Measuring and mitigating capital procyclicality in South African banks

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of North-West University

Promotor: Dr GW van Vuuren

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It all starts here ™

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To

Aileen, Doris and Floors Visser

Preface

This thesis was completed in fulfilment of the requirements for the degree of *Philosophiae Doctor* in published article format at the School of Economics of North-West University (Potchefstroom campus, South Africa) under the supervision of Dr Gary van Vuuren.

This study comprises three distinct studies and represents the original work of the author. These studies have not been submitted in any form to another university. Where use was made of the work of others it has been duly acknowledged in the text. Service providers used for obtaining data have also been duly acknowledged in the text.

The work described in this thesis was carried out whilst in the employ of Nedbank Ltd. (Sandton, South Africa) and Barclays (London, UK). Some theoretical and practical work was carried out in collaboration with Dr Gary van Vuuren from the Department of Risk Management at the School of Economics, North-West University (South Africa).

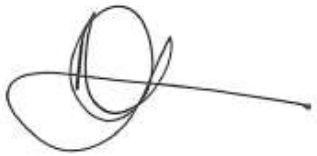
Chapter 2 presents research detailing trading book risk measures and how they have evolved since the introduction of Value at Risk (VaR) in 1996. Numerous variations of VaR-like metrics have been used extensively in the market, however, ones that account for procyclicality have been minimal. A forward-looking, coherent metric which accounts for procyclicality was employed in the South African market and compared to other measures. A mathematical approach to derive the Expected Shortfall through the integration of the probability density function of the normal and t-distributions was suggested. The article was published in the *South African Journal of Economic and Management Sciences* (SAJEMS) 19(1): 118-138 (2016).

The work detailed in Chapter 3 investigated the procyclicality of tradable credit risk and attempted to combine default and spread risk in a single forward-looking measure. The buVaR metric employs forward-looking Credit Default Swap data and does not rely on rating transition matrices. This article provides calibration on such a model, allowing for the calculation of countercyclical credit risk capital. This article has been submitted to SAJEMS for publication and is currently (July 2017) in review.

The final study in Chapter 4 researched various filters for the estimation of a suitable gap (deviation from the relevant metric's long-term trend) to guide the initiation of the regulatory Countercyclical Capital Buffer (CCB). The article compared the increasingly-popular Kalman filter to the regulatory-suggested one-sided Hodrick-Prescott (HP) filter. The article con-

firmed the procyclicality of the commonly-used regulatory metric for South Africa and thus questioned its use. The work also found different results for different crisis periods with the respective filters. This article has been accepted by SAJEMS for publication (July 2017).

The results obtained from the respective articles and the contributions they have made to the existing body of work are summarised in Chapter 5. This chapter suggests future possible research opportunities that may stem from this work. These opportunities aim to resolve unanswered questions relating to procyclicality, its measurement and mitigation and point research in new directions regarding this important financial problem.



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- My wife, Aileen Visser for all the support and love throughout the years.
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- Daniel Thomson for providing data.
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Abstract

The regulatory market risk metric – Value at Risk (VaR) – has remained virtually unchanged since its introduction by JP Morgan in 1996. Many prominent examples of market risk underestimation have undermined the credibility of VaR, prompting the search for better, more robust measures. Expected shortfall and countercyclical capital buffers have been proposed by regulatory authorities, but neither is without problems. Bubble VaR (buVaR) – a coherent measure which avoids many of the pitfalls to which other measures have succumbed – was designed to be both forward-looking and countercyclical. Although tested on other markets, here it was applied to various South African instruments and the results compared with both international observations and other market risk measures. buVaR is found to perform consistently and reliably under all market conditions.

Tradeable credit assets are vulnerable to two varieties of credit risk: default risk (which manifests itself as a binary outcome) and spread risk (which arises as spreads change continuously). Current (2017) regulatory credit risk rules require banks to hold capital for both these risks. It is a non-trivial exercise to aggregate these capital amounts as different approaches and models are required for each type. The buVaR approach was proposed by Wong (2011) to overcome the risk aggregation problem, and account for both diversification and procyclicality. The buVaR methodology operates by inflating the positive side of the underlying return distribution in direct proportion to prevailing credit spread levels (usually liquid credit default swap (CDS) spreads). Wong's (2011) framework required the calibration of some input parameters: this was undertaken for several markets, but South Africa was not among them. The model is calibrated – and tested – using South African data. The results exposed some unique features of the South African milieu and found considerable differences compared with other markets.

Procyclicality plays a pivotal role in finance in both thriving and crisis periods. This influence stems not only from the way market participants behave, but also from risk metrics used and regulatory capital amassed and released during bust and boom periods respectively. The introduction of the regulatory Countercyclical Capital Buffer (CCB) aims to thwart procyclicality by accumulating (releasing) capital in upswings (downswings), subsequently reducing the amplitude of the financial cycle and promoting macroprudential stability. The timing of the accumulation and release of buffer capital is critical so identifying accurate indicators is important. Indicators must be established for all jurisdictions: the standard metric suggested by the Basel Committee on Banking Supervision (BCBS) has been questioned. For South Africa, studies suggest alternatives such as residential property indices since research has demonstrated that the BCBS proposal is procyclical rather than countercyclical. A superior method used to estimate the buffer has not yet been established. A Kalman filter was applied to South African data and the procyclicality of the BCBS proposal confirmed. Results suggest that buffer signals are dependent upon the filter employed.

Keywords: Procyclicality, Value at Risk, Bubble Value at Risk, Expected Shortfall, Countercyclical Capital Buffer, Kalman Filter, Hodrick Prescott Filter, credit risk, market risk

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List of abbreviations

ALSI	All Share Index
ASRF	Asymptotic Single Risk Factor
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlements
buVaR	Bubble Value at Risk
CCB	Countercyclical Capital Buffer
CDS	Credit Default Swap
CVA	Credit Valuation Adjustment
cVaR	Conditional Value at Risk
DSR	Debt Service Ratio
ES	Expected Shortfall
EWMA	Exponentially Weighted Moving Average
FX	Foreign Exchange
GDP	Gross Domestic Product
HP	Hodrick-Prescott
i.i.d	Independent and Identically Distributed
IARCP	International Association of Risk and Compliance Professionals
IDR	Incremental Default Risk
IMF	The International Monetary Fund
JIBAR	Johannesburg Interbank Average Rate
JSE	Johannesburg Stock Exchange
MTM	Mark-to-Market
OPEC	Organisation of the Petroleum Exporting Countries
PD	Probability of Default
RSW	Rapid Spread Widening
SA NCA	South African National Credit Act 34 of 2005
SARB	South African Reserve Bank
sVaR	Stressed VaR
US	United States
USD	United States Dollar
VaR	Value at Risk
ZAR	South African Rand

Chapter 1

Introduction

1.1 Background

Basel II was formulated and introduced to promote soundness within the global banking system and has been both criticised and applauded alike since the accord was finalised in 2006 and implemented in 2008. The criticisms stem from key flaws identified within the accord, some identified even prior to its implementation (end 2007) (Heid, 2003). Hence the development of Basel III, which aims to rectify lessons learned during and after the crisis of 2008 (Basel Committee on Banking Supervision (BCBS, 2010a)). The onset of the financial crisis in 2008 was merely a precursor to many years of financial turmoil, as this crisis gave rise to severe sovereign debt crises in several countries including Spain, Greece, Italy, Portugal and Cyprus.

Basel III, first published in 2010, has undergone several updates with further changes proposed including those in January 2013 (BCBS, 2013).[1] Two ways in which the reform package sets out to reach its objective are to focus on:

- the quality and quantity of global regulatory capital and
- liquidity rules governing the banking sector (BCBS, 2010a).

The former may be strengthened through increasing the existing capital buffer (8%) with a capital conservation buffer (2.5%) as well as a countercyclical capital buffer (up to 2.5%) (BCBS, 2010a). These additional buffers are being phased in from January 2016 and will continue through January 2019 (BCBS, 2010a). Informally, several BCBS publications are being labelled as Basel IV by industry participants.

Procyclicality was not addressed by Basel II. This omission was identified as one of Basel II's shortcomings and provided the motivation for the introduction of the CCB in Basel III. Procyclicality refers to those economic quantities that are positively correlated with the overall state of the economy (van Vuuren, 2012). This phenomenon's existence in financial markets was identified long before the implementation of Basel II (e.g. Heid, 2003, Catarineu-Rabell, Jackson and Tsomocos, 2003 and Goodhart and Taylor, 2006) and the significant role it played in the financial crisis has increased the need for methods and metrics to effectively

[1] Changes include alterations to the definitions of high quality liquid assets to be used in the Liquidity Coverage Ratio and Net Stable Funding Ratio.

counter the cyclicality of financial markets. The effect of procyclicality in the financial crisis stems from a period (2003 – 2007) of financial proliferation where both procyclicality of capital and leverage were ubiquitous in global financial markets. The procyclicality of *capital* refers to the situation in which favourable market conditions are experienced, with financial institutions being profitable thereby allowing them to take up larger market positions (Youngman, 2009).

The role that accounting rules play in the amplification of procyclicality in a mark-to-market environment also presents an interesting research topic. One view asserts that accounting rules are neutral while others argue that accounting rules create incentives and influences behaviour, thereby ultimately impacting the dynamics of financial systems. The contribution of mark-to-market accounting rules is not the focus of this study, however, but it is worth mentioning that they affect and contribute to procyclicality in financial markets. The procyclicality of *leverage* affects financial institutions through their balance sheets as the balance sheets expand and contract with economic cycles (Adrian & Shin, 2008). Several mechanisms contribute to this procyclicality in the leverage positions of financial institutions. One of these is the risk management technique, VaR, used to determine regulatory market risk capital (Youngman, 2009). Several of these risk management model-based techniques – like VaR – have been criticised for being highly procyclical (Yamai & Yoshiba, 2002, Krause, 2003 and BCBS, 2013).

VaR models, the foundation of the Market Risk Amendment to Basel I (BCBS, 1996) used for regulatory capital regulation in financial institutions, have been blamed as a key failure of the financial crisis. A VaR model estimates future profits and losses of a bank's trading portfolio (Youngman, 2009), the final output being defined as a maximum amount that a bank would expect to lose over a certain period at a defined confidence level (Youngman, 2009). Since the mandatory use of VaR models for regulatory capital calculation was introduced in the Market Risk Amendment and Basel II the metric has been significantly researched with several shortcomings recognised by academics and practitioners (Yamai & Yoshiba, 2002, Krause, 2003, Wong, (2011a, b) and BCBS,2012). Through this research, institutions have developed several variants of VaR with all of them still using historical data to determine probability distributions for future outcomes (Youngman, 2009).

Other criticisms of VaR include the metric's inability to model asset prices especially in the tails of distributions (e.g. Wong, 2011a). The metric has also been blamed for being late in crisis detection as it lags sharp market movements due to the use of a rolling window for the

VaR computation (Wong, 2011a, b). Finally, mark to market accounting practices have also been identified as contributors to VaR model procyclicality (Wong, 2011a, b). Due to these shortcomings, several market participants (BCBS, 2009c, the Board of Governors of the Federal Reserve System, 2012 and the International Monetary Fund, 2013) have proposed stress testing to better understand market positions and exposures and to capture the possible impact tail events might have on financial institutions. The focus of this study, procyclicality, was exposed as a dangerous phenomenon in finance throughout the credit crisis where banks posted considerable trading losses which exceeded their VaR estimates as well as their losses estimated from stress testing scenarios (BCBS, 2009c).

This study also addresses how the countercyclical buffer, suggested by the BCBS (2010a) to counter VaR procyclicality and related metrics, is measured. The Hodrick-Prescott (HP) and Kalman filters are two such countercyclical metrics assessed in this study to determine what their contribution would have been in prior crises. This allows an assessment of their relative usefulness and helps establish which is the superior filter. Countercyclical methods must recognise bubbles/excess growth in financial market trends and thus the relevance of the credit-to-GDP ratio as bubble indicator will be determined and implemented. Further research in the study includes the analysis of a bubble VaR (buVaR) introduced by Wong (2011a, b) which offers a more robust form of conventional VaR and addresses some of the shortcomings identified and associated with it throughout financial turmoil. The buVaR metric offers a more robust countercyclical forward-looking metric compared to VaR, with the ability to determine a countercyclical buffer in financial expansion to serve as relief in times of financial distress. The Expected Shortfall (ES), employed by the BCBS to replace VaR as an internal regulatory capital metric, will also be analysed and implemented with the aim of comparing VaR, buVaR and ES methods (BCBS, 2013). The ES metric provides an improved method of tail analysis. The metric probability-weights possible losses beyond the VaR confidence level to estimate a more accurate loss estimate.

All methods (VaR, buVaR and ES) will be adapted and applied to both market and credit risk. This approach attempts to identify how the above-mentioned metrics identifies, promotes or counters procyclicality in the South African financial market. This may also offer significant insight on how old and new variants of VaR contribute to the shortcomings identified in the recent financial period of distress with regards to metrics being forward looking and accurate in tail estimations. This will also indicate whether measurement tools have improved compensating for the changing global financial environment.

1.2 Thesis structure

This thesis is structured as follows: Chapter 2 presents a South African perspective on trading book risk metrics including the application of a novel market risk metric (bubble VaR or buVaR) to South African data. Chapter 3 addresses the consequences for South African banks of procyclicality in tradeable credit risk. Use is again made of a novel bubble VaR approach, this time as an alternative to traditional *credit* risk metrics.

Because economic cycles and the risk metrics for determining regulatory capital requirements are procyclical, early detection of an overheating economy is critical. Significant positive deviation from the long-run trend of a market indicator is the standard regulatory approach for identifying market 'bubbles', but these data can be noisy and subject to measurement errors and lags. The implementation of a suitable filter to smooth these signals is non-trivial. No filter is perfect, all are subject to pros and cons. Chapter 4 addresses the issue of countercyclical capital buffer filter selection and poses some challenging questions to regulators.

Chapter 5 concludes the thesis by summarising the findings of the entire study and proposing suggestions for future research in this challenging field.

1.3 Problem statement

Procyclical capital regulations applied in the South African financial market have not been adequately addressed to date.

1.4 Research question

What improvements can be made and solutions can be implemented to ameliorate problems associated with procyclicality in the South African financial market?

1.5 Research objective

The research objectives are divided into general and specific objectives.

1.5.1 General objective

The general objective of this research is to establish the best methods for measuring countercyclical metrics for the South African financial sector. This goal includes an assessment of the measurement of:

1. the mandatory countercyclical capital buffer,
2. procyclicality of *market* risk (and the mitigation thereof) and
3. procyclicality of *credit* risk (and the mitigation thereof).

1.5.2 Specific objectives

The specific objectives of this research are:

1. to assess the literature regarding the problems regarding market procyclicality,
2. to explore the background regarding regulatory countercyclical capital buffer proposals,
3. to evaluate the relevance of metrics proposed by the BCBS for measuring procyclicality,
4. to determine the accuracy (through back testing and statistical acceptance tests) of how the procyclical metric is calculated (using the Hodrick-Prescott and Kalman filters respectively),
5. to evaluate the VaR metric, its characteristics, advantages and shortcomings thereby identifying how the regulatory capital metric can be made more robust and improved,
6. to assess the buVaR and ES metrics and their characteristics, advantages and shortcomings aiming to determine how of these measurement tools can improve the conventional VaR metric,
7. to apply a countercyclical, more robust metric, to the fat-tail form of VaR which accounts for the current market cycle position and the different risk exposures between long and short market risk positions,
8. to apply a countercyclical forward-looking metric combining spread and default risk, adequately accounting for diversification possibilities between these two risks in the South African financial sector,
9. to apply both ES and buVaR to securities and indices to identify possible shortcomings they may exhibit, and
10. to motivate why both the ES and buVaR metrics contribute to current relevant research.

1.6 Research design

The research design of this thesis follows in the outline below:

Pose research problem statement and question: A broad problem statement attempts to encompass procyclicality in its entirety as it is a phenomenon rooted in the entire financial system. Even before the credit crisis, gaps in risk management theory and practice were becoming increasingly obvious with regards to procyclicality and the treatment thereof. To achieve macroeconomic stability, the issue of procyclicality must be addressed from both credit and market risk perspectives as well as how to conduct measurements within these forms of risk.

Critical literature review: Critical literature reviews are conducted through Chapters 2 through 4 by consulting and considering existing literature. Adjustments to existing risk management procedures, techniques and methodologies to solve problems are documented and highlighted in the literature studies. The existing literature for this particular research theme is copious in this case, as in most. Where an entirely new approach to risk practices is required, the literature was less obliging, but this was not a constraint in this study, because popular, well-established mathematical techniques are almost always available for research endeavours and again, abundant literature exists to address and divulge these mathematical techniques.

Theory building/adapting/testing: Adaptation of existing risk management tools and methods for practical implementation into market or credit risk estimations usually enjoys rich precedent. In these cases, pursuing existing, well-established methodologies allows subtle, but significant, improvements to be made to risk measurement practice. The replacement of VaR with ES is a practical example of how metrics have evolved. Developing new ideas does, however, require much back-testing, validation and endorsement from other practitioners. Ultimately, the bulk of the results reported in this thesis were from empirical analyses of historical data derived using known risk metrics with slight innovations for some.

Data collection: Data used were from original sources where possible (e.g. South African Reserve Bank for proprietary regulatory capital data) or third-party, internet databases (e.g. Bloomberg for USD/ZAR FX rates, crude oil and share prices). Adequate data were available for all the chapters, so sample error was minimised.

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 Excel™ since this tool is used by most financial institutions. These spreadsheet-based models use visual basic programming language (a flexible, functional desktop tool available to all quantitative analysts and risk managers) to develop macros to replace onerous and repetitive computing tasks.

Illustrate and reason 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. Chapter 2 has already been published as detailed in Table 1.2.

Further work: To complement major findings of and ensure the continuation of much needed work not addressed in this thesis, future work regarding the many components of procyclicality is then proposed for risk theorists and practitioners.

1.6.1 Literature review

The literature reviews focus on the origin, development, history and applications of the issues identified through problem statements and research questions, in this case the prevalence of procyclicality in the South African banking and financial environment. These literature studies explain and clarify the problem of procyclicality and elucidate how previous studies have addressed these problems.

1.6.2 Empirical study

The empirical study comprises the practical implementation of the research method, using techniques and models developed in Microsoft Excel™.

The variables used refer to data assembled from various historical time series. All these data are available in the public domain and are refreshed either quarterly (e.g. GDP, credit ratings), monthly or daily (risk free rates, CDS spreads, share prices, crude oil prices etc.).

1.6.3 Data

Data in this study comprised several published, historical time series, available from both proprietary (e.g. Bloomberg) and non-proprietary sources (e.g. internet databases).

Table 1.1: Data requirements, frequency and source.

#	Topic	Data required	Frequency	Sources
1	Trading book risk metrics: A South African perspective	JSE All Share Index, S&P500 Index USD/ZAR FX rate Crude oil/barrel price in ZAR/USD	Weekly January 1982 to January 2015	Bloomberg time-series data
2	Procyclicality in tradeable credit risk: Consequences for South Africa	5-year and 10-year South African government credit default swaps (CDS) spreads, risk free rates. South African credit ratings South African risk-free rate (3-month Johannesburg Interbank Agreed Rate (JIBAR))	Daily January 2000 to November 2016	Proprietary bank databases Fitch Ratings Bloomberg time-series data
3	Filter selection for countercyclical capital buffers	Nominal GDP and credit extended by all monetary institutions to the domestic private sector South African Small Residential price index data From these data, growth rates and the credit growth/GDP ratio were determined	Quarterly January 1965 to November 2016	SARB BIS

1.6.4 Research output

Figure 1 provides an overview of the origin and interaction of procyclical problems and each article's contribution to the resolution of these problems.

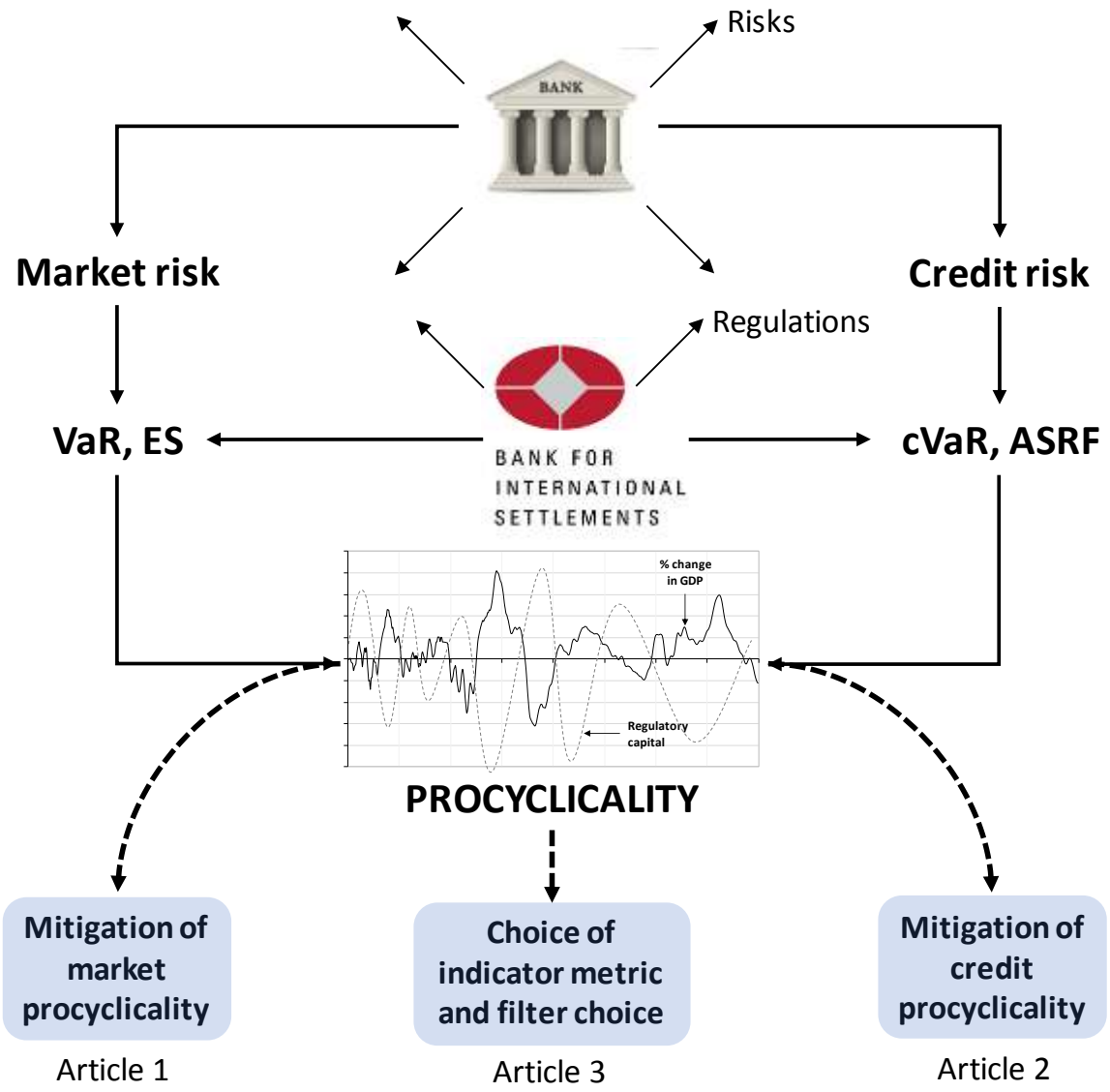

Figure 1: Schematic of problems investigated and contribution of each article to their resolution.

The research output is indicated in Table 1.2 below.

Topic 1 has been published in the *South African Journal of Economics and Management Sciences*, 19(1): 118-138 (2016),

Topic 2 has been submitted for publication in the *South African Journal of Economics and Management Sciences* (November 2016), and

Topic 3 has been accepted for publication in the *South African Journal of Economics and Management Sciences* (July 2017).

Table 1.2: Research output.

#	Topic	Models required	Research methodology
1	Trading book risk metrics: A South African perspective. Visser, D and van Vuuren, G. 2015. *South African Journal of Economics and Management Sciences*, 19(1): 118–138.	HP filter Fourier transform Bespoke market risk buVaR models	Using the HP filter, data are smoothed and noise is reduced Fourier transform establishes cycle frequencies and amplitudes buVaR model determines market risk regulatory capital
2	Procyclicality in tradeable credit risk: Consequences for South Africa Submitted for publication in *South African Journal of Economics and Management Sciences*, Nov 2016.	Bespoke credit risk buVaR models	buVaR model determines credit risk regulatory capital
3	Filter selection for countercyclical capital buffers Accepted for publication in *South African Journal of Economics and Management Sciences*, Jul 2017.	HP filter Kalman filter BCBS countercyclical buffer trigger model	HP filter used to establish long run trend Kalman filter uses recursive techniques and Bayesian statistics to generate accurate forecasts BCBS regulatory capital calculator determines capital requirements

1.6.5 Trading book risk metrics: a South African perspective

The regulatory market risk metric – VaR – has remained virtually unchanged since its introduction by JP Morgan in 1996. Many prominent examples of market risk underestimation have undermined the credibility of VaR, prompting the search for better, more robust measures. Expected shortfall and countercyclical capital buffers have been proposed by regulatory authorities, but neither is without problems. Bubble VaR (buVaR) – a coherent measure which avoids many of the pitfalls to which other measures have succumbed – was designed to be both forward-looking and countercyclical. Although tested on other markets, here it is applied to various South African prices and the results compared with both international observations and other market risk measures. buVaR is found to perform consistently and reliably under all market conditions.

1.6.6 Procyclicality in tradeable credit risk: Consequences for South Africa

Tradeable credit assets are vulnerable to two varieties of credit risk: default risk (which manifests itself as a binary outcome) and spread risk (which arises as spreads change continuously). Current (2017) regulatory credit risk rules require banks to hold capital for both these risks. It is a non-trivial exercise to aggregate these capital amounts as different approaches and models are required for each type. The buVaR approach was proposed by Wong (2011a) to overcome the risk aggregation problem, and to account for diversification and procyclicality. The buVaR methodology operates by inflating the positive side of the underlying return distribution in direct proportion to prevailing credit spread levels (usually liquid credit default swap (CDS) spreads). Wong's (2011a) framework required the calibration of some input parameters: this was undertaken for several markets, but South Africa was not among them. In this article, the model is calibrated – and tested – using South African data. The results exposed some unique features of the South African milieu and found considerable differences compared with other markets.

1.6.7 Filter selection for countercyclical capital buffers

Procyclicality plays a pivotal role in finance in both thriving and crisis periods. This influence stems not only from the way market participants behave, but also from risk metrics used and regulatory capital amassed and released during bust and boom periods respectively. The introduction of the regulatory CCB aims to thwart procyclicality by accumulating (releasing) capital in upswings (downswings), subsequently reducing the amplitude of the financial cycle and promoting macroprudential stability. The timing of the accumulation and release of buffer capital is critical so identifying accurate indicators is important. Indicators must be established for all jurisdictions: the standard metric suggested by the Basel Committee on Banking Supervision (BCBS) has been questioned. For South Africa, studies suggest alternatives such as residential property indices since research has demonstrated that the BCBS proposal is procyclical rather than countercyclical. A superior method used to estimate the buffer has not yet been established. This paper applies a Kalman filter to South African data and confirms the procyclicality of the BCBS proposal. Results suggest that buffer signals are dependent upon the filter employed.

1.7 Conclusion

The conclusion presents a summary of the findings of all three topics, and provides details of recommendations for possible future research.

Chapter 2

Trading book risk metrics:

A South African perspective

Trading book risk metrics: a South African perspective

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ABSTRACT

The regulatory market risk metric – Value at Risk – has remained virtually unchanged since its introduction by JP Morgan in 1996. Many prominent examples of market risk underestimation have undermined the credibility of VaR, prompting the search for better, more robust measures. Expected shortfall and procyclical capital buffers have been proposed by regulatory authorities, but neither is without problems. Bubble VaR – a coherent measure which avoids many of the pitfalls to which other measures have succumbed – was designed to be both forward-looking and countercyclical. Although tested on other markets, here it is applied to various South African prices and the results compared with both international observations and other market risk measures. Bubble VaR is found to perform consistently and reliably under all market conditions.

JEL classification: *C01, C22, C54, G32*

Key words: *Value at Risk, Bubble VaR, Expected Shortfall, procyclical, trading book.*

1. INTRODUCTION

The regulatory market risk metric – Value at Risk (VaR) – was introduced by JP Morgan's RiskMetrics in 1994 (JP Morgan, 1996) and later popularised by the Basel Committee for Banking Supervision's (BCBS) 1996 amendment to the Basel I accord (BCBS, 1996). The revision encouraged qualifying banks to use internal models – invariably a VaR variant – if sufficient sophistication had been demonstrated to use the BCBS's internal models approach for market risk in the trading book. A standardised approach (a stylised, formulaic methodology which employed supervisory-determined parameters) was permitted (by the BCBS) for banks with no internal or poorly-performing models. In essence, the VaR methodology determines the possible loss on a current portfolio of securities over a specified time frame with a given probability. The method re-values the portfolio to establish potential losses under different scenarios (historical, simulated or those selected from a prescribed profit and loss distribution).

After the 2007/8 credit crisis, the G20 demanded that the BCBS improve regulations governing bank capital (G20, 2009). This was a complex task, requiring not only

considerable improvements, but also substantial re-design of large parts of the entire regulatory framework. In response, the BCBS introduced an assortment of regulatory capital revisions in July 2009 to address failings exposed by the credit crisis (BCBS, 2009). Known collectively as Basel 2.5, these rules were primarily designed to reduce procyclicality of the market risk framework by adding a stressed VaR (in which the current portfolio is re-valued under severe market shock scenarios – SvaR) to the current VaR. Under the Basel II accord, although counterparty default risk and credit migration risk were addressed, mark-to-market (MTM) losses due to credit valuation adjustments (CVA) were omitted. Since two-thirds of losses attributed to counterparty credit risk during the credit crisis were due to CVA losses (with one-third due to actual defaults), an incremental risk charge was introduced to address default risk and credit migration in the trading book (BCBS, 2011a). The new rules also harmonised the treatment of securitisation exposures across banking and trading books.

Further regulatory amendments were established with the issue of the Basel III rules in December 2010 (BCBS, 2011a). These introduced a countercyclical capital buffer (designed to increase capital requirements in boom times and release capital in downturns), instituted two liquidity risk measures (the shorter term Liquidity Coverage Ratio and the longer term Net Stable Funding Ratio), established a Pillar one leverage ratio, incrementally improved the quality and quantity of qualifying capital and augmented the regulatory treatment of market risk in the trading book via three specific provisions: (i) a capital requirement to protect against changes in counterparty creditworthiness (and associated MTM losses), (ii) a direct influence of unrealised MTM gains and losses on Tier one capital, and (iii) the exclusion of Tier 3 capital as eligible capital for market risk regulatory capital requirements.

Despite the modifications and amendments to the regulatory treatment of the trading book, several deficiencies in the internal models approach were noted:

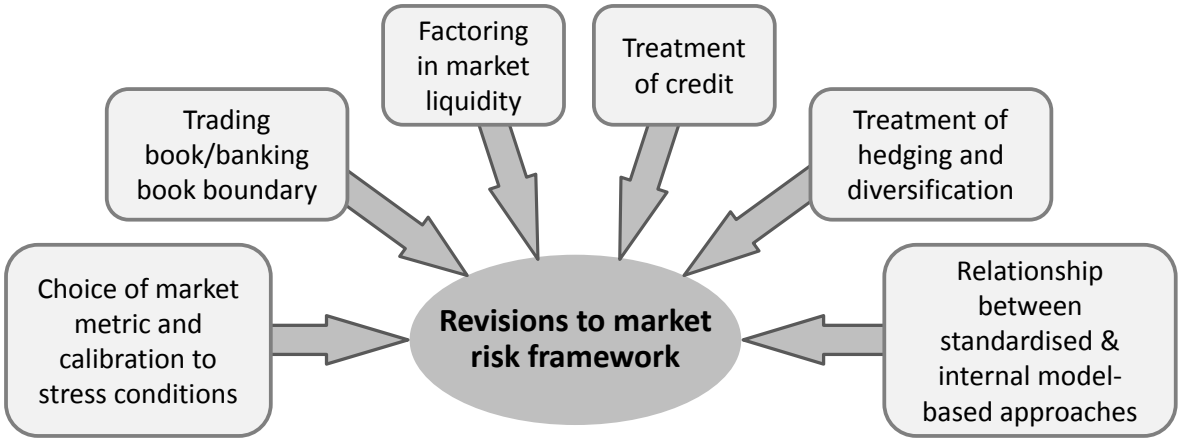
1. VaR informs nothing about loss *severity*, only loss *probability*. This feature has long been a criticism of VaR yet despite this (and other factors) VaR's prominence in the regulatory framework has remained virtually unchanged since its introduction in 1996 (Duffie & Pan, 1997 and Balbas, Garrido & Mayoral, 2009),
2. some capital charges overlap and are occasionally duplicated (e.g. SVaR/current VaR) (Coste, Douhady & Zovko, 2011 and Choudhry, 2013),
3. the boundary between the trading book and banking book remains confusing (interest rate risk is only capitalised in the trading book, not the banking book (Yeh, Twaddle & Frith,

2005)) and vulnerable (the treatment of securitisation products between banking and trading books is inconsistent (Bank of England, 2014)), and

4. the measurement of market illiquidity is inconsistent and inadequately captured (the liquidity horizon or holding period is capped at ten trading days, even though this was demonstrably insufficient during the credit crisis (International Monetary Fund, 2008)).

The standardised approach fared little better than the internal models approach. It had been shown to be risk-insensitive, inadequately capturing risks associated with complex instruments and dealing with hedging and diversification ineffectively (Prescott, 1997 and Penza & Bansal, 2001).

The BCBS acknowledged that the incremental changes introduced by Basel 2.5 were both temporary and insufficient, and that a detailed review of mistakes made (and ways to repair them) was required. The fundamental review of the trading book, a substantially-revised market risk framework, was a direct result of that enterprise (BCBS, 2013). To strengthen capital standards for market risks, the BCBS proposed six sweeping changes to the measurement and management of trading book risks in a recent consultative document (BCBS, 2013). Figure 1 provides a summary of the framework constituents.



Source: BCBS (2013).

Figure 1: Components of the revisions to the market risk framework.

Although the proposals cover several facets of the trading book, banks' market risk capital will be most affected by four significant changes (BCBS, 2013):

1. VaR will be replaced as the desired market risk metric by expected shortfall (ES), the probability-weighted average of tail losses beyond a given VaR,

2. the VaR confidence level will be reduced from 99.0% to 97.5%;

3. expected shortfall (ES) will be scaled using stressed observations (thereby reducing the double-counting introduced by SVaR) and
4. holding periods will be asset-dependent and calculated using overlapping windows (no longer just 10 days for all trading book assets).

Prior to the 2013 BCBS proposals, Wong (2011) suggested a novel risk measure – bubble VaR (buVaR) – to address problems associated with market risk measures. Wong (2011) demonstrated that buVaR could transform VaR into a countercyclical measure, account for large tail losses and distinguish between long and short positions by modelling *all* portfolio return components simultaneously (unlike VaR which models only noise). Wong (2011) asserted that well-known VaR data requirements (such as portfolio return data stationarity and independent and identically distributed (i.i.d.) portfolio returns) may be relaxed using buVaR and empirical portfolio return observations, such as fat tails, high skewness and heteroskedasticty, could be included in the formulation. buVaR generates supplemental buffers for these deviations from normality by only allowing crashes to occur counter to current market trends.

The suggestions put forward by the BCBS (2013) and Wong (2011) are attempts to improve the regulatory market risk milieu and, although not contradictory, are quite different in their respective approaches. Claims of buVaR's superiority over traditional VaR are tested in a South African framework, by applying it to local market data. The results obtained are compared to current and proposed regulatory measures including some of the BCBS proposals (such as the procyclical buffer and the ES measure).

The remainder of this article proceeds as follows: Section 2 explores problems with current and proposed regulatory measures including the non-subadditivity of VaR, issues with liquidity scaling, the omission of procyclicality from the market risk formulation and time-varying volatility issues. Section 3 explains the reasoning behind Wong's (2011) buVaR concept and details how the measure may alleviate many regulatory issues with current and proposed metrics. The data used to explore differences between the metrics are explained in Section 4, as well as all relevant mathematics. The results obtained from an analysis of South African data using various market risk metrics follows in Section 5 and Section 6 concludes.

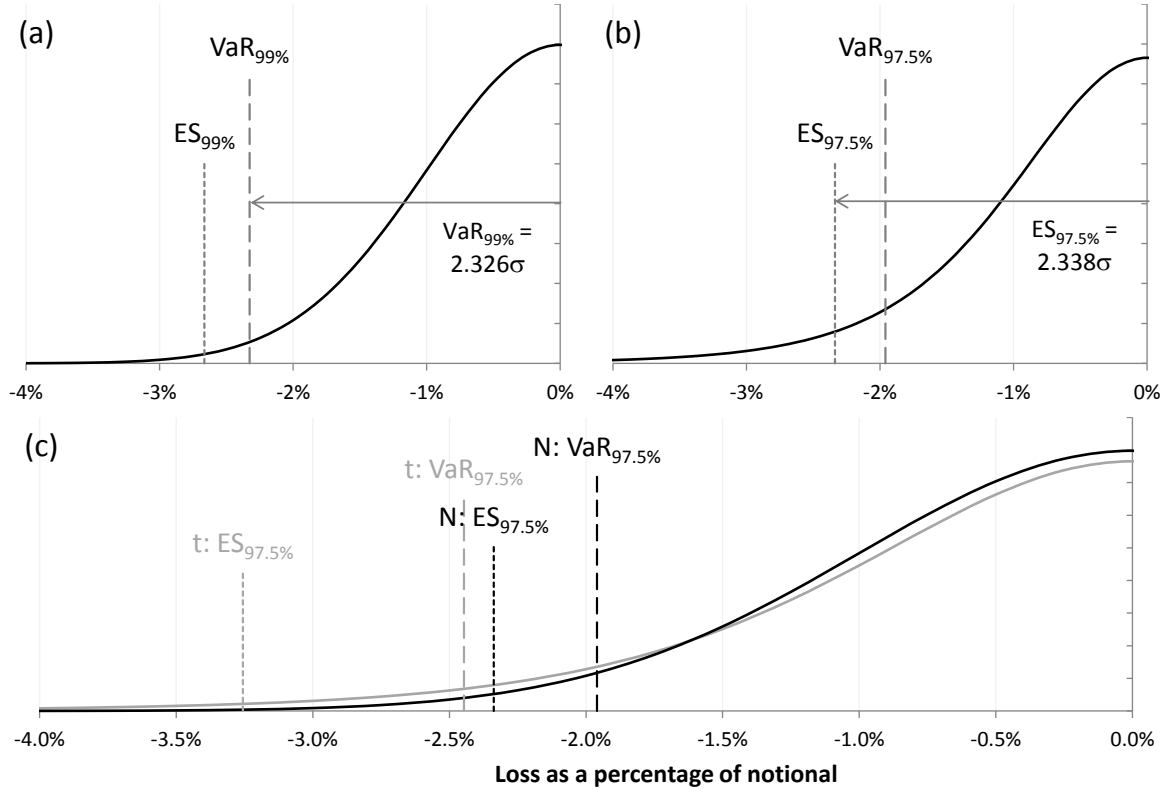
2. PROBLEMS WITH REGULATORY MARKET RISK MEASURES

2.1. Choice of market metric

VaR does not capture the tail risk of loss distributions (Rosenberg & Schuermann, 2004), and thus a conditional measure (i.e. given that a VaR threshold has been exceeded, what is the severity of the resulting losses?) is required. ES refers to the probability-weighted losses (thereby accounting for both loss severity and likelihood) in the tail beyond VaR (Nadarajah, Zhang & Chan, 2013).

A common criticism of VaR is that it employs historical data and therefore is of limited use for predicting uncertain futures, but the same is also true of ES. The Basel proposals (BCBS, 2013) stipulate that both the internal models-based approach capital requirements as well as the risk weights for the revised standardised approach must be determined using ES.

The BCBS has proposed a new VaR confidence level of 97.5% (current: 99%), so the ES will measure probability-weighted losses beyond this threshold. This new confidence level provides a similar risk level as the existing 99% VaR threshold ($\mathbf{2.326}^{\boldsymbol{VaR}}_{\mathbf{99\%}}$ versus $\mathbf{2.338}^{\boldsymbol{ES}}_{\mathbf{97.5\%}}$ – a 0.5% difference for the normal distribution) as shown in Figure 2. With more observations in the 2.5% tail (compared with the previous 1% tail), the move to ES is expected to provide more stable model output and reduce sensitivity to extreme outlier observations. Banks may choose to use fatter-tailed distributions: Figure 2(c) indicates the difference between normal distribution and $\boldsymbol{t}$-distributed assumptions.



Source: Author calculations using Microsoft Excel and BCBS (2013).

Figure 2: (a) Normal distribution $VaR_{99\%}$ and $ES_{99\%}$,(b) normal distribution $VaR_{97.5\%}$ and $ES_{97.5\%}$ and (c) normal and *t*-distribution (excess kurtosis = 3, $\nu = 6$) $VaR_{97.5\%}$ and $ES_{97.5\%}$ for a portfolio volatility of 1%.

The expected shortfall at a certain quantile, q, is ES_q , the probability weighted average of values in the tail of the distribution to the left of q such that:

$$ES_q = E\left(L \middle| L < VaR_q\right)$$

For a normal distribution, $$ES_q = \frac{f\left(VaR_q\right)}{q} \quad \text{where} \quad f(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right).$$

i.e. the probability density of the normal distribution, where σ_t is the volatility, $f(x)$ denotes the probability density function of $N(0, \sigma^2)$ and it has been assumed that $\mu = 0$.

To calculate ES_q for any volatility, σ, and at any significance level, q, the function below must be integrated:

$$\begin{aligned} ES_q &= \int_{-\infty}^{q} x \cdot f(x) dx \\ &= \int_{-\infty}^{q} \frac{x}{\sqrt{2\pi} \cdot \sigma} \cdot \exp\left(-\frac{x^2}{2\sigma^2}\right) dx. \end{aligned}$$

Let

$$\chi = \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad \text{then} \quad d\chi = -\frac{x}{\sigma^2}\exp\left(-\frac{x^2}{2\sigma^2}\right)dx \quad \text{so} \quad -\sigma^2 d\chi = x\exp\left(-\frac{x^2}{2\sigma^2}\right)dx$$

Substituting

$$ES_q = -\frac{\sigma}{\sqrt{2\pi}}\int_{-\infty}^{q} d\chi \qquad = -\frac{\sigma}{\sqrt{2\pi}}\cdot\exp\left(-\frac{x^2}{2\sigma^2}\right)\Big|_{-\infty}^{q} \qquad = -\frac{\sigma}{\sqrt{2\pi}}\cdot\exp\left(-\frac{q^2}{2\sigma^2}\right).$$

For other distributions, say the t-distribution, which has fat-tails and is occasionally considered a better representation of VaR, integrate:

$$ES_q = \int_{-\infty}^{q} t\cdot f(t)dt$$

In this case, $f(t)$ is the probability density function of the t-distribution which is (for $\mu = 0$ and standard deviation, σ):

$$f(t) = \frac{\Gamma(\nu+1)}{\sqrt{\nu\pi}\cdot\Gamma\left(\frac{\nu}{2}\right)\cdot\sigma}\left(1+\frac{t^2}{\sigma^2\nu}\right)^{-\left(\frac{\nu+1}{2}\right)}$$

where ν counts the degrees of freedom, calculated using:

$$k = \frac{6}{\nu-4} + 3,$$

and where k is the kurtosis of the data (Rozga & America, 2009).

For ν even: $$\frac{\Gamma(\nu+1)}{\sqrt{\nu\pi}\cdot\Gamma\left(\frac{\nu}{2}\right)} = \frac{(\nu-1)\cdot(\nu-3)\cdots 5\cdot 3}{2\sqrt{\nu}(\nu-2)\cdot(\nu-4)\cdots 4\cdot 2}$$

and for ν odd: $$\frac{\Gamma(\nu+1)}{\sqrt{\nu\pi}\cdot\Gamma\left(\frac{\nu}{2}\right)} = \frac{(\nu-1)\cdot(\nu-3)\cdots 4\cdot 2}{\pi\sqrt{\nu}(\nu-2)\cdot(\nu-4)\cdots 5\cdot 3}$$

To calculate ES_q for any volatility, σ, any number of degrees of freedom, ν, and any significance level, q, the integral below must be determined:

$$ES_q = \int_{-\infty}^{q} t\cdot\frac{\Gamma(\nu+1)}{\sigma\sqrt{\nu\pi}\cdot\Gamma\left(\frac{\nu}{2}\right)}\cdot\left(1+\frac{t^2}{\sigma^2\nu}\right)^{-\left(\frac{\nu+1}{2}\right)}dt.$$

Let $\Theta = \frac{\Gamma(\nu+1)}{\sqrt{\nu\pi}\cdot\Gamma\left(\frac{\nu}{2}\right)}$ and $\chi = 1 + \frac{t^2}{\sigma^2\nu}$ then $d\chi = \frac{2t}{\sigma^2\nu}dt$ so $\frac{\sigma^2\nu}{2}d\chi = tdt.$

Substituting

$$\begin{aligned} ES_q &= \frac{\Theta\sigma\nu}{2}\int_{-\infty}^{q}\chi^{-\left(\frac{\nu+1}{2}\right)}d\chi \\ &= \frac{\Theta\sigma\nu}{1-\nu}\cdot\chi^{\frac{1-\nu}{2}}\Big|_{-\infty}^{q} \\ &= \frac{\Gamma(\nu+1)}{\Gamma\left(\frac{\nu}{2}\right)}\cdot\left(\frac{\sigma}{1-\nu}\right)\cdot\sqrt{\frac{\nu}{\pi}}\cdot\left(1+\frac{q^2}{\sigma^2\nu}\right)^{\frac{1-\nu}{2}}. \end{aligned}$$

Advanced simulation and sampling techniques are needed for ES tail event measurements: these require orders of magnitude more simulation scenarios so banks will find it considerably more difficult to back test ES (which considers both loss size and likelihood) than VaR (which only considers loss likelihood) (Yamai & Yoshiba, 2002). For VaR, violations are observable variables, facilitating the application of formal statistical procedures to determine if the distribution of the violations conforms to a (known) underlying model, i.e. model predictions are compared to *observed* outcomes. This is not true for ES model predictions as these may only be compared to *model* outcomes. Despite the variety of procedures available for back testing ES, these are substantially inferior to the VaR equivalents (Nadarajah et al., 2013).

2.2. Scaling of liquidity horizon

Market illiquidity manifests itself in two ways: exogenously and endogenously. Exogenous liquidity refers to market-specific, average transaction costs and is taken into account using a "liquidity-adjusted VaR" approach (Diebold, Hickman, Inoue & Schuerman, 1998,), usually by scaling of short-horizon VaR to a longer time horizon with the commonly used square-root-of-time scaling rule. This method has, however, been found to be an inaccurate approximation in many studies (see, e.g. Diebold et al., 1998, Danielsson & Zigrand, 2006 and Skoglund, Erdman & Chen, 2012) and it also ignores future changes in portfolio composition (Berkowitz & O'Brien, 2002).

Endogenous liquidity refers to the price impact of the liquidation of specific positions (Bervas, 2006). It becomes relevant for trades large enough to alter market prices and is

characterised by the collective liquidation of positions, or when all market participants react similarly – giving rise to extreme liquidity risk. Costs associated with endogenous liquidity are not accounted for in the valuation of trading books, so attempts have been made to incorporate this risk in a VaR measure (Bervas, 2006). The time to liquidate positions depends on transaction costs, position size, trade execution strategy, and prevailing market conditions (Berkowitz & O'Brien, 2002). Current work suggests that endogenous liquidity risk could also be addressed by extending the VaR risk measurement horizon (see, e.g. Emna & Chokri, 2014 and Dionne, Pacurar & Zhou, 2014).

2.3. Time varying volatility

Time-varying volatility and stochastic jumps in the data are features of many financial time series. The former can be effectively modelled using the exponentially weighted moving average (EWMA) technique or various versions of GARCH models (e.g. Galdi & Pereira, 2012 and Tripathy & Gil-Alana, 2010). However, these techniques can still give rise to procyclical effects of VaR-based capital measures (Gabrielsen, Zagaglia, Kirchner, & Liu, 2012). As time horizons lengthen, time-varying volatility also diminishes the accuracy of VaR measures.

Volatility estimates using stochastic jump models, in contrast, diminish the accuracy of long-horizon VaR measures (Eberlein, Kallsen & Kristen, 2003 and Witzany, 2013). Distinguishing between time-varying volatility and volatility changes that owe to stochastic jump process realisations can be important for VaR measurement (Tasca & Battiston, 2012).

2.4. Backtesting

The BCBS requires VaR models to be regularly backtested as regulatory capital is assigned based upon the accuracy of the backtest results (BCBS, 1996). Banks are required to demonstrate that all material trading book exposures are captured, and that the methodology implemented for the subsequent VaR calculation accurately (defined by the BCBS) estimates the likely maximum loss at a given confidence level.

The BCBS approach, however, exhibits limited power to control the probability of accepting an incorrect VaR model (Type oneerror) (Pena, Rivera & Ruiz-Mata, 2006). Unconditional backtests have also been shown to be inconsistent for backtesting historical simulation models (Escanciano & Pei, 2012). In addition, backtesting procedures that only focus on the number of VaR violations have been shown to be insufficient to determine the appropriateness of model assumptions (International Association of Risk and Compliance

Professionals (IARCP), 2012). No consensus has yet emerged on the relative benefits of using actual or hypothetical results (i.e. Profit and Loss (P&L)) to conduct backtesting exercises (IARCP, 2012).

2.5. Procyclicality

Several have criticised VaR-based capital requirements because of their procyclical nature (see, e.g. International Monetary Fund, 2007, Marcucci and Quagliariello, 2008 and Youngman, 2009). Capital rules based on VaR require lower capital in boom times and higher capital in downturns (BCBS, 2010), thereby inducing cyclical lending behaviour by banks, exacerbating the business cycle. No convincing solutions to how these concerns could be addressed in the regulatory framework have yet been offered (BCBS, 2011b). The BCBS proposed a solution in the form of a countercyclical capital buffer, which has the primary objective of protecting the banking sector against excess aggregate credit growth through an additional capital buffer (BCBS, 2010). The buffer attempts to reduce cyclical lending behaviour introduced by VaR-like models. To implement this metric the BCBS has suggested a one-sided Hodrick-Prescott (HP) filter to determine the long-run trend of economic activity. Considerably different results are obtained using the two different filters (van Vuuren, 2012).

The long-term trend of aggregate credit growth normalised by real Gross Domestic Product (GDP) growth ratio is extracted using the one-sided HP filter. The countercyclical buffer is activated when the difference between the ratio and its long-term trend exceeds a specified amount. Thus, if economic activity expands too rapidly the current ratio will exceed the long-term trend and trigger the buffer's implementation.

2.6. Systemic behaviour

When all banks follow a VaR-based capital rule, financial institutions may be incentivised to act in a similar way during economic up and downswings. This gives rise to endogenous instabilities in asset markets but these risks are not generally included in individual bank measures of trading book risks (BCBS, 2011b). This might also reinforce and strengthen existing procyclicality as similar actions might precipitate either a boom or a bust cycle.

2.7. Subadditivity

VaR has been criticised for lacking the property of sub-additivity, i.e. compartmentalised, VaR-based risk measurements are not necessarily conservative (Artzner, Delbaen, Eber, & Heath, 1999 and Danielsson, Jorgensen, Sarma, Gennady, & de Vries, 2005). Expected shortfall, which is subadditive (Acerbi & Tasche, 2001), continues to gain popularity among

financial risk managers (Chen, 2014), yet faces criticism because of its relative complexity, computational burden, and backtesting issues (Yamai & Yoshiba, 2002).

Spectral risk measures (weighted average of outcomes in which bad outcomes attract larger weights) are a promising generalisation of expected shortfall. Like expected shortfall, spectral risk measures are coherent, but their results may also be related to risk aversion and utility functions through the weights given to the possible portfolio returns and as they exhibit favourable smoothness properties (Cotter & Dowd, 2006). Spectral risk measures require little additional computational effort if underlying risk models are simulation-based (Costanzino & Curran, 2014).

3. ALTERNATIVE MEASURES: Bubble VaR

Wong (2011) asserts that buVaR is based on the principle that financial variables are extremistan, thus precise measurements of tail risk are not achievable and that trading book measurements should only aim to become as accurate as possible. The purpose of buVaR is to make VaR more robust by rendering it countercyclical, i.e. able to act as a buffer against fat-tail losses, but also incorporate the benefits of ES. The metric accomplishes these aims by leading crashes and being able to distinguish between long and short positions.

VaR-like metrics and financial markets behave procyclically (BCBS, 2011a), but financial market participants also act in a manner which promotes this phenomenon. Institutions in times of financial proliferation chase profitable positions and in recessions reduce their credit extensions to avoid declining volatile market positions. This amplifies the market cycle and, subsequently, procyclicality. The BCBS's best cure for this phenomenon to date (January 2015) has been the introduction of the countercyclical buffer (BCBS, 2011a). buVaR may provide a sensible alternative as it accounts for the current cycle position and subsequently inflates either side of return distributions to counter both the procyclical nature of VaR-like models (via inflated return distributions) and financial markets (via buffer increases).

Wong (2011) asserted that buVaR relaxes standard VaR assumptions including the stationarity and i.i.d. property of portfolio returns. Research has demonstrated that relaxing these assumptions compromises model tractability, estimation consistency and precision (Emna & Chokri, 2014 and Escanciano & Pei, 2012), but Wong (2011) argues that these assumptions are regularly violated in any case during stressed market periods. In addition, if variables are extremistan (irreproducible and unpredictable) the assumptions of i.i.d. and stationarity might create an illusion of measurement precision of events that are inherently

unpredictable (Wong, 2011). buVaR requires that these assumptions be relaxed to glean the cyclical information present in price series (in contrast to return series). Using original prices relaxes the assumptions of i.i.d. and stationarity and can provide cyclical information, but may introduce the risk of increasing serial correlation in residuals leading to biased estimations.

Some problems associated with VaR may be explored by decomposing a price time series:

$$X_t = L_t + S_t + Z_t(\varepsilon_t)$$

where the original price series, X_t, comprises the long-term trend, L_t, a cyclical component, S_t and a noise factor, Z_t. Z_t is derived by taking first differences and thus is the only component to be stationary and driven by an i.i.d. process. L_t and S_t can be extracted using, for example, an HP filter or Fourier analysis. Conventional VaR, which uses portfolio returns only, deals with Z_t and thus loses valuable information embedded in the cyclical component, S_t. Wong (2011) suggests that crashes are only corrections of market cycles disturbed by bubbles. The introduction of buVaR penalises asset bubbles detected in S_t by inflating the portfolio return distribution in such a way that 'bubble chasing' is discouraged. Note that L_t is not penalised, so participation in real economic growth is not discouraged.

buVaR has two essential properties which distinguish it from conventional VaR which collectively transform the original return distribution for calculation of regulatory capital in a forward-looking countercyclical manner. The ability of buVaR to detect the formation of market bubbles is made possible through the bubble indicator.

3.1. Bubble Indicator

The bubble indicator, B_t, is defined in Section 4. For the moment, it suffices to know that it measures the formation of market bubbles (defined as the degree of price deviation from a series equilibrium level) and, in order to qualify as suitable, it must adhere to several requirements (Wong, 2011):

- for a model to detect and respond to market procyclicality and introduce countercyclicality the indicator must be synchronised with – or ideally lead – the market,
- the model must avoid bubbles, however, it should not penalise investments and growth by mistaking these for the possible onset of a bubble. Thus, the indicator must

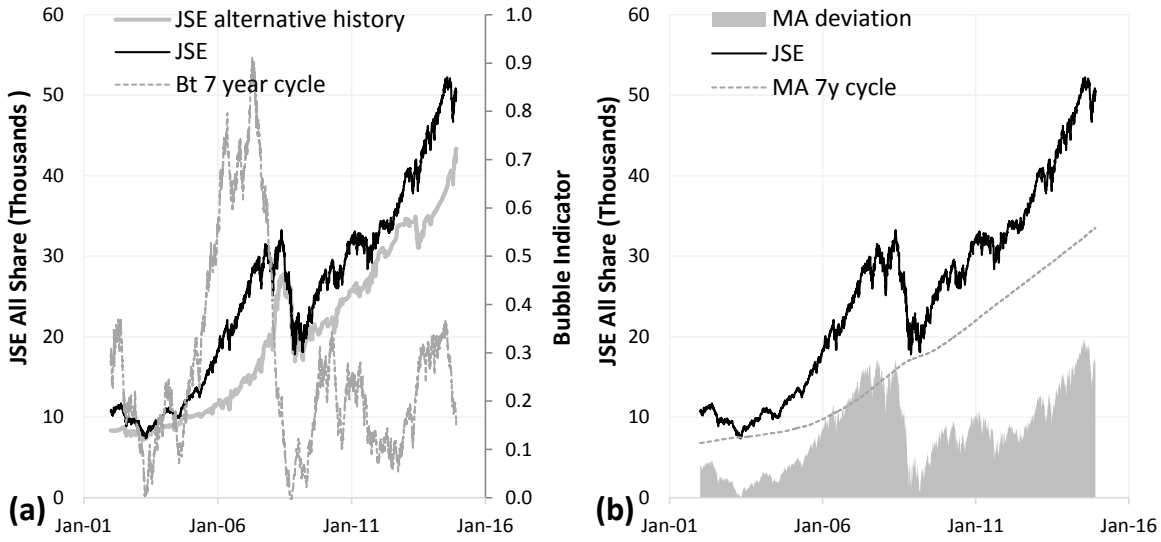
be able to differentiate between the initiation of unsustainable bubble in S_t and sustainable long-term trends in L_t,

- the indicator must be able to punish positions continuously that are against the crash (i.e. long positions in a dwindling market) throughout the entire crash. This should prevent institutions from entering these positions thereby exacerbating an already failing market. Institutions might look to over-expose themselves at favourable prices which the indicator attempts to limit, and
- the indicator must be sufficiently stable to be used for estimating regulatory capital.

The bubble indicator must be constructed in such a way that if the bubble forms in an uptrend the bubble indicator triggers (inflating the negative side of the return distribution and *vice versa*):

$$R_n \rightarrow \begin{cases} \Delta_t R_n \text{ if } sign & (R_n) \neq sign(B_t) \\ R_n \text{ if } sign & (R_n) = sign(B_t) \end{cases}$$

Wong (2011) stresses that using a deviation of a price from its moving average (MA) as a bubble indicator will fail as it only satisfies the first property mentioned above. Figure 3 illustrates the calculation of B_t and a deviation from a simple MA respectively.



Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 3: (a) B_t from derived Johannesburg Stock Exchange (JSE) alternative history and (b) deviation from 7 year MA.

The B_t in Figure 3a is smoother than the deviation from the seven year MA in Figure 3b making it more stable for the calculation of regulatory capital. The deviation from the MA behaves procyclically as it neither detects nor avoids bubbles.

3.2. Inflator

The second unique element of the buVaR metric is the inflator, calculated using a boundary argument. VaR is known to underestimate risk (Kourouma, Dupré, Sanfilippo & Taramasco, 2010), and thereby provides a lower boundary. A structural upper limit must also be determined: the inflator provides this upper limit as it increases in severity to ensure the avoidance of bubble formation during market stress. Wong (2011) suggests the inflator should also meet certain criteria to be deemed suitable. It should:

- increase monotonically with the bubble indicator,
- determine a structural upper limit which is logical and reasonable, but also sufficiently severe to prevent the manifestation of bubbles. A structural upper limit exists because of imposition of circuit breakers by regulators, and
- not be generic, but rather should be adaptable to several assets as they have different characteristics. Wong (2011) refers to the "avoidance of a one-size-fits-all" multiplier.

The risk measure to calculate regulatory capital completes the buVaR model. Wong (2011) points out that ES is superior to conventional VaR because:

- ES is sub-additive and thus more coherent,
- ES is relatively stable for the purpose of minimal regulatory capital estimations, ES seems to be suitably responsive to new market prices and regime switches and it aligns to suggestions and recommendations from the regulatory milieu.

In practice, the implementation and calculation of ES has been shown to be difficult (Taylor, 2006). ES is estimated conditional on VaR, giving rise to the possibility that estimation and model risk for ES will be higher than for VaR, although the smoothing of the tails implies ES could be more stable than VaR. Risk forecasts which use 97.5% ES risk forecasts are more volatile than 99% VaR forecasts. For example, for a Student-t (distribution), the 97.5% ES is over 40% more volatile than the 99% VaR counterpart, while for the conditional normal it is more than 10% higher (Danielsson, 2013).

The next section describes the data and methodology employed.

4. DATA AND METHODOLOGY

4.1. Data

The data employed in the buVaR risk metric were daily closing prices for the following variables: JSE All Share Index, S&P500 Index, United States Dollar (USD) per South African Rand (ZAR) exchange rate, crude oil/barrel in ZAR and crude oil/barrel in USD. Weekly JSE All Share (ALSI) index data were also used for trend extractions. The period of the data spans January 1982 to January 2015. All calculations were performed in Microsoft® Excel®.

4.2. buVaR calculation

The process to determine buVaR commences with the first differencing of the price series $R_n = ln\left(\frac{X_n}{X_{n-1}}\right)$ deriving returns for all previous days of n.

An inflator, Δ_t, is generated via rank filtering which is commonly used in digital signal processing. This process is used to remove the exceedences (outliers) from the price series and Wong (2011) found an 8% filter applied to a 1 000-day rolling window to be appropriate. The 1000-day (four years' worth of trading days) window was found effective for US and Euro data as this period embraces at least one recent financial cycle. This may be adjusted accordingly depending on the data used as cycle lengths differ in markets and economies. van Vuuren (2012) used Fourier analysis on the credit growth/GDP ratio (prescribed by the BCBS for determination of the countercyclical capital buffer) and found the South African market cycle to have a frequency of approximately seven years (see also Botha, 2009). Wong (2011) does, however, warn that ideally only one crisis (cycle-trough) should be present in a window period at a time as large amounts of volatile data could distort the window period.

Applying a rank filter of 8% reduces $R_n = 0$ for all returns $< 8\%$ and $> 92\%$ quantiles for the rolling window $\{R_n, \ldots R_{n-1000}\}$ respectively. Wong (2011) sets the threshold for the rank filtering process at 8% with the motivation that increasing it further would filter out too much information and subsequently flatten out bubbles and remove cyclical information. Reducing the bubble threshold would transform the method to a deviation from a simple MA which Wong (2011) showed to be ineffective.

The creation of growth factors for each n is accomplished using

$$D_n = \exp(R_n)$$

An alternative history is then created, thus for each day, n, a 1 000-day new price vector $\{P_n, \dots, P_{n-1\,000}\}$ is created working backwards from X_n with $P_n = X_n$.

$$P_{n-1} = \frac{P_n}{D_n}$$

In this alternative history, calculated growth was sustainable, gradual and market bubbles and manias did not occur.

Wong (2011) identifies the equilibrium μ_n as the m-day MA of the alternative history created, where m is non-constant and driven by:

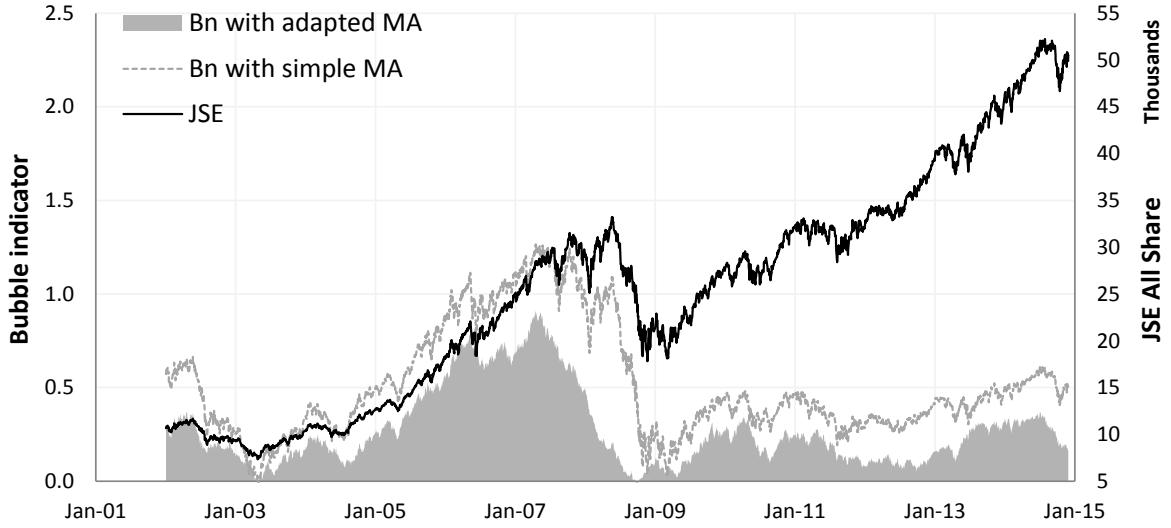
$$m = \text{Int}\left[\min\left\{\frac{\text{Stdev}(X_n, X_{n-1}, \dots X_{n-500})}{\text{Stdev}(X_n, X_{n-1}, \dots X_{n-1\,000})} \times 1\,000{,}1\,000\right\}\right]$$

Wong (2011) labels this as the adaptive MA and asserts that it has the effect of being able to reduce the bubble indicator (by reducing the window length m) when it detects that rallies conform more to long-term growth (L_t) than formation of assets bubbles. This is how the metric attempts not to penalise long-term growth but only the formation of assets bubbles.

The bubble indicator is a simple construction defined as the price deviation from the equilibrium:

$$B_n = \frac{X_n}{\mu_n} - 1$$

This metric is intended to measure the degree of cyclical bubble formation and unlike a simple MA the criteria mentioned in Section 2 for a suitable bubble indicator. This advantage compared to a simple MA is shown in Figure 4 illustrating the bubble indicator estimated using a simple MA and Wong's (2011) suggested adaptive MA.



Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 4: Bubble indicator estimated using simple MA and adaptive MA.

1. An inflator adhering to the criteria mentioned in Section 3 can be presented as:

$$\Delta_t = \left(\frac{\psi}{2\sigma_t}, exp\left\{ \left(\frac{\text{Abs}(B_t)}{B_{max}} \right)^{w_2} \times \text{In}\left(\frac{\psi}{2\sigma_t} \right) \right\} \right)$$

where:

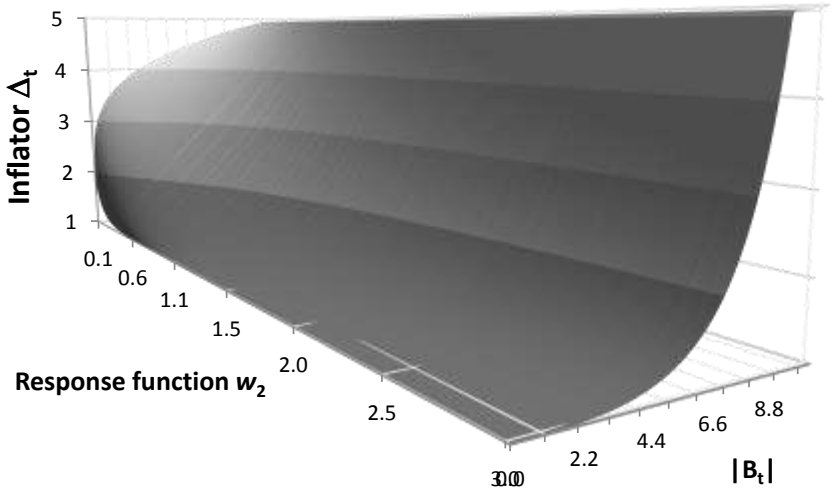
ψ is (in absolute values) the average of the five largest losses and gains throughout the entire price history of the asset capped by a circuit-breaker, if applicable

B_{max} is the largest absolute B_n observed throughout the entire history of the asset

σ_t is the standard deviation of returns for the last 250 trading days and

w_2 = 0.5.

Figure 5 illustrates a stress testing analysis of w_2 in order to assess which level of w_2 would provide the smoothest day-to-day variation of buVaR.



Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 5: Changing response function (w_2). A $w_2 = 0.5$ [similar to Wong (2011)] was found to be the most workable estimate providing the smoothest variation of day-to-day buVaR.

The inflator acts as a multiplicative adjustment for every scenario, but only on side of the return distribution of a 250-day observation period in line with the 12-month observation period for VaR as suggested by Basel II. As demonstrated in Section 3, the return distribution undergoes a transformation to the extent that if on day t:

- $B_t > 0$, then all scenarios on the negative side should be multiplied by Δ_t in order penalise long positions, but should be set to $\Delta_t = 1$ for all positive returns
- $B_t < 0$, then all scenarios on the positive side should be multiplied by Δ_t in order penalise short positions, but should be set to $\Delta_t = 1$ for all negative returns.

The buVaR metric, based on a historical approach evaluates a portfolio on shifted levels (X_i') which are based on a set of scenarios. To ensure that these shifted levels of the portfolio, asset or risk factor do not become negative they are calculated using log returns:

$$X_i' = X_t \exp(R_n \Delta_t)$$

Where the scenario $i = 1,2, \ldots ,250$ is the number days that have passed from day t and R_n is the original return series prior to applying the rank filter. Also $n = t - i + 1$. In this univariate case a bank's portfolio is first evaluated using a product pricing function $g(.)$.Then for each scenario i the portfolio is evaluated at state X_i' to produce a value $g(X_i')$. The profit and loss (P&L) vector at day t is just the distribution of values $\{g(X_i') - g(X_t)\}$, where $g(X_i')$ is a 250-vector and $g(X_t)$ a scalar. Let the sample distribution of this P&L be y. The

buVaR at confidence level q% is the ES of the P&L distribution y estimated over a one-day horizon at $(1-q)$ coverage:

$BuVaR_q = E(y|y < \mu)$

where:

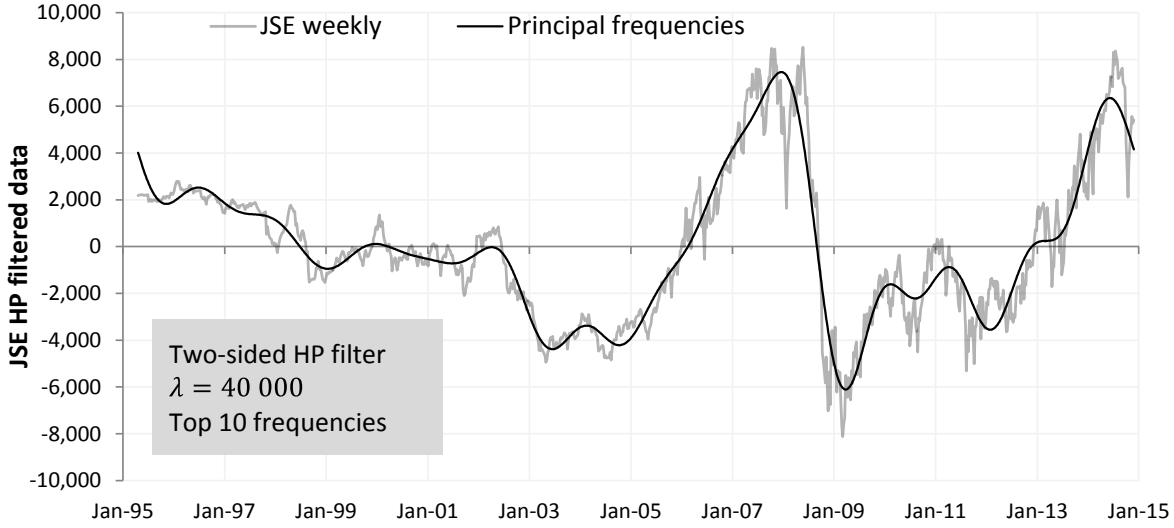
$\Pr(y < \mu) = 1 - q$.

The next section details the results obtained from various indices, commodity prices and exchange rates.

5. RESULTS AND DISCUSSION

buVaR's two distinct features (the bubble indicator, B_t and the inflator, Δ_t) distinguish it from other market risk measurement tools. In addition, an essential element of buVaR is the use of an adaptive MA to calculate the growth factors, which in turn contributes to the estimations of B_t and Δ_t. Wong (2011) suggests and conducts buVaR using a four-year window period in the adaptive MA, arguing that the data should not include more than one crisis period. However, a four-year window period is not necessarily optimal for all economies and markets. Visual analysis, trend extraction and standard Fourier analysis are used in order to determine the most prominent cycle frequencies of the data used.

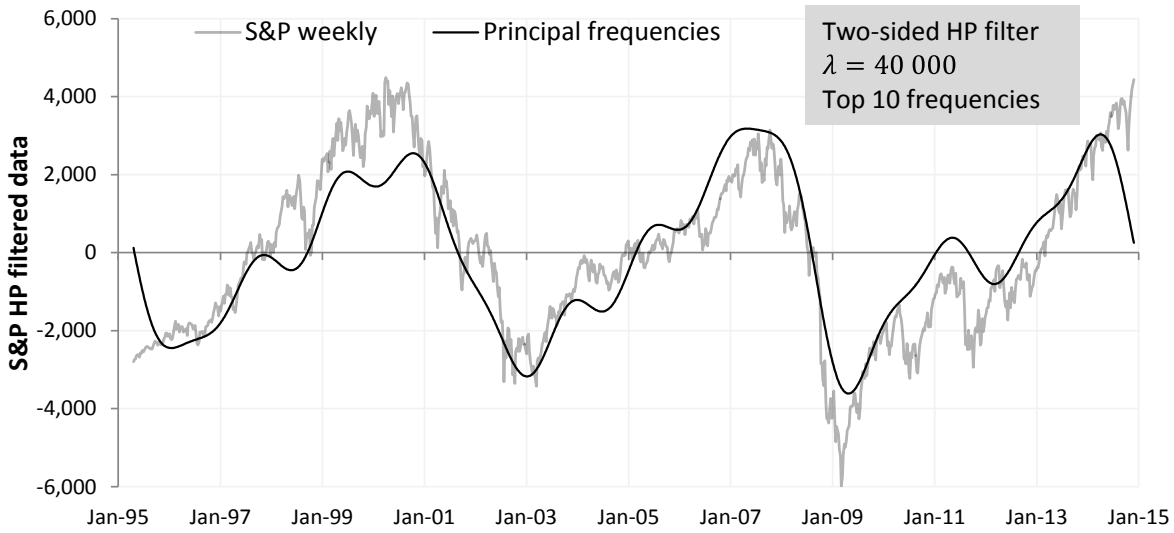
Figures 6 and 7 show weekly, HP-filtered prices for the ALSI and the S&P500 indices respectively, as well as the reconstructed time series using the top ten (by amplitude) cycle frequencies from Fourier analysis.



Source: Author calculations using Microsoft Excel and Bloomberg data.

Figure 6: Weekly JSE prices, HP filtered and reconstructed time series using the top ten most prominent frequencies by amplitude.

While the HP filter establishes and extracts the trend and results in a smooth series, the appropriate window period to use in buVaR must still be calculated.

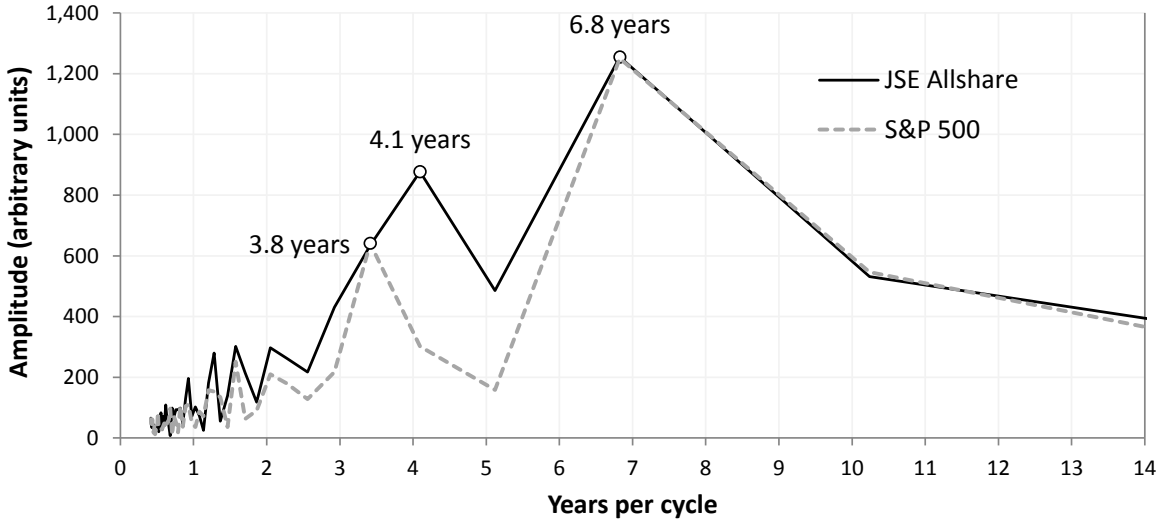


Source: Author calculations using Microsoft Excel and Bloomberg data.

Figure 7: Weekly S&P500 prices, HP filtered and reconstructed time series using the top ten most prominent frequencies by amplitude.

The weekly price changes of the S&P500 (see Figure 7) shows similar obvious downturns to that of the ALSI (see Figure 6), however, the effects of the Internet bubble were very severe in in the US market. This bubble's inception in 1997 saw several internet-based and related companies perform well, boosted by exceptional market confidence. However, the downturn caused several companies to close down as they had little tangible assets to absorb losses. The trend extracted in Figure 8 through visual inspection looks to show a frequency of between six and eight years, however this is not conclusive.

Standard Fourier analysis was used to extract cyclical market behaviour information and determine the relevant underlying frequency components. Results are shown in the frequency spectrum (Figure 8) for the ALSI and the S&P500. The frequency components for both time series indicate a principal frequency of approximately 6.8 years. The JSE has a secondary cycle of 4.1 years and the S&P 3.8 years.

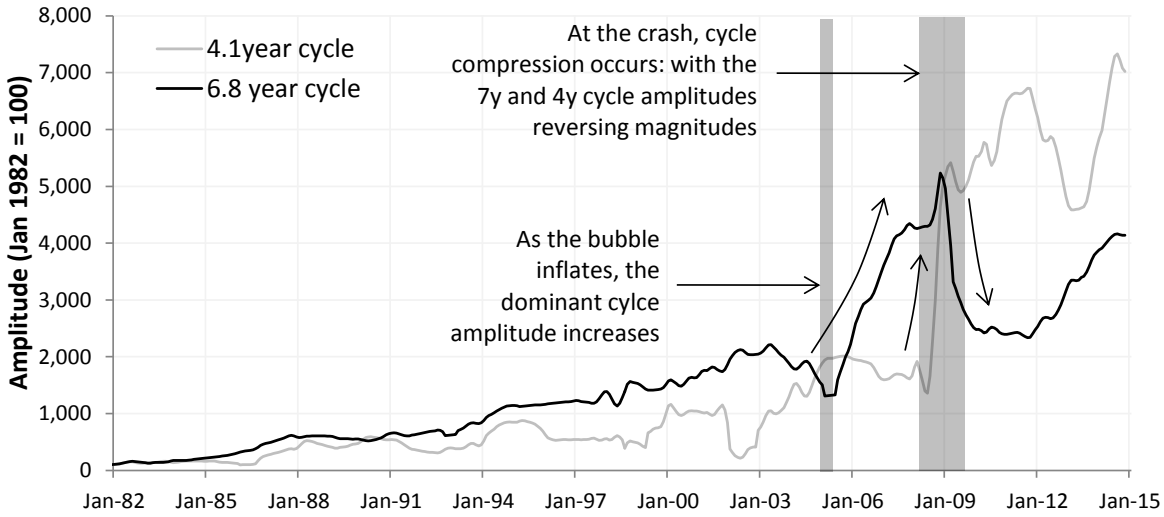


Source: Author calculations using Microsoft Excel and Bloomberg data.

Figure 8: Cycle frequencies for the ALSI and S&P500 using Fourier analysis.

The frequency amplitudes in Figure 8 shows that a seven-year window period might account for a more prominent market cycle, making the adaptive MA more accurate by accounting for an entire cycle. The seven-year window will also only account for one crisis at a time (avoiding the distortion of data) as the last three major crises occurred approximately 10 years apart (Wong, 2011). However, using a four-year window period still has the possibility to yield noteworthy results as the frequency for this cycle length is till high and it makes it comparable to Wong's (2011) work.

The periodicity of market cycles and the amplitudes (prominence) of these cycles are affected in times of changing and volatile market conditions. The compression of market cycles is associated with increased serial correlation in the return series leading to volatility clustering (Wong, 2011). In stressed conditions cycle compression causes cycle lengths to shorten and the amplitudes of these shorter cycles to increase. The use of cycle compression in Figure 9 allows the analysis of cycle frequency amplitudes through different market conditions.

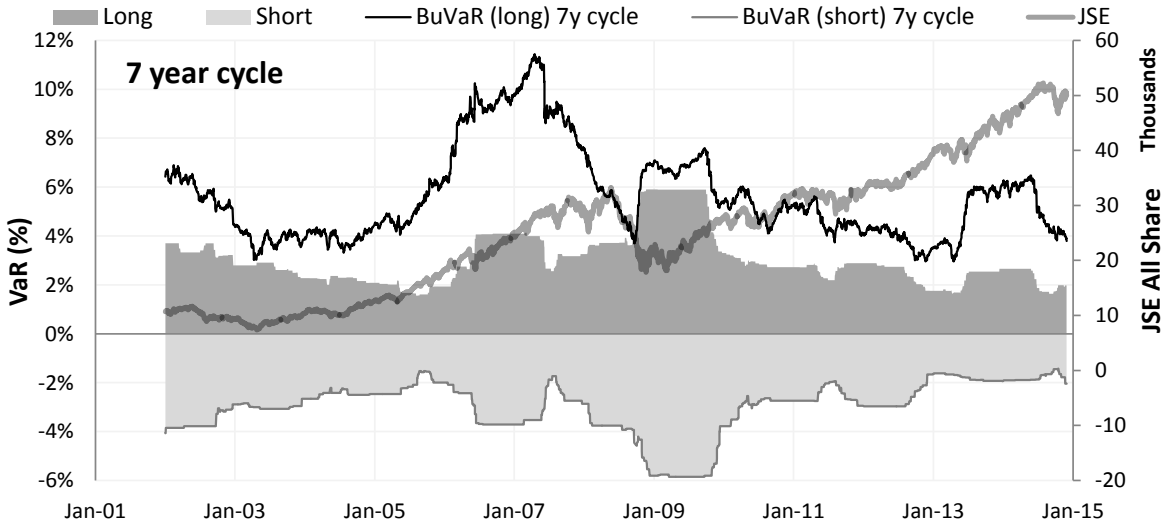


Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 9: Cycle Compression for the ALSI.

Figure 9 illustrates that the seven-year cycle remains the prominent cycle for most of the analysis. From approximately 2005 the amplitude of the seven-year cycle increases severely due to the prolonged market euphoria preceding the financial crisis (which began in Q3 2008). However, the onset of the crisis sees both series rapidly changing direction and the four-year cycle amplitude becoming the prominent cycle. This is not unexpected for the presence of the shorter cycle length to increase in volatile, uncertain times. The cycle amplitudes converge again as stability returns to the market.

Figure 10 shows the application of buVaR on the ALSI from January 2002 until December 2014. A seven-year window period prior to January 2002 is used for applying the rank filtering process and subsequently creating the alternative history where Wong (2011) suggests no market bubble or manias exist.



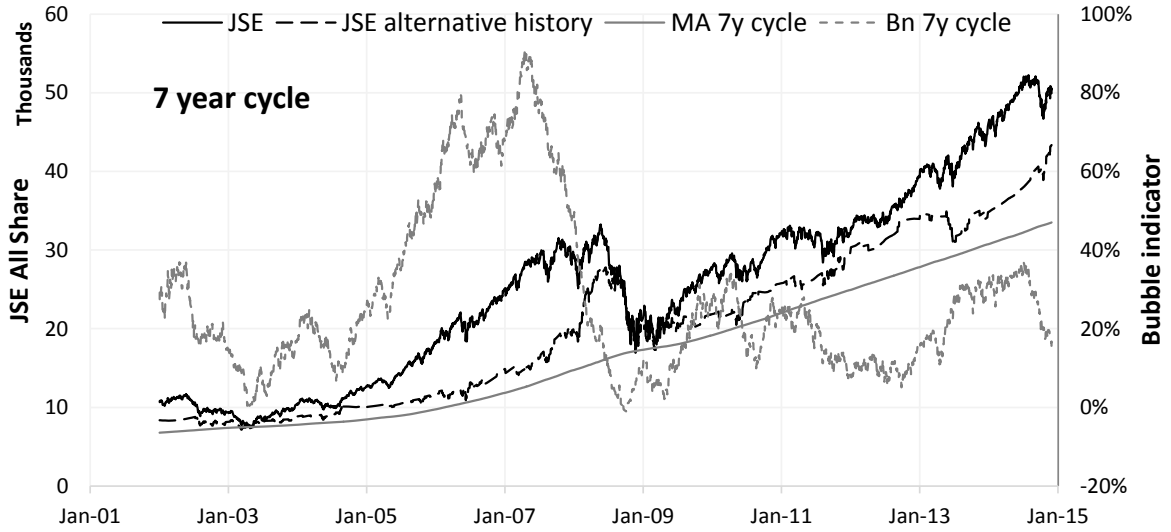
Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 10: ALSI buVaR.

Figure 10 shows how the ALSI doubles in the two years commencing January 2004, however, buVaR and conventional ES move in opposite directions throughout this two-year period. buVaR peaks approximately a year before the market does and this highlights the countercyclical capabilities of the metric. The procyclical nature of conventional ES is illustrated in the periods from approximately January 2003 to January 2006, and January 2008 and January 2010, respectively. In the former period, the market increases gradually, but ES decreases due to the non-volatile favourable data being used to estimate ES.

buVaR (through the bubble indicator and subsequent inflator) increases significantly, in an attempt to avoid the formation of a market bubble. In the latter period, the market declines sharply with a significant increase in ES only followed three months later. The decline in buVaR after the financial crisis throughout the market rise is due to the metric avoiding the penalisation of long-term growth.

The decline of buVaR before the onset of the crisis could be argued as an underestimation of risk, however, the effect of the significant regulatory capital estimation by buVaR prior to the crisis may dissolve or avoid bubble formation. Hindsight will provide no benefit here: Wong (2011) asserts that due to buVaR leading crashes. Statistical back-testing is not appropriate and hence visual testing has to be relied upon. buVaR components for the seven-year cycle estimations are shown in Figure 11.

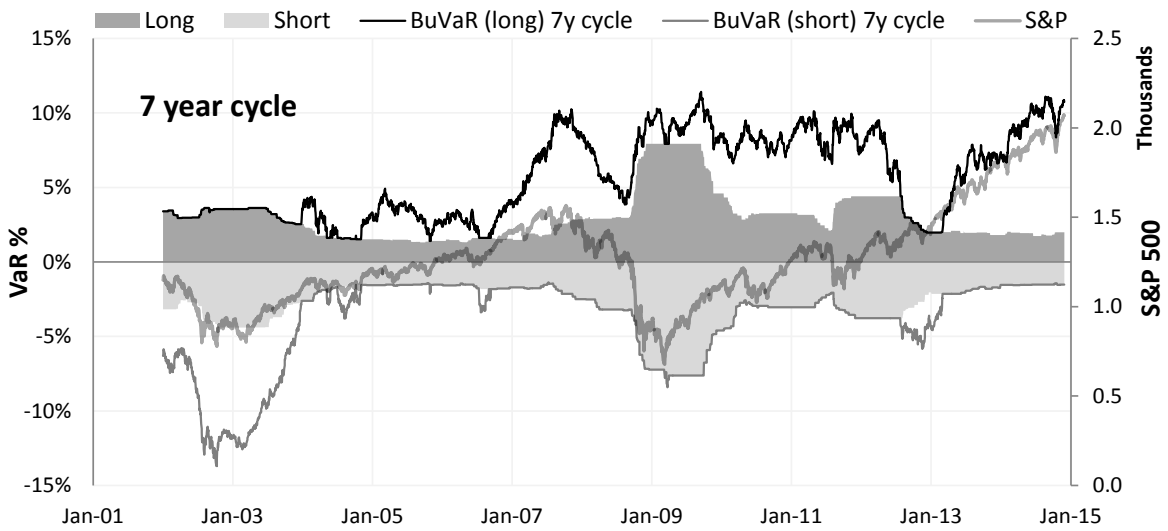


Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 11: ALSI buVaR components.

The significant increase in the bubble indicator (used in the subsequent inflator) in Figure 11 illustrates how buVaR attempts to identify potential market bubbles for penalisation. The bubble indicator is estimated from the JSE alternative history time series which in turn is estimated through the rank filtering process. The seven-year MA of the original price series, which Wong (2011) asserts would not work as it does not conform to suitable characteristics for the estimation of the bubble indicator is also illustrated. The seven-year cycle results are illustrated as estimations (Fourier analysis, HP filter and cycle compression) showed that the bubble indicator using this window period is more responsive. This is due to the more prominent seven-year market cycle being accounted for ensuring that the full boom and bust of the cycle are taken into account while not over-distorting the data and modifying them enough to get reputable results. The results produced by the four-year cycle window period are also not flawed as this cycle was prominent throughout periods of increased volatility. However, for buVaR to be effective as a countercyclical risk measure it has to be consistently and continuously applied to a series in order to punish bubbles and prevent crises.

Applying buVaR to S&P500 data for the same period in Figure 12 produces comparable results to not only the ALSI, but also to that of Wong (2011).



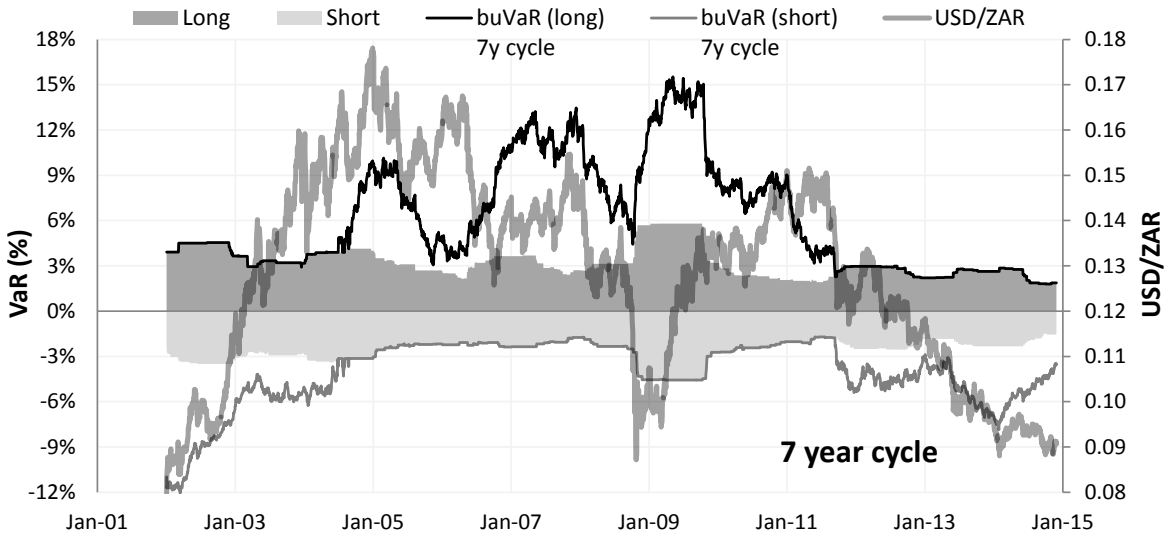
Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 12: S&P500 buVaR.

Figure 12 resembles Figure 11 with regards to buVaR peaking approximately a year before the onset of the financial crisis. The S&P500 suffered the financial crisis far worse than the ALSI as illustrated by their respective original price series in Figures 11 and 12. Conventional ES similar to the JSE analysis is late in crisis detection by almost an entire year. buVaR shows spikes throughout the market euphoria from 2004 to 2008 possibly attempting to curb excessive growth in countercyclical manner. buVaR peaks as volatility increases in the market in the latter part of 2007, however, the risk measure peaks again in the second half 2009 and remains prominent for about three years. This might be due to the volatility of the market, but also the metric's countercyclical capability. This period in global finance is also highlighted by the sovereign credit crisis.

Noteworthy is the significant increase in buVaR from late 2013 up until January 2015, which might indicate the formation of a market bubble. Further, several economists have suggested that 2015 will be a good year for the global economy reinforced by the weak international oil price and a strengthening US economy (The World Bank, 2015 and Mitchell, 2014).

The application of buVaR on the USD/ZAR exchange is illustrated in Figure 13.

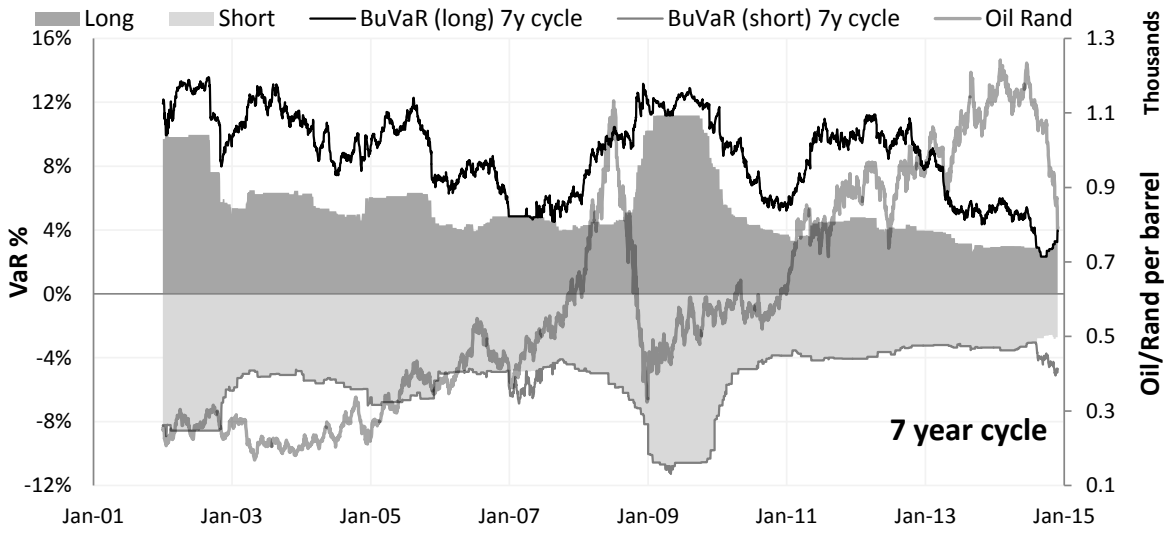


Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 13: USD/ZAR exchange rate buVaR.

Applying buVaR to exchange rates may not only act as a warning signal to fluctuations, but may be used in conjunction with instruments affected by exchange rates. buVaR produces similar results as conventional ES for the weakening rand between January 2002 and midway through 2004. However, for all the periods or just before these periods where the rand experiences sharp declines buVaR is elevated above conventional ES. The crisis period from 2008 to 2010 shows a significantly elevated buVaR initially with ES again being late in the detection of the severe decrease in the value of the exchange rate. This reduction in the exchange rate might be due to investors divesting from emerging markets like South Africa. Also, in a challenging economic environment exports might drop possibly causing lower demand for this specific currency as well.

Figure 14 illustrates the application of buVaR on the price of crude oil per barrel in ZAR.

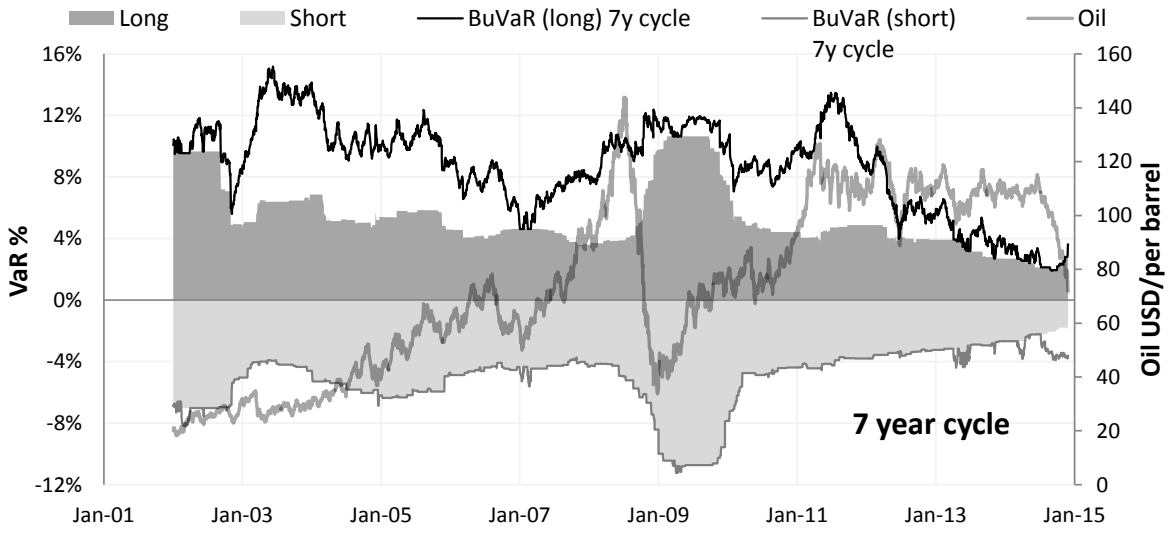


Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 14: Crude oil in ZAR/barrel buVaR.

buVaR in Figure 14 diminishes as price of oil increases gradually, however, as oil prices starts increasing significantly buVaR detects the bubble and changes direction whereas ES keeps decreasing. The spike in ES only occurs several months after the actual crash happens, this emphasising the countercyclical ability of buVaR. buVaR again swings upwards in about 2011 and stays significantly elevated as the price of the commodity increases rapidly.

Oil peaks early in 2014 only to slump at the end of 2014 due to increased competition from the US and no decrease in supply from the Organisation of the Petroleum Exporting Countries (OPEC) (The World Bank, 2015). The depreciating ZAR is prominent in Figure 15. The price of oil increases constantly from 2011 onwards in Figure 14. In Figure 15, the price of crude oil in USD fluctuates, but on average remains flat for the same period.



Source: Author calculations using Microsoft Excel with Wong (2011) methodology and Bloomberg data.

Figure 15: Crude oil in USD/barrel.

Figure 15 reflects similar results to that of Figure 14, with buVaR decreasing as the price of oil increases gradually. This aligns with the goal of buVaR not to punish growth, only bubbles. Again, buVaR increases as it detects the bubble whereas ES declines and only increases sharply months after the severe decline in the oil price. buVaR subsides quicker from 2011 onwards compared to Figure 14 where the depreciating ZAR – as shown in Figure 13 – has an effect.

6. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

Relaxing the assumptions of i.i.d. and stationarity reduces the statistical estimation consistency and precision, but such assumptions are untrue when the market experiences stressed conditions anyway.

The buVaR metric was demonstrated by Wong (2011) to be more accurate (rather than more *precise*) than VaR, providing a 'best guess' of losses. These values are situated somewhere between the VaR measured by traditional methods and a reasonable capped value. buVaR does not generate a single solution for potential losses, but rather a practical value that may be effectively employed for determining risk capital. This value will be higher than a conventionally calculated VaR number, leading to a higher capital buffer, but this compensates for the complex, fat-tailed loss distribution.

The financial crisis of 2008 emphasised the severe effects of behaviour, markets and risk metrics being procyclical in nature. This significantly underestimated phenomenon

contributed to both the market euphoria and subsequent turmoil in global finance in the first decade of the 21st century. The replacement of VaR by ES although an improvement on risk measurement, has not provided a solution in terms procyclicality. The BCBS has suggested the countercyclical capital buffer to be implemented January 2016 driven by the credit growth/GDP ratio (which has not been confirmed as the most suitable variable for all economies). However, the system wide implementation of countercyclical capital buffer might not be a straight forward process as all bank specific effects are still unidentified. For instance, banks in smaller or illiquid economies might struggle to implement minimum countercyclical regulatory requirements. Further, what if one bank is an outlier in an economy and has to retain capital when it is in a downward slump or *vice versa*?

buVaR provides a forward-looking alternative to VaR attempting to account for procyclicality while incorporating the benefits of ES. Determining the appropriate length of market cycles is crucial in buVaR in order to calculate an effective alternative history. Fourier analysis and cycle compression provide adequate analysis of data in order to determine the length and prominence of market cycles. The analysis in Section 5 illustrates that buVaR detects bubbles and increases required regulatory capital significantly before ES does. This confirms the metric's countercyclical abilities to calculate regulatory capital in a forward-looking manner.

Future research opportunities include the application of buVaR to considerably more portfolios, indices and commodities with different cycle characteristics. By observing output from many, disparate source, fat-tail loss patterns may be evaluated and connections established. The VaR measured under different market cycles (i.e. with different frequencies and amplitudes (severity)) is different using conventional VaR methods; comparing these against buVaR estimates may provide some insight into the subtle interplay between market dynamics and portfolio or single asset losses.

Alternative histories may also be derived using different metrics, including the HP filter. The buVaR technique and the HP filter (for example) could be applied to relevant data and alternative histories constructed. The results obtained could be compared to establish differences and similarities and, with the benefit of hindsight, could lead research to the superior technique (since backtesting could easily establish which method produced the most accurate VaR estimates).

REFERENCES

Acerbi, C. and Tasche, D. 2002. Expected shortfall: A natural coherent alternative to value at risk. *Economic notes*, 31(2):379-388.

Artzner, P., Delbaen, F., Eber, J. and Heath, D. 1999. Coherent measures of risk, *Mathematical Finance*, 9(3): 203–228.

Balbas, A., Garrido, B. and Mayoral, S. 2009. Properties of distortion risk measures, *Methodology and Computing in Applied Probability*, 11(3): 385–399.

Bank of England. 2014. The case for a better functioning securitisation market in the European Union. [Accessed 01-11-2014] https://www.ecb.europa.eu/pub/pdf/other/ecb-boe_case_better_functioning_securitisation_marketen.pdf

BCBS. 1996. Amendment to the capital accord to incorporate market risks. [Accessed 01-11-2014] http://www.bis.org/publ/bcbs24.pdf

BCBS. 2009. Revisions to the Basel II market risk framework (updated 31 Dec 2010). [Accessed 01-11-2014] http://www.bis.org/publ/bcbs148.pdf

BCBS. 2010. Guidance for national authorities operating the countercyclical capital buffer. [Accessed 05-11-2014] http://www.bisorg/publ/bcbs187.pdf

BCBS. 2011a. Basel III: A global regulatory framework for more resilient banks and banking systems. [Accessed 01-11-2014] http://www.bis.org/publ/bcbs189.pdf

BCBS. 2011b. Messages from the academic literature on risk measurement for the trading book. [Accessed 02-11-2014] http://www.bis.org/publ/bcbs_wp19.pdf

BCBS. 2013. Fundamental review of the trading book: A revised market risk framework (updated 31 Dec 2010). [Accessed 01-11-2014] http://www.bis.org/publ/bcbs265.pdf

Berkowitz, J. and O'Brien, J. 2002. How accurate are Value-at-Risk models at commercial banks?, *The Journal of Finance*, 57(3): 1093–1111.

Bervas, A. 2006. Market liquidity and its incorporation into risk management, Banque de France, *Financial Stability Review*, 8(May): 63–79.

Botha, I. 2009. Modelling the business cycle of South Africa: linear vs. non-linear methods, PhD thesis, University of Johannesburg. [Accessed 22-11-2014] https://ujdigispace.uj.ac.za/bitstream/handle/10210/605/master.pdf?sequence=1

Chen, J. 2014. Coherence versus elicitability in measures of market risk, *International Advances in Economic Research*, 20(3): 355–356.

Choudhry, M. 2013. An introduction to Value-at-Risk. 5th ed., Wiley: Chichester UK, 224p.

Costanzino, N. and Curran, M. 2014. Backtesting general spectral risk measures with application to expected shortfall, working paper. [Accessed 02-11-2014] http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2514403

Coste, C., Douady, R. and Zovko, I. 2011. The Stress VaR: a new concept or extreme risk and fund allocation, *Journal of Alternative Investments*, 13(3): 10–23.

Cotter, J. and Dowd, K. 2006. Extreme spectral risk measures: An application to futures clearinghouse margin requirements, *Journal of Banking & Finance*, 30(12): 3469–3485.

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.

Danielsson, J., Jorgensen, B., Sarma, M., Gennady, S and de Vries, C. 2005. Subadditivity re–examined: the case for Value-at-Risk. Discussion paper 549. *Financial Markets Group*, London School of Economics and Political Science, London, UK.

Danielsson, J. 2013. The new market risk regulations. VOX CEPR's Policy Portal. [Accessed 24-01-2015] http://www.voxeu.org/article/new-market-risk-regulations

Diebold, F., Hickman, A., Inoue, A. and Schuermann, T. 1998. Converting 1-Day Volatility to h-Day Volatility: Scaling by Root-h is Worse than You Think, *Wharton Financial Institutions Center*, Working Paper 97-34. Published in condensed form as Scale Models, *Risk*, 11: 104-107.

Dionne, G., Pacurar, M. and Zhou, X. 2014. Liquidity-adjusted intraday Value at Risk modeling and risk management: An application to data from Deutsche Börse. [Accessed 02-11-2014] http://ssrn.com/abstract=2398620

Duffie, D. and Pan, J. 1997 An overview of Value at Risk, *The Journal of Derivatives*, Spring, 4(3): 7–49.

Eberlein, E., Kallsen, J. and Kristen, J. 2003. Risk management based on stochastic volatility, *The Journal of Risk*, 5(2): 19–44.

Emna, R. and Chokri, M. 2014. Measuring liquidity risk in an emerging market: liquidity adjusted Value at Risk approach for high frequency data, *International Journal of Economics and Financial Issues*, 4(1): 40–53.

Escanciano, J. and Pei, P. 2012. Pitfalls in backtesting historical simulation VaR models, *Journal of Banking & Finance*, 36(8): 2233–2244.

G20. 2009. G20 Leaders Statement: The Pittsburgh Summit. [Accessed 01-11-2014] https://g20.org/wp-content/uploads/2014/12/Pittsburgh_Declaration_0.pdf

Gabrielsen, A., Zagaglia, P., Kirchner, A. and Liu, Z. 2012. Forecasting Value-at-Risk with time-varying variance, skewness and kurtosis in an exponential weighted moving average framework. *Econometrics Journal*, 12(1): 82–104.

Galdi, F. and Pereira, L. 2012. Value at Risk using volatility forecasting models: EWMA, GARCH and stochastic volatility, *Brazilian Business Review*, 4(1): 74–94.

IARCP (International Association of Risk and Compliance Professionals). 2012. 120 developments in risk management and compliance, ed. George Lekatis. [Accessed 02-11-2014] http://www.risk-compliance-
associa-
tion.com/120_Developments_Risk_Management_Compliance_April_to_June_2012.html

International Monetary Fund. 2007. Do market risk management techniques amplify systemic risks?" *Global Financial Stability Report*, October: 52–76.

International Monetary Fund. 2008. Market and funding illiquidity: when private risk becomes public. *Global Financial Stability Report*, April. [Accessed 01-11-2014] https://www.imf.org/external/pubs/ft/gfsr/2008/01/pdf/sum3.pdf

JP Morgan. 1996. RiskMetrics Technical Document. [Accessed 01-11-2014] http://yats.free.fr/papers/td4e.pdf

Kourouma, L., Dupré, D., Sanfilippo, G. and Taramasco, O. 2010. Extreme Value at Risk and expected shortfall during the financial crisis. [Accessed 22-11-2014] http://dx.doi.org/10.2139/ssrn.1744091

Marcucci, J. and Quagliariello, M. 2008. Is bank portfolio riskiness procyclical? Evidence from Italy using a vector autoregression, *Journal of International Financial Markets, Institutions and Money*, 18(1): 46–63.

Mitchell, J. 2014. U.S. Job Openings Hit 13-Year High, *The Wall Street Journal.* [Accessed 20-01-2015] http://blogs.wsj.com/economics/2014/08/12/rising-job-openings-quits-point-to-strengthening-labor-market/

Nadarajah, S., Zhang, B. and Chan, S. 2013. Estimation methods for expected shortfall, *Quantitative Finance*, 14(2): 271–291.

Pena, V., Rivera, R. and Ruiz-Mata, J. 2006. Quality control of risk measure: backtesting VaR models, *The Journal of Risk*, 9(2): 39–54.

Penza, P. and Bansal, V., 2001. Measuring market risk with Value-at-Risk. Financial Engineering Series, Wiley: New York, United States, 320p.

Prescott, E. 1997. The pre-commitment approach in a model of regulatory banking capital, *Economic Quarterly*, Federal Reserve Bank of Richmond, Virginia, United States.

Rosenberg, J. V. and Schuermann, T. 2004. A General Approach to Integrated Risk Management with Skewed, Fat-Tailed Risks, *Federal Reserve Bank of New York,* Staff Report no. 185. Online: https://www.newyorkfed.org/medialibrary/media/ research/staff_reports/ sr185.pdf accessed 12 January 2017.

Rozga, A. and America, J. 2009. Dependence between volatility persistence, kurtosis and degrees of freedom, *Revista Investigación Operacional*, 30(1): 32–39.

Skoglund, J., Erdman, D. and Chen, W. 2012. On the time scaling of Value at Risk with trading, *Journal of Risk Model Validation*, 5(4): 17–26.

Tasca, P. and Battiston, S. 2012. Market procyclicality and systemic risk, ETH Risk Center – Working Paper Series, ETH-RC-12-012. [Accessed 02-11-2014] http://web.sg.ethz.ch/ethz_risk_center_wps/pdf/ETH-RC-12-012.pdf

The World Bank. 2015. Global Economic Prospects [Accessed 20-01-2015] http://www.worldbank.org/content/dam/Worldbank/GEP/GEP2015a/pdfs/GEP15a_web_full.pdf

Tripathy T. and Gil-Alana, L. 2010. Suitability of volatility models for forecasting stock market returns: A study on the Indian national stock exchange, *American Journal of Applied Sciences*, 7(11): 1487–1494.

Van Vuuren, G. 2012. Basel III Countercyclical Capital Rules: Implications For South Africa, *South African Journal of Economic and Management Science*, 15(3): 309-324.

Witzany, J. 2013. Estimating correlation jumps and stochastic volatilities, *Prague Economic Papers*, 2(1): 251 – 283.

Wong, M. 2011. Market buVaR: a countercyclical risk metric. *Journal of Risk management in Financial Institutions*, 4(4): 419–432.

Yamai, Y. and Yoshiba, T. 2002. On the validity of Value-at-Risk: comparative analyses with expected shortfall, *Monetary and Economic Studies*, 20(1): 57–85.

Yeh, A., Twaddle, J. and Frith, M. 2005. Basel II: a new capital framework, *Reserve Bank of New Zealand Bulletin*, 68(3): 4–15.

Youngman, P. 2009. Procyclicality and Value at Risk, *Bank of Canada Financial System Review*, June: 51–54.

Chapter 3

Procyclicality in tradeable credit risk: Consequences for South Africa

Procyclicality in tradeable credit risk: consequences for South Africa

ABSTRACT

Tradeable credit assets are vulnerable to two varieties of credit risk: default risk (which manifests itself as a binary outcome) and spread risk (which arises as spreads change continuously). Current (2017) regulatory credit risk rules require banks to hold capital for both these risks. It is a non-trivial exercise to aggregate these capital amounts as different approaches and models are required for each type. The *bubble Value at Risk* (buVaR) approach was proposed by Wong (2011) to overcome the risk aggregation problem, account for diversification and for procyclicality. The buVaR methodology operates by inflating the positive side of the underlying return distribution in direct proportion to prevailing credit spread levels (usually liquid credit default swap (CDS) spreads). Wong's (2011) framework required the calibration of some input parameters: this was undertaken for several markets, but South Africa was not among them. In this article, the model is calibrated – and tested – using South African data. The results exposed some unique features of the South African milieu and found considerable differences compared with other markets.

Key words: Credit risk, Value at Risk, Bubble VaR, procyclical, spread risk.

JEL Classification: C21, C54, G31

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1. INTRODUCTION

Credit losses experienced in the financial crisis of 2008 – 2009 emphasised the complexities surrounding tradable credit instruments. In their fundamental review of the trading book (Basel Committee on Banking Supervision (BCBS), 2013), the BCBS asserted that credit-related products had been a major source of losses and the approach and treatment of these positions were severely flawed. The crisis also prompted financial institutions to change their evaluation and management of credit risk substantially (BCBS, 2015).

A 2013 global survey conducted by the Joint Forum on Banking Firms and Supervisors revealed that since the crisis banks have improved governance and risk reporting and that risk

aggregation has become far more sophisticated (BCBS, 2015). Modelling enhancements driven by regulatory requirements, stress testing and crisis experience has significantly shifted institutions reliance to internal models as the "search for yield" intensifies in a post-crisis low interest rate environment (BCBS, 2015). Despite these promising developments, the BCBS has attempted to align the requirements of the trading book more closely with those of the banking book (BCBS, 2013). The BCBS (2013) proposes substantial revisions to many aspects of the treatments of market risk – these have now (2017) been reviewed by market participants and approved for implementation in 2017 (BCBS, 2014).

In the trading book, tradable credit instruments are associated with two sources of risk. Firstly, default risk in which a probability that the underlying issuer may forfeit its obligation through contractual non-compliance (Brown & Moles, 2014) and secondly, spread risk in which losses arise from changes in an instrument's credit spread. This spread can be defined as the instrument's yield relative to that of a comparable-duration default free instrument and is not attributable to defaults or credit migrations (BCBS, 2009). The complicated relationship between credit and market risk and the aggregation of these risks are emphasised by the fact that approximately two thirds of financial crisis (2008-2009) losses were attributable to spread risk with only a third of the losses stemming from actual defaults (BCBS, 2011). Sophisticated financial instruments based on securitisation played a pivotal role in the financial crisis masking risk and increasing the interconnectedness of financial markets. A downward spiral of the quality of the securities backing these instruments caused several rating downgrades of these instruments and precipitated chaos within globally interconnected financial markets. Further, the procyclical nature of these markets, albeit contributing significantly to the pre-crisis market euphoria, fuelled one of the biggest busts in financial history (Bank for International Settlements, 2008 and Papaioannou, Park, Pihlman, & van der Hoorn, 2013).

Procyclicality – defined as those economic quantities that are positively correlated with the overall state of the economy (van Vuuren, 2012) – leads to institutions reducing lending capacity throughout market busts. Regulatory capital models using data from busts would recommend banks keep higher levels of capital as well (this is also influenced by stress testing of models): the opposite is true in financial booms. This procyclical characteristic of markets, methods and metrics has been countered by the introduction of the countercyclical capital buffer (CCB) by the BCBS in 2010 which is based on the aggregate credit-to-GDP gap ratio (BCBS, 2010). The buffer is mostly untested in emerging and developing markets and thus

the complexities regarding its implementation and timing have not been comprehensively divulged.

Value at Risk (VaR) has been the preferred market risk measurement tool since 1994 but suffers from significant shortcomings, many of which played a significant role in the crisis. These problems were partially ameliorated by the replacement of VaR with Expected Shortfall (ES) in 2018 (BCBS, 2013). Although VaR is relatively simple to calculate it does not account for risk aggregation and is also procyclical in nature. Further, VaR models used in credit risk measurement are mostly dependant on regulatory information such as rating transition matrices making these models slow to reflect current market conditions. ES solves some of VaR's shortcomings as it embraces not only the likelihood of losses, but also the size of losses beyond the VaR confidence level thus accounting for risk in a more comprehensive manner (BCBS, 2013). However, procyclicality remains an issue as ES uses the same historical data produced by markets as VaR does. This necessitates the use of a CCB. However, further analysis of the proposed buffer components has suggested alternatives to the credit-to-GDP gap. The research includes that of Barrell, Davis, Karim and Liadze (2010), Shin (2013) and Behn, Detken, Peltonen and Schudel (2013) who all proposed alternatives to this metric. Drehmann and Tsatsaronis (2014) review these studies and argue that the credit-to-GDP gap is the best standalone early warning indicator over forecast horizons of two to five years. They further find that the debt service ratio (DSR) is the best single indicator for forecast horizons shorter than two years. Drehmann and Tsatsaronis (2014) assert that both judgement and quantitative analysis are required by policymakers as there are no foolproof models that provide an effective rule-based countercyclical measure. Further, although the credit-to-GDP gap ratio was found to be optimal, Drehmann and Tsatsaronis (2014) found that a combination of other indicators may work better for certain jurisdictions.

Applying conventional VaR to tradeable credit instruments poses challenges as all the risks pertaining to these instruments are not adequately captured in the measurement. Further, under the Basel Market Risk framework it is also not a requirement to measure multiple risks in one model. Spread and default risk are currently simply added together after individually measured without accounting for diversification possibilities as prescribed. Although aggregation issues present problems regarding diversification and even compounding of risks, Wong's (2011) Bubble VaR proposes a unified method of combining these two forms of risks avoiding the problem of risk aggregation. Further, the model relies on credit spread data avoiding transition matrices or ratings information. Credit Default Swap (CDS) data are for-

ward-looking and highly liquid as they are readily available daily (Huang, Zhou & Zhu, 2009). Using these data, Wong (2011) illustrates the asymmetry between defaults and spread movements and asserts that spread widening will always precede defaults. Although Wong (2011) calibrated the buVaR credit risk model for several countries, South Africa was not among them. This article explores that calibration, estimates potential standardisation and provides deeper insight into the model's applications in the South African milieu.

The remainder of this article proceeds as follows: Section 2 explores tradeable credit instruments and the regulatory treatment thereof. The section also highlights difficulties in the measurement of credit risk under regulatory recommendations. The choice of data and relevance thereof is explained in Section 3 along with the mathematics of the metrics being assessed. The logic behind Wong's (2011) Credit buVaR and how the metric may sufficiently account for diversification possibilities when spread and default risk are combined into one metric are also discussed here. Results obtained from analysis and scenario simulations are illustrated and discussed in Section 4 and Section 5 concludes.

2. LITERATURE STUDY

2.1. Regulatory treatment of tradeable credit instruments

Conventionally, a bank's trading book is predominantly affected by market risk, with the banking book being mostly susceptible to credit risk (BCBS, 2009). However, tradable credit instruments introduce credit risk to the trading book and the regulatory capital calculated for these in the crisis were woefully insufficient. These tradable credit instruments do, however, provide for price discoveries in secondary markets through credit spreads.

Institutions holding portfolios of debt securities or derivatives to hedge risk stemming from their securities face several forms of risk. Spread movements is one such risk, while the possibility of issuer defaults of tradable credit instruments being another. Correlated defaults between issuers of securities pose further risk to banks and financial institutions (Wong, 2011).

2.2. Spread risk

Spread risk is traditionally modelled using historical simulations and applying a Value at Risk (VaR) approach. Simulated returns are generated from the spread variable over an observation period – between one and three years under the Basel formulation. The return vector is

$$R_t = \frac{P_{t+1} - P_t}{P_t}$$

and each portfolio position is mapped to benchmark issuer risk factors, so if the portfolio is subject to N risk factors, there are N return vectors. Return vectors are combined to derive a portfolio profit and loss distribution. Under the Basel II formulation, spread VaR is the VaR over a 10-day period at a 99% confidence level (as it is for standard market risk instruments and portfolios).

In what has been informally labelled as Basel IV, the BCBS have suggested changes to the trading book/banking book boundary by addressing issues such as the trading book definition, trading book components and ineligible trading book instruments (BCBS, 2013). Such rigorous proscriptions were limited to mere footnotes in the revisions of the Basel II market risk framework (BCBS, 2011) – now, they have become standard features of the way banks will need to treat trading books. A summary of the current boundary definitions compared to proposals are highlighted in Table 1.

	Current intent based boundary	**Revised boundary**
Trading book definition	Mostly self-determined by banks	Instruments must be included in the trading book if certain criteria are met
Contents of the Trading Book:	None prior to the trading book review	Guidance for appropriate trading book instruments include: • Accounting trading assets and liabilities • Instruments resulting from market making and underwriting activities. • Listed equities, Equity investments in funds, options • All short positions in cash instruments
Guidance for instruments that do not qualify:	Only one footnote	Any unutilised equity Instruments for securitisation warehousing Real estate holdings Equity instruments where daily real prices are available
Boundary permeability:	Switching between trading and banking book is allowed	Only under exceptional circumstances which do not include market conditions. Require supervisory approvals
Capital Arbitrage Mitigation:	N/A	Reduced capital charges stemming from the rare instances where portfolio switching is allowed will not be enjoyed. Charges as if switch did not happen will still be incurred until such time the instruments mature/expire
Supervisory Authority to re-designate:	N/A	If assets are improperly designated supervisors can

		switch between trading and banking book
Valuation Requirements:	Use readily available closed out prices for daily valuation	All trading book instruments must be fair-valued daily through the P&L statement
Reporting to ease boundary supervision:	N/A	Banks must have comprehensive reports on the decision making regarding boundary determination. These reports should include amongst other inventory ageing, daily limits and market liquidity

Table 1: Boundary definitions of Basel II and Basel III trading book.

Source: Fundamental review of the trading book (BCBS, 2013).

2.3. Default risk

Because entities only default once, an historical simulation approach is impossible since there is no time series of observable default history available. Monte Carlo simulations are used instead. Possible occurrences of ratings migration (of which default is a special case) are generated over a one-year simulation horizon. The Monte Carlo simulation assumes that credit default driver follows a particular distribution: simulated values are mapped to an end-state rating (upgrades, downgrades or a default). The probabilities of these trajectories from the current rating to the end-state ratings (including default) are embedded within the rating transition matrix. These matrices are populated with single-year transition rates assembled by credit rating agencies using empirical historical statistics of defaults and upgrades/downgrades in selected benchmark sectors. The portfolio positions are mapped to relevant sectors before the simulation begins. Correlation coefficients are determined independently and used to capture correlation risk between the sectors. Regulatory capital rules requires that the VaR of this distribution is determined at a 99.9% confidence level and a time horizon of one year — this is known as Credit VaR. Crouhy, Galai, and Mark (2000) provide a comprehensive overview of contemporary, available credit risk models.

The responses received by the BCBS from commentators mostly suggested that integrating the default component of the trading book in to market risk models present several challenges and complexities. The BCBS thus decided that the total credit risk capital charge for both the standardised and models-based approaches would comprise two components: an integrated credit spread risk capital risk charge and an incremental default risk (IDR) charge (BCBS, 2013).

2.4. Aggregation problems

The complex relationship between market and credit risk gives way to aggregation issues including the inability to clearly identify diversification issues and for that compounding af-

fects. This challenge also fuelled the perception that adding separately estimated risk components for market and credit risk will most certainly be conservative due to not all diversification possibilities considered. However, the BCBS suggests from the financial crisis learnings that non-linear interactions between market and credit risk may reinforce each other and lead to even more severe losses. The BCBS further suggests that under a top-down aggregation approach (as commonly used in practice) diversification benefits should be approached with caution (indeed, the BCBS now restricts the use of negative correlations in portfolio assembly and construction (BCBS, 2013)).

Adding independently-estimated risk measurements in a top-down approach is flawed in that it assumes that perfect correlations between market and credit risks exist. Since both risk forms are affected by the same economic factors, *some* diversification benefits are expected. However, non-linear interactions between market and credit risk may lead to instances where the combined total risk is higher than the sum of individually measured components.[2] These compounding effects often arise when market and credit risks are inseparably connected i.e. default losses from instruments depend on the movements in market risk factors or conversely when the values of instruments affected by market risk factors are dependent on defaults or rating changes.

Diversification benefits are, however, not unobtainable and the BCBS highlights this by showing the interactions between interest rates and credit risk in the banking book. Creating a hypothetical bank, Drehmann, Sorensen and Stringa (2008) places emphasis on modelling the entire banking book including assets, liabilities and interest sensitive off-balance sheet items. Drehmann, Sorensen and Stringa (2008) argues that non-linear effects created by the interaction between interest rates and default probabilities may be difficult to capture outside of integrated models measuring total risk. Alessandri and Drehmann (2007) further assess aggregate risk and required capital by using a set of stylised assumptions to calibrate the model to the profile of a typical UK bank. Through this they show diversification benefits such that the capital kept for an integrated risk measurement for interest rate and credit risk is less than would have been kept for credit risk if measured separately.

Diversification benefits are not guaranteed when using VaR since the market risk measure is neither coherent nor sub-additive. Coherent risk measures such as expected shortfall guarantee the diversification benefits if an integrated measurement of total risk is measured. If sepa-

[2] The interaction of market and credit risk (IMCR) working group established by the BCBS give several examples where this can occur (BCBS, 2009d).

rate measurements are done for market and credit risk, diversification benefits cannot be guaranteed even if coherent measurements are used. The choice of metric is not the only challenge related to integrated risk measurement. The metrics used in credit and market risk are not entirely comparable. For example, market risk models capture complete return distributions whereas credit risk models account mostly for losses stemming from defaults and ignore gains. A further challenge emerges in the different horizons that the risks are measured in, despite credit risk becoming more tradable in the 21st century because of financial innovations such as securitisation.

The BCBS conclude that although integrated risk models have high data and technological demands, the aggregation and integrated measurement of market and credit risk should be done consistently in such a way that a common horizon is imposed and all income, profits and losses are accounted for. However, the challenges mentioned as well as the fact that a top-down approach is favoured by most banks with these approaches involving simple correlations ignoring non-linear interactions suggest that even under integrated measurements diversifications benefits are not guaranteed.

3. DATA AND METHODOLOGY

3.1. Data

The data employed in the credit buVaR risk metric were daily credit spreads for 5-year and 10-year South African government credit default swaps (CDSs), from January 2000 to November 2016. South African credit ratings were obtained from Fitch ratings (Fitch Ratings, 2016). The South African risk-free rate (3-month Johannesburg Interbank Agreed Rate (JIBAR)) used in this analysis is sourced from the South African Reserve Bank (SARB, 2016). Other data were simulated where necessary.

3.2. Methodology

Spread risk

Credit buVaR combines both spread and default risk and Wong (2011) asserts that the all-in credit loss measure lies between spread VaR and a logical upper bound. This upper bound represents the default event where the difference between the principal amount and the recovery is lost. Spread VaR is thus calculated as usual, but the inflator allows default risk to also be accounted for.

Default risk

Compared with conventional default risk measures, the way in which default risk in the credit buVaR model is accounted for contrasts with spread VaR. The reliance on slow-reacting, backward-looking rating transition matrices is entirely replaced by the derivation of the cap on the spread level used in the subsequent inflator. This inflator imposed on the spread VaR measurement ensures a forward-looking, all-in credit loss measurement.

Aggregation problems

The credit buVaR model allows for credit and market risks in a diversifiable manner while solely relying on credit spread data. Wong (2011) asserts that credit spread is the most forward-looking and direct indication of an issuer's probability to default. Wong (2011) also suggests that rapid spread widening (RSW) is the dominant forerunner for default and presents evidence from the financial crisis. Using data from issuers including Lehman brothers and AIG, Wong (2011) illustrates how spreads throughout the crisis period increased to such an extent that potential default could be detected weeks earlier than if relying on credit VaR alone. Through this Wong (2011) deduced that a credit model conditional on RSW could be forward-looking and may overcome shortcomings of conventional credit models.

This straightforward method using an historical simulation approach does not produce a statistically precise method, but neither do other VaR approaches (Wong, 2011). Credit buVaR, like other VaR approaches, is affected by the subjective choice of parameters and has a free parameter calibrated by the user.

Credit buVaR's ability to account for both default and spread risk in one regulatory capital calculation is made feasible when the calculation metric aims to detect widening of the issuers credit spreads. Wong (2011) suggests that credit spreads are arguably one the most direct and forward-looking measures of an issuer's default probability. To penalise increasing default probability Wong (2011) asserts that an inflator (Δ_+) is used to increase the VaR measure as required.

Since increased spreads precede defaults, long positions incur losses due to these changes while negative changes in spreads cause losses for short positions. However, defaults only affect long positions and thus the inflator is only applied to the positive side of the distribution. To incorporate the inflator the original return distribution undergoes a transformation when the returns are positive as shown in (1).

$$R_n = \begin{cases} \Delta_+ \cdot R_n \text{ if sign} & R_n > 0 \\ R_n \text{ if sign} & R_n \leq 0 \end{cases} \quad (1)$$

where the inflator (Δ_+) is always > 1, so it amplifies the positive returns (positive returns in this case represent an *increase* in spreads which represent a loss scenario), n is the scenario numbers in the historical VaR simulation. Wong (2011) proposed the inflator in (2) to rapidly penalise the initiation of rapid spread widening (RSW):

$$\Delta_+ = \exp(\omega_1 S^{\omega_2}) \quad (2)$$

with S being the benchmark CDS spread while ω_1 and ω_2 are free parameters. A pricing function is used to cap the inflator as spreads cannot widen indefinitely without the benchmark bond entering default at some stage. Wong (2011) suggests that the pricing function such as that from an Excel spreadsheet will suffice:

$$\text{Yield} = (\text{today, maturity, coupon rate, bond price,redemption price, coupon frequency})$$

To calculate the spread cap, S_{cap}, Wong (2011) using the Lehman Brothers bankruptcy as a guide assumes that the recovery rate in the event of a default will be 10%. Most bonds are assumed to be issued close to par when the outlook of the issuing company is attractive so much that the coupon rate can be set to (or close to) the risk-free rate. The final assumption is that bonds give the same quarterly cashflows like a CDS, to be consistent with CDS quotes. The assumptions allow for the spread of the bond at the point of default to be stated as:

$$S_{\text{cap}} = Y_{\text{defaulted}} - r_f \quad (3)$$

Where $Y_{\text{defaulted}}$ is the yield of the bond at the point of default. Wong (2011) illustrates a basic example on how to perform this calculation using a standard discounted pricing function (e.g. the yield function in Excel outlined above) and defines the maximum inflator (Δ_+) as an adjustment that will inflate two standard deviations of spread returns up to the percentage loss at the point of default calculated as (S_{cap}). This two-standard deviation in (4) represents a 97.7% VaR under a normal distribution (chosen only because it simplifies the formulation. In principal, any level would suffice).

$$\frac{S_{\text{cap}}}{S} - 1 \equiv 2\sigma\Delta_{\text{max}} \quad (4)$$

However, S_{cap} satisfies (3), so

$$\Delta_{\text{max}} = \exp\left(\omega_1 S_{\text{cap}}^{\omega_2}\right) \quad (5)$$

Substituting (5) into (2) produces the response function:

$$\Delta_{+} = \exp\left\{\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2} \cdot \ln\left(\frac{\frac{S_{\text{cap}}}{S} - 1}{2\sigma}\right)\right\} \tag{6}$$

The free parameter ω_2 in (6) must still be calibrated. Wong (2011) argues that $\omega_2 = 0.5$ is the most suitable as it produces an inflator that increases rapidly to penalise RSW, however it decreases in such a way that the spread inflated through the inflator will never exceed S_{cap}. This ensures that the holder of the bond will never lose more than the principal amount less the recovery amount. An advantage of ω_2 as a free parameter is that it can be adjusted and calibrated as required by a regulator depending on the requisite level of conservatism.

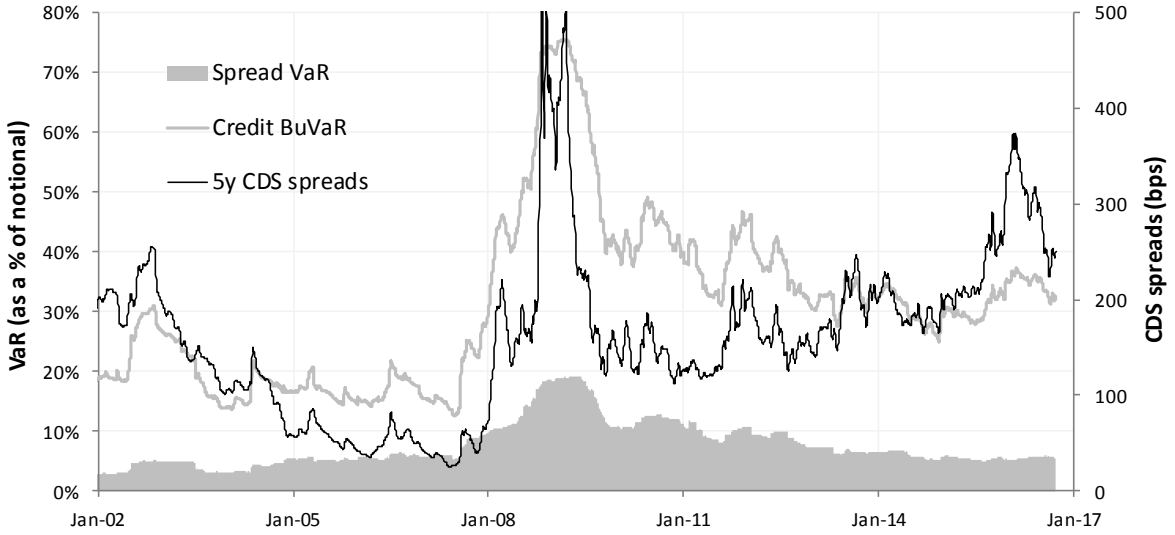
4. RESULTS AND DISCUSSION

4.1. Current (2017) South African milieu

The credit buVaR model relies integrally on the simulation of S_{cap}indicating the moment of default. This is fundamental to the model as it enables the aggregation of spread and default risk. Central to S_{cap} is the risk-free rate of the market as well as the assumed bond recovery rate in the event of default. Firstly, compared with the US, SA is a high interest rate environment and thus the risk-free rate used to calibrate S_{cap} is considerably elevated. JIBAR (November 2016) is used as the risk-free rate for calibration. In addition, the lack of CDS data for the South African market complicates the assumption of a recovery rate since no noteworthy government or corporate bonds for which there are CDS data defaulted in the analysis period.

4.2. Simulation results – calibration assumptions

Figure 1 shows the performance of spread VaR and credit buVaR relying on VaR for the calculation of credit buVaR on SA 5-year government bond CDS spreads. Figure 1 assumes the same recovery assumption (10%) and more importantly the same $\omega_2 = 0.5$ to that of Wong (2011). The risk-free rate has, however, been calibrated for South Africa.



Source: Author calculations and Bloomberg data.

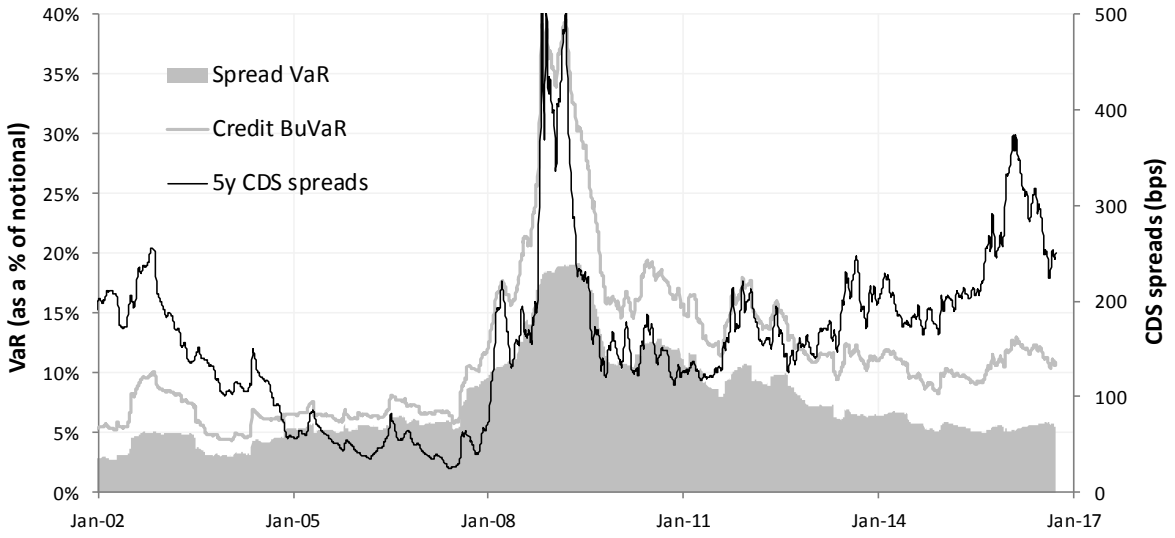
Figure 1: Credit risk measures on 5-year CDS spreads using standard deviation as a measure of volatility (risk-free rate = 7.00%, bond recovery rate = 10%, $\boldsymbol{\omega_2 = 0.5}$).

The uncalibrated buVaR output in Figure 1 shows significantly elevated capital estimations compared to spread VaR throughout the observation period. The purpose of buVaR, as a countercyclical measure, is to assist banks in their determination of the "correct" amount of credit risk capital during different stages of the business cycle. However, capital requirements under buVaR are excessive and would require institutions to keep between two and seven times more capital than measured using conventional VaR (as observed during the observation period indicated in Figure 1), placing an onerous burden on capital requirements and diverting liquidity to less-profitable operational areas. This highlights the necessity of appropriate model parameter calibration.

Wong (2011) advised that each jurisdiction calibrate its own model input parameters. For the South African market, a bond recovery rate of 50% was assumed (Esterhuysen, 2016) – far more than the 10% used in Wong's (2011) exposition. South Africa's historical experience of corporate defaults has been less detrimental than that faced in developed economies, partially due to the stringency of the National Credit Act which curtailed institutions' reckless lending activities (South African National Credit Act 34 of 2005 (SA NCA), 2005).

The bond recovery rate assumption is implemented first as it is based on empirical market data and insight, whereas the free parameter ω_2 is calibrated to a suitable level and chosen at the discretion of the user. An $\omega_2 = 1.0$ (c.f. Wong, 2011: $\omega_2 = 0.5$) reduces the increase of buVaR over conventional VaR to levels that may be acceptable to banks, i.e. between 1.0 and

2.5. Figure 2 illustrates a calibrated buVaR model output based on assumptions for the South African market.

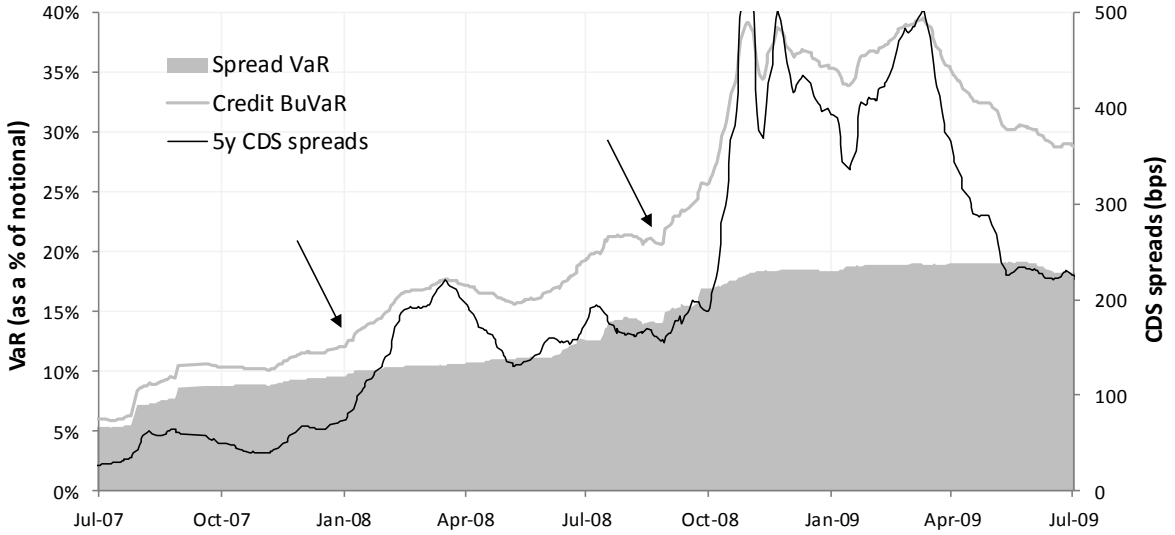


Source: Author calculations and Bloomberg data.

Figure 2: Credit risk measures on 5-year CDS spreads using standard deviation as a measure of volatility (risk-free rate = 7.00%, bond recovery rate = 50%, $\omega_2 = 1.0$).

Assuming better bond recovery rates and applying a larger ω_2 produces results that are still-elevated – but more sensible using buVaR – shown in Figure 2. The spike in CDS spreads in 2015 was a direct result of the political instability (which led to economic instability) caused by the removal of the Minister of Finance (Nhlanhla Nene) in December 2015. Subsequently, rating agencies warned of further downgrades – possibly to junk status – still faced by the country (Moody's Investor Services, 2016).[3] Figure 3 concentrates on the crisis period from Figure 2 and shows the elevated capital requirements (which would have been required under the buVaR metric). This reinforces buVaR's countercyclical objective.

[3] South African credit ratings relative to spreads and buVaR are provided in Figure 11.



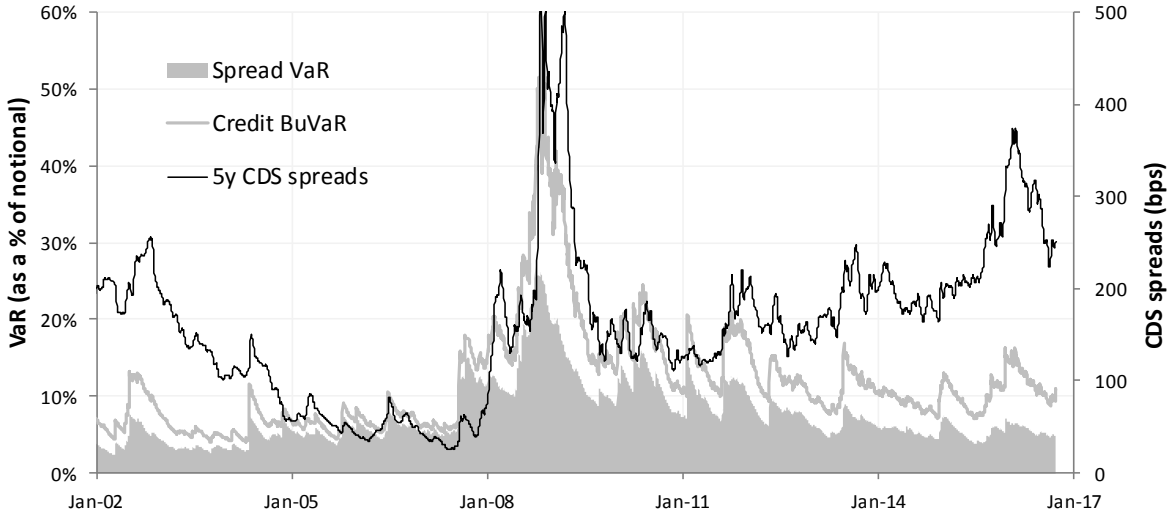
Source: Author calculations and Bloomberg data.

Figure 3: Credit risk measures on 5-year CDS spreads using standard deviation as a measure of volatility in the months preceding the credit crisis. Arrows indicate focus regions.

Figure 3 illustrates the end of the non-volatile pre-crisis period and subsequent crisis period in which spreads increased significantly. buVaR reacts quicker and to a greater extent than spread VaR to what Wong (2011) described as "rapid spread widening". This results in a quicker increase in capital requirements which further motivates the use of buVaR because of its potential countercyclical capabilities. Both indicated areas might have curbed rapid expansion and potentially avoided bubble formation. Estimating these higher capital requirements cannot be backtested so hindsight does not offer much benefit.

The choice of volatility measure may influence buVaR's suitability. It is well-known that better, more reactive measures of volatility are frequently used in practice, such as GARCH and EWMA models. Figure 4 shows spread VaR and buVaR using an Exponentially Weighted Moving Average (EWMA) volatility methodology. The difference in required capital under an EWMA volatility approach and a standard deviation volatility approach (Figure 2) are not material.

4.3. Calibration of required parameters to South African market



Source: Author calculations and Bloomberg data.

Figure 4: Credit risk measures on 5 year CDS spreads using the EWMA approach as a measure of volatility ($\boldsymbol{\omega_2 = 1.0, \lambda_{\text{EWMA}} = 0.95}$).

The EWMA approach in Figure 4 places reliance on more recent data when estimating volatility. Credit buVaR and spread VaR provide more reactive measurements to time series changes under EWMA.

The choice of VaR measure may also influence buVaR's suitability. Despite being widely used in finance, the BCBS has decided to replace VaR with ES or "conditional VaR" (BCBS, 2013). Recall that the ES – the probability-weighted average of losses beyond a specified value of VaR:

$$\begin{aligned} ES_\alpha &= E\big(X \big| X \leq \text{VaR}_\alpha(X)\big) \\ &= -\frac{\sigma}{\sqrt{2\pi}} \cdot \exp\left(-\frac{\alpha^2}{2\sigma^2}\right) \end{aligned} \tag{7}$$

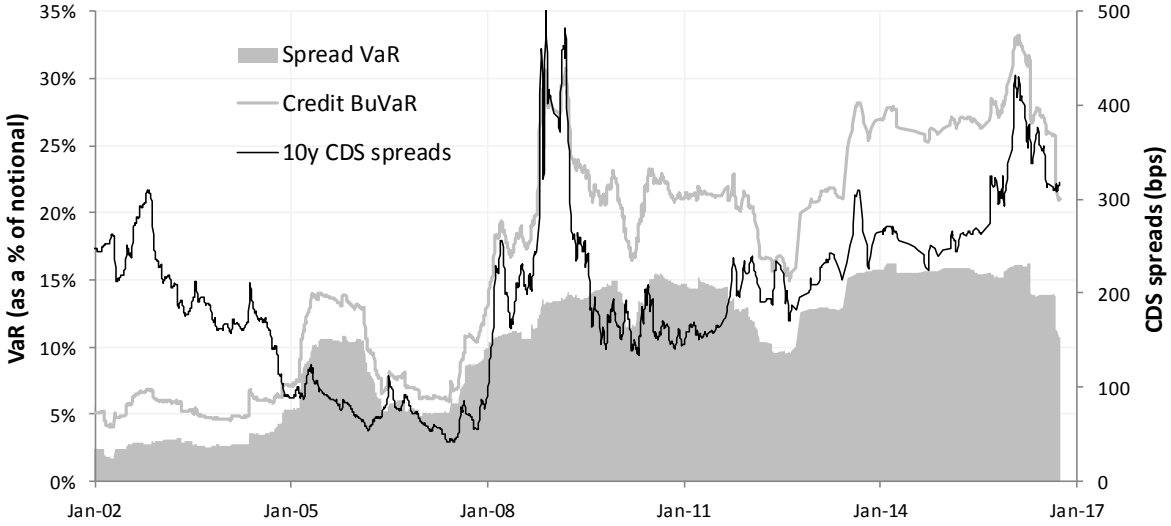
where σ is the portfolio standard deviation and α is the VaR value beyond which the ES is desired. The two metrics were used in the buVaR model: the results are compared in Figure 5.

Source: Author calculations and Bloomberg data.

Figure 5: Credit buVaR using VaR and ES.

Figure 5 illustrates that buVaR using ES is more reactive than buVaR using conventional VaR. ES provides a more conservative measure compared with spread VaR because it considers not only the likelihood of losses, but also their magnitude, leading to a more coherent measure. This is illustrated by the severe fluctuations of ES buVaR in the post-crisis period because ES measures the loss *severity*, whilst VaR provides an estimate of loss *frequency*.

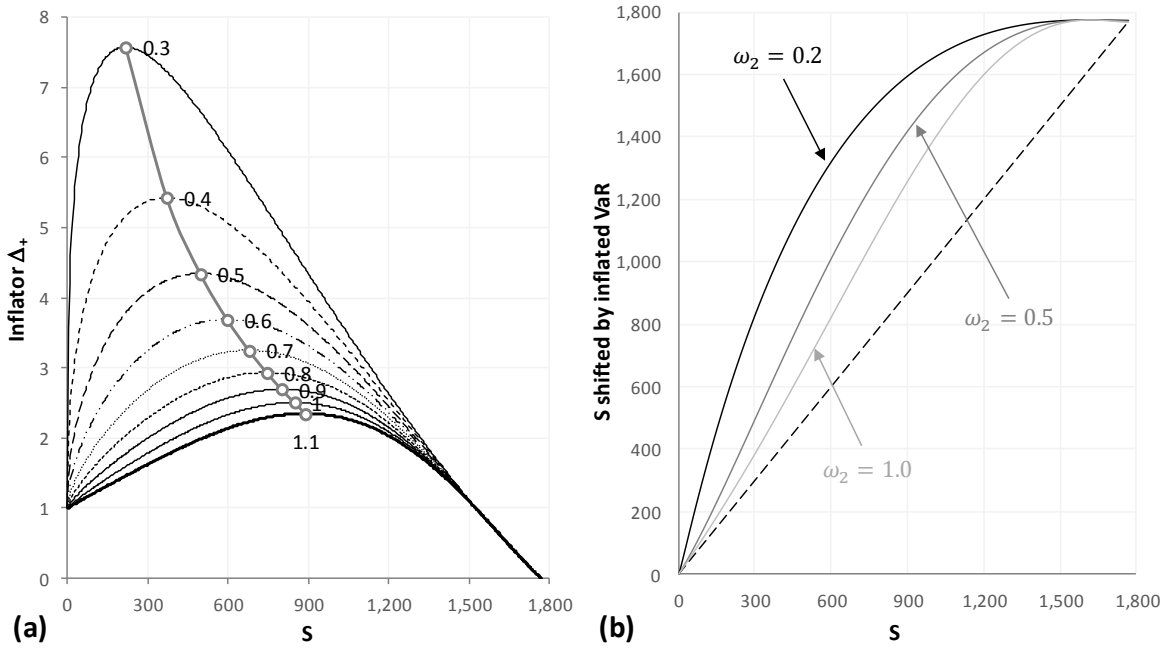
Figure 6 applies the buVaR model to 10-year South African government bond CDS spreads. The calibration of ω_2 $(= 1.0)$ remains identical to that chosen for 5-year South African government bond CDS spreads: this value produces similar capital retention levels (c.f. Figure 2).



Source: Author calculations and Bloomberg data.

Figure 6: Credit buVaR for 10y CDS spreads (risk-free rate = 7.00%, bond recovery rate = 50%, $\boldsymbol{\omega_2 = 1.0}$).

Figure 7a illustrates the effect of changing spread levels, S, on the inflator, Δ_+. Each line represents Δ_+ versus S at various ω_2 values (these ω_2 values are the numbers on the graph at the maximum value of Δ_+ for each fixed ω_2). Figure 7b shows the spread after application of Δ_+ versus the current spread, S. See (4).



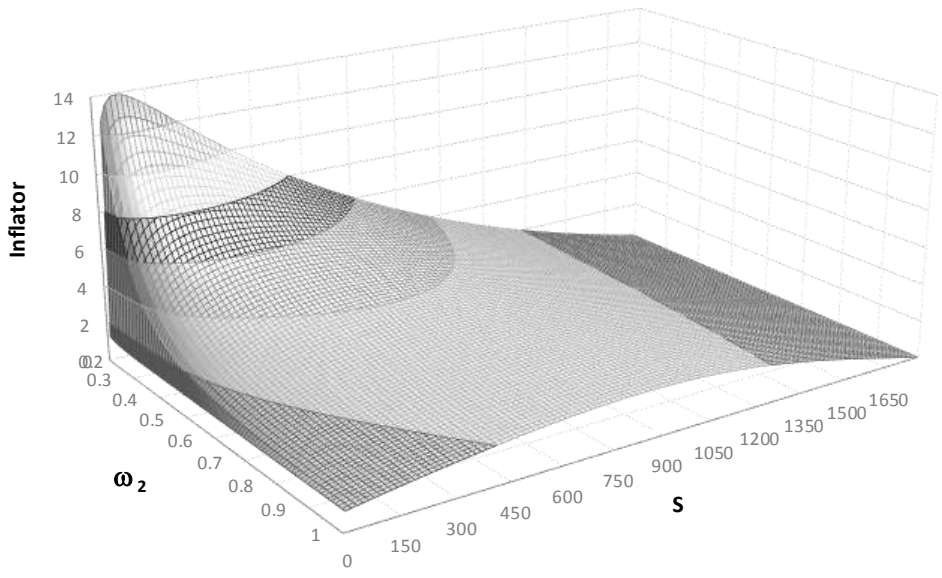
Source: Author calculations.

Figure 7: a) The effect of the spread level, $\boldsymbol{S}$, on Δ_+ (as well as an indication of the maximum Δ_+ for different levels of $\boldsymbol{\omega_2}$ and b) the effect of spread level, $\boldsymbol{S}$, on VaR for various levels of $\boldsymbol{\omega_2}$.

The first derivative of (6) (see Appendix) gives the rate of change of the Δ_+ with respect to S. Setting this derivative to 0 determines the value of S where Δ_+ is a maximum (i.e. the open circles in Figure 7a).

Lower ω_2 values generate inflators which elevate spreads early, i.e. far from levels at which the bond would default. Wong (2011) asserted that Δ_+ should penalise excessive growth as soon as possible and thus applies an $\omega_2 = 0.5$. Higher ω_2 values elevate spreads more slowly than lower ω_2 values, so excess growth is only penalised severely enough at spread levels close to those which would results in a bond default.

Figure 8 shows a surface plot of Δ_+ for various levels of ω_2 and S.

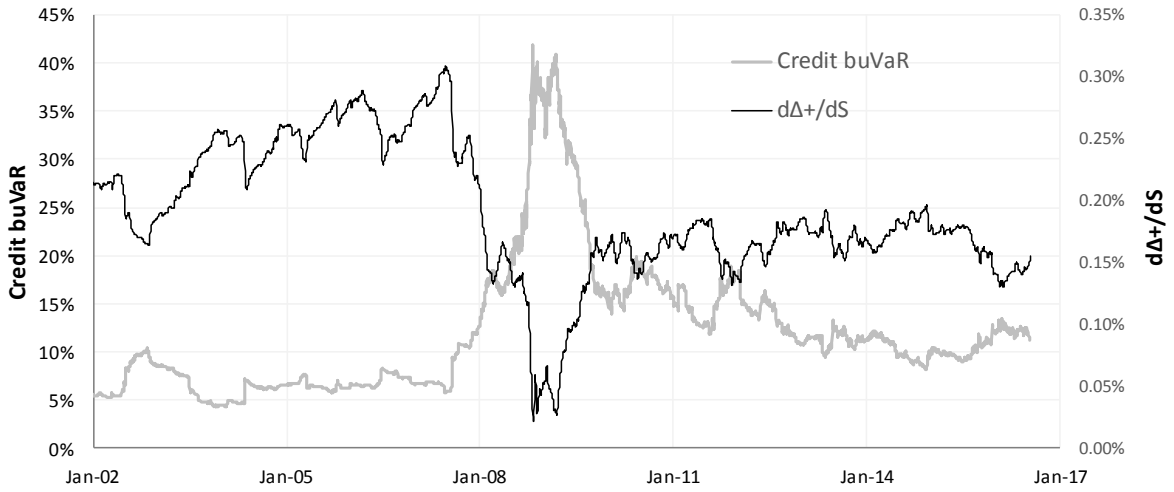


Source: Author calculations.

Figure 8: Surface plot showing the impact of $\boldsymbol{\omega_2}$ and spread level, $\boldsymbol{S}$, on Δ_+.

Figure 8 illustrates the importance of calibrating the buVaR model for the market to which it is applied. As shown in Figure 1, Wong's (2011) $\boldsymbol{\omega_2 = 0.5}$ value would apply too harsh a capital requirement for institutions as buVaR is five times higher than spread VaR during crisis periods. This quantity of capital retention would be too punitive for most institutions. At low $\boldsymbol{\omega_2}$ values, the inflator imposes severe liquidity constraints on institutions. A higher $\boldsymbol{\omega_2}$ is thus preferred in this study. Using Figure 8, the inflator can be calibrated to the bank's relevant, acceptable value.

Figure 9 illustrates the rate of change of the Δ_+ (its first derivative) with respect to $\boldsymbol{S}$.

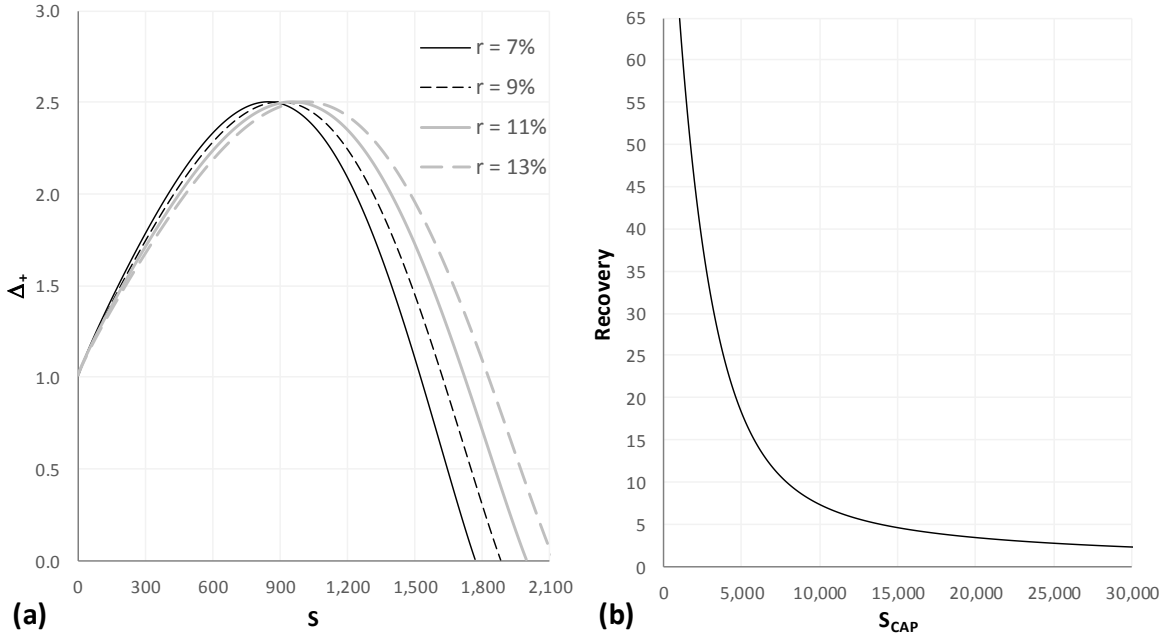


Source: Author calculations.

Figure 9: First derivative of $\boldsymbol{\Delta_+}$ with respect to spread level, $\boldsymbol{S}$.

The rate of change of Δ_+ is considerably elevated in the pre-crisis period. This highlights model's ability to anticipate market bubbles and subsequently elevate buVaR through Δ_+ to potentially retard or halt the bubble's development.

Figures 10a and b illustrate the effects of model components, r_f and the assumed bond recovery rate on S_{cap} respectively.



Source: Author calculations.

Figure 10: Impact of a) the risk-free rate on the inflator as a function of $\boldsymbol{S}$ and b) the bond recovery rate on $\boldsymbol{S}_{\text{cap}}$.

An increase in r_f increases S_{cap} as well as the value of S at which Δ_+ experiences a maximum. Using (3), as r_f increases, the yield at default, $Y_{\text{defaulted}}$, increases at a faster rate, so $S_{\text{cap}} = Y_{\text{defaulted}} - r_f$ increases. This influence is trivial compared with the impact of the recovery rate on S_{cap} (Figure 10b). Low recovery rates result in dramatically elevated levels of S_{cap}.

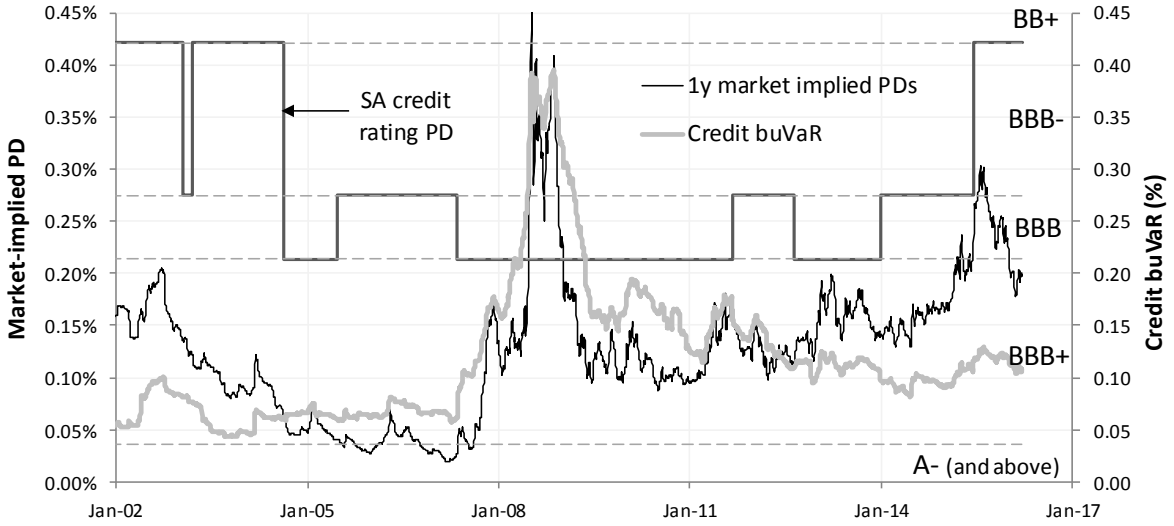
Denzlera, Dacorognaa, Müllera and McNeil (2006) showed that probabilities of default could be derived from credit spreads using:

$$S = -\frac{1}{t}\ln\left(1 - PD_{\text{implied}} \cdot LGD\right) \tag{8}$$

Where S is the credit spread level in basis points, t is the maturity of the CDS in years, PD is the probability of default and LGD is the loss given default of the CDS instrument – both expressed as percentages. ETF (2011) showed (8) could be approximated using:

$$PD_{\text{implied}} \approx 1 - \frac{1}{\left(1 + \frac{S}{LGD}\right)^{t}} \tag{9}$$

Figure 11 illustrates the market implied PD's as derived using (9) in conjunction with the South African credit rating (supplied by Fitch Ratings) and the 5y CDS spreads.



Source: Author calculations and Bloomberg and Fitch Ratings data.

Figure 11: Market implied PDs (using 10y and 5y CDS spreads from Figure 1), South African credit rating (mapped to relevant PD) and buVaR on the same timescale.

Source: Fitch Ratings and authors' calculations.

South Africa's credit rating is currently (Nov 16) just above junk and has a negative outlook (Moody's Investor Service, 2016) as shown in Figure 11. This suggests that *political actions* (including the removal of Finance Minister Nene) rather than *only* market implied PDs, weigh heavily on the opinions and confidence of rating agencies. Were only the latter considered, the current lower spreads (relative to credit crisis levels) imply that South Africa should be assessed at a better (higher) credit rating. Unsurprisingly, there is a strong correlation between credit buVaR (using data from Figure 1) and market implied annual PDs.

4.4. Consequences for South African banks and Regulators

Implementation of a buVaR-like model in the banking environment would require significant cooperation between the regulator and regulated institutions. buVaR models effectively attempt to replace the BCBS countercyclical buffer and thus thresholds and parameters would have to be tested and agreed upon. What would be an evident advantage of such a model is that it would not be burdened by complicated timing issues regarding the retention and release of capital buffers. These timing issues under the current BCBS formulation would be a

key focus area as they would have to be analysed and compared with continuous capital estimates under buVaR models.

Initial research between regulators and banks could focus on the optimal value for ω_2, as a comparison of this work compared with Wong (2011) shows considerably different results for different values of this parameter. This research could analyse banks' portfolios to ensure that the model would perform consistently across the market. In jurisdictions where data are scant for both CDS spreads and historical defaults, regulators would have to cooperate with market experts on defaults and recovery assumptions. Wong (2011) highlighted that under a buVaR model environment there would be macro-prudential advantage in that institutions not affected by buVaR capital requirements could price more competitively thereby transferring credit risk from the banking sector to other global investors as well.

5. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

Regulatory capital recommendations for financial markets are constantly evolving. A combination of several BCBS publications[4] has been informally labelled as Basel IV (Nooman, 2016). These recommendations aim to regulate the banking environment where complex interconnected financial instruments have historically masked risk and exhibit considerable measurement complexity. Wong's (2011) buVaR model provides a risk metric combining both spread and default risk. Relying on liquid forward-looking CDS spread data, the model bypasses the problem of risk aggregation by employing a single model under the historical VaR/ES approach. Wong (2011) stressed that, like all VaR approaches, the model is influenced by subjective choices of parameters and thus does not provide a statistically precise measurement. This emphasises the necessity for regulators and banks to cooperate to ensure the "correct" parameters are used in their jurisdiction.

buVaR results using Wong's (2011) original calibrations and assumptions illustrate excessive capital requirement estimates and suggested further calibration requirements. A higher bond recovery assumption after default and a higher ω_2 produces more feasible estimates. Applying buVaR to five and ten-year South African government bond CDS spreads produced results showing that buVaR is more responsive and conservative prior to periods of severe CDS spread increases. This highlights the metric's countercyclical properties that would potentially have countered bubble developments. Depicting buVaR results on the same timescale as market implied PDs and the South African credit rating shows that buVaR does ramp up sig-

[4] Basel IV comprises: BCBS 306, BCBS 319, BCBS 347, BCBS 362, BCBS 303, BCBS 279, BCBS 352, BCBS 355, BCBS 325, BCBS 349 (PWC, 2016).

nificantly in the pre-crisis bubble development period. However, the model is robust when shocks occur such as the removal of the Minister of Finance in late 2015.

A tractable solution is provided in (10), which simplifies the selection of the free parameter, ω_2. Within any jurisdiction, institutions and policy makers' will have local knowledge of bond recovery and risk free rates which, in turn, determine S_{Cap}. Using this information in conjunction with the results from (10), the inflator level can be quickly calculated for any ω_2 and thus, the associated increase in capital can be ascertained. This can be used as a guide for regulatory and institutional capital calibration.

The procyclical nature of financial markets and the way in which its participants react to fuelling this phenomenon are well documented. The BCBS proposed the implementation of a CCB, but this has raised concerns regarding uncertainty whether the right data are used for estimation: the credit-to-GDP ratio may not be optimal for jurisdictions with unique markets (Drehmann & Tsatsaronis, 2014). Further timing issues are a concern as capital for the buffer can be released immediately, but retention notices must optimally be made 12 months in advance. The credit buVaR model provides a continuous forward-looking metric that is not burdened by timing issues and is not subject to procyclicallity as it does not rely on credit ratings or transition matrices.

Future research opportunities include the optimal calibration of the free parameter ω_2. This parameter has a significant impact on the buVaR model and appropriate guidance is required if it were to be implemented. Research on the parameter would include analysis across multiple economies, markets and scenarios to ensure suitable implementation guidelines are created. Further research may also include investigation on the relationship between model outputs, CDS spreads and actual credit ratings as it was not the central focus of this study. Finally, as capital requirements for tradable credit instruments arise both from default and spread risk, further research may analyse combined capital requirements from separate conventional models to that of aggregating buVaR like models.

APPENDIX

First derivative of (6)

$$\frac{d\Delta_+}{dS} = \frac{d\exp\left(\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}\right)}{dS}$$

$$= e^{\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}} \cdot \frac{d}{dS}\left[\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}\right]$$

$$= \left(\frac{d}{dS}\left[\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\right]\cdot\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2} + \ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\cdot\frac{d}{dS}\left[\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}\right]\right) e^{\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}}$$

$$= \left(\frac{\omega_2 \ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}}{S} - \frac{S_{\text{cap}}\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}}{\left(\frac{S_{\text{cap}}}{S}-1\right)S^2}\right) e^{\ln\left(\frac{\frac{S_{\text{cap}}}{S}-1}{2\sigma}\right)\left(\frac{S}{S_{\text{cap}}}\right)^{\omega_2}}$$

This function $= 0$ (since when $\frac{d\Delta_+}{dS} = 0$ the function is at its maximum value of Δ_+) where:

$$\omega_2 = \frac{\left(\frac{S_{\text{cap}}}{S_{\text{cap}}-S}\right)}{\ln\left(\frac{S_{\text{cap}}-S}{2\sigma\cdot S}\right)} \tag{10}$$

REFERENCES

Alessandri, P. and Drehmann, M. 2007. An economic capital model integrating credit and interest rate risk in the banking book, *European Central Bank Working Paper Series*, NO 1041 April 2009.

Bank for International Settlements, 2008. Addressing financial system procyclicality: a possible framework, *Note for the FSF Working Group on Market and Institutional Resilience*. Online: http://www.fsb.org/wp-content/uploads/r_0904e.pdf?page_moved=1 accessed 11 Nov 2016

Barrell, R., Davis, E., Karim, D. and Liadze, I. 2010. Calibrating macroprudential policy, *NIESER Discussion Papers*, no 354.

BCBS, 2009. Guidelines for computing capital for incremental risk in the trading book - consultative document. Online: http://www.bis.org/publ/bcbs149.pdf, accessed 12 Jun 2016.

BCBS, 2009d. Findings on the interaction of market and credit risk. Online: http://www.bis.org/publ/bcbs_wp16.pdf accessed 12 January 2017.

BCBS, 2010. Guidance for national Authorities operating the countercyclical capital buffer. Online: http://www.bis.org/publ/bcbs187.pdf, accessed 1 June 2016.

BCBS, 2011. Capital treatment for bilateral counterparty credit risk finalised by the Basel Committee - Press release. Online: http://www.bis.org/press/p110601.htm, accessed 13 Jun 2016.

BCBS, 2013. Fundamental review of the trading book: A revised market risk framework. Online: http://www.bis.org/publ/bcbs265.pdf, accessed 22 Oct 2016.

BCBS, 2014. Fundamental review of the trading book: outstanding issues - consultative document. Online: https://www.bis.org/bcbs/publ/d305.htm, accessed 22 Oct 2016.

BCBS, 2015. Interest rate risk in the banking book - consultative document. Online: http://www.bis.org/bcbs/publ/d319.pdf, accessed 1 June 2016.

Behn, M., Detken, C., Peltonen, T. and Schudel, W. 2013. Setting countercyclical capital buffers based on early warning models: would it work? *ECB Working Paper Series, no 1604, November.*

Brown, K. and Moles, P. 2014. Credit Risk Management. Online: https://www.ebsglobal.net/EBS/media/EBS/PDFs/Credit-Risk-Management.pdf, accessed: 1 Jun 2016.

Crouhy, M., Galai, D. and Mark, R. 2000. A comparative analysis of current credit risk models. *Journal of Banking and Finance*, 24(1–2): 59–117.

Denzlera, S. M., Dacorognaa, M. M., Müllera, U. A. and McNeil, A. J. 2006. From default probabilities to credit spreads: Credit risk models do explain market prices. *Finance Research Letters*, 3(2): 79–85.

Drehmann, M., Sorensen, S. and Stringa, M. 2008. The integrated impact of credit and interest rate risk on banks. *Bank of England Working Paper,* 339, Online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=966270, accessed 1 Jun 2016.

Drehmann, K. and Tsatsaronis, K. 2014. The credit-to-GDP gap and countercyclical capital buffer: questions and answers, *BIS Quarterly Review, March 2014*. Online: http://www.bis.org/publ/qtrpdf/r_qt1403g.pdf, accessed 15 Nov 2016.

Esterhuysen, J. 2016. Private communication.

ETF, 2011. Market-implied default probabilities and credit indexes. ETF.com. Online: http://www.etf.com/publications/journalofindexes/joi-articles/10605-market-implied-default-probabilities-and-credit-indexes.html, accessed 8 Sep 2016.

Fitch Ratings, 2016. Fitch Affirms South Africa at BBB-. Online: https://www.fitchratings.com/site/pr/1005740 Accessed: 15 Nov 2016.

Huang, X., Zhou, H. and Zhu, H. 2009. A framework for assessing the systemic risk of major financial institutions. Finance and Economics Discussion Series, Division of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C. Online: https://www.federalreserve.gov/pubs/feds/2009/200937/200937pap.pdf, accessed 22 Sep 2016.

Moody's Investor Service, 2016. Moody's confirms South Africa's sovereign rating at Baa2. Online: https://www.moodys.com/research/Moodys-confirms-South-Africas-sovereign-rating-at-Baa2-and-assigns--PR_348291, accessed 19 Sep 2016.

Nooman, L. 2016. Basel IV spectre looms for battle-worn bankers, *Financial times 14 March 2016.* Online: https://www.ft.com/content/a9d6eb94-ce5d-11e5-831d-09f7778e7377, accessed: 15 Nov 2016.

Papaioannou, M. G., Park, J., Pihlman, J. and van der Hoorn, H. 2013. Procyclical behaviour of institutional investors during the recent financial crisis: causes, impacts, and challenges. *International Monetary Fund Working Paper, Monetary and Capital Markets Department,* WP/13/193

PWC, 2016. Basel IV at a glance. Online: http://www.pwc.com/gx/en/services/advisory/basel-iv.html accessed: 15 Nov 2016.

SA NCA, 2005. South African National Credit Act 34 of 2005. Online: http://www.justice.gov.za/mc/vnbp/act2005-034.pdf, accessed 22 Oct 2016.

SARB, 2016. South African Reserve Bank. Online: https://www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx, accessed: 15 Nov 2016.

Shin, H. S. 2013. Procyclicality and the search for early warning indicators, *IMF Working Papers,* no 13/258.

Van Vuuren, G. 2012. Basel III countercyclical capital rules: Implications for South Africa, *South African Journal of Economic and Management Sciences*. 15(3): 309-324.

Wong, M. 2011. Credit BuVaR: Asymmetric spread VaR with default. *Journal of Risk management in Financial Institutions*, 5(1): 86–95.

Chapter 4

Countercyclical Capital buffer: South African filter measurements

Filter selection for countercyclical capital buffers

Dirk Visser[5] and Gary van Vuuren[6]

ABSTRACT

Procyclicality plays a pivotal role in finance in both thriving and crisis periods. This influence stems not only from the way market participants behave, but also from risk metrics used and regulatory capital amassed and released during bust and boom periods respectively. The introduction of the regulatory Countercyclical Capital Buffer aims to thwart procyclicality by accumulating (releasing) capital in upswings (downswings), subsequently reducing the amplitude of the financial cycle and promoting macroprudential stability. The timing of the accumulation and release of buffer capital is critical so identifying accurate indicators is important. Indicators must be established for all jurisdictions: the standard metric suggested by the Basel Committee on Banking Supervision (BCBS) has been questioned. For South Africa, studies suggest alternatives such as residential property indices since research has demonstrated that the BCBS proposal is procyclical rather than countercyclical. A superior method used to estimate the buffer has not yet been established. This paper applies a Kalman filter to South African data and confirms the procyclicality of the BCBS proposal. Results suggest that buffer signals are dependent upon the filter employed.

Key words: Procyclicality, Countercyclical Capital Buffer, Kalman filter.

JEL Classification: C21, C54, G31

1. INTRODUCTION

The procyclical nature of financial markets is well-documented as are the intrinsic procyclical characteristics of regulatory capital regulations prior to Basel III. Several studies including Heid (2003), Gordy and Howells (2004) and Goodhart and Taylor (2006) forewarn that the procyclical nature of regulatory requirements impede macroeconomic stability as these regulations force institutions to retain more capital in low-profit, liquid divisions when they may need to continue extending credit. This institutional behaviour and the inability of risk measurements to capture this phenomenon proved to be disastrous in the 2008/9 financial crisis. Conventional measures such as Value at Risk (VaR) and its successor, expected shortfall (ES) (BCBS, 2013), do not account for procyclicality as these metrics are volatility-based measures which use procyclical historical data (these have no components which indicate the financial cycle's position).

The BCBS proposed the implementation of a Countercyclical Capital Buffer (CCB) to promote the macroprudential goal of protecting banking sectors from periods of excess aggregate

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credit growth (BCBS, 2010a and BCBS, 2010b). These periods have historically been associated with the build-up of system-wide risk and the CCB thus aims to ensure institutions are not only solvent through stress periods, but also able to maintain the flow of credit. Research on the CCB since its introduction has been plentiful, but the metric has several indicator components that signal the *retention* of a CCB buffer as well as indicators that signal the buffer's *release*. Determining these signals has received significant interest, since, initially, the BCBS (2010b) only mentioned a one-sided Hodrick-Prescott (HP) filter[7] in a footnote.

Use of the one-sided HP filter has been questioned (Edge & Meisenzahl, 2011, van Vuuren 2012 and Kelly, McQuinn & Stuart, 2013) due to the endpoint problem associated with the metric as well its sensitivity to changes or revisions of many macroeconomic variables such as GDP and inflation. Hosszú, Körmendi and Mérő (2015) applied several univariate and multivariate filters to decompose the credit-to- GDP ratio into trend and cyclical components. Their research finds a multivariate HP filter to be most effective as its endpoint uncertainty is the least, with the result that new data do not materially affect previous estimates too much. Galati, Hindrayanto, Koopman and Vlekke (2016) apply a Kalman filter[8] to extract cycles from financial time series data for the United States (US) and the Euro area. They find that series including credit, credit-to-GDP and real house prices demonstrate medium-term cyclical behaviour and that the periodicity and amplitude of these cycles vary over time and between countries. They further find that, since the mid-1980s, US financial cycles have increased in duration and amplitude whereas such conclusions cannot be made for the Euro area.

Procyclicality research in South Africa includes that of Akinboade and Makina (2009, 2010) in which the linkage between the behaviour of bank lending and business cycles in South Africa is assessed. They found new mortgage lending to be countercyclical prior to 1993 and that bank lending and interest rates moved in tandem with business cycles. Fourie, Botha and Mears (2011) attempted to determine the role banks play with regards to the amplification of business cycles and the subsequent macroeconomic impact. These studies did not, however, focus expressly on the credit-to-GDP gap. South African research on the credit-to-GDP gap and the CCB is increasing as its implementation is currently (2017) in a staggered implementation approach. van Vuuren (2012) implemented both a one and two-sided HP filter on South African data to illustrate the possible CCB capital charges under both approaches.

[7] See Section 3.
[8] See Section 3.

Burra, de Jongh, Raubenheimer, van Vuuren and Wiid (2014) discussed practical considerations for the CCB in South Africa as proposed in Basel III. They found several series including credit extension, advances to the domestic private sector and house prices to be positively correlated with GDP growth. However, the credit-to-GDP gap was found to be negatively correlated with GDP growth suggesting that buffers would accumulate in downturns, thereby fuelling procyclicality rather than countering it. They affirm that accurate build-up signals remain; however, they were significantly weaker in the buffer's release phase. Bernstein, Raputsoane and Schaling (2014) applied a Logistic Smooth Transition Autoregressive model to assess the credit-to-GDP as the recommended common reference for countercyclical capital buffer implementation. The authors found that the credit-to-GDP gap decreased when the economic cycle experienced upturns and vice versa and thus caution the use of this standard as a uniform or mechanical estimate of countercyclical South African capital buffers.

The Kalman filter – which was originally developed to provide aeronautical navigation – offers a different, but parsimonious and accurate solution to the problem of time-dependent variable estimation. The Kalman filter enjoys the advantage of real-time application. Time series observations are used to forecast future observations (as in most forecast applications), but in the Kalman filter case, the state variables (which define the forecast framework) are 'optimal', being determined via minimisation of the variance between prediction and observation differences by rapidly reacting to changing conditions. This makes the Kalman approach to the problem of time-dependent variable estimation extremely practical to financial practitioners (see, e.g., Jain, Yongvanich & Zhou, 2011 and Thomson & van Vuuren, 2017).

The Kalman filter is a recursive procedure for computing the optimal estimator of the state vector at time $t + 1$, based on information available at time t (Kalman, 1960 and Arnold et al., 2008) which provides a linear estimation method for equations represented in a state space form. Estimation problems are transformed into state-space by defining state vectors. The Kalman filter output is governed by two equations: a measurement equation and a transition equation. The measurement equation unites unobserved data (x_t where t represents the time of measurement) and observed data (y_t) by the equation, $y_t = mx_t + v_t$, where $E[v_t] = 0$ and the variance of the error term, $Var[v_t]$, is known (r_t). The transition equation describes the evolution in time of unobserved data, such that $x_{t+1} = ax_t + w_t$, where $E[w_t] = 0$ and the variance of the error term, $Var[w_t]$, is unknown (q_t).

The remainder of this paper proceeds as follows: Section 2 explores the literature regarding procyclicality and the CCB from an international and South African perspective, respectively.

The choice and extent of the data is explained in Section 3 as well as the mathematics of the various filters including the Kalman filter. The logic behind how filters reduce signal variance when estimating unobserved moments is also discussed here. Results obtained from analysis are illustrated and discussed in Section 4 and Section 5 concludes.

2. LITERATURE STUDY

2.1. Procyclicality

The Basel III accord, introduced to address shortcomings of Basel II (recall that Basel III did not *replace* Basel II) places significant emphasis on reducing procyclicality through the introduction of several regulatory measures. Subsequent guidelines by the BCBS address implementation and measurement considerations of these measures including the CCB. The BCBS identified procyclicality as one of the most destabilising elements with regards to the amplification of financial shocks in the banking sector throughout the 2008/9 financial crisis (BCBS, 2010a).

Procyclicality's ability to act as a financial accelerator in both expansions and contractions lies in information asymmetries between borrowers and lenders (Borio, Furfine & Lowe, 2001). In distressed economic environments (where collateral values decline) even profitable borrowers struggle to find access to credit as institutions are more risk averse and must retain more capital as suggested by procyclical regulatory capital models. In benign economic conditions, where credit extensions occur with fewer restrictions, institutions chase profitable positions as capital does not have to be kept in liquid reserves – thereby temporarily reinforcing the cycle's upswing. Borio, Furfine and Lowe (2001) argued that the worst excesses of financial cycles can be mitigated, however, this requires the acknowledgement of increased risk in boom periods and that the materialisation of bad loans does not necessarily imply an increase in risk. Measurement difficulties and biases have also contributed to the effects of cycle excesses and procyclicality. Market participants often struggle to optimally assess how correlations between credit losses across borrowers and the financial institutions change over time. This, along with other measurement complications, has led to short horizons and extrapolation of current conditions further into the future than possibly deemed appropriate (Borio, Furfine & Lowe, 2001). Complicated risk measurement techniques, market participant behaviour and existing regulatory capital have all contributed to the phenomena of procyclicality and are all being addressed in the drive to mitigate it. Borio (2012) asserts that it is

critical to rediscover the role of the financial cycle and its empirical features like procyclicality in macroeconomics as it is closely related to systemic crises.

The financial crisis accelerated endeavours to mitigate procyclicality (van Vuuren, 2012), with regulators proposing changes to accounting standards, risk measurement practices and the conduct of monetary policy. Further measures included the introduction of non-cyclical probability of default (PD) proxies in internal rating models and the CCB to address the phenomena.

2.2. Countercyclical capital buffer

Basel III's countercyclical objectives attempt to dampen the cyclical effects stemming from minimum capital requirements as well as promote forward looking provisioning. The build-up of capital buffers to be used in stress periods at individual bank and sector level aims to achieve a macroprudential goal of guarding the banking sector against periods and aftermaths of excessive credit growth (BCBS 2010a). Drehmann, Claudio, Gambacorta, Jimenez and Trucharte (2010) suggest that the ultimate goals for CCB schemes are twofold. Firstly, the schemes should attempt to limit risk of large scale strains on banking systems. Secondly, the schemes should attempt to limit the banking system and its participants from amplifying economic (cycle) fluctuations. To achieve these closely related goals, the authors suggest desirable characteristics off a CCB scheme which include:

- correct implementation and timing
- appropriate size (the buffer should not impede growth)
- robust to capital arbitrage and manipulation
- internationally enforceable
- rules-based
- low implementation cost, and
- simple and transparent.

Drehmann et al., (2010) suggest that achieving all these features present significant challenges as fully rules-based schemes allow for no judgement of false signals. Further, making these schemes simple and transparent as well as internationally enforceable limits modelling-based measures. The top-down approach is preferred by the BCBS for CCB schemes because credit-to-GDP gap data are readily available for all jurisdictions, whereas this is not case for bottom-up data. Bottom-up data also produced substantial individual components, suggesting

that differences in the values of bank-adjusted factors would be large even under periods of broad financial stability (Drehmann et al., 2010).

2.3. Measurement techniques

Galati et al., (2016) asserts that previous investigations into financial cycles and their statistical properties focussed on three approaches. Firstly, attempts to identify turning points focussed on positions of peaks and troughs. Claessens, Kose and Terrones, (2011) rely on a classical[9] definition of a cycle to analyse how business and financial cycles interact and the implications thereof. Their data for housing, equity and credit markets and GDP from 44 countries accounting for 90% of global output are grouped into advanced and emerging economies. Similar research by Boshoff (2006) analyses the cyclicality of financial markets in relation to the cyclical behaviour of the South African real economy and identifies turning points for several domestic and international variables. Both Boshoff (2006) and Claessens et al., (2011) rely on the fundamental methodological foundations produced by Burns and Mitchell (1946) for business cycle turning point analyses.

Secondly, Galati et al., (2016) suggest that statistical frequency-based filters include the HP filter, the Baxter-King filter (1999) and the Christiano Fitzgerald (2003) filter. These require pre-specification of the range of cycle frequencies and thus are referred to as non-parametric filters. These have been increasingly interrogated and compared since the introduction Basel III to determine superiority under different scenarios compared to the BCBS's one-sided HP filter.

International research for these filters are plentiful as the BCBS (in its guidance for national authorities operating the countercyclical capital buffer (BCBS, 2010b)) conduct analysis for several countries using a one-side HP filter. This was followed by several studies affirming or contradicting the use of a one-sided HP filter and other frequency based filters. These studies include Drehman et al., (2010), Drehmann, Claudio and Trucharte (2012) and Aikman, Haldane and Nelson (2015). South African research includes that of van Vuuren (2012) who estimated the credit-to-GDP gap using both a one and two-sided HP filter to illustrate the implications of CCB charges. Unresolved questions include the lack of BCBS clarification on why a one-sided HP filter has been suggested and how the jurisdiction-wide measure will influence individual bank operations. A Basel III update has since clarified how bank specific CCBs can be calculated using their individual credit exposures (BCBS, 2010a).

[9] A classical methodology focuses purely on changes in the levels of economic activity and not on the fluctuations of these activities around their long-term trend.

Finally, the third approach involves unobserved-component time series models which include the Kalman filter. These have several advantages compared with non-parametric filters including no requirements regarding self-imposed, ad-hoc parameters and the relaxation of the requirement for predetermined frequencies required to extract cycles. Kalman filters function with non-normal data; a useful attribute since financial data commonly exhibit fat tails. These models also present more accurate estimations since model-based filter diagnostics can be used to validate models and estimate their goodness of fit. International research for the Kalman filter include numerous studies analysing business cycles i.e. Valle, Azevedo, Koopman and Rua (2006), Koopman and Azevedo (2008) and Creal, Koopman and Zivot (2010), however, few have expressly focused on financial variables. Galati et al., (2016) attempted to measure financial cycles for the US and the Euro using a Kalman filter and found that financial cycles are longer than business cycles and have higher amplitudes. Extracting cycles from business failure rates, real GDP and credit spreads, Koopman and Lucas (2005) found comparable medium-term cycles for US data. South African research on financial cycles using the Kalman filter has not yet been conducted.

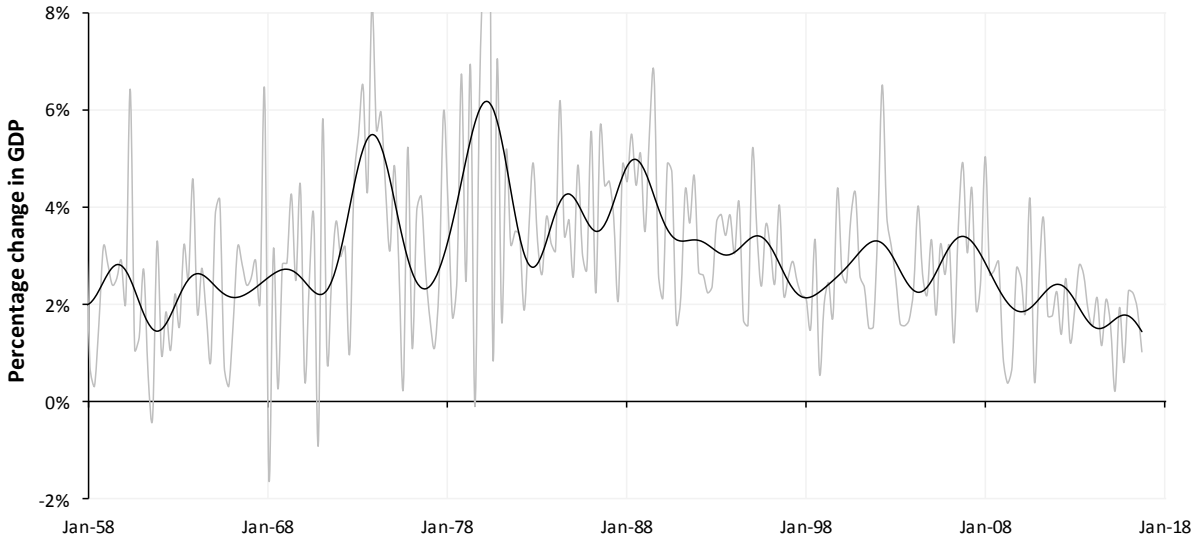
A more dynamic, forward-looking buffer variation suggested by Wong (2011a, 2011b) manipulates time series data through an inflator to produce increased capital requirements for both market and credit risk. The credit version of the author's buVaR model further attempts to combine default and spread risk under a single risk measure, arguing that this measure lies between spread risk and the principal loss of the bond (total loss). The benefit of the Wong's (2011a, 2011b) methods is that they avoid timing issues of a CCB buffer currently faced by regulators and financial institutions. South African applications of Wong's buVaR methodology (and the performance thereof) have been conducted by Visser and van Vuuren (2015, 2016).

3. DATA AND METHODOLOGY

3.1. Data

The data chosen were monthly nominal GDP and credit extended by all monetary institutions to the domestic private sector since 1965. These data are prescribed by the BCBS (BCBS, 2010b) and obtained from the Reserve Bank of South Africa (SARB, 2016). From these data, growth rates were determined and the credit growth/GDP ratio determined. South African Small Residential price index data obtained from the BIS are also used in a similar manner as the credit growth/GDP data (BIS data, 2016).

South African data from January 1966 were used to determine the credit growth/GDP growth ratio as well as this ratio's long-run trend. Detailed examination of these data, using standard Fourier analysis, indicates that they exhibit cyclical behaviour. This result is not unexpected since they comprise several macroeconomic components (such as the economic – or business – cycle) which are inherently cyclical. A Fourier frequency analysis of these data indicate that the main component has a frequency of approximately seven years: the duration of South Africa's business cycle, found previously (Botha, 2004) and confirmed in later studies (e.g. Thomson & van Vuuren, 2016). Figure 1 illustrates monthly nominal percentage changes in GDP with a Fourier-fitted cycle.



Source: Author calculations and Bloomberg data.

Figure 1: Monthly nominal percentage changes in GDP (grey line) and Fourier-fitted cycle. The most prominent cycle has a frequency of 28 quarters (7 years).

Using these macroeconomic data, the credit growth/GDP growth ratio was constructed as well as the long-run trend using both the one-sided HP filter. The difference between the ratio and its long-run trend is shown in Figure 2.

3.2. Methodology

3.2.1. HP filter

A popular method of trend-extraction from data is the HP filter. The HP filter was first introduced (Hodrick & Prescott, 1981) in the context of estimating business cycles, but the research was only published in 1997 after the filter had gained widespread popularity in macroeconomics (Hodrick & Prescott, 1997). The BCBS also chose the HP filter to detrend rele-

vant macroeconomic ratio data and thus extract the information required to evaluate excessive growth in economies.

The HP filter has been criticised for several limitations and undesirable properties (Ravn & Uhlig, 2002). Canova (1994 and 1998) agreed in principle with the use of the HP filter to extract business cycles (of average duration between four to six years) from macroeconomic data, but doubted the methodology for determining key parameter inputs. Spurious cycles and distorted estimates of the cyclical component when using the HP filter were obtained by Harvey and Jaeger (1993) who argued that this property may lead to misleading conclusions regarding the relationship between short-term movements in macroeconomic time series data. Cogley and Nason (1995) also found spurious cycles (and extreme second-order properties in detrended data) when using the HP filter on difference-stationary input data. Application of the HP filter to US time series data was found to alter measures of persistence, variability and co-movement dramatically (King & Rebelo, 1993). Many of these critiques do not provide sufficient compelling evidence to discourage use of the HP filter. As a result, it remains widely used among macroeconomists for detrending data which exhibit short term fluctuations superimposed on business cycle-like trends (Ravn & Uhlig, 2002).

The idea on which the HP filter rests is that an observable macroeconomic time series (x_t) may be decomposed into its long-run, non-stationary secular trend (τ_t) and a stationary residual, or cyclical, component (c_t):

$$\underbrace{x_t}_{\text{Observed series}} = \underbrace{\tau_t}_{\text{Long-run trend}} + \underbrace{c_t}_{\text{Cycle}} \tag{1}$$

Neither the long-run trend nor the cycle is directly observable so detrending approaches generally define these elements somewhat arbitrarily. The HP filter extracts the cycle by solving (2), a standard-penalty program:

$$\underbrace{\min_{\tau_t}}\ \underbrace{\sum_{t=1}^{T}(x_t-\tau_t)^2}_{\text{Goodness of fit}} + \underbrace{\lambda\cdot\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})]^2}_{\text{Penalty for deviations}} \text{ for } \lambda>0 \tag{2}$$

where the parameter, λ, controls the smoothness of the adjusted trend series, $\hat{\tau}_t$, i.e., as $\lambda \to 0$, the trend approximates the actual series, x_t, while as $\lambda \to \infty$ the trend becomes linear and the procedure converges to a standard least squares solution (Yakhim, 2001). The optimisation procedure in (2) maximises the fit to the trend of the series, i.e. minimise the cycle component c_t by minimising changes in the gradient of the trend τ_t. Note that both τ_t and c_t are

unobservable and since c_t is a stationary process, x_t may be thought of as a noisy signal for the non-stationary trend τ_t.

Hodrick and Prescott (1981) originally suggested an exogenous and subjective value of 1 600 for the value of λ for quarterly data, but Backus, Kehoe and Kydland (1992) proposed adjusting λ based upon the square of the frequency of observations relative to quarterly data. The relative frequency is 3 for monthly data and 0.25 for annual data, so the corresponding λs are 14 400 and 100, respectively. Despite on-going research (e.g. Ravn and Uhlig (2002) and Marcet and Ravn (2003) who derived endogenous values for λ by solving (2) as a constrained minimisation problem) the values for λ discussed above are still in common use (Mise, Kim & Newbold, 2005). The optimal value for λ for South African business cycle data was explored by du Toit (2008) who argued that the optimal smoothing constant was that value of λ that least distorts the frequency information of the time series (in this case, $\lambda = 254$ for quarterly data was used to determine the South African business cycle frequency).

Drehman et al., (2010) found $\lambda = 1600$ and $\lambda = 25\,000$ performed poorly on historical data whilst $\lambda = 125\,000$ and $\lambda = 400\,000$ performed well with quarterly data. The higher value of $\lambda = 400\,000$ is considered important from a policy perspective as it provides both a greater range and more time when the indicator provides strong and reliable signals.

The HP filtering procedure optimises the fit to the data series, but this optimality is based on the application of the filter to an infinitely long time series. For practical purposes, the estimation of the trend and cycle components works well for a moderately long series (Mise, Kim & Newbold, 2005), but at the end points the HP filter is demonstrably suboptimal. The two-sided, symmetrical filter applies large symmetrical weights to the end points of the observed values to determine the corresponding trend value (Ley, 2006) disproportionately distorting the filtered values at the most recent time (Baxter & King, 1995, Apel, 1996 and St-Amant & van Norden 1997).

3.2.2. Kalman filter

The Kalman filter (Kalman, 1960) is a Bayesian updating scheme that maximises the likelihood of correctly estimating unknown parameter values (Koch, 2006). The filter addresses the general problem of determining the state $[x \in \Re^n]$ of a time-controlled, discrete process which is governed by the linear stochastic difference equation:

$$x_t = \boldsymbol{F}x_{t-1} + \boldsymbol{B}u_{t-1} + w_{t-1}$$

with a measurement $[z \in \Re^n]$:

$$z_t = \boldsymbol{H}x_t + v_t.$$

The random variables w and v, which are assumed to be independent (i.e. 0 correlation between them) and normally distributed:

$$w(\cdot) \sim N(0, \boldsymbol{Q})$$
$$v(\cdot) \sim N(0, \boldsymbol{R})$$

represent *process* white noise and *measurement* white noise respectively.

In practice, the process noise covariance $\boldsymbol{Q}$ and measurement noise covariance $\boldsymbol{R}$ matrices (here *variance* matrices because the correlation is zero) change with each time step. In this case, they are assumed to be constant (Koch, 2006) – a common assumption – and these values are obtained using maximum likelihood methods (Tommaso & Alessandra, 2012).

The 2×1 (in this case) state transition matrix, F, links the state at the previous time step $t-1$ to the current state at step t, assuming no driving function nor process noise. The 2×2 control matrix B relates the optional control input $u \in \Re^l$ to the state x. The 2×1 matrix H in the measurement relates the state to the measurement z_k. In practice F and H might change with each time step, but here again they are both assumed to be constant.

The mechanical process to be followed is:

PREDICT

Project state 1 time step ahead $\quad \hat{x}_{t|t-1} = F_t \hat{x}_{t-1|t-1} + B_t u_t$

Project error covariance 1 step ahead $\quad P_{t|t-1} = F_t P_{t-1|t-1} F_t^T + Q_t$

UPDATE

Compute Kalman gain $\quad K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + R_t\right)^{-1}$

Update estimate with measurement y_t $\quad \hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t\left(y_t - H_t \hat{x}_{t|t-1}\right)$

Update error covariance $\quad P_{t|t} = (I - K_t H_t) P_{t|t-1}$

where $\hat{x}$ is the estimated state, F is the state transition matrix (i.e., transition between states), u represents the control variables, B is the control matrix (i.e., mapping control to state variables), P is the state variance matrix (i.e., error of estimation), Q is the process variance matrix (i.e., error due to process), y represents the measurement variables, H is the measurement

matrix (i.e., mapping measurements onto the state), K is the Kalman gain and R is the measurement variance matrix (i.e., measurement error).

Subscripts represent:

$t|t$: the current time period

$t-1|t-1$: the previous time period, and

$t|t-1$: intermediate steps.

For this analysis, let y_t denote a vector that contains the time series values at time t, for $t = 1, \dots, n$. An unobserved components model comprises a trend-cycle decomposition:

$$y_t = \mu_t + \psi_t + \varepsilon_t \tag{3}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, y_t is the value of the series at time t, μ_t is the long-term trend and ψ_t is a variable representing the dynamics of the underlying cycles. The residuals ε_t are assumed to be normally distributed with variance σ^2. All components are unobserved and the Kalman filter must be used to estimate them. Two important decisions must be made regarding the assembly of y_t.

Trend smoothness: i.e. how much variable fluctuation is assigned to the *trend* as opposed to the *cycle*. Galati et al., (2016) defined a general form of the m^{th}-order trend as,

$$\begin{aligned} \mu_{t+1}^m &= \mu_t^m + \mu_t^{m-1} \\ \mu_{t+1}^{m-1} &= \mu_t^{m-1} + \mu_t^{m-2} \\ &\vdots \\ \mu_{t+1}^1 &= \mu_t^1 + \xi_t \end{aligned} \tag{4}$$

where $\xi_t \sim N\left(0, \sigma_\xi^2\right)$ and $\Delta^m \mu_{t+1}^m = \xi_t$. The trend's smoothness depends on the differencing order m, so as m increases, the trend becomes smoother. For $m = 0$, y_t is stationary, for $m = 1$, y_t is a random walk process and for $m = 2$, y_t is an integrated random walk used in most macroeconomic time series (e.g. see Koopman & Lucas, 2005 and Valle e Azevedo, Koopman, & Rua, 2006):

$$\begin{aligned} \mu_{t+1} &= \mu_t + \beta_t \\ \beta_{t+1} &= \beta_t + \xi_t \end{aligned} \tag{5}$$

where $\xi_t \sim N\left(0, \sigma_\xi^2\right)$.

Cycle stochastic process: using Harvey's (1989) approach, the cycle is modelled as a 2nd order autoregressive process. A trigonometric process is used to specify ψ_t:

$$\begin{bmatrix}\psi_{t+1}\\ \psi^*_{t+1}\end{bmatrix} = \phi \begin{bmatrix}\cos\lambda & \sin\lambda\\ -\sin\lambda & \cos\lambda\end{bmatrix}\begin{pmatrix}\psi_t\\ \psi^*_t\end{pmatrix} + \begin{pmatrix}\omega_t\\ \omega^*_t\end{pmatrix} \quad (6)$$

where $\begin{pmatrix}\omega_t\\ \omega^*_t\end{pmatrix} \sim N(0, \sigma^2_\omega)$, λ, the frequency, is measured in radians and bounded by $0 \leq \lambda \leq \pi$, the period of the stochastic cycle is $2\pi/\lambda$ and the persistence (or damping factor) parameter, ϕ, is bounded by $0 < \phi < 1$ which ensures that the cycle, ψ_t, is a stationary stochastic process. The disturbances $(\omega_t, \omega^*_t)'$ are assumed to be uncorrelated and normally distributed with mean 0 and variance σ^2_ω.

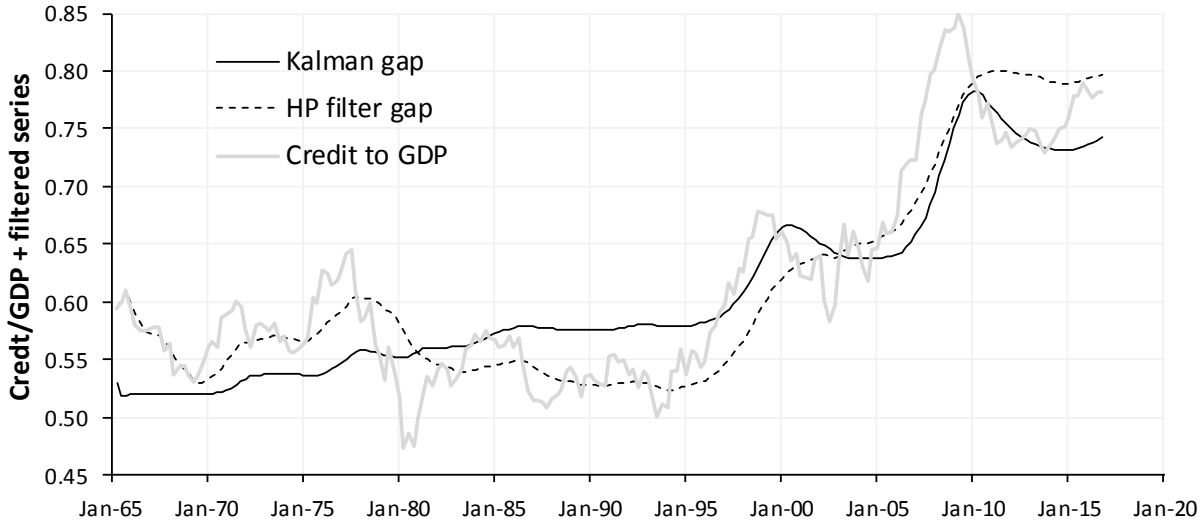
The state space forms of (3) through (6) are:

$$y_t = Z_t\alpha_t + \varepsilon_t$$
$$\alpha_{t+1} = T\alpha_t + \eta_t$$

where the state vector α_t encapsulates the cycle and trend and the system matrices Z_t and T_t contain the parameters from (3) through (6). The state disturbance vector, η_t, contains the disturbances of the trend and cycle equations. It is at this stage that the Kalman filter is invoked to determine the estimates of the unobserved components contained in α_t. Maximum likelihood methods are used to estimate the unknown variances of unobserved component disturbances, the persistence parameter, ϕ, and the frequency parameter, λ. Details of these estimations may be found in Schweppe (1965) and Koopman and Ooms (2011).

4. RESULTS AND DISCUSSION

Although the credit-to-GDP gap is disputed with regards to its appropriateness as CCB buffer indicator for South Africa the purpose of this paper is to primarily focus on the measurement technique of a CCB and then on the indicator variables. As it is recommended as a common reference guide by the BCBS it is used as an investigation point of departure. Thus, Figure 2 illustrates South African credit-to-GDP data and the long-term trend estimated with a one-sided HP and Kalman filter respectively.

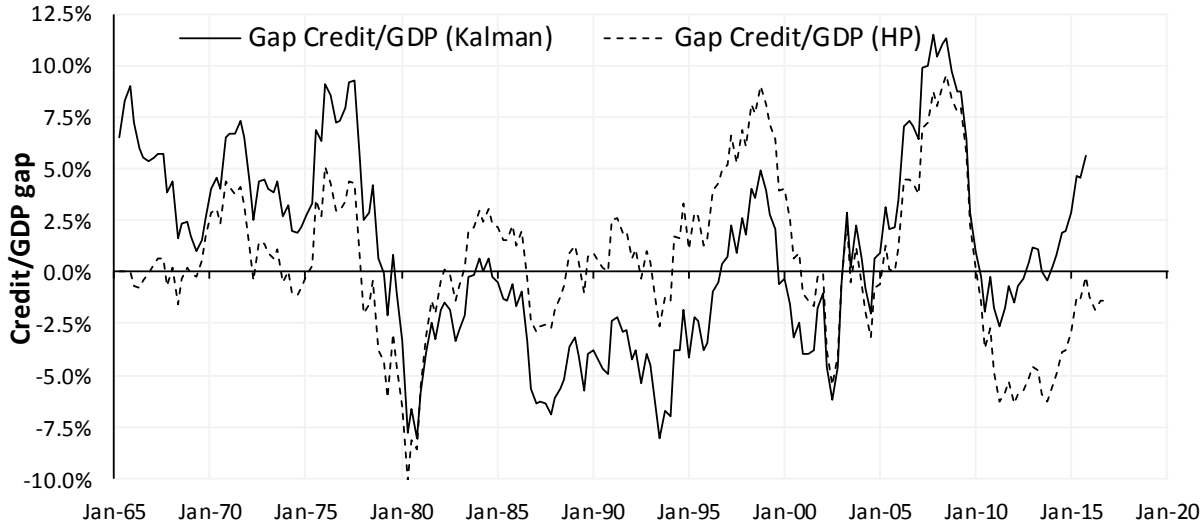


Source: Author calculations and Bloomberg data.

Figure 2: South African Credit/GDP, HP-filtered ($\lambda = 14\ 400$) and Kalman-filtered series.

The gap obtained using the Kalman filter is smoother (flatter) than that obtained using the HP filter during low and stable credit/GDP ratios. In an increasing credit/GDP ratio environment, the Kalman filter is more reactive than the HP filter and tends to accentuate the peaks and troughs to a greater extent. This is a critical difference between the two filters, the results from which affect the magnitude and timing of the capital buffer injection and release.

The Kalman filtered trend series in Figure 2 presents a smoother trend to that of the HP filtered series up until the 1995. This affects the credit-to-GDP gap materially prior to and during the housing bubble of the 1980s. Actual gaps from both approaches are shown in Figure 3 as these drive suggested buffer levels.

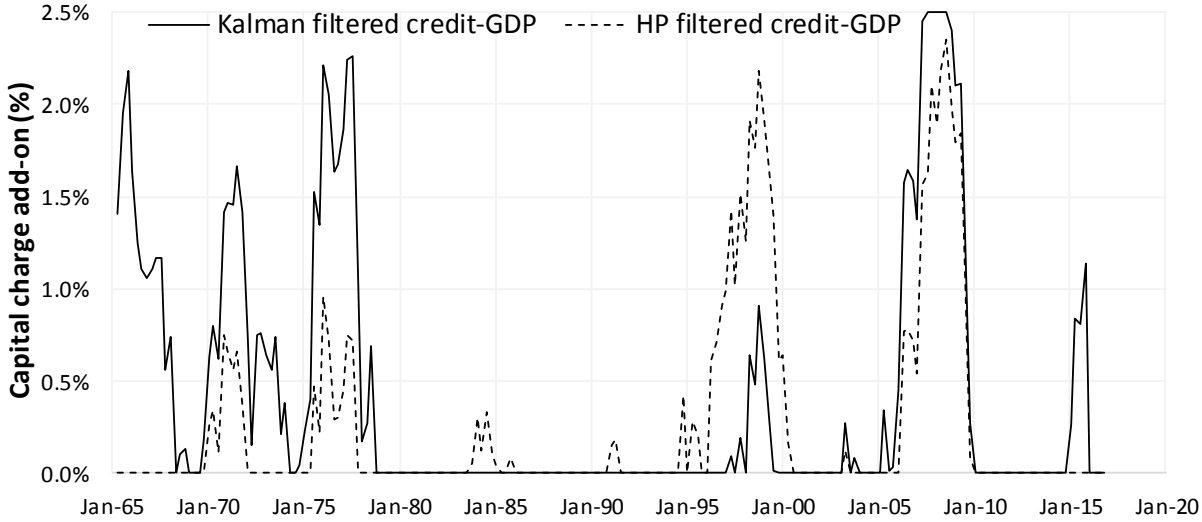


Source: Author calculations and Bloomberg data.

Figure 3: South African Credit/GDP gaps using the HP ($\lambda = 14\ 400$) and Kalman filters.

The Kalman filter trend does not deviate significantly from the actual credit-to-GDP ratio for the Asian crisis period suggesting that capital retention would be less under a Kalman filter approach compared to the HP filter approach. Both filters deviate substantially from the actual ratio before the onset of the financial crisis with the Kalman doing so before the HP filtered series. Gaps from both approaches drive suggested buffer levels (Figure 3).

Positive credit-to-GDP gaps are the focus in Figure 3 as CCB buffers are only accrued in these periods where the gap exceeds 2%. The impact of these elevated gaps on the capital charge add-on is shown in Figure 4.



Source: Author calculations and Bloomberg data.

Figure 4: Historical CCB capital charge using the HP ($\lambda = 14\,400$) and Kalman filters.

The Kalman-filtered series in Figure 3 illustrates superior gaps in both the late 80s and the most recent crisis period. The HP filtered gap exceeds the Kalman with regards to capital requirements in the period associated with the Asian crises. The capital charge add-on is affected by these elevated gaps (Figure 4).

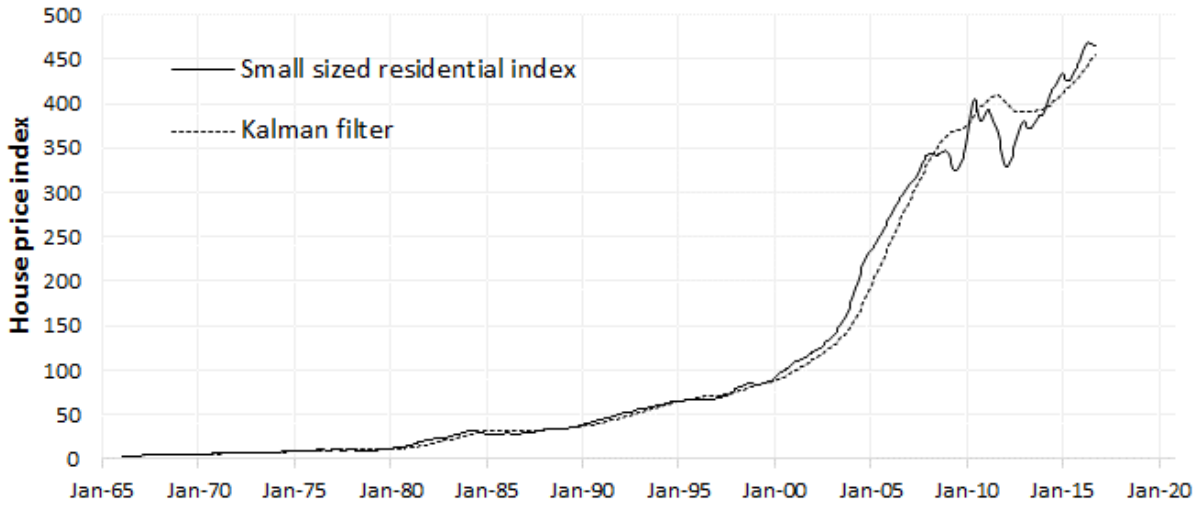
Additional capital charges in Figure 4 shows dominance if derived using a Kalman filtered series up until 1980. This period preceding the house price bubble collapse in the early 1980s was characterised by high inflation in developed markets as well as a lack of confidence in the US dollar (Luüs, 2005). This led to a surge in the gold price, and positive spin-off effects on the South African economy. Luüs (2005) notes that, in this period, 50% of South African export revenue could be attributed to gold. Further, increased household wealth due to a combination of increased incomes and income tax cuts improved liquidity conditions and reduced mortgage lending rates. Subsequently, increased local and international political

tensions as well as pressure on the balance of payments led to significant increases in mortgage lending rates. This ultimately caused the market to collapse and house prices to decline by 42% in real terms (Luüs, 2005).

In the last decade of the 20th century the HP filtered series increases additional capital by more than 2% - although only briefly. This is due to the long-term trend derived through the HP filtered series (Figure 2) being notably lower compared to the Kalman filtered long term trend. Additional capital charges in the late 1990s are partially due to the lack of global demand for commodities as result of the Asian crisis and the severe depreciation of the South African rand in 1998.

In the 2008/9 crisis period the Kalman filtered credit-to-GDP gap produces an elevated capital charge compared to the HP-filter and also reaches the maximum add-on of 2.5% as prescribed by the BCBS. Both metrics throughout this period illustrate a similar release rate of the buffer after the crisis period.

Applying the Kalman filter to the small residential price index allows for the estimation of a small residential gap and subsequent capital charge based on a residential series (Figure 5). This draws from Burra et al, (2014) where it is found that the ABSA house price index for all sizes of properties is positively correlated with GDP growth, suggesting that CCB buffers would build up in prosperous periods.

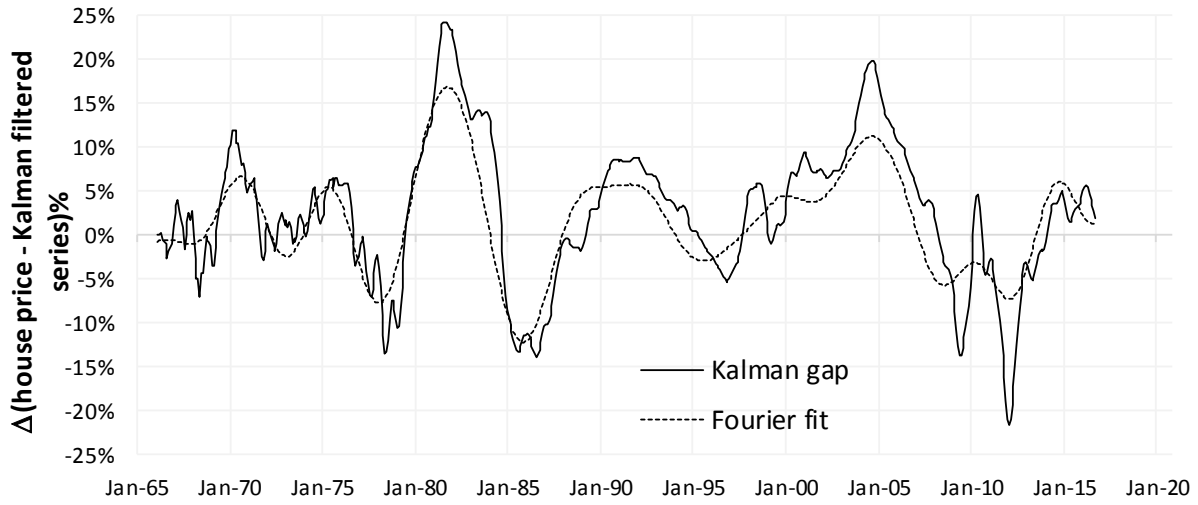


Source: Author calculations and Bloomberg data.

Figure 5: South African small residential price index and Kalman-filtered series.

The South African small residential price index and its Kalman filtered long-run trend in Figure 5 illustrate how the South African residential market benefited from the pre-crisis global

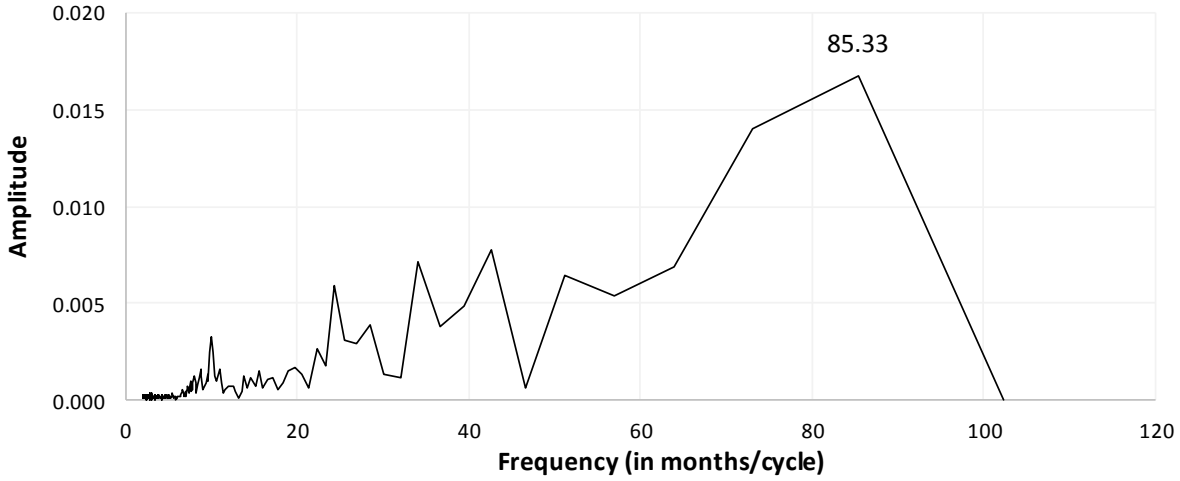
housing market boom. The subsequent crisis did not have such a severe effect on the South African market when compared to the housing markets of other countries, with some of this being attributed to the National Credit Act (SA NCA) of 2005. This legislation along with other measures curbed reckless lending by financial institutions, partially protecting the quality of assets on intuitions' books. Figure 6 illustrates the gap produced from the difference between the actual index and the trend in Figure 5.



Source: Author calculations and Bloomberg data.

Figure 6: South African small residential price index gap and Fourier-fitted series.

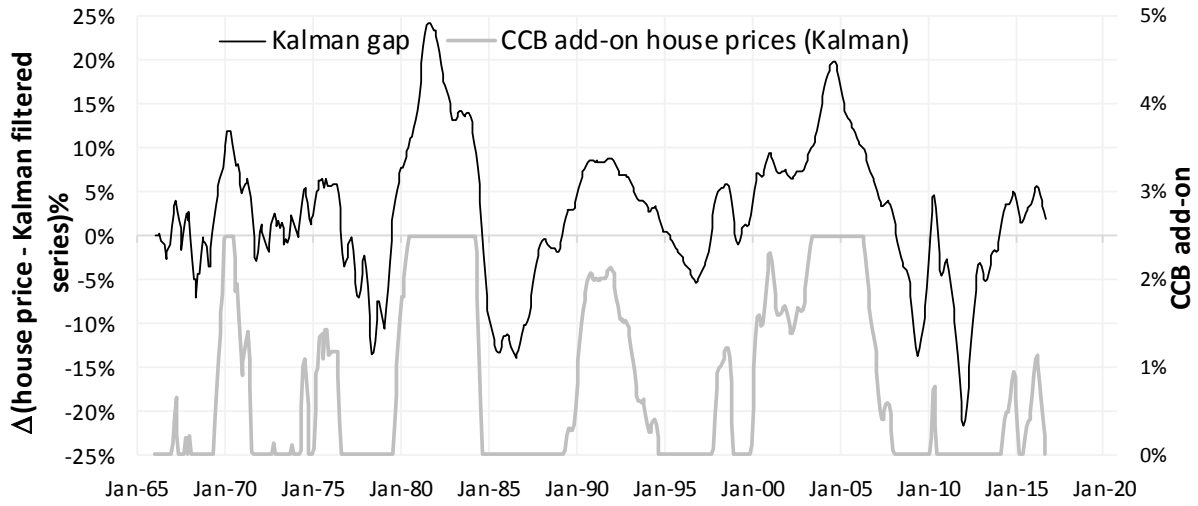
The South African small residential price index gap in Figure 6 indicates the severe shocks of both the 1980s and latest financial crisis on the residential market. The gap falls and remains negative for more than two years in the 1980s. In the recent crisis, the gap recovers more rapidly, however, relapses to turn towards the biggest negative gap in the observation period. These shocks are also prevalent in the credit-to-GDP gap in Figure 3, however, there timing is different, indicating that the two measures will certainly provide different capital requirements at different periods (Figures 9 and 10). Figure 6 imposes a Fourier fit to the residential price index gap to determine whether there is a cycle component for the purposes of cyclical capital requirements. Figure 7 illustrates a frequency spectrum of South African small residential price index gap.



Source: Author calculations and Bloomberg data.

Figure 7: Frequency spectrum for South African small house price gap.

The spectrum in Figure 7 illustrates that principal component has a duration of 85 months (corresponding to a seven-year cycle). The semi-cycle found at ±43 months is encouraging as the Fourier analysis also detects semi-cycles which suggests that the 85-month cycle is correct. This 7-year cycle further aligns with the findings of van Vuuren (2012) for credit/GDP growth and Botha (2004) and Thomson and van Vuuren (2016) for the South African business cycle. Figure 8 illustrates the additional CCB capital requirements estimated using the residential gap and the BCBS CCB implementation suggestions.

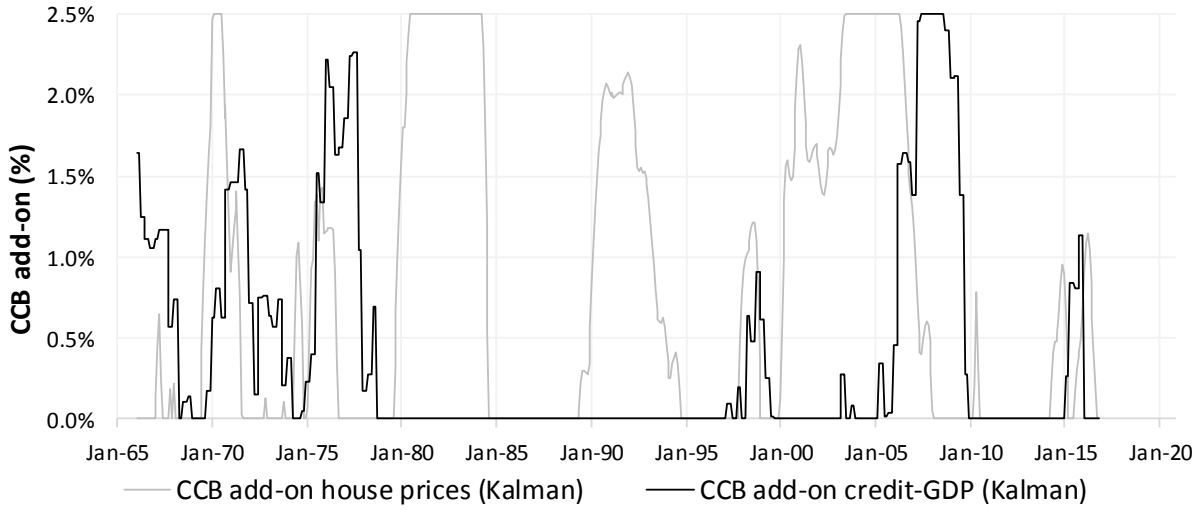


Source: Author calculations and Bloomberg data.

Figure 8: Small residential gap using the Kalman filter and CCB capital charge add-on.

CCB capital requirements are at a maximum three times in the observation period with two of these being associated with the respective crises mentioned. The bursting of the 1980s hous-

ing bubble occurred in 1984 and CCB capital requirement indicators begin as early as the late 1970s. This suggests that the measure might have had the ability to impose countercyclical capital effectively in the years building up to the crisis. This is similar in the latest financial crisis with CCB capital imposed as early as the year 2000 up until mid-2007. Figure 9 illustrates additional CCB capital charges calculated for both the credit-to-GDP gap and the residential gap using the Kalman filter approach for trend extraction.



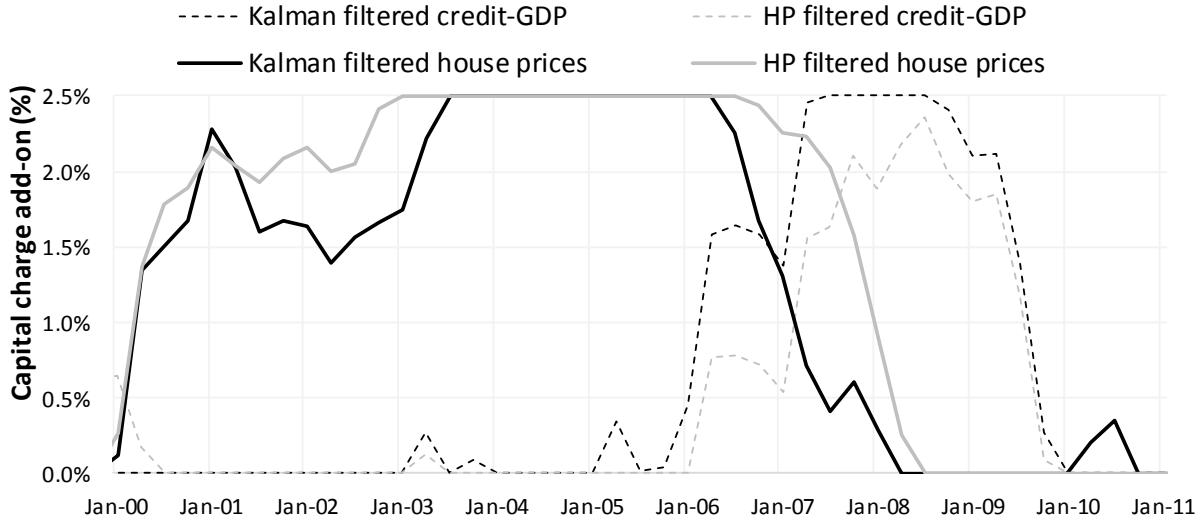
Source: Author calculations and Bloomberg data.

Figure 9: CCB capital charge add-on for credit/GDP and housing index series using the Kalman filter.

The CCB charge requirements differ significantly for the two series analysed with the credit-to-GDP gap raising no CCB requirements for the pre-crisis period of 1980. The residential price index does however increase the CCB requirement to its maximum allowable threshold for almost five years prior to the crisis. The residential index further solely suggests a CCB between 1990 and 1995, this due to political uncertainties and an exodus of professionals placing significant pressure on the housing market. The investigation of signals like these is of utmost importance as they may not be appropriate for CCB indications, particularly if signals are isolated to their sector and not applicable to the entire banking or financial sector.

The pre-2008 crisis period shows significant CCB retentions if the measure is based on the residential price index, suggesting that it would have been countercyclical in the pre-crisis period potentially countering excessive credit growth. The CCB measure based on the credit-to-GDP gap also indicates maximum capital retention, however, in the crisis period. This aligns with research of Burra et al., (2014) and Bernstein et al., (2014) cautioning the use the credit-to-GDP gap as an indicator for the CCB. Figure 10 focusses solely on the most recent

financial crisis comparing the credit-to-GDP gap and the residential property price gap, both estimated using the Kalman filter and HP filter respectively.



Source: Author calculations and Bloomberg data.

Figure 10: CCB capital charge add-on for credit/GDP and housing index series using the Kalman and HP filters pre- and during the credit crisis.

Figure 10 illustrates that the residential price index would have suggested a CCB long before the onset of the crisis. Suggesting stringent buffer requirements from the onset of the millennium might have been too severe and would potentially have hindered economic and financial market growth. The superiority of the Kalman filter over the HP filter cannot be concretely established for the buffer (estimated using the residential price gap) as buffer-retention signals leading up to 2003 are similar. The buffer's release signal under the Kalman filter approach is more rapid: this should be further explored in future research.

The credit-to-GDP gap buffer estimated with the Kalman filter for the crisis period is more conservative compared to the buffer estimated with the HP filter. The Kalman filter-estimated buffer reaches the maximum prescribed 2.5% and maintains it throughout the crisis period, eventually diminishing along with the HP-filtered buffer. The accumulation of the buffer also begins a few months prior to that of the HP-filtered approach and may have countered procyclicality and acted as a warning signal.

5. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

Procyclicality is not isolated to one element of a financial market or economy, it emerges because of the combination of several elements including regulatory requirements and market participant actions. The identification and isolation of a single metric which captures all relevant features of procyclicality is unlikely: regulators and financial institutions will have to

identify the optimal measures and variables which describe its effects in order to attain macroeconomic stability.

The CCB was introduced to limit the effects of procyclicality, but several aspects need to be considered. These include retention and release signals as well as techniques to determine these signals with appropriate variables. The information used in setting the countercyclical capital buffer must capture up and downswings inherent in the financial cycle. The development of system-wide risks are associated with the buffer's build-up phase while financial contractions correspond to the buffer's release phase. Doubts have been expressed about a single measure reliably capturing both the build-up phase and the release phase: robust leading-indicator properties are required for the former and a reliable contemporaneous indicator is required for the latter, as pointed out by Drehmann et al. (2010). In addition, a good proxy for the buildup phase should vary considerably from its long-run trend during the build-up phase (a feature which would rule out non-performing loans – bounded at zero – for example and would limit the information content of credit spreads). Credit spreads, however, would provide much useful information about release phase timing (Chen & Christensen, 2010).

Indicators may provide more useful information in combination than in isolation. Borio and Drehmann (2009) showed that aggregate credit growth and real estate prices jointly contain more predictive information about future financial crises than either in isolation. If adequately implemented, the chosen metric (or metrics) has the potential to reduce the financial cycle amplitude and thereby, potentially, reduce all (or the majority of) credit risk in the financial cycle. The metric may thus lead to a reduction in credit risk regulatory capital: the relationship between the two capital requirements is yet to be fully explored.

This paper applies a Kalman filter to the BCBS-prescribed and other financial variables to determine the appropriate signal for the implementation of the CCB. Results indicate that for different crises results obtained from the Kalman filter and the one-sided HP filter suggest substantially different signals – excluding for the most recent crisis (where the results are similar). This paper corroborates the findings of other studies which find that the credit-to-GDP gap would likely fuel procyclicality rather than dampen it (e.g. Borio, Furfine & Lowe, 2001, Koopman & Azevedo, 2008 and Creal, Koopman and Zivot 2010) for South Africa if employed as a sole measure. The Small Residential Price Index gap identifies countercyclical signals that would have suggested full CCB retention for substantial periods prior to historical crises. This emphasises that, although the metric used to calculate signals is important, the variable used to calculate these signals is a critical input as the incorrect one may fuel procy-

clicality. The South African Reserve Bank (SARB) suggested that it would still use the credit-to-GDP as a principal indicator for the CCB, however, it further asserted that it would use other indicators in conjunction with the credit-to-GDP gap (SARB, 2015).

Future research opportunities include an investigation into how the Kalman filter approach performs in conjunction with other variables that have been found to be more suitable for CCB buffers in South Africa than the credit-to-GDP gap. Work may also focus on buffer-release signals and how measures such as the Kalman filter recognise these occurrences. A combination of models that avoid timing issues such as Wong's (2011) BuVaR model and filter-based approach also present future research opportunities. Solutions to such an approach would be of considerable value to regulators and financial institutions in resolving their current (2017) dilemma regarding CCB timing issues.

In addition, we note the possibility of ultimately incorporating machine-learning into the processes described here. Machine-learning and artificial intelligence (AI) are already widespread in the financial industry and pattern identification – on the skill and timeliness of which this paper is based – is ideally suited to AI applications. Thus it is probably only a matter of time before AI is used for cyclical identification and thus mitigation. It could be argued that embracing AI has thus been proposed in this paper because the Kalman filter is, effectively, a Bayesian variance-reduction tool; a fundamental building block of machine-learning.

REFERENCES

Aikman, D., A. G. Haldane, and Nelson, B. D. 2015. Curbing the Credit Cycle. *The Economic Journal*, 125(585): 1072–1109.

Akinboade O. A. and Makina, D. 2009. Bank lending and business cycles: South African evidence. *African Development Review*, 21(3): 476-498.

Akinboade O. A. and Makina, D. 2010. Econometric analysis of bank lending and business cycles in South Africa. *Applied Economics*, 42(29): 3803-3811.

Apel, M., Hansen, J. and Lindberg, H. 1996. Potential output and output gap. *Quarterly Review of the Bank of Sweden*, 3(1): 24–35.

Arnold, T., Bertus, M. and Godbey, J. 2008. A simplied approach to understanding the Kalman filter technique. *The Engineering Economist*, 53(2): 140–155.

Backus, D. K., Kehoe, J. and Kydland, F. E. 1992. International Real Business Cycles. *The Journal of Political Econom,*. 100(4): 745-775.

Baxter, M. and King, R. G. 1995. Measuring business cycles approximate band-pass filters for economic time series. National Bureau of Economic Research Working Paper No. 5022. Online: http://www.nber.org/papers/w5022.pdf, accessed 10 Dec 2016.

Baxter, M., and King, R. G. 1999. Measuring business cycles: approximate band-pass filters for economic time series. *The Review of Economics and Statistics*, 81(4): 575-593.

BCBS, 2010a. Basel III: A global regulatory framework for more resilient banks and banking systems. *Bank for International Settlements*. Online: http://www.bis.org/publ/bcbs189_dec2010.pdf, accessed 21 Nov 2016.

BCBS, 2010b. Guidance for national Authorities operating the countercyclical capital buffer. Online: http://www.bis.org/publ/bcbs187.pdf, accessed 1 June 2016.

BCBS, 2013. Fundamental review of the trading book: A revised market risk framework. Online: http://www.bis.org/publ/bcbs265.pdf, accessed 22 October 2016.

Bernstein, J., Raputsoane, L and Schaling, E. 2014. Credit Procyclicality and Financial Regulation in South Africa. *Economic Research South Africa.* ERSA Working Paper 445, July 2014.

BIS. 2016. Property price statistics. Online: http://www.bis.org/statistics/pp.htm, accessed 22 Dec 2016.

Borio, C. 2012. The financial cycle and macroeconomics: What have we learnt? *BIS Working Paper No 395.* Online: http://www.bis.org/publ/work395.pdf, accessed: 5 Jan 2017.

Borio, C., Furfine, C. and Lowe, P. 2001. Procyclicality of the financial system and financial stability: issues and policy options. *BIS working paper No 1.* Online: http://www.bis.org/publ/bppdf/bispap01a.pdf, accessed: 5 Jan 2017.

Boshoff, W. H. 2006. The properties of cycles in South African financial variables and their relation to the business cycle. *South African Journal of Economics*, 73(4):694-709.

Botha, I. 2004. *Modelling the business cycle of South Africa: linear vs non-linear methods.* Johannesburg: PhD thesis - Rand Afrikaans University.

Burns, A. F. and Mitchell, W. C. 1946. Measuring Business Cycles. *National Bureau of Economic Research.*

Burra, P., de Jongh, P. J., Raubenheimer, H., van Vuuren, G. and Wiid, H. 2014. Implementing the Countercyclical capital Buffer in South Africa: Practical Considerations. *South African Journal of Economic and Management Sciences,* 18(1): 105-127.

Canova, F., 1994. Detrending and turning points. *European Economic Review,* 38(3-4): 614-623.

Canova, F., 1998. Detrending the business cycle. *Journal of Monetary Economics,* 41(2): 475-512.

Christiano, L. J. and Fitzgerald, T. J. 2003. The band pass filter. *International Economic Review*, 44(2): 435 – 465.

Claessens, S., M. A. Kose, and Terrones, M. E. 2012. How do business and financial cycles interact? *Journal of International Economics,* 87(1): 178-190.

Cogley, T., and Nason, J. M., 1995. Effects of the Hodrick-Prescott Filter on trend and difference stationary time series: implications for business cycle research. *Journal of Economic Dynamics and Control,* 19(1): 253-278.

Creal, D., Koopman, S. J. and Zivot, E. 2010. Extracting a robust US business cycle using a time-varying multivariate model-based bandpass filter. *Journal of Applied Econometrics,* 25(4): 695-719

Drehmann, M., Claudio, B. Gambacorta, L., Jimenez, G. and Trucharte, C. 2010. Countercyclical capital buffers: exploring options. *BIS Working Papers No 317.* Online: http://www.bis.org/publ/work317.pdf Accessed 10 Dec 2016.

Du Toit, L. 2008. Optimal HP filtering for South Africa., University of Stellenbosch, Department of Economics. Working Paper.

Edge, R. and Meisenzahl, R. 2011. The Unreliability of Credit-to-GDP Ratio Gaps in Real-Time: Implications for Countercyclical Capital Buffers. Working Paper 2011-37, Washington DC: Federal Reserve Board.

Fourie, L., Botha, I. and Mears, R. 2011. Credit extension in South Africa: A business cycle perspective for the period 1985 to 2009. *African Journal of Business Management*, 5(34): 13 074-13 083.

Galati, G., Hindrayanto, I., Koopman, S. J. and Vlekke, M. 2016. Measuring Financial Cycles with a Model-Based Filter: Empirical evidence for the United States and the Euro Area. *De Nederlandsche Bank.* Working Paper No. 495.

Goodhart, C. and Taylor, A. 2006. Procyclicality and volatility in the financial system – the implementation of Basel II and IAS39. In S. Gerlach and P. Gruenwald (eds.) Procyclicality of financial systems in Asia, pp. 230-251. Palgrave Macmillan.

Gordy, M. B. and Howells, B. 2004. Procyclicality in Basel II: can we treat the disease without killing the patient? Bank for International Settlements. Available at: http://www.bis.org/bcbs/events/rtf04gordy_howells.pdf, accessed 23 October 2016.

Harvey, A. C. 1989. Forecasting, structural time series models and the Kalman filter. Cambridge University Press.

Harvey, A. C., and Jaeger, A. 1993. Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics,* 8(3): 231-247.

Heid, F. 2003. Is regulatory capital pro-cyclical? A macroeconomic assessment of Basel II. Deutsche Bundesbank working paper.

Hodrick, R. J. and Prescott, E. C. 1981. Postwar U.S. Business Cycles: An Empirical Investigation. *Carnegie Mellon University discussion paper no. 451*. Online: http://www.kellogg.northwestern.edu/research/math/papers/451.pdf Accessed 10 Dec 2016.

Hodrick, R. J., and Prescott, E. C. 1997. Postwar U.S. business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 29(1): 1-16.

Hosszú, Z., Körmendi, G. and Mérő, B. 2015. Univariate and multivariate filters to measure the credit gap. Magyar Nemzet Bank Occasional papers 1178. Online: https://www.mnb.hu/letoltes/mnb-op-118-final.pdf, accessed 23 Nov 2016.

Jain, S., Yongvanich, A. and Zhou, X. 2011. α characteristics of hedge funds, *UBS Alternative Investments*. [online] http://ssrn.com/abstract=2014430, accessed 26 Dec 2013.

Kalman, R. E. 1960. A new approach to linear filtering and prediction problems. ASME Transcripts, *Journal of Basic Engineering*, Series D., 82(2): 35–45.

Kelly, R., McQuinn, K. and Stuart, R. 2013. Exploring the Steady-State Relationship Between Credit and GDP for a Small Open Economy: The Case of Ireland. *Working Paper 1531*, Frankfurt: European Central Bank.

King, R. G., and Rebelo, S. T. 1993. Low frequency filtering and real business cycles. *Journal of Economic Dynamics and Control*, 17(1-2): 207-231.

Koch, W. 2006. Advanced target tracking techniques. In *Advanced Radar Signal and Data Processing*, Educational Notes RTO-EN-SET-086, Paper 2, Neuilly-sur-Seine, France, 2-1–2-34.

Koopman, S. J. and Azevedo, J. V. E. 2008. Measuring synchronization and convergence of business cycles for the Euro area, UK and US. *Oxford Bulletin of Economics and Statistics*, 70(1): 23-51.

Koopman, S. J. and Lucas, A. 2005. Business and default cycles for credit risk. *Journal of Applied Econometrics.* 20(2): 311-323.

Koopman, S. J., and Ooms, M. 2011. Forecasting economic time series using unobserved components time series models. In M. P. Clements, & D. F. Hendry (Eds.), *Oxford Handbook on Economic Forecasting* (pp. 5). Oxford: Oxford University press.

Ley, E., 2006. The Hodrick-Prescott filter. Knowledge Brief for Bank Staff. The World Bank, Washington DC. Online: http://beathespread.com/file/download/16067 Accessed 10 Dec 2016.

Luüs, C. 2005. The ABSA residential property market database for South Africa – key data trends and implications. *BIS Papers No21*. Online: http://www.bis.org/publ/bppdf/bispap21l.pdf, accessed 10 Dec 2016.

Marcet, A. and Ravn, M. O. 2003. The HP-Filter in Cross-Country Comparisons. *CEPR discussion papers.* Online: https://econ-papers.upf.edu/papers/588.pdf, accessed: 10 Dec 2016.

Mise, E., Kim, T. and Newbold, P. 2005. On suboptimality of the Hodrick Prescot filter at time series endpoints. *Journal of Macroeconomics*, 27(1): 53-67.

NCA, 2005. South African National Credit Act 34 of 2005. Online: http://www.justice.gov.za/mc/vnbp/act2005-034.pdf, accessed 22 October 2016.

Ravn, M. O., and Uhlig, H. 2002. On adjusting the Hodrick Prescott filter for the frequency of observations. *The Review of Economics and Statistics*, 84(2): 371-375.

SARB. 2015. Countercyclical capital buffer for South African based on Basel III framework. *Circular 8/2015 issued in terms of section 6(4) of banks Act, No. 94 of 1990.* Online: https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/7005/C8%20of%202015.pdf Accessed 7 Jan 2017.

SARB, 2016. South African Reserve Bank. Online: https://www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx, accessed 15 Nov 2016.

Schweppe, F. 1965. Evaluation of likelihood functions for Gaussian signals. *IEEE Transaction Information Theory*, 11(1): 61-70.

St-Amant, P. and van Norden, S. 1997. Measurement of the Output Gap: A Discussion of Recent Research at the Bank of Canada. *Bank of Cancada Technical Report No. 79.* Online: http://www.bankofcanada.ca/wp-content/uploads/2010/01/tr79.pdf, accessed: 10 Dec 2016.

Thomson, D. and van Vuuren, G. 2017. Attribution of hedge fund returns using a Kalman filter. *Applied Economics*, 47(1): 1 – 17.

Thomson, D. and van Vuuren, G. 2016. Forecasting the South African business cycle using Fourier analysis. *International Business and Economics Research Journal*, 15(4): 175 – 192.

Tommaso, P. and Alessandra, L. 2012. Maximum likelihood estimation of time series models: the Kalman filter and beyond. Munich Personal RePEc Archive, *Business Analytics*, BAWP – 2012_02.

Valle Azevedo, J., Koopman, S. J. and Rua, A. 2006. Tracking the business cycle of the Euro Area: A multivariate model-based bandpass filter. *Journal of Business and Economic Statistics*, 24(2): 278-290.

van Vuuren, G. 2012. Basel III countercyclical capital rules: Implications for South Africa. *South African Journal of Economic and Management Sciences*, 15(3): 309-324.

Visser, D. and van Vuuren, G. 2015. Trading Book Risk Metrics: A South African Perspective. *South African Journal of Economic and Management Sciences,* 19(1): 118-138.

Visser, D. and van Vuuren, G. 2016. Measuring tradeable credit risk: consequences for South Africa. *Submitted for publication to South African Journal of Economic and Management Sciences,* Nov (2016)

Wong, M. 2011a. Credit BuVaR: Asymmetric spread VaR with default. *Journal of Risk management in Financial Institutions*, 5(1): 86–95.

Wong, M. 2011b. Market BuVaR: a countercyclical risk metric. *Journal of Risk management in Financial Institutions*, 4(4): 419–432.

Yakhim, Y. 2001: Business Cycle Fluctuations and the Hodrick-Prescott Filter. Online: www.bgu.ac.il/~yossiya/teaching/macro_graduate/LN1_bc_hpf.pdf, accessed 23 Jan 2011.

Chapter 5

Conclusions and suggestions for future research

5.1. Summary and conclusions

Procyclicality is not isolated to one element of a financial market or economy; it emerges because of the combination of several elements including regulatory requirements and market participant actions. The identification and isolation of a single metric which captures all relevant features of procyclicality is unlikely: regulators and financial institutions must identify the optimal measures and variables which describe its effects to attain macroeconomic stability. The financial crisis of 2008 emphasised the severe effects of behaviour, markets and risk metrics being procyclical in nature. This significantly underestimated phenomenon contributed to both market euphoria and the subsequent turmoil in global finance in the first decade of the 21st century. The replacement of VaR by ES, although an improvement regarding market risk measurement, has not provided a tractable solution in terms of procyclicality.

The BCBS's proposed procyclicality mitigation measure – the CCB (which began to be implemented January 2016) is driven by the credit growth/GDP ratio (which some studies have shown is an unsuitable metric for several economies). However, the system-wide implementation of a CCB may not be a straightforward process as all *bank-specific effects* remain unidentified. For instance, banks in smaller or illiquid economies might struggle to implement minimum countercyclical regulatory rules because of the onerous capital requirements. Further, a bank may be a (positive) outlier in an economy yet it will have to retain capital when other banks have contributed to the economy's overheating.

The BCBS has subsequently suggested an institutional-specific approach to the CCB to address some of these concerns, but this approach brings its own difficulties. If the CCB is institution-specific, the institutions might not be able to pursue opportunities they deem appropriate. If an institution has a good, new lending product with low probability of default debtors, it may be forced to retain a higher level of CCB just because it is outwitting its market competition. The question arises how newer institutions – with rapidly growing credit exposures – will be treated and affected. Such institutions may not be overextending, but rather just *accumulating*, their competitive share of the market.

Regulatory capital recommendations involving procyclicality for financial markets are constantly evolving and may still. A combination of several BCBS publications[10] has been informally labelled as Basel IV (Nooman, 2016). These recommendations aim to regulate the banking environment where complex interconnected financial instruments have historically masked risk and exhibit considerable measurement complexity.

5.1.1. Trading book risk metrics: A South African perspective

The buVaR model used relaxes the assumptions of independent and identically distributed (i.i.d.) returns and stationarity. This reduces the statistical estimation consistency and precision, but such assumptions are untrue for current measures when the market experiences stressed conditions anyway. The buVaR metric was shown by Wong (2011) to be more accurate (rather than more *precise*) than VaR, by providing a 'best guess' of losses. These values are situated somewhere between the VaR measured by traditional methods and a reasonable, capped value. buVaR does not generate a single solution for potential losses, but rather a practical value that may be effectively employed for determining risk capital. This is higher than conventionally-calculated VaR, leading to a higher capital buffer, but this compensates for the complex, fat-tailed loss distribution commonly observed in the market.

buVaR provides a forward-looking alternative to VaR attempting to account for procyclicality while incorporating the benefits of ES. Determining the appropriate length of market cycles is crucial in buVaR in order to calculate an effective alternative history. Fourier analysis and cycle compression provide the length and prominence of market cycles. The analysis in Chapter 2 illustrates that buVaR does detect bubbles and increases required regulatory capital significantly before ES does. This confirms the metric's countercyclical characteristics in the calculation of forward-looking regulatory capital.

5.1.2. Procyclicality in tradeable credit risk: consequences for South Africa

Wong's (2011) credit buVaR model – which provides a risk metric combining both spread and default risk - was employed. Relying on liquid, forward-looking CDS spread data, the model bypasses the problem of risk aggregation by employing a single model under the historical VaR/ES approach. Wong (2011) stressed that, like all VaR approaches, the model is influenced by subjective choices of parameters and thus does not provide a statistically precise measurement. This emphasises the necessity for regulators and banks to cooperate to ensure the "correct" parameters are used in their jurisdiction.

[10] Basel IV comprises: BCBS 306, 319, 347, 362, 303, 279, 352, 355, 325 and 349 (PWC, 2016).

buVaR results using Wong's (2011) original calibrations and assumptions illustrate excessive capital requirement estimates for South Africa and suggested further calibration requirements. A higher bond recovery assumption after default and a higher ω_2 produces more feasible estimates. Applying buVaR to five and 10-year South African government bond CDS spreads produced results showing that buVaR is more responsive and conservative prior to periods of severe CDS spread increases. This highlights the metric's countercyclical properties that would potentially have countered bubble developments. Depicting buVaR results on the same timescale as market implied PDs and the South African credit rating shows that buVaR does ramp up significantly in the pre-crisis bubble development period. However, the model is robust when shocks occur such as the removal of the Minister of Finance in late 2015.

A tractable solution is provided which simplifies the selection of the free parameter, ω_2. Within any jurisdiction, institutions' and policy makers' will have local knowledge of bond recovery and risk-free rates which, in turn, determine S_{Cap}. Using this information, the inflator level can be quickly calculated for any ω_2 and thus, the associated increase in capital can be ascertained. This can be used as a guide for regulatory and institutional capital calibration.

The procyclical nature of financial markets and the way in which its participant's reactions exacerbate this phenomenon are well documented. The BCBS proposed the implementation of a CCB, but this has raised concerns regarding uncertainty whether the right data are used for its estimation: the credit-to-GDP ratio may not be optimal for jurisdictions with unique markets (Drehmann & Tsatsaronis, 2014). Further timing issues are a concern as capital for the buffer can be released immediately, but retention notices must optimally be made 12 months in advance. The credit buVaR model provides a continuous forward-looking metric that is not burdened by timing issues and is not subject to procyclicallity as it does not rely on credit ratings or transition matrices.

5.1.3. Countercyclical Capital buffer: South African filter measurements

The CCB was introduced to limit the effects of procyclicality, but several aspects need to be considered. These include retention and release signals as well as techniques to determine these signals with appropriate variables. If adequately implemented, the chosen metric has the potential to reduce the financial cycle amplitude and thereby, potentially, reduce all credit risk in the financial cycle. The metric may thus lead to a reduction in credit risk regulatory capital: the relationship between the two capital requirements is yet to be fully explored.

This paper applies a Kalman filter to the BCBS-prescribed and other financial variables to determine the appropriate signal for the implementation of the CCB. Results indicate that for different crises results obtained from the Kalman filter and the one-sided HP filter suggest substantially different signals – excluding for the most recent crisis (where the results are similar). This paper corroborates the findings of other studies which find that the credit-to-GDP gap would likely fuel procyclicality rather than dampen it for South Africa if employed as a sole measure. The Small Residential Price Index gap identifies countercyclical signals that would have suggested full CCB retention for substantial periods prior to historical crises. This emphasises that, although the metric used to calculate signals is important, the variable used to calculate these signals is a critical input as the incorrect one may fuel procyclicality. The South African Reserve Bank (SARB) suggested that it would still use the credit-to-GDP as a principal indicator for the CCB, however, it further asserted that it would use other indicators in conjunction with the credit-to-GDP gap (SARB, 2015).

5.2. Contributions

This research has made several contributions all impacting the accomplishment of the stated objectives. All contributions also set the scene for further research to be conducted on the topic of procyclicality and how it is measured and mitigated. All articles present relevant literature regarding procylicality and its relevant components.

Further contributions from the first article include the implementation of a forward-looking market risk metric. This metric suggests increasing regulatory capital before conventional VaR would signal such an increase, thereby confirming the measure's countercyclical capabilities while also incorporating the benefits of ES.

The second article contributes by providing a measure capable of combining both spread and default risk. The measure is countercyclical and only depends on credit spread data rather than backward-looking information like transition matrices. The model is calibrated for South Africa.

The third article argues that the commonly-used (and BCBS-prescribed) HP filter, selected for signalling the implementation of a CCB, can be outperformed by the Kalman filter which raises the question which other filters may also be better suited for the task.

5.3. Suggestions for future research

Procyclicality is broad theme and the research articles in this study investigate several components of it, thus providing several future research opportunities. As the first article investigates trading book risk metrics future research includes include the application of buVaR to considerably more portfolios, indices and commodities with different cycle characteristics. buVaR can also be applied to diversified portfolios which may produce unique results and reveal characteristics about the metric which may warrant further development and research. Observing output from many, disparate sources, fat-tail loss patterns may be evaluated and connections established. The VaR measured under different market cycles (i.e. with different amplitudes (severity) and frequencies) is different using conventional VaR methods; comparing these with buVaR estimates may provide some insight into the subtle interplay between market dynamics and portfolio or single-asset losses.

Alternative histories may also be derived using different metrics, including the HP filter. The buVaR technique and the HP filter (for example) could be applied to relevant data and alternative histories constructed. The results obtained could be compared to establish differences and similarities and, with the benefit of hindsight, could lead research to the superior technique (since backtesting could easily establish which method produced the most accurate VaR estimates).

The article which constitutes Chapter 3 and which focusses on credit risk procyclicality, may provide considerable research opportunities as it, inter alia, combines default and spread risk.Although substantially researched, the complex relationship between market and credit risk and the effects of procyclicality on this relationship are still ambiguous. Future research opportunities include the optimal calibration of the free parameter ω_2 in the Credit buVaR model. This parameter has a significant impact on the model and appropriate guidance is required if it were to be implemented. Research on the parameter would include analysis across multiple economies, markets and scenarios to ensure suitable implementation guidelines are created. Further research may also include investigation on the relationship between model outputs, CDS spreads and actual credit ratings as these were not the central focus of this study.

The final article focussed on metrics to measure CCB signals as well as variables to be used in these measures. Future research opportunities from this article include an investigation into how the Kalman filter approach performs in conjunction with other variables that have been

found to be more suitable for CCB buffers in South Africa than the credit-to-GDP gap. Work could also focus on buffer-release signals and how measures such as the Kalman filter recognises these occurrences. A combination of models (which avoid timing issues) such as Wong's (2011) buVaR model and filter-based approach also present future research opportunities. Solutions to such an approach would be of considerable value to regulators and financial institutions in resolving their current (2017) dilemma regarding CCB timing issues.

The introduction of the CCB and the application thereof presents several research opportunities. The current (2017) one-size-fits-all CCB methodology raises several questions including whether more country classification-specific regulations would be better suited.

Bibliography

Acerbi, C. and Tasche, D. 2002. Expected shortfall: A natural coherent alternative to value at risk. *Economic notes*, 31(2):379-388.

Adrian, T. and Shin, H. S. 2008. Procyclical Leverage and Value at Risk. *Federal Reserve Bank of New York Staff Reports.* Online: www.newyorkfed.org/research/staff_reports/sr338.pdf, accessed 28 Dec 2013.

Aikman, D., A. G. Haldane, and Nelson, B. D. 2015. Curbing the Credit Cycle. *The Economic Journal*, 125(585): 1072–1109.

Akinboade O. A. and Makina, D. 2009. Bank lending and business cycles: South African evidence. *African Development Review*, 21(3): 476-498.

Akinboade O. A. and Makina, D. 2010. Econometric analysis of bank lending and business cycles in South Africa. *Applied Economics*, 42(29): 3803-3811.

Alessandri, P. and Drehmann, M. 2007. An economic capital model integrating credit and interest rate risk in the banking book, *European Central Bank Working Paper Series*, NO 1041 April 2009.

Apel, M., Hansen, J. and Lindberg, H. 1996. Potential output and output gap. *Quarterly Review of the Bank of Sweden*, 3(1): 24–35.

Arnold, T., Bertus, M. and Godbey, J. 2008. A simplied approach to understanding the Kalman filter technique. *The Engineering Economist*, 53(2): 140–155.

Artzner, P., Delbaen, F., Eber, J. and Heath, D. 1999. Coherent measures of risk, *Mathematical Finance*, 9(3): 203–228.

Backus, D. K., Kehoe, J. and Kydland, F. E. 1992. International Real Business Cycles. *The Journal of Political Economy*, 100(4): 745-775.

Balbas, A., Garrido, B. and Mayoral, S. 2009. Properties of distortion risk measures, *Methodology and Computing in Applied Probability*, 11(3): 385–399.

Bank for International Settlements, 2008. Addressing financial system procyclicality: a possible framework, *Note for the FSF Working Group on Market and Institutional Resilience*. Online: http://www.fsb.org/wp-content/uploads/r_0904e.pdf?page_moved=1, accessed 11 Nov 2016.

Bank of England. 2014. The case for a better functioning securitisation market in the European Union. Online: https://www.ecb.europa.eu/pub/pdf/other/ecb-boe_case_better_functioning_securitisation_marketen.pdf, accessed 28 Dec 2015.

Barrell, R., Davis, E., Karim, D. and Liadze, I. 2010. Calibrating macroprudential policy, *NIESER Discussion Papers*, no 354.

Baxter, M. and King, R. G. 1995. Measuring business cycles approximate band-pass filters for economic time series. National Bureau of Economic Research Working Paper No. 5022. Online: http://www.nber.org/papers/w5022.pdf, accessed 10 Dec 2016.

Baxter, M., and King, R. G. 1999. Measuring business cycles: approximate band-pass filters for economic time series. *The Review of Economics and Statistics*, 81(4): 575-593.

BCBS. 1996. Amendment to the capital accord to incorporate market risks. Online: http://www.bis.org/publ/bcbs24.pdf, accessed 18 Nov 2015.

BCBS. 2009a. Guidelines for computing capital for incremental risk in the trading book - consultative document. Online: http://www.bis.org/publ/bcbs149.pdf, accessed 12 Jun 2016.

BCBS. 2009b. Revisions to the Basel II market risk framework (updated 31 Dec 2010). Online: http://www.bis.org/publ/bcbs148.pdf, accessed 12 Jun 2016.

BCBS. 2009c. Principles for Sound Stress Testing Practices and Supervision. *Consultative Document*. Online: www.bis.org/publ/bcbs155.htm, accessed 28 Dec 2015.

BCBS, 2009d. Findings on the interaction of market and credit risk. Online: http://www.bis.org/publ/bcbs_wp16.pdf accessed 12 January 2017.

BCBS. 2010a. Guidance for national authorities operating the countercyclical capital buffer. Online: http://www.bisorg/publ/bcbs187.pdf, accessed 13 Jan 2015.

BCBS. 2010b. Basel III: A global regulatory framework for more resilient banks and banking systems. *Bank for International Settlements*. Online: http://www.bis.org/publ/bcbs189_dec2010.pdf, accessed 21 Nov 2016.

BCBS. 2011a. Capital treatment for bilateral counterparty credit risk finalised by the Basel Committee - Press release. Online: http://www.bis.org/press/p110601.htm, accessed 13 Jun 2016.

BCBS. 2011b. Basel III: A global regulatory framework for more resilient banks and banking systems. Online: http://www.bis.org/publ/bcbs189.pdf, accessed 27 Aug 2016.

BCBS. 2011c. Messages from the academic literature on risk measurement for the trading book. Online: http://www.bis.org/publ/bcbs_wp19.pdf, accessed 28 Dec 2015.

BCBS. 2013. Fundamental review of the trading book: A revised market risk framework. Online: http://www.bis.org/publ/bcbs265.pdf, accessed 22 Oct 2016.

BCBS. 2014. Fundamental review of the trading book: outstanding issues - consultative document. Online: https://www.bis.org/bcbs/publ/d305.htm, accessed 22 Oct 2016.

BCBS. 2015. Interest rate risk in the banking book - consultative document. Online: http://www.bis.org/bcbs/publ/d319.pdf, accessed 1 Jun 2016.

Behn, M., Detken, C., Peltonen, T. and Schudel, W. 2013. Setting countercyclical capital buffers based on early warning models: would it work? *ECB Working Paper Series, no 1604, November.*

Berkowitz, J. and O'Brien, J. 2002. How accurate are Value-at-Risk models at commercial banks?, *The Journal of Finance*, 57(3): 1093–1111.

Bernstein, J., Raputsoane, L and Schaling, E. 2014. Credit Procyclicality and Financial Regulation in South Africa. *Economic Research South Africa.* ERSA Working Paper 445, July 2014.

Bervas, A. 2006. Market liquidity and its incorporation into risk management, Banque de France, *Financial Stability Review*, 8(May): 63–79.

BIS. 2016. Property price statistics. Online: http://www.bis.org/statistics/pp.htm, accessed 22 Dec 2016.

Board of Governors of the Federal Reserve System. 2012. Guidance on Stress Testing for Banking Organizations. *Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency.* Online: www.federalreserve.gov/bankinforeg/srletters/sr1207a1.pdf, accessed 3 Jan 2013.

Borio, C. 2012. The financial cycle and macroeconomics: What have we learnt? *BIS Working Paper No 395.* Online: http://www.bis.org/publ/work395.pdf, accessed 5 Jan 2017.

Borio, C., Furfine, C. and Lowe, P. 2001. Procyclicality of the financial system and financial stability: issues and policy options. *BIS working paper No 1.* Online: http://www.bis.org/publ/bppdf/bispap01a.pdf, accessed 5 Jan 2017.

Boshoff, W. H. 2006. The properties of cycles in South African financial variables and their relation to the business cycle. *South African Journal of Economics,* 73(4):694-709.

Botha, I. 2004. *Modelling the business cycle of South Africa: linear vs non-linear methods.* Johannesburg: PhD thesis - Rand Afrikaans University.

Botha, I. 2009. Modelling the business cycle of South Africa: linear vs. non-linear methods, PhD thesis, University of Johannesburg. Online: https://ujdigispace.uj.ac.za/bitstream/handle/10210/605/master.pdf?sequence=1, accessed 8 Sep 2015.

Brown, K. and Moles, P. 2014. Credit Risk Management. Online: https://www.ebsglobal.net/EBS/media/EBS/PDFs/Credit-Risk-Management.pdf, accessed 1 Jun 2016.

Burns, A. F. and Mitchell, W. C. 1946. Measuring Business Cycles. *National Bureau of Economic Research.*

Burra, P., de Jongh, P. J., Raubenheimer, H., van Vuuren, G. and Wiid, H. 2014. Implementing the Countercyclical capital Buffer in South Africa: Practical Considerations. *South African Journal of Economic and Management Sciences,* 18(1): 105-127.

Canova, F., 1994. Detrending and turning points. *European Economic Review*, 38(3-4): 614-623.

Canova, F., 1998. Detrending the business cycle. *Journal of Monetary Economics*, 41(2): 475-512.

Catarineu-Rabell, E., Jackson, P. and Tsomocos, D.P. 2003. Procyclicality and the new Basel Accord–banks' choice of loan rating system. *Bank of England. Working Paper No. 181*. Online: http://eprints.lse.ac.uk/24863/1/dp464.pdf, accessed 27 Dec 2013.

Chen, J. 2014. Coherence versus elicitability in measures of market risk, *International Advances in Economic Research*, 20(3): 355–356.

Choudhry, M. 2013. An introduction to Value-at-Risk. 5th ed., Wiley: Chichester UK, 224p.

Christiano, L. J. and Fitzgerald, T. J. 2003. The band pass filter. *International Economic Review*, 44(2): 435 – 465.

Claessens, S., M. A. Kose, and Terrones, M. E. 2012. How do business and financial cycles interact? *Journal of International Economics*, 87(1): 178-190.

Cogley, T., and Nason, J. M., 1995. Effects of the Hodrick-Prescott Filter on trend and difference stationary time series: implications for business cycle research. *Journal of Economic Dynamics and Control*, 19(1): 253-278.

Costanzino, N. and Curran, M. 2014. Backtesting general spectral risk measures with application to expected shortfall, working paper. Online: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2514403, accessed 4 Jun 2015.

Coste, C., Douady, R. and Zovko, I. 2011. The StressVaR: a new concept or extreme risk and fund allocation, *Journal of Alternative Investments*, 13(3): 10–23.

Cotter, J. and Dowd, K. 2006. Extreme spectral risk measures: An application to futures clearinghouse margin requirements, *Journal of Banking & Finance*, 30(12): 3469–3485.

Creal, D., Koopman, S. J. and Zivot, E. 2010. Extracting a robust US business cycle using a time-varying multivariate model-based bandpass filter. *Journal of Applied Econometrics*, 25(4): 695-719

Crouhy, M., Galai, D. and Mark, R. 2000. A comparative analysis of current credit risk models. *Journal of Banking and Finance*, 24(1–2): 59–117.

Danielsson, J. 2013. The new market risk regulations. VOX CEPR's Policy Portal. Online: http://www.voxeu.org/article/new-market-risk-regulations, accessed 1 Jul 2015.

Danielsson, J. and Zigrand, J. 2012. On time-scaling of risk and the square-root-of-time rule, *Journal of Banking & Finance*, 30(10): 2701–2713.

Danielsson, J., Jorgensen, B., Sarma, M., Gennady, S and de Vries, C. 2005. Subadditivity re–examined: the case for Value-at-Risk. Discussion paper 549. *Financial Markets Group*, London School of Economics and Political Science, London, UK.

Denzlera, S. M., Dacorognaa, M. M., Müllera, U. A. and McNeil, A. J. 2006. From default probabilities to credit spreads: Credit risk models do explain market prices. *Finance Research Letters*, 3(2): 79–85.

Diebold, F., Hickman, A., Inoue, A. and Schuermann, T. 1998. Converting 1-Day Volatility to h-Day Volatility: Scaling by Root-h is Worse than You Think, *Wharton Financial Institu-*

tions Center, Working Paper 97-34. Published in condensed form as Scale Models, *Risk*, 11: 104-107.

Dionne, G., Pacurar, M. and Zhou, X. 2014. Liquidity-adjusted intraday Value at Risk modeling and risk management: An application to data from Deutsche Börse. Online: http://ssrn.com/abstract=2398620, accessed 1 Jul 2015.

Drehmann, K. and Tsatsaronis, K. 2014. The credit-to-GDP gap and countercyclical capital buffer: questions and answers, *BIS Quarterly Review, March 2014*. Online: http://www.bis.org/publ/qtrpdf/r_qt1403g.pdf, accessed 15 Nov 2016.

Drehmann, M., Claudio, B. Gambacorta, L., Jimenez, G. and Trucharte, C. 2010. Countercyclical capital buffers: exploring options. *BIS Working Papers No 317.* Online: http://www.bis.org/publ/work317.pdf, accessed 10 Dec 2016.

Drehmann, M., Sorensen, S. and Stringa, M. 2008. The integrated impact of credit and interest rate risk on banks. *Bank of England Working Paper,* 339, Online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=966270, accessed 1 Jun 2016.

Du Toit, L. 2008. Optimal HP filtering for South Africa., University of Stellenbosch, Department of Economics. Working Paper.

Duffie, D. and Pan, J. 1997 An overview of Value at Risk, *The Journal of Derivatives*, Spring, 4(3): 7–49.

Eberlein, E., Kallsen, J. and Kristen, J. 2003. Risk management based on stochastic volatility, *The Journal of Risk*, 5(2): 19–44.

Edge, R. and Meisenzahl, R. 2011. The Unreliability of Credit-to-GDP Ratio Gaps in Real-Time: Implications for Countercyclical Capital Buffers. Working Paper 2011-37, Washington DC: Federal Reserve Board.

Emna, R. and Chokri, M. 2014. Measuring liquidity risk in an emerging market: liquidity adjusted Value at Risk approach for high frequency data, *International Journal of Economics and Financial Issues*, 4(1): 40–53.

Escanciano, J. and Pei, P. 2012. Pitfalls in backtesting historical simulation VaR models, *Journal of Banking & Finance*, 36(8): 2233–2244.

Esterhuysen, J. 2016. Private communication.

ETF, 2011. Market-implied default probabilities and credit indexes. ETF.com. Online: http://www.etf.com/publications/journalofindexes/joi-articles/10605-market-implied-default-probabilities-and-credit-indexes.html, accessed 8 Sep 2016.

Fitch Ratings, 2016. Fitch Affirms South Africa at BBB-. Online: https://www.fitchratings.com/site/pr/1005740, accessed 15 Nov 2016.

Fourie, L., Botha, I. and Mears, R. 2011. Credit extension in South Africa: A business cycle perspective for the period 1985 to 2009. *African Journal of Business Management*, 5(34): 13 074-13 083.

G20. 2009. G20 Leaders Statement: The Pittsburgh Summit. Online: https://g20.org/wp-content/uploads/2014/12/Pittsburgh_Declaration_0.pdf, accessed 1 Jul 2015.

Gabrielsen, A., Zagaglia, P., Kirchner, A. and Liu, Z. 2012. Forecasting Value-at-Risk with time-varying variance, skewness and kurtosis in an exponential weighted moving average framework. *Econometrics Journal*, 12(1): 82–104.

Galati, G., Hindrayanto, I., Koopman, S. J. and Vlekke, M. 2016. Measuring Financial Cycles with a Model-Based Filter: Empirical evidence for the United States and the Euro Area. *De Nederlandsche Bank.* Working Paper No. 495.

Galdi, F. and Pereira, L. 2012. Value at Risk using volatility forecasting models: EWMA, GARCH and stochastic volatility, *Brazilian Business Review*, 4(1): 74–94.

Goodhart, C. and Taylor, A. 2006. Procyclicality and volatility in the financial system – the implementation of Basel II and IAS39. In S. Gerlach and P. Gruenwald (eds.) Procyclicality of financial systems in Asia, pp. 230-251. Palgrave Macmillan.

Gordy, M. B. and Howells, B. 2004. Procyclicality in Basel II: can we treat the disease without killing the patient? Bank for International Settlements. Available at: http://www.bis.org/bcbs/events/rtf04gordy_howells.pdf, accessed 23 Oct 2016.

Harvey, A. C. 1989. Forecasting, structural time series models and the Kalman filter. Cambridge University Press.

Harvey, A. C., and Jaeger, A. 1993. Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics*, 8(3): 231-247.

Heid, F. 2003. Is regulatory capital pro-cyclical? A macroeconomic assessment of Basel II. Deutsche Bundesbank working paper.

Hodrick, R. J. and Prescott, E. C. 1981. Postwar U.S. Business Cycles: An Empirical Investigation. *Carnegie Mellon University discussion paper no. 451*. Online: http://www.kellogg.northwestern.edu/research/math/papers/451.pdf, accessed 10 Dec 2015.

Hodrick, R. J., and Prescott, E. C. 1997. Postwar U.S. business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 29(1): 1-16.

Hosszú, Z., Körmendi, G. and Mérő, B. 2015. Univariate and multivariate filters to measure the credit gap. Magyar Nemzet Bank Occasional papers 1178. Online: https://www.mnb.hu/letoltes/mnb-op-118-final.pdf, accessed 23 Nov 2015.

Huang, X., Zhou, H. and Zhu, H. 2009. A framework for assessing the systemic risk of major financial institutions. Finance and Economics Discussion Series, Division of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C. Online: www.federalreserve.gov/pubs/feds/2009/200937/200937pap.pdf, accessed 22 Sep 2016.

IARCP (International Association of Risk and Compliance Professionals). 2012. 120 developments in risk management and compliance, ed. George Lekatis. Online: http://www.risk-compliance-
associa-

tion.com/120_Developments_Risk_Management_Compliance_April_to_June_2012.html, accessed 1 Jul 2015.

International Monetary Fund. 2007. Do market risk management techniques amplify systemic risks?" *Global Financial Stability Report*, October: 52–76.

International Monetary Fund. 2008. Market and funding illiquidity: when private risk becomes public. *Global Financial Stability Report*, April. Online: https://www.imf.org/external/pubs/ft/gfsr/2008/01/pdf/sum3.pdf, accessed 1 Jul 2015.

International Monetary Fund. 2013. Stress testing of banks, Technical Note. *Monetary and Capital Markets Department.* www.imf.org, accessed 3 Jan 2014.

Jain, S., Yongvanich, A. and Zhou, X. 2011. α characteristics of hedge funds, *UBS Alternative Investments*. Online: http://ssrn.com/abstract=2014430, accessed 26 Dec 2013.

JP Morgan. 1996. RiskMetrics Technical Document. Online: http://yats.free.fr/papers/td4e.pdf, accessed 1 Jul 2016.

Kalman, R. E. 1960. A new approach to linear filtering and prediction problems. ASME Transcripts, *Journal of Basic Engineering*, Series D., 82(2): 35–45.

Kelly, R., McQuinn, K. and Stuart, R. 2013. Exploring the Steady-State Relationship Between Credit and GDP for a Small Open Economy: The Case of Ireland. *Working Paper 1531*, Frankfurt: European Central Bank.

King, R. G., and Rebelo, S. T. 1993. Low frequency filtering and real business cycles. *Journal of Economic Dynamics and Control*, 17(1-2): 207-231.

Koch, W. 2006. Advanced target tracking techniques. In *Advanced Radar Signal and Data Processing*, Educational Notes RTO-EN-SET-086, Paper 2, Neuilly-sur-Seine, France, 2-1–2-34.

Koopman, S. J. and Azevedo, J. V. E. 2008. Measuring synchronization and convergence of business cycles for the Euro area, UK and US. *Oxford Bulletin of Economics and Statistics*, 70(1): 23-51.

Koopman, S. J. and Lucas, A. 2005. Business and default cycles for credit risk. *Journal of Applied Econometrics.* 20(2): 311-323.

Koopman, S. J., and Ooms, M. 2011. Forecasting economic time series using unobserved components time series models. In M. P. Clements, & D. F. Hendry (Eds.), *Oxford Handbook on Economic Forecasting* (pp. 5). Oxford: Oxford University press.

Kourouma, L., Dupré, D., Sanfilippo, G. and Taramasco, O. 2010. Extreme Value at Risk and expected shortfall during the financial crisis. Online: http://dx.doi.org/10.2139/ssrn.1744091, accessed 2 Aug 2015.

Krause, A. 2003. Exploring the Limitations of Value at Risk: How Good is it in Practice. *The Journal of Risk Finance.* Winter 2003.

Ley, E., 2006. The Hodrick-Prescott filter. Knowledge Brief for Bank Staff. The World Bank, Washington DC. Online: http://beathespread.com/file/download/16067, accessed 10 Dec 2016.

Luüs, C. 2005. The ABSA residential property market database for South Africa – key data trends and implications. *BIS Papers No21*. Online: http://www.bis.org/publ/bppdf/bispap21l.pdf, accessed 10 Dec 2016.

Marcet, A. and Ravn, M. O. 2003. The HP-Filter in Cross-Country Comparisons. *CEPR discussion papers.* Online: https://econ-papers.upf.edu/papers/588.pdf, accessed 10 Dec 2016.

Marcucci, J. and Quagliariello, M. 2008. Is bank portfolio riskiness procyclical? Evidence from Italy using a vector autoregression, *Journal of International Financial Markets, Institutions and Money*, 18(1): 46–63.

Mise, E., Kim, T. and Newbold, P. 2005. On suboptimality of the Hodrick Prescot filter at time series endpoints. *Journal of Macroeconomics*, 27(1): 53-67.

Mitchell, J. 2014. U.S. Job Openings Hit 13-Year High, *The Wall Street Journal.* Online: http://blogs.wsj.com/economics/2014/08/12/rising-job-openings-quits-point-to-strengthening-labor-market/, accessed 1 Jul 2015.

Moody's Investor Service, 2016. Moody's confirms South Africa's sovereign rating at Baa2. Online: https://www.moodys.com/research/Moodys-confirms-South-Africas-sovereign-rating-at-Baa2-and-assigns--PR_348291, accessed 19 Sep 2016.

Nadarajah, S., Zhang, B. and Chan, S. 2013. Estimation methods for expected shortfall, *Quantitative Finance*, 14(2): 271–291.

NCA, 2005. South African National Credit Act 34 of 2005. Online: http://www.justice.gov.za/mc/vnbp/act2005-034.pdf, accessed 22 Oct 2016.

Nooman, L. 2016. Basel IV spectre looms for battle-worn bankers, *Financial times 14 March 2016.* Online: https://www.ft.com/content/a9d6eb94-ce5d-11e5-831d-09f7778e7377, accessed 15 Nov 2016.

Papaioannou, M. G., Park, J., Pihlman, J. and van der Hoorn, H. 2013. Procyclical behaviour of institutional investors during the recent financial crisis: causes, impacts, and challenges. *International Monetary Fund Working Paper, Monetary and Capital Markets Department*, WP/13/193

Pena, V., Rivera, R. and Ruiz-Mata, J. 2006. Quality control of risk measure: backtesting VaR models, *The Journal of Risk*, 9(2): 39–54.

Penza, P. and Bansal, V., 2001. Measuring market risk with Value-at-Risk. Financial Engineering Series, Wiley: New York, United States, 320p.

Prescott, E. 1997. The pre-commitment approach in a model of regulatory banking capital, *Economic Quarterly*, Federal Reserve Bank of Richmond, Virginia, United States.

PWC, 2016. Basel IV at a glance. Online: http://www.pwc.com/gx/en/services/advisory/basel-iv.html accessed 15 Nov 2016.

Ravn, M. O., and Uhlig, H. 2002. On adjusting the Hodrick Prescott filter for the frequency of observations. *The Review of Economics and Statistics*, 84(2): 371-375.

Rosenberg, J. V. and Schuermann, T. 2004. A General Approach to Integrated Risk Management with Skewed, Fat-Tailed Risks, *Federal Reserve Bank of New York,* Staff Report no. 185. Online: https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr185.pdf accessed 12 January 2017.

Rozga, A. and America, J. 2009. Dependence between volatility persistence, kurtosis and degrees of freedom, *Revista Investigación Operacional*, 30(1): 32–39.

SA NCA, 2005. South African National Credit Act 34 of 2005. Online: http://www.justice.gov.za/mc/vnbp/act2005-034.pdf, accessed 22 Oct 2016.

SARB, 2016. South African Reserve Bank. Online: https://www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx, accessed 15 Nov 2016.

SARB. 2015. Countercyclical capital buffer for South African based on Basel III framework. *Circular 8/2015 issued in terms of section 6(4) of banks Act, No. 94 of 1990.* Online: https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/7005/C8%20of%202015.pdf, accessed 7 Jan 2017.

Schweppe, F. 1965. Evaluation of likelihood functions for Gaussian signals. *IEEE Transaction Information Theory*, 11(1): 61-70.

Shin, H. S. 2013. Procyclicality and the search for early warning indicators, *IMF Working Papers,* no 13/258.

Skoglund, J., Erdman, D. and Chen, W. 2012. On the time scaling of Value at Risk with trading, *Journal of Risk Model Validation*, 5(4): 17–26.

St-Amant, P. and van Norden, S. 1997. Measurement of the Output Gap: A Discussion of Recent Research at the Bank of Canada. *Bank of Cancada Technical Report No. 79.* Online: http://www.bankofcanada.ca/wp-content/uploads/2010/01/tr79.pdf, accessed 10 Dec 2016.

Tasca, P. and Battiston, S. 2012. Market procyclicality and systemic risk, ETH Risk Center – Working Paper Series, ETH-RC-12-012. Online: http://web.sg.ethz.ch/ethz_risk_center_wps/pdf/ETH-RC-12-012.pdf, accessed 2 Jul 2015.

The World Bank. 2015. Global Economic Prospects Online: http://www.worldbank.org/content/dam/Worldbank/GEP/GEP2015a/pdfs/GEP15a_web_full.pdf, accessed 1 Jul 2016.

Thomson, D. and van Vuuren, G. 2017. Attribution of hedge fund returns using a Kalman filter. *Applied Economics*, 47(1): 1 – 17.

Thomson, D. and van Vuuren, G. 2016. Forecasting the South African business cycle using Fourier analysis. *International Business and Economics Research Journal*, 15(4): 175 – 192.

Tommaso, P. and Alessandra, L. 2012. Maximum likelihood estimation of time series models: the Kalman filter and beyond. Munich Personal RePEc Archive, *Business Analytics*, BAWP – 2012_02.

Tripathy T. and Gil-Alana, L. 2010. Suitability of volatility models for forecasting stock market returns: A study on the Indian national stock exchange, *American Journal of Applied Sciences,* 7(11): 1487–1494.

Valle Azevedo, J., Koopman, S. J. and Rua, A. 2006. Tracking the business cycle of the Euro Area: A multivariate model-based bandpass filter. *Journal of Business and Economic Statistics,* 24(2): 278-290.

van Vuuren, G. 2012. Basel III Countercyclical Capital Rules: Implications For South Africa, *South African Journal of Economic and Management Science,* 15(3): 309-324.

Visser, D. and van Vuuren, G. 2015. Trading Book Risk Metrics: A South African Perspective. *South African Journal of Economic and Management Sciences,* 19(1): 118–138.

Visser, D. and van Vuuren, G. 2016. Measuring tradeable credit risk: consequences for South Africa. *Submitted for publication to South African Journal of Economic and Management Sciences,* Nov (2016)

Witzany, J. 2013. Estimating correlation jumps and stochastic volatilities, *Prague Economic Papers*, 2(1): 251 – 283.

Wong, M. 2011a. Market buVaR: a countercyclical risk metric. *Journal of Risk management in Financial Institutions*, 4(4): 419–432.

Wong, M. 2011b. Credit BuVaR: Asymmetric spread VaR with default. *Journal of Risk management in Financial Institutions*, 5(1): 86–95.

Yakhim, Y. 2001: Business Cycle Fluctuations and the Hodrick-Prescott Filter. Online: www.bgu.ac.il/~yossiya/teaching/macro_graduate/LN1_bc_hpf.pdf, accessed 23 Jan 2015.

Yamai, Y. and Yoshiba, T. 2002. On the validity of Value-at-Risk: comparative analyses with expected shortfall, *Monetary and Economic Studies*, 20(1): 57–85.

Yeh, A., Twaddle, J. and Frith, M. 2005. Basel II: a new capital framework, *Reserve Bank of New Zealand Bulletin*, 68(3): 4–15.

Youngman, P. 2009. Procyclicality and Value at Risk, *Bank of Canada Financial System Review*, June: 51–54.