM, i.e. investors should only expect risk compensation for exposure to non-diversifiable or systematic risk (Treynor, 1973). In addition, Sharpe (1994) provides improvements and reinterpretations of the Sharpe ratio, and introduces a relative performance measure, the Information ratio.

Modigliani and Modigliani (1997) present a further extension of Sharpe. They develop the M2 measure (where M2 stands for Modigliani and Modigliani) that compares portfolios by leveraging or de-leveraging them until they have identical volatility (normally chosen as the market volatility). This allows the comparison of portfolios by examining the resulting returns. The fund with the highest M2 will have the highest return for a given amount of risk. Muralidhar (2003) proposed the M3 measure that accounts for differences in the correlations of the various portfolios being compared.

The Sharpe ratio and its progeny are still limited by their inability to adequately capture higher statistical moments of the distribution. If standard assumptions regarding higher moments and the normality constraint are abandoned, a new approach is required. Sharma (2005) showed that the Sharpe ratio could be extended by replacing the denominator by the VaR at a given confidence interval. VaR is based upon a mean-variance normal distribution but can easily be modified to incorporate skewness and kurtosis using the Cornish-Fisher expansion (Jaschke, 2002).

Although an improvement, this measure only incorporates the third and fourth moments of the distribution. Sharma therefore proposes a measure called Alternative Investment Risk Adjusted Return (AIRAP), which draws on the economic theory of expected utility.

Sharpe's traditional mean-variance paradigm has severe shortcomings which have not yet been satisfactorily resolved. In addition, the risks associated with traditional funds do not always translate into the hedge fund arena. A wide variety of hedge fund return distributions are encountered in the current marketplace: many are highly non-normal with non-negligible higher statistical moments. Since higher statistical moments are not captured by traditional fund performance measures, other measures must be sought. The next section discusses these pertinent hedge fund risk characteristics.

Being relatively new financial instruments, hedge funds are affected by risks which are not yet exhaustively understood. The hedge fund investment arena was originally the almost exclusive domain of high net worth individuals for whom capital preservation was paramount. This has changed in recent years. The investment community has rallied to share in promised above-average returns and it is now not unusual for even well-established, conventionally risk-averse pension funds to experiment with these strategies (UK FSA, 2005). Higher returns are accompanied by higher risk and thus higher volatility, but the demand for low volatility⁶ is much less important in hedge funds than low downside volatility. This has given rise to two types of measures based on the downside volatility: the Sortino ratio and the maximum drawdown (MDD).

The Sortino ratio is closely related to the Sharpe ratio as it compares the return of a portfolio with a chosen minimum acceptable return or MAR (often the risk free rate), and divides it by the downside volatility, i.e. returns below the MAR.

Maximum Drawdown (MDD) measures describe the worst peak-to-trough fall in fund value over the history of the fund. However, the MDD has some limitations. For example, it can only be used for funds with the same time scale and similar reporting frequency. Though, in general, relatively new funds will have smaller MDDs than long-established funds, it is clearly a fallacious conclusion (based on the MDD) to only invest in new funds.

An adaptation of the 'historical' MDD is the numerical Monte Carlo approach. Estimated parameters of the return distribution (usually only the mean and variance) are used to generate many scenarios, of which the actual outcome is only one. Investors select a confidence level, say 95% or 99%, and ascertain the MDD. This provides a better guide to the underlying downside risk compared with the actual MDD. However, this approach, firstly, is based upon the assumption that the selected parameters accurately and fully describe the underlying returns and, secondly, that the parameters are relatively stable. Both of these are strong assumptions and not, in general, accurate. Although a further variation – the Calmar ratio – has been incorporated into the Sharpe ratio with mixed success, MDD is now widely considered to be an inefficient statistic for describing the performance of a fund and carries a high potential level of error (Acar and Middleton, 2004).

Large and abrupt movements in portfolio returns are of great concern to investors. Depending upon the investment strategy employed, hedge fund returns generally have large outliers in

⁶ A staple of traditional funds.

both tails of their distributions; an indication of large risky bets that often succeed, but occasionally fail (Darwinian survivorship bias applies here: if a hedge fund fails more often than it succeeds, it will be quickly eradicated (Lo, 2006 and Rajan et al. 2005)). In addition, funds that are robustly and effectively hedged, exhibit severely skewed return distributions. The argument for the approximation of 'small risks' is thus also untenable. The return distributions of hedge funds are, as a result, markedly non-normal and it is thus not appropriate to evaluate their performance within a mean-variance framework. A performance measurement tool that takes several order moments of the distribution function into account is thus required.

A relatively recent development, the Omega ratio (Shadwick and Keating, 2002), is based on novel interpretations of existing performance measurement techniques. The Omega ratio divides returns into losses and gains above and below a return threshold and determines the probability-weighted ratio of returns above and below this threshold.

Most performance ratios are of the form [expected return]/risk, as is the case with Sharpe, Sortino and the Information ratio, but the Omega ratio is different, expressed rather as a ratio of gains to losses (a direct consequence of which is that the Omega ratio is sensitive to the potential for excess returns, not only the mean return).⁷ The Omega ratio is ideally suited for evaluating the performance of hedge funds because it considers the entire distribution function of the investment under scrutiny. One weakness is its sensitivity to the size of the sample: at least 40–50 observations are necessary to obtain stable results. This is, however, no more or less onerous than several other performance ratios that have endured despite their reliance on abundant data.

This measure (and its continuous counterpart, measured at all thresholds – the Omega function) is discussed in detail by Kazemi et al. (2003), Polakow and de Araújo (2004), Polakow et al. (2005), Urbani (2005), du Toit, (2005) and sources therein.⁸ Most of the above sources relate specifically to the application of the Omega ratio and function to South African hedge fund data. The South African hedge fund return data have been analysed (Botha, 2005) using both the Omega ratio as well as the more traditional Sharpe ratio to ascertain which of the two provides a better measure of performance. Better, in this sense, is taken to mean more reliable and more robust. Since the distribution of hedge fund return data is highly non-

⁷ Despite the differences in the nature and estimation of the Sharpe and Omega ratios as performance measures, the point of convergence is that both claim to rank funds according to investor preference. Thus, while comparisons of other attributes may be invalid, comparing the rankings attributed to funds by these measures is not.

⁸ The website <http://www.edge-fund.com/bibliography.html> provides invaluable resources for readers interested in hedge fund performance.

normal, being leptokurtic and fat tailed, measures which rely on distributional normality are bound to fail. Indeed, the Omega ratio emerges as the superior measure of the two.

3. INCORPORATION OF LIQUIDITY RISK INTO VaR

The Basel I Accord, published in 1988, set down the agreement among the G-10 central banks to apply common minimum capital standards to their banking industries by the end of 1992 (BIS, 1988). The standards largely addressed the main (credit) risk incurred by banks, but five amendments to the accord were agreed to subsequently and the fifth introduced parallel capital requirements for market risk. A key development of the Basel Accord was the introduction of VaR, a measure to consolidate an institution's market risk into a single number. The idea was embraced by the finance community and has subsequently come to dominate the field of market risk.

Whilst VaR is not a complex quantity to calculate in principle, estimating its input parameters and determining both their robustness and validity are non-trivial. The late 1980s and most of the 1990s witnessed a profusion of research articles dedicated to the refinement of the VaR measure (Risk, 2004 and sources therein). Exponential weighting techniques improved volatility and correlation estimates (JP Morgan, 1996), GARCH⁹ introduced a mean-reverting volatility model (Alexander 2001 and sources therein), alternative distributions were applied to non-Gaussian data (Bouchaudy and Potters, 1999) and Extreme Value Theory became a popular measure to elucidate the structure in the data-poor region of distribution tails (McNeil, 1996: 121). Adjustments for portfolios with non-linear pay-off profiles – i.e. comprised in part of options or interest rate dependent instruments – were also introduced and are now standard fare (Ammann and Reich, 2001: 9).

Changes in market conditions as well as the size and nature of financial risk have necessitated the drafting and construction of Basel II – essentially a revised and augmented framework of Basel I (BCBS, 2006a). This revision, implemented in Europe in January 2008 (later in the USA), leaves the treatment of market risk largely unchanged from Basel I and instead focuses almost entirely upon the previously neglected areas of credit and operational risk.¹⁰ A large number of research articles are now engaged in the exploration of the complexities of credit and operational risk: market risk articles have consequently diminished significantly in num-

⁹ Generalised Autoregressive Conditional Heteroscedasticity.

¹⁰ The Bank's primary exposure to counterparty credit risk is through its investment portfolio, however, it can also have exposure to derivative counterparties (which may default on obligations) in the trading book. Banks seek to minimize the risk that a credit loss from a counterparty default or downgrade could cause either a financial loss or damage the Bank's reputation. Basel II addresses this counterparty risk problem in detail, but leaves the basic tenets of the measurement and management of market risk untouched (BIS, 2005).

ber (Risk Magazine, 2004). The VaR concept, however, has by no means been exhaustively explored: in its standard form it is still plagued by limiting assumptions, but some of these standards evade deeper examination on the basis of being 'widely-accepted'. One such feature is liquidity risk which, because of its tendency to compound other risks, is difficult to isolate and analyse. In all but the most simple of circumstances, comprehensive liquidity risk metrics do not exist and standard VaR models usually ignore liquidity risk completely.

The growth in hedge funds worldwide since the early 2000s, meanwhile, has been explosive, both in terms of number of funds and investment capital (Mulvey, 2003: 24 and HFRX, 2006) and there are increasing indications that the process is accelerating. Ever since the collapse of the Long Term Capital Management (LTCM) hedge fund in August 1998 hedge fund risk managers have been forced to concentrate ever more on liquidity risk (Lowenstein, 2002). It was this aspect of risk – more than any other – that brought LTCM to financial ruin.

The severe asset value deterioration that has accompanied the credit crisis was initiated by the collapse of the subprime credit market in the US,¹¹ but it was the collapse of Lehman Brothers which heralded an acceleration of the crisis. Lehman's disintegration (mid-September 2008) (Luby, 2008) was entirely attributable to a dearth of liquidity (Orlowski, 2008) as shown in Figure 2. The colossal increase in volatility that dominated the market after the Lehman Brothers collapse and continues at this time of writing (February 2009) has shown that the assumption of unlimited market liquidity is hopelessly inaccurate. Bank losses have been estimated (as at end 2008) at USD1tn (Baxter, 2008) and although it is as yet uncertain from whence these losses originate, it is certain that a large part of these stem from undervalued market risk losses, i.e., underestimated bank VaR values (Bank of England, 2008).

Despite this, no standard approach for measuring liquidity risk has emerged.¹² Liquidity-adjusted VaR models certainly exist, and some are fairly sophisticated (e.g. Cosandey, 2001: 116), but these are based upon single instrument VaR approaches and their application to portfolios is not uniform. Less sophisticated approaches such as those that rely on conventional measures of leverage to estimate liquidity risk sometimes provide meaningless results (Bangia, 1999: 70). In addition, the existence of both endogenous and exogenous liquidity risk (which are quite different in both structure and manifestation), autocorrelation and scaling in time of return data and the aggregation of single-instrument liquidity VaR into portfo-

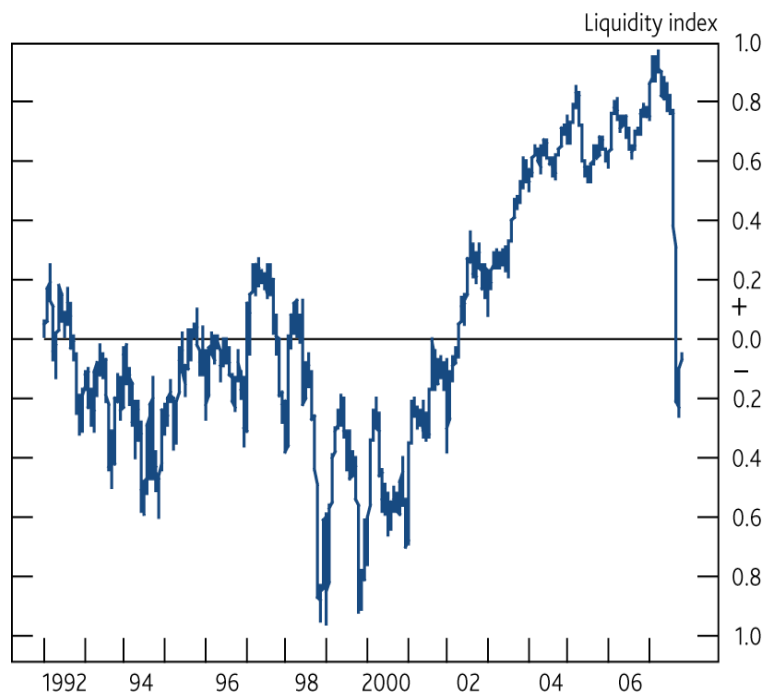
¹¹ The crisis began in the US subprime market, but it quickly spread to other areas of finance and ultimately to the global economy.

¹² This study is by no means confined to the risks associated with hedge funds – these funds merely amplify the effects of liquidity risk through their unique investment strategies.

lio liquidity VaR (Umut, 2004: 315) all involve non-trivial and computer-intensive implementation.

Liquidity may be defined as a range of characteristics rather than a one-dimensional attribute of assets and of the markets on which they are traded. It is also a relative concept, as the more liquid the asset, the more easily it is traded for cash, i.e. at low cost, at short notice and with no risk of a notable change in price. A perfectly liquid market would therefore guarantee a single bid/ask price at all times, irrespective of the quantities being traded. Financial markets, even those deemed most liquid, conform less than perfectly to this ideal configuration. Liquidity risk is thus the risk of being unable to liquidate or hedge a position immediately and at current market prices.

Figure 2: Financial market liquidity from 1992 to 2008.



Sources: Bank of England, Bloomberg, Chicago Board Options Exchange, Debt Management Office, London Stock Exchange, Merrill Lynch, Thompson Datastream and Bank calculations (December 2008).

Notes: The liquidity index shows the number of standard deviations from the mean. It is a simple unweighted average of nine liquidity measures, normalised on the period 1999-2004. Data are calculated using rolling exponentially weighted moving averages.

The use of VaR as the standard market risk measure has enjoyed ever-increasing popularity since its formulation in the late 1980s: it is now the most widely-used risk metric for the determination of market risk (Holton, 2003: 405). Whilst considerable attention has been given to the measurement of financial instrument volatility and correlation as well as the incorporation of these values into portfolio VaR, the liquidity risk of these instruments remains se-

verely under-examined. It is included in standard VaR calculations only in an ad hoc fashion, namely by increasing the time horizon over which VaR is calculated to account for the time taken to liquidate a large position (JP Morgan, 1996). Not only does this technique not distinguish between exogenous and endogenous liquidity (defined and discussed below), but it employs the 'square root of time' rule, in which it is assumed that no autocorrelation exists between rates of return from one measurement period to another. This assumption of a lack of autocorrelation allows for simple arithmetic summation of individual variances to produce the overall 'period under investigation' variance.

This assumption has been challenged over the past decade by several authors (see for example, Diebold (1996) and Blake et al. (2000)). In addition, Danielsson and Zigrand (2006: 2711) recently again demonstrated that the square root of time rule leads to a systematic underestimation of risk – but also found that the degree of underestimation worsens with time horizon, jump intensity and confidence level. They conclude that despite the widespread application and implementation of the square root of time rule in the Basel Accords, it nevertheless fails to address the objective of the Basel Accords. It is clear that a more thorough investigation into the nature of liquidity risk and its effect on portfolios of illiquid instruments is required.

Two types of liquidity risk have been identified, namely exogenous and endogenous liquidity risk. These are defined below.

(a) **Exogenous liquidity risk** is the result of market characteristics; it is common to all market players and unaffected by the actions of any one participant (Bangia et al. 1998). In response to a market shock (and the resultant loss of predictability), a vicious cycle with a corresponding loss of liquidity is initiated. The perceived need to hold larger prudential reserves in situations of greater uncertainty along with reduced liquidity and leverage may not break the self-reinforcing dynamics of market dislocations. Exogenous liquidity can be affected by the joint action of all or almost all market participants as occurred in several markets in the summer of 1998 (Lowenstein, 2002). The market for liquid securities, such as G7 currencies, is typically characterized by heavy trading volumes, stable and small bid-ask spreads, stable and high levels of quote depth. Liquidity costs may be negligible for such positions when marking to market provides a proper liquidation value. In contrast, markets in emerging currencies or thinly traded junk bonds are illiquid and are characterized by high volatilities of spread, quote depth and trading volume.

(b) **Endogenous liquidity risk**, in contrast, is specific to the position in the market and varies across market participants (Bangia et al. 1998). The exposure of any one participant is affected by the actions of that participant. It is mainly driven by the size of the position: the larger the size, the greater the endogenous illiquidity. If the market order to buy/sell is smaller than the volume available in the market at the quote, then the order transacts at the quote. In this case the market impact cost, defined as the cost of immediate execution, will be half of the bid-ask spread. If the size of the order exceeds the quote depth, the cost of market impact will be higher than the half-spread. The difference between the total market impact and half-spread is called the incremental market cost, and constitutes the endogenous liquidity component.

Le Saout (2002) reported that neither exogenous liquidity risk (which accounts for about half of total market risk) nor endogenous liquidity risk (also a potentially significant component of market risk) should be ignored by financial institutions subject to market risk.

Recent work has begun to incorporate vanishing liquidity in times of crisis. Le Saout (2002) provides a good review of liquidity risk in VaR models and gives a comprehensive overview of recent research in the field. Lawrence and Robinson (1995: 64) were among the first to identify and establish that conventional VaR models often exclude asset liquidity risk. They argued that the best way to capture liquidity issues within the VaR framework would be to match the VaR time horizon with the time investors believed it could take to exit or liquidate the portfolio. They established that the liquidation of a portfolio over several trading days generated additional liquidity costs.

Diebold et al. (1996) pointed out that the scaling of volatilities by the square root of time is only applicable if log changes of price returns are i.i.d. (independently and identically distributed) and, in addition, normally distributed. They noted that high frequency financial asset returns are not i.i.d. and that, even if they are conditional mean independent they are definitely not mean variance independent (see also Bollerslev, Chou and Kroner (1992: 20) and Diebold and Lopez (1995: 433) for evidence of strong volatility persistence in financial asset returns.) Diebold et al. (1996) showed that scaling by the square root of time magnifies the volatility fluctuations i.e. scaling results in large conditional variance fluctuations of long horizon returns, when in fact the opposite is true.

Jarrow and Subramanian (1997: 171, 2001: 450) considered optimal liquidation of an investment over a fixed horizon. They characterised the costs and benefits of block sales versus

slow liquidation and they proposed an endogenous liquidity adjustment to the standard VaR measure. The model requires three quantities which increase the loss level – namely a liquidity discount, the volatility of the liquidity discount and the volatility of the time horizon to liquidation. The authors themselves acknowledge that traders or firms must collect time series data on the shares traded, prices received and time to execution in order to estimate these quantities. Whilst this model is robust and fairly easy to implement, estimating these quantities is by no means trivial. Indeed, some may only be determined empirically with the accompanying introduction of significant bias.

Fernandez (1999: 2) examined liquidity risk in the aftermath of the 1998 LTCM liquidity crisis. He argued that:

"...financial markets are undergoing rapid structural change, which may be contributing to liquidity risk. These changes along with rising homogeneity of market participants' behaviour are increasing concentration and 'herding behaviour' and eliminating 'friction' which may prove disadvantageous in a market correction." (Fernandez, 1999:3)

Fernandez concluded that no single measure captured the various aspects of liquidity in financial markets, but rather a composite of measures, incorporating quantitative and qualitative factors. His treatment of the problem, however sound, does not address the mathematical issues underlying this complex problem.

Bangia et al. (1999: 71) explored exogenous liquidity risk. They treated the liquidity risk and market risk jointly and made the assumption that in adverse market environments extreme events in returns and extreme events in spreads occur concurrently. They noted that while the correlation between mid-price movements and spreads was not perfect – it was strong enough during extreme market conditions to encourage the treatment of extreme movements in market and liquidity risk simultaneously. They incorporated both a 99th percentile movement in the underlying and a 99th percentile movement in the spread.

Almgren and Chriss (1999: 59) examined endogenous liquidity risk by considering the problem of portfolio liquidation. They aimed to minimise a combination of volatility risk and transaction costs arising from permanent and temporary market impact. From a simple linear cost model, they built an efficient frontier in the space of time-dependant probability. They considered the risk-reward trade-off both from the point of view of classic mean-variance optimisation and the standpoint of VaR. Their analysis led to general insights into optimal portfolio trading, and to several applications including a definition of liquidity-adjusted VaR.

Hisata and Yamai (2000: 84) proposed a practical framework for the quantification of liquidity-adjusted VaR which incorporated the market liquidity of financial products. Their framework incorporates the mechanism of the market impact caused by the investor's own dealings through adjusting VaR according to the level of market liquidity and the scale of the investor's position. In addition, Hisata and Yamai (2000: 86) proposed a closed-form solution for calculating liquidity-adjusted VaR as well as a method of estimating portfolio liquidity-adjusted VaR.

Erwan (2002: 11) demonstrated that the standard VaR model largely neglects the liquidity aspect of market risk because no single measure captures the various aspects of liquidity in financial markets. Erwan (2002: 8) extended the liquidity adjusted VaR model developed by Bangia et al. (1999) by incorporating a weighted average spread to bid and offer prices and applied the resulting model to the French stock market. Both endogenous and exogenous liquidity risk were found to be important components of market risk.

Çetin et al. (2004) assume the existence of a stochastic supply curve for a security's price as a function of transaction size. Specifically, a second argument incorporates the size (number of shares) and direction (buy versus sell) of a transaction to determine the price at which the trade is executed. For a given supply curve, traders act as price takers. The more liquid an asset, the more horizontal its unique supply curve. In the context of continuous trading, necessary and sufficient conditions on the supply curve's evolution are characterised such that no arbitrage opportunities arise in the economy. Furthermore, given an arbitrage free evolution for the supply curve, conditions for an approximately complete market are also provided. In the most general setting with unrestricted predictable trading strategies, Çetin et al. obtain three primary conclusions with respect to the pricing of derivatives. First, all liquidity costs are avoidable when (approximately) replicating a derivative's payoff using continuous trading strategies of finite variation. Second (and as a consequence of the previous conclusion) the derivative's price is the price obtained by ignoring the bid-ask spread and other illiquidities. Third, no implied bid-ask spreads or illiquidities exist for a derivative's price. Note that these conclusions follow from continuous trading of infinitesimal quantities. Although related mainly to derivative pricing, this work was used by Jarrow and Protter (2005: 9) to modify current risk measures to account for liquidity risk, though they admit that although more complex adjustments are possible, these await subsequent research.

Angelidis and Benos (2005) relaxed the traditional, yet unrealistic, assumption of a perfect, frictionless financial market (i.e. investors can either buy or sell any amount of stock without

causing significant price changes). Angelidos and Benos extended the work of Hausman et al., (1992: 323) and Madhavan et al., (1997: 1041) (who argued that traded volume can explain price movements) and developed a liquidity VaR measure based on spread components, following the work of Bangia et al., (1999: 72). Under this framework, the liquidity risk was decomposed into its endogenous and exogenous components, thereby permitting an assessment of the liquidation risk of a specific position. As with much other research, this relevant and detailed work does not address portfolio liquidity – the chief focus of this article.

The problem of ignoring liquidity risk is amplified in – but not confined to portfolios which constitute – hedge funds. Hedge fund manager styles were addressed by L'Habitant (2000: 12, 2001: 18) who noted that there was a need to introduce new quantitative tools to assist investors assessing the investment characteristics and the risks of hedge funds. Using only net asset values from a hedge fund, L'Habitant proposed a methodology to identify strategic and tactical hedge fund asset allocations and compare their performance against an ad-hoc benchmark. The method on which he relied was a returns-based style analysis introduced by Sharpe (1988). L'Habitant also notes that:

"...there are numerous directions for future research. In particular, the framework presented in this paper does not incorporate all the risk components to which a hedge fund investor is exposed. For instance, we have completely omitted credit and liquidity risks, which are also essential parts of the full risk picture of a hedge fund." (L'Habitant, 2001: 13).

Hisata and Yamai (2000: 90) provide the only coherent portfolio approach to liquidity risk. The possibility of combining Jarrow and Subramanian's model¹³ (1997, 2001) for evaluating individual instrument liquidity-adjusted VaR¹⁴ and standard portfolio theory to produce a robust portfolio LVaR approach under normal trading conditions was explored in this thesis. The technique is a variation on Hisata and Yamai's (2000: 90) portfolio approach, but also incorporates several elements discussed by them. The aim is thus to construct a LVaR at a portfolio level.

Whilst many LVaR models exist, the JS model is increasing in importance as the endogenous liquidity model of choice (for example, see Umut (2004: 322). Although Çetin's (2004) work is currently enjoying some popularity – see Jarrow and Protter (2005: 12) – more work is required before the adjustments recommended can be effectively and robustly implemented into existing VaR models).

¹³ Henceforth JS-model.

¹⁴ Henceforth LVaR.

Figure 3 below provides an overview of the main difference between the work of Jarrow and Subramanian (1997: 173) and the portfolio adjusted LVaR.

Figure 3: Schematic representation of the core equations governing portfolio LVaR

$$LVaR_P = \sqrt{\begin{pmatrix} LVaR_A & LVaR_B \end{pmatrix} \begin{pmatrix} 1 & \tau_{AB} \\ \tau_{BA} & 1 \end{pmatrix} \begin{pmatrix} LVaR_A \\ LVaR_B \end{pmatrix}}$$

Simple liquidity adjusted VaR

 $w_A N(CI - S_A) \sqrt{T}$

JS model liquidity adjusted VaR

 $w_A \rho_A S_A \left| \begin{array}{l} \mu_A \{E(\Delta S_A) + E(\ln[S_A])\} \\ - CI \left(\begin{array}{l} \sigma_A \sqrt{E(\Delta S_A)} + |\mu_A| \sigma_{\Delta S_A} \\ + \sigma_{\ln[S_A]} \end{array} \right) \end{array} \right|$

4. PROBABILITY OF DEFAULT DISCRIMINATION

The Basel Accord of 1988 was the first attempt by the Basel Committee on Banking Supervision (BCBS) to improve risk management practices in banks (BCBS, 1988). With much of the mathematics of risk management then still in its infancy, the accord did not address all risks faced by banks. Those risks that were covered required several amendments and improvements to the 1988 accord as practitioner's skills were honed and theory became best practice (BCBS, 1996 and 1998). Basel I addressed only credit and later market risk, but it soon became apparent that the former was too punitive in some aspects and too lenient in others. Basel I also completely ignored operational risk. These shortcomings and omissions have now been addressed in the new Capital Accord (or Basel II, as it has come to be known) with a much-improved treatment of credit risk as well as the incorporation of a set of methodologies to assist in the estimation of operational risk (BCBS, 2006). Market risk has been left largely unchanged in Basel II and weaknesses that do remain in the treatment of operational risk will no doubt be addressed in future versions of the accord.

The impact of the BCBS's new credit risk methodologies on bank's regulatory capital calculations are yet to be fully ascertained. The BCBS rolled out five versions of the Quantitative Impact Study (QIS) questionnaire to determine precisely this impact, but the results were mixed and not well accepted (BCBS, 2005). Basel II was implemented (January 2008) in many developed and emerging countries; and those not yet fully Basel II compliant are expected to follow suit by 2011. Thus, the theoretical results gleaned from the BCBS's QIS surveys have begun to be replaced by empirical data from bank's risk and compliance depart-

ments. The BCBS relies on practitioner feedback to adjust shortcomings in the accords: the Basel Accords themselves are not legislation, but rather "global best practice" guidelines established and implemented by representatives from major central banks.

The Basel Accords, however, seek to be all things to all banks in order to level the global playing field and provide useful benchmarks. As a result, a necessarily limited set of models have been developed to cover all risky possibilities facing banking institutions worldwide. Whilst these efforts are to be applauded, it is perhaps inevitable that some flaws and inconsistencies will appear. A feature of Basel II's treatment of credit risk measurement will be explored that is incompatible with its stated goal of providing capital incentives for better risk management practices.

The implementation of the new Basel Accord's non-advanced approaches in January 2008 heralded the inauguration of an ambitious, global banking project to encourage improved risk management in banks. The timetable established by the Banking Committee of the Bank for International Settlements originally intended this implementation to commence one year earlier, in 2007. The hiatus was blamed on implementation difficulties and a largely unprepared banking community. The situation has only marginally improved: many institutions – in both developed and emerging markets – remain woefully ill-prepared and local regulators sometimes lack the requisite sophistication.

Many of these problems stem from the complexities of credit risk measurement. The enormous popularity of VaR (as the metric of choice for measuring market risk) is largely due to its endorsement by the 1996 amendment to the 1988 Basel Accord, but its relative simplicity, adaptability and applicability to a wide range of products have also played a role. Credit risk – by contrast – is more complex: the distribution of institutional credit losses is highly skewed, it relies on complicated mathematics (e.g. copulas) to explain links between the economic milieu and loan values, it involves an understanding and differentiation of equity, asset and default correlations and it requires several more parameters (e.g. loss given default, probability of default, exposure at default) – each related to the other in complex ways – than market risk.

The new accord has undergone (planned) multiple revisions, augmentations and excisions and, given the experience garnered from the 1996 amendment to the 1988 Accord, it is likely that Basel II will be further revised at some or several points in the future. These alterations are generally welcomed as they represent an egalitarian, best-practice approach to global

banking. For the moment, the credit risk environment is highly fluid, constantly evolving and improving as techniques are honed and perfected. Enthusiastic debate and concentrated research is in progress and it is to be expected that the fruits of these labours will yield results that will show segments of the new accord to be inadequate, inaccurate or completely wrong. Given the intensity of the research that has already incorporated into Basel II, complete rewrites seem unlikely, but it is inevitable that models will improve as more information becomes available (Kaltofen, Paul and Stein, 2006).

Banks may choose between two approaches to calculate the capital requirement for credit risk: the standardised approach (a slightly modified version of the current Basel I Accord) and the internal ratings based (IRB) approach (in which banks are permitted to use their own internal estimates of prescribed key risk drivers as inputs to the capital calculation). In the IRB approach, regulatory minimum capital for a loan portfolio is calculated in a bottom-up manner, by estimating and then summing capital requirements at the individual loan level. Loan capital requirements are derived using the Asymptotic Single Risk Factor (ASRF) model. Although the BCBS neither cites nor documents this model, it is widely believed that Gordy's (2003) work (itself largely derived from an adaptation of the single asset model of Merton (1974), later extended to an entire portfolio by Vasicek (1977) was the precursor to the regulatory equations. Pykhtin and Dev (2002) further extended Gordy's work.

In this model, portfolio credit risk is separated into two categories: systematic and idiosyncratic risk. Systematic risk represents the effect of unexpected changes in macroeconomic and financial market conditions on borrower performance. Idiosyncratic risk represents the effects of risk connected to individual companies. One of the ASRF approaches key assumptions is that the credit portfolio comprises a large number of relatively small exposures. As the portfolio becomes more and more fine-grained (i.e. the largest individual exposures account for smaller and smaller portfolio exposures), portfolio idiosyncratic risk is diversified away and all systematic risk – such as industry or regional risk – is modelled with only a single, common systematic risk factor which drives all dependence across credit losses in the portfolio. The model thus assumes that banks are well-diversified across all geographic and industrial sectors in large economies.

The ASRF model also assumes that the capital charge for a lending exposure is based solely on loan-specific information. Capital charges are thus calculated on a decentralised loan-by-loan basis first, and then aggregated up to portfolio-wide VaR afterwards.

Principal inputs supplied by the bank include the exposure at default (EAD), the probability of default (PD), the loss given default (LGD) and the effective remaining loan maturity (M). Given these inputs the IRB capital charge is computed by calculating capital charges on a decentralised loan-by-loan basis and then aggregating these up to a portfolio-wide capital charge.

The Standardised approach essentially mimics the Basel I approach to credit risk (with some minor adjustments) in which all loan types are assigned a risk weighting determined by the BCBS. The IRB approach – which comprises the Foundation (FIRB) and the Advanced (AIRB) approach – allows banks to assign their own internal ratings to loans. In the Foundation IRB Approach banks may only determine and use their own internal ratings (and associated probabilities of default), while in the Advanced Approach, banks may measure and use other inputs (over and above their own internal ratings) in the specified regulatory capital equations.

Banks are expected to forecast the average level of credit losses they can reasonably expect to experience over a one year horizon, known as expected losses (EL). Losses above this expected level – known as unexpected losses (UL) – occur occasionally, but their timing and severity are both unknown. Banks cover their EL continuously by provisions, write-offs and the incorporation of these expected losses into instrument pricing. Basel II requires banks to only hold capital against UL: the required capital per unit of currency exposure. A number of approaches exist to determine a bank's requisite capital. Basel II's IRB approach estimates the annual loss which will be exceeded with a small, pre-selected probability. This is considered the probability of bank insolvency (meant in a broad sense, including, e.g., the case of a bank failing to meet senior loan obligations).

A remarkable characteristic of the ASRF equation (apart from its simplicity) is its property of asymptotic capital additivity: the total capital for a large portfolio of loans is the weighted sum of the marginal capital for individual loans. That is, the capital required to add a loan to a large, diversified portfolio depends only on the properties of that loan and not on the portfolio to which it is added. The ASRF credit model is thus said to be portfolio invariant, a property that depends strongly on the asymptotic assumption, and especially on the assumption of a single systematic risk-factor. In addition, portfolios that are not asymptotically fine-grained (i.e. any single obligor represents a negligible share of the portfolio's total exposure) contain undiversified idiosyncratic risk. In this case, the marginal contributions to the economic capital depend on the rest of the portfolio.

A brief description of each of the principal input parameters follows.

Probability of default

Under the IRB approach, PDs are obtained from banks' internal rating systems. These should be averages, reflecting expected default rates under normal business conditions (BCBS, 2006a).

Two kinds of models for determining probabilities of default are commonly addressed in the literature, namely accounting based models and market based models. Discriminant analysis and logistic regression models belong to the first class. The popular Z-score (Altman, 1968) is based on linear discriminant analysis, while Ohlson's O-Score (Ohlson, 1980) is based on generalised linear models (GLM) with the logit link function. Newer accounting based models are founded on neural networks (Wilson and Sharda, 1994) and Generalised Additive Models (GAM) (Berg, 2004).

Market models are based on the firm's asset value, determined by the market, such as Moody's KMV model. Stock prices are used as proxies for the asset value of the firm – implying that these models require stock exchange-registered (publicly listed) firms: a circumstance not fulfilled for many small and medium-sized borrowers.

Loss given default

In the capital formula it is assumed that the loss given default rate (which is equal to one minus the recovery rate) is known and non-stochastic. During an economic downturn, losses on defaulted loans are likely to be higher than under normal business conditions, because for instance collateral values may decline. Average loss severity figures over long periods of time can understate LGD rates during an economic downturn, and may therefore need to be adjusted upward to appropriately reflect adverse economic conditions.

Hence, conservative values should be chosen so as not to underestimate portfolio risk. The Basel formulation thus requires that a "downturn" LGD is estimated for each client/risk segment. Due to the evolving nature of bank practices in the area of loss given default quantification, the BCBS has not proposed a specific rule for estimating the LGDs. Instead banks are required to provide their own estimates, but they may use supervisory estimates if they have adopted the foundation IRB approach for wholesale exposures.

Exposure at default

Under the advanced IRB approach, banks are allowed to use their own estimates of expected exposure at default for each facility. EAD comprises two parts: the amount currently drawn and an estimate of future draw downs of available, but untapped, credit. Estimates of potential future draw downs (i.e. how the client may decide to draw unused commitments) are known as credit conversion factors (CCFs). Since the CCF is the only random or unknown proportion of EAD, estimating EAD amounts to estimating this CCF. CCFs depend on both the type of loan and the type of borrower.

Default correlations

The single systematic risk factor required in the ASRF model may be interpreted as reflecting the state of the global economy. The degree of an obligor's exposure to this systematic risk factor is expressed by the asset correlation. Asset correlations link the movements of how asset values of one borrower depend on the asset values of another. In a similar way, the correlation can be described as the dependence of the asset value of a borrower on the general state of the economy – all borrowers are linked to each other by this single risk factor.

Asset correlations influence the structure the risk weight formulas. They are asset class-dependent since different borrowers and/or asset classes show different degrees of dependency on the overall economy. It is important to note that asset correlation and default correlation are not the same: the way in which they are related is explained elsewhere (Zhang, Zhu and Lee, 2008).

In the IRB approach, asset correlations are not estimated by banks. Instead they are calculated according to equations provided by the BCBS. These are based on two empirical observations (Lopez, 2004), namely that asset correlations decrease with increasing probability of default and increase with firm size.

This implies that the higher the probability of default the higher the idiosyncratic risk components of an obligor. Moreover, conditional on a certain probability of default, assets of small and medium sized enterprises are less correlated. If two companies of different size have the same PD, it follows that the larger one is assumed to have a higher exposure to the systematic risk factor. Larger firms are therefore more closely related to the general conditions in the economy, while smaller firms are more likely to default for idiosyncratic reasons. The BCBS has provided different formulas for computing the asset correlations for different business segments. These are discussed in detail in BCBS (2006).

Many banks have reported significant regulatory capital relief due largely to more accurate capital allocation in, e.g., large mortgage portfolios. This is due to the significant reduction in risk weights applied to loans in this asset class by the shift from Basel I (50%) to Basel II (variable). Although risk weights vary, for a loan portfolio comprising high quality mortgage loans (i.e. PDs), it is not unusual to observe significant capital charge reductions through the use of Basel II.

Despite this – and other – capital charge reductions, most banks in the transition from Basel I to Basel II have remained approximately "capital neutral" with capital benefits (derived from more accurate capital allocation for credit risk) being re-absorbed by capital charges for operational risk. Many banks continue to emphasise that the reduction of capital charges by ever more refined methods will become a principal focus in the future (Calem and Follain, 2007; Calem and LaCour-Little, 2003; and Herring, 2007).

In the light of these efforts, this study was instituted to investigate the possibility of minimising the capital charges by optimising the allocation of risk grades. More obvious methods of capital charge reduction involve improving the loan portfolio quality (lower PDs and LGDs, for example). As such considerations are the chief business of banks, they remain outside the orbit of scrutiny and influence of academic studies and will thus not be considered here. Optimising the capital charge an institution faces involves minimising these charges within both the Basel II framework and actual loan parameters unique to each bank. It should be noted, however, that 'optimisation' in this context refers to capital charge optimisation through PD grade allocation and not to capital charge optimisation through 'improved risk management'. The BCBS endeavours to encourage banks to embrace the latter aim, not the former. It has been found, however, that over a range of loan quality for some loan types, enhanced borrower discrimination (and hence enhance PD discrimination) increase regulatory capital charges despite the employment of expensive resources for this Committee-endorsed, laudable aim for no empirical reason. The effect – entirely due to underlying mathematics – could discourage banks from improving risk management for such loans, thereby contravening the Committee's aims. The source of the problem is located, investigated and its effect on regulatory capital explored (Botha and van Vuuren, 2009).

5. EMPIRICAL ASSET CORRELATIONS FOR RETAIL LOANS

In order to remain solvent under all but the most severe of circumstances, banks dedicate a battery of resources to the accurate, timely calculation of their economic capital. This is an

internal measure, designed to cushion against calamitous events, and it embraces the catholic array of risks faced by banks as well as any diversification benefits that arise between disparate risks. As such, economic capital is distinct from regulatory capital which is externally imposed by national regulatory bodies, covers only a handful of risks, ignores inter-risk diversification and applies fairly rigid constraints on the way capital reserves should be measured. Regulatory capital and all matters pertaining thereto is governed by two accords, designed and disseminated by the Basel Committee on Banking Supervision (BCBS). The accord of 1988 (Basel I) was an attempt by the BCBS to improve the risk management procedures practiced by banks (BCBS, 1988). Basel I addressed only credit (and, later, market (BCBS, 1996)) risk, but somewhat coarsely across loan quality with little or no distinction made between superior and inferior borrowers. Capital charges determined using the 1988 accord were considered by banks to be punitive and inequitable (Repullo, 2004). The assembly and extensive implementation of the Basel II Accord has heralded, amongst other changes,¹⁵ a much improved treatment of credit risk (BCBS, 2006a). In their treatment of credit risk, banks now have the option of adopting either the Standardised approach (in which risk weights for loan exposure amounts are specified by the BCBS – similar to Basel I) or the Internal Ratings Based (IRB) approach (in which specific capital requirement formulas are specified by the BCBS, but some flexibility regarding the input parameters is allowed).

The IRB approach harnesses quantitative estimates of obligor-level risk (e.g., the probability of default (PD) and loss given default (LGD)) and is grounded in well-established concepts from modern portfolio-based risk management, thereby providing a sophisticated and more meaningful capital framework than Basel I. The IRB approach employs an asymptotic single-risk factor (ASRF) calculation methodology that allows relatively straightforward analytical solutions, rather than a full-blown multi-factor model typical of internal bank credit economic capital systems. Nevertheless, the IRB approach is based upon credit risk modelling concepts that are broadly consistent with capital models used increasingly by banks to measure portfolio-level risk and to manage and allocate capital across the enterprise.

The single systematic risk factor required by ASRF models can be interpreted as a reflection of the state of the global economy. All borrowers are linked to one another by this single risk factor and the way in which strength of that linkage is measured by the asset correlation. The BCBS has calibrated and set predetermined values for the asset correlation within each of the IRB formulas, which are broadly segmented by asset class definitions specified under Basel

¹⁵ In the treatment of operational risk, for example.

II (e.g., corporates, commercial mortgages, residential mortgages, credit cards and consumer lending) (Gore, 2006). Asset correlations thus determine the shape of the risk weight formulas and, because different borrowers and/or asset classes show different degrees of dependency on the overall economy, asset correlations are asset class dependent.

Banks must comply with regulatory rules to sustain capital adequacy and in so doing they must use the BCBS pre-specified asset correlation values. Economic capital models provide valuable additional information that banks use in their overall assessment of their capital adequacy (Burns, 2005) and they therefore retain an avid interest in the estimation of implied asset correlations embedded in their empirical loss data – independent of the BCBS specifications. These values are of critical import in internal economic capital models.

The BCBS explained and defended the choice of credit risk framework, equations and correlation values in a special 'explanatory note' (BCBS, 2005). The note does not divulge the analytical reasoning nor the mathematical foundations upon which the IRB approach is based, presenting broad conclusions instead. This was a deliberate attempt by the BCBS to allow pertinent credit modelling concepts to be cemented into the consciousness of a select, non-technical audience. Much of the underlying technical formulation is described in Gordy (2002).

Lopez (2004) examined the empirical relationship between the average asset correlation, firm PD and firm asset size measured by the book value of assets by imposing the ASRF approach within the KMV methodology for determining credit risk capital requirements (Lopez, 2004). In a later, but related, paper, Lopez (2005) empirically examined the asset correlation using portfolios of U.S. publicly-traded real estate investment trusts (REITs) as a proxy for commercial real estate (CRE) lending more generally. CRE lending as a whole was found to have the same calibrated average asset correlation as corporate lending, providing support for the U.S. regulatory decision to treat these two lending categories similarly for regulatory capital purposes (Lopez, 2005).

Duchemin *et al.* (2003) measured the asset correlations for automotive lease exposures using a single systematic factor ordered probit model in which the obligor status was limited to two states: default and survival. This model made use of a restricted version of CreditMetrics™ (Gordy, 2000). The results of this analysis showed that the empirically estimated correlations were significantly lower than those specified by the BCBS. The authors suggested taking one

extra dimension (the volatility of the probability of default) into account in order to ascertain an adequate, empirical asset correlation (Duchemin, 2003).

Düllmann and Scheule (2003) addressed the gap between the impact of systematic risk on the loss-distribution of a credit-risky loan portfolio and the lack of empirical estimates of the default correlation. Ten years of monthly default data were used for over 50 000 German corporates. Results from this study suggested that the asset correlation parameter depends on both the probability of default as well as on the obligor firm size.

A comprehensive review of corporate defaults and the role of asset correlation was provided by Chernih, *et al.* (2006) and sources therein. It was acknowledged that asset correlations are only one source of dependence; explicitly modelling other dependencies (such as dependence between LGD and PD) underestimates unexpected losses unless empirical asset correlations (from default data) are increased. The authors concluded that default data is the best source of default correlations as no intermediate process is assumed, but admit that default data is invariably either sparse or unavailable.

Gore (2006) stresses that, for corporate loans, banks have developed sophisticated internal ratings-based models, and have collected abundant BCBS input IRB data including correlation parameters. In addition, for corporate loans, much academic research has been published on credit risk modelling (Fatemi and Fooladi, 2006). The picture for retail portfolios, however, is very different. Few academic papers have been published on the modelling of retail portfolio risks and the PD, LGD and exposure at default (EAD) data collected by banks is often sparse and lacking in detail (Gore, 2006).

Banks continue to struggle with systems and procedures required for retail loan portfolios in Basel II; many are not sufficiently sophisticated and some are inundated with other, more pressing implementation issues (Reeves, 2006). While various large banks have performed some retail loan analysis, the majority continue to apply the Basel rules without any focus on whether or not the BCBS-specified parameters produce realistic outcomes (Reeves, 2006).

A real need, therefore, exists for the development of a robust, yet practical, methodology to measure retail loan portfolio implied asset correlations. However, the lack of individual exposure default data coupled with the overall dearth of data for retail portfolios conspire to severely constrain detailed asset and default correlation studies for these asset classes. A full analysis of the Vasicek distribution from first principles, including a brief introduction to the

underlying processes responsible for driving asset values, can be found in Vasicek (2002) and sources therein.

Vasicek (1987, 1991, 2002) derived an expression for the distribution of credit portfolio losses using a Merton-type model. In this approach, the portfolio credit risk is quantified due to its potential default rate using a VaR approach. Vasicek achieved analytical tractability by assuming an ASRF framework (Gordy, 2003 and Bank and Lawrenz, 2003) which – apart from assuming only one systematic risk factor influences the default risk of all loans in the portfolio – also assumes the portfolio is infinitely fine grained (i.e. it comprises nearly an infinite number of credits with infinitely small exposures).

The retrieval of implied asset correlation values from empirical gross loss data – while possible – is non-trivial. The extraction of retail asset correlations, the assessment of their robustness and the comparison of these correlations to those specified by the BCBS are given by Botha and van Vuuren, (2009). On the whole, BCBS specified correlations are higher than empirically derived values. The derived correlations from the Vasicek and Beta distributions indicate broadly similar results while the Vasicek correlation appears to be more sensitive to the changing loss milieu now being experienced (February 2009). A possible reason for this is the relative sensitivity of the underlying distribution drivers, i.e., the mean and the mode of the gross losses for the Vasicek distribution and the mean and the standard deviation of the gross losses for the Beta distribution. The standard deviation changes relatively slowly with time, even during periods of abrupt loss data changes, because it is an average of squared deviations from the mean. The effect of this averaging is effectively to smooth out any large spikes that arise in the underlying data.

Even though the current, unfolding "credit crisis" has resulted in significantly elevated losses and increasing empirical asset correlations, the BCBS-specified correlation remains significantly higher than those derived empirically. These elevated correlations impose punitive regulatory capital charges on retail portfolios which, given the severity and atypical nature of the crisis, look increasingly unfair.

6. CONCLUSIONS

This paper presented the relevant literature regarding the assumptions of normal return distributions and the omission of liquidity risk in standard VaR models. The support for these notions – although previously widespread – has dwindled since the eruption of the credit crisis and was arguably the root cause thereof. In addition, the relevant literature regarding the BCBS's ASRF model and the assumptions associated therewith was discussed. Though com-

prehensive and robust, the model hides some flaws which could be exploited by banks to reduce regulatory capital (thereby violating the intention of the accord). Banks ignorant of Basel II's implicit, internal inconsistencies could be penalised (i.e. face increased capital charges) even if they apply extra effort into discriminating between loan probabilities of default.

The accord also enforces the use of correlation values determined by the BCBS which are far in excess of those asset correlations measured empirically. This mismatch of theory (Basel II) and reality (economic capital models) – although designed to be conservative – is overly punitive and completely insensitive to changing market conditions.

7. BIBLIOGRAPHY

- ACAR, E. and Middleton, A. 2004. Maximum drawdown: Further results. *Intelligent Hedge Fund Investing*, Ed. Schachter, B. London, *Risk Books*.
- ALEXANDER, C. 2001. Market models: A guide to financial data analysis. London, *Wiley Publishing*.
- ALMGREN, R. and Chriss, N. 1999. Value under liquidation. *Risk*, 12: 58 – 64.
- ALTMAN, E. 1968. Financial ratios, discrimination analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 4(8): 589 – 610.
- AMMANN, M. and Moerth, P. 2005. Impact of fund size on hedge fund performance. *Journal of Asset Management*, 6(3): 219 – 238.
- AMMANN, M. and Reich, C. 2001. VaR for nonlinear financial instruments — linear approximation or full Monte Carlo? *Financial Markets and Portfolio Management*, 15(6): 1 – 18.
- ANGELIDIS, T. and BENOS, A. 2005. Liquidity adjusted value at risk based on the components of the bid-ask spread. [Internet:] <http://ssrn.com/abstract=661281> [Date of access: 31 August 2007]
- BANGIA, A., Diebold, F. X., Schuermann, T. and Stroughair, J. 1998. Modelling liquidity risk. [Internet:] www.ssc.upenn.edu/~fdiebold/papers/paper25/bds.pdf [Date of access: 22 September 2006]
- BANGIA, A., Diebold, F. X., Schuermann, T. and Stroughair, J. 1999. Liquidity on the outside. *Risk*, 12(7): 68 – 73.
- BANK OF ENGLAND. 2008. Financial stability report: October 2008, 24. [Internet:] <http://www.bankofengland.co.uk/publications/fsr/2008/fsrfull0810.pdf>, [Date of access: 16 January 2009]
- BANK OF JAPAN. 2006. Recent Developments in hedge funds. *Financial Systems and Bank Examination Department*, Financial Markets Department: 1 – 65.
- BANK, L. and Lawrenz, J. 2003. Why simple, when it can be difficult? *Kredit und Kapital*, 36(4): 534–556.
- BAXTER, M. 2008. Bank losses – how do they compare with past profits? [Internet:] <http://defaqto.blog.com/iabn/2008/09/01/bank-losses-compare-profits/>, [Date of access: 16 January 2009]
- BCBS. 1988. International convergence of capital measurement and capital standards. [Internet:] <http://www.bis.org/publ/bcbsc111.htm>, [Date of access: 23 January 2008]
- BCBS. 1996. Amendment to the capital accord to incorporate market risks. [Internet:] <http://www.bis.org/publ/bcbs24.htm>, [Date of access: 17 June 2008]

- BCBS. 1998. Amendment to the Basel capital accord of July 1988. [Internet:] <http://www.bis.org/publ/bcbs36.htm>, [Date of access: 22 January 2008]
- BCBS. 2005. An explanatory note on the Basel II IRB risk weight functions. [Internet:] <http://www.bis.org/bcbs/irbriskweight.pdf>, [Date of access: 21 May 2008]
- BCBS. 2005. QIS 5: Fifth Quantitative Impact Study. [Internet:] <http://www.bis.org/bcbs/qis/qis5.htm>, [Date of access: 22 January 2008]
- BCBS. 2005. The application of Basel II to trading activities and the treatment of double default effects. [Internet:] www.bis.org/publ/bcbs111.htm [Date of access: 28 December 2006]
- BCBS. 2006a. International convergence of capital measurement and capital standards: A revised framework - Comprehensive Version. [Internet:] <http://www.bis.org/publ/bcbs128.htm>, [Date of access: 23 November 2007]
- BCBS. 2006b. Results of the fifth quantitative impact study (QIS 5). [Internet:] <http://www.bis.org/bcbs/qis/qis5results.pdf> [Date of access: 21 June 2008]
- BERG, D. 2004. Bankruptcy prediction by generalized additive models. [Internet:] , http://www.math.uio.no/eprint/stat_report/2005/01-05.pdf, [Date of access: 12 October 2007]
- BIRGER, J. 2006. Investing: Don't hedge your bets after all. *Fortune*, [Internet:] http://money.cnn.com/magazines/fortune/fortune_archive/2006/05/15/8376864/ [Date of access: 7 November 2007]
- BIS. 1988. International convergence of capital measurement and capital standards. [Internet:] www.bis.org/publ/bcbs04a.htm [Date of access: 12 August 2006]
- BIS. 2004. International convergence of capital measurement and capital standards: A revised framework. [Internet:] www.bis.org/publ/bcbsca.htm [Date accessed: 17 December 2006]
- BIS. 2005. The application of Basel II to trading activities and the treatment of double default effects. [Internet:] www.bis.org/publ/bcbs111.htm [Date of access: 28 December 2006]
- BLAKE, D., Cairns, A. and Dowd, K. 2000. Extrapolating VaR by the square-root rule. *Financial Engineering News*, [Internet:] www.fenews.com/fen17/var.html [Date of access: 14 November 2006]
- BOLLERSEV, T., Chou, R. Y. and Kroner, K. F. 1992. ARCH modelling in finance: a selective review of the theory and empirical evidence. *Journal of Econometrics*, 52(3): 5 – 59.
- BOTHA, M. 2005. Risk Management in Hedge funds, *Masters dissertation*, University of the North West, South Africa.
- BOTHA, M., and van Vuuren, G. 2009. Retail credit capital charge optimisation and the new Basel Accord, *Risk Management in Financial Institutions*, 2(3): 45 – 68.
- BOUCHAUDY, J. P. and Potters, M. 1999. Worst fluctuation method for fast value at risk estimates. *Service de Physique de l'etat Condense.*, Centre d'etudes de Saclay, [Internet:] <http://ssrn.com/abstract=181949>, [Date of access: 11 September 2006]
- BURNS, R. L. 2005. Economic capital and the assessment of capital adequacy. *FDIC Supervisor Insights*, [Internet:] http://www.fdic.gov/regulations/examinations/supervisory/insights/siwin04/economic_capital.html, [Date of access: 12 June 2008]
- CALEM, P. and Follain, J. R. 2007. Regulatory capital arbitrage and the potential competitive impact of Basel II in the market for residential mortgages. *The Journal of Real Estate Finance and Economics*, 35(2): 197 – 219.
- CALEM, P. and LaCour-Little, M. 2003. Risk-based capital requirements for mortgage loans. *Journal of Banking and Finance*, 28(3): 647 – 672.
- ÇETIN, U., Jarrow, R. A., Protter, P. and Warachka, M. 2004. Option pricing with liquidity risk. [Internet:] www.orie.cornell.edu/~protter/WebPapers/bspaper3.pdf, [Date of access: 2 October 2006]

- CHENG, C. 2002. Securitization & hedge funds: creating a more efficient market. *Intangis Funds Research Report*: 1 – 11.
- CHERNIH, A. V. and Henrard, S. 2006. Asset correlations: A literature review and analysis of the impact of dependent loss given defaults. *Working Paper*. [Internet:] http://www.econ.kuleuven.be/insurance/pdfs/CVH-AssetCorrelations_v12.pdf [Date of access: 22 May 2008]
- COSANDEY, D. 2001. Adjusting value at risk or market liquidity. *Risk*, 10:115 – 118.
- DANIELSSON, J. and Zigrand, J. 2006. On time-scaling of risk and the square-root-of-time rule. *Journal of Banking & Finance*, 30(10): 2701 – 2713.
- DIEBOLD, F. X. and Lopez, J. 1995. Modelling volatility dynamics. Kevin Horner (ed): *Macroeconomics: developments, tensions and prospects*. Boston: Kluwer Academic Press.
- DIEBOLD, F. X., Hickman, A., Inoue, A. and Schuerman, T. 1996. Converting 1-day volatility to h -day volatility: scaling by \sqrt{h} is worse than you think. [Internet:] www.ssc.upenn.edu/~diebold/, [Date of access: 18 October 2006]
- DU TOIT, B. 2005. The Omega function: part 1: An Introduction. *Vikela*, 3: 4 – 6.
- DUCHEMIN, S., Laurent, M. and Schmit, M. 2003. Asset return correlation: The case of automotive lease portfolios. *Working Paper: WP-CEB 03/007* Centre Emile Bernheim, Solvay Business School, Université Libre de Bruxelles, [Internet:] <http://www.solvay.edu/EN/Research/Bernheim/documents/wp03007.pdf>, [Date of access: 2 June 2008]
- DÜLLMANN, K. and Scheule, H. 2003. Asset correlation of German corporate obligors: Its estimation, its drivers and implications for regulatory capital. *Deutsche Bundesbank*. [Internet:] <http://www.bis.org/bcbs/events/wkshop0303/p02duelsche.pdf>, [Date of access: 2 June 2008]
- ERWAN, L. 2002. Incorporating liquidity risk in VaR models, June. [Internet:] www.gloriamundi.org/picsresources/els.pdf, [Date of access: 17 December 2006]
- FATEMI, A. and Fooladi, I. 2006. Credit risk management: a survey of practices. *Managerial finance*, 32(3): 227 – 233.
- FERNANDEZ, F. A. 1999. Liquidity risk: new approaches to measurement and monitoring. [Internet:] www.sia.com/research/pdf/workingpaper.pdf, [Date of access: 21 November 2006]
- FIFORD, C. 2004. South African hedge fund industry grows by stealth. *Alternative Investment Management Association Journal*, 7(2): 11 – 13.
- FINANCIAL TIMES. 2006. Call to abolish hedge fund rules limiting investor access. July 4.
- FINANCIAL TIMES. 2006. Performance of hedge funds steadies but the fears persist, July 10.
- FSA. 2006. Private equity: a discussion of risk and regulatory engagement. *Working Paper, 06/06*. [Internet:] http://www.fsa.gov.uk/pubs/discussion/dp06_06.pdf [Date of access: 5 June 2006]
- FUNG, W., Hsieh, D. A., Naik, N. Y. and Ramadorai, T. 2006. Hedge funds: Performance, risk and capital formation. *Cepr Discussion Paper No. 5565* [Internet:] SSRN: <http://ssrn.com/abstract=912465>, [Date of access: 28 July 2008]
- GÉHIN, W. 2005. Is performance persistence a viable criterion for selecting hedge funds? *Hedge Funds Review*, 5(8): 40 – 41.
- GORDY, M. 2000. A comparative anatomy of credit risk models. *Journal of Banking & Finance*, 24(1): 119 – 149.
- GORDY, M. 2002. A risk-factor model foundation for ratings-based bank capital rules. *Working Paper #2002-55*, Board of Governors of the Federal Reserve System. [Internet:] <http://www.federalreserve.gov/pubs/feds/2002/200255/200255pap.pdf>, [Date of access: 11 June 2008]

- GORDY, M. 2003. A risk-factor model foundation for ratings-based bank capital rules. *Journal of Financial Intermediation*, 12(9):199 – 232.
- GORE, G. 2006. Correlation confusion. *Risk*, 19(7): 7 – 9.
- HAUSMAN, J., Lo, A. and MacKinlay, A. C. 1992. An ordered probit analysis of transaction stock prices. *Journal of Financial Economics*, 31(1): 319 – 379.
- HEDGEWEEK. 2009. Hedge funds outflows take assets below USD1bn. [Internet:] http://www.hedgeweek.com/articles/detail.jsp?content_id=288265, [Date of access: 15 January 2009]
- HENNESSEE GROUP LLC. 2007. [Internet:] <http://www.hennesseegroup.com/>, [Date of access: 19 January 2009]
- HERRING, R. 2007. The rocky road to implementation of Basel II in the United States. *Atlantic Economic Journal*, 35(4): 411 – 429.
- HFRX Indices. 2006. [Internet:] https://www.hedgefundresearch.com/hfrx_reg/index.php?fuse=login&1162138035, [Date of access: 12 December 2008]
- HISATA, Y. and Yamai, Y. 2000. Research toward the practical application of liquidity risk evaluation methods. *Monetary and Economic Studies*, 12(1): 83 – 128.
- HOLTON, G. A. 2003. Value at risk: theory and practice. New York, *Academic Press*.
- JARROW, R. A. and Protter, P. 2005. Liquidity risk and risk measure computation. *Review of Futures Markets*, 14(1): 2 – 17.
- JARROW, R. and Subramanian. A. 1997. Mopping up liquidity. *Risk*, 12: 170 – 173.
- JARROW, R. and Subramanian. A. 2001. The liquidity discount. *Mathematical Finance*, 11(4): 447 – 474.
- JASCHKE, S. R. 2002. The Cornish–Fisher expansion in the context of Delta–Gamma-normal approximations. *Journal of Risk*, 4(4): 33 – 52.
- JP MORGAN. 1996. Riskmetrics™ Technical Document. [Internet:] www.riskmetrics.com [Date of access: 12 January 2007]
- KALTOFEN, D., Paul, S. and Stein, S. 2006. Retail loans & Basel II: using portfolio segmentation to reduce capital requirements. *ECRI Research Report*, 8. [Internet:] <http://ssrn.com/abstract=958204> [Date of access: 13 October 2008]
- KAZEMI, H., Schneeweis, T. and Gupta, R. 2003. Omega as a performance measure. [Internet:] <http://www.edge-fund.com/bibliography.html> [Date of access: 7 January 2006]
- L'HABITANT, F. S. 2000. Hedge funds and investment partnerships: a primer. *Discussion Paper, Thunderbird*. The American Graduate School of International Management: 1 – 35.
- L'HABITANT, F. S. 2001. Assessing market risk for hedge funds and hedge fund portfolios. *The Journal of Risk Finance*, 2(4): 16 – 32.
- LAWRENCE, C. and Robinson, G. 1995. Liquidity, dynamic hedging and value at risk. *Risk Management for Financial Institutions*. Risk Pubs: 63 – 72.
- LE SAOUT, E. 2002. Incorporating liquidity risk in VaR models. [Internet:] www.site.voila.fr/erwanlesaout/eng/rech/abstract.htm#artc01 [Date of access: 19 September 2006]
- LEMKE, T. P., Lins, G. T., Hoenig, K. L. and Rube, P. S. 2006. Hedge Funds and Other Private Funds: Regulation and Compliance, Securities Handbook Series. New York, *Thomson West*.
- LO, A. 2006. Darwinian investing, *Business Week Online*, [Internet:] www.businessweek.com/magazine/content/06_08/b3972033.htm, [Date of access: 4 January 2009]

- LOPEZ, J. A. 2004. The empirical relationship between average asset correlation, firm probability of default, and asset size. *Journal of Financial Intermediation*, 13(2): 265 – 283.
- LOPEZ, J. A. 2005. Empirical analysis of the average asset correlation for real estate investment trusts. *Federal Reserve Bank of San Francisco*, Working Paper Series. [Internet:] <http://www.frbsf.org/publications/economics/papers/2005/wp05-22bk.pdf>, [Date of accessed: 11 June 2008]
- LOWENSTEIN, R. 2002. When genius failed: The rise and fall of long term capital management. New York, *Fourth Estate*.
- LUBY, W. 2008. The VIX, Lehman Brothers and forecasting. [Internet:] <http://www.greenfaucet.com/technical-analysis/the-vix-lehman-brothers-and-forecasting/43057>, [Date of access: 17 February 2009]
- MADHAVAN, A., Richardson, M. and Roomans, M. 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. *Review of Financial Studies*, 10(2): 1035 – 1064.
- MANDELBROT, B. and Hudson, R. 2005. *The misbehaviour of markets*. London, *Profile Books*.
- MCLEOD, W. and van Vuuren, G. W. 2004. Interpreting the Sharpe Ratio when excess returns are negative. *Investment Analysts Journal*, 59: 15 – 20.
- MCNEIL, A. J. 1996. Estimating the tails of loss severity distributions using extreme value theory, *Mimeo*, ETH Zentrum, Zürich: 117 – 137.
- MERTON, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(7): 449 – 470.
- MODIGLIANI, F. and Modigliani, L. 1997. Risk-adjusted performance. *Journal of Portfolio Management*, 17(3): 45 – 54.
- MULVEY, J. 2003. The role of hedge funds for long-term investors, *Journal of Financial Transformation*, The Capco Institute, 14(2): 23 – 28.
- MURALIDHAR, A. 2000. Risk-adjusted performance – the correlation correction. *Financial Analysts Journal*, 56(5): 63 – 71.
- OHLSON, J. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1): 109 – 131.
- ORLOWSKI, L. T. 2008. Stages of the 2007/2008 global financial crisis: Is there a wandering asset-price bubble? *Sacred Heart University*, Halle Institute for Economic Research. [Internet:] http://mpira.uni-muenchen.de/12696/1/MPRA_paper_12696.pdf, [Date of access: 19 February 2009]
- POLAKOW, D. and de Araújo, M. 2004. Procrustes and the poisonous portfolio: Introducing Omega. *Peregrine Securities Internal Report*, Peregrine Securities.
- POLAKOW, D., de Araújo, M. and Greyling, Y. 2006. Hedge fund bean encounters. *Derivative and Quantitative Research*: 1 – 22.
- PYKHTIN, M. and Dev, A. 2002. Analytical approach to credit risk modelling. *Risk*, 15: 26 – 32.
- RAJAN, A., Martin, B., Brown, T. and Johnson, M. 2005. Hedge funds: a catalyst reshaping global investment. [Internet:] www.kpmg.dk/getMedia.asp?mb_GUID=0F02D46B-F29E-4A43-8672-86A80B9750E5.pdf, [Date of access: 12 November 2007]
- REEVES, R. 2006. Managing director of SunGuard's Basel II Capital Manager Business Unit, London. Quoted in Gore, G. 2006.
- REPULLO, R. and Suarez, J. 2004. Loan pricing under Basel capital requirements. *Journal of Financial Intermediation*, 13(4): 496 – 521.
- RISK Magazine journalists, 2004. Private communication.

- SHADAB, H. B. 2007. The challenge of hedge fund regulation. *Regulation*, 30(1): 36 – 41.
- SHADWICK, W. F. and Keating, C. 2002. A universal performance measure. *Journal of Performance Measurement*, 6(3): 59 – 84.
- SHARMA, M. 2005. Sharper risk adjusted performance measures (RAPMs): From Omega to AIRAP. *HedgeQuest*: 12 – 19.
- SHARPE, W. F. 1966. Mutual fund performance. *Journal of Business*, 4(2): 119 – 138.
- SHARPE, W. F. 1988. Determining a fund's effective asset mix. *Investment Management Review*, 2(6): 59 – 69.
- SHARPE, W. F. 1994. The Sharpe ratio. *Journal of Portfolio Management*, 21(4):49 – 58.
- SONG, S. H. 2006. Risk and liquidity in a system context. *BIS Working Papers*, Monetary and Economic Department. [Internet:] www.bis.org/publ/work212.pdf [Date of access: 12 October 2007]
- STEVENS, G. 2006. Risk and the Financial System, *Reserve Bank of Australia*, Hong Kong Monetary Authority and Hong Kong Association of Banks. [Internet:] http://www.rba.gov.au/Speeches/2006/sp_dg_150906.html [Date of access: 1 May 2007]
- THE ECONOMIST. 2006a. Alpha betting. September 16, p. 97.
- THE ECONOMIST. 2006b. Still Free. July 1, p. 78.
- THE ECONOMIST. 2007. Exchange traded funds: revolution or pollution?' April 19, p 56.
- TREYNOR, J. L. 1966. How to rate management investment funds. *Harvard Business Review*, 43(1): 63 – 75.
- TREYNOR, J. L. and Black, F. 1973. How to use security analysis to improve portfolio selection. *Journal of Business*, 46(3): 66 – 86.
- UK FSA. 2005. Hedge funds: A discussion of risk and regulatory engagement. [Internet:] www.fsa.gov.uk/pubs/discussion/dp05_04.pdf [Date of access: 23 March 2006]
- UMUT, C., Jarrow, R. A. and Protter, P. 2004. Liquidity risk and arbitrage pricing theory. *Finance and Stochastics*, 8(11): 311 – 341.
- URBANI, P. 2005. The Omega risk measure. [Internet:] <http://www.edge-fund.com/UrbaniXXXXX.pdf>, [Date of access: 16 January 2006]
- VASICEK, O. 1977. An equilibrium characterization of the term structure. *Journal of Financial Economics*, 5(3): 177 – 188.
- VASICEK, O. 1987. Probability of loss on loan portfolio. *KMV Corporation*. [Internet:] <http://www.kmv.com>, [Date of access: 14 June 2008]
- VASICEK, O. 1991. Limiting loan loss probability distribution, *KMV Corporation*. [Internet:] <http://www.kmv.com>, [Date of access: 4 May 2008]
- VASICEK, O. 2002. The distribution of loan portfolio value. *Risk*, 15(12): 160 – 162.
- VON NEUMANN, J. and Morgenstern, O. 1947. *Theory of games and economic behaviour*. New Jersey, *Princeton University Press*.
- WILSON, R. and Sharda, R. 1994. Bankruptcy prediction using neural networks. *Decision Support Systems*, 11(5): 545 – 557.
- ZHANG, J., Zhu, F. and Lee, J. 2008. Asset correlation, realized default correlation, and portfolio credit risk. *Moody's KMV*. [Internet:] http://www.moodykmv.com/research/files/wp/Asset_Correlation_and_Portfolio_Risk.pdf, [Date of access: 1 June 2008]

Chapter 3

A comparison of South African hedge fund performance measures

A COMPARISON OF SOUTH AFRICAN HEDGE FUND PERFORMANCE MEASURES

MARIUS BOTHA *

Abstract

Although hedge funds have enjoyed unrivalled dominance after years of stellar returns, a combination of low interest rates, sustained economic growth and diminished arbitrage opportunities now threaten them. Distinguishing between funds – an onerous task with notoriously opaque investment strategies – has become paramount in the search for optimal returns. Simple risk and return performance measures cannot cope with the demands of an increasingly complex financial milieu. Interest has thus focussed on more effective discriminatory performance measures. The innovative Omega ratio is calculated for South African hedge funds and compared with both Sharpe and Sortino ratios. Omega emerges as the superior measure.

J.E.L. Classification: C13, C22, C32, C41, C53

Keywords: Hedge funds, Omega ratio, risk measurement, risk management.

1. INTRODUCTION

A benign global interest rate environment combined with indifferent regulatory scrutiny and a lack of viable investment alternatives has ushered in a flourishing hedge fund business for several years (HFRX, 2006). This situation is now being challenged on three fronts.

First, money in the global arena is becoming more expensive as interest rates continue to increase in the US, Japan and Euro area, putting pressure on equities and addressing the problems experienced by severely neglected fixed income markets.

Secondly, the ongoing education of the investment community has allowed investors to become far more able to discriminate between market returns (b) and manager out-performance (a), with investors increasingly expecting to pay only for the latter. Hedge funds have historically charged a (high) basic fee plus a percentage of profits, but the rise of exchange traded funds (ETFs) is calling these fees into question. Over 130 ETFs were launched internationally in the first half of 2006 – more than in the entire previous year. These quoted

*Threadneedle Investments, 60 St Mary Axe, London, EC3A 8JQ, UK and Visiting professor, School of Management, University of the Free State, PO Box 339, Bloemfontein, 9300, South Africa.

The author gratefully acknowledges the collation of data supplied by Sheldon Macdonald as well as the thorough proofreading and valuable comments provided by Dr Gary van Vuuren and Prof Philippe Burger – both of the School of Management, University of the Free State, South Africa.

securities track pre-specified indices and enable investors to acquire portfolios comprising a wide range of assets at relatively small fees compared to hedge funds. Some US\$500 billion of assets are now controlled by ETFs, and it is estimated that they will control over US\$2 trillion by 2011 (*The Economist*, 2006b). Private equity and large property portfolios (so-called 'alternative asset investments'), which grew by 20% in 2005, now have assets in excess of US\$1.25 trillion and enjoy enormous popularity for their flexibility and low fees.

Finally, the relatively unrestricted and unregulated milieu – so enjoyed by hedge funds – is coming under increased scrutiny. Legislators, regulators and a nervous public are beginning to demand the imposition of investment controls and restrictive policy rules on hedge funds (*The Economist*, 2006b, *Financial Times*, July 4 2006). This is unlikely to diminish, despite the overwhelming opposition of financial markets to these measures. It has been argued (Ammann and Moerth, 2005) that, in this age of electronic trading and highly complex automated searches for market value, arbitrage gaps in foreign exchange, equity and other markets have shrunk considerably. The quest for investment returns has become ever more frenetic (Bank of Japan, 2006). Hedge funds have provided a new vehicle for experimentation and improvisation: the highest returns since 2002 have been from these funds. Hedge fund assets currently total some US\$1.5 trillion from a global total of 10 000 funds (Géhin, 2005 and updated values in Fung *et al.* 2006, *The Economist*, 2006a and *Financial Times*, July 10 2006). The innovations that distinguish one hedge fund from another are *necessarily* covert: forced disclosure can only stifle originality.

Increased regulatory activity (Sarbanes Oxley, Basel II, IFRS standards) have loaded the market with onerous, costly (and some argue, *unnecessary*. See, for example, Lemke *et al.* 2006 and articles therein) scrutiny. Wary investors have shrunk from previously well-tested markets in an effort to forestall or forego regulatory penalties. This has drained the system of liquidity: the lubricant which ensures efficient, reduced-friction functioning (Song Shin, 2006). Historically, hedge funds have proved remarkably adept at pumping in liquidity to a thirsty market where and when such is lacking and mopping it up in times of critical oversupply. Free from regulatory scrutiny, hedge funds have proved to be efficient resource-allocators in recent years, surviving and indeed thriving, even in the recent lengthy benign credit environment which flooded the market with cheap money. Defenders of this view claim that:

"...by exploiting (and thereby eliminating) pricing anomalies and by being less encumbered by prudential controls than most other financial institutions, hedge

funds promote efficiency in the allocation of capital by searching out returns more effectively than others. On the assumption, moreover, that those who put money into hedge funds know what risks they are taking...people might take the view that what investors do with their money is their own business." (Stevens, 2006)

Hedge funds, however, are still highly risky investments: stellar returns cannot be achieved without spectacular risks. Critics claim that hedge funds

"...can overwhelm and distort small markets. A tendency for herd behaviour, and application of leverage, amplifies the problem, in the view of these critics. When hedge funds decide simultaneously to get into or out of a position, they can disrupt market functioning." (Stevens, 2006)

If no justification for high fees is forthcoming, it is unlikely hedge funds will continue to enjoy their vaunted status in the alternative investment arena. Hence the ongoing need for new measures to assess and manage hedge fund risk. The better the knowledge of the relative riskiness of a fund, the more efficient the allocation of investment capital and the fairer the apportionment of fees charged. In this regard, the recently introduced Omega ratio (Shadwick and Keating, 2002, and later adaptations thereof) has been met with cautious optimism (see, for example, Kazemi, 2003 and du Toit, 2005). While research in this field is still in its relative infancy, ongoing exploration has yielded innovations which highlight aspects of traditional performance ratios as well as explored limiting assumptions. This article explores the differences between the Omega and Sharpe ratios in their ranking of hedge fund risk-adjusted performance and analyses which of the two is the more accurate and reliable.

The remainder of this article is structured as follows: all investments have associated risks and the measurement and management of these is critical. Section 2 discusses traditional risk measures – usually performance indicators that combine the returns with the risk of a fund. Hedge funds, however, are subject to the same risks that plague other traditional investment vehicles, although arguably in different ways. In addition, risks unique to the investment strategy employed to generate exceptional returns have been identified. Assessment, monitoring and management of these risks have required a rethink of traditional performance measures – Section 3 provides a qualitative review of these traditional performance measures. Subsequently section 4 discusses mathematical descriptions of new (and adaptations of existing) performance measures – specifically designed to assess hedge fund risk, while Section 5 examines the data sample used for this study. Section 6 presents the results of the analysis and Section 7 concludes the article.

2. RISK IN TRADITIONAL FUNDS

Arguably the most widely used of the traditional risk-adjusted performance measures is the Sharpe ratio (Sharpe, 1966), defined as the quotient of the excess portfolio return over a risk-free rate and the portfolio standard deviation – in essence it is the price of excess return per unit of risk.

The traditional Sharpe ratio has enjoyed much success in the modelling of empirical financial data. It distinguishes reliably between two or more alternative investments, provided the returns to the assets in question are normally distributed and uncorrelated with the returns to the existing portfolio of a fund. The fund with the higher Sharpe ratio is chosen as the superior performer. In effect, the Sharpe ratio is taken as a proxy for the risk-adjusted return and the investment whose risk-adjusted return is highest is chosen. However, the traditional Sharpe ratio presupposes that the return of each prospective investment is uncorrelated with the return of the existing portfolio of the institution. Sharpe himself acknowledged that the Sharpe ratio may not give a reliable ranking if one or more of the assets involved are correlated with the rest of the portfolio (Sharpe, 1994). The Sharpe ratio has many desirable properties and it is relatively straightforward to comprehend and implement. This is evidenced by its use in the assessment of investment returns for over 40 years. However, the Sharpe ratio is a far from a perfect risk-adjusted performance measure.

The limitations inherent in the Sharpe ratio obscure some risks, particularly when considered against the background of the fundamental economic theory of decision making under uncertainty of Von Neumann and Morgenstern (1947). This theory is only consistent with the mean-variance portfolio approach under the following severely limiting conditions:

1. investment returns are normally distributed
2. the investor's utility function is quadratic (i.e. higher moments of the statistical distribution are ignored, which implies (unlikely) increasing absolute risk aversion) and
3. investment risk is 'small', i.e. second order Taylor approximation to the utility function is sufficient.

The common assumption that investment returns are normally distributed has been challenged repeatedly and vigorously (Mandelbrot and Hudson, 2005, and sources therein). The assumption of normality truncates the right tail of the returns distribution (profits) at the expense of fat left tails – i.e. the market crashes (Sharma, 2005). The Sharpe ratio is thus incapable of handling large risks concealed in higher statistical moments.

In addition, the Sharpe ratio is leverage invariant, while it also does not account for correlations. The market has recently expressed concern regarding the "increasingly high levels of correlation between supposedly diverse strategies, reduced liquidity in the financial system and excessive bullishness" (*Financial Times*, July 10 2006). Merrill Lynch claim that the correlation between hedge funds and the S&P500 index is 0.96, up from 0.32 measured in 2000 (Birger, 2006). Emerging market correlations are similarly implicated.

McLeod and van Vuuren (2004) argue that the fund with the maximum Sharpe ratio in declining markets is the fund with the highest probability of outperforming a risk-free investment. This contrasts with the standard interpretation that it is the fund with the largest excess return per unit of risk that has the maximum Sharpe ratio.

In order to address these shortcomings, Treynor (1966) extended the work of Sharpe and proposed his Treynor ratio. This ratio replaces the volatility of the portfolio with a measure of *systematic* risk. In addition, it makes use of the CAPM, i.e. investors should only expect risk compensation for exposure to non-diversifiable or systematic risk (Treynor, 1973). In addition, Sharpe (1994) provides improvements and reinterpretations of the Sharpe ratio, and introduces a relative performance measure, the Information ratio.

Modigliani and Modigliani (1997) present a further extension of Sharpe. They develop the M2 measure (where M2 stands for Modigliani and Modigliani) that compares portfolios by leveraging or de-leveraging them until they have identical volatility (normally chosen as the market volatility). This allows the comparison of portfolios by examining the resulting returns. The fund with the highest M2 will have the highest return for a given amount of risk. Muralidhar (2003) proposed the M3 measure that accounts for differences in the correlations of the various portfolios being compared.

The Sharpe ratio and its progeny are still limited by their inability to adequately capture higher statistical moments of the distribution. If standard assumptions regarding higher moments and the normality constraint are abandoned, a new approach is required. Sharma (2005) showed that the Sharpe ratio could be extended by replacing the denominator by the Value at Risk (VaR) at a given confidence interval. VaR – the expected return in a defined set of worst case scenarios – is based upon a mean-variance normal distribution but can easily be modified to incorporate skewness and kurtosis using the Cornish-Fisher expansion (Jaschke, 2002).

Although an improvement, this measure only incorporates the third and fourth moments of the distribution. Sharma therefore proposes a measure called Alternative Investment Risk Adjusted Return (AIRAP), which draws on the economic theory of expected utility.

Sharpe's traditional mean-variance paradigm has severe shortcomings which have not yet been satisfactorily resolved. In addition, the risks associated with traditional funds do not always translate into the hedge fund arena. Hedge funds by their nature aim to secure high, positive returns (and hopefully few large losses) so their return distribution is fat-tailed by design. Since higher statistical moments are not captured by traditional fund performance measures, others must be sought. The next section discusses these pertinent hedge fund risk characteristics.

3. RISK IN HEDGE FUNDS

Being relatively new financial instruments, hedge funds are affected by risks which are not yet exhaustively understood. This section provides a qualitative review of these risks.

The hedge fund investment arena was originally the almost exclusive domain of high net worth individuals for whom capital preservation was paramount. This has changed in recent years. The investment community has rallied to share in promised above-average returns and it is now not unusual for even well-established, conventionally risk-averse pension funds to experiment with these strategies (UK FSA, 2005). Higher returns are accompanied by higher risk and thus higher volatility, but the demand for low volatility¹ is much less important in hedge funds than low *downside* volatility. This has given rise to two types of measures based on the downside risk: the Sortino ratio and the maximum drawdown (MDD).

The Sortino ratio is closely related to the Sharpe ratio as it compares the return of a portfolio with a chosen minimum acceptable return or MAR (often the risk free rate), and divides it by the semi-standard deviation, which measures only the volatility of the downside, i.e. returns below the MAR. The next section presents the mathematical description of the Sortino ratio and its relationship with the Omega ratio.

Maximum Drawdown (MDD) measures describe the worst peak-to-trough fall in fund value over the history of the fund. However, the MDD has some limitations. For example, it can only be used for funds with the same time scale and similar reporting frequency. Though, in general, relatively new funds will have smaller MDDs than long-established funds, it is clearly a fallacious conclusion (based on the MDD) to only invest in new funds.

¹ A staple of traditional funds.

An adaptation of the 'historical' MDD is the numerical Monte Carlo approach. Estimated parameters of the return distribution (usually only the mean and variance) are used to generate many scenarios, of which the actual outcome is only one. Investors select a confidence level, say 95% or 99%, and ascertain the MDD. This provides a better guide to the underlying downside risk compared with the actual MDD. However, this approach, firstly, is based upon the assumption that the selected parameters accurately and fully describe the underlying returns and, secondly, that the parameters are relatively stable. Both of these are strong assumptions and not, in general, accurate. Although a further variation – the Calmar ratio – has been incorporated into the Sharpe ratio with mixed success, MDD is now widely considered to be an inefficient statistic for describing the performance of a fund and carries a high potential level of error (Acar and Middleton, 2004).

Having ascertained the nature of the unique risks associated with hedge fund investment strategies in general, measures employed to measure and manage these are explored in the next section.

4. THE OMEGA AND SORTINO RATIOS

Large and abrupt movements in portfolio returns are of great concern to investors. Depending upon the investment strategy employed, hedge fund returns generally have large outliers in both tails of their distributions; an indication of large risky bets that often succeed, but occasionally fail (Darwinian survivorship bias applies here. If a hedge fund fails more often than it succeeds, it will be quickly eradicated (Lo, 2006 and Rajan *et al.* 2005)). In addition, funds that are robustly and effectively hedged, exhibit severely skewed return distributions. The argument for the approximation of 'small risks' is thus also untenable (see Point 3, Section 2). The return distributions of hedge funds are, as a result, markedly non-normal and it is thus not appropriate to evaluate their performance within a mean-variance framework. A performance measurement tool that takes several order moments of the distribution function into account is thus required.

A relatively recent development, the Omega ratio (Shadwick and Keating, 2002), is based on novel interpretations of existing performance measurement techniques. The Omega ratio divides returns into losses and gains above and below a return threshold and determines the probability-weighted ratio of returns above and below this threshold. This is defined mathematically as

$$W(\tau) = \frac{\int_{\tau}^{\infty} (1 - F(R_t)) dR}{\int_{\tau}^{\infty} F(R_t) dR} \quad (1)$$

where

$W(\tau)$ is the Omega Ratio evaluated at a chosen threshold, τ ,

R_t is the random one-period return on an investment or fund and

$F(\cdot)$ is the cumulative density function for total returns on an investment.

Most performance ratios are of the form [expected return]/risk, as is the case with Sharpe, Sortino and the Information ratio, but the Omega ratio is different, expressed rather as a ratio of gains to losses (a direct consequence of which is that the Omega ratio is sensitive to the *potential* for excess returns, not only the mean return). The Omega ratio is ideally suited for evaluating the performance of hedge funds because it considers the entire distribution function of the investment under scrutiny. One weakness is its sensitivity to the size of the sample: at least 40–50 observations are necessary to obtain stable results. This is, however, no more or less onerous than several other performance ratios that have endured despite their reliance on abundant data.

The threshold level is selected by the practitioner – no level is 'better' than another: the choice of threshold level reflects a particular risk preference. A conservative investor might assign all returns below 0% as 'losses', and those above as 'gains'. A gain might also be considered to at least exceed the risk free rate (this is the most common choice of threshold level). A more aggressive strategy might demand a threshold more similar to the Minimum Acceptable Return described above.

The Omega function is simply the Omega ratio evaluated at all threshold levels from the highest observed return to the lowest. To understand the shape of the Omega function (see Figure 1, for example) and the information it provides, it is instructive to first consider the extremes of the function. To the left of the x -axis origin, as the threshold value is chosen to be increasingly more negative, fewer and fewer returns will count as losses in the data set. At some point the threshold will be lower than the lowest return in the data set, at which point the denominator in Equation 1 becomes 0 and the ratio tends to infinity. The sooner the ratio heads for infinity, the less risky the portfolio on the downside, because this implies that there

are few negative returns – or at least not very large ones. Moving to the right of the x -axis origin, increasingly fewer returns greater than the threshold are found, and eventually none. At this point the numerator (and thus the ratio) becomes 0. The slower the Omega ratio tends to 0, the bigger the potential for positive returns (or 'gains'). In general the steeper the slope of the Omega function, the lower the risk.

This measure (and its continuous counterpart, measured at all thresholds – the Omega function) has been discussed in detail by Polakow, *et al.* (2005), Urbani (2005), du Toit, (2005), Polakow and de Araújo (2004), and Kazemi, *et al.* (2003) and sources therein.² Most of the above sources relate specifically to the application of the Omega ratio and function to South African hedge fund data.

Before proceeding to the analysis and discussion of results, some mathematical detail is now provided on relevant ratios.

As stated earlier, the Sortino ratio is closely related to the Sharpe ratio and is defined as:

$$S = \frac{m - \tau}{\sqrt{\int_{-\infty}^{\tau} (\tau - R_t)^2 dF(R)}} \quad (2)$$

where

m is the average return on the investment

τ is the selected return threshold

R_t is the random one-period fund return

$F(\cdot)$ is the cumulative density function for total returns on an investment and

T is the sample size, measured at intervals of t .

The Omega and Sortino ratios have been shown (Kaplan, 2004) to be mathematically related by their lower partial moments (LPMs) which Harlow (1991) defined as

$$LPM_n(\tau) = \int_{-\infty}^{\tau} (\tau - R_t)^n dF(R) \quad (3)$$

where

² The website <http://www.edge-fund.com/bibliography.html> provides invaluable resources for readers interested in hedge fund performance.

n is the order of the lower partial moment and

τ is the chosen return threshold.

The Sortino ratio may be written (combining Equations 2 and 3)

$$S_o = \frac{m - \tau}{\sqrt{LPM_2(\tau)}} \quad (4)$$

where

$LPM_2(\tau)$ is the second order lower partial moment.

However, the Omega ratio may be written as (combining Equation 1 and 3, and see Harlow (1991))

$$W(\tau) = \frac{m - \tau}{LPM_1(\tau)} + 1 \quad (5)$$

The first order lower partial moment (i.e. the relevant LPM for the Omega ratio) can be estimated from a sample of fund returns by treating the observations as points in a discrete return distribution. This leads to

$$LPM_n(\tau) = \frac{1}{T} \sum_{t=1}^T \max[\tau - R_t, 0]^n \quad (6)$$

where

T is the sample size, measured at intervals of t

n is the order of the lower partial moment and

R_t is the t^{th} return observation and

τ is the chosen return threshold.

Equation 6 was used to measure the relevant lower partial moments and hence both the Omega and the Sortino ratios. These ratios will be compared and contrasted with Sharpe ratio calculations, under identical conditions, of the same data.

The one-period Sharpe ratio, S_p , is defined as

$$S_p = \frac{m_p - R_f}{S_p} \quad (7)$$

where

m_p is the average return on the portfolio measured by determining the geometric average of a minimum of 36 return observations

R_f is the risk free rate, *measured over the same period as the portfolio*, and in the same way (i.e. the geometric average of a minimum of 36 observations) and

s_p is the one-period volatility of the portfolio, measured using the conventional standard deviation formula, namely:

$$s_p = \frac{1}{T-1} \sum_{t=1}^T (R_t - m)^2 \quad (8)$$

where

R_t is the one-period portfolio return, measured at t -intervals over the full period under investigation, T and

m is the average portfolio return over the full period.

The methodologies reviewed in this section were applied to South African hedge fund data and the three ratios (Omega, Sharpe and Sortino) were calculated for each of these funds. The data chosen for this analysis span some 6½ years and comprise a range of hedge fund returns from various investment strategies. The next section discusses the selection and vetting of the relevant data.

5. SOUTH AFRICAN HEDGE FUND DATA

The data sample comprises monthly data selected from 35 South African hedge funds over a period of 90 months, starting in January 1999. The speed of the growth in hedge funds is emphasised by the number of reporting funds in the sample. Only two funds submitted data to NedGroup Investments (the group responsible for the collation and dissemination of these data) in January 1999, 11 by 2003 and 35 by January 2006. However, it is important to note that hedge funds are not required by statute to report fund returns, though the general trend is encouraging.

Four different types of hedge fund were selected for the survey: fixed interest (3), long-short equity (13), market neutral (11) and trading (8). These descriptive labels are imposed by the funds themselves. Results indicate that, on average, the risk/return profiles of specific funds do indeed behave in line with their stated strategy. The investment strategies employed by these categories are outlined below.

Fixed interest: These employ strategies to exploit relative mispricings among related fixed income securities. Strategies typically focus on mispricing relative to a single risk factor – duration, convexity, or yield curve changes – increasing risk control by neutralizing residual factors. Unanticipated changes in a yield spread can result in losses even on basic trades, such as trading futures against cash, if the securities are marked to market before adjustments are made. Their primary focus is on yield or current income rather than solely on capital gains. These funds may utilize leverage to buy bonds and sometimes fixed income derivatives in order to profit from principal appreciation and interest income. Their expected volatility is low (Magnum funds, 2006).

Long-short equity: combine purchases (long positions) with short sales typically using various quantitative models to rank stocks, then buying top-tier stocks and shorting those in the bottom tier, seeking to 'double alpha'.³ Portfolios often are net long or net short with systematic risk exposure and bets on size, industry, sector, and/or country risk factors. Expected volatility is low.

Market neutral: employ individual stock-selection strategies in a market-, industry- and sector-neutral portfolio to identify small but statistically significant return opportunities both long and short. Market risk is greatly reduced, but effective stock analysis and stock picking is essential to obtaining meaningful results. These funds use quantitative risk control to minimize systematic risk and balance long and short positions. Imperfect hedges may result from poor stock selection or from the impact of selection uncertainty and leverage may be used to enhance returns. There is usually low or no correlation to the market and these funds sometimes use market index futures to hedge out systematic (market) risk. The relative benchmark index is usually a portfolio of government bonds. The expected volatility is low (Magnum funds, 2006).

Trading: traders (in this context) are equity long-short managers who tend to select positions (which are very short-lived – usually a few days at most) based on technical analysis or some other mechanical, quantitative model that relies on some analysis of price movements or other share trading data. Expected volatility is high (Macdonald, 2006).

The risk free rate chosen was the 3-month JIBAR call rate available from the Reserve Bank (Reserve Bank, 2006) and the daily JSE ALSI price index was obtained from Bloomberg.

³ Alpha and beta are the coefficients of a single factor regression between a stock/fund and a relevant index (with alpha the intercept and beta the gradient of the regression line) as required by the Capital Asset Pricing Model. Positive alpha refers to a positive fund return even when the index return is zero. As hedge funds are permitted to use leverage (i.e. hold short positions) it is possible they can generate positive alpha from both long and short positions – hence 'double alpha'.

Equipped with these data, the Sharpe, Sortino and Omega ratios were measured for a sample of South African hedge funds using the methodologies discussed in the previous section. The next section presents the results of this analysis.

6. ANALYSIS AND RESULTS

The Omega ratio was first measured over a range of selected threshold returns (from -10% to +10% in discrete 0.2% increments) for each of the hedge funds in the sample using the full 90-month data set. This resulted in a set of Omega functions. Five representative Omega functions are shown below in Figures 1(a) through (e) (for typical fixed interest, long-short equity, market neutral and trading funds and – for comparison – the JSE ALSI index).

Figure 1: Typical Omega functions for (a) fixed interest funds, (b) long-short equity funds, (c) market neutral funds, (d) trading funds and (e) the JSE ALSI index, for comparison.

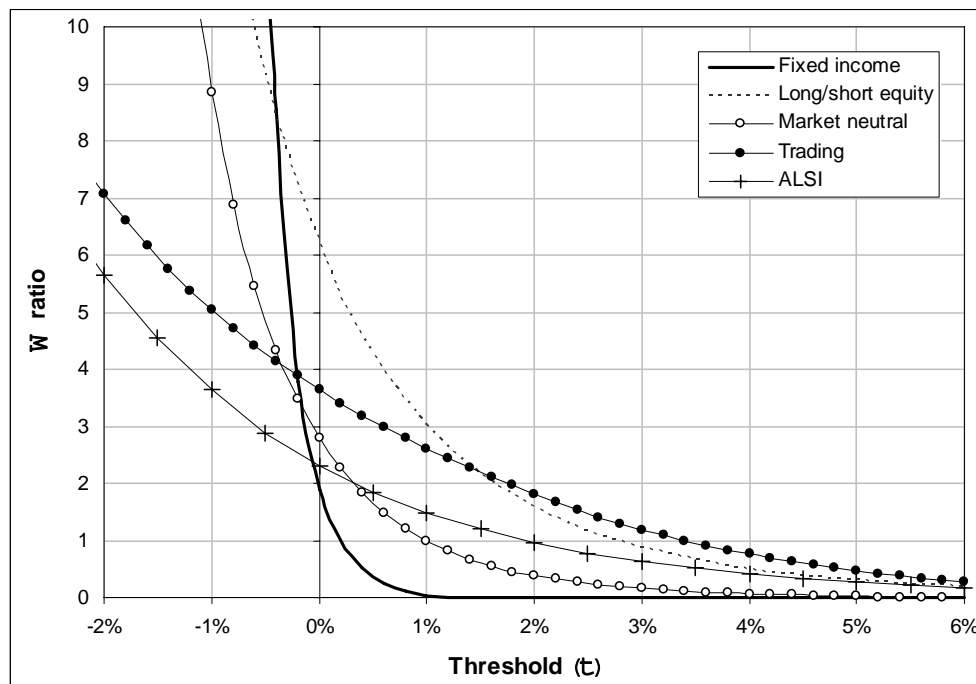


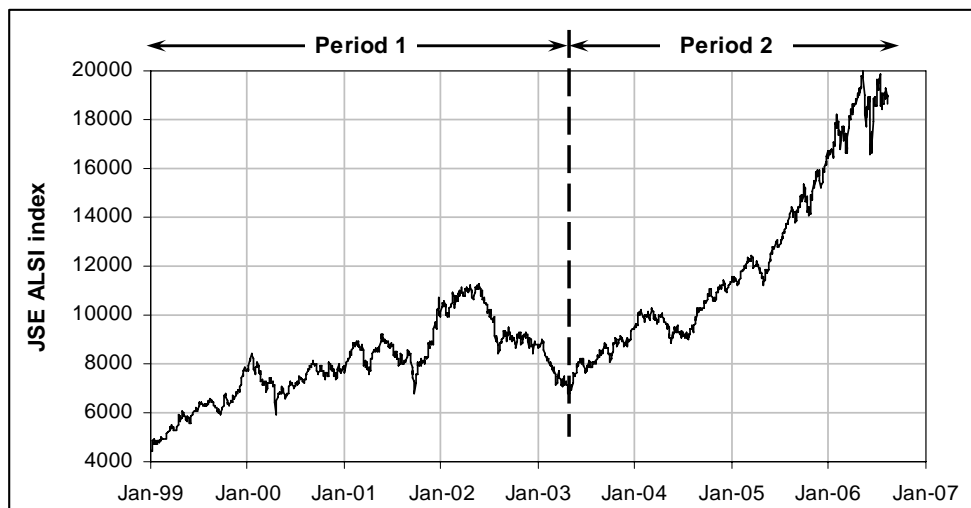
Table 1: Comparison of fund Omega functions.

Fund	Ω function: -ve thresholds	Ω function: +ve thresholds	Ω ratio at $t = 0$	Comments
Fixed income	Steepest Indicates lowest risk	Fastest drop to 0 – not much up-side W ratio > 1 for $t < +0.3\%$	Lowest	Lowest risk, lowest return fund

Long-short equity	Steep gradient – little high upside potential	2 nd best fund W ratio > 1 for $\tau < +3\%$	Highest by factor of 2	Better fund than Market neutral for all threshold levels
Market neutral	Steep gradient Low risk but little upside	2 nd worst fund Drops sharply W ratio > 1 for $\tau < +1\%$	Central	Higher risk and higher return than fixed income, no market exposure
Trading	Significant upside but also higher risk Shallow gradient	Best fund W ratio > 1 for $\tau < +3.5\%$	Second highest	Better fund than ALSI for all threshold levels
ALSI	Highest risk Shallow gradient	Central Potentially high returns W ratio > 1 for $\tau < +2\%$	Lowest with fixed income	Higher risk than Long/Short but not higher upside.

The section also examined the effect of investment strategy on broad market conditions. Figure 2 shows the ALSI 40 index for the period January 1999 to July 2006 – i.e. the period over which hedge fund data were inspected for this study.

Figure 2: Performance of South African ALSI 40 Index over the period Jan 1999 to Aug 2006.



Two periods of interest were selected, labelled in Figure 2 as Period 1 and Period 2.

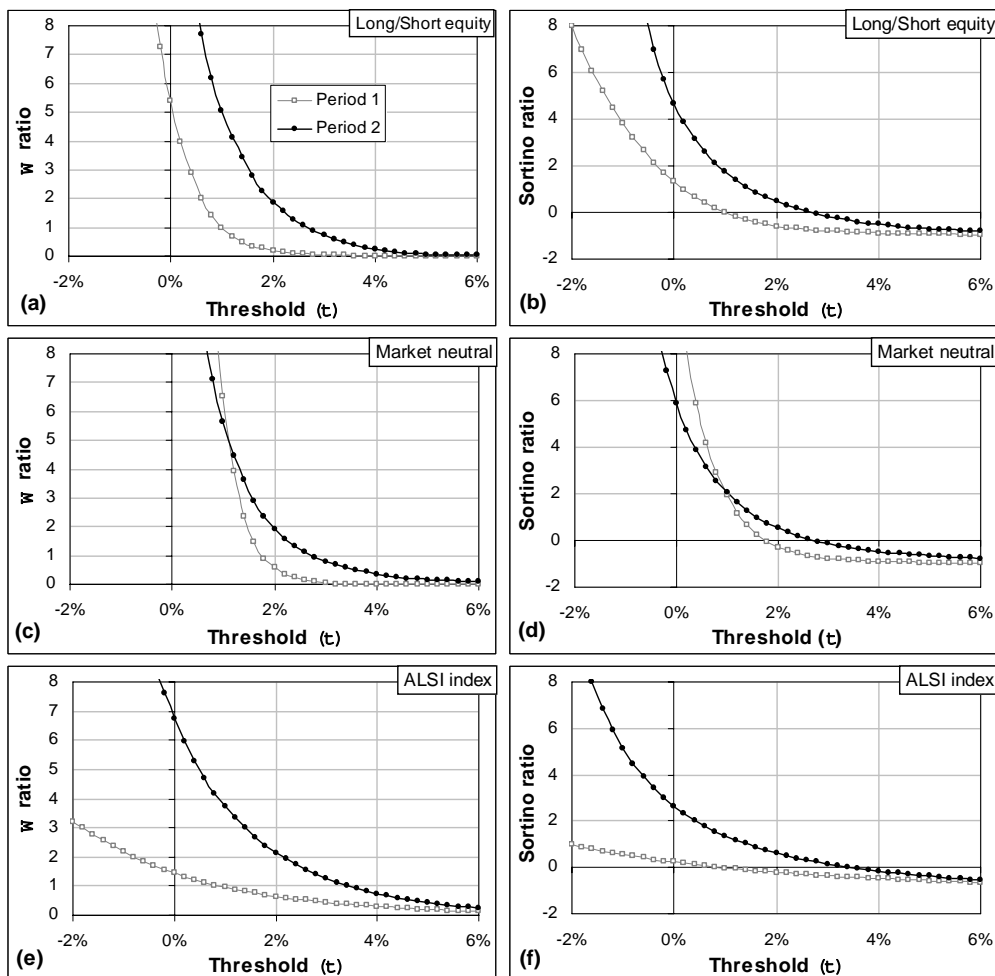
Period 1: January 1999 to May 2003. This period was characterised by a South African market still recovering from the Asian crisis of 1999 as well as the April 2000 dotcom crash. The

events of September 11 plunged the still-vulnerable market into further turmoil and the global recession (albeit relatively minor) of 2002 also took its toll.

Period 2: June 2003 to August 2006. Since June 2003, South Africa has experienced significant positive stock market growth – buoyed by international market strengthening and partially fuelled by the global collapse of interest rates. This period saw over 100% growth in the stock market over only a few years.

All fund returns were split into the two distinct periods described above and the Omega functions and Sortino ratios measured for each. Representative results are shown in Figures 3(a) through (f) below in which (a), (c) and (e) show the Omega ratios for Long-Short equity strategy, the market-neutral strategy and the ALSI index respectively and (b), (d) and (f) show the Sortino ratios for the same funds.

Figure 3: Typical Omega functions and Sortino ratios (at two periods of distinct market activity) for (a, b) long-short equity, (c, d) market neutral, and (e, f) the JSE ALSI index for comparison.



For the long-short equity funds examined as well as the ALSI index, the Omega and Sortino ratios are much improved during periods of strong market growth (see, in particular, Figure 3(e)). Gradients are steeper and the Omega function is higher for all thresholds. Due to the fund strategy of being long or short market exposure, these funds can take advantage of market movements in either direction. Although this analysis did not encompass periods of strong market retraction, it is expected that a very similar Omega function will be observed in such periods as well.

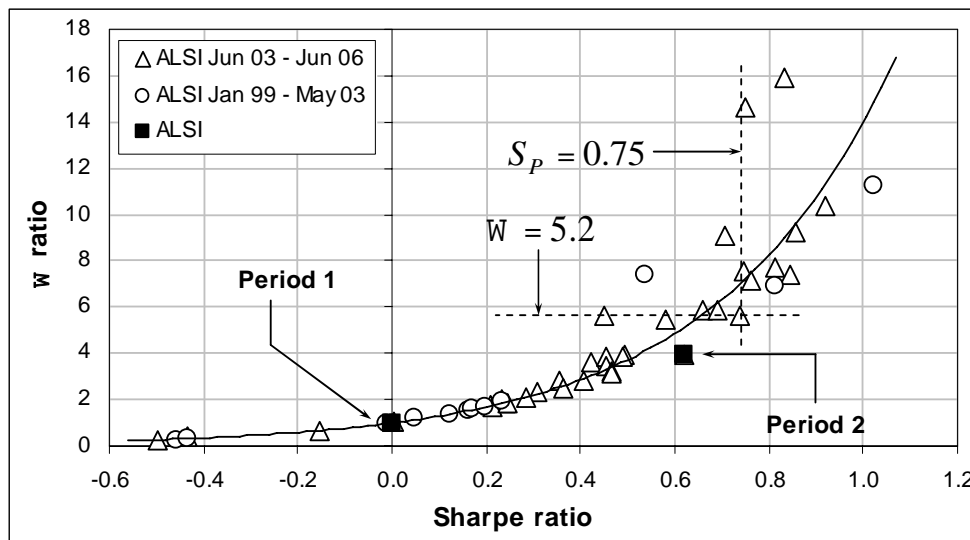
For the market neutral funds, however, there are a few differences between the Omega and Sortino ratios for the two periods. This is because the fund, being market neutral, generates its returns irrespective of the prevailing market conditions. Since market risk is effectively eliminated, these funds are relative immune to market growth or decline. Ascertaining which of these measures is the superior one is not the intention of this analysis. The Omega and Sortino ratios measure different quantities and are merely related by the Lower Partial Moment function (Equation 6). However, a comparison of the Omega and the Sharpe ratios – as hedge fund performance measures – is important and requires further investigation.

Next, the Sharpe ratio – calculated according to Equation 7 – was measured and compared with the Omega function measured over the same two periods of market activity. To estimate the Omega ratio (and hence, the Omega function) Equations 5 and 6 were used with the threshold chosen in each case such that $t = R_f$ for the relevant period. The Sharpe ratio is determined according to Equation 7 in which R_p – the portfolio returns – are calculated by first measuring the cumulative return over the full period and from this, calculating the one-period (i.e. one month) average return. The risk free rate, R_f is calculated in a similar way – using the 3-month call rate each month. The volatility, s_p is the one-period volatility calculated using Equation 8. The results are shown in Figure 4. The coordinate [0, 1] on this graphs follows from Equation 2, namely that the Omega function = 1 when the Sharpe ratio = 0.

It is clear that for low Sharpe and Omega ratios the ranking of funds is accurate (i.e. Sharpe and Omega rank the relevant fund identically). However, for higher Sharpe ratios (> 0.4) the ranking accuracy deteriorates considerably – precisely in those funds where an accurate ranking would provide valuable information regarding the choice of fund. Consider, for example, the dashed line at $s_p = 0.75$. This line intersects three funds, meaning that the Sharpe ratio for these three funds is identical. However, their Omega ratios are very different. The fund with

an Omega ratio of 14.6, for example, is ranked 2nd in terms of Omega ratio, but 9th in terms of the Sharpe ratio.

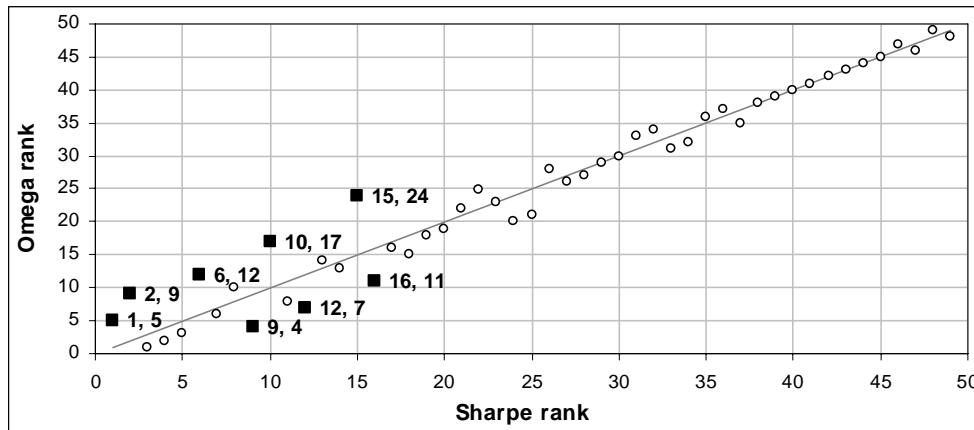
Figure 4: Omega ratio versus the Sharpe ratio for all funds in the sample, measured over Period 1 and Period 2 as shown in Figure 2. The ALSI index is shown as black squares for each of the periods.



In a similar way, the five funds intersected by the line $w = 5.2$ share an identical Omega ratio, yet have Sharpe ratios spanning the range $0.45 \pm S_p \pm 0.75$. To show this variation, Figure 5 plots the Omega ratio versus the Sharpe ratio for the funds indicated in Figure 4. If the two measures ranked the funds identically, the points would lie on the straight line indicated. For lower ranked funds (those ranked lower than the 25th) this relationship is reasonably maintained. Higher ranked funds fare far worse. A selection of funds for which this ranking cardinality is violated are indicated in Figure 5. The numbers on the right of these points are the [Omega ratio, Sharpe ratio] coordinates.

For lower rankings – both the Sharpe and the Omega ratios agree well. There is little agreement between the Omega and Sharpe ratio rankings allocated to the higher ranked funds, i.e. those funds that will generate the most interest and will be the ones most closely scrutinised. In all cases, the Omega ratio allocates a higher ranking than the Sharpe ratio to the better performing fund.

Figure 5: Omega rank versus Sharpe ratio rank for the funds indicated in Figure 4.



7. CONCLUSIONS

The hedge fund industry continues to thrive despite high profile disasters such as Long Term Capital Management (1998) and, more recently, Amaranth Advisors – a large US hedge fund – that lost up to US\$6 billion in September 2006 whilst speculating on gas prices (*The Economist*, 2006c). Nevertheless, pressure on hedge funds is mounting on all fronts.

Hedge fund investment capital is increasingly being diverted into private equity and other popular funds, calls for hedge fund investment strategy transparency are amplifying and savvy, discriminating investors are demanding ever higher returns for lower fees. The need to distinguish – accurately – between poor and good quality fund returns has never been greater. Methods for estimating risk-adjusted returns, though well-established, embrace a simple mean-variance regime, widely considered to be almost obsolete in today's world of highly non-normal, return distributions. Higher statistical moments of return distributions *must* be taken into account if an accurate ranking of fund returns is desired.

The Omega function, though not a perfect measure, offers an arguably considerable improvement. While the Sharpe ratio consistently misallocates the best performing funds, the Omega function describes much about the rich underlying distribution structure. Not only does it consistently rank fund returns accurately, but its shape discriminates between different underlying fund strategies as well as between periods of various types of market activity.

It is not often that so revolutionary and respected a risk/return measure as the Sharpe ratio is displaced by another, but it is clear from the expanding body of analysis that this is indeed the case.

8. REFERENCES

- ACAR, E and Middleton, A (2004) "Maximum drawdown: further results", in *Intelligent Hedge Fund Investing* ed by Barry Schachter, Risk Books.
- AMENC, N., Malaise, P. and Vaissié, M (2005) "Edhec Funds of Hedge Funds Reporting Survey: A Return-Based Approach to Funds of Hedge Funds Reporting", *Alternative Investments*, March 08, 2005 [Online] http://www.edhec-risk.com/edhec_publications/RISKArticle.2005-03-08.5902
- AMMANN, M and Moerth, P (2005) "Impact of Fund Size on Hedge Fund Performance", *Journal of Asset Management*, 6, 3, October 2005, pp. 219 – 238.
- BANK OF JAPAN (2006) "Recent Developments in Hedge Funds", *Financial Systems and Bank Examination Department*, Financial Markets Department, Bank of Japan, pp 1 – 65.
- Birger, J (2006) "Investing: Don't hedge your bets after all", *Fortune*, May. [Online] http://money.cnn.com/magazines/fortune/fortune_archive/2006/05/15/8376864/
- BOTHA, M (2005) "Risk Management in Hedge funds", Masters dissertation, University of the North West, Potchefstroom, South Africa.
- DU TOIT, B (2005) "The Omega function: part 1: An Introduction", *Vikela*, March 3, p. 4 – 6.
- FINANCIAL TIMES, 'Call to abolish hedge fund rules limiting investor access', July 4 2006.
- FINANCIAL TIMES, 'Performance of hedge funds steadies but the fears persist', July 10 2006.
- FUNG, W., Hsieh, D. A., Naik, N. Y and Ramadorai, T (2006) "Hedge Funds: Performance, Risk and Capital Formation", March 2006, CEPR Discussion Paper No. 5565 [Online] SSRN: <http://ssrn.com/abstract=912465>
- GÉHIN, W (2005) "Is performance persistence a viable criterion for selecting hedge funds?", *Hedge Funds Review*, January 2005, pp. 40 – 41.
- HARLOW, W. V, "Asset allocation in a Downside Risk Framework", *Financial Analysts Journal*, Sept./Oct. 1991. 47, 5. pp. 28 – 40.
- HFRX indices, 2006. [Online] https://www.hedgefundresearch.com/hfrx_reg/index.php?fuse=login&1162138035
- JASCHKE, S. R (2002) "The Cornish–Fisher expansion in the context of Delta–Gamma-normal approximations", *Journal of Risk*, 4, 4, pp. 33 – 52.
- KAPLAN, Paul, D and Knowles, James, A. (2004) Kappa: A generalised downside risk-adjusted performance measure. *Journal of Performance Measurement* 8(3) *The Journal Performance Measurement*, 8 (3): pp. 42 – 54.
- KAZEMI, H, Schneeweis, T and R. Gupta (2003). Omega as a performance measure. 2003 [Online] <http://www.edge-fund.com/bibliography.html>
- LEMKE, T. P., Lins, G. T., Hoenig, K. L. and Rube, P. S (2006) *Hedge Funds and Other Private Funds: Regulation and Compliance*, Securities Handbook Series, Thomson West, New York.
- LO, Andrew (2006) "Darwinian investing", *Business Week Online*, February 20 2006 [Online] www.businessweek.com/magazine/content/06_08/b3972033.htm
- MACDONALD, S (2006) Private communication.
- MAGNUM FUNDS (2006) [Online] <http://www.magnum.com/hedgefunds/strategies.asp>

- MANDELBROT, B. & R. Hudson (2005) *The Misbehaviour Of Markets*, London: Profile Books.
- MCLEOD, W and van Vuuren, G. W (2004). "Interpreting the Sharpe Ratio when excess returns are negative", *Investment Analysts Journal*, 59, pp. 15 – 20.
- MODIGLIANI, Franco, and Leah Modigliani (1997) "Risk-adjusted performance", *Journal of Portfolio Management*, Winter, pp. 45 – 54.
- MURALIDHAR, A (2000) "Risk-Adjusted Performance – The Correlation Correction", *Financial Analysts Journal*, 56 (5) pp. 63 – 71.
- POLAKOW, D and M de Araújo (2004) "Procrustes and the poisonous portfolio: Introducing Omega. Peregrine Securities", November 2004.
- POLAKOW, D., de Araújo, M and Y. Greyling (2006) "Hedge Fund Bean Encounters, Derivative and Quantitative Research", February 2006. pp. 1 – 22.
- RAJAN, A., Martin, B., Brown, T. and Johnson, M (2005) "Hedge funds: a catalyst reshaping global investment" [Online] www.kpmg.dk/getMedia.asp?mb_GUID=0F02D46B-F29E-4A43-8672-86A80B9750E5.pdf
- RESERVE Bank, 2006. [Online] <http://www.reservebank.co.za/>
- SHADWICK, W.F., and Keating, C (2002). "A universal performance measure", *Journal of Performance Measurement*, Spring. 6, 3 pp. 59 – 84.
- SHARMA, M (2005) "'Sharper' Risk Adjusted Performance Measures (RAPMs): From Omega to AIRAP", HedgeQuest, Summer.
- SHARPE, W. F (1966) "Mutual Fund Performance", *Journal of Business*, pp. 119 – 138.
- SHARPE, W. F (1994) "The Sharpe Ratio", *Journal of Portfolio Management*, 21, pp. 49 – 58.
- SONG SHIN, H (2006) "Risk and liquidity in a system context", August 2006, *BIS Working Papers*, No 212, Monetary and Economic Department, [Online] www.bis.org/publ/work212.pdf
- STEVENS, G (2006) "Risk and the Financial System", Reserve Bank of Australia, Hong Kong Monetary Authority and Hong Kong Association of Banks [Online] http://www.rba.gov.au/Speeches/2006/sp_dg_150906.html
- THE ECONOMIST (2006a), 'Alpha Betting', September 16, p. 97.
- THE ECONOMIST (2006b), 'Still Free', July 1, p. 78.
- THE ECONOMIST (2006c), 'Flare-up', September 23, p. 87.
- TREYNOR, J. L., and F. Black (1973) "How to use security analysis to improve portfolio selection", *Journal of Business*, 46, pp. 66 – 86.
- TREYNOR, Jack. L (1966) "How to rate management investment funds", *Harvard Business Review*, 43, pp. 63 – 75.
- UK FSA – Financial Services Authority (2005) "Hedge funds: A discussion of risk and regulatory engagement" [Online] www.fsa.gov.uk/pubs/discussion/dp05_04.pdf
- URBANI, P (2004) "The Omega Risk Measure" [Online] <http://www.edge-fund.com/bibliography.html>
- VON NEUMANN, J. & O. Morgenstern (1947) *Theory of Games and Economic Behavior*, Princeton University Press, Princeton, New Jersey.

Chapter 4

Portfolio liquidity-adjusted value at risk

PORTFOLIO LIQUIDITY-ADJUSTED VALUE AT RISK

MARIUS BOTHA

School of Management, P O Box 339, University of the Free State, Bloemfontein 9300,
South Africa.

Abstract

An important, yet neglected, aspect of risk management is liquidity risk; changes in value due to reduced availability of traded financial instruments. This ubiquitous risk has emerged as one of the key drivers of the developing “credit crunch” with global financial liquidity plummeting since the crisis began. Despite massive cash injections by governments, the crisis continues. Contemporary research has focussed on the liquidity component of single instruments’ value at risk (VaR). This work is extended in this article to measure portfolio VaR, employing a technique which integrates individual instruments’ liquidity-adjusted VaR into a portfolio environment without a commensurate increase of statistical assumptions.

JEL Classification: C1, C2, C5, C13, C22

Keywords: Liquidity, value at risk, credit crisis, risk measurement, risk management.

1. INTRODUCTION

The Basel Capital Accord, published in 1988, set down the agreement among the G-10 central banks to apply common minimum capital standards to their banking industries by the end of 1992 (BIS, 1988). The standards largely addressed the main risk incurred by banks – credit risk – but five amendments to the Accord were agreed to subsequently and the fifth introduced parallel capital requirements for market risk. A key development of the Basel Accord was the introduction of VaR, a measure to consolidate an institution's market risk into a single number. The idea was embraced by the finance community and has subsequently come to dominate the field of market risk.

Whilst VaR is not a complex quantity to calculate in principle, estimating its input parameters and determining both their robustness and validity are non-trivial. The late 1980s and most of the 1990s witnessed a profusion of research articles dedicated to the refinement of the VaR measure (Risk Magazine, 2004 and sources therein). Exponential weighting techniques improved volatility and correlation estimates (JP Morgan, 1996), GARCH¹ introduced a mean-reverting volatility model (Alexander 2001 and sources therein), alternative distributions were applied to non-Gaussian data (Bouchaudy, 1999) and Extreme Value Theory became a popular measure to elucidate the structure in the data-poor region of distribution tails

(McNeil, 1996: 121). Adjustments for portfolios with non-linear pay-off profiles – i.e. comprised in part of options or interest rate dependent instruments – were also introduced and are now standard fare (Ammann and Reich, 2001: 9).

Changes in market conditions as well as the size and nature of financial risk have necessitated the drafting and construction of Basel II – essentially a revised and augmented framework of Basel I (BIS, 2006). This revision, implemented in Europe in January 2008 (later in the USA), leaves the treatment of market risk largely unchanged from Basel I and instead focuses almost entirely upon the previously neglected areas of credit and operational risk.² A large number of research articles are now engaged in the exploration of the complexities of credit and operational risk: market risk articles have consequently diminished significantly in number (Risk Magazine, 2004). The VaR concept, however, has by no means been exhaustively explored: in its standard form it is still plagued by limiting assumptions, but some of these standards evade deeper examination on the basis of being 'widely-accepted'. One such feature is liquidity risk which, because of its tendency to compound other risks, is difficult to isolate and analyse. In all but the most simple of circumstances, comprehensive liquidity risk metrics do not exist and standard VaR models usually ignore liquidity risk completely.

The growth in hedge funds worldwide since the early 2000s, meanwhile, has been explosive, both in terms of number of funds and investment capital (Mulvey, 2003: 24 and HFRX, 2006) and there are increasing indications that the process is accelerating. Ever since the collapse of the Long Term Capital Management (LTCM) hedge fund in August 1998 hedge fund risk managers have been forced to concentrate ever more on liquidity risk (Lowenstein, 2002). It was this aspect of risk – more than any other – that brought LTCM to financial ruin. Despite this, no standard approach for measuring liquidity risk has emerged.³ Liquidity-adjusted VaR models certainly exist, and some are fairly sophisticated (e.g. Cosandey, 2001: 116), but these are based upon single instrument VaR approaches and their application to portfolios is not uniform. Less sophisticated approaches such as those that rely on conventional measures of leverage to estimate liquidity risk sometimes provide meaningless results (Bangia, 1999: 70). In addition, the existence of both endogenous and exogenous liquidity risk (which are quite different in both structure and manifestation), autocorrelation and scaling in time of return data and the aggregation of single-instrument liquidity VaR into portfolio liquidity VaR (Umut, 2004: 315) all involve non-trivial and computer-intensive implementation.

This article explores the dual and related problems of:

1. adjusting for endogenous liquidity (without invoking the square root of time rule),
2. the incorporation of individual liquidity-adjusted VaRs into portfolio liquidity-adjusted VaR

and introduces a technique to integrate these twin methodologies.

Section 2 explores the available literature on liquidity risk from an endogenous and exogenous viewpoint. The calculation of each – with associated implementation difficulties – is also discussed here.

A brief literature survey on associated topics, such as the scaling of volatility with the square root of time and the autocorrelation of equity returns, are also examined. This section is by no means exhaustive and aims to provide only a general background to what is rapidly becoming a large body of research.

Section 3 provides a brief overview of the mathematical complexity of endogenous liquidity risk and provides the basis for extending previous work. The problems and limitations of the current research are explored and some questions are posed which are then answered in Section 4, which introduces a formal explanation of a new portfolio liquidity VaR measure. Section 5 presents the results of simulation trials conducted on market data and Section 6 concludes the article.

2. LIQUIDITY RISK

Liquidity may be defined as a range of characteristics rather than a one-dimensional attribute of assets and of the markets on which they are traded. It is also a relative concept, as the more liquid the asset, the more easily it is traded for cash, i.e. at low cost, at short notice and with no risk of a notable change in price. A perfectly liquid market would therefore guarantee a single bid/ask price at all times, irrespective of the quantities being traded. Financial markets, even those deemed most liquid, conform less than perfectly to this ideal configuration. Liquidity risk is thus the risk of being unable to liquidate or hedge a position immediately and at current market prices.

The use of VaR as the standard market risk measure has enjoyed ever-increasing popularity since its formulation in the late 1980s: it is now the most widely-used risk metric for the determination of market risk (Holton, 2003: 405). Whilst considerable attention has been given to the measurement of financial instrument volatility and correlation as well as the incorporation of these values into portfolio VaR, the liquidity risk of these instruments remains severely under-examined. It is included in standard VaR calculations only in an *ad hoc* fashion,

namely by increasing the time horizon over which VaR is calculated to account for the time taken to liquidate a large position (JP Morgan, 1996). Not only does this technique not distinguish between exogenous and endogenous liquidity (defined and discussed below), but it employs the 'square root of time' rule, in which it is assumed that no autocorrelation exists between rates of return from one measurement period to another. This assumption of a lack of autocorrelation allows for simple arithmetic summation of individual variances to produce the overall 'period under investigation' variance. Thus, for example:

$$\text{variance}_{10\text{ day}} = 10 \text{ variance}_{1\text{ day}},$$

and, as a direct consequence this leads to the statistical conclusion that:

$$s_{10\text{ day}} = \sqrt{10} s_{1\text{ day}}.$$

This assumption has been challenged over the past decade by several authors (see for example, Diebold (1996) and Blake *et al.* (2000)). In addition, Danielsson and Zigrand (2006: 2711) recently again demonstrated that the square root of time rule leads to a systematic underestimation of risk – but also found that the degree of underestimation worsens with time horizon, jump intensity and confidence level. They conclude that despite the widespread application and implementation of the square root of time rule in the Basel regulatory accords, it nevertheless fails to address the objective of the Basel accords. It is clear that a more thorough investigation into the nature of liquidity risk and its effect on portfolios of illiquid instruments is required.

Two types of liquidity risk have been identified, namely exogenous and endogenous liquidity risk. These are defined below.

(a) **Exogenous liquidity risk** is the result of market characteristics; it is common to all market players and unaffected by the actions of any one participant (Bangia *et al.* 1998). In response to a market shock (and the resultant loss of predictability), a vicious cycle with a corresponding loss of liquidity is initiated. The perceived need to hold larger prudential reserves in situations of greater uncertainty along with reduced liquidity and leverage may not break the self-reinforcing dynamics of market dislocations. Exogenous liquidity can be affected by the joint action of all or almost all market participants as occurred in several markets in the summer of 1998 (Lowenstein, 2002). The market for liquid securities, such as G7 currencies, is typically characterized by heavy trading volumes, stable and small bid-ask spreads, stable and high levels of quote depth. Liquidity costs may be negligible for such positions when

marking to market provides a proper liquidation value. In contrast, markets in emerging currencies or thinly traded junk bonds are illiquid and are characterized by high volatilities of spread, quote depth and trading volume.

(b) **Endogenous liquidity risk**, in contrast, is specific to the position in the market and varies across market participants (Bangia *et al.* 1998). The exposure of any one participant is affected by the actions of that participant. It is mainly driven by the size of the position: the larger the size, the greater the endogenous illiquidity. If the market order to buy/sell is smaller than the volume available in the market at the quote, then the order transacts at the quote. In this case the market impact cost, defined as the cost of immediate execution, will be half of the bid-ask spread. If the size of the order exceeds the quote depth, the cost of market impact will be higher than the half-spread. The difference between the total market impact and half-spread is called the incremental market cost, and constitutes the endogenous liquidity component.

Le Saout (2002) reported that neither exogenous liquidity risk (which accounts for about half of total market risk) nor endogenous liquidity risk (also a potentially significant component of market risk) should be ignored by financial institutions subject to market risk.

This section introduced liquidity risk as an autonomous and important component of overall portfolio risk and provided broad definitions of the different types of liquidity encountered in the market. The following section supplies a literature review of relevant liquidity risk research.

3. LITERATURE SURVEY

Recent work has begun to incorporate vanishing liquidity in times of crisis. Le Saout (2002) provides a good review of liquidity risk in VaR models and gives a comprehensive overview of recent research in the field.

Lawrence and Robinson (1995: 64) were among the first to identify and establish that conventional VaR models often exclude asset liquidity risk. They argued that the best way to capture liquidity issues within the VaR framework would be to match the VaR time horizon with the time investors believed it could take to exit or liquidate the portfolio. They established that the liquidation of a portfolio over several trading days generated additional liquidity costs.

Diebold *et al.* (1996) pointed out that the scaling of volatilities by the square root of time is only applicable if log changes of price returns are i.i.d. (independently and identically distrib-

uted) and, in addition, normally distributed. They noted that high frequency financial asset returns are *not* i.i.d. and that, even if they are conditional mean independent they are definitely not mean variance independent (see also Bollerslev, Chou and Kroner (1992: 20) and Diebold and Lopez (1995: 433)) for evidence of strong volatility persistence in financial asset returns.) Diebold *et al.* (1996) showed that scaling by the square root of time magnifies the volatility fluctuations i.e. scaling results in large conditional variance fluctuations of long horizon returns, when in fact the opposite is true.

Jarrow and Subramanian (1997: 171, 2001: 450) considered optimal liquidation of an investment over a fixed horizon. They characterised the costs and benefits of block sales versus slow liquidation and they proposed an endogenous liquidity adjustment to the standard VaR measure. The model requires three quantities which increase the loss level – namely a liquidity discount, the volatility of the liquidity discount and the volatility of the time horizon to liquidation. The authors themselves acknowledge that traders or firms must collect time series data on the shares traded, prices received and time to execution in order to estimate these quantities. Whilst this model is robust and fairly easy to implement, estimating these quantities is by no means trivial. Indeed, some may only be determined empirically with the accompanying introduction of significant bias.

Fernandez (1999: 2) examined liquidity risk in the aftermath of the 1998 LTCM liquidity crisis. He argued that:

"...financial markets are undergoing rapid structural change, which may be contributing to liquidity risk. These changes along with rising homogeneity of market participants' behaviour are increasing concentration and 'herding behaviour' and eliminating 'friction' which may prove disadvantageous in a market correction."
(Fernandez, 1999:3)

Fernandez concluded that no single measure captured the various aspects of liquidity in financial markets, but rather a composite of measures, incorporating quantitative and qualitative factors. His treatment of the problem, however sound, does not address the mathematical issues underlying this complex problem.

Bangia *et al.* (1999: 71) explored exogenous liquidity risk. They treated the liquidity risk and market risk jointly and made the assumption that in adverse market environments extreme events in returns and extreme events in spreads occur concurrently. They noted that while the correlation between mid-price movements and spreads was not perfect – it was strong enough during extreme market conditions to encourage the treatment of extreme

movements in market and liquidity risk simultaneously. They incorporated both a 99th percentile movement in the underlying and a 99th percentile movement in the spread.

Almgren and Chriss (1999: 59) examined endogenous liquidity risk by considering the problem of portfolio liquidation. They aimed to minimise a combination of volatility risk and transaction costs arising from permanent and temporary market impact. From a simple linear cost model, they built an efficient frontier in the space of time-dependant probability. They considered the risk-reward trade-off both from the point of view of classic mean-variance optimisation and the standpoint of VaR. Their analysis led to general insights into optimal portfolio trading, and to several applications including a definition of liquidity-adjusted VaR.

Hisata and Yamai (2000: 84) proposed a practical framework for the quantification of liquidity-adjusted VaR which incorporated the market liquidity of financial products. Their framework incorporates the mechanism of the market impact caused by the investor's own dealings through adjusting VaR according to the level of market liquidity and the scale of the investor's position. In addition, Hisata and Yamai (2000: 86) proposed a closed-form solution for calculating liquidity-adjusted VaR as well as a method of estimating portfolio liquidity-adjusted VaR.

Erwan (2002: 11) demonstrated that the standard VaR model largely neglects the liquidity aspect of market risk because no single measure captures the various aspects of liquidity in financial markets. Erwan (2002: 8) extended the liquidity adjusted VaR model developed by Bangia *et al.* (1999) by incorporating a weighted average spread to bid and offer prices and applied the resulting model to the French stock market. Both endogenous and exogenous liquidity risk were found to be important components of market risk.

Çetin *et al.* (2004) assume the existence of a stochastic supply curve for a security's price as a function of transaction size. Specifically, a second argument incorporates the size (number of shares) and direction (buy versus sell) of a transaction to determine the price at which the trade is executed. For a given supply curve, traders act as price takers. The more liquid an asset, the more horizontal its unique supply curve. In the context of continuous trading, necessary and sufficient conditions on the supply curve's evolution are characterised such that no arbitrage opportunities arise in the economy. Furthermore, given an arbitrage free evolution for the supply curve, conditions for an approximately complete market are also provided. In the most general setting with unrestricted predictable trading strategies, Çetin *et al.* obtain three primary conclusions with respect to the pricing of derivatives. First, all liquidity costs

are avoidable when (approximately) replicating a derivative's payoff using continuous trading strategies of finite variation. Second (and as a consequence of the previous conclusion) the derivative's price is the price obtained by ignoring the bid-ask spread and other illiquidities. Third, no implied bid-ask spreads or illiquidities exist for a derivative's price. Note that these conclusions follow from continuous trading of infinitesimal quantities. Although related mainly to derivative pricing, this work was used by Jarrow and Protter (2005: 9) to modify current risk measures to account for liquidity risk, though they admit that although more complex adjustments are possible, these await subsequent research.

Angelidis and Benos (2005) relaxed the traditional, yet unrealistic, assumption of a perfect, frictionless financial market (i.e. investors can either buy or sell any amount of stock without causing significant price changes). Angelidos and Benos extended the work of Hausman et al., (1992: 323) and Madhavan et al., (1997: 1041) (who argued that traded volume can explain price movements) and developed a liquidity VaR measure based on spread components, following the work of Bangia et al., (1999: 72). Under this framework, the liquidity risk was decomposed into its endogenous and exogenous components, thereby permitting an assessment of the liquidation risk of a specific position. As with much other research, this relevant and detailed work does not address portfolio liquidity – the chief focus of this article.

The problem of ignoring liquidity risk is amplified in – but not confined to portfolios which constitute – hedge funds. Hedge fund manager styles were addressed by L'Habitant (2000: 12, 2001: 18) who noted that there was a need to introduce new quantitative tools to assist investors assessing the investment characteristics and the risks of hedge funds. Using only net asset values from a hedge fund, L'Habitant proposed a methodology to identify strategic and tactical hedge fund asset allocations and compare their performance against an ad-hoc benchmark. The method on which he relied was a returns-based style analysis introduced by Sharpe (1988). L'Habitant also notes that:

"...there are numerous directions for future research. In particular, the framework presented in this paper does not incorporate all the risk components to which a hedge fund investor is exposed. For instance, we have completely omitted credit and liquidity risks, which are also essential parts of the full risk picture of a hedge fund." (L'Habitant, 2001: 13)

This section provided a literature review of recent research in the field of liquidity risk as well as insight into some of the methods which have been developed to mitigate and manage it. Hisata and Yamai (2000: 90) provide – to our knowledge – the only coherent *portfolio* approach to liquidity risk. The next section will explore the possibility of combining Jarrow and

Subramanian's (1997, 2001) – henceforth JS-model (for evaluating individual instrument liquidity-adjusted VaR – henceforth LVaR) and standard portfolio theory to produce a robust portfolio LVaR approach under normal trading conditions, i.e. *endogenous* liquidity risk. This technique represents a variation on Hisata and Yamai's (2000: 90) portfolio approach, but also incorporates several elements discussed by them. The aim is thus to construct a *liquidity-adjusted* VaR (LVaR) at a portfolio level.

4. LIQUIDITY VaR

Whilst many LVaR models exist, the JS model is increasing in importance as the endogenous liquidity model of choice (for example, see Umut (2004: 322). Although Çetin's (2004) work is currently enjoying some popularity – see Jarrow and Protter (2005: 12) – more work is required before the adjustments recommended can be effectively and robustly implemented into existing VaR models). The JS model's results will be used later to combine individual LVaRs into a portfolio LVaR. *No attempt will be made here to reproduce in full the underlying theoretical framework of the JS model.* Nevertheless, it is instructive to provide a brief summary of the structure and constituents of the JS model equations. Having established this JS model overview, the individual instrument LVaRs will be combined using standard portfolio theory to produce a portfolio LVaR equation. This formula will then be tested on actual profit and loss and accompanying non-liquidity-adjusted VaR data from several South African equity portfolios and the results compared.

The equation governing liquidity adjusted VaR according to the JS model is given by:

$$LVaR_{JS} = \rho S \left[\mu \{E(\Delta S) + E(\ln c(S))\} - CI \sigma_E \sqrt{E(\Delta S)} + |\mu| \sigma_{\Delta S} + \sigma_{\ln c(S)} \right] \quad (1)$$

where x is the quantity of equity purchased (or short-sold)

S is the equity price (hence $x \cdot S$ is essentially the nominal amount invested: ie quantity · price)

m is the average portfolio return

$E(\Delta S)$ is the expected value of the time horizon to liquidation

$c(S)$ is the liquidity discount – ie the difference between the market value of a trader's position and its value when it is ultimately liquidated

CI is the confidence interval

$\sigma_{\Delta S}$ is the volatility of the time horizon to the position's liquidation

σ_E is the equity return volatility and

$\sigma_{\ln \{c(S)\}}$ is the volatility of the natural logarithm of the liquidity discount.

The standard parametric VaR equation (Dowd *et al.* 2003) is given by:

$$VaR = N \left(\mu T - CI \sigma_p \sqrt{T} \right) \quad (2)$$

where N is the notional investment amount

μ is the average T -period return⁴

CI is the confidence interval

\sqrt{T} is the square root of the time horizon to liquidation⁵ and

σ_p is the portfolio volatility.

Using matrix notation, the portfolio volatility, σ_p , for two⁶ stocks A and B, is written as (Dowd *et al.* 2003):

$$\sigma_p = \sqrt{\begin{pmatrix} w_A & w_B \end{pmatrix} \begin{pmatrix} \sigma_A^2 & \sigma_A \sigma_B r_{AB} \\ \sigma_B \sigma_A r_{BA} & \sigma_B^2 \end{pmatrix} \begin{pmatrix} w_A \\ w_B \end{pmatrix}} \quad (3)$$

where w_A and w_B are the investment weights in the respective equities, σ_A and σ_B are the respective equity return volatilities and r_{AB} is the correlation between the equity returns of A and B. The central matrix under the square root is the covariance matrix. The diagonals are the constituent variances and the off-diagonal terms are identical since the matrix is positive semi-definite.

Mechanisms which govern equity risk are broadly similar – regardless of the models used to describe these. It is therefore no coincidence that the JS model (Equation 1) closely resembles the parametric VaR equation (Equation 2) in which the terms $N \left(\mu T - CI \sigma_p \sqrt{T} \right)$ and $\left(\mu \{E \Delta S + E \ln \{c(S)\}\} - CI \left(\sigma_E \sqrt{E \Delta S} + |\mu| \left(\sigma_{\Delta S} + \sigma_{\ln \{c(S)\}} \right) \right) \right)$ terms.

Using the common assumption that the average portfolio return is sufficiently small to be considered equal to 0% (JP Morgan, 1996: 8), Equation 1 simplifies to

$$LVaR_{JS} = \rho S \left(CI \left(\sigma_E \sqrt{E \Delta S} + \sigma_{\ln \{c(S)\}} \right) \right) \quad (4)$$

and Equation (2) to:

$$LVaR_{\text{simple}} = N \text{ CI } S_P \sqrt{T} \quad (5)$$

where the portfolio VaR, VaR_p , has been replaced in Equation 5 with $LVaR_{\text{simple}}$ or the “simple liquidity adjusted VaR” since the square root of time term reflects the simple manner in which liquidity is taken into account in the standard VaR model.

The goal now is to expand the mathematics of Equations 4 and 5 (liquidity-adjusted VaRs for *single* instruments) to incorporate *portfolios* of instruments.

Using Equation 3, Equation 5 may be written (in matrix notation):

$$LVaR_{\text{simple}} = N \text{ CI } \sqrt{(w_A \quad w_B) \begin{pmatrix} S_A^2 & S_A S_B r_{AB} \\ S_B S_A r_{BA} & S_B^2 \end{pmatrix} \begin{pmatrix} w_A \\ w_B \end{pmatrix}} \sqrt{T}$$

Decomposing the covariance matrix into its constituent volatilities and correlation matrices gives:

$$LVaR_{\text{simple}} = N \text{ CI } \sqrt{(w_A S_A \quad w_B S_B) \begin{pmatrix} 1 & r_{AB} \\ r_{BA} & 1 \end{pmatrix} \begin{pmatrix} w_A S_A \\ w_B S_B \end{pmatrix}} \sqrt{T}$$

Extending the square root and incorporating the notional investment and liquidation horizon gives:

$$LVaR_{\text{simple}} = \sqrt{(N w_A \text{ CI } S_A \sqrt{T} \quad N w_B \text{ CI } S_B \sqrt{T}) \begin{pmatrix} 1 & r_{AB} \\ r_{BA} & 1 \end{pmatrix} \begin{pmatrix} N w_A \text{ CI } S_A \sqrt{T} \\ N w_B \text{ CI } S_B \sqrt{T} \end{pmatrix}} \text{ which}$$

may be rewritten as:

$$LVaR_{\text{simple}} = \sqrt{(LVaR_{\text{simple}}^A \quad LVaR_{\text{simple}}^B) \begin{pmatrix} 1 & r_{AB} \\ r_{BA} & 1 \end{pmatrix} \begin{pmatrix} LVaR_{\text{simple}}^A \\ LVaR_{\text{simple}}^B \end{pmatrix}} \quad (6)$$

where

$$LVaR_{\text{simple}}^A = N w_A \text{ CI } S_A \sqrt{T} \text{ and } LVaR_{\text{simple}}^B = N w_B \text{ CI } S_B \sqrt{T}.$$

It is not unreasonable to conclude, in an analogous manner to Equation 6, that $LVaR_{\text{JS}}$ (Equation 4) may be written:

$$LVaR_{JS} = \sqrt{\begin{pmatrix} LVaR_{JS}^A & LVaR_{JS}^B \end{pmatrix} \begin{pmatrix} 1 & r_{AB} \\ r_{BA} & 1 \end{pmatrix} \begin{pmatrix} LVaR_{JS}^A \\ LVaR_{JS}^B \end{pmatrix}} \quad (7)$$

where the component $LVaR_{JS}$ are defined by Equation 4.

Equations 6 and 7 both purport to estimate the portfolio liquidity adjusted VaR. Since VaR is a one day forecast of a portfolio's P&L, the VaR may be calculated using Equations 4 and 5 above and the results may be compared with realised P&L from portfolio returns.

In order to compare results, data from 14 South African equity portfolios were assembled. These included realised P&L data as well as all of the required inputs for both the $LVaR_{JS}$ model (Equation 4) and the $LVaR_{simple}$ model (Equation 5).

The quantity of equity purchased, x , is determined using actual trading quantities executed, ie successful bids or offers. Equity prices, S , are determined at the time of the transaction's execution, while the expected value of the time horizon to liquidation – $E(DS)$ – is the simple average time taken between placing a bid/offer and the successful execution of the transaction. The liquidity discount, $c(S)$, measures the difference between the market value of traders' positions at the time of bid/offer and the value when they are ultimately liquidated. The volatility of this time horizon (from bid/offer to the position's liquidation), σ_{DS} , may also be estimated from liquidity discount data, $c(S)$, and σ_E is the exponentially weighted moving average volatility of the equity data. The volatility of the natural logarithm of the liquidity discount, $\sigma_{\ln[c(S)]}$, may also be estimated from liquidity discount data, $c(S)$.

Liquidity adjusted VaRs were estimated using Equations 6 and 7. Correlation values for both methods were determined using a 250-day rolling window of equity returns and the exponentially weighted moving average technique (JP Morgan, 1996: 78) with decay constant $\lambda = 0.92$ for South African equities.

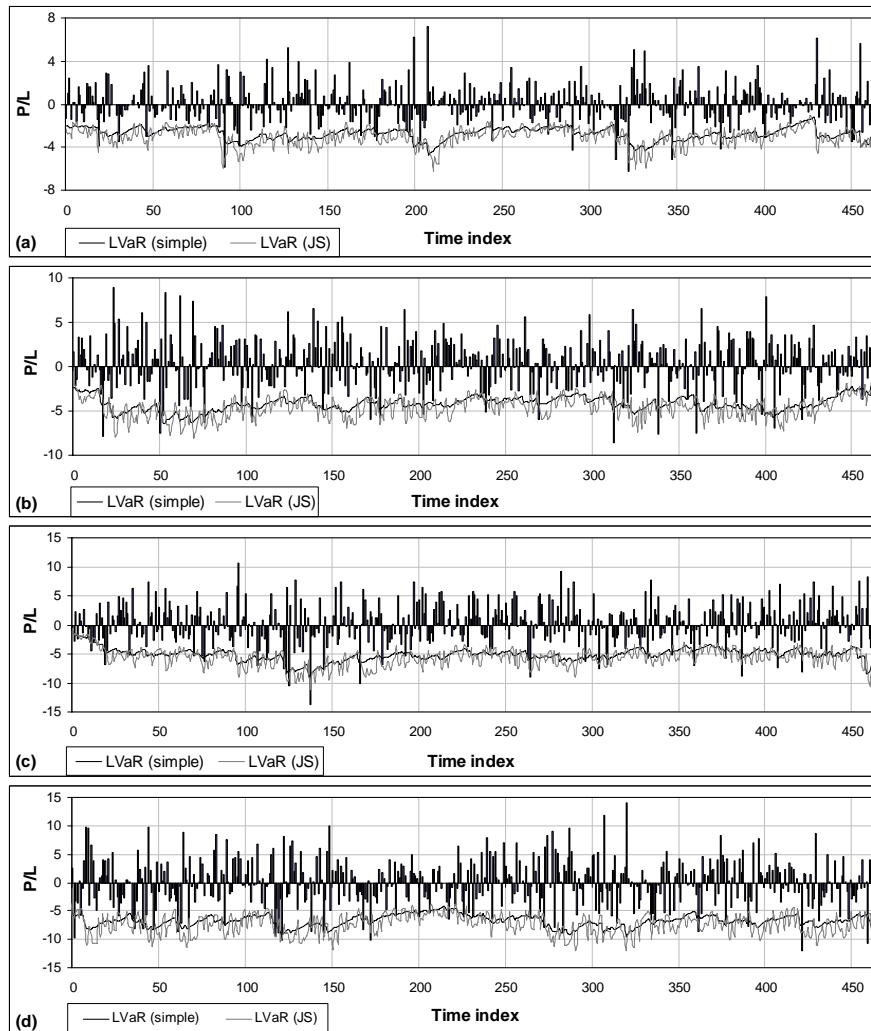
These data provide an opportunity to back test the VaR forecasts using both the simple approach (Equation 5) and the JS model approach (Equation 4) against realised P&Ls. The results of this investigation are presented in the following section.

5. RESULTS

The forecast $LVaR_{JS}$ (Equation 7) was calculated for each equity portfolio, using parameters obtained from portfolio data and compared with the daily forecast 95% $LVaR_{simple}$ (Equation 6). These are shown for only four different portfolios⁷ in Figure 1(a) through (d). In line

with common practice, the measured daily P&L is indicated on the same graph in each case (as a means of comparing forecast 95% VaR with realised P&Ls).

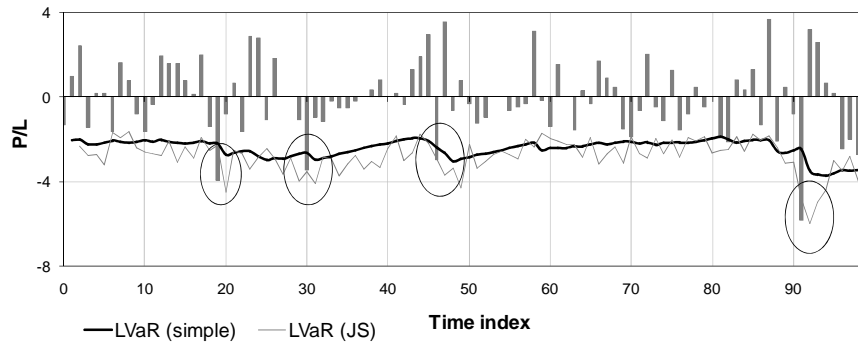
Figure 1: Realised P&Ls, simple 95% $LVaR_{\text{simple}}$ and 95% $LVaR_{\text{JS}}$ for four separate equity portfolios (a) through (d) over a 466-day period between January 2004 and November 2006.



The $LVaR_{\text{JS}}$ were found to be more volatile than the $LVaR_{\text{simple}}$, due to the combination of the two volatility terms, namely $\sigma_E \sqrt{E[\Delta S]}$ and $\sigma_{\ln[f(S)]}$ over short timescales (days), but the two $LVaR$ terms track one another closely over longer timescales (months).

A section of data (100 days) was selected from the portfolio represented in Figure 1(a) to highlight obscured detail. These are shown in Figure 2. The circled regions show four cases in which the $LVaR_{\text{simple}}$ forecast the VaR incorrectly, whilst the $LVaR_{\text{JS}}$ succeeded.

Figure 2: Detail of time series selected from fund P/L data represented in Figure 1(a).



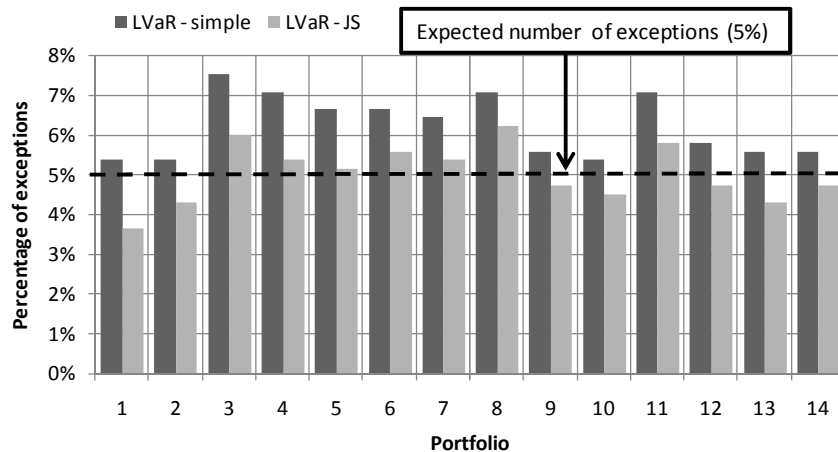
Back testing the accuracy of VaR forecasts against realised P&L is not only common practice but also a requirement by many bank regulators to establish the validity of banks' internal VaR models. The Basel committee (BIS, 2004) has stipulated that, for VaR measured at a 95% confidence interval over 250 days, a maximum of five exceptions (ie cases in which the forecast VaR *underestimated* the following day's P&L) are allowed over and above the 5% expected exceptions (due to the 95% confidence interval). The more exceptions (up to 10) that occur than those allowed by the Basel accord incur increasing capital charges for market risk. If more than 10 exceptions in a 250 day period occur, the regulator will order an investigation into the bank's market risk model. Since it is in the best interests of banks to install and maintain accurate VaR models, the returns from 14 equity portfolios were back tested to ascertain the accuracy of the two liquidity-adjusted VaR models.

Using 466 days of data to generate Figure 1, the number of exceptions (ie instances in which VaR forecasts *underestimated* the following day's losses) were measured using both $LVaR_{\text{simple}}$ and $LVaR_{\text{JS}}$ for all 14 portfolios in this sample. Whilst it is *expected* that 5% of forecasts will be 'outliers' or exceptions – by definition – Table 1 (and Figure 3) below shows that the 95% $LVaR_{\text{JS}}$ forecast estimate is more accurate than the 95% $LVaR_{\text{simple}}$, especially at times of high market turbulence (reduced liquidity).

Table 1: Comparison of 95% $LVaR$ forecast exceptions measured over 466 days for all portfolios. Note that $5\% \times 466 = 23$ exceptions are expected.

Fund number	95% $LVaR_{simple}$		95% $LVaR_{JS}$	
	Exceptions	% of total (5% expected)	Exceptions	% of total (5% expected)
1	25	5.38%	17	3.66%
2	25	5.38%	20	4.30%
3	35	7.53%	28	6.02%
4	33	7.10%	25	5.38%
5	31	6.67%	24	5.16%
6	31	6.67%	26	5.59%
7	30	6.45%	25	5.38%
8	33	7.10%	29	6.24%
9	26	5.59%	22	4.73%
10	25	5.38%	21	4.52%
11	33	7.10%	27	5.81%
12	27	5.81%	22	4.73%
13	26	5.59%	20	4.30%
14	26	5.59%	22	4.73%

Figure 3: Graphical comparison of VaR forecast accuracy for both $LVaR_{simple}$ and $LVaR_{JS}$ techniques clearly showing – for all portfolios – superior accuracy using the latter.



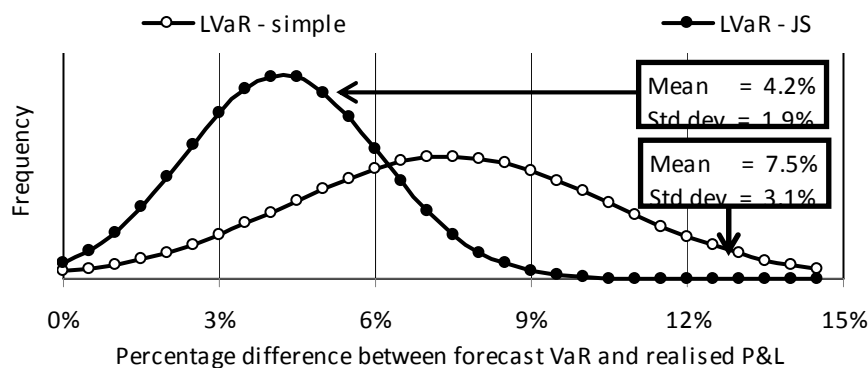
VaR has been criticised for failing to forecast the degree of inaccuracy should an exception occur. Although this gap has been largely plugged by expected shortfall (ES) measures (Yamai and Yoshida, 2002), the accuracy of liquidity VaR measures could be compared using the portfolio data from this study. Thus, in addition to the number of exceptions, the Rand difference between realised P&L and forecast VaR was also determined using both measures of liquidity VaR. The results are shown in Figure 4 below. For each of the 14 portfolios here investigated – each using 466 data points – the $LVaR_{simple}$ measure underestimated actual

losses to a greater extent than the $LVaR_{JS}$. For $LVaR_{simple}$ the average underestimation was 7.5% with a standard deviation, $\sigma = 3.1\%$ while for $LVaR_{JS}$ the average underestimation was only 4.2% with $\sigma = 1.9\%$.

6. CONCLUSION

LVaR using the JS methodology has been successfully incorporated into a portfolio framework. It has been shown to be superior to LVaR estimated using the simple square root of time technique using realised P/L (in terms of both *frequency of underestimation* and *accuracy of P&L estimation*) values as a comparison. Simple LVaR employs only the square root of time as a suitable scaling factor to accommodate liquidity constraints, while the JS LVaR model uses the JS approach to liquidity risk. The latter has already been demonstrated to be superior to the square root of time model at the individual instrument level (Jarrow and Subramanian, 1997: 172).

Figure 4: Comparison of VaR forecast versus realised P&L for both $LVaR_{simple}$ and $LVaR_{JS}$ techniques. For all portfolios, the latter's estimated losses were more accurately forecast.



The implementation of the JS model is by no means simple: obtaining and estimating the required parameters is onerous and requires constant recalculation to accommodate the rapidly changing portfolio LVaR. However, these parameters are available (though often not disclosed publicly) and, having them, incorporation into a portfolio model is relatively straightforward and requires only knowledge of the linear correlations between equity returns to complete the calculation as well as a technique borrowed from standard portfolio theory.

The payoff received from this complex calculation is a much-improved VaR forecast with greater accuracy than that obtained from standard VaR models.

7. REFERENCES

- ALEXANDER, C. 2001. Market models: a guide to financial data analysis, *Wiley Publishing*, London.
- ALMGREN, R. and Chriss, N. 1999. Value under liquidation, *Risk*, December, pp. 58 – 64.
- AMMAN, M and Reich, C. 2001. VaR for nonlinear financial instruments — linear approximation or full Monte Carlo?, *Financial Markets and Portfolio Management*, 15, pp. 1 – 18.
- ANGELIDIS, T and Benos, A. 2005. Liquidity adjusted value at risk based on the components of the bid-ask spread. <http://ssrn.com/abstract=661281> [Date of access: 31 August 2007]
- BANGIA, A., Diebold, F.X., Schuermann, T. and Stroughair, J. 1998. Modelling liquidity risk. www.ssc.upenn.edu/~fdiebold/papers/paper25/bds.pdf [Date of access: 22 September 2006]
- BANGIA, A., Diebold, F.X., Schuermann, T. and Stroughair, J. 1999. Liquidity on the outside, *Risk*, 12, pp. 68 – 73.
- BIS, 1988. International convergence of capital measurement and capital standards. www.bis.org/publ/bcbs04a.htm [Date of access: 12 August 2006]
- BIS, 2004. International convergence of capital measurement and capital standards: a revised framework. www.bis.org/publ/bcbsca.htm [Date of access: 17 December 2006]
- BIS, 2005. The application of Basel II to trading activities and the treatment of double default effects. www.bis.org/publ/bcbs111.htm [Date of access: 28 December 2006]
- BLAKE, D., Cairns, A. and Dowd, K. 2000. Extrapolating VaR by the Square-Root Rule, *Financial Engineering News*, August 2000. www.fenews.com/fen17/var.html [Date of access: 14 November 2006]
- BOLLERSEV, T., Chou, R. Y. and Kroner, K. F. 1992. ARCH modelling in finance: a selective review of the theory and empirical evidence, *Journal of Econometrics*, 52, pp. 5 – 59.
- BOUCHAUDY, J. P. and Potters, M. 1999. Worst fluctuation method for fast value at risk estimates, *Service de Physique de l'etat Condense*, Centre d'etudes de Saclay, September. <http://ssrn.com/abstract=181949> [Date of access: 11 September 2006]
- ÇETIN, U., Jarrow, R. A., Protter, P. and Warachka, M. 2004. Option pricing with liquidity risk, www.orie.cornell.edu/~protter/WebPapers/bspaper3.pdf [Date of access: 2 October 2006]
- COSANDEY D. 2001. Adjusting value at risk or market liquidity, *Risk*, October, pp.115 – 118.
- DANIELSSON, J. and Zigrand, Jean-Pierre. 2006. On time-scaling of risk and the square-root-of-time rule, *Journal of Banking & Finance*, 30, 10, pp. 2701 – 2713.
- DIEBOLD, F. X. and Lopez, J. 1995. Modelling volatility dynamics, in Kevin Horner (ed): *Macroeconomics: developments, tensions and prospects*. Boston: Kluwer Academic Press, pp. 427 – 472.
- DIEBOLD, F. X., Hickman, A., Inoue, A. and Schuerman, T. 1996. Converting 1-day volatility to h -day volatility: scaling by \sqrt{h} is worse than you think. www.ssc.upenn.edu/~diebold/ [Date of access: 18 October 2006]
- DOWD, K. Blake, D and Cairns, A. 2003. Long term value at risk. www.lse.ac.uk/ubs/pdf/dp17.pdf [Date of access: 7 November 2006]
- ERWAN L. 2002. Incorporating Liquidity Risk in VaR models, June. www.gloriamundi.org/picsresources/els.pdf [Date of access: 17 December 2006]
- FERNANDEZ, F. A. 1999. Liquidity risk: new approaches to measurement and monitoring. www.sia.com/research/pdf/workingpaper.pdf [Date of access: 21 November 2006]
- HAUSMAN, J., Lo, A. and MacKinlay, A. C. 1992. An ordered probit analysis of transaction stock prices, *Journal of Financial Economics*, 31, pp. 319 – 379.

- HFRX indices, 2006. www.hedgefundresearch.com/hfrx_reg/index.php?fuse=login&1162138035 [Date of access: 12 December 2006]
- HISATA, Y. and Yamai, Y. 2000. Research toward the practical application of liquidity risk evaluation methods, *Monetary and Economic Studies*, December, pp. 83 – 128.
- HOLTON, G. 2003. *Value at risk: Theory and Practice*, Academic Press, New York, pp 405.
- JARROW, R. A. and Protter, P. 2005. Liquidity Risk and Risk Measure Computation, *Review of Futures Markets*, 14, 1, pp. 2 – 17.
- JARROW, R. and Subramanian, A. 1997. Mopping up liquidity, *Risk*, December, pp. 170 – 173.
- JARROW, R. and Subramanian, A. 2001. The liquidity discount, *Mathematical Finance*, 11, 4, pp. 447 – 474.
- JP Morgan, 1996. Riskmetrics Technical Document. www.riskmetrics.com [Date of access: 12 January 2007]
- L'HABITANT, F. S. 2000. Hedge funds and investment partnerships: a primer, *Discussion Paper, Thunderbird*, The American Graduate School of International Management, pp. 1 – 35.
- L'HABITANT, F. S. 2001. Assessing market risk for hedge funds and hedge fund portfolios, *The Journal of Risk Finance*, 2, 4, pp. 16 – 32.
- LAWRENCE, C. and Robinson, G. 1995. Liquidity, dynamic hedging and value at risk, *Risk Management For Financial Institutions*, Risk Pubs, pp. 63 – 72.
- LE SAOUT, E. 2002. Incorporating liquidity risk in VaR models. www.site.voila.fr/erwanlesaout/eng/rech/abstract.htm#artc01 [Date of access: 19 September 2006]
- LOWENSTEIN, R. 2002. When Genius Failed: The rise and fall of Long Term Capital Management, *Fourth Estate*, January, New York.
- MADHAVAN, A., Richardson, M. and Roomans, M. 1997. Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies*, 10, pp. 1035 – 1064.
- MCNEIL, A. J. 1996. Estimating the tails of loss severity distributions using extreme value theory, *Mimeo*, ETH Zentrum, Zürich, pp. 117 – 137.
- MULVEY, J. 2003. The role of hedge funds for long-term investors, *Journal of financial transformation*, The Capco Institute, pp. 23 – 28.
- Risk Magazine journalists, 2004. Private communication.
- SHARPE W. F. 1988. Determining a fund's effective asset mix, *Investment Management Review*, 2, 6, December, pp. 59 – 69.
- UMUT, C., Jarrow, R. A. and Protter, P. 2004. Liquidity risk and arbitrage pricing theory, *Finance and Stochastics*, 8, pp. 311 – 341.
- YAMAI, Y. and Yoshihara, T. 2002. Comparative analyses of expected shortfall and value at risk: their validity under market stress, *IMES Discussion Paper #2002-E-2*, Bank of Japan, 2002, pp. 216 – 270.

END NOTES

¹ Generalised Autoregressive Conditional Heteroscedasticity.

² The Bank's primary exposure to counterparty credit risk is through its investment portfolio. However, it can also have exposure to derivative counterparties (which may default on obligations) in the trading book. Banks seek to minimize the risk that a credit loss from a counterparty default or downgrade could cause either a financial loss or damage the Bank's reputation. Basel II addresses this counterparty risk problem in detail, but leaves the basic tenets of the measurement and management of market risk untouched (BIS, 2005).

³ This study is by no means confined to the risks associated with hedge funds – these funds merely amplify the effects of liquidity risk through their unique investment strategies.

⁴ It is commonly assumed that $\mu = 0$ (JP Morgan, 1996: 8).

⁵ In the standard parametric equation, only the term \sqrt{T} is assumed to adjust for market illiquidity.

⁶ This portfolio volatility equation may, of course, be extended for n stocks.

⁷ Similar results were obtained for the remaining ten portfolios in the data sample.

Chapter 5

Credit capital charge optimisation and the new Basel Accord

RETAIL CREDIT CAPITAL CHARGE OPTIMISATION AND THE NEW BASEL ACCORD

MARIUS BOTHA & GARY VAN VUUREN *

Abstract

The Basel Committee for Banking Supervision's new Basel Accord and accompanying credit risk capital equations are designed to encourage the improvement of risk management practices. However, over a range of loan quality for some loan types, improvement of risk management practices by enhanced borrower discrimination leads to increased regulatory capital charges. The effect — entirely due to underlying mathematics — could discourage banks from improving risk management for such loans, thereby contravening the Committee's aims. This paper locates and investigates the source of the problem and illustrates its effect on regulatory capital.

JEL Classification: C0, L5, G21, G32

Key words: Basel II, probability of default, credit risk, capital requirements.

1. INTRODUCTION

The Basel accord of 1988 was the first attempt by the Basel Committee on Banking Supervision (BCBS) to improve risk management practices in banks.¹ With much of the mathematics of risk management then still in its infancy, the accord did not address all risks faced by banks. Those risks that *were* covered required several amendments and improvements to the 1988 accord as practitioner's skills were honed and theory became best practice.^{2,3} Basel I addressed only credit and later market risk, but it soon became apparent that the former was too punitive in some aspects and too lenient in others. Basel I also completely ignored operational risk. These shortcomings and omissions have now been addressed in the new Capital Accord (or Basel II, as it has come to be known) with a much-improved treatment of credit risk as well as the incorporation of a set of methodologies to assist in the estimation of operational risk.⁴ Market risk has been left largely unchanged in Basel II and weaknesses that do remain in the treatment of operational risk will no doubt be addressed in future versions of the accord.

*Visiting professors, School of Management, University of the Free State, PO Box 339, Bloemfontein, 9300, South Africa.

The detailed proofreading and helpful suggestions provided by Andrew Shenton of Fitch Ratings are gratefully acknowledged.

The impact of the BCBS's new credit risk methodologies on bank's regulatory capital calculations are yet to be fully ascertained. The BCBS rolled out five versions of the Quantitative Impact Study (QIS) questionnaire to determine precisely this impact, but the results were mixed and not well accepted.⁵ Basel II has now been implemented (January 2008) in many developed and emerging countries; and those not yet fully Basel II compliant are expected to follow suit by 2011. Thus, the theoretical results gleaned from the BCBS's QIS surveys have begun to be replaced by empirical data from banks' risk and compliance departments. The BCBS relies on practitioner feedback to adjust shortcomings in the accords: it is important to remember that the Basel accords themselves are not legislation, but rather "global best practice" guidelines established and implemented by representatives from major central banks.

The Basel accords, however, seek to be all things to all banks in order to level the global playing field and provide useful benchmarks. As a result, a necessarily limited set of models have been developed to cover all risky possibilities facing banking institutions worldwide. Whilst these efforts are to be applauded, it is perhaps inevitable that some flaws and inconsistencies will appear. One of these potential inconsistencies will be explored in this paper – a feature of Basel II's treatment of credit risk measurement that is incompatible with its stated goal of providing capital incentives for better risk management practices.

The remainder of this paper is arranged as follows: Section 2 establishes the relevance of Basel II in banks by providing a brief background to its development and implementation. Section 3 provides a survey of current, popular credit risk models including the single and multi factor models.

The credit risk model adopted by Basel II is the asymptotic single risk factor (ASRF) model. This is introduced in Section 4 which also explains the components of the model and discusses the problems introduced by convex variation of minimum capital with probability of default. Section 5 explores analytical results from hypothetical portfolios using different numbers of pooled probabilities of default. Analysis is then extended to real portfolios and the results discussed. Section 6 concludes the paper.

2. THE BASEL ACCORDS

The implementation of the new Basel Accord's non-advanced approaches in January 2008 heralded the inauguration of an ambitious, global banking project to encourage improved risk management in banks. The timetable established by the Banking Committee of the Bank for International Settlements originally intended this implementation to commence one year earlier, in 2007. The hiatus was blamed on implementation difficulties and a largely unprepared

banking community. The situation has only marginally improved: many institutions – in both developed and emerging markets – remain woefully ill-prepared and local regulators sometimes lack the requisite sophistication.

Many of these problems stem from the complexities of credit risk measurement. The enormous popularity of Value at Risk (as *the* metric of choice for measuring market risk) is largely due to its endorsement by the 1996 amendment to the 1988 Basel Accord, but its relative simplicity, adaptability and applicability to a wide range of products have also played a role. Credit risk – by contrast – is more complex: the distribution of institutional credit losses is highly skewed, it relies on complicated mathematics (e.g. copulas) to explain links between the economic milieu and loan values, it involves an understanding and differentiation of equity, asset and default correlations and it requires several more parameters (e.g. loss given default, probability of default, exposure at default) – each related to the other in complex ways – than market risk.

The new accord has undergone (planned) multiple revisions, augmentations and excisions and, given the experience garnered from 1996 amendment to the 1988 Accord, it is likely that Basel II will be further revised at some or several points in the future. These alterations are generally welcomed as they represent an egalitarian, best-practice approach to global banking. For the moment, the credit risk environment is highly fluid, constantly evolving and improving as techniques are honed and perfected. Enthusiastic debate and concentrated research is in progress and it is to be expected that the fruits of these labours will yield results that will show segments of the new accord to be inadequate, inaccurate or completely wrong. Given the intensity of the research that has already incorporated into Basel II, complete rewrites seem unlikely, but it is inevitable that models will improve as more information becomes available.⁶

Banks may choose between two approaches to calculate the capital requirement for credit risk: the standardised approach (a slightly modified version of the current Basel I accord) and the internal ratings based (IRB) approach (in which banks are permitted to use their own internal estimates of prescribed key risk drivers as inputs to the capital calculation). In the IRB approach, regulatory minimum capital for a loan portfolio is calculated in a bottom-up manner, by estimating and then summing capital requirements at the individual loan level. Loan capital requirements are derived from the Asymptotic Single Risk Factor (ASRF) model. Although the BCBS neither cites nor documents this model, it is widely believed that Gordy's⁷ work (itself largely derived from an adaptation of the single asset model of Merton,⁸ later ex-

tended to an entire portfolio by Vasicek⁹) was the precursor to the regulatory equations. Pykhtin and Dev¹⁰ further extended Gordy's work.

In this model, portfolio credit risk is separated into two categories: systematic and idiosyncratic risk. Systematic risk represents the effect of unexpected changes in macroeconomic and financial market conditions on borrower performance. Idiosyncratic risk represents the effects of risk connected to individual companies. One of the ASRF approaches key assumptions is that the credit portfolio comprises a large number of relatively small exposures. As the portfolio becomes more and more fine-grained (i.e. the largest individual exposures account for smaller and smaller portfolio exposures), *portfolio* idiosyncratic risk is diversified away and all systematic risk – such as industry or regional risk – is modelled with only a single, common systematic risk factor which drives all dependence across credit losses in the portfolio. The model thus assumes that banks are well-diversified across all geographic and industrial sectors in large economies.

The ASRF model also assumes that the capital charge for a lending exposure is based solely on loan-specific information. Capital charges are thus calculated on a decentralised loan-by-loan basis first, and then aggregated up to portfolio-wide value at risk (VaR) afterwards.

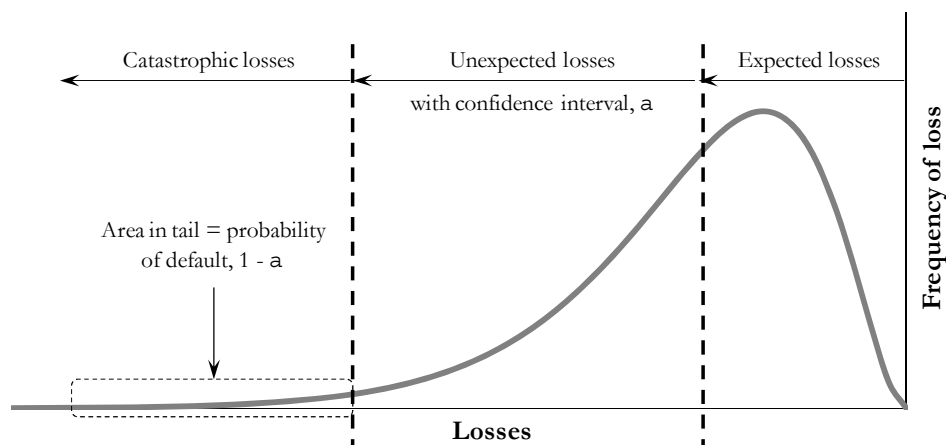
Principal inputs (Section 3) supplied by the bank include the exposure at default (EAD), the probability of default (PD), the loss given default (LGD) and the effective remaining loan maturity (M). Given these inputs the IRB capital charge is computed by calculating capital charges on a decentralised loan-by-loan basis and then aggregating these up to a portfolio-wide capital charge.

3. REGULATORY CAPITAL USING THE IRB APPROACH

The Standardised approach essentially mimics the Basel I approach to credit risk (with some minor adjustments) in which all loan types are assigned a risk weighting determined by the BCBS. The IRB approach – which comprises the Foundation (FIRB) and the Advanced (AIRB) approach – allows banks to assign their own internal ratings to loans. In the Foundation IRB Approach banks may only determine and use their own internal ratings (and associated probabilities of default), while in the Advanced Approach, banks may measure and use other inputs (over and above their own internal ratings) in the specified regulatory capital equations.

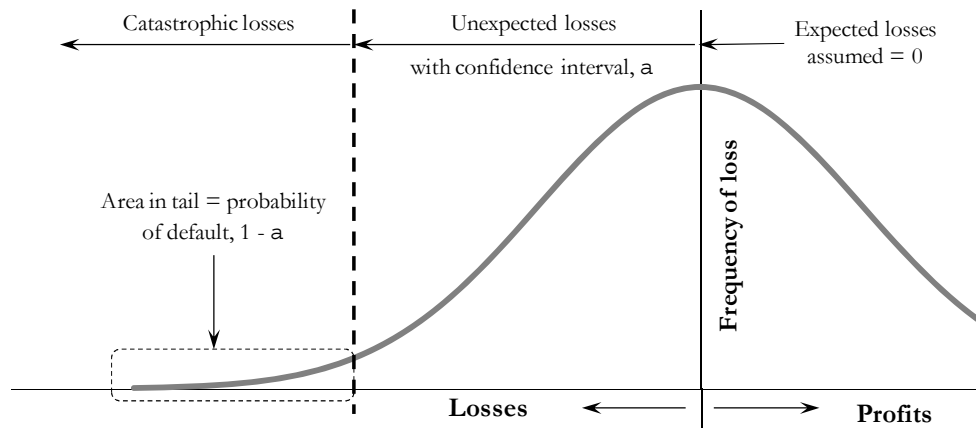
Banks are expected to forecast the average level of credit losses they can reasonably expect to experience over a one year horizon, known as expected losses (EL). Losses above this expected level – known as unexpected losses (UL) – occur occasionally, but their timing and severity are both unknown. Banks cover their EL continuously by provisions, write-offs and the incorporation of these expected losses into instrument pricing. Basel II requires banks to only hold capital against UL: the required capital per unit of currency exposure. A number of approaches exist to determine a bank's requisite capital. Basel II's IRB approach estimates the annual loss which will be exceeded with a small, pre-selected probability, $1 - a$ (see Equation 1 below). This is considered the probability of bank insolvency (meant in a broad sense, including, for example, the case of a bank failing to meet senior loan obligations) and is shown graphically in Figure 1.

Figure 1: Characteristic shape and relevant parameters of credit loss distributions.



It is instructive to compare the distribution of credit losses and relevant loss regions with the more familiar equivalent graph for market risk losses, shown in Figure 2. For regulatory capital purposes the expected loss here is assumed to be zero, the confidence interval is set at a much lower value (99%) and the period over which the losses are expected to occur is ten days rather than one year (c.f. confidence interval = 99.9% and period over which losses are expected to occur = 1 year for credit risk).

Figure 2: Characteristic shape and relevant parameters of market loss distributions.



Basel II's regulatory capital charge for the IRB approach – per unit of currency exposure – is specified by BCBS:

$$K = LGD \cdot \left(N \left[\sqrt{\frac{1}{1-r}} N^{-1}(PD) + \sqrt{\frac{r}{1-r}} N^{-1}\left(\frac{a}{2}\right) \right] - PD \right) M^* \quad (1)$$

where

LGD is the loss given default

$N[x]$ denotes the cumulative distribution function for a standard normal random variable (i.e. the probability that a normal random variable with mean zero and variance of one is less than or equal to x).

$N^{-1}(z)$ denotes the inverse cumulative distribution function for a standard normal random variable (i.e. the value of x such that $N(x) = z$).

PD is the probability of default

r is the asset correlation which indicates the dependence of the asset value of a borrower on the general state of the economy – all borrowers are linked to each other by this single risk factor

a is the confidence level – set at 99.9%, i.e. an institution is expected to suffer losses that exceed its economic capital only once in a thousand years on average and

M^* is a maturity adjustment which embraces the empirical evidence that long-term loans are riskier than short-term loans and the fact that downgrades from a higher rating category to a lower one, are more likely for long-term loans. Maturity effects are also more pronounced for obligors with low probabilities of default. This maturity adjustment, M^* , is given by

$$M^* = \frac{1 + (M - 2.5) b}{1 - 1.5 b} \quad (2)$$

where

M is the maturity of the (wholesale) loan and

b is a scaling factor dependant only on PD , given by $b = 0.11852 - 0.05478 \ln(PD))^2$.

Whilst Equation 1 differs by loan type, these differences are relatively minor, e.g. linear adjustment scaling for turnover in small to medium corporate (SME) loans.

A remarkable characteristic of Equation 1 (apart from its simplicity) is its property of asymptotic capital additivity: the total capital for a large portfolio of loans is the weighted sum of the marginal capital for individual loans. That is, the capital required to add a loan to a large, diversified portfolio depends only on the properties of that loan and not on the portfolio to which it is added. The ASRF credit model is thus said to be portfolio invariant, a property that depends strongly on the asymptotic assumption, and especially on the assumption of a single systematic risk-factor. In addition, portfolios that are not asymptotically fine-grained (i.e. any single obligor represents a negligible share of the portfolio's total exposure) contain undiversified idiosyncratic risk. In this case, the marginal contributions to the economic capital depend on the rest of the portfolio. For a loan portfolio of unit of currency exposure EAD , the capital charge is (using Equation 1) simply $K EAD$.

A brief description of each of the principal input parameters follows.

Probability of default

Under the IRB approach, the PDs are obtained from the internal rating system of the bank. According to the BCBS, these should be average quantities, reflecting expected default rates under normal business conditions.

Two kinds of models for determining probabilities of default are commonly addressed in the literature; accounting based models and market based models. Discriminant analysis and logistic regression models belong to the first class. The popular Z-score¹¹ is based on linear discriminant analysis, while Ohlson's O-Score¹² is based on generalised linear models (GLM)

with the logit link function. Newer accounting based models are founded on neural networks¹³ and Generalised Additive Models (GAM).¹⁴

Market models are based on the firm's asset value, determined by the market, such as Moody's KMV model. Stock prices are used as proxies for the asset value of the firm – implying that these models require stock exchange-registered (publicly listed) firms: a circumstance not fulfilled for many small and medium-sized borrowers.

Loss given default

In the capital formula (Equation 1) it is assumed that the loss given default rate (which is equal to one minus the recovery rate) is known and non-stochastic.⁵ During an economic downturn, losses on defaulted loans are likely to be higher than under normal business conditions, because for instance collateral values may decline. Average loss severity figures over long periods of time can understate LGD rates during an economic downturn, and may therefore need to be adjusted upward to appropriately reflect adverse economic conditions.

Hence, conservative values should be chosen so as not to underestimate portfolio risk. Equation 1 thus requires that a "downturn" LGD is estimated for each client/risk segment. Due to the evolving nature of bank practices in the area of loss given default quantification, the BCBS has not proposed a specific rule for estimating the LGDs. Instead banks are required to provide their own estimates, but they may use supervisory estimates if they have adopted the foundation IRB approach for wholesale exposures.

Exposure at default

Under the advanced IRB approach, banks are allowed to use their own estimates of expected exposure at default for each facility. EAD comprises two parts: the amount currently drawn and an estimate of future draw downs of available, but untapped, credit. Estimates of potential future draw downs (i.e. how the client may decide to draw unused commitments) are known as credit conversion factors (CCFs). Since the CCF is the only random or unknown proportion of EAD, estimating EAD amounts to estimating this CCF. CCFs depend on both the type of loan and the type of borrower.

Default correlations

The single systematic risk factor required in the ASRF model may be interpreted as reflecting the state of the global economy. The degree of an obligor's exposure to this systematic risk factor is expressed by the asset correlation. Asset correlations link the movements of how

asset values of one borrower depend on the asset values of another. In a similar way, the correlation can be described as the dependence of the asset value of a borrower on the general state of the economy – all borrowers are linked to each other by this single risk factor.

Asset correlations influence the structure of the risk weight formulas. They are asset class-dependent since different borrowers and/or asset classes show different degrees of dependency on the overall economy. It is important to note that *asset* correlation and *default* correlation are not the same: the way in which they are related is explained elsewhere.¹⁵

In the IRB approach, asset correlations are not estimated by banks. Instead they are calculated according to equations provided by the BCBS. These are based on two empirical observations,¹⁶ namely:

- asset correlations decrease with increasing probability of default and
- asset correlations increase with firm size.

This means that the higher the probability of default, the higher the idiosyncratic risk components of an obligor. Moreover, conditional on a certain probability of default, assets of small and medium sized enterprises are less correlated. Hence, if two companies of different size have the same PD, it follows that the larger one is assumed to have a higher exposure to the systematic risk factor. In other words, larger firms are more closely related to the general conditions in the economy, while smaller firms are more likely to default for idiosyncratic reasons. The BCBS has provided different formulas for computing the asset correlations for different business segments. These are discussed in detail in BCBS (2006) and are summarised in Table 1 below.

Table 1: Loan input parameters under Basel II's Advanced IRB.

	LOAN TYPE	LGD	CORRELATION	
RETAIL	Mortgage	25%	Fixed	15%
	Qualifying revolving	85%		4%
	Other retail	85%	Varies with PD	$0.03 \left(\frac{1 - e^{-35PD}}{1 - e^{-35}} \right) + 0.16 \left[1 - \left(\frac{1 - e^{-35PD}}{1 - e^{-35}} \right) \right]$
Corporate, Sovereign, Banks	45%	$0.12 \left(\frac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.24 \left[1 - \left(\frac{1 - e^{-50PD}}{1 - e^{-50}} \right) \right]$		

Note the differences – for asset correlations – between upper and lower bounds as well as the exponent coefficients for "other retail" and corporate loans.

4. CAPITAL CHARGE OPTIMISATION

For the remainder of this article, capital charges refer specifically to those incurred due to credit risk. Market risk capital charges are usually much smaller than credit risk capital charges¹⁷ and remain outside the scope of this investigation. Operational risk charges – where applicable – are referred to explicitly.

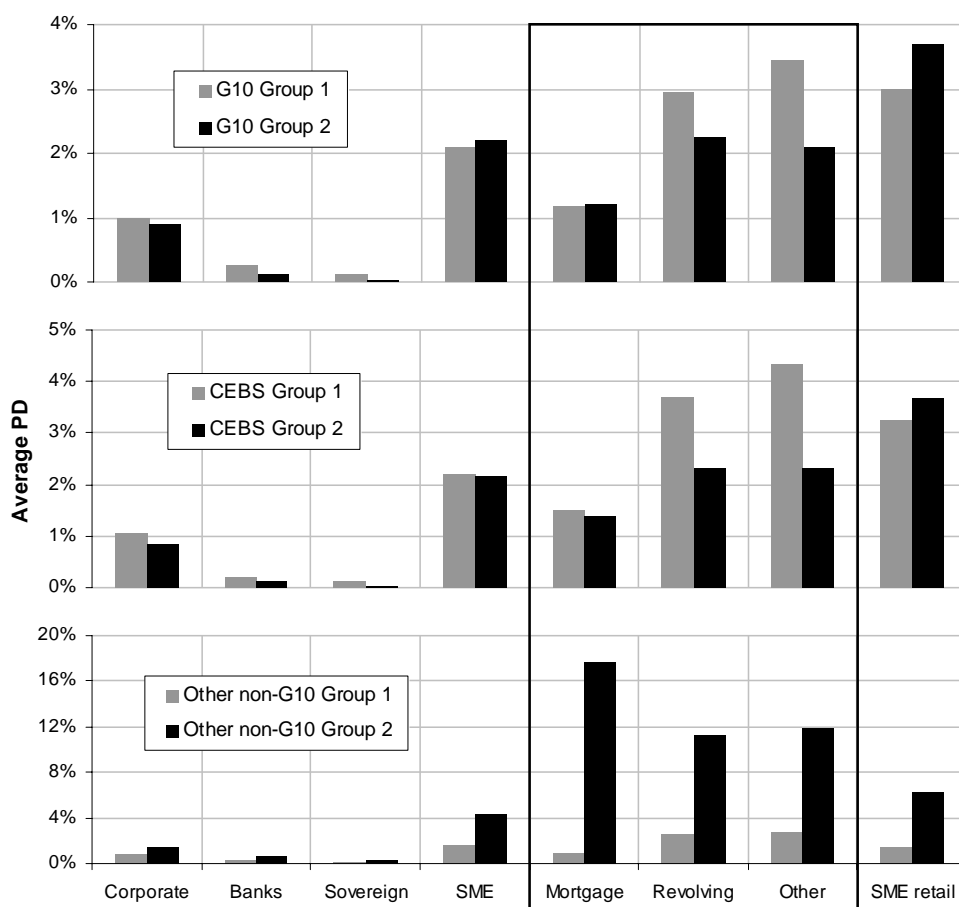
Many banks have reported significant regulatory capital relief due largely to more accurate capital allocation in, e.g., large mortgage portfolios. This is due to the significant reduction in risk weights applied to loans in this asset class by the shift from Basel I (50%) to Basel II (variable). Although risk weights vary (Equation 1), for a loan portfolio comprising high quality mortgage loans (i.e. PDs $\leq 1\%$), it is not unusual to observe significant capital charge reductions through the use of Basel II.

Despite this – and other – capital charge reductions, most banks in the transition from Basel I to Basel II have remained approximately "capital neutral" with capital benefits (derived from more accurate capital allocation for credit risk) being re-absorbed by capital charges for operational risk. Many banks continue to emphasise that the reduction of capital charges by ever more refined methods will become a principal focus in the future.^{18,19,20}

In the light of these efforts, this study investigated the possibility of minimising the capital charges by optimising the allocation of risk grades. More obvious methods of capital charge reduction involve improving the loan portfolio quality (lower PDs and LGDs, for example). As such considerations are the chief business of banks, they remain outside the orbit of scrutiny and influence of academic studies and will thus not be considered here. Optimising the capital charge an institution faces involves *minimising* these charges within both the Basel II framework and actual loan parameters unique to each bank. It should be noted, however, that 'optimisation' in this context refers to capital charge optimisation through PD grade allocation and not to capital charge optimisation through 'improved risk management'. The BCBS endeavours to encourage banks to embrace the latter aim, not the former.

The fifth and final Quantitative Impact Study (QIS 5) was instituted and reported by the BCBS in 2005.²¹ The principal focus of the study was to ascertain the impact of Basel II on banks before actual implementation of the Foundation IRB approach in 2007 and the Advanced IRB approach in 2008. The results of the study indicated – inter alia – that all of the six categories of banks held retail portfolios with significantly higher average PDs than other loan types. In particular, the average retail loan portfolio PD of "other non-G10" countries exceeds 10%, as shown in Figure 3.

Figure 3: Average PD results from the BCBS 5th Quantitative Impact Study.



5. DATA ANALYSIS

Loan parameters and PD buckets

The BCBS requires banks using the IRB approach to develop a rating system that estimates the PD of each obligor based on data such as historic and projected financial performance, industry risk and non-financial contingencies such as labour problems. The risk rating system must have a sufficient number of PD grades (usually taken to mean at least eight, including default²²) to allow for a meaningful differentiation of credit risk.²³

Further discrimination is introduced within the range (i.e. from best to worst) of obligor PDs. Since the PD grades are not (necessarily) of the same width, this added discrimination – Called PD buckets – serves only to facilitate the optimal allocation of PD grades.

Since retail loan portfolios suffer the highest PDs (and hence, via Equation 1, the highest capital charges) the goal of optimisation focussed on loan asset type. A loan portfolio was constructed with characteristics as described in Table 2.

Table 2: Loan portfolio parameters.

PARAMETER	VALUE
EAD	1
Minimum PD	0.001%
Maximum PD	15%
Number of PD regions (buckets)	5
LGD	Dependant on loan type: specified by FIRB approach.
Correlation	No FIRB approach currently exists for retail (Oct 2008) so these correlations are determined using AIRB

The PD buckets in Table 2 are constructed such that each embraces an equal fraction of the total loan exposure, in this case one-fifth per bucket, or 20%. This retail loan portfolio structure was chosen since it is fairly typical of non-G10 banks' portfolio composition.¹⁹ These buckets, and their corresponding loan quality, are defined in Table 3.

Table 3: PD buckets and corresponding loan quality.

PD BUCKET RANGE	CORRESPONDING LOAN QUALITY
0.001% < PD ≤ 0.1%	Excellent – highest grade
0.1% < PD ≤ 1%	Very good
1% < PD ≤ 5%	Good to fair
5% < PD ≤ 10%	Fair to poor
10% < PD ≤ 15%	Poor – lowest grade

Optimisation constraints

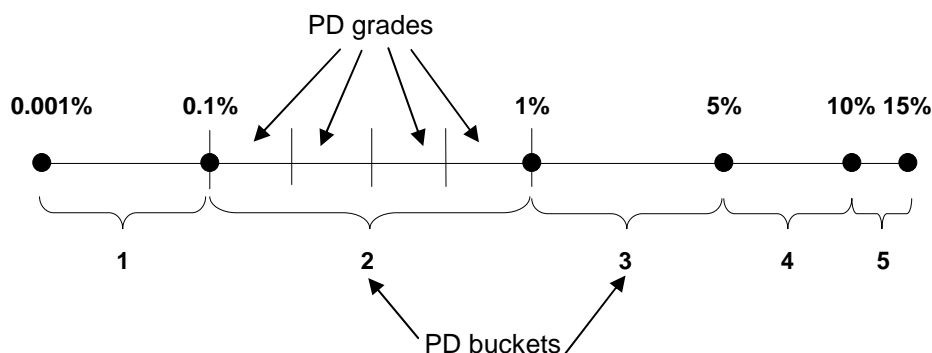
The optimisation of loan portfolios involves allocating the bank's internally-chosen PD grades (8, 12, 16, 20, 24 PD grades were used) into five PD buckets in such a way that the capital charge for each portfolio is minimised. This process is shown graphically in Figure 4.

This optimisation procedure is subject to the following constraints:

1. Each PD bucket must contain *at least one* PD grade (recall that the range of PDs for the simulated loan portfolio is from 0.001% to 15% – Table 2)
2. All PD grades *must* be utilised – i.e. allocated to one of the PD buckets.
3. The width of each PD bucket may differ.
4. Within each PD bucket, the width of each PD grade is identical. Thus, if there were two PD grades in PD Bucket 1 (Figure 4), the width of each PD grade would be $[0.1\% - 0.001\%]/2 = 0.05\%$, whilst if, for example, there were six PD grades in PD Bucket 2, these would each be of width $[1\% - 0.1\%]/6 = 0.015\%$, and so on.
5. Portfolio exposure is equally distributed among buckets.

6. Portfolio exposure is equally distributed among *grades* within a bucket.

Figure 4: PD grade allocation into PD buckets, shown on a logarithmic scale.



Optimisation procedure

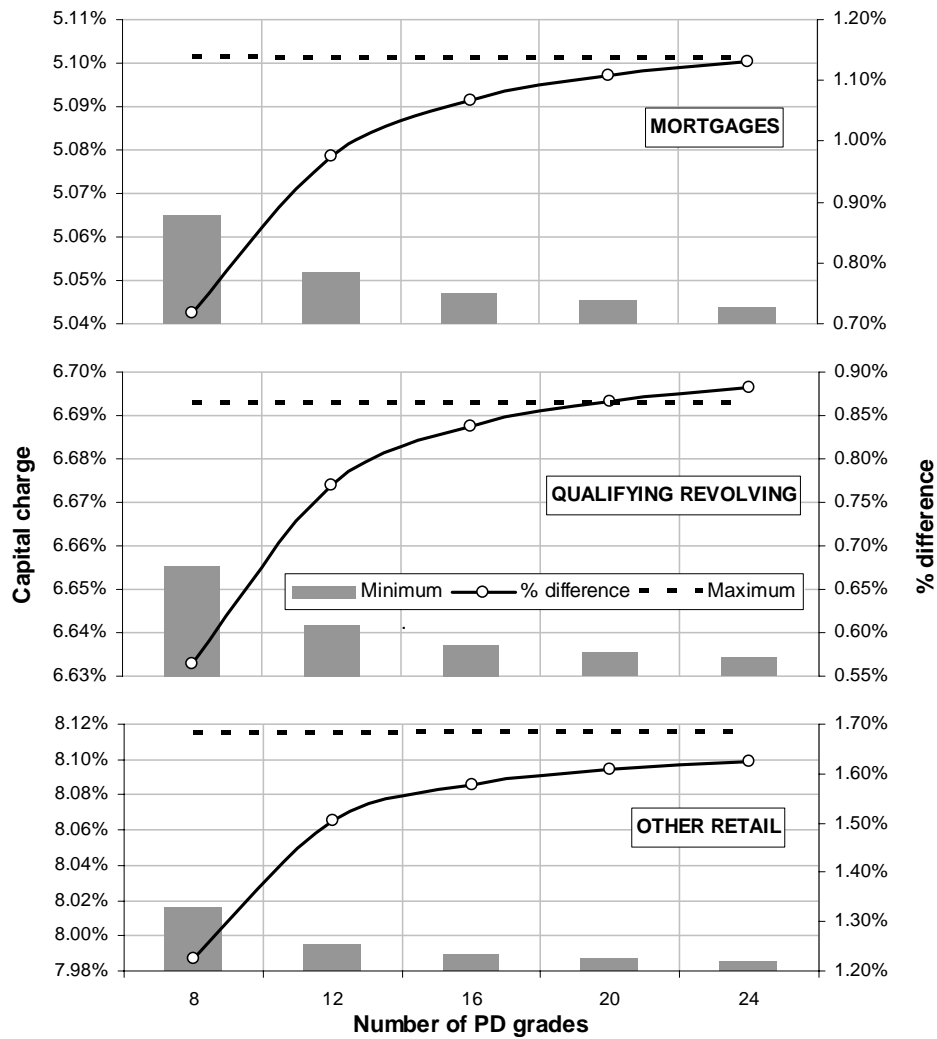
A variety of methods exist for solving constrained, non-linear programming (NLP) problems. Widely used methods are the Generalized Reduced Gradient²⁴ (GRG) and Sequential Quadratic Programming²⁵ (SQP) methods. Both of these methods were employed to optimise PD grade allocation within PD buckets (and determining the corresponding minimum capital charge) subject to the requisite constraints.

The arrangement of PD grades within PD buckets that yielded the lowest and highest capital charge (the latter for comparison purposes only) was then selected for each portfolio listed in Table 2 i.e. for the portfolio comprising 8 PD grades, 12 PD grades etc., up to 24 PD grades. The results are shown in Figure 5. For each loan type, it is possible to reduce capital charges by efficient allocation of PD grades. "Other retail" portfolios benefit the most from this allocation. Figure 6 shows the optimal allocation of PD grades – within the five PD buckets – for each loan type.

Optimisation results

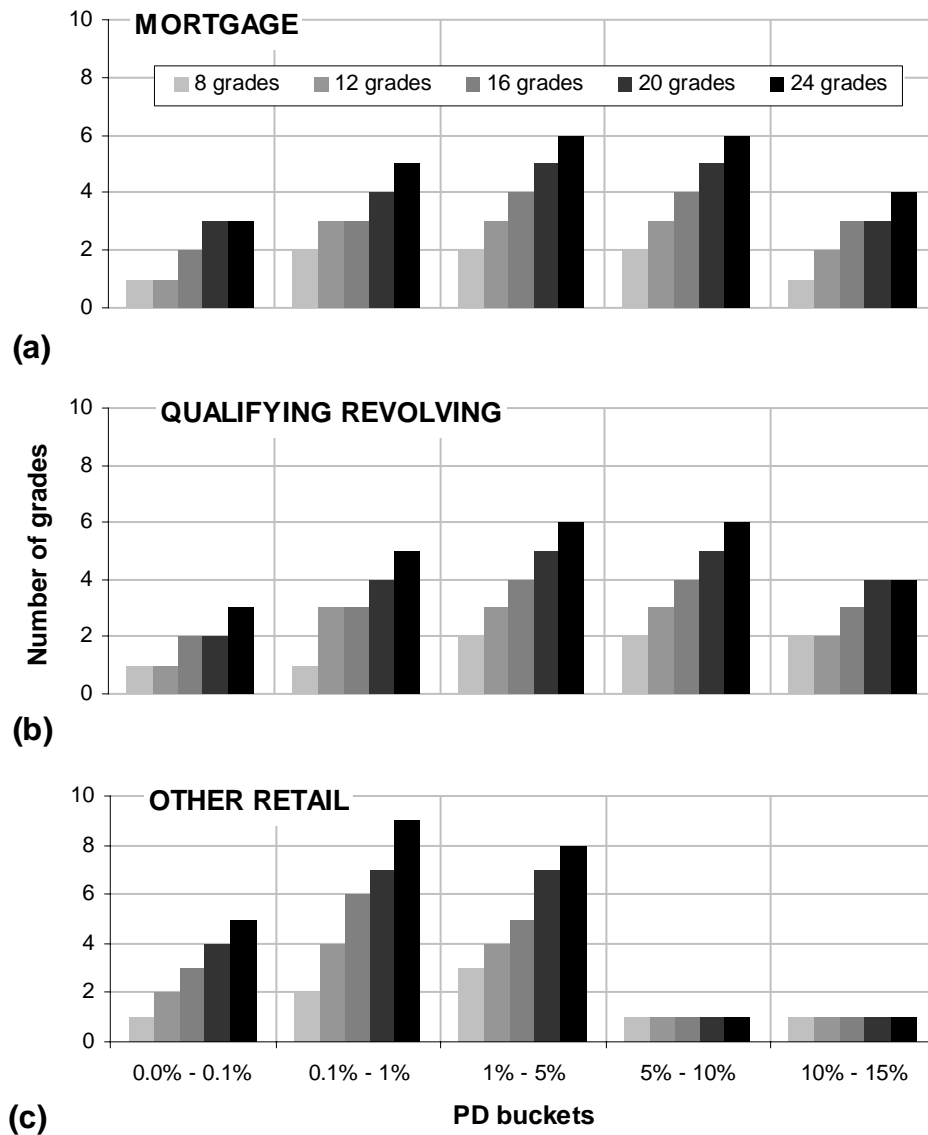
The results for mortgage and qualifying revolving portfolios are quite similar. Minimum capital charges arise from those portfolios with few PD grades within the range 0.001% to 0.1%, more with PD grades between 0.1% and 1.0%, more still between 1% to 5% and 5% to 10% and then a slightly declining number of PD grades from 10% to 15%. This trend holds for all numbers of PD grades.

Figure 5: Minimum/maximum capital and percentage differences for retail exposures.



The allocation of PD grades to the five buckets in "other retail" portfolios, however, shows significant differences. While the trend remains broadly the same for PDs < 5%, for PDs > 5% – and in all cases – the minimum capital charge portfolio has only a single PD grade allocated to both the $5\% < PD \leq 10\%$ and $10\% < PD \leq 15\%$ buckets. These results seem to indicate that discrimination for PDs between 5% and 15% in "other retail" portfolios is detrimental to the goal of capital charge minimisation. All loans with PDs between 5% and 15% should be grouped into a single grade if the minimum capital charge is sought. It is not immediately obvious why this should be so.

Figure 6: Retail loan portfolio capital charge optimisation.

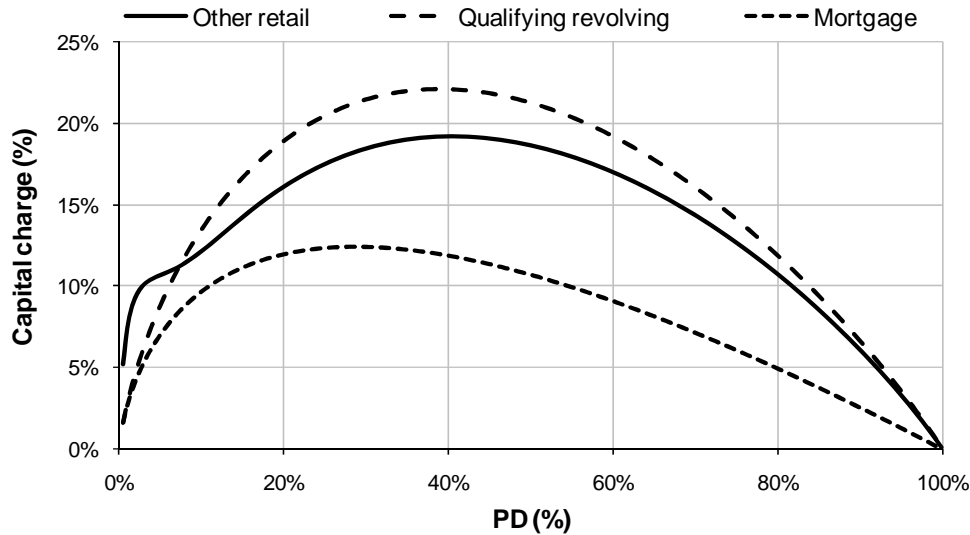


Local convexity in "other retail" capital charges

The relationship between capital charges and PD for mortgage and qualifying revolving portfolios is convex (using Equation 1 and the relevant parameters for these portfolios): capital charges increase steeply for low PDs with an ever decreasing gradient which reaches 0 between 30% \leq PD \leq 40% and then becomes negative for PDs greater than this range (Figure 7). Whilst on a broad scale this relationship holds true for "other retail" portfolios as well, closer examination reveals a region of local negative convexity between 5% $<$ PD $<$ 15% as shown in Figure 8(a). A similar effect has been noted in the market,²⁶ but the problem was approached from a stressed PD point of view with the GINI coefficient employed to determine the effect of discrimination on minimum capital requirements. This range was deter-

mined by differentiating Equation 1 (using the relevant asset correlation equation from Table 1). The results indicate that the capital charge curve is concave over $[0\%, 4.903\%)$, convex over $(4.903\%, 15.184\%)$ and concave over $(15.184\%, 100\%)$.²⁷

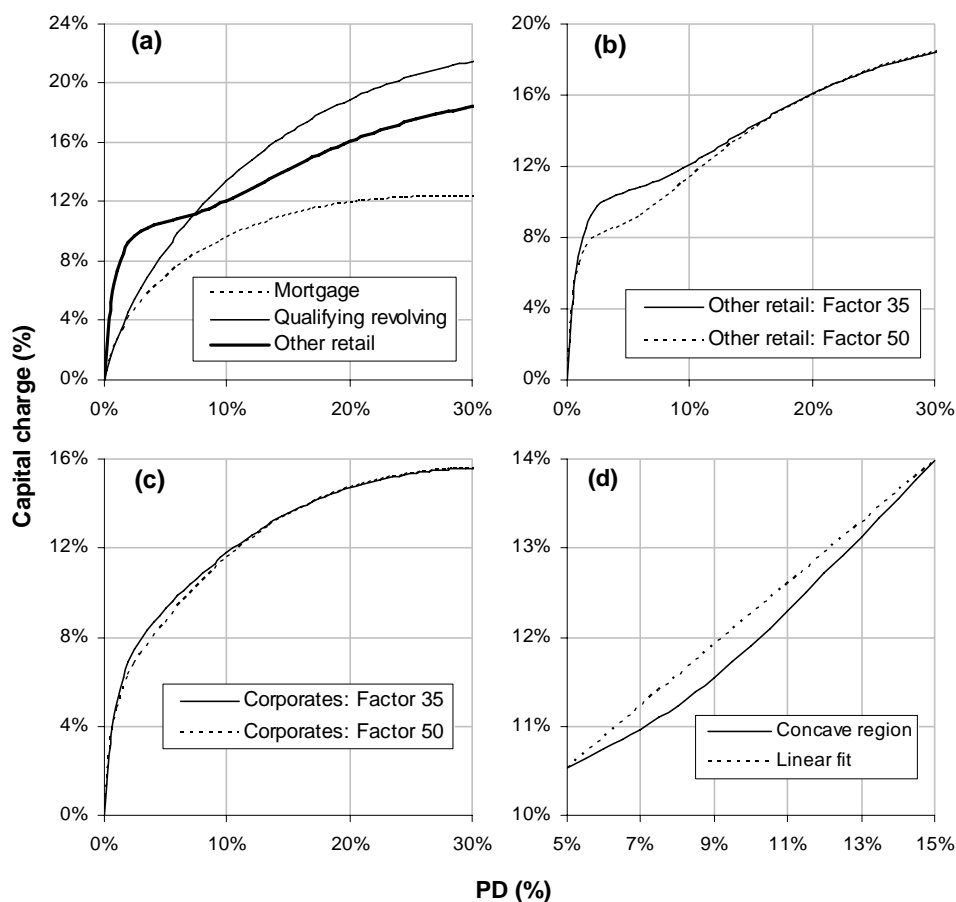
Figure 7: Variation of retail capital charge versus PD for retail exposures.



The explanations of this local negative convexity must be embedded within the mathematics of Equation 1. In fact, it must lie within the formulation of the asset correlation as this is the only real difference between the treatment of mortgage + qualifying revolving portfolios and that of "other retail" portfolios. The obvious difference between these loan types is the fixed versus variable asset correlation formulation. This observation provides a necessary – but insufficient – explanation for the negative convexity. It is insufficient because corporate loans also employ variable asset correlation and yet do not exhibit this local negative convexity. Note from Table 1, however, that corporate loan asset correlations are bounded by 0.12 and 0.24 and the exponential coefficient is 50 whilst "other retail" loan asset correlations are bounded by 0.03 and 0.16 with exponential coefficient 35. Figure 8(b) shows the shape of the capital charge versus PD curve using a fixed asset correlation range between 0.03 and 0.16 with exponential coefficients of 35 and 50 (i.e. the asset correlation curve for "other retail" portfolios using both exponential coefficients). Figure 8(c) shows the capital charge versus PD curve using a fixed asset correlation range between 0.12 and 0.24 with exponential coefficients of 35 and 50 (i.e. the asset correlation curve for *corporate* portfolios using both exponential coefficients). No negative convexity is observed in Figure 8(c). The parameter responsible for the local negative convexity, then, must be the asset correlation. Figure 8(d) shows an expanded portion of the capital charge versus PD curve between $4\% < PD \leq 15\%$,

clearly showing the negative convexity. Since this region of negative convexity is the sole cause of the difference between optimal allocation of PD grades for mortgage, qualifying revolving and "other retail" portfolios, an explanation must be sought as to why these different-shaped capital charge curves yield such disparate PD grade allocations for capital charge minimisation.

Figure 8: (a) Retail portfolio capital charges, (b) effect of changes in exponent coefficient on capital charge for "other retail" loan capital charges, (c) effect of changes in exponent coefficient on capital charge for corporate loan capital charges and (d) detail of the negative convexity capital charge region for "other retail" portfolios.



Worked examples

Consider two mortgage loans each with EAD of 0.5, but one with a PD of 1% and the other with PD of 3%. If the financial institution which issued these loans did not discriminate between these PDs, but rather grouped them into the same PD grade (say between 0.001% and 4%) then these loans would both be assigned a PD of 2% – the average PD of the grade into which they fall (i.e. $[4\% + 0.001\%]/2 = 2\%$). The capital charge for these loans is, using

Equation 1, $2 \cdot 0.5 \cdot 8.763\% = 8.763\%$ where the factor of 2 arises from the two loans and the 0.5 is the EAD for each loan. The value of 8.763% is calculated using Equation 1.

Now consider the case in which a bank had employed a more discriminating rating system, i.e. one which allocated, say *two* grades between $0.001\% < PD \leq 4\%$. Assume also that these grades were of equal width – i.e. 2% in each case: one grade from $0.001\% < PD \leq 2\%$ and another from $2\% < PD \leq 4\%$. The average PDs for these grades are 1% and 3% respectively. In this case, the first loan (with $PD = 1\%$) will fall into the first grade and the second loan (with $PD = 3\%$) into the second. The capital charges for these two loans (each of EAD 0.5) are: $0.5 \cdot 6.917\% = 3.458\%$ and $0.5 \cdot 9.489\% = 4.744\%$. Due to the additive property of the Basel II capital charge equations, the capital charge for this latter portfolio of loans is 8.203% – or some 6.4% *less* than the capital charge obtained from the portfolio of identical loans but with less discrimination between them. This disparity is clearly shown in Figure 9(a): a single PD grade embracing both loans results in a capital charge read from the actual capital charge versus PD curve (thick black line) while a more discriminating PD grade allocation results in the *linear average* of the two individual capital charges. This capital charge is read from the straight line joining the two individual capital charges. Adding more loans to the portfolio and increasing the discrimination between these loans results in lower and lower capital charges. It is clear, in this example, how the BCBS's stated goal of rewarding improved risk management practices is accomplished.

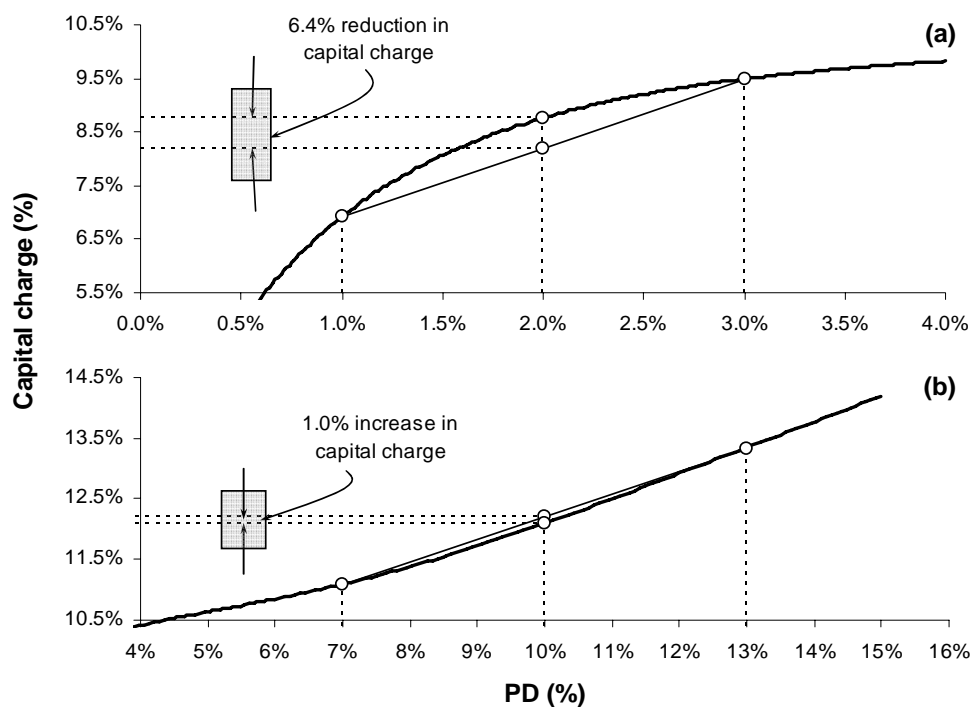
Figure 9(b) shows a region of the capital charge versus PD curve for the "other retail" loan category. This region, from $4\% < PD < 16\%$, was deliberately chosen because it is this range over which the capital charge curve exhibits negative convexity.

Consider again two loans, one with EAD 0.5 and PD 7% and another with EAD 0.5 and PD 13%. Again assume that both loans are grouped – in the first case – into a single PD grade spanning say $4\% < PD \leq 16\%$. This PD range is chosen for ease of calculation. Although not specifically encompassing the full PD range over which negative convexity occurs, this range falls well within it. The average PD of this grade is $[4\% + 16\%]/2 = 10\%$. The capital charge for these two loans is (using Equation 1) $2 \cdot 0.5 \cdot 12.100\% = 12.100\%$ where, as before, the factor of 2 arises from the fact that there are two loans, the factor of 0.5 is the EAD for each loan and the value of 12.100% is derived from Equation 1.

Assume now that the bank adopts a more discriminatory PD grade allocation: in this case assume the bank splits the PD region into two grades spanning $4\% < PD \leq 10\%$ and $10\% <$

PD \leq 16%. In this case, the first loan will fall into the first bucket (of average PD 7% and capital charge 5.547%) and the second loan into the second bucket (of average PD 13% and capital charge 6.674%). The capital charge for this portfolio of loans is 12.212% or 1.0% *more* than the charge paid for a *less* discriminating PD allocation. Adding more loans – and more grades – only exacerbates the problem: capital charges *increase* the more grades that are applied.

Figure 9: PD discrimination effect on "other retail" portfolio for (a) PD \leq 4% and (b) 5% \leq PD \leq 16% .



Influence on PD discrimination

The outcome of this investigation may now be applied to the results obtained in Figure 6. When the capital charge versus PD curve is convex, greater PD discrimination leads to a *reduction* in capital charges. Thus, no matter how many grades a financial institution employs with which to attribute loans of different quality (and hence PD), PD grades are more or less evenly spaced over the PD range for mortgages and qualifying revolving loans. The convexity lends itself to greater discrimination: the more grades, the lower the capital charge and the allocation of those grades within the PD region is more or less equal.

On the other hand, in the region of the "other retail" capital charge versus PD curve that exhibits negative convexity, *greater* PD discrimination leads to an *increasing* capital charge. At best, assuming a financial institution actually has loans of low PD quality (i.e. 5% $<$ PD \leq

15%), only a single PD grade should be allocated to this region since further discrimination yields comparatively higher capital charges.

6. CONCLUSION

Basel II proposes novel and improved risk sensitive methodologies for the allocation of adequate capital requirements to cover credit risk. Derived from single factor credit models which are known not to provide the perfect framework for capital charge allocation, these methodologies introduce convexity into the otherwise concave capital charge function for "other retail" portfolios. The stated goal of Basel II is to provide capital incentives for better risk management practices. The results from this study, however, indicate that, in poor quality loan portfolios (i.e. precisely the type of portfolio most in need of stringent PD discrimination), greater loan quality discrimination leads to *higher* capital charges – thereby illuminating a potential weakness of the Basel II calculations for credit capital charges under the IRB approach. It has been shown that even for simple examples of "other retail" retail loan portfolios presented in this study, capital charge reductions are easily affected with non-complex segmentation of the PD grades.

This anomaly is unsatisfactory from a regulatory point of view. Any incentives to allocate time and resources to better PD discrimination are effectively reduced since capital requirements can be reduced simply by decomposing the relevant portfolio into segments (the most favourable segmentation determined via optimisation). In addition, there are incentives to segment portfolios purely for capital allocation purposes rather than improved risk management. Future studies will concentrate on real, large, heterogeneous retail loan portfolios to ascertain the degree of regulatory arbitrage attainable through optimised PD segmentation.

7. REFERENCES

¹ BCBS (1988), 'International convergence of capital measurement and capital standards'. Available at [<http://www.bis.org/publ/bcbsc111.htm>], last accessed on 23 Jan 2008.

² BCBS (1996), 'Amendment to the capital accord to incorporate market risks'. Available at [<http://www.bis.org/publ/bcbs24.htm>], last accessed on 22 Jan 2008.

³ BCBS (1998), 'Amendment to the Basel Capital Accord of July 1988'. Available at [<http://www.bis.org/publ/bcbs36.htm>], last accessed on 22 Jan 2008.

⁴ BCBS (2006), 'International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version'. Available at [<http://www.bis.org/publ/bcbs128.htm>], last accessed 23 Jul 2008.

⁵ BCBS (2005), 'QIS 5: Fifth Quantitative Impact Study'. Available at [<http://www.bis.org/bcbs/qis/qis5.htm>], last accessed on 22 Jan 2008.

⁶ Kaltofen, D., Paul, S. and Stein, S. 2006, 'Retail loans & Basel II: Using portfolio segmentation to reduce capital requirements', ECRI Research Report No. 8. Available from [http://www.ecri.be/media/research_report/ECRI_RR_No.8.pdf], last accessed 29 Sep 2008.

-
- ⁷ Gordy, M. (2003), 'A risk-factor foundation for risk-based capital rules', *Journal of Financial Intermediation*, 12(3), p199–232.
- ⁸ Merton, R. C. (1974), 'On the pricing of corporate debt: The risk structure of interest rates', *Journal of Finance*, 29(2), p449–470.
- ⁹ Vasicek, O. (1977), 'An equilibrium characterization of the term structure', *Journal of Financial Economics*, 5(2), p177–188.
- ¹⁰ Pykhtin, M. and Dev, A. (2002), 'Analytical approach to credit risk modelling', *Risk*, 15, p26–32.
- ¹¹ Altman, E. (1968), 'Financial ratios, discrimination analysis and the prediction of corporate bankruptcy', *Journal of Finance*, 4(8), p589–610.
- ¹² Ohlson, J. (1980), 'Financial ratios and the probabilistic prediction of bankruptcy', *Journal of Accounting Research*, 18(1), p109–131.
- ¹³ Wilson, R., and Sharda, R. (1994), 'Bankruptcy Prediction Using Neural Networks', *Decision Support Systems*, 11(5), p545–557.
- ¹⁴ Berg, D. (2004), 'Bankruptcy Prediction by Generalized Additive Models'. Available at [http://www.math.uio.no/eprint/stat_report/2005/01-05.pdf], last accessed on 12 Oct 2007.
- ¹⁵ Zhang, J., Zhu, F. and Leebasset, J. 2008, 'Correlation, realized default correlation, and portfolio credit risk', *Modelling Methodology*. Available at [http://www.moodyskmv.com/research/files/wp/Asset_Correlation_and_Portfolio_Risk.pdf] last accessed on 28 Sep 2008.
- ¹⁶ Lopez, A. (2004), 'The empirical relationship between average asset correlation, firm probability of default and asset size', *Journal of Financial Intermediation*, 13(2), p.265–283.
- ¹⁷ Cruz, M. (2002), 'Modeling, measuring and hedging operational risk', Wiley Finance. New York.
- ¹⁸ Calem, P. S and Follain, J. R. (2007), 'Regulatory Capital Arbitrage and the Potential Competitive Impact of Basel II in the Market for Residential Mortgages', *The Journal of Real Estate Finance and Economics*, 35(2), p197–219.
- ¹⁹ Calem, P. S and LaCour-Little, M. (2003), 'Risk-based capital requirements for mortgage loans', *Journal of Banking and Finance*, 28(3), p647 – 672.
- ²⁰ Herring, R. J. (2007), 'The Rocky Road to Implementation of Basel II in the United States', *Atlantic Economic Journal*, 35(4), p419–429.
- ²¹ BCBS (2005), QIS 5: Fifth Quantitative Impact Study. Available at [<http://www.bis.org/bcbs/qis/qis5.htm>], last accessed on 22 Jan 2008.
- ²² Rice, G. 2006, 'Getting ready for Basel II'. *International Financial Law Review*. Available at [<http://www.stblaw.com/content/publications/pub572.pdf>], last accessed 19 Sep 2008.
- ²³ BCBS (2006), 'International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version', paragraph 826. Available at [<http://www.bis.org/publ/bcbs128.htm>], last accessed on 23 Jul 2008.
- ²⁴ Lasdon, L. S., Fox, R. L. & Ratner, M. W., 1973, 'Nonlinear optimization using the Generalized Reduced Gradient method', Technical memo, *Case Western Reserve University Cleveland Dept of Op Research*. Available at [<http://handle.dtic.mil/100.2/AD774723>], last accessed, 28 Sep 2008.
- ²⁵ Boggs, P. T. & Tolle, J. W., 2000, 'Sequential quadratic programming for large-scale nonlinear optimization', *Journal of Computational and Applied Mathematics*, 124(1–2), p123 – 137.
- ²⁶ Experian Scorex (2007), 'Influence of default prediction over the minimum capital requirements: New Basel Accord and the IRB approach for retail credit risk'. Available at [<http://www.crc.man.ed.ac.uk/conference/archive/2003/presentations/dautais.pdf>], last accessed 12 Aug 2008.
- ²⁷ Laurent, M. P. 2004, 'Asset Return Correlation in Basel II: Implications for Credit Risk Management', Université Libre de Bruxelles, Solvay Business School, Centre Emile Bernheim, Working Papers CEB. Available at [<http://www.solvay.edu/EN/Research/Bernheim/documents/wp04017.pdf>], last accessed 28 Sep 2008.

Chapter 6

Implied asset correlation in retail loan portfolios

IMPLIED ASSET CORRELATION IN RETAIL LOAN PORTFOLIOS

MARIUS BOTHA & GARY VAN VUUREN *

ABSTRACT

Credit risk arises from the interaction of multiple connected factors, but the most frequently-used models designed to measure it assume only one. These models – which, *inter alia*, fit distributions to loss data – are heavily influenced by the common correlation between loan values and the single factor (commonly assumed to be some gauge of economic health). Scarce and shoddy loss data for retail loan classes hampers the estimation of this correlation. A technique is proposed to calculate asset correlations embedded in empirical loss data. These values are then compared with those stipulated by the Basel II accord for minimum capital requirements.

JEL Classification: C134, C16, C53

Key words: Retail loans, asset correlation, Vasicek distribution, Basel II.

1. INTRODUCTION

In order to remain solvent under all but the most severe of circumstances, banks dedicate a battery of resources to the accurate, timely calculation of economic capital. This is an internal measure, designed to cushion against calamitous events, and it embraces the catholic array of risks faced by banks as well as any diversification benefits that arise between disparate risks. As such, economic capital is distinct from regulatory capital which is externally imposed by national regulatory bodies, covers only a handful of risks, ignores inter-risk diversification and applies fairly rigid constraints on the way capital reserves should be measured. Regulatory capital and all matters pertaining thereto is governed by two accords, designed and disseminated by the Basel Committee on Banking Supervision (BCBS). The accord of 1988 (Basel I) was an attempt by the BCBS to improve the risk management procedures practiced by banks (BCBS, 1988). Basel I addressed only credit risk (and, later, market risk (BCBS, 1996)), but this was somewhat coarsely determined across loan quality with little or no distinction made between superior and inferior borrowers. Capital charges determined using the 1988 accord were considered by banks to be punitive and inequitable (Repullo, 2004). The assembly and extensive implementation of the new capital accord (Basel II) has heralded, amongst other changes,¹ a much improved treatment of credit risk (BCBS, 2006a). In their

*Visiting professors, School of Management, University of the Free State, PO Box 339, Bloemfontein, 9300, South Africa.

¹ The treatment of operational risk, for example.

management of credit risk, banks now have the option of adopting either the Standardised approach (in which risk weights for loan exposure amounts are specified by the BCBS – similar to Basel I) or the Internal Ratings Based (IRB) approach (in which specific capital requirement formulas are specified by the BCBS, but some flexibility regarding the input parameters is allowed).

The IRB approach harnesses quantitative estimates of obligor-level risk (e.g., the probability of default (PD) and loss given default (LGD)) and is grounded in well-established concepts from modern portfolio-based risk management, thereby providing a sophisticated and more meaningful capital framework than Basel I. The IRB approach employs an asymptotic single-risk factor (ASRF) calculation methodology that allows relatively straightforward analytical solutions, rather than a full-blown multi-factor model typical of internal bank credit economic capital systems. Nevertheless, the IRB approach is based upon credit risk modelling concepts that are broadly consistent with capital models used increasingly by banks to measure portfolio-level risk and to manage and allocate capital across the enterprise.

The single systematic risk factor required by ASRF models can be interpreted as a reflection of the state of the global economy. All borrowers are linked to one another by this single risk factor and the strength of that linkage is measured by the asset correlation. The BCBS has calibrated and set predetermined values for the asset correlation within each of the IRB equations, which are broadly segmented by asset classes specified under Basel II (e.g., corporates, commercial mortgages, residential mortgages, credit cards and consumer lending) (Gore, 2006). Asset correlations thus determine the shape of the risk weight formulas and, because different borrowers and/or asset classes show different degrees of dependency on the overall economy, asset correlations are asset class dependent.

Banks *must* comply with regulatory rules to sustain capital adequacy and in so doing they *must* use the BCBS pre-specified asset correlation values. Economic capital models provide valuable additional information that banks use in their overall assessment of their capital adequacy (Burns, 2005) and they therefore retain an avid interest in the estimation of implied asset correlations embedded in their empirical loss data – independent of the BCBS specifications. These values are of critical import for internal economic capital models. The retrieval of implied asset correlation values from empirical gross loss data – while possible – is non-trivial. This paper examines the extraction of retail asset correlations, assesses their robustness and compares them to those specified by the BCBS.

The remainder of this paper is arranged as follows: Section 2 provides a brief literature survey of the field of asset correlation in credit-risky portfolios and establishes the relevance of the asset correlation to the Basel II Pillar 1 formulation. Section 3 introduces and evaluates the Vasicek distribution, including a robust methodology which can be used to extract relevant parameters from it. Section 4 introduces and employs the beta distribution as a tool to compare results obtained from the Vasicek distribution. Retail loan loss data spanning several decades are then analysed and the results obtained from this analysis are presented and discussed. Section 5 concludes the paper.

2. LITERATURE SURVEY

The BCBS explained and defended the choice of credit risk framework, equations and correlation values in a special 'explanatory note' (BCBS, 2006). The note does not divulge the analytical reasoning nor the mathematical foundations upon which the IRB approach is based. Instead, only broad conclusions are presented. This was a deliberate attempt by the BCBS to allow pertinent credit modelling concepts to be cemented into the consciousness of a select, non-technical audience. Much of the underlying technical formulation is described in Gordy (2002).

Lopez (2004) examined the empirical relationship between the average asset correlation, firm PD and firm asset size measured by the book value of assets by imposing the ASRF approach within the KMV methodology for determining credit risk capital requirements (Lopez, 2004). In a related paper, Lopez (2005) later empirically examined the asset correlation using portfolios of U.S. publicly-traded real estate investment trusts (REITs) as a proxy for commercial real estate (CRE) lending more generally. CRE lending as a whole was found to have the same calibrated average asset correlation as corporate lending, providing support for the U.S. regulatory decision to treat these two lending categories similarly for regulatory capital purposes (Lopez, 2005).

Duchemin *et al.* (2003) measured the asset correlations for automotive lease exposures using a single systematic factor ordered probit model in which the obligor status was limited to two states: default and survival. This model made use of a restricted version of CreditMetrics™ (Gordy, 2000). The results of this analysis showed that the empirically estimated correlations were significantly lower than those specified by the BCBS. The authors suggested taking one extra dimension (the volatility of the probability of default) into account in order to ascertain an adequate, empirical asset correlation (Duchemin, 2003).

Düllmann and Scheule (2003) addressed the gap between the impact of systematic risk on the loss-distribution of a credit-risky loan portfolio and the lack of empirical estimates of the default correlation. Ten years of monthly default data were used for over 50 000 German corporates. Results from this study suggested that the asset correlation parameter depends on both the probability of default as well as on the obligor firm size.

A comprehensive review of corporate defaults and the role of asset correlation was provided by Chernih, *et al.* (2006) and sources therein. It was acknowledged that asset correlations are only one source of dependence; explicitly modelling dependencies other than unexpected losses (such as dependence between LGD and PD) will be underestimated unless empirical asset correlations (from default data) are increased. The authors concluded that default data are the best source of default correlations as no intermediate process is assumed, but admit that default data are invariably either sparse or unavailable.

Gore (2006) stresses that, for corporate loans, banks have developed sophisticated internal ratings-based models and have collected abundant BCBS input IRB data including correlation parameters. In addition, for corporate loans, much academic research has been published on credit risk modelling (Fatemi and Fooladi, 2006). The picture for retail portfolios, however, is very different. Few academic papers have been published on the modelling of retail portfolio risks and the PD, LGD and exposure at default (EAD) data collected by banks are often sparse and lacking in detail (Gore, 2006).

Banks continue to struggle with systems and procedures required for retail loan portfolios in Basel II; many are not sufficiently sophisticated and some are inundated with other, more pressing implementation issues (Reeves, 2006). While various large banks have performed some retail loan analysis, the majority continue to apply the Basel rules without any focus on whether or not the BCBS-specified parameters produce realistic outcomes (Reeves, 2006).

A real need, therefore, exists for the development of a robust, yet practical, methodology to measure retail loan portfolio implied asset correlations. However, the lack of *individual* exposure default data coupled with the overall dearth of data for retail portfolios conspire to severely constrain detailed asset and default correlation studies for these asset classes. A non-exhaustive presentation, analysis and evaluation of the Vasicek distribution follows in the next section. A full analysis of this distribution from first principles, including a brief introduction to the underlying processes responsible for driving asset values, can be found in Vasicek (2002) and sources therein.

3. THE VASICEK DISTRIBUTION

Vasicek (1987, 1991, 2002) derived an expression for the distribution of credit portfolio losses using a Merton-type model. In this approach, the portfolio credit risk is quantified due to its potential default rate using a value at risk approach. Vasicek achieved analytical tractability by assuming an ASRF framework (Gordy, 2003 and Bank/Lawrenz, 2003) which – apart from assuming only one systematic risk factor influences the default risk of all loans in the portfolio – also assumes the portfolio is infinitely fine grained (i.e. it comprises nearly an infinite number of credits with infinitely small exposures). Vasicek asserted that the cumulative probability that the portfolio loss, L , will be less than some variable, x , is given by:

$$P[L \leq x] = N \left[\frac{\sqrt{1-x} N^{-1}(x) - N^{-1}(p)}{\sqrt{x}} \right], \quad (1)$$

where

x is the asset correlation between all loans and the systematic single risk factor

p is the average probability of default for the portfolio and

$N(\cdot)$ and $N^{-1}[\cdot]$ refer to the cumulative standard normal distribution and the inverse standard normal cumulative distribution function, respectively.

This cumulative distribution – which describes the portfolio losses and is driven by two parameters (p and x) – is defined over the interval $0 \leq x \leq 1$ and is given by:

$$F(x; p, x) = N \left[\frac{\sqrt{1-x} N^{-1}(x) - N^{-1}(p)}{\sqrt{x}} \right], \quad (2)$$

with $p > 0$ and $0 < x < 1$. As $x \rightarrow 0$, the distribution converges to a 0, 1 distribution with probabilities p and $1 - p$ respectively. When $p \rightarrow 0$ or $p \rightarrow 1$, the distribution becomes concentrated at $L=0$ or $L=1$ respectively. A further important property is $F(x; p, x) = 1 - F(1-x; 1-p, x)$.

It is important to note that Equation 2 defines the 'total loss' shown in Figure 1, i.e. the cumulative probability of obtaining a loss value less than x .

The highly skewed and leptokurtic loss distribution has density

$$f(x; p, x) = \sqrt{\frac{1-x}{x}} \exp \left(\frac{1}{2} (N^{-1}(x))^2 - \frac{1}{2} \left(\frac{\sqrt{1-x} N^{-1}(x) - N^{-1}(p)}{\sqrt{x}} \right)^2 \right), \quad (3)$$

and it is unimodal with the most prevalent loss – the mode – located at

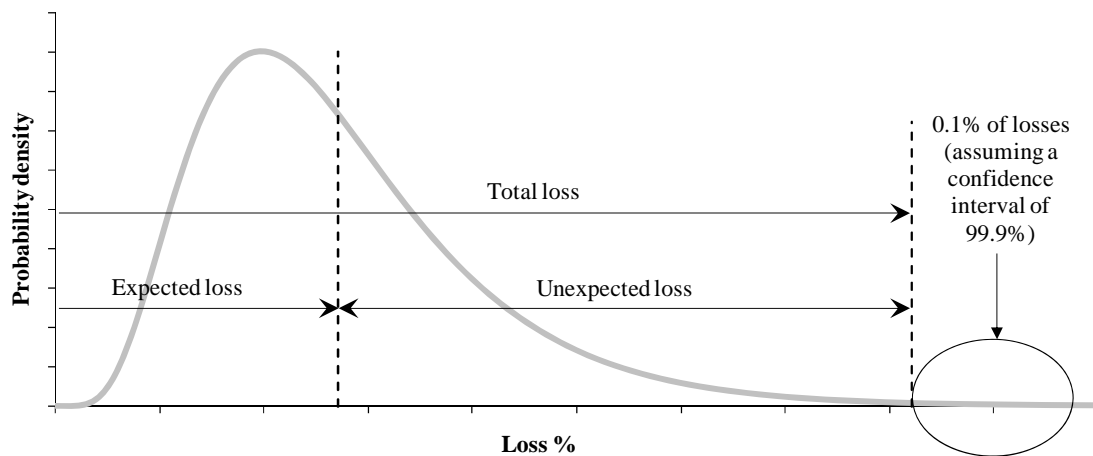
$$L_{\text{mode}} = N \left[\frac{\sqrt{1-r}}{1-2r} N^{-1}(p) \right]. \quad (4)$$

The inverse of this distribution – i.e. the a -percentile value of L is given by

$$L_a = F(a; 1-p, 1-r). \quad (5)$$

Figure 1 provides the relevant features of a typical, skewed distribution for a collection of loan losses. The expected loss (EL) is the average portfolio loss and the total loss is a *defined* point – in this case, the point below which 99.9% of all losses fall. In Figure 1, the area under the curve to the left of the total loss position represents 99.9% of all portfolio losses. The unexpected loss, or UL, depends upon the definition of the total loss point, being the difference between the total loss and the expected portfolio loss.

Figure 1: Important features of a typical loss distribution.



The extraction of empirical asset correlations from loss data proceeds as follows:

1. Source gross loss time series data as a percentage of total loan value.
2. Calculate the mean (p in Equations 2, 3, 4 and 5) and the mode (L_{mode} in Equation 4).
These values are obtained analytically from the simple *average* gross loss and the most *prevalent* gross loss, respectively, over the time period under scrutiny. These values are easily calculated using standard statistical software or simple spreadsheets.
3. Knowing p and L_{mode} , the empirical asset correlation may be extracted using Equation 4:

$$\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)} = \frac{\sqrt{1-r}}{1-2r}, \text{ so } \left[\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)} \right]^2 = \frac{1-r}{(1-2r)^2}$$

Substituting for $x = \left[\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)} \right]^2$ gives

$$\begin{aligned} x(1 - 2x)^2 &= 1 - x \\ 4x^2 + (1 - 4x)x + (x - 1) &= 0 \end{aligned}$$

which is a quadratic equation in x (the asset correlation) with solutions:

$$x: \frac{(4x - 1) - \sqrt{8x + 1}}{8x}. \quad (6)$$

Both components of x (L_{mode} and p) are known (Step 2), so x is easily calculated. The lower of the two possible values for x is chosen because the higher x results in unrealistic values of UL.

The total portfolio loss measured at a confidence interval of 99.9%, may also be measured empirically by combining Equations 5 and 2 (note that a confidence interval of 99.9% implies $a = 0.1\%$):

$$\begin{aligned} F(a; 1 - p, 1 - r) &= N \left[\frac{\sqrt{1 - (1 - r)} N^{-1}(a) - N^{-1}(1 - p)}{\sqrt{1 - r}} \right] \\ \text{Total gross loss} &= N \left[\frac{N^{-1}(p) + \sqrt{x} N^{-1}(a)}{\sqrt{1 - r}} \right]. \end{aligned}$$

The gross total loss is simply the sum of unexpected and expected gross losses ($UL^{99.9\%} + EL$: see Figure 1). Subtracting the gross expected loss from the total loss gives:

$$UL^{99.9\%} = N \left[\frac{N^{-1}(p) + \sqrt{x} N^{-1}(a)}{\sqrt{1 - r}} \right] - EL,$$

but $EL = p$, the portfolio expected loss and since gross loss data are used, this value is also portfolio probability of default. Thus:

$$UL^{99.9\%} = N \left[\frac{N^{-1}(p) + \sqrt{x} N^{-1}(a)}{\sqrt{1 - r}} \right] - p. \quad (7)$$

No assumptions regarding recoveries have been made or assigned. When the analysis is complete and the values calculated, both sides of Equation 7 are multiplied by the LGD and the result is the familiar UL in the 'net loss' sense.² No other adjustments need be made and the

² This is also the well-known total loss estimate from the Pillar I equations in the BCBS formulation.

inclusion of LGD here only serves to obfuscate an otherwise relatively straightforward explanation – hence the omission from this (and later) discussions. The UL^{99.9%} is thus presented here as a *gross* unexpected loss.

Armed with the analytics to extract asset correlation values from empirical loss data, several aspects of implied retail asset correlations were investigated. The details of these investigations – and the results obtained from them – are presented and discussed in the next section.

4. DATA AND ANALYSIS

The analysis which constitutes this section explores aspects of the empirical correlations derived from gross loss data.

These data span some 24 years (i.e. Q1 1985 to Q1 2009) and were compiled from the quarterly Federal Financial Institutions Examination Council Consolidated Reports of Condition and Income.³ The data span the turbulent early and late 1990s, the benign credit conditions which characterised the 2003 – 2008 period as well as the recent downturn in the credit environment leading to the 'credit crunch' which began in mid 2007 and has yet to run its course. Charge-offs⁴ from the 100 largest US banks are measured by consolidated foreign and domestic assets. The US Federal Reserve uses annualised charge-off rates, net of recoveries and outstanding as of quarter-end. The charge-off rates are calculated from data available in the Report of Condition and Income (Call Report), filed each quarter by all commercial banks. Charge-off rates for any category of loan are defined as the flow of a bank's net charge-offs (gross charge-offs – recoveries) during a quarter divided by the average level of its loans outstanding over that quarter. These ratios are multiplied by 400 to express them as annual percentage rates (Federal Reserve Board, 2008).

Since $\text{Net losses} = \text{Gross losses} \times \text{Loss given default}$, only knowledge of LGDs are required to convert net losses to gross losses. These average LGDs were obtained from the BCBS's 5th Quantitative Impact Study (BCBS, 2006b), using the 'G10 group 1: Including US' group (since loss data used in this study were obtained from US commercial banks), shown in Table 1.

Table 1: LGD averages for different retail portfolios.

	Residential Mortgage	Qualifying revolving	Other retail	HVCRE
LGD averages	20.3%	71.6%	48.0%	35.0%

³ Data for each calendar quarter become available approximately 60 days after quarter end.

⁴ Charge-offs are the values of loans and leases removed from the books and charged against loss reserves.

First, the influence of the distribution assumption on the asset correlations is explored. The Vasicek and beta distributions were used to fit the loss data, even though losses – which are invariably assumed to be highly skewed and leptokurtic – do not always embrace this pattern. The former distribution is the one chosen by the BCBS for the Pillar 1 regulatory capital calculations and the latter lends itself to robust analysis within a relatively simple mathematical framework. The beta distribution is also used elsewhere in the Basel accords (e.g. in the treatment of securitisation, for example (BCBS, 1988)). Results from other distributions were also explored, but because conclusions reached were broadly similar, these have been omitted for clarity.⁵

Next, empirical correlations (extracted from the loss data and deduced from both the Vasicek distribution and the beta distribution) are then compared with BCBS *specified* asset correlations using the entire data set as described above, i.e. spanning some 24 years.

Finally, the time evolution of the empirical correlation and the BCBS specified correlations are compared. Basel specifies that a minimum of seven years of data must be used to estimate the LGD (paragraph 472) and the EAD (paragraph 478). Using seven years of loss data as a benchmark, relevant asset correlations were calculated. The seven-year quarterly loss data window was then rolled forward one quarter (maintaining a seven-year rolling window) to calculate the next asset correlation value. This process was continued until Q1, 2009 (i.e. March 2009).

a. Effect of distribution assumption

Employed by the BCBS in the first pillar of the Basel II capital requirement calculations, the Vasicek distribution is used to describe the dispersion of credit losses of many banks whose local regulators have approved them for the IRB approach. However, many fat-tailed, leptokurtic distributions exist and may be used as a 'best fit' to the loss data.

Using several retail loan classes, empirical asset correlations were compared using both the Vasicek and beta distributions. The latter is popular in the BCBS analysis of securitisation and is completely characterised by two parameters, a and b , which can be calculated from the mean (m) and standard deviation (ε) of the gross losses. These quantities are linked to the beta distribution shape parameters as follows:

⁵ Goodness of fit tests were applied to all distributions and the beta distribution consistently performed the best.

$$a = m \left(\frac{m(1-m)}{s^2} - 1 \right) \quad (8)$$

$$b = \frac{a}{m} (1 - m). \quad (9)$$

It is straightforward to measure the gross mean loss $m (= p)$ and s over the period under scrutiny so a and b are easily calculated. The probability density function for the beta distribution is given by

$$f(x; a, b) = \frac{1}{B(a, b)} x^{a-1} (1-x)^{b-1},$$

where $B(a, b)$ is the beta function given by $\frac{\Gamma(a) \Gamma(b)}{\Gamma(a+b)}$ and where $\Gamma(\cdot)$ is the gamma function.

The cumulative beta distribution is fully specified by:

$$P(x) = \frac{\int_0^x (1-t)^{b-1} t^{a-1} dt}{B(a, b)} \quad (10)$$

$$= \frac{\Gamma(a+b)}{\Gamma(a) \Gamma(b)} \int_0^x (1-t)^{b-1} t^{a-1} dt \quad 1 \neq x \neq 0, \quad a, b > 0$$

where x is the distribution variable.

The total losses (EL + UL) are simply the value of x when $P(x) = 99.9\%$ (so chosen to comply with Basel II).

The asset correlation is derived by calculating the correlation value which equates the *BCBS* total loss at a 99.9% confidence interval to the *empirical* total loss at a 99.9% confidence interval (using the beta distribution).⁶ The extraction of empirical asset correlations from loss data proceeds as follows:

1. Source gross loss time series data as a percentage of total loan value.
2. Calculate the mean, m and standard deviation, s of these gross loss data. These values are obtained analytically from the simple average and the standard deviation of the gross losses, respectively, over the time period under scrutiny.
3. Using Equations 8 and 9, calculate a and b .

⁶ Note that all estimates – as with the Vasicek distribution and Equation 7 – are based on gross loss data, no recoveries are taken into account at this stage.

4. Using Equation 10, determine the value of x when $P(x) = 99.9\%$. This is the total gross loss at the 99.9th percentile $(L_{total}^{99.9\%})$ of the fitted beta distribution.

5. Substitute the $L_{total}^{99.9\%}$ value obtained from Step 4 into the BCBS equation for the total gross loss value (measured at a 99.9% confidence interval), i.e.

$$UL^{99.9\%} = N \left[\frac{N^{-1}(p) + \sqrt{x} N^{-1}(0.999)}{\sqrt{1-x}} \right] - EL$$

$$EL + UL^{99.9\%} = \text{Total gross loss} = L_{total}^{99.9\%}$$

$$L_{total}^{99.9\%} = N \left[\frac{N^{-1}(p) + \sqrt{x} N^{-1}(0.999)}{\sqrt{1-x}} \right] \quad (11)$$

But the left hand side of Equation 11 is known (empirically) from Step 4 above.

Equation 11 becomes $N^{-1}(L_{total}^{99.9\%}) \sqrt{1-x} = N^{-1}(p) + \sqrt{x} N^{-1}(0.999)$, with x the only unknown in this equation.

Letting $w = N^{-1}(L_{total}^{99.9\%})$, $p = N^{-1}(p)$ and $y = N^{-1}(0.999)$ and squaring both sides gives

$$w^2 (1-x) = p^2 + y^2 x + 2py \sqrt{x}$$

$$0 = (y^2 + w^2) x + 2py \sqrt{x} + (p^2 - w^2),$$

which is a quadratic in \sqrt{x} with solutions: $x = \left[\frac{-2py - \sqrt{(2py)^2 - 4(y^2 + w^2)(p^2 - w^2)}}{2(y^2 + w^2)} \right]^2$,

and which is easily solved as w , p and y are all known quantities.

The results are shown in Figure 2 for US consumer loan gross losses. Figure 1(a) shows the cumulative density function for the respective distributions as well as the cumulative empirical loss data. Figure 2(b) illustrates the density functions for the respective distributions as well as a histogram of empirical losses for comparison. Recall that the Vasicek distribution is unimodal so fitting an (apparent) bimodal distribution (as seen in Figure 2(b)) results – in this case – in a sub-optimal fit. While in this example, the beta distribution provides the better fit to the empirical data, this is by no means always the case.

Figure 2:(a) Cumulative and (b) density function for US consumer loan losses from Q1 85 to Q1 09.

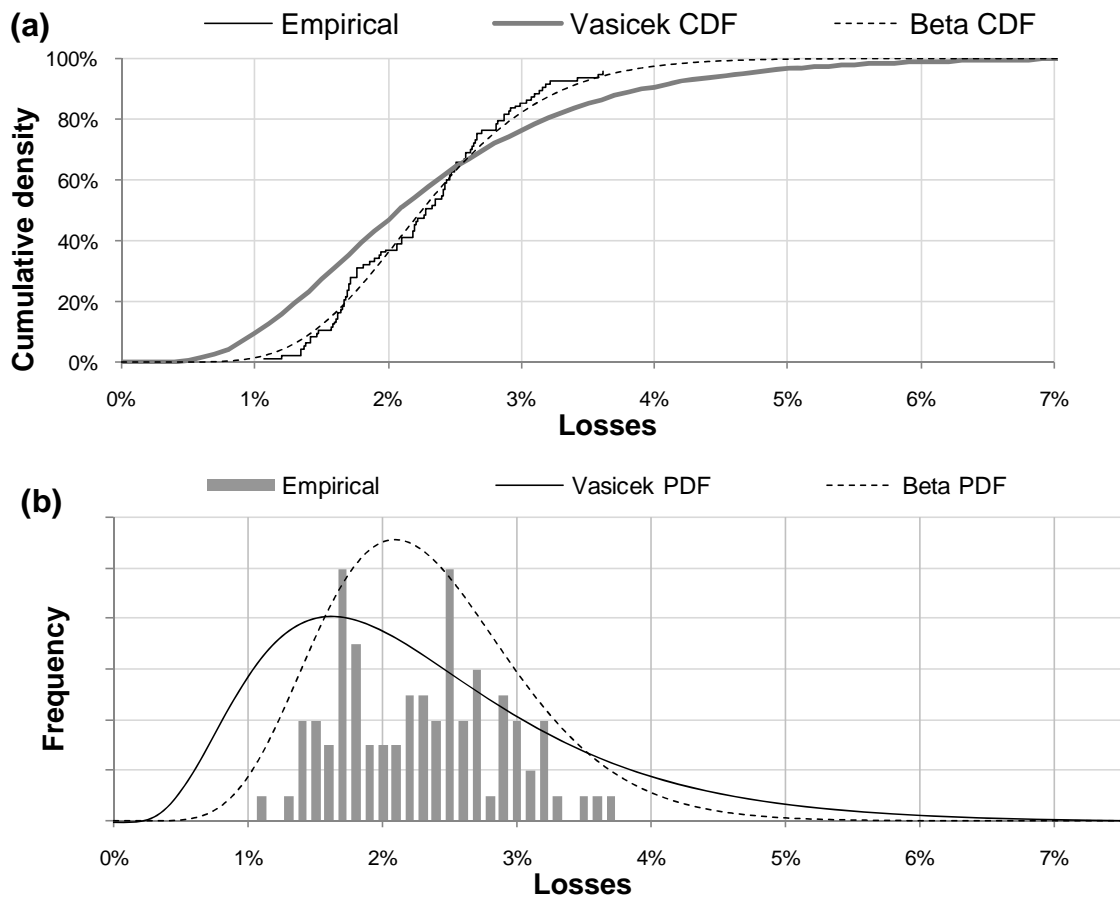
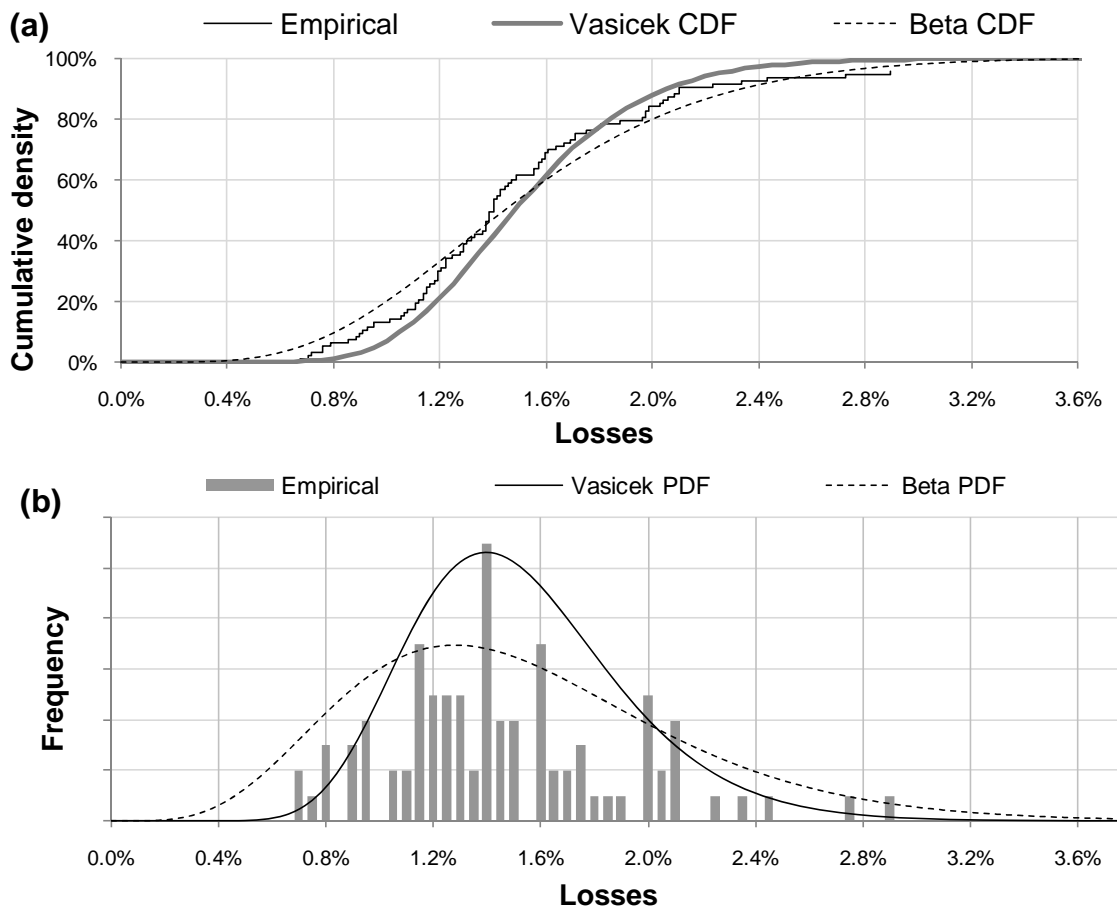


Figure 3 shows results obtained for US 'other consumer' loans. In this case, the Vasicek distribution provides a good fit to the main body of loss data but a poor fit to the tail region, while the reverse is true for the beta distribution (Figure 3(a)). For these losses, the unimodal data are well-suited to the Vasicek distribution which effectively models the bulk of the losses (Figure 3(b)).

Figure 3:(a) Cumulative and density function for US other consumer losses from Q1 85 to Q1 09.



The analysis performed does not support preference of one distribution over the other.

b. Comparison with Basel correlations

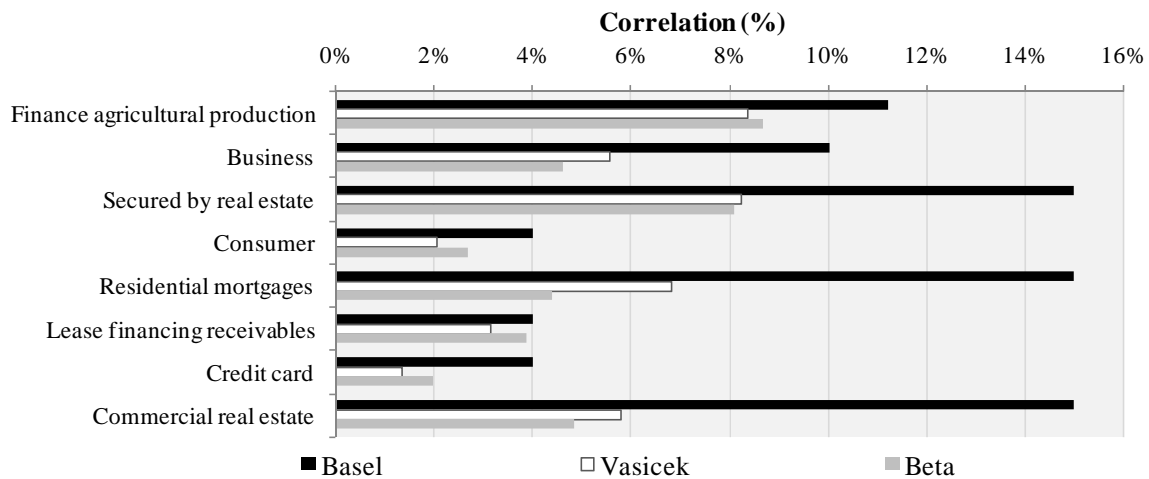
The BCBS specifies the asset correlations to be used in the IRB Foundation approach – these are summarised in Table 2 below.

Table 2: Loan input parameters under Basel II's Foundation IRB.

RETAIL LOAN TYPE	CORRELATION	
Mortgages	Fixed	15%
Qualifying revolving		4%
Other retail	Varies With PD	$0.03 \left(\frac{1 - e^{-35PD}}{1 - e^{-35}} \right) + 0.16 \left[1 - \left(\frac{1 - e^{-35PD}}{1 - e^{-35}} \right) \right]$
High volatility commercial real estate		$0.12 \left(\frac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.30 \left[1 - \left(\frac{1 - e^{-50PD}}{1 - e^{-50}} \right) \right]$

Using the full 24-year span of gross loss data, the empirical asset correlations (using both the Vasicek and beta distributions) were compared with the Basel-specified asset correlations as shown in Figure 4 below.

Figure 4: Comparison of empirical asset correlations (derived from the Vasicek and beta distributions respectively) and Basel II specified asset correlations.

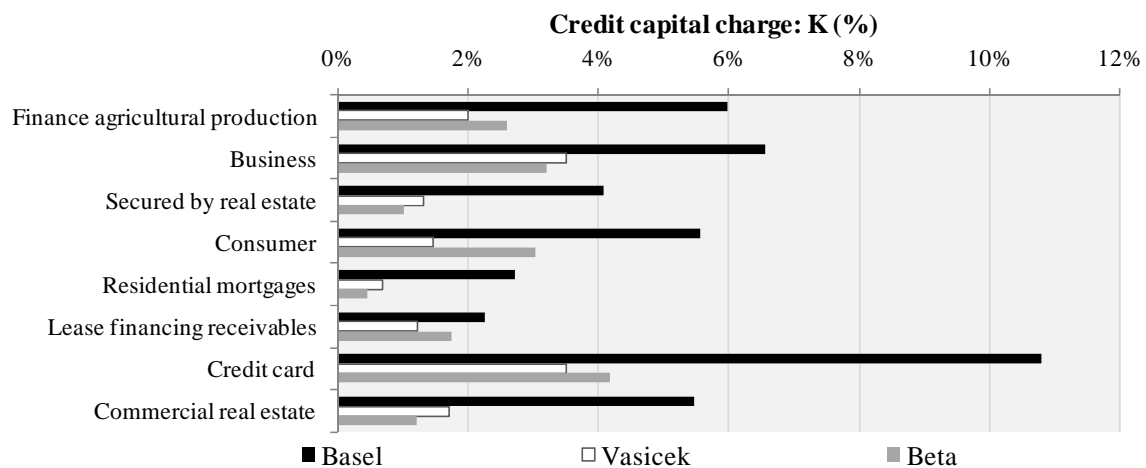


The empirically measured correlations are all lower than those specified by the BCBS, but are fairly similar for most retail asset classes. The residential mortgage and commercial real estate asset classes are an exception: in these cases, the BCBS specified value of 15% is considerably higher than the values obtained by either the Vasicek or beta distributions (see Figure 6).

Capital charges for each asset class using the three approaches are given in Figure 5. The BCBS (2005) specified that to take into account the omission of PD and LGD correlations, a 'downturn LGD' must be used in the IRB approach. A principles-based approach was suggested for the estimation of downturn LGDs which requires banks to identify appropriate downturn conditions and the adverse dependencies between default and recovery rates. From these, banks must produce LGD parameters for their exposures which are consistent with the identified downturn conditions (Miu, and Ozdemir, 2006). The implicit assumption made by the BCBS is that a credit risk model with systematic correlation between PD and LGD using long-run LGD inputs should give comparable capital to a credit risk model without correlated PD and LGD using downturn LGD inputs. Miu and Ozdemir (2006) showed that mean LGDs need to be increased by about 35% to 41% in order to compensate for the lack of correlation. Downturn LGDs were obtained from the LGDs used in this study (from Table 1) by increasing the latter by (on average) 38%, i.e. by multiplying these by 1.38. The downturn LGDs

were then used to estimate the capital charges using the BCBS IRB approach. For the Vasicek and beta distribution empirical approaches, unaltered LGDs were used, i.e. values taken from Table 1.

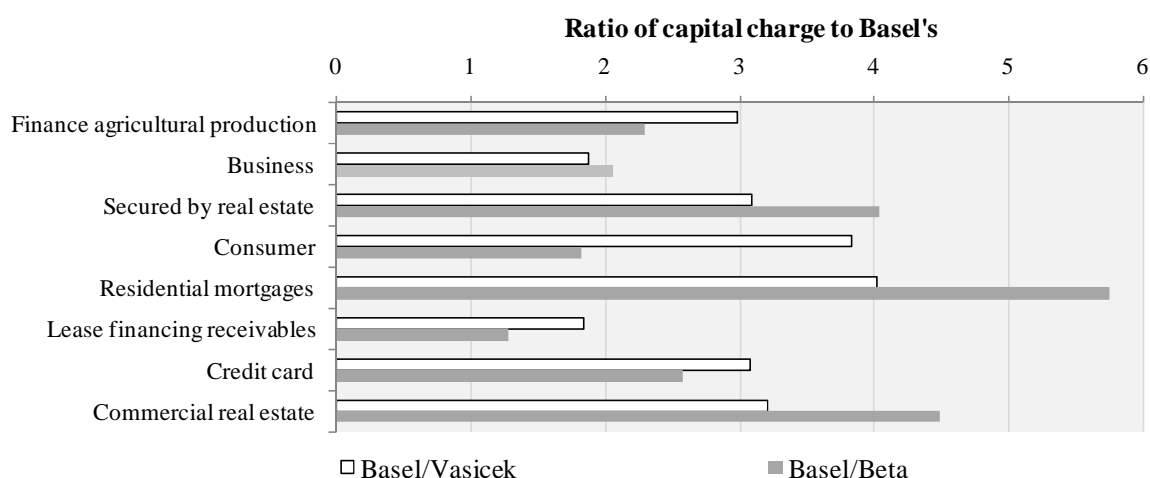
Figure 5: Comparison of capital charges. For the BCBS capital charges, specified correlations and downturn LGDs were used. For Vasicek and beta distribution capital charges, implied correlations and standard average LGDs were used.



The capital charges as specified by the BCBS are similar to the charges calculated using the Vasicek distribution for all asset classes except for residential mortgages and commercial real estate where capital charges are considerably higher using BCBS-specified values.

A comparison of capital charges relative to the BCBS-specified charges is given in Figure 6, below.

Figure 6: Comparison of capital charge ratios: BCBS-specified/Vasicek derived and BCBS-specified/beta derived.



Average capital charges using the beta distribution's implied asset correlation value are $2.8\times$ the average of the BCBS-specified values while capital charges using the Vasicek distribution's implied asset correlation value are $2.9\times$ the average of the BCBS-specified values. These results are both interesting and encouraging from an empirical point of view. Given the assumptions made in this analysis, the values agree well for most retail asset classes – particularly if the Vasicek distribution is used. Capital charges using BCBS-specified values for residential mortgages appear somewhat punitive, i.e. they are $4.0\times$ those derived using correlations derived empirically from the Vasicek distribution and $5.8\times$ those derived using correlations derived empirically from the beta distribution. A similar situation exists for capital charges for commercial real estate. These charges are $3.3\times$ those derived using correlations derived empirically from the Vasicek distribution and $3.9\times$ those derived using correlations derived empirically from the beta distribution.

That the Basel capital charges are higher for *all* retail loan types is not an unexpected result. The BCBS has repeatedly stressed the goal of conservatism and a sufficiently large capital cushion to shield banks from insolvency. Using its current formulation, the BCBS, however, does not have many parameters that can be adjusted to achieve these aims, particularly if banks use the IRB approach for analysing their credit risk. The LGD is one such adjustable parameter, asset correlation is another. Taking both these parameters into account, the capital charges for most retail asset classes compare favourably. While these values are elevated, they are not punitive. For residential mortgages and commercial property, however, BCBS specified capital charges are between 3 to $6\times$ larger than those obtained empirically. It is not

immediately clear why this should be the case. It is true that banks which employ the IRB approach (rather than Basel I or the Basel II standardised approach) significantly reduce their capital charges for residential mortgage and commercial property portfolios. It may be the case that the BCBS simply wish to reduce the rate of capital charge reduction for these portfolios at least until some time has passed and the validity of this reduction can be assessed.

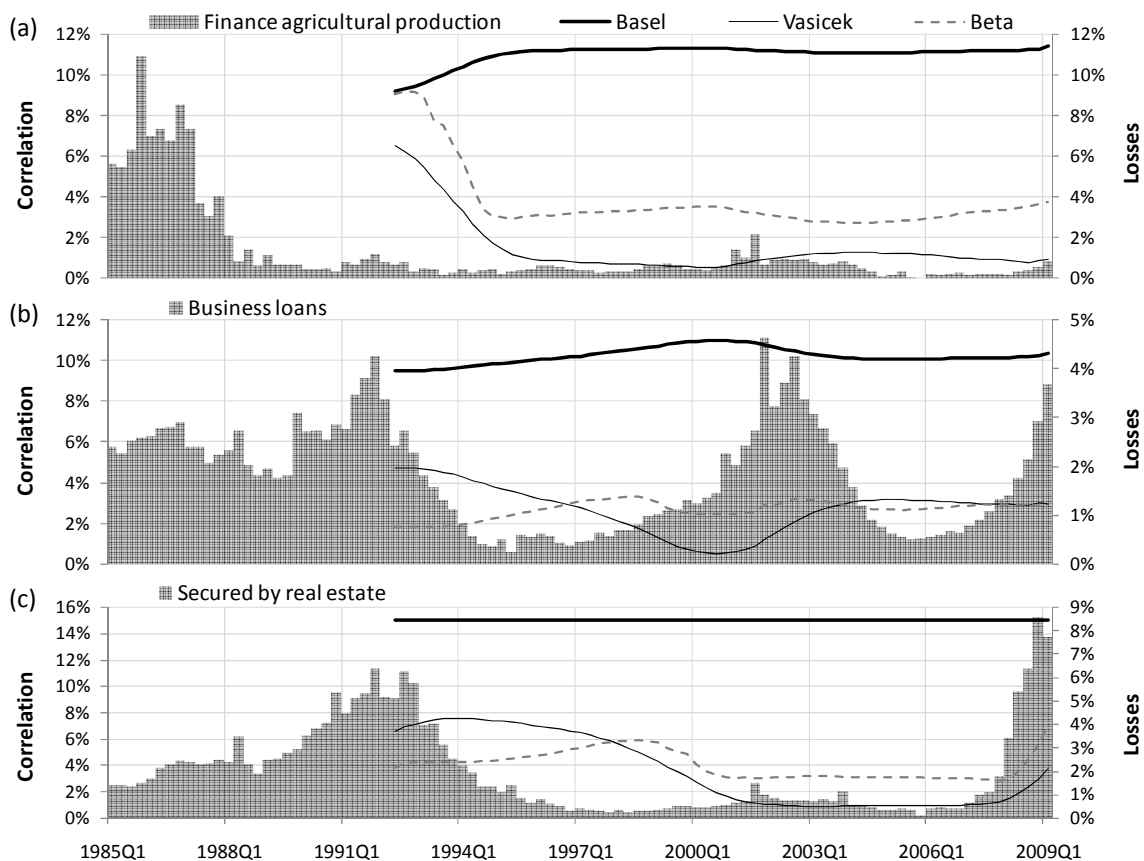
Results from the BCBS's QIS 4 indicates the following decreases in capital charges for Basel II banks: 79% for home equity loans, 73% for residential mortgage loans and 27% for small business loans. Under Basel I, the minimum capital requirement for mortgage loans is 4%, thus an average drop of 79% implies that minimum capital requirements for Basel II banks would be >1% for these asset classes. Since there is a cost to maintaining capital, lower capital requirements would result in a cost (and correspondingly a *pricing*) advantage, for large bank retail credits under Basel II. Lower capital requirements will also make it easier for Basel II banks to achieve higher returns on equity (ROE). To compete with the cost advantage and higher ROEs of Basel II banks, smaller community banks may be forced to make concessions in pricing and underwriting guidelines that could impair their profitability and ultimately their viability (ICBA, 2006). It is possible the BCBS wished to avoid these possibilities and hence adjusted the one variable at their disposal – namely the asset correlation, which ultimately resulted in higher capital charges for Basel II compliant banks.

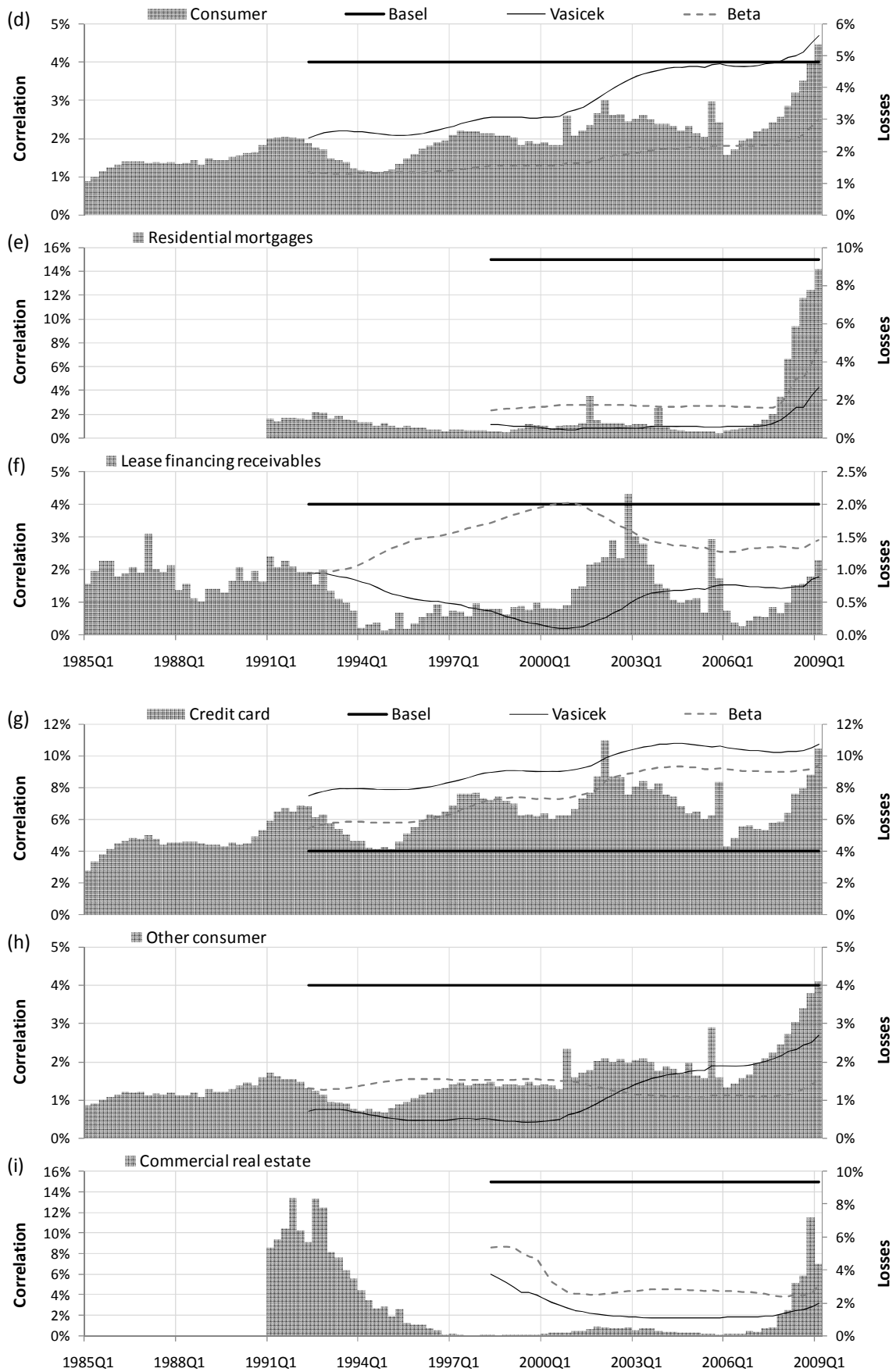
c. **Effect of economic milieu**

The empirical correlation values are highly sensitive to the parameters estimated from portfolio gross loss data. Clearly, losses change over time. The global economy recently (mid 2007) witnessed the end of a benign, half decade-long period characterised by low interest rates, constrained inflation, universally loose monetary policy and low default rates – for all loan types particularly residential mortgages. This munificent epoch came to an abrupt end in August 2007 and has continued apace. The current milieu (January 2009) is circumscribed by surging inflation, stagnant or rising interest rates, tightening monetary policy and elevated default rates, delinquencies and foreclosures. Bank losses have surged in the resulting credit crunch with several seemingly invincible institutions, including investment banks and building societies, suffering significant losses. Global losses from the credit crunch are currently (January 2009) estimated to be US1tn (IMF, 2008) but the number continues to grow. There are also strong indications that this market turmoil will last for some time – estimates vary from end 2009 to several years into the next decade of the new millennium (IMF, 2008).

The loss profiles of most banks in the current climate, then, are very different to those which preceded August 2007 and correspondingly, empirical correlations embedded in the loss data could also be substantially different. To investigate this effect, a rolling, seven year window of quarterly losses was used to estimate the empirical asset correlations (using both Vasicek and beta distributions) and to compare these to the BCBS specified correlations. These results are shown in Figure 7(a) through (h) below for various categories of retail loans. The effect of the credit crunch is only now being recorded in the loss data: elevated losses are evident from the last two quarters of 2008 and the first quarter of 2009. The duration and severity of these losses remain unknown.

Figure 7:(a) through (i) Comparison of rolling seven-year empirical correlations and Basel II specified correlations (right hand axis). To assess how the underlying gross loss data affects the empirical correlations, these data are shown as grey histograms on the same scales.





On the whole, BCBS specified correlations are higher than empirically derived values – in most cases, considerably so. The derived correlations from the Vasicek and beta distributions show broadly similar results. For the most part, changes in correlations, are 'in phase' with one another although the Vasicek implied correlations are more sensitive to changes in underlying loss data: these correlations experience larger swings than those implied by the beta distribution. In addition, the Vasicek correlation appears to be more sensitive to the changing loss milieu. A possible reason for this is the relative sensitivity of the underlying distribution drivers, i.e., the mean and the mode of the gross losses for the Vasicek distribution and the mean and the standard deviation of the gross losses for the beta distribution. The standard deviation changes relatively slowly with time, even during periods of abrupt loss data changes, because it is an *average* of squared deviations from the mean. This averaging has the effect of smoothing out any large spikes that arise in underlying data. This smooth changing of σ feeds through into the shape of the beta distribution.

The mode, on the other hand, changes discretely – in varying step sizes – changing value only when (and if) the data under scrutiny yield a more populous gross loss value than the previous mode. If data are analysed during a period of diminished and then elevated losses, the mode will undergo a discrete 'jump' between a low value and a high value with no intermediate values in between. This will have the effect of amplifying changes in the correlations implied by the Vasicek distribution (as shown in Figure 7).

An interesting feature of the BCBS specified correlations – at least those which depend on the PD value – is that they appear to be counter-cyclical to the derived correlation values. In Figures 7(b) and (f) the BCBS specified asset correlation move counter to the way in which the derived correlations change. A possible explanation is that the BCBS specified asset correlations use a *current* PD and are therefore far more reactive to changing economic conditions than the empirical distributions which use gross loss *averages* measured (in these cases) over seven years to estimate asset correlations.

5. CONCLUSIONS

The decision by the BCBS to set pre-specified correlations was designed to introduce a level of conservatism into the credit risk IRB framework and elevate capital charges to a satisfactory level. Analysis of empirically derived asset correlations in retail portfolios demonstrates that this is indeed the case: empirical correlations embedded in gross loss data are lower than those set by the BCBS. The theoretical basis on which the IRB approach is built is non-trivial, but nevertheless accessible and extracting empirical correlations from loss data need

not necessarily be an onerous affair. Using two different distribution assumptions, it has been shown how these empirical correlations may be calculated from minimal input data (i.e. only gross losses over, at least, a seven year period), how these differ from the BCBS specified correlations and how they change over changing economic conditions. The analysis should be of benefit to banks interested in establishing their own internal measure of correlation for both regulatory and economic capital purposes.

REFERENCES

- BANK, L.** and Lawrenz, J. 2003. Why simple, when it can be difficult? *Kredit und Kapital*, **36**, 4, pp. 534–556.
- BCBS**, 1996. Amendment to the capital accord to incorporate market risks. Available at <http://www.bis.org/publ/bcbs24.htm>, last accessed on 17 June 2008.
- BCBS**, 2005. An explanatory note on the Basel II IRB risk weight functions. Available at <http://www.bis.org/bcbs/irbriskweight.pdf>, last accessed on 21 May 2008.
- BCBS**, 2006a. International convergence of capital measurement and capital standards: a revised framework. Paragraphs 634, 625. Available at <http://www.bis.org/publ/bcbs128a.pdf>, last accessed on 23 Jun 2008.
- BCBS**, 2006b. Results of the fifth quantitative impact study (QIS 5). Table 23, p30. Available at <http://www.bis.org/bcbs/qis/qis5results.pdf>, last accessed on 21 June 2008.
- BURNS, R. L.**, 2004. Economic capital and the assessment of capital adequacy, *FDIC Supervisor Insights*, Available at http://www.fdic.gov/regulations/examinations/supervisory/insights/siwin04/economic_capital.html, last accessed on 12 June 2008.
- CHERNIH, A., V.** and Henrard, S. 2006. Asset correlations: A literature review and analysis of the impact of dependent loss given defaults, *working paper*, Available at http://www.econ.kuleuven.be/insurance/pdfs/CVH-AssetCorrelations_v12.pdf, last accessed on 22 May 2008.
- DUCHEMIN, S.,** Laurent, M. and Schmit, M. 2003. Asset return correlation: The case of automotive lease portfolios, *Centre Emile Bernheim*, Solvay Business School, Université Libre de Bruxelles, Working Paper: WP-CEB 03/007. Available at <http://www.solvay.edu/EN/Research/Bernheim/documents/wp03007.pdf>, last accessed 2 June 2008.
- DÜLLMANN, K.** and Scheule, H. 2003. Asset correlation of German corporate obligors: Its estimation, its drivers and implications for regulatory capital, *Deutsche Bundesbank*. Available at <http://www.bis.org/bcbs/events/wkshop0303/p02duelsche.pdf>, last accessed on 2 June 2008.
- FATEMI, A.** and Fooladi, I. 2006. Credit risk management: a survey of practices, *Managerial Finance*, **32**, 3, pp. 227–233.
- FEDERAL RESERVE BOARD**, 2008. Charge off and delinquency rates of loans and leases at commercial banks. Available at https://www.federalreserve.gov/releases/chargeoff/calc_method.htm, last accessed July 12 2008.
- GORDY, M.** 2000. A comparative anatomy of credit risk models, *Journal of Banking & Finance*, **24**, 1, pp. 119–149.
- GORDY, M.** 2002. A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules, *Board of Governors of the Federal Reserve System*, Working Paper #2002–55. Available at <http://www.federalreserve.gov/pubs/feds/2002/200255/200255pap.pdf>, last accessed on 11 June 2008.

- GORDY, M. B.** 2003. A risk-factor model foundation for ratings-based bank capital rules, *Journal of Financial Intermediation*, **12**, pp. 199–232.
- GORE, G.** 2006. Correlation confusion, *Risk*, **19**, 7, July/August, pp. 7–9.
- ICBA**, 2006. Independent Community Banks of America: Basel Capital Accord Update. Available at <http://www.icba.org/files/ICBASites/PDFs/stmt092606.pdf>, last accessed on 22 July 2008.
- IMF**, 2008. Global Financial Stability Report, April 2008. Available on <http://www.imf.org/External/Pubs/FT/GFSR/2008/01/pdf/text.pdf>, last accessed on 1 July 2008.
- LOPEZ, Jose A.** 2004. The empirical relationship between average asset correlation, firm probability of default, and asset size, *Journal of Financial Intermediation*, **13**, 2, pp. 265–283.
- LOPEZ, Jose A.** 2005. Empirical analysis of the average asset correlation for Real Estate Investment Trusts, *Federal Reserve Bank of San Francisco, Working Paper Series*. Available at <http://www.frbsf.org/publications/economics/papers/2005/wp05-22bk.pdf>, last accessed 11 June 2008.
- MIU, P. and Ozdemir, B.** 2006. Basel requirement of downturn LGD: Modeling and estimating PD & LGD correlations, *Journal of Credit Risk*, **2**, 2, pp. 43–68.
- REEVES, R.** 2006. Managing director of SunGuard's Basel II Capital Manager Business Unit, London. Quoted in Gore, G (2006).
- REPULLO, R. and Suarez, J.** 2004. Loan pricing under Basel capital requirements, *Journal of Financial Intermediation*, **13**, 4, pp. 496–521.
- VASICEK, O.** 1987, Probability of Loss on Loan Portfolio, KMV Corporation. Available at <http://www.kmv.com>, last accessed on 14 June 2008.
- VASICEK, O.** 1991, Limiting loan loss probability distribution, KMV Corporation. Available at <http://www.kmv.com>, last accessed on 4 May 2008.
- VASICEK, O.** 2002. The distribution of loan portfolio value, *Risk*, **15**, 12, pp. 160 – 162.

Chapter 7

Conclusions and recommendations

7.1 Summary and conclusions

Financial products, of ever increasing complexity, are constantly materialising from trading desks, academic research and arbitrageurs who notice convenient gaps in inefficient markets. New financial products, almost by definition, arise first in the race between the pursuit of profit and the need for measured reflection on the risks involved. Risk measurement and management therefore, constantly lags behind, always requiring data from new investment or trading strategies, longer historical periods on which to base generalities or more information to accurately assess risk. As a result, contemporary financial risk management employs vast resources to measure, manage and report on the ubiquitous risks that plague the markets. The goal of the modern risk manager is not only to use existing risk measurement methods to describe and define risk, but also to adapt these models (or develop entirely new ones) to cope with the burgeoning financial product innovation.

The credit crisis, which began in 2008, has affected most areas of the global financial system. Credit has been curtailed, asset prices have crashed and interest rates in developed markets have been reduced to historic lows. Fiscal stimuli from developed economies have injected vast amounts of capital into the fragile system.¹ Among the common culprits blamed for the calamity are banks, regulatory authorities, banking supervisors, rating agencies and hedge funds. While some accusations are unfounded, some blame is at least partially deserved for all the above protagonists. Nevertheless, the crisis looks likely to continue for the foreseeable future.

In the light of these events and contemporary failings of finance in general, the need to continuously improve existing and originate new techniques to measure and manage financial risks are vitally important. This thesis explored four significant problems facing modern risk management in a portfolio context and set out four possible solutions to these problems.

7.1.1 The Omega ratio

High profile disasters (e.g., Long Term Capital Management in 1998 and the large US hedge fund (Amaranth Advisors) that lost up to US\$6 billion in 2006 whilst speculating on gas

¹ These efforts have, as yet (March 2009) had virtually no effect.

prices (*The Economist*, 2006c: 68)) have shaken the hedge fund industry to its core. Despite remarkable resilience in the face of these disasters, hedge funds continued to outperform all other funds. Nevertheless, pressure on hedge funds is mounting on all fronts.

Hedge fund investment capital is increasingly being diverted into private equity and other popular funds, calls for hedge fund investment strategy transparency are amplifying and savvy, discriminating investors are demanding ever higher returns for lower fees. Investors fleeing the effects of the credit crisis have indiscriminately withdrawn US\$ billions in assets also contributing to recent hedge fund misery (2009). The need to distinguish accurately between poor and good quality fund returns has never been greater. Survival of the fittest hedge funds is only guaranteed if hedge fund performance can be *accurately* and *impartially* measured. Methods for estimating risk-adjusted returns, though well-established, embrace a simple mean-variance regime, widely considered to be almost obsolete in today's world of highly non-normal, return distributions. Higher statistical moments of return distributions *must* be taken into account if an accurate ranking of fund returns is desired.

The Omega function, though not a perfect measure, offers considerable improvement. While the Sharpe ratio consistently misallocates the best performing funds, the Omega function describes much about the rich underlying distribution structure. Not only does it consistently rank fund returns accurately, but its shape discriminates between different underlying fund strategies as well as between periods of various types of market activity. It is not often that so revolutionary and respected measure as the Sharpe ratio is displaced by another, but it is clear from the expanding body of analysis that this is increasingly the case.

7.1.2 Liquidity adjusted VaR

LVaR – or liquidity adjusted VaR – using the Jarrow Subramanian (JS) methodology has been successfully incorporated into a portfolio framework. It was shown to be superior to LVaR estimated using the simple square root of time technique using realised P/L (in terms of both *frequency of underestimation* and *accuracy of P&L estimation*) values as a comparison. Simple LVaR employs only the square root of time as a suitable scaling factor to accommodate liquidity constraints, while the JS LVaR model uses the JS approach to liquidity risk. The latter has already been demonstrated to be superior to the square root of time model at the individual instrument level (Jarrow and Subramanian, 1997: 172).

The implementation of the JS model is by no means simple: obtaining and estimating the required parameters is onerous and requires constant recalculation to accommodate the

rapidly changing portfolio LVaR. However, these parameters are available (though often not disclosed publicly) and, incorporating them into a portfolio model is relatively straightforward and requires only knowledge of the linear correlations between equity returns to complete the calculation as well as a standard technique borrowed from portfolio theory.

The payoff received from this complex calculation is a much-improved VaR forecast with greater accuracy than that obtained from standard VaR models which ignore liquidity.

7.1.3 PD discrimination

The Basel II Accord proposes novel and improved risk sensitive methodologies for the allocation of adequate capital requirements to cover credit risk. Derived from single factor credit models which are known to provide an imperfect framework for capital charge allocation, these methodologies introduce convexity into the otherwise concave capital charge function for 'other retail' portfolios. The stated goal of the Basel II Accord is to provide capital incentives for better risk management practices. The results from this study, however, indicate that, in poor quality loan portfolios (i.e. precisely the type of portfolio most in need of stringent PD discrimination), greater loan quality discrimination leads to *higher* capital charges, thereby illuminating a potential weakness of the Basel II calculations for credit capital charges under the IRB approach. It has been shown that even for simple examples of 'other retail' retail loan portfolios presented in this study, capital charge reductions are easily affected with non-complex segmentation of the PD grades.

This anomaly is unsatisfactory from a regulatory point of view. Any incentives to allocate time and resources to better PD discrimination are effectively reduced since capital requirements can be reduced simply by decomposing the relevant portfolio into segments (the most favourable segmentation determined via optimisation). In addition, there are incentives to segment portfolios purely for capital allocation purposes rather than improved risk management.

7.1.4 Extraction of empirical asset correlations from retail loan losses

The decision by the BCBS to set pre-specified correlations was designed to introduce a level of conservatism into the credit risk IRB framework and elevate capital charges to a satisfactory level. Analysis of empirically derived asset correlations in retail credit portfolios demonstrates that this is indeed the case: empirical correlations embedded in gross loss data are lower than those set by the BCBS. The theoretical basis on which the IRB approach is built is non-trivial, but nevertheless accessible and extracting empirical correlations from loss

data need not necessarily be an onerous affair. Using two different distribution assumptions, it was shown how these empirical correlations may be calculated from minimal input data (i.e. only gross losses over, at least, a seven year period), how these differ from the BCBS specified correlations and how they adapt to changing economic conditions. The analysis should be of benefit to banks interested in establishing their own internal measure of correlation for both regulatory and economic capital purposes.

Both risk measurement and management need to constantly adapt to a complex and ever-changing financial environment. Adopting a more comprehensive portfolio approach to market and credit risk measurement and management has led to significant improvements of existing risk methodologies and considerably enhanced the development of entirely new risk processes.

7.2 Recommendations

7.2.1 Omega ratio

The Omega ratio, having proved its mettle and resilience prior to the credit crisis, should be studied using returns during and after the crisis. Returns may be highly skewed in the light of the crisis, indeed, moves of several standard deviations were observed many times in the months spanning September to December 2008 for most financial assets. The effect on volatility and inter-asset correlations has been considerable: the return profiles of hedge fund and 'standard' fund portfolios may now look very different. The Omega ratio could be applied to these returns, along with the Sharpe ratio as undertaken in Chapter 3, to examine the flexibility and reliability of the two measures under extreme conditions to see if the former maintains its superiority as a ranking gauge.

7.2.2 Liquidity VaR

Research regarding liquidity adjusted VaR has begun to increase. The BCBS has already released research detailing best market practice after seeking participant feedback (BCBS, 2008). The details contained in this document should be further explored taking into consideration the work and results of Chapter 4. The abundance of liquidity-starved return data should now provide a wealth of information about the way in which portfolios react in diminished-liquidity milieus.

7.2.3 PD discrimination

Although the results discussed in Chapter 5 have been confirmed and verified mathematically, the BCBS has yet to respond (March 2009) to the allegation that the mathematical formulation of the Basel equations could lead to 'regulatory arbitrage' or at least encourage potentially irresponsible lending for 'other retail' asset classes. Further mathematical analysis could take place in which an alternative parameter was chosen to address the problem. The work in Chapter 5 only drew attention to the problem (and the cascade of potential knock-on effects); the solution was not provided in this study. The resolution could have a significant impact on banks' internal capital measurements and economic capital projections. Future studies should concentrate on real, large, heterogeneous retail loan portfolios to ascertain the degree of regulatory arbitrage that can be attained through optimised PD segmentation.

7.2.4 Empirical asset correlations

Retail loan asset correlations (as set by the BCBS) are punitively high (even in times of severe market upheaval), as are the associated credit capital charges for portfolios comprising such loans. In many banks, these portfolios are of considerable size and it is also here (e.g. home loans) where much of the pain of the credit crisis is being felt. Empirical results show these correlations to be much lower, even after taking into account the elevated losses now being experienced in all credit portfolios, but particularly in retail loan portfolios. The data used in this study were sourced from the US Federal Reserve: many banks are understandably reluctant to part with these proprietary data.

Future investigations could make use of real bank loss data – preferably a large data source involving many banks – to ascertain the robustness of the conclusions in Chapter 6. If it is found that, indeed, empirical retail correlations are much lower than those stipulated by the BCBS, this could have a profound effect on banks' internal capital allocation. This, in turn, could affect banks' allocation of economic capital although more loan loss data from the period spanning the credit crisis is required before any significant conclusions can be drawn.

7.3 Contribution

The ways in which the five studies which constitute this thesis and contribute to portfolio risk management theory and practice, are shown in Table 7.1.

Table 7.1: Summary of thesis contributions.

Attribute	Problem statement	Analysis	Results
Collate an inclusive literature survey on market and credit portfolio risk	Comprehensive literature survey for market and credit portfolio risks not readily available	Literature survey: submitted for publication in <i>South African Journal of Economics</i> .	Market and credit portfolio risk literature survey completed.
Accurately rank investment portfolios according to risk/return profile	Sharpe ratio does not function well for portfolios with non-normal P/L distributions	Omega ratio: published in <i>South African Journal of Economics</i> , 75 (3), Sep 2007.	A better ratio – makes use of entire empirical P/L distribution. All moments of distribution are captured.
Incorporate liquidity in market risk portfolios	VaR uses only 'square root of time' rule to account for liquidity – shown to be woefully inadequate	Liquidity VaR: published in <i>South African Journal of Economic and Management Sciences</i> , 11 (2), Jun 2008.	Extends previous work to embrace portfolio liquidity risk. Works well and performs better statistically than traditional VaR.
Assess a fair and consistent charge for credit risk	Over a probability of default range for some loan types, BCBS accord penalises prudent risk management and rewards the opposite	Default discrimination: published in <i>Risk Management in Financial Institutions</i> , 2 (3), Jun 2009.	PD range over which problem exists (and loan type affected) ascertained. This flaw can be arbitrated while awaiting Basel II updates.
Accurately assess empirical asset correlations in retail loan portfolios	BCBS imposes punitive correlation estimates for use in credit risk calculations which, for retail loan portfolios, are extremely conservative	Asset correlations: to be published in <i>Risk Management in Financial Institutions</i> , 3 (1) Dec 2009.	Using Federal Reserve loan loss data, implied empirical asset correlations derived and compared with those imposed by Basel.

A comprehensive literature survey for market and credit portfolio risks was presented in Chapter 2, bringing together traditional and contemporary risk measures and establishing the context for further exploration and analysis of the problems facing modern market and credit risk management.

The Sharpe ratio (the widely used portfolio risk adjusted return measure) assumes that profit and loss distributions of investment portfolios are normally distributed. This assumption has always been flawed but with the introduction of hedge funds into the investment arena, has been shown to be completely false and dangerously inaccurate. The Omega ratio offers a superior measure of relative portfolio performance, as demonstrated when applied to a selection of South African hedge fund returns. The results and analysis were presented in Chapter 3.

Historically, market risk practitioners have invested the bulk of their efforts into assessing accurate volatility or correlation metrics. The liquidity component of market risk, however,

has been largely neglected, using only the 'square root of time' rule to account for this important component. The credit crisis revealed the depth of this flawed assumption, so future market risk measures will incorporate liquidity (or a lack thereof) into standardised techniques. Chapter 4 discusses this problem and – building on previous work – proposes and tests a liquidity adjusted VaR measure using a broad portfolio framework. Employment of this technique takes account of diminished liquidity and determines a more accurate VaR than that obtained using the square root of time rule.

Over a probability of default range for some retail loan types, the Basel Accord rules penalise prudent risk management and encourage the opposite. This inconsistency violates the spirit of the Basel Accord which was primarily designed to reward better risk management practices through fairer apportioning of regulatory risk capital. The anomaly is explored in Chapter 5 using simulated portfolio loan loss data and found to be wholly due to the mathematical underpinnings of Basel's credit risk equations. The feature only emerges when examining portfolios of credit-risky instruments, not single instruments. Awareness of this attribute will enable credit risk practitioners to take advantage of this flaw until it is corrected or amended by the BCBS.

The Basel Accord imposes correlation estimates for use in credit risk calculations. Using US loan loss data, a method is devised in Chapter 6 to extract empirical portfolio asset correlations. Comparison of these empirical asset correlations reveals them to be extremely conservative, even during the credit crisis. While regulatory rules are (for the moment) imposed by the BCBS and local regulators, banks are at liberty to use their own correlations for internal economic capital models. Knowledge of a comprehensive technique for calculating empirical correlations using only loan loss data will enable banks to more accurately assess internal risks.

7.4 Final statement

The role of risk managers will almost certainly alter in the wake of the severe upheavals which now (April 2009) rock the financial marketplace. Whether this will involve increased prominence and authority of risk managers or a complete reshuffling of the way in which risks are measured (managed and reported) is not yet known. What is clear is that risk management must match the inexorable march of financial innovation in order to remain relevant. This involves understanding clearly what older risk models inform of the underlying risk environment, the adaptation of these older risk models when they cease to be relevant

and the development of entirely new risk models when situations require them. Because the risk milieu is vast and complex, the areas of concern addressed in this thesis necessarily constitute only a small fraction of the work that is (constantly) required. Nevertheless, significant progress toward enhanced portfolio risk management can be – and has been – made via the implementation of the studies detailed in this research.

References

- ACAR, E. and Middleton, A. 2004. Maximum drawdown: Further results. *Intelligent Hedge Fund Investing*, Ed. Schachter, B. London, *Risk Books*.
- ALEXANDER, C. 2001. Market models: A guide to financial data analysis. London, *Wiley Publishing*.
- ALMGREN, R. and Chriss, N. 1999. Value under liquidation. *Risk*, 12: 58 – 64.
- ALTMAN, E. 1968. Financial ratios, discrimination analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 4(8): 589 – 610.
- AMMANN, M. and Moerth, P. 2005. Impact of fund size on hedge fund performance. *Journal of Asset Management*, 6(3): 219 – 238.
- AMMANN, M. and Reich, C. 2001. VaR for nonlinear financial instruments — linear approximation or full Monte Carlo? *Financial Markets and Portfolio Management*, 15(6): 1 – 18.
- ANGELIDIS, T. and BENOS, A. 2005. Liquidity adjusted value at risk based on the components of the bid-ask spread. [Internet:] <http://ssrn.com/abstract=661281> [Date of access: 31 August 2007]
- BANGIA, A., Diebold, F. X., Schuermann, T. and Strouhair, J. 1998. Modelling liquidity risk. [Internet:] www.ssc.upenn.edu/~fdiebold/papers/paper25/bds.pdf [Date of access: 22 September 2006]
- BANGIA, A., Diebold, F. X., Schuermann, T. and Strouhair, J. 1999. Liquidity on the outside. *Risk*, 12(7): 68 – 73.
- BANK OF ENGLAND. 2008. Financial stability report: October 2008, 24. [Internet:] <http://www.bankofengland.co.uk/publications/fsr/2008/fsrfull0810.pdf>, [Date of access: 16 January 2009]
- BANK OF JAPAN. 2006. Recent Developments in hedge funds. *Financial Systems and Bank Examination Department*, Financial Markets Department: 1 – 65.
- BANK, L. and Lawrenz, J. 2003. Why simple, when it can be difficult? *Kredit und Kapital*, 36(4): 534–556.
- BAXTER, M. 2008. Bank losses – how do they compare with past profits? [Internet:] <http://defaqto.blog.com/iabn/2008/09/01/bank-losses-compare-profits/>, [Date of access: 16 January 2009]
- BCBS. 1988. International convergence of capital measurement and capital standards. [Internet:] <http://www.bis.org/publ/bcbsc111.htm>, [Date of access: 23 January 2008]
- BCBS. 1996. Amendment to the capital accord to incorporate market risks. [Internet:] <http://www.bis.org/publ/bcbs24.htm>, [Date of access: 17 June 2008]
- BCBS. 1998. Amendment to the Basel capital accord of July 1988. [Internet:] <http://www.bis.org/publ/bcbs36.htm>, [Date of access: 22 January 2008]
- BCBS. 2005. An explanatory note on the Basel II IRB risk weight functions. [Internet:] <http://www.bis.org/bcbs/irbriskweight.pdf>, [Date of access: 21 May 2008]
- BCBS. 2005. QIS 5: Fifth Quantitative Impact Study. [Internet:] <http://www.bis.org/bcbs/qis/qis5.htm>, [Date of access: 22 January 2008]
- BCBS. 2005. The application of Basel II to trading activities and the treatment of double default effects. [Internet:] www.bis.org/publ/bcbs111.htm [Date of access: 28 December 2006]
- BCBS. 2006a. International convergence of capital measurement and capital standards: A revised framework - Comprehensive Version. [Internet:] <http://www.bis.org/publ/bcbs128.htm>, [Date of access: 23 November 2007]
- BCBS. 2006b. Results of the fifth quantitative impact study (QIS 5). [Internet:] <http://www.bis.org/bcbs/qis/qis5results.pdf> [Date of access: 21 June 2008]

- BCBS. 2008. Principles for sound liquidity risk management and supervision. [Internet:] <http://www.bis.org/publ/bcbs144.pdf?noframes=1>, [Date of access: 17 January 2009]
- BERG, D. 2004. Bankruptcy prediction by generalized additive models. [Internet:] , http://www.math.uio.no/eprint/stat_report/2005/01-05.pdf, [Date of access: 12 October 2007]
- BIRGER, J. 2006. Investing: Don't hedge your bets after all. *Fortune*, [Internet:] http://money.cnn.com/magazines/fortune/fortune_archive/2006/05/15/8376864/ [Date of access: 7 November 2007]
- BIS. 1988. International convergence of capital measurement and capital standards. [Internet:] www.bis.org/publ/bcbs04a.htm [Date of access: 12 August 2006]
- BIS. 2004. International convergence of capital measurement and capital standards: A revised framework. [Internet:] www.bis.org/publ/bcbsca.htm [Date accessed: 17 December 2006]
- BIS. 2005. The application of Basel II to trading activities and the treatment of double default effects. [Internet:] www.bis.org/publ/bcbs111.htm [Date of access: 28 December 2006]
- BLAKE, D., Cairns, A. and Dowd, K. 2000. Extrapolating VaR by the square-root rule. *Financial Engineering News*, [Internet:] www.fenews.com/fen17/var.html [Date of access: 14 November 2006]
- BOLLERSEV, T., Chou, R. Y. and Kroner, K. F. 1992. ARCH modelling in finance: a selective review of the theory and empirical evidence. *Journal of Econometrics*, 52(3): 5 – 59.
- BOTHA, M. 2005. Risk Management in Hedge funds, *Masters dissertation*, University of the North West, Potchefstroom, South Africa.
- BOTHA, M., and Van Vuuren, G. 2009. Retail credit capital charge optimisation and the new Basel Accord, *Risk Management in Financial Institutions*, 2(3): 45 – 68.
- BOUCHAUDY, J. P. and Potters, M. 1999. Worst fluctuation method for fast value at risk estimates. *Service de Physique de l'etat Condense.*, Centre d'etudes de Saclay, [Internet:] <http://ssrn.com/abstract=181949>, [Date of access: 11 September 2006]
- BURNS, R. L. 2005. Economic capital and the assessment of capital adequacy. *FDIC Supervisor Insights*, [Internet:] http://www.fdic.gov/regulations/examinations/supervisory/insights/siwin04/economic_capital.html, [Date of access: 12 June 2008]
- CALEM, P. and Follain, J. R. 2007. Regulatory capital arbitrage and the potential competitive impact of Basel II in the market for residential mortgages. *The Journal of Real Estate Finance and Economics*, 35(2): 197 – 219.
- CALEM, P. and LaCour-Little, M. 2003. Risk-based capital requirements for mortgage loans. *Journal of Banking and Finance*, 28(3): 647 – 672.
- CARLSON, M. 2006. A brief history of the 1987 Stock market crash. *Board of Governors of the Federal Reserve System (US)*, Finance and Economics Discussion Series, 2007–13.
- CBOE. 2009. [Internet:] <http://www.cboe.com/micro/vix/introduction.aspx>, [Date of access: 14 January 2009]
- ÇETIN, U., Jarrow, R. A., Protter, P. and Warachka, M. 2004. Option pricing with liquidity risk. [Internet:] www.orie.cornell.edu/~protter/WebPapers/bspaper3.pdf, [Date of access: 2 October 2006]
- CHENG, C. 2002. Securitization & hedge funds: creating a more efficient market. *Intangis Funds Research Report*: 1 – 11.
- CHERNIH, A. V. and Henrard, S. 2006. Asset correlations: A literature review and analysis of the impact of dependent loss given defaults. *Working Paper*. [Internet:] http://www.econ.kuleuven.be/insurance/pdfs/CVH-AssetCorrelations_v12.pdf [Date of access: 22 May 2008]

- CHRISTENSEN, M. M. and Platen, E. 2005. When are Sharpe ratio based investments superior? [Internet:] <http://www.sam.sdu.dk/~mmc/Mortens%20hjemmeside/Papers/superior.pdf>, [Date of access: 3 February 2009]
- COSANDEY, D. 2001. Adjusting value at risk or market liquidity. *Risk*, 10:115 – 118.
- CRUZ, M. 2002. Modeling, measuring and hedging operational risk. *New York: Wiley Finance*.
- DANIELSSON, J. and Zigrand, J. 2006. On time-scaling of risk and the square-root-of-time rule. *Journal of Banking & Finance*, 30(10): 2701 – 2713.
- DASH, J. 2004. *Quantitative finance and risk management*. World Scientific Publishing Company, New York.
- DIEBOLD, F. X. and Lopez, J. 1995. Modelling volatility dynamics. Kevin Horner (ed): *Macroeconomics: developments, tensions and prospects*. Boston: Kluwer Academic Press.
- DIEBOLD, F. X., Hickman, A., Inoue, A. and Schuerman, T. 1996. Converting 1-day volatility to h -day volatility: scaling by \sqrt{h} is worse than you think. [Internet:] www.ssc.upenn.edu/~diebold/, [Date of access: 18 October 2006]
- DORAN, J. S., Boney, V. and Peterson, D. R. 2006. The Effect of the Spider exchange traded fund on the cash flow of funds of S&P Index mutual funds, *Working Paper Series*. [Internet:] <http://ssrn.com/abstract=879777>, [Date of access: 21 February 2009]
- DOWD, K. Blake, D. and Cairns, A. 2003. Long term value at risk. [Internet:] www.lse.ac.uk/ubs/pdf/dp17.pdf, [Date of access: 7 November 2006]
- DU TOIT, B. 2005. The Omega function: part 1: An Introduction. *Vikela*, 3: 4 – 6.
- DUCHEMIN, S., Laurent, M. and Schmit, M. 2003. Asset return correlation: The case of automotive lease portfolios. *Working Paper: WP-CEB 03/007* Centre Emile Bernheim, Solvay Business School, Université Libre de Bruxelles, [Internet:] <http://www.solvay.edu/EN/Research/Bernheim/documents/wp03007.pdf>, [Date of access: 2 June 2008]
- DÜLLMANN, K. and Scheule, H. 2003. Asset correlation of German corporate obligors: Its estimation, its drivers and implications for regulatory capital. *Deutsche Bundesbank*. [Internet:] <http://www.bis.org/bcbs/events/wkshop0303/p02duelsche.pdf>, [Date of access: 2 June 2008]
- ELING, M. 2006. Performance measurement of hedge funds using data envelopment analysis. *Journal Financial Markets and Portfolio Management*, 20(4): 442 – 471.
- ENGLE, R. 2009. Risk management and the financial system. [Internet:] <http://economistsview.typepad.com/economistsview/2009/01/robert-engle-on-risk-management.html>, [Date of access: 15 February 2009]
- ERWAN, L. 2002. Incorporating liquidity risk in VaR models, June. [Internet:] www.gloriamundi.org/picsresources/els.pdf, [Date of access: 17 December 2006]
- EXPERIAN SCOREX. 2007. Influence of default prediction over the minimum capital requirements: New Basel accord and the IRB approach for retail credit risk. [Internet:] <http://www.crc.man.ed.ac.uk/conference/presentations/dautais.pdf>, [Date of access: 1 October 2007]
- FATEMI, A. and Fooladi, I. 2006. Credit risk management: a survey of practices. *Managerial finance*, 32(3): 227 – 233.
- FEDERAL RESERVE BOARD. 2008. Charge off and delinquency rates of loans and leases at commercial banks. [Internet:] https://www.federalreserve.gov/releases/chargeoff/calc_method.htm, [Date of access: 12 July 2008]
- FENDER, I. and Kiff, J. 2004. CDO rating methodology: Some thoughts on model risk and its implications. *BIS Working Papers*, 163. [Internet:] <http://www.bis.org/publ/work163.pdf>, [Date of access: 14 February 2004]

- FERNANDEZ, F. A. 1999. Liquidity risk: new approaches to measurement and monitoring. [Internet:] www.sia.com/research/pdf/workingpaper.pdf, [Date of access: 21 November 2006]
- FIFORD, C. 2004. South African hedge fund industry grows by stealth. *Alternative Investment Management Association Journal*, 7(2): 11 – 13.
- FINANCIAL TIMES. 2006. Call to abolish hedge fund rules limiting investor access. July 4.
- FINANCIAL TIMES. 2006. Performance of hedge funds steadies but the fears persist, July 10.
- FITCH RATINGS. 2009. [Internet:] www.fitchratings.com, [Date of access: 13 January 2009]
- FSA. 2006. Private equity: a discussion of risk and regulatory engagement. *Working Paper*, 06/06. [Internet:] http://www.fsa.gov.uk/pubs/discussion/dp06_06.pdf [Date of access: 5 June 2006]
- FUNG, W., Hsieh, D. A., Naik, N. Y. and Ramadorai, T. 2006. Hedge funds: Performance, risk and capital formation. *Cepr Discussion Paper* No. 5565 [Internet:] SSRN: <http://ssrn.com/abstract=912465>, [Date of access: 28 July 2008]
- GÉHIN, W. 2005. Is performance persistence a viable criterion for selecting hedge funds? *Hedge Funds Review*, 5(8): 40 – 41.
- GILBERT, R. 2008. Who is to blame for the credit crisis? [Internet:] <http://www.willyhoops.com/credit-crisis.htm>, [Date of access: 12 February 2009]
- GORDY, M. 2000. A comparative anatomy of credit risk models. *Journal of Banking & Finance*, 24(1): 119 – 149.
- GORDY, M. 2002. A risk-factor model foundation for ratings-based bank capital rules. *Working Paper #2002-55*, Board of Governors of the Federal Reserve System. [Internet:] <http://www.federalreserve.gov/pubs/feds/2002/200255/200255pap.pdf>, [Date of access: 11 June 2008]
- GORDY, M. 2003. A risk-factor model foundation for ratings-based bank capital rules. *Journal of Financial Intermediation*, 12(3):199 – 232.
- GORE, G. 2006. Correlation confusion. *Risk*, 19(7): 7 – 9.
- HARLOW, W. V. 1991. Asset allocation in a downside risk framework. *Financial Analysts Journal*, 47(5): 28 – 40.
- HAUSMAN, J., Lo, A. and MacKinlay, A. C. 1992. An ordered probit analysis of transaction stock prices. *Journal of Financial Economics*, 31(1): 319 – 379.
- HAY, C. 2004. Explosive growth of credit products. [Internet] http://www.ipe.com/magazine/Explosive_growth_of_credit_products_16821.php, [Date of access: 14 February 2009]
- HEDGEWEEK. 2009. Hedge funds outflows take assets below USD1bn. [Internet:] http://www.hedgeweek.com/articles/detail.jsp?content_id=288265, [Date of access: 15 January 2009]
- HENNESSEE GROUP LLC. 2007. [Internet:] <http://www.hennesseegroup.com/>, [Date of access: 19 January 2009]
- HERRING, R. 2007. The rocky road to implementation of Basel II in the United States. *Atlantic Economic Journal*, 35(4): 411 – 429.
- HFRX Indices. 2006. [Internet:] https://www.hedgefundresearch.com/hfrx_reg/index.php?fuse=login&1162138035, [Date of access: 12 December 2008]
- HISATA, Y. and Yamai, Y. 2000. Research toward the practical application of liquidity risk evaluation methods. *Monetary and Economic Studies*, 12(1): 83 – 128.
- HOLTON, G. A. 2003. Value at risk: theory and practice. New York: *Academic Press*.

- ICBA. 2006. Independent community banks of America: Basel capital accord update. [Internet:] <http://www.icba.org/files/ICBASites/PDFs/stmt092606.pdf>, [Date of access: 22 July 2008]
- IMF. 2008. Global Financial Stability Report, April 2008. [Internet:] <http://www.imf.org/External/Pubs/FT/GFSR/2008/01/pdf/text.pdf>, [Date of access: 1 July 2008]
- JACQUES, R. 2004. Global banks' IT not ready for Basel II. [Internet:] <http://www.financialdirector.co.uk/vnunet/news/2125360/global-banks-ready-basel-ii>, [Date of access: 28 January 2009]
- JARROW, R. A. and Protter. P. 2005. Liquidity risk and risk measure computation. *Review of Futures Markets*, 14(1): 2 – 17.
- JARROW, R. and Subramanian. A. 1997. Mopping up liquidity. *Risk*, 12: 170 – 173.
- JARROW, R. and Subramanian. A. 2001. The liquidity discount. *Mathematical Finance*, 11(4): 447 – 474.
- JASCHKE, S. R. 2002. The Cornish–Fisher expansion in the context of Delta–Gamma-normal approximations. *Journal of Risk*, 4(4): 33 – 52.
- JORION, P. 2003. *Financial risk manager handbook*. 2nd ed. New York: Wiley
- JP MORGAN. 1996. Riskmetrics™ Technical Document. [Internet:] www.riskmetrics.com [Date of access: 12 January 2007]
- KALTOFEN, D., Paul, S. and Stein, S. 2006. Retail loans & Basel II: using portfolio segmentation to reduce capital requirements. *ECRI Research Report*, 8. [Internet:] <http://ssrn.com/abstract=958204> [Date of access: 13 October 2008]
- KAPLAN, P. D. and Knowles, J. A. 2004. Kappa: A generalised downside risk-adjusted performance measure. *Journal of Performance Measurement*, 8(3): 42 – 54.
- KAZEMI, H., Schneeweis, T. and Gupta, R. 2003. Omega as a performance measure. [Internet:] <http://www.edge-fund.com/bibliography.html> [Date of access: 7 January 2006]
- KROSZNER, R. S. 2008. Risk management and Basel II. Speech delivered at the Federal Reserve Bank of Boston AMA Conference, *Boston, MA*, May 14, 2008. [Internet:] <http://www.federalreserve.gov/newsevents/speech/kroszner20080514a.htm> [Date of access: March 1 2009]
- L'HABITANT, F. S. 2000. Hedge funds and investment partnerships: a primer. *Discussion Paper, Thunderbird*. The American Graduate School of International Management: 1 – 35.
- L'HABITANT, F. S. 2001. Assessing market risk for hedge funds and hedge fund portfolios. *The Journal of Risk Finance*, 2(4): 16 – 32.
- LAGORIO, J. 2009. Moody's sees severe recession, rising defaults. [Internet:] <http://www.reuters.com/article/bondsNews/idUSN0644335520090106>, [Date of access: 14 January 2009]
- LAWRENCE, C. and Robinson, G. 1995. Liquidity, dynamic hedging and value at risk. *Risk Management for Financial Institutions*. Risk Pubs,???, p. 63 – 72. Indication of page numbers
- LE SAOUT, E. 2002. Incorporating liquidity risk in VaR models. [Internet:] www.site.voila.fr/erwanlesaout/eng/rech/abstract.htm#artc01 [Date of access: 19 September 2006]
- LEMKE, T. P., Lins, G. T., Hoenig, K. L. and Rube, P. S. 2006. Hedge Funds and Other Private Funds: Regulation and Compliance, Securities Handbook Series. New York, *Thomson West*.
- LEVINE, J. 2007. Assigning unsecured credit ratings to hedge funds, *Moody's Investor Service*, Special Comment: April, 1 – 24. [Internet:] <http://www.moody's.com/research>, [Date of access: 14 December 2008]

- LIPPER Hedgeworld Education Centre, 2007. [Internet:] http://www.hedgeworld.com/education/index.cgi?page=hedge_fund_styles, [Date of access: 11 December 2008]
- LO, A. 2006. Darwinian investing, *Business Week Online*, [Internet:] www.businessweek.com/magazine/content/06_08/b3972033.htm, [Date of access: 4 January 2009]
- LOPEZ, J. A. 2004. The empirical relationship between average asset correlation, firm probability of default, and asset size. *Journal of Financial Intermediation*, 13(2): 265 – 283.
- LOPEZ, J. A. 2005. Empirical analysis of the average asset correlation for real estate investment trusts. *Federal Reserve Bank of San Francisco, Working Paper Series*. [Internet:] <http://www.frbsf.org/publications/economics/papers/2005/wp05-22bk.pdf>, [Date of accessed: 11 June 2008]
- LOWENSTEIN, R. 2002. When genius failed: The rise and fall of long term capital management, New York: *Fourth Estate*.
- LUBY, W. 2008. The VIX, Lehman Brothers, and forecasting. [Internet:] <http://www.greenfaucet.com/technical-analysis/the-vix-lehman-brothers-and-forecasting/43057>, [Date of access: 17 February 2009]
- MACDONALD, S. 2006. Old Mutual Asset Managers, Private communication.
- MADHAVAN, A., Richardson, M. and Roomans, M. 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. *Review of Financial Studies*, 10(2): 1035 – 1064.
- MAGDON-ISMAIL, M and Atiya, A. 2004. Maximum drawdown. *Risk Magazine*, 17(10): 99 – 102.
- MAGNUM FUNDS. 2006. [Internet:] <http://www.magnum.com/hedgefunds/strategies.asp>, [Date of access: 22 July 2008]
- MANDELBROT, B. and Hudson, R. 2005. *The misbehaviour of markets*. London, *Profile Books*.
- MARTIN, P. 2003. RMA retail credit economic capital estimation—best practices. [Internet:] www.rmahq.org/Basel2/Basel_intro.htm, [Date of access: 15 February 2009]
- MCLEOD, W. and van Vuuren, G. W. 2004. Interpreting the Sharpe Ratio when excess returns are negative. *Investment Analysts Journal*, 59: 15 – 20.
- MCNEIL, A. J. 1996. Estimating the tails of loss severity distributions using extreme value theory, *Mimeo*, ETH Zentrum, Zürich: 117 – 137.
- MERTON, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2): 449 – 470.
- MIU, P. and Ozdemir, B. 2006. Basel requirement of downturn LGD: Modeling and estimating PD & LGD correlations. *Journal of Credit Risk*, 2(2): 43 – 68.
- MODIGLIANI, F. and Modigliani, L. 1997. Risk-adjusted performance. *Journal of Portfolio Management*, 17(3): 45 – 54.
- MOODYS INVESTMENT SERVICES. 2009. [Internet:] www.moodyskmv.com, [Date of access: 13 January 2009]
- MULVEY, J. 2003. The role of hedge funds for long-term investors, *Journal of Financial Transformation*, The Capco Institute, 14(2): 23 – 28.
- MURALIDHAR, A. 2000. Risk-adjusted performance – the correlation correction. *Financial Analysts Journal*, 56(5): 63 – 71.
- OHLSON, J. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1): 109 – 131.
- ORLOWSKI, L. T. 2008. Stages of the 2007/2008 global financial crisis: Is there a wandering asset-price bubble? *Sacred Heart University, Halle Institute for Economic Research*. [Internet:]

- http://mpira.ub.uni-muenchen.de/12696/1/MPRA_paper_12696.pdf, [Date of access: 19 February 2009]
- PHALIPPOU, L. and Gottschalg, O. 2005. Performance of private equity funds. *EFA 2005 Moscow Meetings*, [Internet: <http://ssrn.com/abstract=473221>], [Date of access: 12 February 2009]
- POLAKOW, D. and de Araújo, M. 2004. Procrustes and the poisonous portfolio: Introducing Omega. *Peregrine Securities Internal Report*, Peregrine Securities.
- POLAKOW, D., de Araújo, M. and Greyling, Y. 2006. Hedge fund bean encounters. *Derivative and Quantitative Research*: 1 – 22.
- PYKHTIN, M. and Dev, A. 2002. Analytical approach to credit risk modelling. *Risk*, 15: 26 – 32.
- RAJAN, A., Martin, B., Brown, T. and Johnson, M. 2005. Hedge funds: a catalyst reshaping global investment. [Internet: www.kpmg.dk/getMedia.asp?mb_GUID=0F02D46B-F29E-4A43-8672-86A80B9750E5.pdf], [Date of access: 12 November 2007]
- REEVES, R. 2006. Managing director of SunGuard's Basel II Capital Manager Business Unit, London. Quoted in Gore, G. 2006.
- REPULLO, R. and Suarez, J. 2004. Loan pricing under Basel capital requirements. *Journal of Financial Intermediation*, 13(4): 496 – 521.
- RESERVE BANK. 2007. [Internet: <http://www.reservebank.co.za/>], [Date of access: 23 June 2007]
- REUTERS, 2009. US corporate bonds: spreads widen as economic picture dims. [Internet: <http://uk.reuters.com/article/oilRpt/idUKN0854478820090108>], [Date of access: 15 January 2009]
- RISK Magazine journalists, 2004. Private communication.
- SAIED, D. 2009. The Specter of Stagflation. [Internet: <http://mises.org/story/2754>], [Date of access: 13 January 2009]
- SCHEMMANN, M. 2008. Why banks keep on failing: money, banking and the Basel II accord, *Central Asia Business*, 1(1): 72 – 76.
- SHADAB, H. B. 2007. The challenge of hedge fund regulation. *Regulation*, 30(1): 36 – 41.
- SHADWICK, W. F. and Keating, C. 2002. A universal performance measure. *Journal of Performance Measurement*, 6(3): 59 – 84.
- SHARMA, M. 2005. Sharper risk adjusted performance measures (RAPMs): From Omega to AIRAP. *HedgeQuest*: 12 – 19.
- SHARPE, W. F. 1966. Mutual fund performance. *Journal of Business*, 4(2): 119 – 138.
- SHARPE, W. F. 1988. Determining a fund's effective asset mix. *Investment Management Review*, 2(6): 59 – 69.
- SHARPE, W. F. 1994. The Sharpe ratio. *Journal of Portfolio Management*, 21(4):49 – 58.
- SONG S. H. 2006. Risk and liquidity in a system context. *BIS Working Papers*, Monetary and Economic Department. [Internet: www.bis.org/publ/work212.pdf] [Date of access: 12 October 2007]
- SPIEGEL, R. 2000. Dot Com crash: Whose fault is it anyway? [Internet: <http://www.businessknowhow.com/manage/dotcomcrash.htm>], [Date of access: 13 February 2009]
- STEVENS, G. 2006. Risk and the Financial System, *Reserve Bank of Australia*, Hong Kong Monetary Authority and Hong Kong Association of Banks. [Internet: http://www.rba.gov.au/Speeches/2006/sp_dg_150906.html] [Date of access: 1 May 2007]
- STIGLITZ, J. E. 2008. Stagflation cometh. *Real-World Economics Review*, 45(8): 68 – 69.
- TARASHEV, N. and Zhu, H. 2007. Measuring portfolio credit risk: modelling versus calibration errors. *BIS Quarterly Review*, March: 83 – 96.

- THE ECONOMIST 2006c. Flare-up. September 23, p. 87.
- THE ECONOMIST. 2006a. Alpha betting. September 16, p. 97.
- THE ECONOMIST. 2006b. Still Free. July 1, p. 78.
- THE ECONOMIST. 2007. Exchange traded funds: revolution or pollution?' April 19, p 56.
- TREYNOR, J. L. 1966. How to rate management investment funds. *Harvard Business Review*, 43(1): 63 – 75.
- TREYNOR, J. L. and Black, F. 1973. How to use security analysis to improve portfolio selection. *Journal of Business*, 46(3): 66 – 86.
- UK FSA. 2005. Hedge funds: A discussion of risk and regulatory engagement. [Internet:] www.fsa.gov.uk/pubs/discussion/dp05_04.pdf [Date of access: 23 March 2006]
- UMUT, C., Jarrow, R. A. and Protter, P. 2004. Liquidity risk and arbitrage pricing theory. *Finance and Stochastics*, 8(11): 311 – 341.
- URBANI, P. 2005. The Omega risk measure. [Internet:] <http://www.edge-fund.com/UrbaniXXXXX.pdf>, [Date of access: 16 January 2006]
- VASICEK, O. 1977. An equilibrium characterization of the term structure. *Journal of Financial Economics*, 5(3): 177 – 188.
- VASICEK, O. 1987. Probability of loss on loan portfolio. *KMV Corporation*. [Internet:] <http://www.kmv.com>, [Date of access: 14 June 2008]
- VASICEK, O. 1991. Limiting loan loss probability distribution, *KMV Corporation*. [Internet:] <http://www.kmv.com>, [Date of access: 4 May 2008]
- VASICEK, O. 2002. The distribution of loan portfolio value. *Risk*, 15(2): 160 – 162.
- VON NEUMANN, J. and Morgenstern, O. 1947. *Theory of games and economic behaviour*. New Jersey, *Princeton University Press*.
- WILSON, R. and Sharda, R. 1994. Bankruptcy prediction using neural networks. *Decision Support Systems*, 11(5): 545 – 557.
- YAMAZAKI, T. 2009. Hedge funds lost \$350 billion in 2008 amid global market rout. [Internet] <http://www.infiniteunknown.net/2009/01/13/hedge-funds-lost-350-billion-in-2008-amid-global-market-rout/>, [Date of access: 12 February 2009]
- ZHANG, J., Zhu, F. and Lee, J. 2008. Asset correlation, realized default correlation, and portfolio credit risk. *Moody's KMV*. [Internet:] http://www.moodykmv.com/research/files/wp/Asset_Correlation_and_Portfolio_Risk.pdf, [Date of access: 1 June 2008]

Summary

The co-evolution of financial innovation and risk management is both a necessity and a product of the modern financial markets. As new products emerge and market participants rush for a share of profits, risk measurement techniques must adapt quickly to address fears of potential catastrophic losses (often stemming from new, unexplored sources). The invention of ever more complex financial products (such as derivatives and structured financial products) to spread risk and smooth earnings, however, often coincides with market 'corrections' or large losses. These new financial instruments precipitate newer, more complicated risks that ultimately result in the very events they were designed to prevent. It is invariably risk management that is blamed for failing to adapt sufficiently quickly to the rapidly-changing environment – an unfortunate consequence given the severity and expectations of the tasks involved.

Achieving the goal of improved risk management requires far more research into the nature and manifestation of financial risks. Methods to manage and mitigate these risks can only be developed when the ways in which risks develop and magnify are sufficiently understood. The major concepts of risk management are all well-researched, reported in depth and then firmly established in mainstream 'best practice'. For the sake of simplicity and implementation ease, however, many generalisations abound. A few (seemingly) inconsequential details are generalised, glossed over or ignored completely, yet it is here that calamities often reside. What is unclear is precisely *where* more detailed investigation is required before events conspire to cause significant losses. *Which* model parameters are flawed? *What* model assumptions proved inadequate? *Why* were certain aspects of the financial instrument's pricing ignored? It is the role of the modern risk manager to understand and anticipate not only where risks arise, but also how they may arise and how severely they may affect the financial system when they do.

The unfolding credit crisis (2009) has affected almost every segment of the financial system. Credit has been severely curtailed as banks struggle to contain further losses caused by reckless lending practices that characterised the last two decades. Asset prices have tumbled as fearful investors flee to safer havens, abandoning traditional investments and hedge funds with resolute consistency. Governments – in an attempt to stave off stagflation and kick-start failing economies – have reduced interest rates to historic lows, initiated stimulus packages and instigated bank bailouts, but the efforts have (as yet) had minimal to no effect on

markets. The dire economic environment characterised by diminishing industrial production, falling house (and other asset) prices and rising unemployment, has only discouraged spending and investing and promoted capital hoarding. In the ensuing crisis, the regulatory economic environment (dominated by the Basel Committee for Banking Supervision's (BCBS) Basel II Accord) has proved woefully inadequate. Potential solutions have not yet presented themselves and the crisis looks likely to continue for the foreseeable future.

In the light of these events and contemporary failings of finance in general, the need to continuously augment existing and invent new techniques to measure and manage financial risks are paramount. This thesis explores four significant problems facing modern risk management in a portfolio context.

The need for risk management to respond rapidly to the constantly-changing financial milieu has never been greater than in the current (2009) climate of uncertainty and fear. Global finance will not witness a decline in turbulence and high volatility until some confidence is restored in the apparatus that sustains it. Improved, highly adaptable risk measures and management processes are not the panacea, but they are certainly components of the framework that will need to be re-established if any semblance of investor activity is to return to the market.

Key terms

Portfolio risk

Performance measures

Basel II

Asset correlation

Probability of default discrimination

Liquidity value at risk

Regulatory capital

Portfolio optimisation

Market risk

Credit risk.

Opsomming

Die gelyktydige ontwikkeling van finansiële innovasie en risikobestuur is 'n noodsaaklikheid asook 'n produk van die hedendaagse finansiële markte. Namate nuwe produkte op die voorgrond tree en markmededingers meeding om 'n aandeel in die winste, moet tegnieke met betrekking tot risikomaatreëls vinnig aanpas om die vrese van potensieel ramspoedige verliese onder die loep te neem (wat dikwels voortspruit uit nuwe, onontginde bronne). Die uitvinding van steeds toenemend komplekse finansiële produkte (soos afgeleide en gestruktureerde finansiële produkte) om risiko te versprei en verdienste uit te stryk, val egter dikwels saam met mark 'regstellings' of groot verliese. Hierdie nuwe finansiële instrumente ontketen nuwer, meer komplekse risiko's wat uiteindelik uitloop op die gebeure wat hulle juis veronderstel was om te voorkom. Dit is sonder uitsondering risikobestuur wat geblameer word dat dit nie daarin slaag om vinnig genoeg aan te pas by die vinnig veranderende omgewing nie – 'n ramspoedige gevolg, gegewe die erns en verwagtinge van die betrokke take.

Die bereiking van die doel van verbeterde risikobestuur vereis veel meer navorsing oor die aard en manifestasie van finansiële risiko. Metodes om hierdie risiko's te bestuur en te temper, kan alleenlik ontwikkel word as die wyses waarop risiko's ontwikkel en toeneem deeglik verstaan word. Die belangrikste begrippe rakende risikobestuur is almal goed nagevors, daar is indringend verslag daaroor gelewer en stewig in hoofstroom-'beste praktyk' gevestig. Ter wille van eenvoud en maklike implementering kom talle veralgemenings egter in groot getalle voor. Enkele (oënskynlik) onsamehangende besonderhede word veralgemeen, verbloem of geheel en al geïgnoreer, maar dit is hier waar ramspoed dikwels gesetel is. Wat onduidelik is, is presies *waar* ondersoek in fyner besonderhede benodig word voordat gebeurlikhede saamspan om noemenswaardige verliese mee te bring. *Watter* modelparameters is gebrekkig? *Watter* model-aannames is ontoereikend? *Waarom* is bepaalde aspekte van die finansiële instrument se prysvasstelling geïgnoreer? Dit is die rol van die hedendaagse risikobestuurder om nie alleen te verstaan en te antisipeer waar risiko's ontstaan nie, maar ook hoe dit moontlik ontstaan en hoe ernstig dit die finansiële stelsel kan beïnvloed wanneer dit wel die geval is.

Die ontvouende kredietkrisis (2009) het feitlik elke segment van die finansiële stelsel geraak. Krediet word grootliks ingekort namate banke worstel om verdere verliese te besnoei wat deur roekelose uitleenpraktyke veroorsaak is – 'n kenmerk van die afgelope twee dekades. Bate-pryse het getuimel omdat bevreesde beleggers na veiliger toevlugsoorde vlug, en tradi-

sionele beleggings laat vaar en fondse ooreenstemmend verskans. In 'n poging om stagflasië af te weer en dalende ekonomieë 'n hupstoot te gee – het regerings rentekoerse tot ongekende lae vlakke laat daal, stimulus-pakkette geïnisieer en bank-reddingsaksies afgekondig, maar die pogings het (tot op hede) minimale of geen uitwerking op markte gehad nie. Hierdie droewige ekonomiese omgewing wat gekenmerk word deur dalende industriële produksie, dalende huis (en ander bate)-pryse en die toename in werkloosheid, het besteding en belegging ontmoedig en die ophoping van kapitaal bevorder. In die gevolglike krisis is daar bewys dat die regulerende ekonomiese omgewing (wat deur die *Basel Committee for Banking Supervision* (BCBS) se *Basel II Accord* ooreenstemmend word) droewiglik ontoereikend is. Tot nog toe is daar nie oplossings gevind nie en die krisis blyk vir die afsienbare toekoms voort te duur.

In die lig van hierdie gebeure en die hedendaagse mislukkinge van die finansiële omgewing in die algemeen bestaan die behoefte om bestaande tegnieke voortdurend uit te brei en ook nuwes te bedink om finansiële risiko's te meet en te bestuur. Hierdie proefskrif ondersoek vier betekenisvolle probleme waardeur hedendaagse risikobestuur in 'n portefeuljekonteks in die gesig gestaar word.

Die behoefte dat risikobestuur vinnig en akkuraat moet reageer op die voortdurend veranderende finansiële milieu was nog nooit sterker as in die huidige (2009) klimaat van onsekerheid en vrees nie. Die globale finansiële omgewing sal nie 'n afname in turbulensie en hoë onbestendigheid ondervind alvorens 'n mate van vertroue daarin herstel nie. Verbeterde, hoogs aanpasbare risikomaatreëls en bestuursprosesse is nie die wondermiddel nie, maar dit bevat komponente van die raamwerk wat hervestig sal moet word om enige skyn van sinvolle beleggingsaktiwiteite tot die mark te verseker.. Hierdie proefskrif ondersoek (en voorsien moontlike oplossings vir) slegs 'n breukdeel van die krediet- en markrisiko-uitdagings wat deur die hedendaagse finansiële omgewing in die gesig gestaar word. Heelwat werk word egter nog ten opsigte van op hierdie onvolledige en hoogs komplekse onderwerp vereis.