Assessing the suitability of regulatory asset correlations applied to South African loan losses

HJ Stoffberg
22210598

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Supervisor: Prof GW van Vuuren

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Abstract

The Basel Committee on Banking Supervision (BCBS) designed the Internal Ratings Based (IRB) approach, which is based on a single risk factor model. This IRB approach was designed to determine banks' regulatory capital for credit risk. The asymptotic single risk factor (ASRF) model they used makes use of prescribed asset correlations, which banks <u>must</u> use for their credit risk regulatory capital, in order to abide by the BCBS's rules. Banks need to abide by these rules to reach an international standard of banking that promotes the health of the specific bank. To evaluate whether these correlations are as conservative as the BCBS intended, i.e. not too onerous or too lenient, empirical asset correlations embedded in gross loss data, spanning different economic milieus, were backed out of the regulatory credit risk model.

A technique to extract these asset correlations from a Vasicek distribution of empirical loan losses was proposed and tested in international markets. This technique was used to extract the empirical asset correlation, and then compare the prescribed correlations for developed (US) and developing (South Africa) economies over the total time period, as well as a rolling time period. For the first analysis, the BCBS's asset correlation was conservative when compared to South Africa and the US for all loan types. Comparing the empirical asset correlation over a seven-year rolling time period for South Africa and the BCBS, the specified asset correlation was found to be as conservative as the BCBS intended. Comparing the US empirical asset correlation for the same rolling period to that of the BCBS, it was found that for all loans, the BCBS was conservative, up until 2012. In 2012 the empirical asset correlation surpassed that of the BCBS, and thus the BCBS was not as conservative as they had originally intended.

Keywords: Asset correlation, Vasicek distribution, retail loans, credit risk, Basel.

Opsomming

Die Basel-komitee vir Bank-toesighouding (BKBT) het die Interne Graderingsbasis (IGB)-benadering ontwerp, wat gebaseer is op 'n enkele risiko-faktor model. Die IGB-benadering is ontwerp om banke se regulatoriese kapitaal vir kredietrisiko te bepaal. Die Asimptotiese Enkele Risiko-faktor (AERF) model wat die BKBT gebruik maak gebruik van voorgeskrewe batekorrelasies wat banke *moet* gebruik vir hul regulatoriese kredietrisiko, ten einde te bly by die BKBT se reëls. Banke moet by hierdie voorgeskrewe reëls hou om 'n internasionale

standaard te bereik, wat die gesondheid van die spesifieke bank bevorder. Om te bepaal of hierdie korrelasies so konserwatief is soos wat die BKBT dit bedoel het, m.a.w. nie te veeleisend of te toegeeflik nie, is empiriese batekorrelasies ingesluit in bruto verliesdata wat strek oor 'n tydperk met verskillende ekonomiese milieus en onttrek uit die regulatoriese kredietrisiko-model.

'n Tegniek om hierdie batekorrelasies uit 'n Vasicek-verdeling van empiriese lenings verliese te onttrek is voorgestel en getoets op internasionale markte. Hierdie tegniek word gebruik om die empiriese batekorrelasies te onttrek en dan te vergelyk met die voorgeskrewe korrelasies vir 'n ontwikkelde (VSA) en ontwikkelende land (Suid-Afrika) se ekonomieë oor die totale tydperk, asook 'n rollende tydperk. Vir die eerste ontleding is gevind dat die BKBT se batekorrelasie konserwatief was in vergelyking met Suid-Afrika en die VSA vir al die leningsklasse. Wanneer die empiriese batekorrelasie vergelyk word oor die sewe-jaar rollende tydperk vir Suid-Afrika en die BKBT, is die voorgeskrewe korrelasie konserwatief gevind, soos die BKBT se bedoeling was. Wanneer dieselfde vergelyking gedoen word vir die VSA, is bevind dat die BKBT konserwatief was vir alle lenings tot in 2012. In 2012 het die empiriese batekorrelasie die voorgeskrewe korrelasie van die BKBT verbygesteek, en was die BKBT nie so konserwatief soos wat hulle oorspronklik bedoel het nie.

Preface

This dissertation comprises two articles. The first has been submitted to the *South African Journal of Economics* for publication and the second will be submitted to the same journal pending acceptance of the first (to form part of a series).

These studies represent the original work of the author and have not been submitted in any form to another university. Where use was made of the work of others, this has been duly acknowledged in the text.

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1. Introduction

One of the most regulated industries in the world is undoubtedly the banking sector, and thus the rules on bank capital constitute one of the most important aspects of such regulation (Santos, 2001). This importance results from the central role that banks play in financial intermediation, the efforts of the international community to adopt common bank capital standards and the importance of bank capital for bank soundness (Bryant, 1980). In virtually all economies around the globe, banks are among the most important financial intermediaries, because of their function as producers of information, providers of liquidity insurance, and monitoring services. The importance of the regulation of bank capital derives from the function it plays in banks' soundness and risk-taking incentives, as well as the role regulation plays in the corporate governance of banks. According to Berger and Bouwman (2009), the two *central* roles of financial institutions are creating liquidity and risk transformation. These two roles are often jointly referred to as banks' qualitative asset transformation function (Berger & Bouwman, 2009), and it is specifically the liquidity creating role of financial institutions that this study is interested in. To investigate this role, banks' liquidity position and bank regulatory capital are concepts that are central to understanding what banks do, the risks they take and how best those risks should be mitigated (Farag et al., 2013). Next, a closer look at these concepts will be taken, after which the relationship between the concepts will be investigated to better understand the specific central role of banks.

Firstly, regulatory capital, in simple terms, is the amount of capital that banks are required to hold against their assets (Tchir, 2012), as determined by the Basel Committee on Banking Supervision (BCBS) (examined in Chapter 1). The regulatory capital, also known as capital adequacy, needs to address the worst of a bank's potential mark to market loss, or eventual loss, to best cover a bank's loss. Banks need regulatory capital to limit risk and reduce potential, unexpected losses (DeChesare, 2012). There are two key concepts to regulatory capital: risk-weighted assets (RWA) and tiers of capital (Abel & Repullo, 2007). Capital requirements need to be set in relation to the riskiness of assets, rather than just by the individual assets, and this concept is called risk-weighted assets. Since assets are not equally risky, not all capital is equally capable of protecting banks, and therefore different tiers of capital exist. Determining the level of capital reserves required, both concepts are taken into account, but the manner in which it is done falls outside the scope of this investigation. A strong capital reserve ("buffer") reduces the potential risk for banks to fail, and promotes financial stability

by reducing the risk of a large institution with systematic risk, failing and adversely impacting other financial institutions (Yang, 2012). Banks are accordingly expected to maintain capital levels that are sufficient relative to their risk of loss. Supervisors have historically prescribed minimum capital requirements to help ensure capital adequacy, which they expect banks to exceed. These supervisors include the BCBS, and as mentioned previously, will be discussed in further detail in the next sub-section.

In the banking sector, capital requirements and liquidity are distinct but related concepts, and both help in understanding a bank's viability and solvency. This study has just investigated "capital requirements", and thus will look at "liquidity" next. Liquidity is a measure of the ability and ease with which assets can be converted to cash (Board of Governors of the Federal Reserve System, 2014), if financial obligations require this. For banks, examples of liquid assets include cash, central bank reserves and government debt. For a financial institution to remain viable, enough liquid assets are needed to meet banks' near-term obligations, such as withdrawals by depositors (Koehn & Santomero, 1980). Thus, the regulatory capital previously mentioned needs to be liquid enough to help banks meet their *near*-term obligations.

The principal reason why banks have a liquidity problem is that the number of deposits the bank has is subject to constant, and sometimes unpredictable, change (Whittlesey, 1945). Banks can run into solvency and/or liquidity problems when borrowers fail to repay loans or when refinancing cannot be secured by means of replacement liabilities when existing funding is withdrawn (Rossouw, 2014). For financial institutions, increased liquidity can paradoxically be bad, as there is a cost to capital reserves in the form of lost income. Although more liquid assets increase an institution's ability to raise cash on short notice, it also reduces its management's ability to commit credibly to an investment strategy that protects the institution's creditors (Myers & Rajan, 1998). Thus, this relationship between capital reserves and liquidity will be investigated next.

Banks make their money by receiving interest when lending the public money (DeYoung & Rice, 2004), so when the money is tied up in capital reserves, banks lose the potential income. Capital is not "set aside" by banks, or kept somewhere in a safe, capital is rather a form of funding that can absorb losses that could otherwise threaten a bank's solvency. Liquidity problems meanwhile arise due to interactions between funding and the asset side of the balance sheet, when a bank does not hold sufficient cash (or assets that can easily be converted into cash) to repay depositors and other creditors (Farag et al., 2013). There is thus a

strong relationship between capital reserves and liquidity of financial institutions. Not only does a bank need to have enough regulatory capital to protect it from severe economic conditions, this capital needs to be liquid enough to ensure that the bank can use this capital. As mentioned previously, the BCBS is responsible for supervising the banking industry, and thus the history of the BCBS will be inspected next. After that the individual history of the US (United States) and South Africa's banking industry will be further investigated.

1.1 The BCBS

Perceptions of the condition of a sovereign's banks influences opinion about the state of the sovereign, and in turn the welfare of that sovereign. As a result, two accords (so far – November 2014) were designed and disseminated by the BCBS to ensure that the capital reserves of banks are regulated (BCBS, 2004). These regulatory rules that the BCBS prescribes, and that are imposed by the local regulator, cover only a few risks and ignore inter-risk diversification (Botha & van Vuuren, 2010). In the US, these accords are imposed by the Federal Reserve Board (2013) and discussed in Chapter 2. In South Africa, these accords are imposed by the South African Reserve Bank (SARB), to ensure the welfare of the country (Botha & Makina, 2011), and the South African banking industry will be further investigated in Chapter 3. In 1988, the international convergence of bank capital regulation started with the Basle Accord on capital standards (Santos, 2001). The Accord was signed by the G10 countries, and was intended to apply only to internationally active banks. The focus of the Accord was the measurement of capital, and ultimately the definition of capital standards for credit risk (Santos, 2001). In January 1996, the BCBS issued the "Market Risk Amendment to the Capital Accord", which was designed to incorporate within the Accord a capital requirement for the market risks arising from banks' exposure to traded debt securities, foreign exchange, commodities, equities and options (BCBS, 2013a). An important aspect that this amendment introduced, specifically of interest for this study, is that banks are allowed to use internal Value-at-Risk models as a basis for measuring their market risk capital requirements.

In 1989 the BCBS released a proposal for comment to amend the Accord's original framework for setting capital charges for credit risk. The Accord was an attempt by the BCBS to improve the risk management procedures practised by banks, by providing broad categories of weighted risk assets (Norton, 1989). This proposal for a new capital adequacy framework led to the release of the "Revised Capital Framework" in June 2004, which became better known as "Basel II" (BCBS, 2013a). The revised framework, which was designed to improve

the way regulatory capital requirements reflect underlying risks, consists of three pillars, namely:

- Minimum capital requirements,

- Supervisory review of capital adequacy and internal assessment processes, and

- Effective use of disclosure as a lever to strengthen market discipline and encourage sound banking practices.

Basel II's attempt to improve the risk management procedures was done by giving banks the option to either make use of the Standardised Approach from Basel I (where the BCBS specified the risk weights for loan exposure) or the new Internal Ratings Based (IRB) approach. In this approach, specific capital requirement formulas are specified, but there is a degree of freedom regarding the input parameters (BCBS, 2004). The IRB approach uses quantitative estimates like loss given default (LGD) and probability of default (PD) which banks calculate themselves to calculate the amount of regulatory capital required. This method is based on well-established concepts from modern portfolio-based risk management, and has since been scrutinized by the field to evaluate its applicability (Lastra, 2004). It was found that the IRB method provides a sophisticated, user-friendly, and more meaningful capital framework than Basel I (Botha & van Vuuren, 2010).

In December 2010 the BCBS announced proposals, better known as "Basel III", to strengthen global capital and liquidity regulations, which was only done after much deliberation (BCBS, 2010). Basel III was developed in response to deficiencies that arise in financial regulation revealed by the financial crisis of 2008 (Kasekende et al., 2012). The liquidity goal of the BCBS was to promote a more resilient banking sector by making use of two standards in liquidity risk supervision: a short-term standard (Liquidity Coverage Ratio) and a long-term standard (Net Stable Funding Ratio). The capital regulations were also strengthened by increasing the global minimum capital standards for commercial banks and strengthening the definition of capital (Federal Reserve Board, 2008). The BCBS also aims to mitigate pro-cyclicality in the regulatory capital framework, but Basel III will be phased in gradually until 2019 (BCBS, 2013b).

The IRB approach makes use of an asymptotic single-risk factor (ASRF) calculation methodology that allows relatively simple analytical solutions, rather than a complicated multi-factor model that is more difficult to use and is typical of internal bank credit economic capital systems (Kim & Kim, 2007). The IRB approach is nevertheless based upon credit risk modelling

concepts that are basically the same as the capital models banks use to measure portfolio-level risk and to manage and allocate capital across the whole bank (Jacobs, 2010).

This single systematic risk factor required by the ASRF model can be seen as a reflection of the global state of the economy (BCBS, 2005a), and can be used to better interpret the results given by the ASRF. All borrowers are linked by this single risk factor and the strength of the relationship between them is measured by the asset correlation. The BCBS has set predetermined values for these asset correlations within each of the IRB equations that are divided into broad asset classes specified under Basel II, for example residential mortgages, commercial mortgages, credit cards, corporates and consumer lending (Gore, 2006). The asset correlation can thus be used to determine the shape of the risk weight formulas specified by the BCBS. Since different borrowers and/or asset classes depend on the overall economy in a different way, asset correlations will also be asset-class dependent.

Banks must comply with regulatory rules set out by the BCBS in order to sustain capital adequacy and must thus make use of given asset correlation values. This is the specific area that this study will focus on, as discussed later on. In the next sub-section, the history of the US banking industry is investigated, and thereafter the history of the South African banking industry.

1.2 Large global economy: the US

For the US, the trigger of the liquidity crisis of 2007 was an increase in sub-prime mortgage defaults, first noted in February of 2007 (Brunnermeier, 2009). Later in the same year, around June, rating downgrades of tranches like Fitch and Moody's unnerved the credit markets, and by mid-June, two hedge funds (run by Bear Stearns) had trouble meeting margin calls. This led to Bear Stearns injecting $3.2 billion in order to protect its reputation (Kelly & Ng, 2007). On July 26th, 2007, an index from the National Association of Home Builders revealed that new home sales had declined by 6.6% year-on-year, and from then through late 2008, house prices and sales continued to drop (Richter, 2007). Many quantitative hedge funds, which use trading strategies based on statistical models, suffered large losses in August of 2007, triggering margin calls and fire sales. During this time period the perceived default and liquidity risks of banks rose significantly, driving up the London Interbank Offered Rate (LIBOR). To alleviate the liquidity crunch, the Federal Reserve reduced their discount rate to 5.75 % on August 17, 2007, broadened the type of collateral that banks could post, and lengthened the lending horizon to 30 days (La Monica, 2007). Due to the stigma associated with banks bor-

rowing at the Fed's discounted rate, i.e. the fear that discount borrowing might signal a lack of creditworthiness on the interbank market, the banks were reluctant to make use of the discount.

On March 11, 2008, the Federal Reserve announced a $200 billion Term Securities Lending Facility (Fleming et al., 2009), which allowed investment banks to swap agency and other mortgage-related bonds for Treasury bonds for up to 28 days. To avoid the previously mentioned stigmatization, the extent to which investment banks made use of this facility was to be kept secret. The Federal Reserve Bank of New York helped broker a deal over the weekend of March 15, 2008, through which JP Morgan Chase would acquire Bear Stearns with a $30 billion loan from the New York Fed (Kelly et al., 2008). The Fed cut the discount rate even further to 3.25%, and opened the discount window for the first time to investment banks, via the new Primary Dealer Credit Facility (PDCF). The PDCF is an overnight funding facility for investment banks, which temporarily eased the liquidity problems of other investment banks, for example Lehman Brothers (Board of Governors of the Federal Reserve System, 2013b). Consequently, Lehman Brothers barely survived the fallout in March 2008, by making heavy use of the Fed's PDCF, but did not issue enough new equity to strengthen their balance sheet. During a special meeting between all major banks' most senior executives, and the president of the Federal Reserve Bank of New York in September, Barclays and Bank of America refused to take over Lehman without a government guarantee (Brunnermeier, 2009). Lehman Brothers finally filed for bankruptcy on 15 September 2008 (CNBC, 2008), which caused a ripple effect throughout the global financial community.

In October 2008, the US Senate passed a $700 billion bank bailout bill to purchase mortgage-backed securities to help save US banks from defaulting (Amadeo, 2008). Despite the US government's best efforts, trillions of USD were lost as a result of the liquidity crisis, and by September 2014, 503 banks had defaulted in the US (Federal Deposit Insurance Corporation, 2014). In the next sub-section, the same investigation will be done on the history of South Africa's banking sector.

1.3 Developing economy: South Africa

South Africa has quite a history of problems pertaining to liquidity in the banking sector, but it is not nearly as wide-ranging as the US history. As early as the 1970s, Nedcor (or Nedbank) needed a bailout by the SARB, due to a false radio announcement that people were queuing up at a Nedcor branch to withdraw money, when they were actually queuing for the

store next door (Van Rooyen, 2002). The public panicked and all raced to their nearest branch to withdraw their money, which led to the liquidity problems. Another example of this was in 2002, when investors lost confidence in Saambou Bank due to concerns about inadequate provisioning levels and withdrew more than R1bn of savings (Whitfield, 2002). This led to Saambou being bought out by FirstRand's First National Bank (Basson, 2002). Over and above all this, South Africa is dependent on investments from developed countries, and is thus vulnerable to the economic environment of their investors (Asiedu, 2006).

1.4 Problem statement and objectives

A technique to extract the asset correlations from a Vasicek distribution of empirical loan losses has been proposed and tested in international markets. The problem is that this technique has not yet been tested on South African loan loss data, as well as the difference between the empirical asset correlations of developing versus developed countries have not been investigated.

This dissertation is divided into two separate articles. The first article examines the extraction of retail asset correlation, assesses their robustness and compares them to those specified by the BCBS for South African data, as well as presenting an updated version of the US model of Botha and van Vuuren (2010). This will then solve the problem of South Africa not knowing what its retail asset correlation is. The second paper takes this study further and determines a rolling asset correlation for South African data which is then compared to the rolling asset correlation of the US. The general objective of this research is to evaluate the applicability of the BCBS's *given* asset correlations on South African loan loss data, compared to US loan loss data. The specific objectives for the different articles are described next.

Article 1:

The specific objectives of Article 1's research are to:

1.   evaluate empirical asset correlation values using South African loan loss data; and

2.   compare these values with those used by the national regulator.

Article 2:

The specific objectives of Article 2's research are to:

3.   determine and compare the rolling retail asset correlation of South Africa and the US; and

4.   assess the impact of changing these values on regulatory capital during the credit crisis.

1.5   Dissertation outline

This dissertation comprises four chapters. Chapter 1 details the topic of empirical asset corre-
lation, as well as providing a brief history on the BCBS, the US and South Africa's banking
industry.

Chapter 2 presents an empirical investigation into the asset correlations in single factor credit
risk models for South Africa and the US, in article form. Chapter 3 presents the second article
on the evolution of South African and US market-implied asset correlations, also using em-
pirical loan losses. Finally, Chapter 4 concludes the dissertation, discussing the limitations,
and making recommendations on further research.

1.6   Research design and procedure

The aim of the research design is to ensure that every step that is taken to arrive at the con-
clusion is based on sound literature, and can thus be trusted. The research design process used
in the articles is outlined in Figure.1 below.
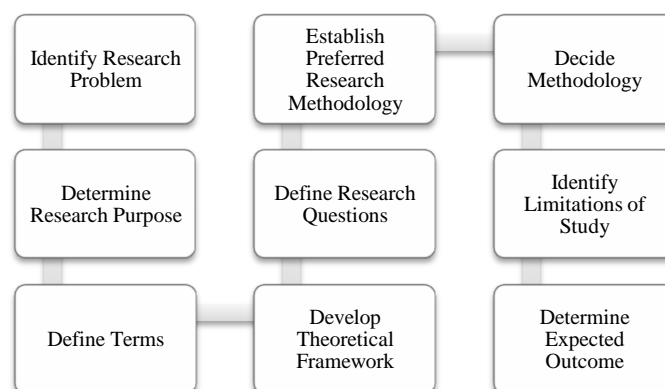
Figure 1.1: Overview of research design process (adapted from Hussey and Hussey, 1997).

The research procedure as set out in Figure 1 has been followed for both articles.

1.7   Conclusion

To ensure liquidity in day-to-day business, banks need to dedicate capital reserves, especially
during severe circumstances. The BCBS and local regulators set parameters which banks
must use to help them calculate the reserves needed to protect them from severe market cir-
cumstances. Defining the terms "capital reserves" and "liquidity" precisely, helps with the
understanding of the role of the BCBS. Examining the history of both South Africa and the

US, shows that further investigation is needed to explore the impact of these economic events on the parameter values.

A research gap is identified in the investigation of empirical asset correlations using the IRB-approach of Basel II. This study aims to fill this gap with thorough research into the topic. Chapter 2 evaluates the empirical asset correlation for South African and US loan losses, over a set period of time. Chapter 3 performs the same calculation, but does this for a rolling period, to evaluate the impact of the economic events. Recommendations for further studies and conclusions drawn from the research are the chief focus of Chapter 4.

2. Asset correlations in single factor credit risk models: an empirical investigation

Asset correlations in single factor credit risk models:

An empirical investigation

Hestia Stoffberg,[1] Gary van Vuuren[2]

Abstract

The Internal Ratings Based approach (based on a single risk factor model) was designed by the Basel Committee on Banking Supervision to determine banks' regulatory credit risk capital. Key inputs of the model – asset correlations – are prescribed by the regulator: relevant banks <u>must</u> use them for capital determination. To ascertain whether these correlations are too onerous or too lenient, empirical asset correlations embedded in loss data spanning different loss milieu were backed out of the regulatory model. These were compared with the prescribed correlations for developed and developing economies and found to be significantly more conservative.

Keywords: *Asset correlation, Vasicek distribution, retail loans, credit risk, Basel.*

JEL Classification: *C134, C16, C53*

1.   Introduction

Banks must dedicate capital reserves to ensure liquidity in their day-to-day business, especially during severe conditions. In South Africa in 2002, investors lost confidence in Saambou Bank due to concerns about inadequate provisioning levels and withdrew more than R1bn of savings (Whitfield, 2002), which led to Saambou being bought out by FirstRand's First National Bank (Basson, 2002). During the financial crisis in 2008, banks in the US suffered a liquidity crisis as sub-prime mortgages defaulted (Grigor'ev & Salikhov, 2009), and as a result trillions of USD were lost when 503 banks had defaulted by August 2014 (Federal Deposit Insurance Corporation, 2014). Liquidity is a significant indication of bank health and since perceptions of banks' health influence opinions regarding the economic health of the sovereign, three accords were designed and implemented by the Basel Committee on Banking Supervision (BCBS) to ensure that the capital reserves of banks are regulated, robust and sufficient (BCBS, 2013). These regulatory rules, however, are imposed by local regulators, but cover only a few risks and ignore inter-risk diversification (Botha & van Vuuren, 2010). In South Africa, these accords are assessed and implemented by the South African Reserve Bank (SARB) and in the US by the Federal Reserve Board (2013). These accords are de-

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[1]Master's student at the School of Economics, North-West University, Potchefstroom Campus, Private Bag X6001, Potchefstroom, 2520, South Africa. This work is submitted in partial fulfilment of the requirements for the Master's degree.

[2]Visiting professor at the School of Economics, North-West University, Potchefstroom Campus, Private Bag X6001, Potchefstroom, 2520, South Africa.

signed to ensure a level playing field for the countries which embrace their principles (Botha & Makina, 2011).

The Basel I accord –introduced in 1988– was the BCBS's attempt to assist banks in the improvement of their credit risk management procedures, by providing broad categories of weighted risk assets (BCBS, 1988). Even at the time it was widely acknowledged that the proposed risk-based capital standards were only the first step in evaluating banks' capital adequacy (Norton, 1989).

The BCBS then assembled and introduced a second accord, Basel II, which, among other aspects, enhanced the treatment of credit risk substantially (BCBS, 2004). This was accomplished by allowing banks the option of using either a Standardised Approach (in which the BCBS specifies the risk weights for loan exposures) or the Internal Ratings Based (IRB) approach (in which the BCBS specifies mandatory capital requirement formulas, but some input parameter flexibility is allowed (BCBS, 2006a)). This IRB approach uses, amongst others, quantitative estimates such as loss given default (LGD) and probability of default (PD) to determine the required regulatory credit risk capital. Advanced banks are permitted to calculate these values themselves. This method is based on well-established and widely-accepted credit portfolio-based risk management concepts, and has since been thoroughly scrutinised by the market to evaluate its applicability (Lastra, 2004; Gup, 2003; Nachane et al., 2005). Overall, the IRB approach provides a sophisticated, user-friendly capital framework that is considerably more meaningful, relevant and accurate than Basel I (Botha & van Vuuren, 2010).

The IRB approach makes use of an asymptotic single-risk factor (ASRF) calculation methodology that provides a simple, closed-form analytical solution which is relatively straightforward to calculate (Vasicek, 1987; 1991). Other approaches employ multi-factor models that are more difficult to implement, use and understand: these are typically used for banks' internal economic capital calculations (Kim & Kim, 2007). The IRB approach is nevertheless based on credit risk modelling concepts that are consistent with the capital models that are used increasingly by large retail banks to measure portfolio-level risk, and to allocate and manage capital across the entire bank (Gordy, 2003).

This single systematic risk factor prescribed by the ASRF model represents the state of the economy as a whole (BCBS, 2005a). The linkage between borrowers is represented by this specific single risk factor, and asset correlation is used to measure the strength of these links (Gore, 2006). The BCBS has calibrated and specified predetermined values for these asset

correlations within each of the IRB equations that are broadly divided by the asset classes that were specified under Basel II, for example corporates, residential mortgages, consumer lending, commercial mortgages and credit cards (Gore, 2006). Since different borrowers and/or asset classes are affected by the overall economy in different ways, asset correlations are asset class-dependent.

To sustain capital adequacy, banks must comply with regulatory rules set out by the BCBS and in doing so, they must use the asset correlation values that the BCBS pre-specifies. Economic capital models provide banks with more accurate criteria to measure and evaluate their overall capital adequacy (Burns, 2004) so implied asset correlations embedded in their empirical loss data, for example, are of considerable interest (Reuters, 2014). Banks trust their own internal models more because banks have control over some of the input parameters in the internal models, whereas with the BCBS's approach, limited control is permitted (Kupiec, 2002).

A technique to extract these asset correlations from a Vasicek distribution of empirical loan losses has been proposed and tested in international markets by Botha and van Vuuren (2010). However, this technique has not yet been applied to South African loan loss data. South Africa, as a developing economy, has experienced failed banks and the consequences thereof (Saambou Bank collapsed in 2002 due to a lack of capital reserves (Whitfield, 2002)) so an investigation into the relevance of the prescribed asset correlations in the South African milieu is warranted. This will help in assessing whether prescribed asset correlations were realistic, too onerous or too conservative and will establish the "true" embedded level of asset correlations present in the South African market. The results gathered from South African loan loss data may then be compared to US (as a developed economy) loan loss experience.

This article explores the mathematical extraction of retail asset correlation from empirical loan losses. It assesses their robustness and compares them to those specified by the BCBS for South African loan loss data. These values are further compared with empirical asset correlations gathered from US loan losses, to determine whether discrepancies exist between the treatment of developed and developing economies by national regulators.

The remainder of this article proceeds as follows: Section 2 explores existing literature, and Section 3 establishes the mathematical formulation of the Vasicek asymptotic single risk factor model and determines a mathematical methodology to extract the relevant empirical correlations using the Vasicek formulation and empirical loan loss data. Section 4 provides the

results obtained from the analysis and a discussion of the results. Section 5 concludes the study.

2.   Literature review

Some research has been undertaken to explore asset correlation in credit-risky portfolios (see, for example, Lee, Lin & Yang (2011) and Byström (2011). The *applicability* of the asset correlation on loan loss data, however, is rarer, and thus further review of this is necessary. Botha and van Vuuren (2010) found that the BCBS's specification of asset correlation is applicable and conservative enough for loan loss data gathered from the US. The Vasicek distribution was used to reverse-engineer asset correlations from empirical loan losses. Botha and van Vuuren (2010) concluded that the embedded empirical correlations – calculated from the gross loan loss data – are lower than the pre-specified correlations that were set by the BCBS, and thus the latter introduce a level of conservatism intended by the BCBS. The research undertaken also indicated how the empirical asset correlations could be calculated using only gross loss data. The way in which empirical correlations change over time was also explored. Studies such as these benefit banks which have established their own internal measures of correlation for economic and regulatory capital purposes. Further investigation into the empirical correlations of other countries will help to evaluate further the BCBS's pre-specified correlation, to see to what extent the BCBS's correlation introduces conservatism to the credit risk IRB framework. It is important to ensure that the capital reserves the banks calculate will be enough to carry them through every economic event, especially in South Africa which is dependent on investment from larger economies (Lederman & Mengistae, 2013). Considerable differences between the BCBS's asset correlation and retail asset correlations were found for residential mortgages. This study updates the previous US correlation data and compares South African loan loss experiences to those encountered in the US.

The BCBS's specified asset correlations (Table 1) are either fixed or vary only with the probability of default (PD) of the loan types. Each correlation specified by the BCBS can be calculated and compared to the empirical asset correlation found by the model.

Table 1: Asset correlations to be used under Basel II's foundation IRB (BCBS, 2005a)

Loan type	Correlation
Residential mortgages	Fixed (15%)
Qualifying revolving retail exposures	Fixed (4%)

Other retail		$0.03 \cdot \left(\dfrac{1 - e^{-35PD}}{1 - e^{-35}} \right) + 0.16 \cdot \left(\dfrac{1 - e^{-35PD}}{1 - e^{-35}} \right)$
High volatility commercial real estate	Varies with PD	$0.12 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.30 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right)$
Corporate, sovereign and bank exposures		$0.12 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.24 \cdot \left(1 - \dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right)$

In Duchemin, Laurent and Schmit (2003) an asset correlation for automotive lease exposures was measured using a single systematic factor ordered probit model, in which debtors' status was limited to survival-state and default-state. This specific model made use of a restricted version of CreditMetrics™ (Gordy, 2000), since this model encompasses a broader notion of credit risk. Duchemin *et al*. (2003) came to similar conclusions as Botha and van Vuuren (2010) in that the empirical correlations they estimated were lower than the correlations specified by the BCBS. In Duchemin *et al.* the BCBS's prescribed asset correlation was found to be conservative. The authors suggested that the volatility of the PD be taken into account, to establish a more accurate empirical asset correlation. Since data in developing countries like South Africa are scarce, this will not be possible in the proposed model of Botha and van Vuuren (2010).

Chernih, Vanduffel and Henrad (2006) undertook an analysis of corporate defaults and the impact of asset correlations. They found that asset correlations are only one source of dependence and that modelling dependencies other than unexpected losses (such as the dependence between PD and LGD) will be under-estimated unless asset correlations embedded in the default data are increased. They deduced that the best source of default correlations can be found when default data are used for the calculations, as no intermediate process is assumed. But they also admitted that default data are often sparse or unattainable, and this makes the estimation difficult. This research employs data from all available commercial banks for the US, rather than the Top 100 that Botha and van Vuuren (2010) used. For South Africa, the only available data were collected from the SARB.

Since the first accord was proposed by the BCBS in 1988, and later as amendments were added and other accords were proposed and implemented (1992 and 2008), banks have developed sophisticated internal ratings-based models to suit their own preferences and risk profiles. Some academic research has been published on credit risk modelling for corporate loans, Fatemi and Fooladi (2006) found that identifying counterparty default risk was the single most important purpose served by the credit risk models that they utilised. Little aca-

demic research has, however, been published on retail portfolio risks, and EAD (exposure at default), LGD and PD data collected by banks, are often thinly dispersed and lacking in detail (Gore, 2006). According to Pillar 3 disclosure requirements, banks were requested by the BCBS to disclose qualitative and quantitative information about their remuneration policies from 1 January 2012 to solve this problem (BCBS, 2011). This revised version of the Pillar 3 disclosure framework, will lead to better data collection of EAD, LGD and PD from banks, but are only in the consultation phase (BCBS, 2014a), and thus the lack of disclosure also proved to be a limitation to this study. This difficulty exists because, while a few large banks have utilised some form of retail loan analysis, most banks continue to utilise the BCBS's rules without any consideration to whether or not realistic outcomes would be produced by the BCBS-specified parameters (Dev, 2006). A real need exists, therefore, for the development of a practical methodology to determine implied asset correlations from retail loan portfolio data. Botha and van Vuuren (2010) developed a non-exhaustive presentation, anal-ysis and evaluation of the Vasicek distribution, to solve the above-mentioned problem. This methodology will thus be applied to South African data as well Botha and van Vuuren's (2010) results (using updated data).

3. Methodology

3.1 Vasicek

The Vasicek distribution was reverse-engineered to determine the retail asset correlation of South Africa as well as the US (Botha & van Vuuren, 2010). Vasicek (1987; 1991; 2002) used a Merton-type model to derive an expression for the distribution of credit portfolio losses. Vasicek's assertion that the cumulative probability that the portfolio loss L, will be less than some variable, x, is given by:

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

where ρ is the asset correlation between all loans and the systematic single risk factor; $N[\dots]$ refers to the cumulative standard normal distribution; $N^{-1}[\dots]$ refers to the inverse standard normal cumulative distribution function; and p is the average probability of default for the portfolio. This cumulative distribution describes the credit portfolio losses and is driven by two parameters (p and ρ), defined over the interval $0 \leq x \leq 1$. This is given by:

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

and defines the total loss shown in Figure 1. Where $0 < \rho < 1$ and $p > 0$. As $\rho \to 0$, the distribution converges to an $N(0,1)$ (or normal) distribution with probability functions: $1 - p$ and p respectively. This indicates that $F(x; p; \rho) = 1 - F(1 - x; 1 - p; \rho)$ and when $p \to 0$ or $p \to 1$, the distribution becomes concentrated at $L = 0$ or $L = 1$ respectively.
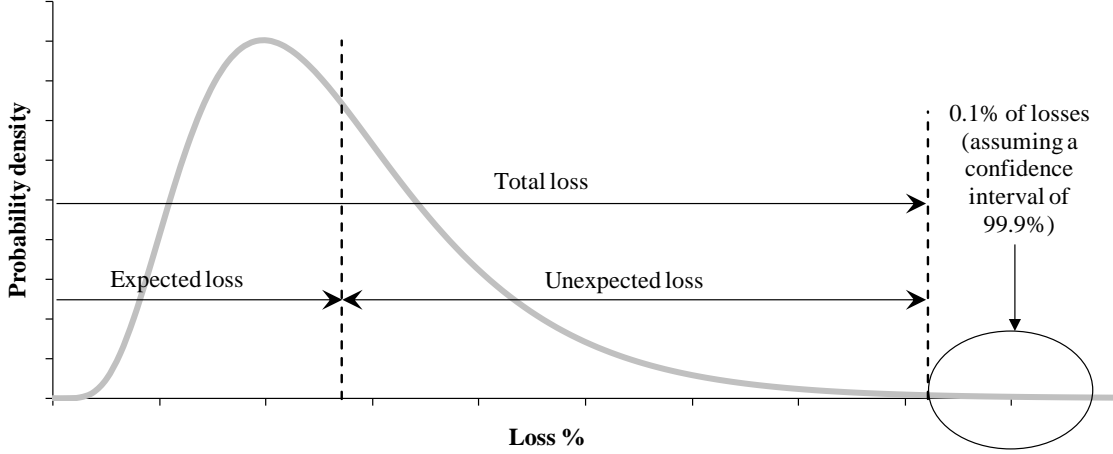
Figure 1: A typical loss distribution in which total loss = the total loss at the 99.9[th] percentile. (Botha & van Vuuren, 2010)

The highly skewed and leptokurtic loss distribution has the following density:

$$f(x; p; \rho) = \sqrt{\frac{1-\rho}{\rho}} \cdot \exp\left[\frac{1}{2}\left(N^{-1}(x)\right)^2 - \frac{1}{2}\left(\frac{\sqrt{1-\rho} \cdot N^{-1}(x) - N^{-1}(p)}{\sqrt{\rho}}\right)\right], \qquad (3)$$

and it is uni-modal with the mode located at:

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

The inverse of this distribution − i.e. the α-percentile value of L is given by:

$$L_\alpha = F(\alpha; 1 - p; 1 - \rho). \qquad (5)$$

All the relevant features of a typical and skewed distribution, for a collection of loan losses, are provided in Figure 1. The 'total loss' (L) is a Basel-*defined* point − in this case, the point below which 99.9% of all losses fall as specified by the BCBS (2005a); and expected loss (EL) is the *average* portfolio (Botha & van Vuuren, 2010). The area under the curve in Figure 1, to the left of the total loss position, represents 99.9% of all portfolio losses, the unexpected loss (UL) however, depends upon the defining of the total loss point, which is the difference between the total- and the expected portfolio-loss.

The procedure for extracting empirical asset correlations from loss data has been created by Botha and Van Vuuren (2010) is:

1. Source gross loss, time series data, as a percentage of total loan value.

2. Calculate the mode (L_{mode} in Equation 4) and the mean (p in Equations 2-5). These values are acquired from the simple *average* gross loss (p) and the most *prevalent* gross loss L_{mode}, over the specified time period.

3. The empirical asset correlation may now be manipulated by using Equation 4:

$$\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)} = \sqrt{\frac{1-\rho}{1-2\rho}}.$$

Thus,

$$\left(\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)}\right)^2 = \frac{1-\rho}{(1-2\rho)^2},$$

substituting

$$\xi = \left(\frac{N^{-1}(L_{\text{mode}})}{N^{-1}(p)}\right)^2,$$

gives:

$$\xi(1-2\rho)^2 = 1-\rho$$

$$4\xi\rho^2 + (1-4\xi)\rho + (\xi-1) = 0$$

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

$$\rho: \frac{(4\xi-1)\pm\sqrt{8\xi+1}}{8\xi}. \tag{6}$$

In Botha and Van Vuuren (2010) it was assumed that only the smaller of the two possible values for ρ should be used. This work, however, makes no such assumption and calculates both ρs to ascertain which one provides an *economically feasible* UL.

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

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

and

$$\text{Gross total loss} = N\left[\frac{N^{-1}(p)+\sqrt{\rho}\cdot N^{-1}(\alpha)}{\sqrt{1-\rho}}\right].$$

The gross total loss at a specified confidence level is the sum of unexpected and expected gross losses ($UL^{99.9\%} + EL$).

The unexpected loss at a 99.9[th] percentile:

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

but $EL = p$, the portfolio expected loss, and as gross loss data are used, this value is also *portfolio* probability of default (since $LGD = 1$). Thus:

$$UL^{99.9\%} = N\left[\frac{N^{-1}(p) + \sqrt{\rho}\cdot N^{-1}(0.999)}{\sqrt{1-\rho}}\right] - p. \qquad (7)$$

No assumptions regarding recoveries are made. Both sides of Equation 7 can be multiplied by the LGD, when the analysis is complete and all the values calculated, to calculate the UL in the 'net loss' sense (also the total loss estimates used in the Pillar 1 equations of the BCBS formulation). The $UL^{99.9\%}$ is thus presented here as a *gross* unexpected loss.

3.2   Data and analysis

The data span some 28 years (i.e. 1985Q1 to 2014Q2 for both the US and SA). The South African data were collected from the SARB (Venter, 2014) by taking the monthly impaired advances as a percentage of the total loans on the balance sheet for the time period January 2001 to April 2014. The US data were compiled from the quarterly Federal Financial Institutions Examination Council Consolidated Reports of Condition and Income (FFIEC, 2014). Charge-offs (the values of loans and leases removed from the books and charged against loss reserves) from all commercial US banks are measured by consolidated domestic and foreign assets, and are not seasonally adjusted for the time period 1985Q1 to 2014Q1. Annualised charge-off rates (as calculated from the report of condition and income), net of recoveries and outstanding at the end of each time period, are used by the US Federal Reserve. The flow of a bank's net charge-offs (gross charge-offs − recoveries) during the time period, divided by the average level of its loans outstanding over that period, are charge-off rates for any category of loan. To express these ratios as annual percentage rates, the ratios are multiplied by 400 for the US, and 1 200 for South Africa (Federal Reserve Board, 2008).

To convert gross losses to net losses, use:

$$\text{net losses} = \text{gross losses} \times LGD.$$

Average US LGDs used in the model were obtained from the BCBS's 5th quantitative impact study (BCBS, 2006b), using the "G10 group 1: including US" group. The LGD averages for the different retail portfolios can be seen in Table 2.

Table 2: LGD averages for the different retail portfolios

Residential mortgage	20.3%
Qualifying revolving	71.6%
Other retail	48.0%
HVCRE	35.0%.

For the approximation of downturn LGDs, a principles-based approach was proposed by the BCBS (2005b). This approach requires banks to identify certain specified downturn conditions and the inauspicious dependencies between recovery and default rates. Banks must produce LGD parameters for their exposures from the dependencies between default and recovery rates, which are consistent with specific downturn conditions (Miu & Ozdemir, 2006). The BCBS made an inherent assumption that a credit risk model with systematic correlation between PD and LGD using long-term LGD inputs should give comparable capital to a credit risk model, without correlated PD and LGD using downturn LGD inputs. Mean LGDs need to be increased by between 35% and 41% in order to compensate for the lack of correlation (Smit, 2009). Downturn LGDs were produced by increasing the LGDs used in this study by 37.5% (the average recommended increase to compensate for the lack of correlation).

First, the effect of the different approaches on the asset correlation is explored. Even though losses – which are repeatedly assumed to be highly skewed and leptokurtic – do not always conform to the Vasicek distribution, this pattern is used to fit the loss data.

Next, empirical correlations from South African data (extracted from the loss data and deducted from the Vasicek distribution) are compared with BCBS *specified* asset correlations conducted using the entire time span mentioned earlier.

Finally, the empirical correlations are compared with the empirical correlation of the US data, to determine how conservative the BCBS assumptions are regarding developing economies such as South Africa, versus developed countries such as the US.

3.2.1 Effect of different approaches

The Vasicek distribution is used to describe the dispersion of credit losses of many banks whose local regulators have approved the banks' usage of the IRB approach. However, many fat-tailed, leptokurtic distributions exist and may be used as a 'best fit' to the loss data. This

article limits its scope to the Vasicek distribution: Botha and van Vuuren (2010) showed that the Vasicek distribution provided a considerably better fit to the empirical loan loss data than, for example, the beta distribution.

Empirical asset correlations were compared to the Vasicek distributions by using several retail loan classes, in Equation 6 and Equation 7.

From Equation 7:

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

with $p + UL^{99.9\%}$ being known empirically from loan loss data.

Thus:

$$N^{-1}(p + UL^{99.9\%}) \cdot \sqrt{1 - \rho} = N^{-1}(p) + \sqrt{\rho} \cdot N^{-1}(0.999)$$

with ρ the only unknown.

Letting $\omega = N^{-1}(p + UL^{99.9\%})$, $\pi = N^{-1}(p)$ and $\psi = N^{-1}(0.999)$ and squaring both sides gives:

$$\omega^2 \cdot (1 - \rho) = \pi^2 + \psi^2 \cdot \rho + 2\pi\psi \cdot \sqrt{\rho}$$
$$0 = (\psi^2 + \omega^2) \cdot \rho + 2\pi\psi \cdot \sqrt{\rho} + (\pi^2 + \omega^2)$$

Which is a quadratic in $\sqrt{\rho}$ with solutions:

$$\rho: \left[\frac{-2\pi\psi \pm \sqrt{(2\pi\psi)^2 - 4 \cdot (\psi^2 + \omega^2) \cdot (\pi^2 - \omega^2)}}{2 \cdot (\psi^2 + \omega^2)}\right]^2 \tag{8}$$

and which is easily solved as ω, π and ψ are all known quantities. $N^{-1}(p + UL^{99.9\%})$ will then simply be the inverse normal distribution of the 99.9[th] percentile of total losses.

4.   Results

A summary of the asset correlations that should be used in the IRB approach, specified by the BCBS, can be seen in Table 1 in Section 2. For South Africa, the "Corporate, Bank and Sovereign" calculation will be used, as confirmed by Hill (2012). The calculation to be used for the US data is subject to the different retail loan classes (Table 1). The Basel-specified asset correlations were compared with the empirical asset correlations calculated using all the gross loss data (using Equation 6 and 8), as shown in Figure 2(a) and (b).
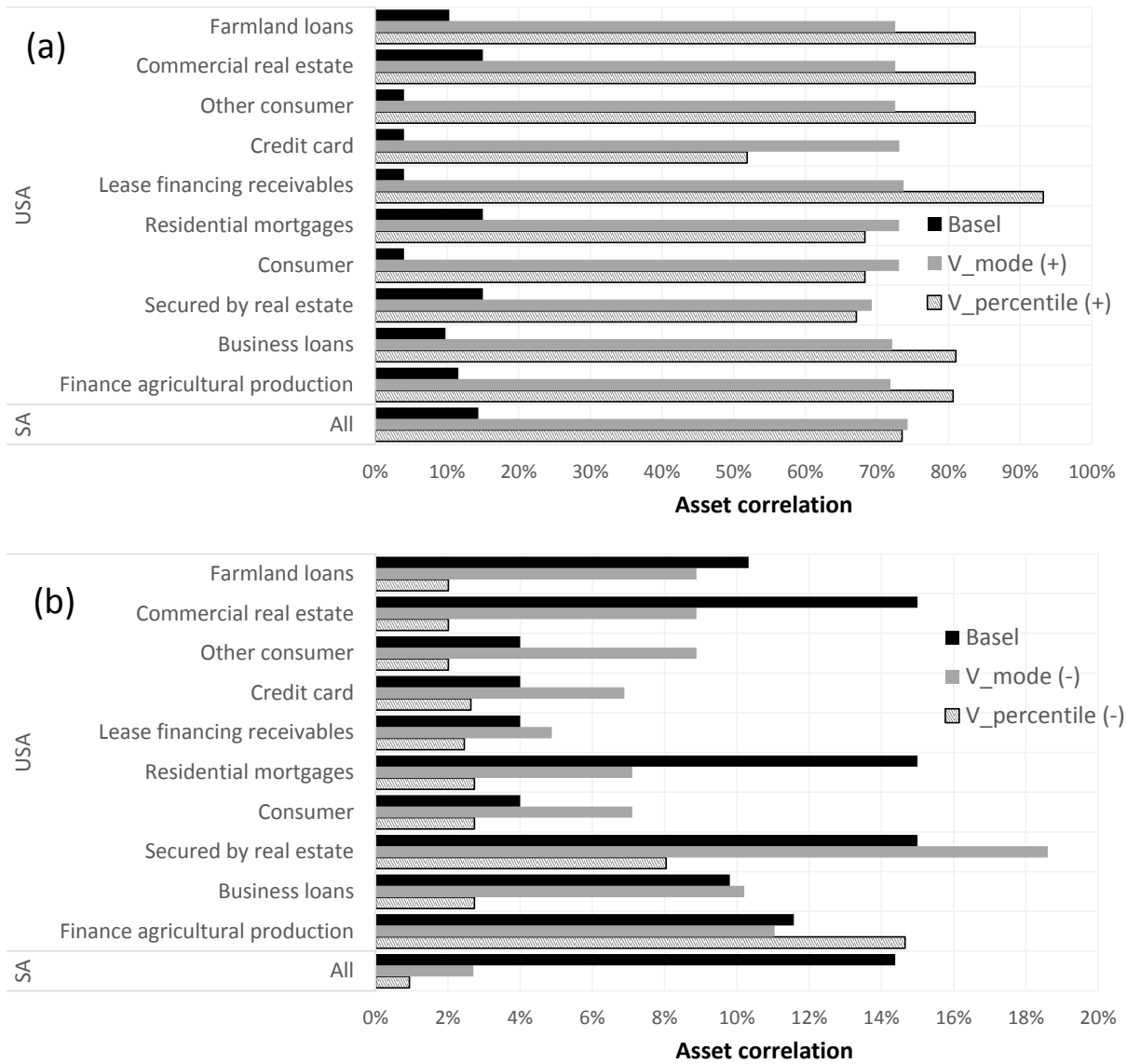
Figure 2(a): Comparison of empirical asset correlations (derived from the Vasicek distributions) and Basel II specified asset correlations for South Africa over the period January 2001 to April 2014 and **(b)** for the US over the period 1985Q1 to 2014Q2.

With V_{mode} the correlation determined using Equation 6 and $V_{percentile}$ the correlation was determined using Equation 8. Figure 2(a) and (b) shows that although both positive and negative signs are included in the mathematics (Equations 6 and 8), the addition part (Figure 2a) may be safely omitted since meaningless results are obtained if it is used. Only the subtraction part (Figure 2b) should be used to obtain economically reasonable values. Although Botha and van Vuuren (2010) had assumed this, this has now been demonstrated: future research may safely ignore the positive solution. For the remaining results, these calculations were omitted.

Figure 3(a) illustrates the cumulative density function for the respective approaches, as well as the cumulative empirical loss data for South Africa for the time period 2001 to 2014. Figure 3(b) shows the density functions for the different approaches, as well as the empirical losses. Figure 4(a) and (b) shows the equivalent density and cumulative functions for the US (all loans) for the period Q1 1985 to Q1 2014. Visually seen from the graphs, the Vasicek distribution formulation, using both approaches, closely fits the empirical data. This was confirmed using the Kolmogorov-Smirnov (K-S) test for goodness of fit (Massey, 1951). South African and US losses were found to follow both specified Vasicek distributions at the 0.05 level. The analysis performed does not significantly prefer one approach above the other, and thus both must be used.
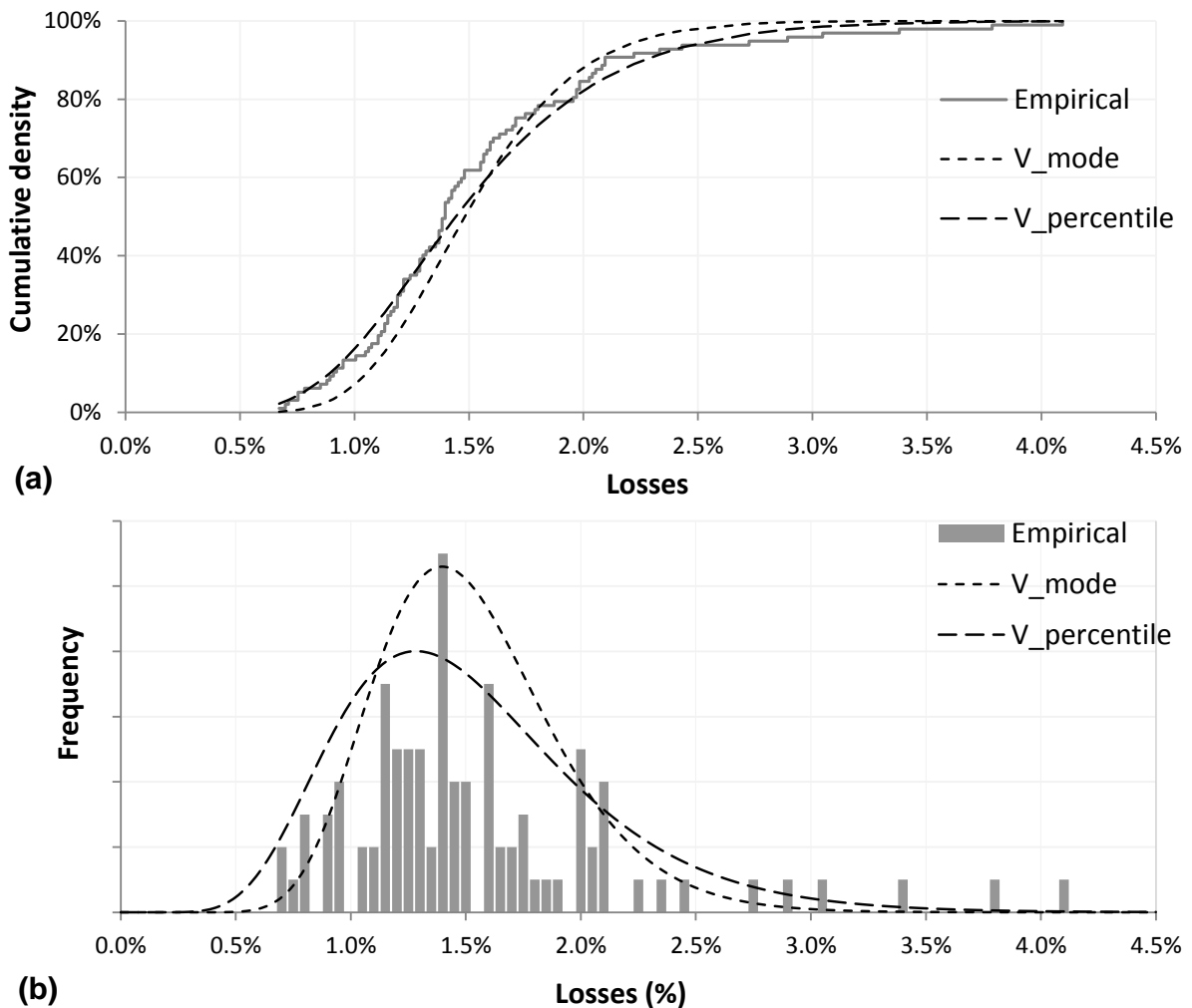
Figure 3: (a) Cumulative and (b) density function for South African loan losses from January 2001 to April 2014.
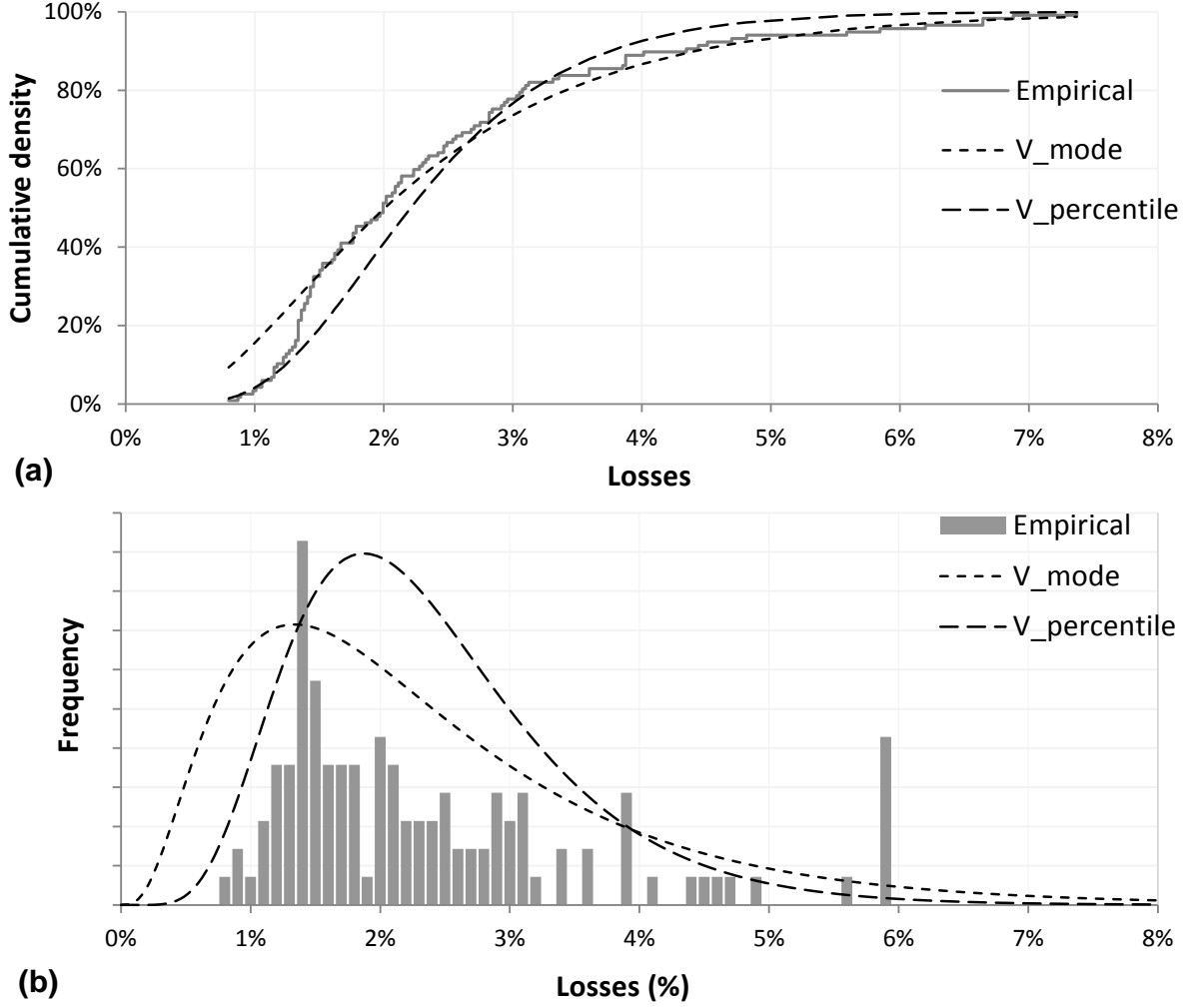
Figure 4: (a) Cumulative and (b) density function for US (all loans) loan losses from January 2001 to April 2014.

Using the 99.9th percentile loss in Equation 8 ($V_{percentile}$) the BCBS's specified correlations are on average two times higher than the empirically-measured correlations, but are moderately similar for most retail asset classes as shown in Figure 2(b). The only exception is for the financing of agricultural production, where this method proves to be higher than the specified correlation of the BCBS. This can be because agricultural production is seasonal, but the true cause is unknown and can be the basis of a future study. The South African empirical correlation is roughly half of that of the US empirical correlations. Using this approach, the BCBS specified asset correlation is more conservative than the empirical asset correlation by a factor of 1.5, which has been expected and is accepted as the BCBS is more conservative. Again, the only exception is for the financing of agricultural production.

Using the mode approach (Equation 6 and V_{mode}) it can be seen in Figure 2(b), that the Basel formulation is not always conservative enough for the US. For South Africa, as well as cer-

tain loans of the US, the BCBS is conservative enough to ensure that the empirical asset correlation is covered. For the remainder, this is not the case and further research should establish the cause of this.

In Figure 5, capital charges for each asset class for the two different countries are given using the three approaches. A *downturn* LGD must be used in the IRB approach, to take into account the omission of PD and LGD correlations (BCBS, 2006b), which are given in Table 2. Again, the capital charges calculated using the 99.9[th] percentile approach are lower than the specified BCBS capital charges for the most part, again except for the financing of agricultural production. This is advantageous for the banks, as it provides the necessary conservatism that the BCBS intended. Using the approach found in Equation 6 (V_{mode}), it is evident that the BCBS's specified capital charges are not always empirically founded enough, which could indicate that the banks' liquidity may not be enough to carry their losses. With credit card, consumer, and other consumer loans in the US, the BCBS's specified capital charges fell short by 0.70%, 0.88% and 1.74% respectively. Since all three of these classes fall under the "Qualifying revolving" asset class of the BCBS, it implies that the required capital charge of the BCBS for this specific asset class is insufficient to ensure enough capital reserves. Capital charges relative to the BCBS-specified charges are shown in Figure 5.
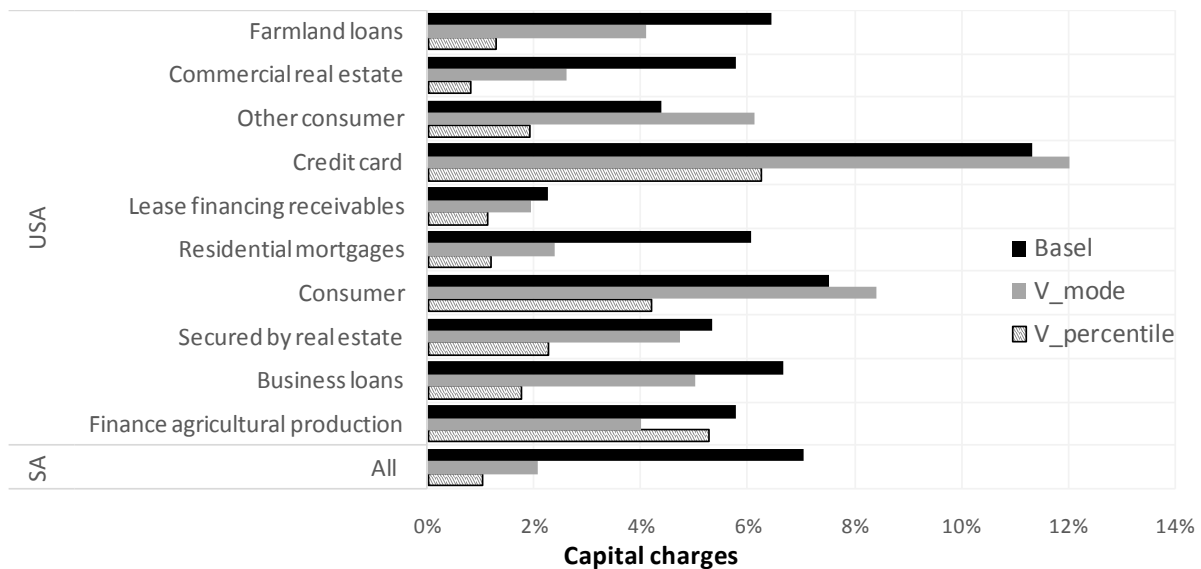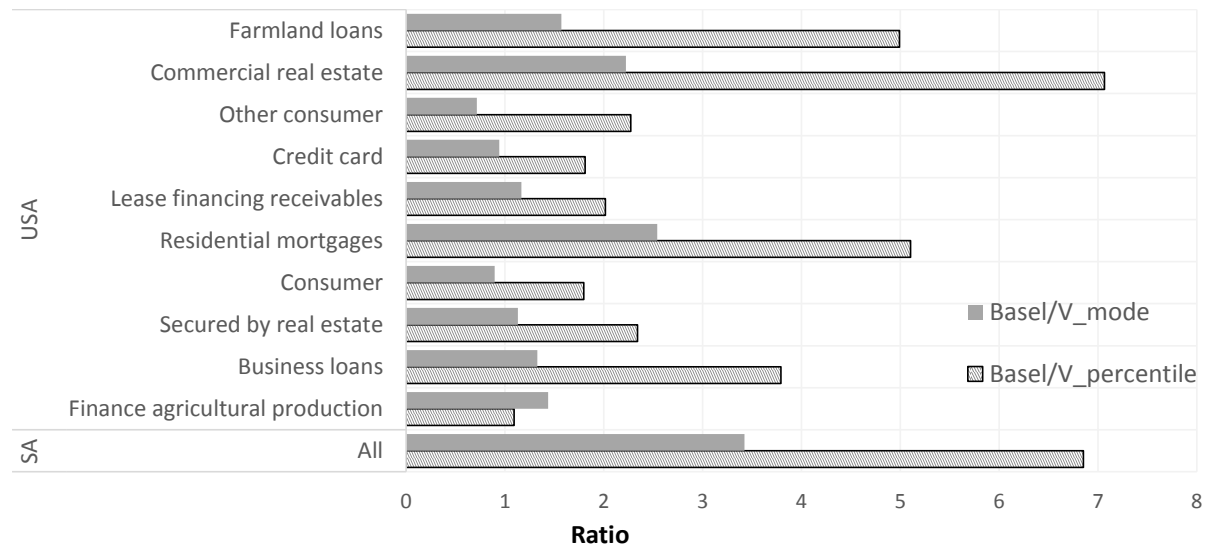

Figure 4: Comparison of capital charges, where with the BCBS capital charges, specified correlations and downturn LGDs were used; and for the two Vasicek-approaches, implied correlations and standard average LGDs were used.

Figure 6 demonstrates that the BCBS-specified capital requirements are more conservative for many developing economy loans, such as South Africa, with the BCBS being 3.5 times

more conservative using the V_{mode} approach and 6.9 times using the $V_{percentile}$ approach) than a developed country like the US (with the BCBS being 2.5 times more conservative using the V_{mode} approach and 2.7 times more using the $V_{percentile}$ approach). The only exception is commercial real estate: using the $V_{percentile}$ approach leads to capital levels that are 7.1 times *less* conservative than those required by the BCBS. This makes sense, as developing countries' banks are not as financially secure and thus may require additional capital to ensure they can be protected against defaults. The empirical capital charge for South African banks total credit risk is about 1%, indicating that the BCBS may be too cautious for developing economies (Figure 5).

From Figure 6 the 99.9[th] percentile approach ($V_{percentile}$) is considerably more conservative in the US, while the average approach (V_{mode}) is more conservative in South Africa.

Figure 5: Comparison of capital charge ratios (relative to Basel capital charges).

Although the BCBS has repeatedly stressed a large enough capital cushion to protect banks from insolvency and emphasised the goal of conservatism (Carver, 2014), it is clear from the empirical data that this is not always the case. In some cases (Other consumer loans) the ratio of the BCBS prescribed capital charge to the empirical capital charge is as low as 0.7. Using this current formulation from the BCBS, few parameters exist that can be altered to make the cushion bigger, especially if banks use the IRB approach for analysing their credit risk. The LGD and asset correlation are some of the few parameters that can be adjusted. The manner in which the asset correlation is calculated clearly impacts on the regulatory capital cushion to shield the banks from insolvency.

As there is a cost to maintaining capital, the bigger the cushion, the higher the costs. Banks should thus perform a balancing act between having enough capital reserves, and limiting the opportunity costs of having the capital reserves. Large retail banks will, under Basel II, have a cost (and with it a pricing) advantage when capital requirements are lower. For Basel II banks to achieve higher returns on equity (ROE) more easily, lower capital requirements are needed. For smaller community banks to compete with the cost advantage and higher ROEs of Basel II banks, they may be forced to make concessions in pricing and underwriting guidelines that could limit their profits, and ultimately limit their viability (Independent Community Banks of America, 2006). The BCBS may have wished to avoid these previously mentioned possibilities, and hence they adjusted the one variable at its disposal – namely the asset correlation, which ultimately resulted, not necessarily to the advantage of Basel II compliant banks, in higher capital charges. This could also be the reason why the BCBS's prescribed asset correlations have such an impact on a developing country's capital charge. The BCBS would want a developing country to have a bigger capital reserve than a developed country, without influencing the competitiveness of the developing countries' banks to those of the developed countries. This is also the reason why the BCBS's prescribed asset correlation is the same for all participating countries, as it promotes fairness.

5. Conclusions

To lower the credit risk as proposed by the IRB framework and to raise capital charges within reasonable levels, a decision was made to set pre-specified correlations by the BCBS. Analysing empirically derived asset correlations for a developed country (US) and a develop-ing country (South Africa) proved that a certain level of conservatism is introduced. This lev-el of conservatism varied for the two countries, with the level of conservatism for South Af-rica being high, while in the US it is sometimes low. Since the IRB approach is built on a significant, yet attainable, theoretical basis, empirically extracting correlations from loss data does not necessarily be a strenuous affair. By making use of two different approaches, it was shown how these empirical correlations may be extracting from simple input data, how only the negative side of the equations yield realistic results, although it differs from the BCBS specified correlations. Banks that are permitted and interested in establishing their own internal measure of correlation will find the analysis interesting not only for regulatory capital purposes, but also economic capital purposes.

Further research should involve evaluating the effect of the asset correlation over different time periods, as well as determining why the financing of agricultural production reacts so differently to other loan types.

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3. The evolution of South African and US market-implied asset correlations using empirical loan losses

Time-varying South African and US market-implied asset correlations from empirical loan losses

Hestia Stoffberg,[3] Gary van Vuuren[4]

Abstract:

The Basel Committee on Banking Supervision (BCBS) designed the Internal Ratings Based approach to determine banks' regulatory capital for credit risk purposes. The ASRF model they used makes use of prescribed asset correlations, which banks <u>must</u> use for their credit risk regulatory capital, in order to abide by the BCBSs rules. To evaluate whether these correlations are as conservative as the BCBS intended, empirical asset correlations embedded in gross loss data spanning different economic milieus were backed out of the regulatory credit risk model. These were compared to the prescribed correlations for developed and developing economies over a rolling time period and found to be conservative.

Keywords: *Asset correlation, Vasicek distribution, retail loans, credit risk, Basel.*

JEL Classification: *C134, C16, C53*

1. Introduction

The importance of having a capital reserve to buffer banks from severe downturn crises, has become more evident as years have gone by. These conditions were observed in 2001 when Saambou, a South African bank facing liquidity problems, was placed under curatorship. Investors lost faith in the bank and withdrew large amounts of their deposits, causing a run on the bank (Van Rooyen, 2002). In October 2008, the United States (US) Senate passed a $700 billion bank bailout bill to purchase mortgage-backed securities to help save US banks from defaulting (Amadeo, 2008). Despite the US government's best efforts, by August 2014, 503 banks had defaulted in the US (Federal Deposit Insurance Corporation, 2014).

The BCBS designed accords to ensure that the capital reserves of banks are regulated (BCBS, 2013a), which is discussed in further detail in the next paragraph. By regulating the capital reserves, local regulators can help prevent banks from the risk of defaulting. The local regulator in the US is the Federal Reserve Board, and in South Africa it is the South African Reserve Bank (SARB) (2013a). Since liquidity is essential to a bank's viability and central to the

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[3] Master's student at the School of Economics, North-West University, Potchefstroom Campus, Private Bag X6001, Potchefstroom, 2520, South Africa. This work is submitted in partial fulfilment of the requirements for the Master's degree.

[4] Visiting professor at the School of Economics, North-West University, Potchefstroom Campus, Private Bag X6001, Potchefstroom, 2520, South Africa.

smooth running of the financial system, it is important for the local regulators to ensure that the banks keep to the specified requirements of the BCBS (Board of Governors of the Federal Reserve System, 2013a).

The Basel accords originated with the Basel I accord – which was established in 1988. This accord was designed to calculate banks' regulatory credit risk capital by improving the banks' credit risk management procedures, and by providing broad categories of risk-weighted assets (BCBS, 1988). Although this provided a blunt, early estimate of banks' requisite credit risk capital, it was widely acknowledged that this was only the first step towards evaluating bank capital adequacy accurately (Norton, 1989). The Basel II accord, introduced in 2008 after several delays, represented the BCBS's second major attempt at enhancing the treatment of regulatory credit risk (BCBS, 2004). The Basel II accord allowed banks the option of either using a Standardised Approach (in which the BCBS specifies the risk weights for different loan exposures), or the novel Internal Ratings Based (IRB) approach (in which the BCBS specifies the capital requirement formulas to be used, but leaving a degree of freedom regarding some of the input parameters (BCBS, 2006)). The IRB approach uses quantitative estimates such as the probability of default (PD) and loss given default (LGD) to determine the required regulatory capital. Advanced banks, which submit them to the specifications of the BCBS to gain the benefits of being a BCBS-accredited bank, are permitted to calculate these values themselves, once the BCBS approves. This method is based on widely accepted and thoroughly researched portfolio-based risk-management concepts, and has since been scrutinised by the market to evaluate its applicability (Lastra, 2004). It was found by various researchers (Botha & van Vuuren, 2010; Stoffberg & van Vuuren, 2014) that the IRB approach provides a considerably more meaningful and more sophisticated, user-friendly capital framework than Basel I.

In December 2010 the BCBS announced proposals collectively known as Basel III to strengthen global capital and liquidity regulations (BCBS, 2010). This was only done after much deliberation, and was only developed in response to the deficiencies in financial regulation revealed by the financial crisis of 2008 (Kasekende et al., 2012). Their liquidity goal was to promote a more resilient banking sector, by making use of two standards in liquidity risk supervision: a short-term standard (Liquidity Coverage Ratio) and a long-term standard (Net Stable Funding Ratio). They also strengthened their capital regulations, by higher the global minimum capital standards for commercial banks and strengthening the definition of capital (Federal Reserve Board, 2008). The BCBS also intends to mitigate pro-cyclicality in the

regulatory capital framework, but Basel III will be phased in gradually until 2019 (BCBS, 2013b).

The IRB approach makes use of an asymptotic single-risk factor (ASRF) calculation methodology that provides a simple, closed-form analytical solution which is relatively easy and simple to calculate (Vasicek, 1987; 1991). Other approaches, such as the Market Risk Amendment which introduced VaR (BCBS, 1996), employ multi-factor models that are more difficult to implement, use and understand, but used by banks in their internal models to improve the risk sensitivity of the bank (Lopez & Saidenberg, 2001). The IRB approach is nevertheless based on credit risk modelling concepts that are in essence the same as the capital models that are used more regularly by large retail banks to measure portfolio-level risk, and to allocate and manage capital across the entire bank (Gordy, 2003).

This single systematic risk factor prescribed by the ASRF model represents the state of the economy as a whole (BCBS, 2005). This specific single risk factor represents the relationship between all borrowers, and the asset correlation measures the strength of the bond of this relationship (Chen, 2012). Predetermined values for these asset correlations have been calibrated and set by the BCBS, and for each of the IRB equations that are broadly divided by the asset classes that were specified under Basel II (Smit, 2010). These asset classes and respective asset correlations are presented in Table 1 below, and are discussed further in Section 2. Since different borrowers and/or asset classes depend on the overall economy in different ways, asset correlations are asset class-dependent (Sharpe, 1992).

Table 1: Asset correlations to be used under Basel II's foundation IRB (BCBS, 2005)

Loan type	Correlation	
Residential Mortgages	Fixed (15%)	
Qualifying revolving retail exposures	Fixed (4%)	
Other retail	Varies with PD	$0.03 \cdot \left(\dfrac{1 - e^{-35PD}}{1 - e^{-35}} \right) + 0.16 \cdot \left(\dfrac{1 - e^{-35PD}}{1 - e^{-35}} \right)$
High volatility commercial real estate		$0.12 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.30 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right)$
Corporate, sovereign and bank exposures		$0.12 \cdot \left(\dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right) + 0.24 \cdot \left(1 - \dfrac{1 - e^{-50PD}}{1 - e^{-50}} \right)$

To sustain capital adequacy, banks must comply with regulatory rules set out by the BCBS and in doing so, they must use the asset correlation values that the BCBS pre-specifies in

their models for calculating capital reserves. Economic capital models provide banks with a more accurate criterion to measure and evaluate their overall capital adequacy (Burns, 2004) and therefore the banks are interested in the implied asset correlations embedded in their empirical loss data – separate from the BCBSs specifications. The empirical asset correlation values are of critical importance for internal economic capital models because the internal models are those the banks trust more when calculating their required capital reserves (Reuters, 2014). Banks trust their own internal models more because banks have control over some of the input parameters in the internal models, whereas with the BCBSs approach, limited control (Kupiec, 2002).

To extract these asset correlations, a method was proposed using the Vasicek distribution of empirical losses, and it has been tested both in international markets such as the US and South Africa (Stoffberg & van Vuuren, 2014). Stoffberg and van Vuuren (2014), used the proposed method to extract a single asset correlation for each of the countries, and compared them with that specified by the BCBS for each loan type. This paper investigates the extraction of retail asset correlations for a rolling time period for both South Africa and the US, and then compares these with the asset correlation specified by the BCBS. These rolling asset correlations are then evaluated over the credit crisis and other economic events, to see the applicability of the BCBS specifications, as well as to determine whether discrepancies exist between the treatment of developed and developing economies by the national regulators.

The remainder of this article proceeds as follows: Section 2 explores the existing literature. Section 3 inspects the relevant data and analysis needed for the calculation and establishes the mathematical formulation of the Hodrick Prescott filter. Section 4 provides the results obtained from the analysis and Section 5 concludes.

2.   Literature review

In a special 'explanatory note', the BCBS explained and defended the choice of a credit risk framework, equations and correlation values, without divulging either the analytical reasoning or the mathematical basis upon which the IRB approach is based (BCBS, 2005). Gordy (2003) described much of the underlying technical formulation, as the BCBS deliberately avoided the technical information for a non-technical audience. A "seal of approval" with regards to capital adequacy is given to banks that comply with the Basel Accords, and this makes it easier for banks to compete (Matten, 2000).

Since Botha and van Vuuren (2010) first published their article, more research has been done on the applicability of asset correlation on loan loss data (Bams et al., 2012; Siarka, 2011) and will be discussed next. Botha and van Vuuren (2010) reverse-engineered the Vasicek distribution to extract the empirical asset correlations embedded in the loan losses. Stoffberg and van Vuuren (2014) adapted this method and developed two approaches to extracting the empirical asset correlations from the gross loan loss data. A combination of both methods is used in this article. This research is useful for banks which have established their own internal measures of correlation for economic capital purposes. The comparison of a developed country's (the US) asset correlation versus a developing country's (South Africa) asset correlation, will evaluate whether or not the BCBS introduces conservatism to the credit risk IRB framework. The BCBS need to ensure that banks capital will be enough to carry them through every economic event, especially in a country that is so dependent on investments from larger economies like South Africa (Lederman et al., 2013).

Botha and van Vuuren (2010) found, using their single approach to extracting the empirical asset correlation, that the BCBS's specified asset correlation is applicable and conservative enough for the loan loss data gathered from the US. They concluded that the embedded empirical calculations are lower than those specified by the BCBS, which results in the intended conservative asset correlation of the BCBS. Botha and van Vuuren (2010) explored the way in which the embedded empirical correlations changed over time, and this will be updated and inspected in this work. They found considerable differences between the empirical correlations and the BCBSs asset correlation for residential mortgages (the empirical asset correlation were found to be 6.8% in the US for the period 1985-2009, BCBSs: 15%).

Stoffberg and van Vuuren (2014) found that both a mode-approach and percentile-approach (see Equations f and h respectively in the Appendix) are needed to fully evaluate the robustness of the data, as well as to evaluate the conservatism of the BCBS, as both approaches' cumulative and density functions closely fit the empirical data. They found that for the most part, the BCBSs pre-specified asset correlation, introduces the level of conservatism that the BCBS intended. The main exception can be seen in the financing of agricultural production, where the 99.9[th] percentile approach receives a higher asset correlation than the pre-specified BCBS asset correlation. They also found that the "Qualifying revolving" asset classes required a capital charge of the BCBS, which is insufficient to ensure enough capital reserves. Stoffberg and van Vuuren (2014) found that the level of conservatism that the BCBS introduces is higher for South Africa than for the US, over the full period of time (1985Q1 to

2014Q2). This work will more closely examine the effect that economic events have on the asset correlation over a rolling period of time.

Asset correlations (Table 3) are specified by the BCBS. These are either fixed or vary only in terms of the loan-type probability of default (PD). Each empirical asset correlation found by the model can be calculated and compared to the BCBSs specified asset correlation. This research employs data from the SARB for South Africa and all available commercial banks for the US.

Banks have developed sophisticated internal ratings-based models to suit their own preferences, and have collected copious amounts of BCBS input IRB data, including correlation parameters (Gore, 2006). Thomas and Wang (2005) inspected this formula specified by the BCBS's IRB approach, which is based on the Vasicek formula (see Equation a in the Appendix). They found that the IRB formula does not correspond to industry best practice, but is a hybrid between a negotiated settlement and a simple statistical model of capital needs for credit risk. The formula (Equation a in the Appendix) represents a negotiated compromise to achieve simplicity, portfolio invariance and bank acceptance of prescribed capital levels.

An alternative way of modelling the dynamics of a firm's asset value from financial securities prices, other than the ASRF model, was proposed by Byström (2011). He then went on to determine the usefulness of the asset values calculated from the model, when computing asset correlations. These correlations were found to be useful as stand-ins for default event correlations in multivariate credit risk models. Byström (2011) also conducted an empirical study on the correlation measure, and computed asset correlations among a group of European banks to evaluate the impact of the financial crisis. He found that the characteristics of the banks in the study, i.e. the size, default risk and location of the banks, influenced the effect of the crisis on the asset value correlations, and that the correlations were higher during the crisis. Although this study was performed on European banks, the same comparisons will be performed in this work to determine the effect of the financial crisis on South Africa and the US.

Siarka (2011) analysed the distribution of the probability of default according to the approach proposed by Vasicek, which provides the basis of estimating losses due to credit risk. Siarka (2011) found that the BCBS adopted a high asset correlation for the asset class "retail exposures" and that the BCBS's approach introduces the level of conservatism intended, which may lead to forecasts over-estimating loss levels.

Bams, Pisa and Wolff (2012) generalised the existing ASRF model to address issues related to industry heterogeneity, default clustering and capital requirement's parameter uncertainty in US retail loan portfolios. Although they only inspected US small businesses from 2005 to 2011, they compared the minimum capital requirements implied by Basel II and the development over the recent credit crisis. Their empirical results concluded that retail exposures are a safer investment than the regulator would suggest, from a credit risk perspective. They concluded that this could be because of Basel II's overly-simplistic way of estimating the asset correlations in retail loan portfolios. Bams *et al.* (2012) also noticed that, regardless of the small business' riskiness, industry or firm size, the estimates of asset correlation are lower than any available estimates for corporate firms.

Byström (2013) continued his research (Byström, 2011) in this field by empirically estimating the size of the exchange rate risk-induced asset correlation bias, using the methods he developed in Byström (2011). Byström (2013) concluded that the asset correlation bias caused by exchange rate risk was economically significant. He recommended that the exact asset correlation be estimated through a careful assessment of the foreign exchange exposure of the borrowing firms. Byström (2013) also found that the empirical asset correlation is the same for all currency exposures, but that the range in which the actual asset correlation lies may differ. Since this article only compares the empirical asset correlations' reaction to economic events over time, the exchange rate impact is not of critical importance.

Little academic research has been published on retail portfolio risks, and the LGD, PD and exposure at default (EAD) data, collected by banks, are often lacking in detail and difficult to assemble (Gore, 2006). Just as in Stoffberg and van Vuuren (2014), these thinly dispersed data are also a limitation to this work, as collecting data was difficult, despite the BCBS implementing disclosure requirements (BCBS, 2014a). While a few larger banks have utilised some form of retail loan analysis, the difficulties in collecting data were due to most banks continuing to use the BCBS's prescriptions without considering whether realistic outcomes would be produced by BCBS-specified parameters (Dev, 2006). Thus, a real need exists for the establishment of a practical methodology to determine the implied asset correlations from retail loan portfolio data. Botha and an Vuuren (2010) developed an evaluation of the Vasicek distribution to solve the problem of determining the empirical asset correlation. Stoffberg and van Vuuren (2014) applied this robust and practical methodology to South African data as well as updated US data (from Botha & van Vuuren, 2014). This paper uses the same

data as Stoffberg and van Vuuren (2014), and the same methodology as prescribed in Botha and Van Vuuren (2010), but calculate them over a *rolling* time period.

3.1 Data and Analysis

3.1.1 Data

The data range for this article covers 28 years (i.e. 1985Q1 to 2014Q2). The South African data were collected from the SARB (Venter, 2014) by taking the monthly impaired advances as a percentage of the total loans on the balance sheet for the time period January 2001 to April 2014. The US data were compiled from the quarterly Federal Financial Institutions Examination Council Consolidated Reports of Condition of Income (FFIEC, 2014). Charge-offs (the values of loans and leases removed from the books and charged against loss reserves) from all commercial US banks are measured by consolidated domestic and foreign assets, and are not seasonally adjusted for the time period 1985Q1 to 2014Q1. Annualised charge-off rates (as calculated from the report of condition of income), net of recoveries and outstanding at the end of each time period, are used by the US Federal Reserve. The flow of a bank's net charge-offs (gross charge-offs − recoveries) during the time period, divided by the average level of its loans outstanding over that period, can be seen as the charge-off rates for any category loan. To express these ratios as annual percentage rates, the ratios are multiplied by 400 for the US, and 1200 for South Africa (Federal Reserve Board, 2008). As net losses = (gross losses x LGD), the only requirement to convert net losses to gross losses, is knowing the value of the corresponding LGDs. These average LGDs for the US that are used in the model, were obtained from the BCBS's fifth quantitative impact study (BCBS, 2006), using the "G10 group 1: including US" group. The LGD averages for the different retail portfolios are thus as follows:

Residential mortgage	20.3%
Qualifying revolving	71.6%
Other retail	48.0%
HVCRE	35.0%

For the approximation of downturn LGDs, a principles-based approach was suggested. This approach requires banks to identify certain specified downturn conditions and the inauspicious dependencies between recovery and default rates. Banks must produce LGD parameters for their exposures from the dependencies between default and recovery rates, which are con-

sistent with specific downturn conditions (Miu & Ozdemir, 2006). The BCBS made an inherent assumption that a credit risk model with systematic correlation between PD and LGD using long-term LGD inputs, should give comparable capital to a credit risk model, without correlated PD and LGD using downturn LGD inputs. Mean LGDs need to be increased by between 35% and 41% in order to compensate for the lack of correlation (Smit, 2010). Downturn LGDs were produced by increasing the LGDs used in this study by 37.5% (the average recommended increase to compensate for the lack of correlation). Even if this value is incorrect, the underlying principles outlined here remained intact.

3.1.2 Analysis

The procedure that Stoffberg and van Vuuren (2014) constructed for extracting empirical asset correlations from loss data is shown in the Appendix. The two different approaches that were reverse-engineered from the Vasicek distribution to determine the retail asset correlation of South Africa as well as the US, is explained in detail in the Appendix. From this, the procedure for extracting empirical asset correlations from loss data is:

1. Source gross loss, time series data, as a percentage of total loan value.

2. Calculate the mode (L_{mode}) and the mean (p). These values are acquired from first principal from the simple *average* gross loss (p) and the most *prevalent* gross loss L_{mode}, over the specified time period. These values can be calculated by using standard statistical software like Excel.

3. Calculate the empirical asset correlation using the two different approaches.

$$\rho: \frac{\left(4\left(\frac{N^{-1}(L_{mode})}{N^{-1}(p)}\right)^2 - 1\right) \pm \sqrt{8\left(\frac{N^{-1}(L_{mode})}{N^{-1}(p)}\right)^2 + 1}}{8\left(\frac{N^{-1}(L_{mode})}{N^{-1}(p)}\right)^2} \tag{1}$$

$$\rho: \left[\frac{-2\pi\psi \pm \sqrt{(2\pi\psi)^2 - 4 \cdot (\psi^2 + \omega^2) \cdot (\pi^2 - \omega^2)}}{2 \cdot (\psi^2 + \omega^2)}\right]^2 \tag{2}$$

Where ρ is the asset correlation between all loans and the systematic single risk factor; $N[...]$ refer to the cumulative standard normal distribution; $N^{-1}[...]$ refers to the inverse standard normal cumulative distribution function; and p is the average probability of default for the portfolio. Also $\omega = N^{-1}(p + UL^{99.9\%})$ (the inverse normal distribution of the 99.9[th] percentile of total loss), $\pi = N^{-1}(p)$ and $\psi = N^{-1}(0.999)$.

Using this methodology, the effect of the different approaches on the asset correlation is firstly explored using the rolling time span. Even though losses – which are repeatedly assumed to be highly skewed and leptokurtic – do not always conform to the Vasicek distribution, this pattern is used to fit the loss data. The mode-approach (V_Mode_HP) was found to be spurious when compared to the percentile-approach (V_Percentile), so the Hodrick Prescott filter was used to de-trend the V_Mode_HP data. This has the effect of rendering the data less volatile and establishes the long run means more reliably.

Next, empirical correlations from South African data (extracted from the loss data and deducted from the Vasicek distribution) are compared with the BCBS *specified* asset correlations conducted using a rolling timespan. Finally, the empirical correlations are compared to the rolling empirical correlation of the US data to determine how conservative the BCBS is towards developing economies such as South Africa versus developed economies such as the US.

3.2   Hodrick Prescott (HP) filter

A method of trend-extraction from data that is commonly used is the HP filter (Kim, 2004) that was first introduced by Hodrick and Prescott in 1980 (Hodrick & Prescott, 1980). They developed it in the context of estimating business cycles, but the research was only published in 1997 after the filter had gained widespread popularity in macro-economics (Hodrick & Prescott, 1997). The BCBS also chose the HP filter to de-trend relevant macro-economic ratio data and thus this filter can be used in our model. The HP filter is a close approximation to an ideal high-pass filter, which is a filter which sharply cuts off components at frequencies below some pre-specified cut-off frequency and leaves components at higher frequencies unchanged (Pedersen, 2001)

A number of limitations and undesirable properties have been associated with the HP filter (Ravn & Uhlig, 2002). The filter has been criticised by Harvey and Jaeger (1993), Cogly and Nason (1995) and Park (1996), amongst others. Harvey and Jaeger (1993) obtained spurious cycles and distorted estimates of the cyclical component when using the HP filter. They argued that this property may lead to misleading conclusions regarding the relationship between short-term movements in macro-economic time series data. Spurious cycles (and extreme second-order properties in de-trended data) were also found by Cogley and Nason (1995), when using the HP filter on difference-stationary input data. King and Rebelo (1993) applied the HP filter to US time-series data, and found that it dramatically altered measures of

persistence, variability and co-movement. The bulk of the critiques against the HP filter provides insufficient evidence to discourage its use, and thus it remains widely-used among macro-economists for de-trending data which exhibit short-term fluctuations superimposed on business cycle-like trends (Ravn & Uhlig, 2002). It can thus be applied to the results obtained from the Mode-approach.

The HP filter rests on the idea that an observable macro-economic 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):

$$x_t \quad = \quad \tau_t \quad + \quad c_t \qquad\qquad (3)$$

Observed series   Long run trend   Cycle

Neither the cycle nor the long run trend is directly observable, and thus de-trending approaches generally define these elements somewhat haphazardly. The HP filter extracts the cycle by solving Equation 4, a standard-penalty programme:

$$\min_{\tau_t} \sum_{t-1}^{T} (x_t - \tau_t)^2 + \lambda \cdot \sum_{t-2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \qquad \lambda > 0 \quad (3)$$

Goodness of fit   Penalty for deviations

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 (Mise et al., 2005). The optimisation procedure in Equation 3 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.

Originally, Hodrick and Prescott (1980) suggested an exogenous and subjective value for λ, where $\lambda = 1600$ for quarterly data. A method was proposed to adjust λ based upon the square of the frequency of observations relative to quarterly data (Backus & Kehoe, 1992), where $\lambda = 14400$ for monthly data and $\lambda=100$ for annual data. Danthine and Giardin (1989) established the solution for Equation 3 is:

$$\hat{\tau} = [I + \lambda \cdot \mathbf{K}'\mathbf{K}]^{-1}x$$

where x $= [x_1, \dots, x_T]'$ (i.e. the entire observed time series), $\tau = [\tau_1, \dots, \tau_T]'$, I is a $I \times I$ identity matrix, and $\mathbf{K} = [k_{ij}]$ is a $(T-2) \times T$ matrix with elements:

$$k_{ij} = \begin{cases} 1 & \text{if } i = j \text{ or } i = j + 2 \\ -2 & \text{if } i = j + 1 \\ 0 & \text{otherwise} \end{cases}$$

which results in

$$K = \begin{pmatrix} 1 & -2 & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & -2 & 1 \end{pmatrix}$$

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. The two-sided, symmetrical filter applies large symmetrical weights to the end points of the observed values to determine the corresponding trend values, which better fit the one-sided filter that demonstrated sub-optimal at the end points of the HP filter. The two-sided filter thus uses past and future data to estimate the components of Equation 3. Van Vuuren (2012) found that the two-sided HP filter is the optimum filter to be used (rather than the traditional one-sided filter). The value for λ that should be used, is 14 400 for South African monthly data. The λ to be used for the quarterly data of the US, is 1 600, as Hodrick and Prescott (1980) proposed. The results using the two-sided HP filter on the spurious V_Mode_HP, can be seen in the next section, along with the V_Percentile results, and the Basel required asset correlation.

4.   Results

A summary of the asset correlations that should be used in the IRB approach, specified by the BCBS, is shown in Table 1. For US data, the calculation methodology is subject to the different retail loan classes (Table 1). The "Corporate, Bank and Sovereign" calculation is used for the South African data (Hill, 2012). The data for this article are those used by Stoffberg and van Vuuren (2014), and thus the conclusion that the data fit the Vasicek distribution still holds. This section explores US loan loss data over the full period and then compares these results to SA's "all loans" for the period 2001-2014. Finally, the individual US loan profiles are explored.
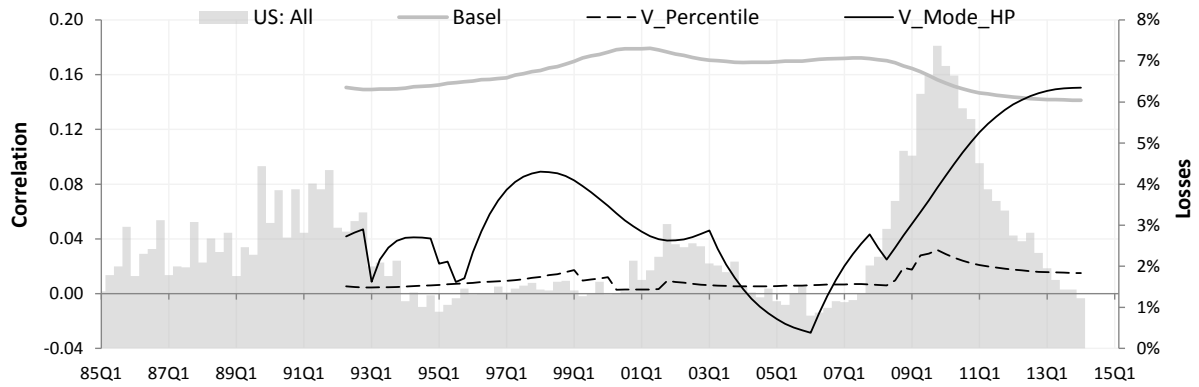
Figure 6: Rolling seven-year empirical correlations compared to Basel II specified correlations for all commercial US loans.

The *empirical* asset correlations are sensitive to parameters estimated from portfolio gross loss data, and Figure 1 illustrates how losses vary over time. The global economy witnessed the end of a benign, five-year-long period of constrained inflation, low interest rates, universally loose monetary policy and low default rates up to mid-2007, for all loan types, particularly residential mortgages (Botha & van Vuuren, 2010). This period came to an abrupt end in August 2007 and has continued apace until the end of 2009. The time-period following August 2007, is limited by surging inflation, stagnant interest rates, tightening monetary policy and elevated default rates, delinquencies and foreclosures. In Figure 1 it is clear that bank losses have burst in on the resulting credit crunch, with the highest loss in the US occurring at the end of 2009. After this high loss, the bank losses started to decrease, and have stabilised in 2014. A possible reason for the turn in 2009 has been the implementation of quantitative easing measures, to stabilise the economy (Benford et al., 2009). In 2012Q2, the empirical asset correlation was the same as the BCBS's prescribed asset correlation, after which the empirical asset correlation surpassed that of the BCBS. The BCBS's asset correlation has thus not been conservative enough from 2012 (see Figure 2).
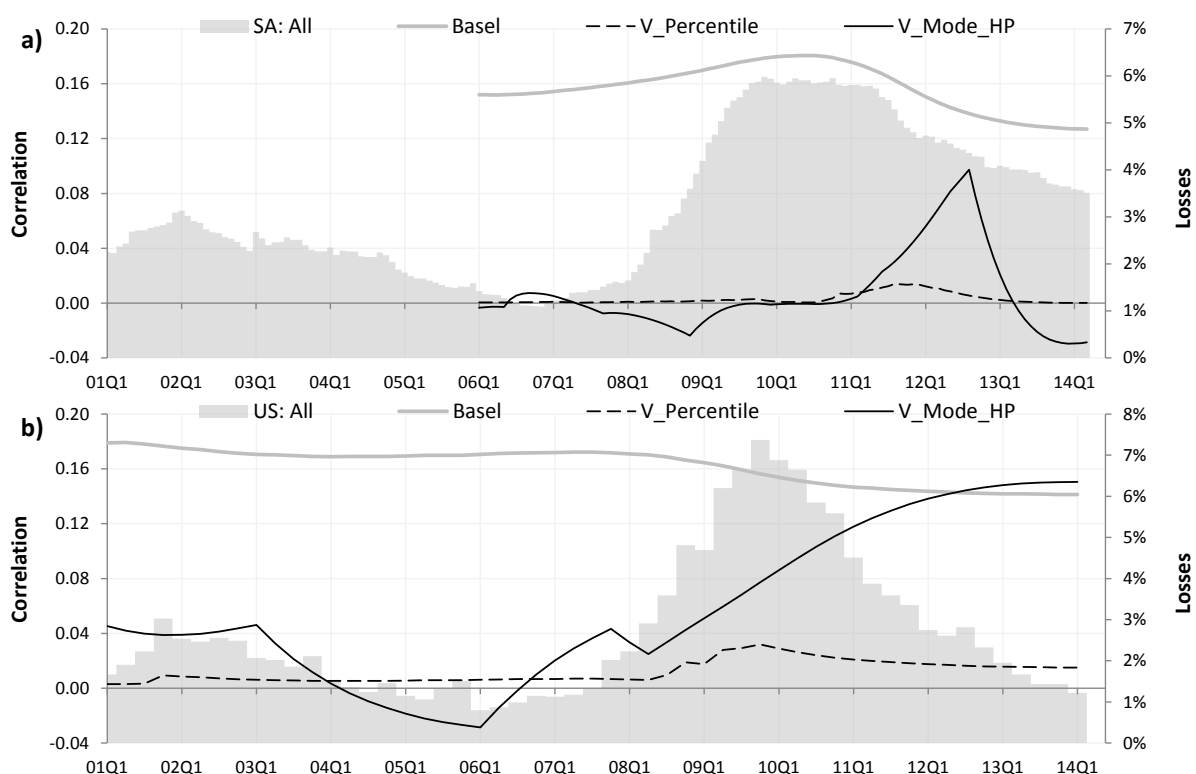
Figure 7(a) and (b): Rolling five-year empirical correlations compared to Basel II specified correlations for all commercial South African loans, compared to all US loans for the time period 2001-2014.

In South Africa, the same global economic events had an impact on the asset correlation as mentioned previously for the US loans. The same spike in gross losses can be seen in South Africa and the US for the period leading up to the end of 2009. The two countries reacted differently to the credit crunch, as can be seen in the duration of the spike. The US only experienced one loss spike (09Q4), after which losses decreased dramatically. In South Africa, the same loss peak occurred at the end of 2009, but the decrease in losses has been more gradual than that experienced in the US. Until mid-2011, SA's losses had only decreased by 0.1%.

Losses for South Africa were about the same as the US before 2007, but after the credit crunch the loss for South Africa is about 2.5 times that of the US. However, at the highest point of losses, the US losses had surpassed those of South Africa. The credit crisis had a much bigger effect on the losses of the US, but that the US had a better reaction to the crisis and recovered more quickly, possibly due to measures implemented to counteract the loss impact (Midthjell, 2011). The BCBSs specified asset correlation was found to be conservative enough for South Africa, but for the US the empirical correlation surpassed the specified asset correlation in 2012. The empirical asset correlation, using the mode-approach, increased

from 2008 (Figure 2b). The reason the implied asset correlation surpassed the specified asset correlation in 2012, can be because of the continued effect of the 2007/2008 financial crisis. During the financial crisis, the asset retail classes started to move closer together, and thus the empirical asset correlation started to rise, continuing until mid-2013, where a deceleration was observed, although still rising. The effects of the financial crisis have thus not yet (2014) worn off, as the empirical correlations have not yet returned to pre-crisis levels.

For both countries, the results of the two approaches to the empirical asset correlation were the same. The percentile approach (V_Percentile) resulted in a very low asset correlation, where the mode approach (V_Mode_HP) gave volatile asset correlations, with the asset correlations being very higher after the credit crisis. It is thus evident that after the credit crisis, with regards to the mode approach, the assets were much more highly correlated, and thus this should be taken into account for the BCBS's calculation. The effect of the credit crisis on various categories of retail loans for the US (using a rolling, seven-year window of quarterly losses estimating the empirical asset correlation using both approaches) can be seen in Figure 3(a) to (j).
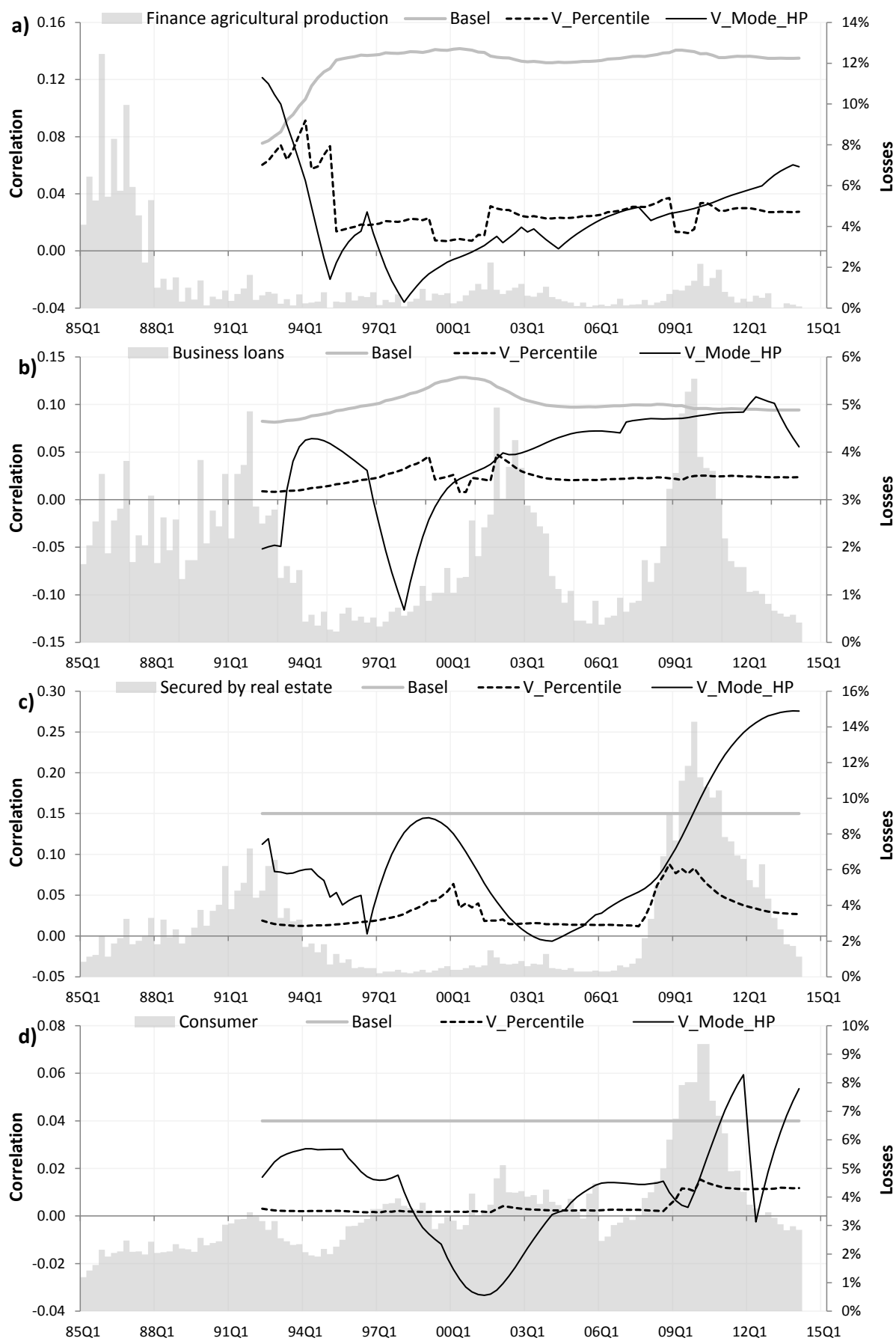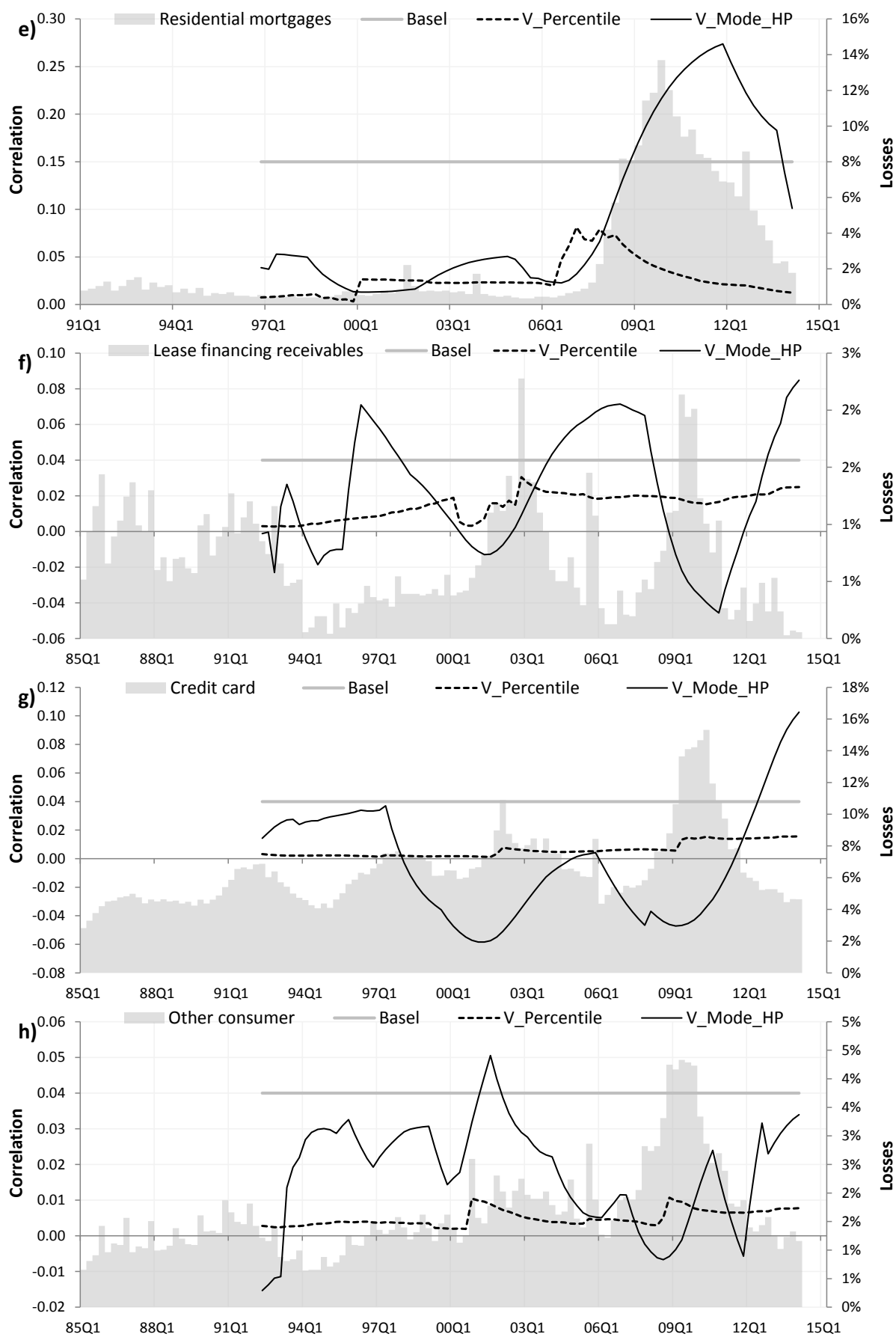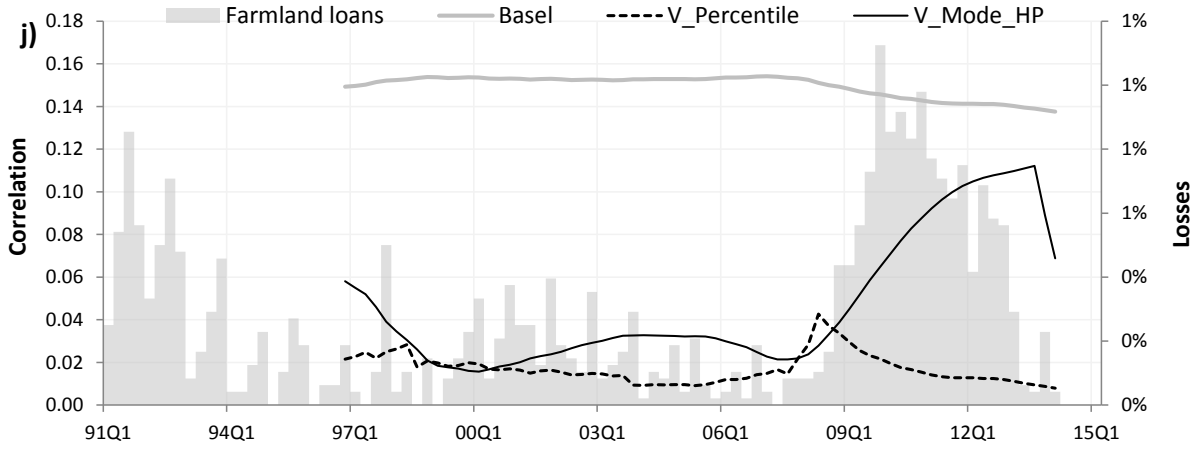
Figure 8: (a) through (j): Comparison of rolling seven-year empirical correlations (left-hand axis) using two approaches to the Vasicek distribution and Basel II specified correlations (right-hand axis). The underlying gross loss data are also shown (right hand axis).

For most of the asset classes, using the percentile approach (V_Percentile), the BCBS specified correlations are higher than the empirically derived values, substantially so for the better part of each time period. This is because the BCBS intends to introduce a level of conservatism to calculate empirical correlation, and in this they were successful. The derived correlations for both approaches move in the same direction, but vary for the most part, but the mode approach is much more sensitive to changes in the underlying loss data, and the changing loss milieu. A possible reason for this is the sensitivity of the underlying distribution drivers, where the mode of the gross losses for the Vasicek distribution is much more sensitive than the 99.9[th] percentile of the gross losses.

The mode approach to the Vasicek distribution changes in varying step sizes only when (and if) the underlying data (gross loss data) yield a more populous gross loss value than the previous mode. If the data are analysed during a period of diminished and then elevated losses, or vice versa, the mode will undergo a 'jump' between a low value and a high value (or otherwise) with no intermediate values in between. This will have the effect of amplifying changes in the correlations implied by this approach. Mode-calculations use the loss value that appears most frequently in a time series of loss data (Sharma, 2010).

The percentile approach (V_Percentile) makes use of the 99.9[th] percentile of the gross loss data, instead of the mode. The smooth empirical asset correlations shown in Figure 3 for the percentile approach are due to the fact that the 99.9[th] percentile values adjust smoothly on a rolling basis.

An interesting feature of the BCBS specified correlations that depend on the PD value, is that they are counter-cyclical to the derived correlation values using the mode approach, but move pro-cyclically using the percentile approach. A possible explanation for the counter-behaviour can be because the BCBS specified asset correlations make use of a *current* PD, and are therefore far more reactive to changing economic conditions than the mode over the seven year estimates. The percentile-approach is not as sensitive to changing economic conditions.

5.   Conclusion

The BCBS intended to introduce a level of conservatism when they set the pre-specified correlations into the credit-risk IRB framework. Analysing empirically-derived asset correlations for a developed country (the US) and a developing country (South Africa) proved that a certain level of conservatism is introduced. Applying the mode-approach to the US data proved that the BCBS did not reach the level of conservatism it intended in every loan type, as the empirical correlations embedded in the gross loss data using this approach were found to be higher than those set out by the BCBS. The theoretical basis on which the IRB approach is built is non-trivial, but nevertheless accessible and extracting empirical correlations from loss data need not be a strenuous affair. Using the two different approaches to calculate the empirical asset correlations, it is evident that the BCBS specified asset correlation is not as sensitive to economic events as the empirical asset correlations. The spurious results found for the mode-approach was explained and adjusted for by using the HP-filter. The analysis should be of benefit to banks interested in establishing their own internal measure of correlation for both regulatory and economic capital purposes.

Future research could investigate the cause for the empirical asset correlation surpassing the BCBS's specified asset correlation in 2012. Further research could also include exploring bank-specific economic models, and evaluate their empirical asset correlation, as well as determining the difference this third approach will have on the empirical asset correlations.

APPENDIX

The Vasicek distribution was reverse-engineered to determine the market-implied retail asset correlation of South Africa as well as the US (Botha & van Vuuren, 2010). Vasicek (1987, 1991, 2002) used a Merton-type model to derive an expression for the distribution of credit portfolio losses. Vasicek's assertion that the cumulative probability that the portfolio loss, L, will be less than some variable, x, is given by:

$$P[L \leq x] = N\left[\frac{\sqrt{1-\rho} \cdot N^{-1}(x) - N^{-1}(p)}{\sqrt{\rho}}\right] \qquad \text{(a)}$$

Where ρ is the asset correlation between all loans and the systematic single risk factor; $N[\ldots]$ refer to the cumulative standard normal distribution; $N^{-1}[\ldots]$ refers to the inverse standard normal cumulative distribution function; and p is the average probability of default for the portfolio. This cumulative distribution describes the portfolio losses and is driven by two parameters (p and ρ), defined over the interval $0 \leq x \leq 1$. This is given by:

$$F(x; p; \rho) = N\left[\frac{\sqrt{1-\rho} \cdot N^{-1}(x) - N^{-1}(p)}{\sqrt{\rho}}\right] \qquad \text{(b)}$$

and defines the total loss shown in Figure 1. Where $0 < \rho < 1$ and $p > 0$. As $\rho \to 0$, the distribution converges to a 0, 1 (or normal) distribution with probabilities $1 - p$ and p respectively. This indicates that $F(x; p; \rho) = 1 - F(1 - x; 1 - p; \rho)$ and when $p \to 0$ or $p \to 1$, the distribution becomes concentrated at $L = 0$ or $L = 1$ respectively.
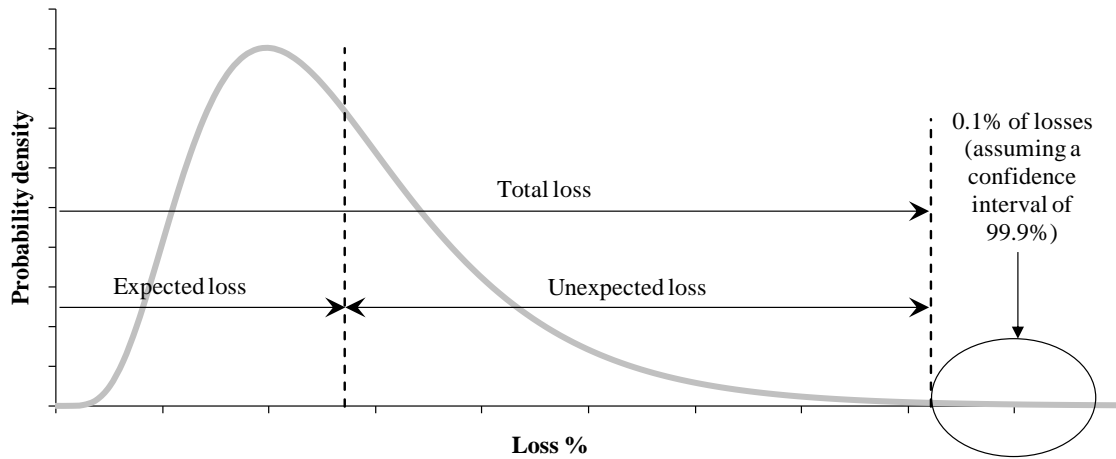
Figure 9: A typical loss distribution *(Botha & van Vuuren, 2010)*. Where "Total loss" = the 99.9[th] percentile of total loss, as specified by the BCBS *(2005)*.

The highly skewed and leptokurtic loss distribution has the following density:

$$f(x; p; \rho) = \sqrt{\frac{1-\rho}{\rho}} \cdot \exp\left[\frac{1}{2}\left(N^{-1}(x)\right)^2 - \frac{1}{2}\left(\frac{\sqrt{1-\rho} \cdot N^{-1}(x) - N^{-1}(p)}{\sqrt{\rho}}\right)\right] \qquad \text{(c)}$$

and it is uni-modal with the mode – i.e. the loss that occurs most frequently – located at:

$$L_{mode} = N\left[\frac{\sqrt{1-\rho}}{1-2\rho} \cdot N^{-1}(p)\right] \qquad \text{(d)}$$

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

$$L_\alpha = F(\alpha; 1 - p; 1 - \rho) \tag{e}$$

All the relevant features of a typical and skewed distribution, for a collection of loan losses, are provided in Figure 1. The total loss (L) is a defined point – in this case, the point below which 99.9% of all losses fall; and expected loss (EL) is the *average* portfolio (Botha & van Vuuren, 2010). The area under the curve in Figure 1, to the left of the total loss position, represents 99.9% of all portfolio losses, the unexpected loss (UL), however, depends upon the defining of the total loss point, which is the difference between the total- and the expected portfolio-loss.

The procedure for extracting empirical asset correlations from loss data has been created by Botha and van Vuuren (2010) and is:

1. source gross loss, time series data, as a percentage of total loan value,

2. calculate the mode (L_{mode} in Equation d) and the mean (p in Equations b-e). These values are acquired from first principal from the simple *average* gross loss (p) and the most *prevalent* gross loss L_{mode}, over the specified time period. These values can be calculated by using standard statistical software like Excel.

3. The empirical asset correlation may now be manipulated by using Equation d:

$$\frac{N^{-1}(L_{mode})}{N^{-1}(p)} = \sqrt{\frac{1 - \rho}{1 - 2\rho}}$$

thus

$$\left(\frac{N^{-1}(L_{mode})}{N^{-1}(p)}\right)^2 = \frac{1 - \rho}{(1 - 2\rho)^2}.$$

Substituting for $\xi = \left(\frac{N^{-1}(L_{mode})}{N^{-1}(p)}\right)^2$ gives:

$$\xi(1 - 2\rho)^2 = 1 - \rho$$

$4\xi\rho^2 + (1 - 4\xi)\rho + (\xi - 1) = 0$ which is a quadratic equation in ρ (the asset correlation) with solutions:

$$\rho: \frac{(4\xi - 1) \pm \sqrt{8\xi + 1}}{8\xi} \tag{f}$$

Equation f represents the mode-approach to calculating asset correlation, and will be referred to as V_Mode_HP.

The total portfolio loss measured at a confidence level of 99.9%, may also be calculated empirically by combining Equations b and e (where a confidence interval of 99.9% implies $\alpha = 0.1\%$):

$$F(x; 1 - p; 1 - \rho) = N\left[\frac{\sqrt{1 - (1 - \rho)} \cdot N^{-1}(\alpha) - N^{-1}(1 - p)}{\sqrt{1 - \rho}}\right]$$

This makes total gross loss:

$$N\left[\frac{N^{-1}(p) + \sqrt{\rho} \cdot N^{-1}(\alpha)}{\sqrt{1 - \rho}}\right]$$

The gross total loss is simply the sum of unexpected and expected gross losses ($UL^{99.9\%} + EL$).

By deducting the gross expected loss from the total loss, the following equation emerges:

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

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

$$UL^{99.9\%} = N\left[\frac{N^{-1}(p) + \sqrt{\rho} \cdot N^{-1}(0.999)}{\sqrt{1 - \rho}}\right] - p \tag{g}$$

No assumptions regarding recoveries are made. Both sides of Equation g can be multiplied by the LGD, when the analysis is complete and all the values calculated, to calculate the UL in the 'net loss' sense (also the total loss estimates used in the Pillar 1 equations of the BCBS formulation). The $UL^{99.9\%}$ is presented here as a *gross* unexpected loss.

Empirical asset correlations were compared to the Vasicek distributions by using several retail loan classes, in Equation f and Equation g.

From Equation g:

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

with $p + UL^{99.9\%}$ being known empirically.

Thus:

$$N^{-1}(p + UL^{99.9\%}) \cdot \sqrt{1 - \rho} = N^{-1}(p) + \sqrt{\rho} \cdot N^{-1}(0.999),$$

with ρ the only unknown in this equation.

Letting $\omega = N^{-1}(p + UL^{99.9\%}), \pi = N^{-1}(p)$ and $\psi = N^{-1}(0.999)$ and squaring both sides gives:

$$\omega^2 \cdot (1 - \rho) = \pi^2 + \psi^2 \cdot \rho + 2\pi\psi \cdot \sqrt{\rho}$$

$$0 = (\psi^2 + \omega^2) \cdot \rho + 2\pi\psi \cdot \sqrt{\rho} + (\pi^2 + \omega^2)$$

Which is a quadratic in $\sqrt{\rho}$ with solutions:

$$\rho: \left[\frac{-2\pi\psi \pm \sqrt{(2\pi\psi)^2 - 4 \cdot (\psi^2 + \omega^2) \cdot (\pi^2 - \omega^2)}}{2 \cdot (\psi^2 + \omega^2)} \right]^2 \qquad \text{(h)}$$

and which is easily solved as ω, π and ψ are all known quantities. $N^{-1}(p + UL^{99.9\%})$ will then simply be the inverse normal distribution of the 99.9[th] percentile of the total loss. Equation h represents the percentile-approach, and will be referred to as V_Percentile.

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4. Conclusions, limitations and recommendations

4.1 Summary and conclusions

The recent financial crisis stressed the importance for banks to have a sufficiently large enough capital reserve to buffer them from severe market downturns. The BCBS has devised regulatory rules to assist banks achieve the desired buffer, and aid them in surviving extreme risks. These rules are imposed by each country's local regulator to ensure international standards are met. Among these rules was the second accord, better known as Basel II. This accord allows banks to make use of an internal models-based approach by setting pre-specified asset correlations but allowing banks some flexibility regarding the input parameters. This specified correlation introduces a level of conservatism into the credit-risk IRB framework, and elevates the capital charges of banks to a satisfactory level (as determined by the BCBS). By doing this, the BCBS tries to ensure that banks are buffered from severe economic conditions. This dissertation explored two significant problems and set out two possible solutions to these specific problems.

Empirical asset correlations from loan loss data

The first problem explored was first to establish the level of South Africa's empirical asset correlations and second to compare these to both the BCBS's set correlations and those derived from a developed economy such as the US. Deriving these asset correlations empirically from retail credit portfolios shows that the BCBS's intended conservatism has been achieved for the fixed period.

Using two different approaches to the Vasicek distribution assumption, it was shown how these empirical correlations may be calculated from minimal input data, how these differ from the BCBS pre-specified correlations and how they adapt to changing economic conditions. Deriving an empirical asset correlation, it was demonstrated that the BCBS accomplished its desired conservatism, since the correlations set by the BCBS are higher than the empirical correlations. It was also shown that the level of conservatism differed for the two countries, with the level of conservatism being high for South Africa, yet low for the US.

Rolling asset correlations from loan loss data

The second problem explored was evaluating South African and US rolling asset correlations, as well as the impact of the economic crisis on these asset correlations. Two different ap-

proaches reached the same result over the time period explored (which included both pre and post crisis), but exploring the second problem revealed that the two approaches differed when evaluation of the impact of changing economic conditions was done. South Africa reacted better to the credit crisis at the point of impact (2007), but the US has recovered better subsequently. The BCBS's asset correlation is more conservative than South Africa's correlation over the rolling time period, but was only conservative in the US leading up to 2012. Although the US's losses recovered better after the credit crisis, the empirical asset correlation increased and surpassed the BCBS's in 2012.

A strong correlation between the loan types in the US exists, which should be of benefit to banks interested in establishing their own internal measures of correlation for both regulatory and economic capital purposes, as well as looking at investing in the US.

4.2 Limitations

The limitations of this study include the difficulty of gathering data in South Africa, as banks consider information proprietary (and thus not shareable) regarding the losses they have made. The only data that could be gathered for South African loan losses were total losses, not bank-specific losses.

Another limitation of this study is that it provides a limited view on determining the empirical asset correlations, since it explores the country as a whole, rather than each bank individually. An in-depth study to determine the empirical asset correlation for each bank, and to determine an unbiased value, would provide more beneficial information for individual banks. The implications for the empirical asset correlations of Basel III have also not been investigated.

4.3 Recommendations

Since there were limitations found in this study, recommendations for further research to overcome these limitations have been provided.

Research into the impact of firm size on correlations, especially during an economic crisis, is recommended. Future investigations can approach large banks individually to procure their loan loss data. The influence of the new Basel III standards on the empirical asset correlation can also be investigated. In Chapter 3, for US rolling empirical asset correlations, it was shown that the BCBS's specified asset correlation was not as conservative as the empirical asset correlation, so an investigation into why this is the case is advised. Although this disser-

tation compared a developing country's asset correlation to that of a developed country, a broader look at other developing (BRICS) and developed countries (G8) can be undertaken.

4.4 Contribution

The ways in which the two studies contribute to portfolio risk management theory and practice, is shown in Table 4.1.

Table 4.1: Summary of dissertation contributions

ATTRIBUTE	PROBLEM STATEMENT	ARTICLE	RESULTS
Assessing empirical asset correlation for South African and US loan losses.	A technique to extract asset correlations from empirical loan losses has not yet been tested on South African loan losses	*"Asset correlations in single factor credit risk models: an empirical investigation"* has been submitted to the *South African Journal of Economics.*	Using local regulators' loss data, implied asset correlations derived and compared with those imposed by the BCBS for both countries
Accurately assessing the impact of the global financial crisis on empirical asset correlations.	Comparing the level of conservatism of the BCBSs asset correlation on loan losses over the financial crisis, has not been done.	*"The evolution of South African and US market-implied asset correlations using empirical loan losses"* Pending acceptance of first article, this research will also be submitted to the *South African Journal of Economics* to form a two-part	The effects of the financial crisis have been studied using a seven-year rolling period for the US and South Africa. The BCBS was only sufficiently conservative for South Africa.

4.5 Final statement

After the global financial crisis that started in 2007, the importance of risk managers have become more evident. Banks are more aware of their loan losses, and the validity of the BCBS with regards to regulatory capital. If stronger measures are imposed by the BCBS, and enforced by the local regulators, another crisis with the same severity can be prevented. Since risk is a complex and ever evolving concept, the concerns outlined in this dissertation are only a small measure of concerns that needs to be addressed in order to promote the health of banks. This dissertation helped towards significant progress in banks' understanding of the empirical asset correlations, and helped guiding them to improving their internal measures.

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