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A CONCURRENT TRIANGULATION MIXED METHODS STUDY ON BASEL II/III CAPITAL MODELING TECHNIQUES IMPLEMENTATION IN ZIMBABWEAN BANKS

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ABSTRACT

Purpose- While extending two extant studies, this paper pioneers a holistic test and critical examination of the usefulness of Basel II/III capital modeling implementation in sixteen Zimbabwean banks.

Methodology- A mixed method approach was adopted where quantitative and qualitative research designs were concurrently combined under equal status. Quantitative data was collected with self-administered structured questionnaires distributed to 120 Risk Managers and manifest archival content analysis carried on 160 audited annual financial statements for 2011-2020. Qualitative data was collected with latent archival content analysis from purposive samples of 35 audited annual financial statements and 20 previous survey reports both for 2011-2020. Data analysis was carried out with descriptive statitistics and interpretative methods.

Findings- This paper finds deep implementation of Basel II/III capital modeling methods, sufficient data and skills, violation of the proportionality principle, existence of information asymmetries and low levels of market discipline and supervision in Zimbabwean banks. The violation of proportionality principle is shown by the fact that local banks are implementing advanced capital modeling methods at the same pace or even higher than internationally active banks. The existence of information asymmetries is shown by divergence of perspectives between regulator and banks. While the regulator is enforcing proportionality, banks are adopting advanced methods for their internal purposes regardless of size. The usefulness of Basel II/III capital modeling in Zimbabwean banks as a tool for managing risk based minimum capital requirements is not clear given the violation of the proportionality principle by banks and existence of other parallel higher capital requirements enforced by the regulator.

Conclusion-This paper makes two specific contributions to knowledge. First it adds empirical evidence to two previous studies thus contributing to literature on proportionality and Basel II/III capital modeling practices in Zimbabwean banks. Second, it proposes policy recommendations to improve capital management in Zimbabwean banks.

Keywords: quantitative risk management, capital modeling, global capital regulation, concurrent triangulation, mixed methods, financial engineering.
JEL Codes: G10, G20, F30

1. INTRODUCTION

The Reserve Bank of Zimbabwe adopted Basel global capital regulations to comply to international capital modeling standards. Precisely the central bank adopted Basel I in 1995, Basel II in 2010 and Basel III in 2019 (Zimbabwe Basel II Technical Guidance, 2011, Zimbabwe Monetary Policy Statement, 2018). However, due to the impact of Covid19 pandemic dates for Basel III implementation were shifted to 2027 (BCBS,2020). Hence currently banks in Zimbabwe are in a transition phase from Basel II to Basel III bringing the reason for using Basel II/III in this paper. Basel II/III aims at promoting financial stability, levelling the plain field of competition, achieving simplicity and comparability among internationally active banks (BCBS ,2006; BCBS ,2011; Dowd et al., 2011; BCBS, 2017). As in other jurisdictions the Reserve Bank of Zimbabwe adopted Basel II/III in a proportionality philosophical manner. According to BCBS (2019) proportionality can be loosely defined as setting tailored prudential and administrative requirements commensurate with the banks' risk profiles to achieve a common objective. This tailored approach seeks to accommodate differences in banks' business models, systemic importance, cross border activity and their risk profiles (BCBS,2019). The Reserve Bank of Zimbabwe in applying a proportionality philosophy, theoretically states that advanced capital modeling methods are the prerogative of Pan African and international banks which are classified as "internationally active banks." On the contrary simple capital modeling methods are designed for local banks falling within the bracket of "smaller banks" (Zimbabwe, Basel II Technical Guidelines,2011). In short bank size is directly correlated to capital modeling methodology.

Since the adoption of Basel regulation in Zimbabwean banks, two empirical studies examine capital modeling methods. First, using mixed methods, Muvingi (2011) studies qualitative factors hampering Basel implementation in Zimbabwean banks. He finds these to be poor governance, weak supervision, presence of imperfect markets, asymmetric information, lack of data, skills shortages, poor technology, poor access to finance and high operational costs. Second, using a survey, Matanda (2015), studies Basel II capital modeling methods adoption in merchant banks. He finds that banks were implementing simple methods such as modified standardised approach for credit risks, alternative standardised approach for operational risks and standardised approaches for market risks. Further he empirically shows that Basel II is not suitable for emerging markets like Zimbabwe, because market circumstances are different to those of developed economies. He agrees with Muvingi (2011) on factors hampering Basel implementation in Zimbabwean banks. While extending on their work, this paper pioneers first, a holistic test of Basel II/III capital modeling implementation and second, critical examination of its usefulness in terms of its proportionality framework and existences in the face of other parallel higher minimum capital requirements. Furthermore, this paper focuses on Basel II/III capital modeling methods implementation in all types of Zimbabwean banks in a strategic practitioner and policy influencing direction.

This paper seeks to answer these research questions. What is Basel II/III capital modeling theory? To what extent have Zimbabwean banks implemented Basel II/III? Are banks following the proportionality principle? How useful is Basel II/III risk based minimum capital requirements given pre-existing higher capital requirements? This paper is structured as follows. Section 2 provides the theoretical perspectives for Basel II/III capital modeling for credit, market and operational risks. Section 3 states and justifies the concurent triangulation mixed methods methodology adopted in this paper. Section 4 provides results and discussion. Section 5 provides conclusion and implications from a risk manager's and policy perspective.

2. LITERATURE REVIEW

Zimbabwe comprises thirteen commercial banks, five building societies, and one savings bank (Zimbabwe Monetary Policy Statement,2021). In this paper two building societies are merged into their parent companies, bringing the number to sixteen banks. Merging is done because both building societies and their parent banks are governed by the same financial regulation. In compliance to Basel II/III banks are supposed to determine regulatory and economic capital. Valdez (2012) defines capital as the amount a firm sets more than assets to withstand and absorb all risks from unexpected losses, remain solvent with high probability and be able to cover its obligations with customers. Regulatory capital is the minimum amount of capital required at a given horizon for a specified confidence interval by the regulator (Elizalde and Repullo, 2007; BCBS, 2009; Valdez,2012; Van Vuuren and De Jongh, 2017). It is calculated using "one size fit" formulas and industry averages (BCBS, 2010). There is no standard definition for economic capital in the banking industry (BCBS, 2009; BCBS, 2010). Several authors agree that economic capital is the self-assessed minimum amount of capital required by a bank to limit the probability of solvency to a given confidence level over a specified time horizon for all material risks (Elizalde and Repullo, 2007; BCBS, 2010; Valdez,2012; Van Vuuren and De Jongh, 2017). According to Basel Committee (2009) economic capital covers the unexpected losses from rare probability events. Economic capital is higher than regulatory capital because it applies higher confidence levels (BCBS, 2010). This paper focuses on strategic financial engineering which does not require intensive mathematical treatment.

2.1. Basel II/III Theoretical Framework

As mentioned in section 1, the Reserve Bank of Zimbabwe adopted Basel I in 1995, Basel II in 2010 and Basel III in 2019 (Zimbabwe Basel II Technical Guidance, 2011, Zimbabwe Monetary Policy Statement, 2018). However due to impact of Covid19 pandemic Basel III implementation have been shifted to 2027 (BCBS,2020). Currently banks in Zimbabwe are in a transition phase from Basel II to Basel III. Basel II/III aims at promoting financial stability, levelling the plain field of competition, achieving simplicity and comparability among internationally active banks (BCBS ,2006; BCBS ,2011; Dowd et al., 2011; BCBS, 2017). As in many other jurisdictions the Reserve Bank of Zimbabwe adopted Basel II/III in a proportionality philosophical manner (BCBS,2019; Zimbabwe Basel II Technical Guidelines,2011). Proponents of capital regulation state that countries implement Basel regulations to enhance financial stability, market discipline, accessibility to international markets, international competitive standing, international perception, risk management practices, reputational image, and production efficiency (Ward, 2002; Alexander,2014; Bessis,2015; Jones and Zeitz, 2017). Other scholars argue that, Basel adoption is not very useful but rather is a result of peer pressure from the international world, standards setting bodies such as International Monetary Fund and World Bank (Ward 2002; Jones and Zeitz, 2017). Opponents of capital regulation theoretically and empirically doubt the usefulness of global capital regulation (Benston and Kaufman, 1996; Dowd,1996; Dowd, et al.,2011; Haldane,2017). Rather they provide evidence that global capital regulation is the source of capital inadequacies and liquidity crises in the banking sector.

Basically Basel II/III is made up of three mutually reinforcing pillars (BCBS, 2006; BCBS,2010; Alexander, 2014). Pillar 1 provides formulae for definitions of capital and determination of minimum capital requirements (BCBS, 2006; BCBS;2017).

The Reserve Bank of Zimbabwe set the minimum capital at 12% (Zimbabwe Basel II Technical Guidance, 2011). The capital adequacy ratio (CAR) is calculated as:

$$\text{CAR} = \frac{\text{Net Capital Base}}{\text{Credit risk weighted assets (RWA)} + 12.5\ (\text{Market RWA} + \text{Operational RWA})} \geq 12\% \ldots\ldots\ldots\ldots\ldots\ldots.(1)$$

$$\text{Net Capital Base} = (\text{Tier 1} + \text{Tier 2} + \text{Tier 3}) - \text{Goodwill} - \text{Investments} \ldots\ldots\ldots (2)$$

Tier 1 is core capital, Tier 2 is supplementary capital, and Tier 3 is subordinated debt allocated to market and operational risks only. Basel III also encompasses changes in quality of capital, macroprudential tools, leverage ratio, operational risk modeling method and liquidity risk management.

Pillar 2 is supervisory review process where the regulator assesses how banks determine their capital needs relative to the material risks, they face. It comprises the Internal Capital Adequacy Process (ICAAP) which is an assessment of the adequacy of regulatory and economic capital done by the bank and the supervisory review process (SREP) done by the supervisor (Zimbabwe Basel II Technical Guidance,2011). Basel III enhances firmwide governance of Pillar 2. Pillar 3 provides market discipline and disclosure framework to promote transparency among banks. As such depositors, investors, and other external parties should access quarterly and annual information on definitions of capital, capital structure, capital adequacy, risk exposure, and assessments (BCBS, 2006; Zimbabwe Basel II Technical Guidance, 2011). Furthermore, Basel III introduces disclosure of key metrics for regulatory and economic capital covering definitions of capital, capital structure, risk exposures and methods of capital modeling. The disclosed information must be complete, readable, timely, reliable, and material (Zimbabwe Basel II Technical Guidance, 2011). This paper focuses on Basel II/III Pillar 1 capital modeling methods for credit, market, and operational risk.

2.2. Credit Risk Capital Modeling

Credit risk is the probability of losses from the borrower's default or deterioration of credit ratings (Bluhm et al., 2010; Bessis, 2015; Baesens, et al., 2016). Since a considerable size of the balance sheet consists of loans to customers and most bank failures are the result of the customer's defaults, credit risk is a major source of bank risk. Modified Standardised and Internal Ratings Based Approaches (IRB) are approved by the Reserve Bank of Zimbabwe for credit risk capital modeling.

2.2.1. Modified Standardised Approach

In the absence of an external ratings market, the Reserve Bank of Zimbabwe adopts the modified standardised approach (MSA). Under this method regulatory capital is determined by risk weights and exposures in book values (Zimbabwe Basel II Technical Guidance, 2011). The risk weights for exposures are provided by the central bank while ratings are determined using either the supervisory rating scale or obtained from an approved external rating agency domiciled in Zimbabwe (RBZ Guideline Number 04/BSD, 2004). MSA is a conservative method designed for simple banks with less sophisticated financial models (Zimbabwe Basel II Technical Guidance, 2011).

2.2.2. Internal Ratings Based Approach

This is an advanced credit risk modeling method approved to banks that have satisfied prescribed minimum quantitative and qualitative criteria set by the regulator (Basel II Technical Guidance,2011). The internal ratings-based approach (IRB) comprises the foundation internal ratings based (FIRB) and advanced internal ratings based (AIRB). Banks that apply FIRB will rely on their own internal estimates for probabilities of default (PD) but are given supervisory estimates for the loss given default (LGD), asset correlations (R), exposure at default (EAD), and effective maturity (M). On the contrary banks that use AIRB methods determine their own internal estimates for all parameters except for asset correlation which is provided by the supervisor (Zimbabwe Basel II Technical Guidance, 2011). Estimates of credit risk are based on internal and external data where necessary, and are rooted on historical, empirical, and judgmental evidence reflecting recessions and booms (BCBS 2006; Zimbabwe Basel II Technical Guidance,2011; BCBS, 2016). The IRB approach is designed for large international banks with sophisticated, large databases, and high-quality internal risk measurement systems.

Theoretically economic and regulatory capital should converge for banks that implement AIRB (BCBS, 2006; Zimbabwe Basel II Technical Guidance, 2011). As a rule, banks that use IRB approaches, should report deviations of regulatory from economic capital to the central bank (Zimbabwe Basel II Technical Guidance, 2011). The Merton- Vasicek Asymptotic Risk Factor Model is used to estimate capital in IRB for banking book exposures viz: corporate, sovereign, bank, retail, and equity exposures (Vasicek,2002; Gordy, 2003; Zimbabwe Basel II, Technical Guidance,2011). The general formula is shown:

$$K = \sum_{i=0}^{N} LGD \left[\times N\left(\frac{N^{-1}(PD) + \sqrt{R}\, N^{-1}(0.999)}{\sqrt{1-R}} \right) - PD \right] \times \frac{1 + (M - 2.5) \times b(PD)}{1 - 1.5 \times b(PD)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where k is the capital requirement, PD is the probability of default, LGD the loss given default, R is the asset correlation, M is maturity, N^{-1} inverse of normal distribution, N is normal distribution and b(PD) is maturity adjustment function. The maturity adjustment function is calculated by:

$$Maturity\ adjustment\ b(PD) = (0.11852 - 0.05478.ln(PD))^2 \quad (4)$$

The risk weighted assets (RWA) for credit risk are thus a function of 12.5 multiplied by capital requirement (k) and exposure at default. Five parameters namely PD, EAD, LGD, M, and asset correlation (R) are used in credit risk capital models. Engelmann and Rauhmeier (2012) defines PD as the likelihood that a loan will not be repaid over a given time horizon. PD is a binary classification problem that is calculated from historical data for all clients' segments. Engelmann and Rauhmeier (2012) states that there is no precise preferred method to estimate PD under Basel II/III, however logit regression is popular in academic literature and practice. Data for PD modeling should be five years and not more than seven years old (BCBS,2006). Financial ratios are used for corporates while obligor specific factors are applied in retail portfolios over a one-year horizon (Zimbabwe Basel II Technical Guidance, 2011).

Exposure at default (EAD) is an estimate of the outstanding amount in case an obligor has defaulted (Engelmann and Rauhmeier,2012). It comprises the amount currently drawn and estimates of the future drawdowns. Estimates of future drawdowns describe how clients may decide to draw unused commitments called credit conversion factors. Since credit conversion factors are the only unknown variables, estimating EAD is equivalent to estimating the credit conversion factors. The credit conversion factor depends on the type of the loan and borrower. According to the Basel Committee (2006), EAD must not be lower than the book value of balance sheet receivables and must be calculated without considering provisions. Long run EAD averages reflecting downturn conditions which are calculated at facility level must be utilised. Four methods namely Credit Conversion Factor (CCF) Method, Current Exposure Method (CEM), Standardized Method (SM) and Internal Model Method (IMM) are used to estimate EAD (see BCBS, 2006).

LGD measures the credit loss a bank is likely to incur in the event of default (BCBS,2006). Once a default event has occurred, LGD has three types of losses: the loss of the principal, the carrying costs of non-performing loans (interest income foregone) and workout expenses (collections, legal etc.). For retail portfolios, long run LGD averages that reflect downturns and data more than five, but less than seven years is used. For banks, sovereigns and corporates data must be no shorter than seven years (Zimbabwe Basel II Technical Guidance, 2011). LGD modeling is done by four methods namely Market LGD, Workout LGD, Implied Historical LGD, and Statistical LGD (see BCBS,2006). Zimbabwean banks are recommended to apply Workout LGD (BCBS, 2006; Zimbabwe Basel II Technical Guidance, 2011).

Credit portfolios comprise instruments with different effective maturities. Intuition and empirical evidence show that capital requirements increase with time to maturity. Long term loans are riskier than short term loans because they are likely to be affected by rating downgrades over time. Maturity has a strong effect to obligors with low probabilities of default as well as loans that will be affected by rating downgrades. The maturity adjustment function in Basel II/III reflects the potential deterioration in credit quality of loans with longer maturities. The average portfolio effective maturity is set at 2.5 years except for repos which are set at 6 months (Zimbabwe Basel II Technical Guidance, 2011). The asset correlation reflects the effect of the systematic risk factor. Banks are supposed to use fixed asset correlations derived by the Basel Committee (BCBS, 2006; Zimbabwe Basel II Technical Guidance, 2011). The asset correlations are based on Lopez (2004)'s empirical observations which are (a) Asset correlations decrease with increasing probabilities of default. The higher the probability of default the higher the idiosyncratic risk component of obligors. (b) Asset correlations increase with firm size meaning that idiosyncratic risks are higher for smaller firms.

2.3. Market Risk Capital Modeling

Market risk is the risk of losses in, on and off-balance sheet positions arising from movements in market prices of interest rates, commodities, equities, and foreign exchange (BCBS, 2017; Hull, 2018). Market risk is calculated for the trading and banking books (BCBS,2017). The trading book comprises assets held for short term trading and hedging such as default, interest rate, credit spread, equity, foreign exchange, and commodities. The banking book is made up assets held for long term trading as foreign exchange and commodities (BCBS, 2017). Market risk in Zimbabwean banks is determined by interest and foreign exchange risk because banks are not permitted to trade in equities and commodities (Zimbabwe Basel II Technical Guidance, 2011). Banks determine the market risk capital using either the standardised approach, internal models' approach or partially both (Zimbabwe Basel II Technical Guidance, 2011).

2.3.1. Standardised Approach

The standardised approach (SA) is a bucket risk weighting method for interest rate risk, equities, commodities, and foreign exchange (BCBS,2006; Jorion 2007). This approach serves two main purposes (Zimbabwe Basel II Technical Guidance,2011). It provides a method for calculating capital requirements for small banks with simple business models and a fallback in the event of inadequate internal market risk models. The second purpose is of importance for larger or more systemically important banks. In Zimbabwe, market risk under SA is calculated for interest and foreign exchange risk. Interest risk is calculated using either the maturity ladder or duration approach (Zimbabwe Basel II Technical Guidance,2011). Foreign exchange risk is computed by measuring the exposure in a single currency position and inherent in a bank's mix of long and short positions in different currencies**.** The SA approach is criticised for lacking risk sensitivity, excluding diversification, and failing to capture risks associated with more complex instruments (BCBS, 2012; BCBS,2013; BCBS,2017). Thus, Basel Committee (2017) propose a new standardised approach but is yet to be approved by the Zimbabwean central bank.

2.3.2. Internal Models Approach

The internal models' approach (IMA) is approved for banks that satisfy quantitative and qualitative standards imposed by the central bank (BCBS, 2006; Zimbabwe Basel II Technical Guidance,2011; BCBS, 2017). The method is designed for sophisticated banks with huge databases and complex financial models. The method theoretically ensures that regulatory and economic capital converge (Zimbabwe Basel II Technical Guidelines,2011). Market risk for internal models' approach is determined by any of these three approaches: value at risk, expected shortfall and bubble value at risk (BCBS, 2006; Wong, 2011; BCBS, 2013; BCBS, 2017). Value at risk (VaR) used to be the sum of traditional VaR and incremental default charge (specific risk charge). Its parameters were 10 trading days or horizon of two calendar weeks, 99% confidence interval, average VaR over 60 trading days, historical data for one-year period updated at least quarterly, supervisory determined multiplier, and the specific risk charge calculated over 250 days at the 99.9% confidence interval (Zimbabwe Basel II Technical Guidance, 2011).

Following the 2008 great financial crisis, the Basel Committee introduced Basel 2.5 for market risk. Under this method, capital for market risk is calculated as the sum of traditional value at risk, stressed value at risk and the incremental risk charge (BCBS, 2009; Smit et al., 2011; Kou et al., 2013; Chen, 2018). The formula for calculating market risk is shown:

$$Market\ risk\ capital = Traditional\ VaR + Stressed\ VaR + Incremental\ risk\ charge \quad \text{………………………………} (5)$$

This method addresses procyclicality and regulatory arbitrage (BCBS, 2013; Chen, 2014; BCBS, 2017; Chen, 2018). Traditional VaR is calculated for 10 days at 99% confidence interval. Stressed VaR is calculated with 10-day 99th percentile and one-tailed confidence interval with model inputs calibrated to historical data from a continuous 12-month period of significant financial stress (BCBS, 2009). This addresses tail events and procyclicality in stressed financial markets. Incremental VaR is the additional charge that captures credit risk in the trading book caused by default and credit migration. The incremental VaR is calculated for one-year horizon at 99.9% confidence interval (BCBS, 2013). From a regulatory perspective Basel 2.5 has not been applied in Zimbabwe (Zimbabwe Basel II Technical Guidance, 2011).

Internal VaR approach is criticised for relying on the 10-day VaR metric which is not subadditive (Dowd and Blake, 2006). It also fails to capture credit and market liquidity risk because there is no distinct boundary between trading and banking books (Kou et al., 2013; BCBS, 2013; Emmer et al., 2015; Visser and Van Vuuren, 2016). Currently the Basel Committee on Banking Supervision suggests replacement of VaR with expected shortfall because it is subadditive, coherent and stable (Wong, 2011; BCBS, 2017; BCBS, 2020). Further, expected shortfall measures tail risk, liquidity and is calibrated to stress conditions on base horizon (BCBS, 2013; BCBS,2017; Chen, 2018). Expected shortfall is calculated at 97.5% confidence level. However, expected shortfall is not elicitable, very sensitive to parameter misspecification, difficult to backtest, increases model risk, and regulatory arbitrage (Gneiting,2011; Emmer et al., 2015). ES is still in early phases of Basel III implementation.

Wong (2011) suggests replacement of both expected shortfall and VaR with bubble value at risk. This is because bubble value at risk accounts for countercyclicality, extreme events, and market bubbles. Wong (2011) argues empirically that BuVaR is more accurate than VaR. Visser and Van Vuuren (2016,2018), based on an empirical study from South African banks show the superiority of bubble value at risk over expected shortfall and VaR. However, bubble value at risk is largely academic and not common in real world practice. VaR and expected shortfall for market risk are estimated with Historical Simulation, Monte Carlo Simulation and Variance Covariance. Historical simulation is a non-parametric method that uses relative historical differences in market prices to create the distribution of potential future losses and profits for a portfolio (Jorion, 2007; Bessis, 2015; Visser and van Vuuren, 2016). As the historical simulation method depends on observed market variations, no statistical calculations are required. Large banks prefer historical simulation because it is simple and intuitively logical (Visser and van Vuuren, 2016). However, this method suffers from instability and reliance on historical data. The data for historical simulation must be robust and furthermore the older the data, the less relevant it is for the current market.

Monte Carlo simulation is a non-parametric method which assumes that information about the combined distribution of market changes is available. Monte Carlo simulations generate the correlated random variables to model a probability distribution for statistical analysis. This method assumes a normal distribution (though this restriction can be relaxed). VaR is calculated by identifying prominent factors and constructing a joint distribution by fusing historical data with observed returns. Simulation is then performed over many scenarios. Monte Carlo simulation is a very flexible approach that incorporates time variations, volatility, expected returns, fat tails and extreme scenarios in risk factors (Jorion, 2007; Bessis 2015; Visser and Van Vuuren, 2016). Its shortcomings are complicated underlying mathematics, considerable computing time and expensive infrastructure from an intellectual capital perspective (Jorion, 2007). The variance covariance approach is applicable to VaR computation only. The variance-covariance method assumes that portfolio returns are normally distributed. VaR is then expressed as a multiple of the standard deviation of the portfolio's return. The method determines the variance-covariance matrix which is a diagonal matrix with all variances of the return and covariances between the assets (Bessis, 2015; McNeil et al., 2015). Variances are calculated using standard deviations of market returns while covariances combine standard deviations of market returns with the correlations between market returns. This method is also called the Delta Analytical Method.

2.4. Operational Risk Capital Modeling

Operational risk is the indirect or direct probability of loss resulting from inadequate or failed internal processes, people, systems, and external events (BCBS,2006). This definition includes legal risk but excludes strategic and reputational risks (BCBS, 2006; BCBS, 2016). Einemann et al., (2017) cites that operational risk modeling is challenging because of the dominancy of low frequency high severity events (LF/HS). These events demand an accurate reflection of heavy tails of the loss distribution. The central bank in Zimbabwe prescribes the Alternative Standardised Approach (ASA), Advanced Measurement Approach (AMA) and Standardised Measurement Approach (SMA) (Zimbabwe Basel II Technical Guidelines,2011).

2.4.1. Alternative Standardised Approach

The alternative standardised approach (ASA) is designed for simple banks with simple financial models (Zimbabwe Basel II Technical Guidance, 2011). Banks categorise their activities into three business lines viz retail banking; commercial banking; and all other activities**.** The operational risk capital charge for a banking institution equals the sum of the average for these three business lines. The capital is calculated as:

$$K = \sum_{t=1}^{6} \left[\frac{0.12\times m\times LAR_t}{6}\right] + \sum_{t=1}^{6} \left[\frac{0.15\times m\times LAC_t}{6}\right] + \sum_{t=1}^{6} max\left[\frac{(0.18\times AGI_t),0}{3}\right] \qquad (6)$$

Where K is the total operational risk regulatory capital charge, m is 0.035 fixed scaling factor, $\mathrm{LAR_t}$ is the total gross outstanding loans and advances for retail area, $\mathrm{LAC_t}$ is the total gross outstanding loans and advances for commercial banking, $\mathrm{AGI_t}$ is adjusted gross income and t is half yearly observation period. The total regulatory capital for operational risk is a function of K multiplied by 10. The capital for retail and commercial segments is determined from the last six consecutive half-yearly balances of total gross outstanding loans and adjusted average gross income over three years for other activities (Zimbabwe Basel II Technical Guidance,2011).

2.4.2. Advanced Measurement Approach

Banks qualifying for advanced measurement approach (AMA) determine their own capital estimates from internal models after satisfying minimum and qualitative criteria prescribed by the regulator (BCBS,2006; Zimbabwe Basel II Technical Guidance, 2011; Peters et al.,2016). AMA is designed for large banks with huge databases. The method theoretically ensures convergence of regulatory and economic capital (Zimbabwe Basel II Technical Guidance, 2011). As a rule, banks must explain deviations between economic and regulatory capital to the Central bank (Zimbabwe Basel II Technical Guidance, 2011).

Under AMA confidence intervals for regulatory capital are set at 99.9%, and economic capital set from 99.95% to 99.99% for one-year horizon (BCBS,2006; Shevchenko and Peters, 2013; Cruz et al., 2015). Dependence modeling is allowed if approved by the regulator (Shevchenko and Peters, 2013; Cruz et al., 2015). Data for modeling should be between five and seven years (BCBS,2006). However, for banks that are still new or have not yet collected data, AMA models can be built from at least three years of data (Zimbabwe Basel II Technical Guidance, 2011). This method is criticised for suffering from data scarcity, unstable parameters, and high sensitivity of data to extreme events (Cope et al., 2009; Embrechts and Hofert, 2011; Cohen, 2018). According to Cohen (2018) AMA lacks theoretical basis and faces difficult dependence modeling.

Three steps are followed in AMA modeling. These are classifying events to business lines, choosing the data elements, and selecting the modeling approach. Events are classified by seven broad risk categories and eight business lines as shown in Table 1.

Table 1: Operational Risk Classification

Business Line Code	Business Line	Event Type	Operational Risk Type
BL1	Corporate Finance	ET1	Internal Fraud
BL2	Trading and Sales	ET2	External Fraud
BL3	Retail Banking	ET3	Employment Practices and Workplace Safety
BL4	Commercial Banking	ET4	Clients Products and Business Practices
BL5	Payment and Settlement	ET5	Damage to Physical Assets
BL6	Agency Services	ET6	Business Disruption and System Failures
BL7	Retail Brokerage	ET7	Execution, Delivery and Process Management
BL8	Asset Management		

Source: Aroda,2016

There exist four data elements for AMA modeling namely internal data, external data, scenario analysis, and business environment and internal factors control exist (Cope, 2012; Aroda et al., 2015; Aroda, 2016). Internal data is the first step in using AMA. Banks must have credible, comprehensive, timely, complete, and robust internal loss data for operational risk measurement (Aroda,2016). Additionally, each bank should determine an appropriate threshold for loss data (Zimbabwe

Basel II Technical Guidance, 2011). This information includes gross loss amounts, date of the loss event and any recoveries, as well as descriptive information about the drivers or causes of the loss event. Data used for regulatory capital purposes must have a minimum of five-year observation period. When a bank first moves to AMA, a three-year historical data window is allowed, subject to written approval by the Reserve Bank (Zimbabwe Basel II Technical Guidance, 2011). Internal loss data is classified into eight business lines by seven event types to determine the unit of measure (UoM) or alternatively a cell.

Relevant external loss data (ELD) must include, where available, data on the gross loss amount and loss event category, information on any recoveries to the extent that these are known, the nature and scale of the operation where the event occurred and any other available information that would assist in assessing the relevance of the loss event to the banking institution (Aroda, 2016). External loss data is obtained from vendor, consortia, and own internal external database (Cruz et al., 2015; Aroda, 2016). However external data suffers from reporting or truncation, control, scale data capture and representativeness biases (Aue and Kalkbrener, 2007; Chaudhury, 2010; Ganegoda and Evans ,2014).

Scenario analysis is based on expert opinion obtained from workshops, surveys, focus group discussions, and so on. This is used as a supplement where internal and external loss data do not provide enough robust estimates of the bank's exposure to operational risk. Scenario analysis should be consistent, comprehensive, and capture all material sources of operational risk across the bank. Scenarios should be reviewed annually to ensure they reflect current operational risk profiles of the bank. Expert opinion data suffers from presentation, anchoring, huddle, context, inexpert opinion, over/under confidence, and gaming biases (Chaudhury, 2010; Aroda et al., 2016).

Business Environment and Internal Factors Control (BEICF) is the transformation of qualitative information into numerical values by a scoring mechanism (Aroda,2016). BEICF transformation differs from bank to bank. However, the most prevalent forms are key risk indicators (KRIs) and risk control (RCSA) self-assessment (Aue and Kalkbrener,2007). Key risk indicators are mostly quantitative factors used as a proxy for the quality of the control environment of the bank. Under risk control self-assessment, the bank collects experts' opinion on status of their business processes. The perceived status is rated as Amber or Green or Red RAG status which is quantified subjectively on scorecards to generate risk scenarios, exposure, and correlation to other risks. The third step is choice of AMA modeling method. Methods of AMA modeling approved in Zimbabwean banks are internal measurement methodology, loss distribution approach, structured scenario analysis, scorecard, and hybrid approach (Zimbabwe Basel II Technical Guidance, 2011).

2.4.2.1. Internal Measurement Approach

Karam (2014) states that the internal measurement approach (IMA) method assumes a linear relationship between expected and unexpected losses. Banks generally use internal data and may sometimes apply external data. According to Karam (2014) applying the internal measurement approach has three steps: categorisation of operational risk into eight business lines by seven event types, supervisory determination of exposure indicator (EI), and the scaling factor γ for each business line. The overall capital charge for a bank is the simple sum of expected loss, scaling factor and Risk Profile Index. The Risk Profile Index (RPI) is a function of exposure indicator, probability of an operational risk and the loss given event. It is a bank- specific adjustment factor that captures leptokurtic properties of the bank's loss distribution (Karam, 2014). RPI of the industry loss distribution is one, hence if the bank loss distribution has a fatter tail than the industry loss distribution then RPI would be larger than one. Thus, two banks with the same expected loss may have different capital charges because of different risk profile indices.

2.4.2.2. The Loss Distribution Approach

The Loss distribution approach (LDA) is a parametric technique based on historical internal loss data (potentially enriched with external data). Established on concepts used in actuarial sciences, the LDA involves estimation of frequency distribution for the occurrence of operational losses and a severity distribution for the economic impact of the individual losses (Moscadelli ,2004; Frachot et al., 2004; Chapelle et al., 2004; Shevchenko and Peters, 2013; Cruz et al., 2015; Morais et al., 2018). This is the most popular and cornerstone method in AMA modeling (Shevchenko and Peters, 2013; Morais et al., 2018). LDA is implemented in five steps (Frachot et al., 2003; Fountnouvelle et al.,2006): (a) Estimation of the loss severity distribution using any of these distributions: Lognormal, Log -Gamma, Weibull (shape parameter less than 1), generalised pareto and burr (BCBS, 2011). This is the most difficult aspect of operational risk modeling because data is plagued with biases. (b) Estimation of the loss frequency distribution using any of these: Binomial, Negative Binomial and Poisson probability distributions. (c) Calculation of capital requirements via the aggregate distribution of losses based on the frequency and severity distributions using Monte Carlo simulation or another equivalent technique. (d) Incorporate self-assessment and scenario analysis i.e., the experts' opinions. (e) After calibration of the frequency and severity distributions, the capital estimation is carried through the convolution of the theoretical distributions selected. The most widely used methods for convolution of distributions are Monte Carlo simulation, the Panjer recursion, and Fast Fourier transform (Morais et al., 2018).

2.4.3.3. Structured Scenario Analysis

Dutta and Babbel (2014) notes that structured scenario analysis (also called Scenario based AMA) combines severity and frequency of a potential loss over a given time horizon as linked to evaluation of scenarios. Experts provide opinions on the probability of occurrence (frequency), and the potential economic impact should the event occur (severity) from data collection methods such as workshops, surveys, questionnaires, Delphi technique, etc (Karam, 2014; Ergashev et al., 2015; Morais et al., 2018). In this case expert opinion is based on historical data, perception, judgment, and experience. Scenario-based AMA is like LDA in that both combine two dimensions of frequency and severity to calculate the aggregate loss distribution. This method is subjective and does not escape biases from human perceptions and judgements. However, the method can be combined easily with other techniques such as LDA, Bayesian inference, Change of Measure approach, and so on (Karam, 2014; Dutta and Babbel,2014; Morais et al., 2018).

2.4.3.4. Scorecard Approach

The Scorecard approach (also called the Risk Drivers and Controls Approach) is a self- assessment with a questionnaire consisting of a series of weighted risk-based questions. The questions focus on principal drivers and controls of operational risk across a broad range of applicable operational risk categories, which may vary across banks (Karam, 2014). This provides the bank's unique operational risk profile and risk weighted scores. The Basel Committee does not offer any kind of mathematical equation, but banks have proposed their own formula for calculating capital as:

$$K_{SCA} = E_{ij} \times \omega_{ij} \times RS_{ij} \qquad (7)$$

Where, EI is the exposure indicator, RS the risk score and ω is the scale factor. The scorecard approach is based on forward looking self-assessment data or business internal control factors. However, if the events are rare, external data can also be applied.

2.4.3.5. Hybrid Approach

In a hybrid approach, a bank may combine different approaches for example LDA and scorecard approach. It is possible to mix scenario analysis with other approaches such as Bayesian networks (Karam, 2014).

2.4.3. Standardised Measurement Approach

The standardised measurement approach (SMA) is the new actuarial operational risk modeling method (BCBS, 2014; BCBS, 2016; BCBS, 2017). According to Cohen (2017) it is a trial-and-error method that utilises internal data only. It aims to achieve a universal solution which is applicable to all banks. External, business environment and internal factors control (BEICF) and scenario analysis data are discarded because they converged as noise in Basel II operational risk models (Cohen, 2017). SMA is made up of the business indicator (BI), the business indicator component (BIC) and the Internal Loss Multiplier (ILM) (BCBS, 2016). Under SMA capital is determined with four steps (BCBS,2016). Firstly, the business indicator is calculated from financial statement-based proxies for operational risk comprising interest, leases, and dividend component (ILDC), the services component (SC) and the financial component (FC) (see formula in BCBS, 2017). Secondly, the Business indicator component is determined by multiplying business indicator with a set of regulatory marginal co-efficient (α). Thirdly, the internal loss multiplier or scaling factor is calculated as a function of average of historical internal losses, loss component and business indicator component (see BCBS,2017). The scaling factor is ideally based on high quality data over a ten-year period. However, banks without five years of high-quality loss data must calculate the capital requirements based solely on the business indicator component. Supervisors may however require a bank to calculate capital requirements using fewer than five years of loss data if the internal loss multiplier is greater than 1 and if they believe the losses are representative of the bank's operational risk exposure (BCBS, 2016). Fourthly, operational risk regulatory capital is calculated by multiplying the internal loss multiplier with business indicator component. Supervisors, at their own discretion can set the internal loss multiplier to 1 for all banks (BCBS, 2016).

There is an ongoing debate on whether standardised measurement approach should replace all Basel II operational risk modeling methods. Some scholars argue that SMA cannot replace AMA because it introduces capital instability, risk insensitivity and super additivity which leads to significant undercapitalisation in too big to fail banks (Peters et al., 2016, Mignola et al.,2016). Again, the method is not forward-looking but an oversimplified "one size fit all" LDA applied at the institution top level (Peters et al., 2016). Moreover, SMA method discards 75 percent of data used in operational risk modeling. Cohen (2017) feels that both SMA and AMA are not practical in operational risk modeling. SMA is still new for banks in Zimbabwe and is in early phases of implementation.

2.5. Challenges of Basel II/III Capital Modeling

Several authors argue that Basel II/III capital modeling has limited application to African markets because it is designed specifically by the G20 in exclusion of most African states except South Africa (Ward, 2002; Powell, 2004; Claessens, 2015; Brownridge, 2015; Gottschalk, 2016; Jones and Zeitz, 2017; Jones and Knaack,2019). Hence due to this dominance by developed countries, Basel II/III is poorly calibrated for least developing countries' financial sectors (Barth et al., 2006; The

Warwick Commission, 2011; Jones and Knaack, 2019). Thus, challenges for Basel implementation in African countries are : higher pre-existing capital and liquidity standards than required for Basel II/III, financial infrastructure gaps because of illiquid markets, absence of derivatives and rating agencies, resource capacity constraints, weak supervision, absence of large data bases, information asymmetries between banks and supervisors, and key macroeconomic threats to financial stability such as large swings in economies and other external shocks which are not addressed in Basel II/III (Kasekende,2014; Jones and Knaack, 2019). Two empirical studies that examine Basel II implementation in Zimbabwean banks supports these views. First, using a survey, Matanda (2015), studies Basel II capital modeling adoption in merchant banks. He discovers that Basel II is not suitable for emerging markets like Zimbabwe, because market circumstances are different to those of developed economies. Second, using mixed methods Muvingi studies qualitative aspects of Basel implementation in Zimbabwean banks. Both Muvingi (2011) and Matanda (2015) find that Basel II implementation in Zimbabwean banks is hampered by poor governance, weak supervision, presence of imperfect markets, asymmetric information, lack of data, skills shortages, poor technology, poor access to finance, high operational costs, and inadequate supervisory skills for implementing Pillar 2.

3. DATA AND METHODOLOGY

This section outlines the research methodology that was used for data collection and analysis in this paper. Data was collected from sixteen Zimbabwean banks. Following the pragmatism philosophy, concurrent triangulation mixed methods where quantitative and qualitative research designs were employed to satisfy both objective and subjective goals of the study (Johnson and Onwuegbuzie,2004; Morgan,2014; Saunders etal.,2019). Pragmatists are not committed to any sort of philosophical stance (Creswell,2007; Dawadi et al.,2021). This is because essentially pragmatism "is pluralistic and oriented towards what works in practice" (Creswell & Plano Clark,2011, p.41). As a result, pragmatists use multiple methods as guided by the research problems rather than the "purist divide and war" between positivism and interpretivism paradigms. Hence, pragmatism uses multiple methods, multiple angles and multiple data collection methods as guided by the research problems (Dawadi et al.,2021).

The pragmatism philosophy was chosen because of its flexibility and ability to work with multiple research philosophies, realities, and ontological assumptions (Morgan, 2007; Creswell, 2009; Saunders et al., 2019). It was also more appropriate to this study which has a "practitioner-based" intuitive appeal. "Practitioner- based" research is often multi-purpose requiring the application of "what works" tactics and addressing objectives within epistemological assumptions of pragmatism (Tashakkori and Teddlie, 2010; Creswell, 2014). Precisely survey and archival strategies were concurrently employed in quantitative and qualitative research designs as highlighted in sections 3.1.

3.1. Research Design

This paper employed concurrent triangulation mixed methods to provide a multiple angles perspective, holistic picture, triangulation, better evidence and reduce weaknesses associated with mono or purist methods and philosophical positions (Denzin,1978; Jick, 1979; Greene et al., 1989; Santos et al., 2017, Dawadi et al.,2021). Furthermore, mixed methods were used for complementarity, provide explanations and to ameliorate validity and reliability of results (Collis and Hussey,2010; Tashakkori and Teddlie, 2010; Bentahar and Cameron,2015). In fact, mixed methods allowed for in-depth study and data consolidation from multiple perspectives in this case positivism, realism and interpretivism philosophies (Shorten and Smith,2017, Dawadi et al.,2017). Mixed methods research is where the researcher mixes or combines quantitative and qualitative research techniques, methods, approaches, concepts, or language into a single study (Johnson and Onwuegbuzie,2004; Castro et al.,2010; Saunders et al., 2019). The abductive logic of inquiry was used (Saunders et al.,2019). Abduction involved the use of induction (discovery of patterns, insights, and new theories) and deduction (testing theories/hypothesis). This entailed moving back and forth from data to theory, and from theory to data.

Creswell et al., (2003)'s mixed methods research design was adopted. The approach classifies mixed methods designs into sequential explanatory, sequential exploratory, sequential transformative, concurrent triangulation/parallel, concurrent nested, and concurrent transformative. This approach was adopted because of its consistence and ability to integrate the most important dimensions needed in this paper (Santos et al., 2017). Four dimensions namely time distribution, weight attribution, degree of combination and theorisation were considered (Creswell,2003, Bentahar and Cameron,2015; Santos et al.,2017). In the spirit of Creswell et al., (2003), Castro et al., (2010) and Dawadi (2021) concurrent triangulation mixed method design was used. This means quantitative and qualitative data were firstly collected and analysed in parallel then secondly merged at data interpretation phase with the aim of determining convergence, differences, and combinations (Creswell,2003; Santos et al.,2017; Shorten and Smith,2017). This was done to give a complete understanding of phenomenon. Using Morse (1991)'s notation the quantitative and qualitative data were given equal weight and mixed upon the integration (QUAN+QUAL) to facilitate "deep structure" data analysis and interpretations (Castro et al.,2010). The theoretical perspective adopted was that Basel II/III risk management in banks is complex and built upon multiple perspectives.

3.1.1 Quantitative Research Design

Two quantitative methods were employed to answer research objectives in line to objectivism ontological and positivism epistemological assumptions. These were survey and manifest archival strategies. These methods answered the objective of testing Basel II/III capital modeling implementation in Zimbabwean banks. According to Check & Schutt, (2012, p.160) survey research is "the collection of information from a large sample of individuals through their responses to questions." Manifest content archival method is statistical analysis of documents for the appearance of a word or content (Potter and Levine-Donnerstein,1999). While many scholars argue that content analysis is qualitative (Krippendorff, 1980; Weber, 1985; Beattie, 2005; Scaltrito, 2015), Kondracki and Wellman (2002) argues that content analysis that examines the frequency of specific words or content and uses regression methods is a quantitative study. The objectives of the quantitative design were to provide factual, measurable, standardised data collection, explanation, and theory confirmation for Basel II/III modeling methods implementation from large sample of banks (Johnson and Onwuegbuzie,2004; Ponto,2015; Saunders et al., 2019). As such a deductive approach was used where known premises, theories and frameworks on Basel II/III were reviewed from literature and subjected to testing (Bryman, 2006). The phenomena in question were understood from an independent, objective, and external point of view (Babbie,2011).

3.1.2. Qualitative Research Design

Consistent with constructivist ontology and interpretivism epistemology a qualitative research design was used to critically examine Basel II/III capital modeling methods implementation in Zimbabwean banks. Interpretivism allowed the researchers to operate in naturalistic settings and obtain in-depth, rich, and contextual critical understanding of Basel II/III modeling methods implementation in Zimbabwean banks (Bryman, 2006; Denzin and Lincon,2005; Mohajan, 2018). This gave room to idealism, relativism, humanism and use of hermeneutics (Guba & Lincoln, 1989; Lincoln & Guba, 2000). The purposes for qualitative research are induction, discovery, exploration, new theory or hypothesis generation and thick qualitative analysis (Johnson and Onwuegbuzie,2004). Following Saunders et al., (2019), an inductive approach was applied that began with data gathering from annual audited financial statements and previous survey reports on capital management with an aim to generate new insights on Basel II/III Pillar 1 capital modeling implementation in Zimbabwean banks. Non-numerical data were collected with non-probability sampling. The few selected archival records were investigated in detail with latent content archival analysis to get contextual meanings not generalisable (Bryman,2004; Denzin and Lincoln,2011; Clough and Nutbrown, 2012). Latent content archival analysis is the understanding of interpretative, implied, and underlying meanings beyond mere frequency analysis of words or content (Holsti,1969; Babbie,1992; Morse and Field,1995).

3.2. Data Collection

Data was collected concurrently from sixteen banks over a period of six months in this manner. Firstly, quantitative data was collected with self-administered structured questionnaire, archival search, and archival disclosure checklist. The structured questionnaire comprised closed questions thus providing standardised responses and least cost data collection from a large sample (Zikmund,2003; Fellegi, 2010; Babbie 2011; Saunders et al.,2019). The questionnaire was designed to collect categorical data with a mixture of Likert scale, and "yes/no" questions. These questions were designed by the researcher based on theoretical constructs from Basel II/III Pillar 1 framework (Easterby-Smith et al., 2015, Saunders, et al.,2012; Fellegi, 2010; Collis and Hussey, 2009). The questionnaire was distributed and collected in person. The data was collected under these Basel II/III Pillar 1 themes or variables formulated from theoretical review: capital modeling method implementation, bank size and capital modeling method adoption, data & skills sufficiency, state of market discipline and supervision.

Secondly, quantitative data was also collected with archival search and a categorisation matrix or Basel II/III capital modeling archival disclosure checklist developed for manifest archival analysis. Annual financial statements and previous survey reports from 2011-2020 were downloaded from banks' and standard setting bodies' (IMF, World Bank, Basel Committee, Financial Stability Institute, Central Bank of Zimbabwe) respectively. The disclosure checklist was developed from theoretical constructs used on structured questionnaire and archival data. Themes and phrases were used as units of measurement. Summative content design was used where codes were defined from theoretical literature review and archival data (Babbie,1992; Hsieh and Shannon,2005). The coding framework was developed firstly from a predetermined structure based on the structured questionnaires, then secondly with data from a sample of five annual audited reports from five banks. The categorisation matrix was designed using Bengtsson (2016)'s four steps of decontextualisation, recontextualisation, categorisation and compilation. The categorisation matrix examined six thematic areas namely definitions of capital, capital adequacy, market risk capital, credit risk capital, operational risk capital and economic capital modeling methods implementation. Extant studies have used themes and phrases from annual reports to understand levels of disclosures in banks (Linsley and Shrives,2005, Oliveira et al., 2011, Campbell,2011; Ieasi,2012, Al-Maghzom et al., 2016; Khalil and Alam,2018). Thirdly, data for qualitative analysis were collected from annual audited financial statements and previous survey reports using thematic questions. In this case manual content analysis, narrative analysis and repetitive reading was used because of their low cost and flexibility (Scaltrito,2015; Bengtsson,2016).

3.2.1. Sampling

The objective of sampling in any study is to obtain a sample representative of the population (Ponto,2015). In this paper stratified, random and purposive sampling were used. First stratified sampling was applied to the survey. Banks were divided into four strata by bank size and ownership structure into International, Pan African, Private owned and Government owned indigenous banks. The sample size was determined at 95% confidence interval using Krejcie and Morgan's (1970) table as in

Sekaran (2003), Yamane's (1967), and Saunders et al., (2012) formulae. This resulted in sample sizes of 132,133 and 132 respectively. As a result, 160 self- administered questionnaires out of a population of 200 Risk Managers were distributed. To reduce non-response bias, questionnaires were distributed beyond those recommended by the three techniques and a follow up mail was used. 131 questionnaires were collected, representing a 75% active response rate. Out of the 131 returned questionnaires, 120 were used for data analysis because they were adequately completed.

Second, the sample size for manifest archival analysis, was determined by random sampling. The author settled for a sample size of 160 audited financial statements from 2011-2020. This sample size was determined to saturation to ensure comprehensiveness, facilitate categorisation and abstraction (Morse et al.,2002; Elo et al.,2014). The annual audited financial statements were downloaded from the banks 'official websites. These were used because they represent an accurate form of fundamental communication to shareholders, regulators, and customers (Lajili and Zeghal,2009). They also provide historical, financial, and corporate pictures (Linsley and Shrives, 2006; Ieasi, 2012). Further they are extensively distributed to the public (Campbell, 2000; Ielasi,2012).

Third, because qualitative research is idiographic in approach focusing on small samples, the sample sizes for latent archival data were determined by purposive sampling (Castro et al., 2010; Creswell, 2013). This allowed the researcher to focus on articles with the best knowledge on the topic (Kyngäs et al.,2011). Out of the 160 audited reports, 35 reports were purposively sampled for latent content analysis based on Saunders, et al., (2012) p.283 table of non- probability samples. Saunders et al. (2012) argues that cases for qualitative methods should not exceed 37 documents. The same approach was used to determine 20 reports from past surveys as adequate for further latent analysis. These previous survey reports from 2011-2020 were downloaded from World Bank, Financial Stability Institute, Central Bank of Zimbabwe, and International Monetary Fund. In both approaches the categorisation matrix provided a guiding framework.

3.2.2. Pilot

The structured questionnaire and disclosure checklist for manifest analysis were piloted in this manner. First, the structured questionnaire was piloted using Babbie and Quinlan (2011)'s two stage procedure. Academics selected from the University of Bolton and ten Risk Managers chosen by stratified random sampling reviewed the questionnaire for correctness and feasibility of study (Saunders et al.,2012). Second, the disclosure checklist and themes for latent analysis were pretested in a pilot phase to ten Risk Managers from five banks as recommended by Schreier (2012). The final structured questionnaire, categorisation matrix and themes were produced after incorporating comments from domain experts. In the three cases, ten risk managers were employed following Brace (2008), who states that pilot testing is successful in identifying the needed changes if few individuals up to ten are willing to complete and provide suggestions

3.3. Data Analysis

Quantitative data was analysed with descriptive statistics on Statistical Package for Social Sciences (SPSS) and Excel. Qualitative data was analysed hermeneutically with manual textual and narrative analysis. Data collected by the structured questionnaire was analysed with SPSS and presented in form frequency tables and bar charts following Tukey (1977)'s exploratory data analysis method (Field, 2009; Saunders et al., 2012; Hair et al., 2014). Data for manifest archival research was analysed on Excel using descriptive statistics in form of frequencies as in Copeland and Fredericks, (1968); Al-Maghzom et al., (2016) & Khalil and Alam, (2018). Data for latent archival analysis was subjected to hermeneutic, thematic, narrative analysis, pattern analysis, coding, and critical realism methods (Elo et al.,2014; Bengtsson,2016). The author was the listener, while annual and previous survey reports provided the banks' narration or story on Basel II/III capital modeling sequentially and logically.

3.4. Validity and Reliability

Validity and reliability for the three methods were done as follows. First, validity and reliability of the structured questionnaire were measured by content validity and Cronbach's alpha respectively. Content validity is established by ensuring that structured questionnaire was reviewed by academic experts from the University of Bolton and ten risk managers who participated in the pilot study (Kimberlin and Winterstein ,2008; Pallant ,2010; Mohajan,2017). The Cronbach alpha was 0.813 (Heale and Twycross, 2015, Saunders et al.,2012; Mohajan 2017). Hence results are valid and reliable. Second, validity and reliability for archival disclosure checklist were measured by content validity and inter-rater reliability. Content validity was ensured by piloting the archival disclosure checklist to a domain of ten Risk Managers (Crocker and Algina ,1986; Schreier 2012; Mohajan, 2017). Moreso, data from annual reports are regarded as valid because they have gone through external criticism by experts and independent auditors before publication respectively. Reliability for manifest content archival analysis was evaluated by inter-rater reliability (Weber,1985). Inter-rater reliability was achieved by engaging two independent economists to count the phrases from annual reports for a fee (Kleinheksel et al.,2020). According to Weber (1985) content analysis is reliable when two or more different people encode a given text the same way and their results have insignificant differences to the researcher's. Results are reliable because the researcher and independent checkers replicated the same results with insignificant differences (Marston and Shrives ,1991; Al-Maghzom et al., 2016). Third, researchers argue that generalisability, replication, reliability, and validity are not very relevant in qualitative research (Denzin and Lincoln 1994; Guba, and Lincoln 2005). Hence for qualitative latent analysis the credibility of these results depends on genuiness of researchers (Mohajan, 2018; Kleinheksel et al.,2020).

3.5. Ethical Considerations

Ethical considerations in this study cover permission to conduct survey, informed consent, data privacy and confidentiality. Permission to conduct survey were obtained from the University of Bolton. Participants completed the questionnaire from informed consent where they had a right to withdraw their participation. The purpose of the research was explained to the participants by the researcher on the cover letter attached to questionnaire. The study ensured data privacy on two matters. Firstly, no reference is made to names of banks where questionnaires were distributed, and archival data collected. Secondly, no reference is made to any individual or bank on data analysis, presentation, and discussion of outcomes.

4. FINDINGS AND DISCUSSIONS

This section reports and discusses the results of Basel II/III Pillar I implementation in Zimbabwean banks. Significant results from quantitative and qualitative analysis are independently reported. The same results are then fused and discussed. The main findings and conclusions are presented.

4.1. Quantitative Results

Two instruments were used in quantitative analysis namely structured questionnaire and manifest content archival analysis. The structured questionnaire was completed by 120 Risk Managers and analysed on Statistical Package for Social Sciences. Table 2 shows that 77 percent of participants had more than three years of experience in risk management. The distribution of the participants were 26 percent Quantitative Risk Managers, 24 percent Operational Risk Managers, 22 percent Operational Risk Managers and 13 percent Market Risk Managers. In tems of skills: 3 pecent had Doctor of Philosophy, 53 percent masters, and 45 percent undergraduate degrees.

Table 2: Experience of Participants

Experience in years	Frequency	Proportion
At most 2	28	23%
3-5	96	38%
6-10	32	27%
11-15	8	7%
Above 15	6	5%
Sample size	120	

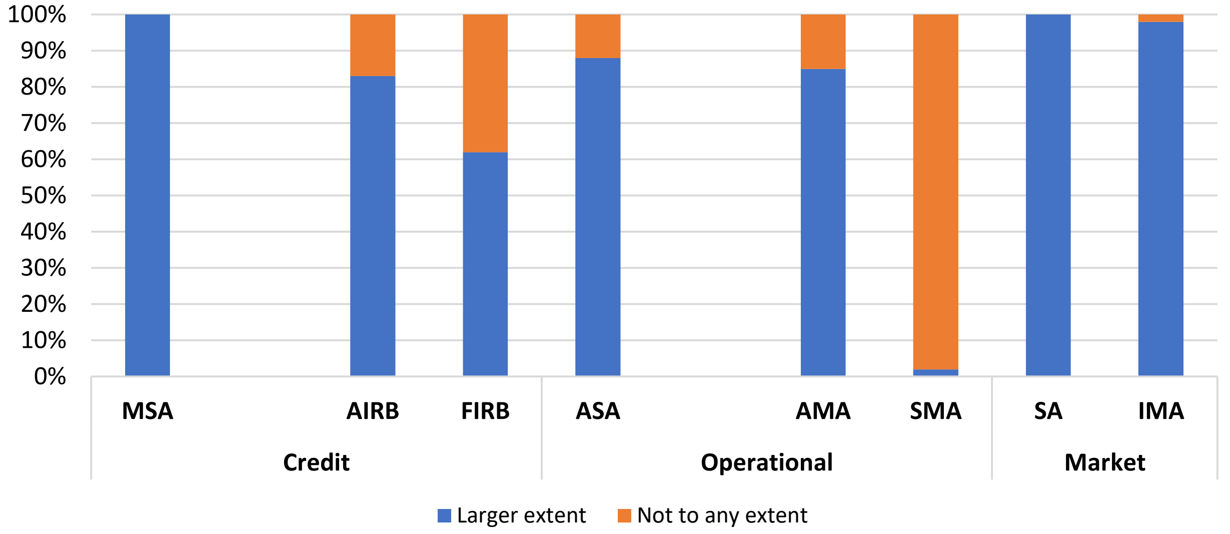
The sample for the archival analysis comprised 160 annual audited financial statements. The disclosure checklist was analysed using Excel. Frequencies, means, and variances were used to analyse the data.

4.1.1. General State of Capital Modeling Methods Implementation

Generally, the results indicate high status of capital modeling methods implementation in Zimbabwean banks. However, implementation status for new approaches such as expected shortfall for market risks and standardised measurement approach (SMA) for operational risks are still very low or almost nil. As shown in Fig 1, first, banks are compliant to credit risk modeling methods in ranking order from highest to lowest: 97 percent Modified Standardised Approach (MSA), 83 percent Advanced Internal Ratings Based Approach (AIRB), and 62 percent Foundation Internal Rating Based Approach (FIRB).

Figure 1: Adoption of Basel II/III Capital Modeling Methods

Question 4:To what extent have you have implemented the following Basel II/III methods for capital modeling. Choose the methods that best apply to your bank from the list below



Second, banks are compliant to Basel II/III operational risk modeling methods in descending order as 88 percent Alternative Standardised Approach (ASA), 85 percent Advanced Measurement Approach (AMA), and 2 percent Standardised Measurement Approach (SMA). Third, banks are compliant to Basel II/III market risk modeling as 100 percent Standardised Approach (SA) and 98 percent internal models' approach. These results show that all banks in Zimbabwe are compliant to both simple and advanced capital modeling techniques. This is contrary to an extant study in merchant banks by Muvingi (2011). He found that banks were implementing simple capital methods such as modified standardised approach for credit risk, alternative standardised approach for operational risk and standardised approach for market risk. Furthermore, these findings confirm that banks in Zimbabwe have adopted Basel II/III in a deep and comprehensive Eurocentric style. This contrasts previous literature that recommends African countries or least developing countries to implement Basel II/III in a shallow selective manner where the simple approaches are employed first rather than advanced techniques (Barth et al., 2006; The Warwick Commission, 2011; Gottschalk,2016; Jones and Knaack, 2019). In addition, these studies recommend adopting proportionality philosophy where advanced modeling techniques are the prerogative for internationally active banks and the simple capital modeling methods are for smaller and domestic banks.

4.1.2. Bank Size and Capital Modeling Method Implementation

To substantiate results in 4.1.1 a further analysis on the relationship between bank size and the capital modeling method was done. This was to prove the Basel II/III proportionality philosophy theoretical postulation that bank size is directly correlated to type of capital modeling method applied (BCBS,2006; Zimbabwe Basel II Technical Guidance, 2011). In other words, advanced modeling methods are the prerogative of larger internationally active banks and simple methods are for local banks.

Table 3: Summary of Bank Size and Capital Methodology Adoption

Question 4: To what extent have you have implemented the following Basel II/III methods for capital modeling. Choose the methods that best apply to your bank from the list below

Risk Type	Capital Modeling Method	Level of Adoption by Bank type (frequencies)			
		Indigenous Private	Indigenous Government Owned	International	Pan African
Credit	MSA	100%	100%	87%	92%
	AIRB	76%	77%	67%	53%
	FIRB	40%	71%	33%	25%
Operational	ASA	90%	100%	93%	78%

	AMA	77%	74%	60%	56%
	SMA	-	-	-	-
Market	SA	68%	61%	73%	61%
	IMA	76%	87%	80%	67%

Contrary to the proportionality philosophy Table 3 shows that smaller domestic banks, international and Pan African banks in Zimbabwe are implementing both simpler and advanced capital modelling methods in the same direction. In fact, smaller indigenous banks are implementing Basel II/III advanced financial modelling faster than larger internationally active banks (Pan African and international banks). Firstly, evidence shows that 77 percent government owned indigenous banks, 76 percent private owned indigenous, 67 percent international, and 53 percent Pan African apply the advanced internal ratings-based approach to determine credit risk capital. Secondly, evidence indicates that 77 percent indigenous private owned, 74 percent government owned indigenous, 60 percent international, and 56 percent Pan African apply advanced measurement approaches to calculate operational risk capital. Thirdly, empirical evidence indicates that 76 percent indigenous private owned, 87 percent government owned, 80 percent international, and 67 percent Pan African have implemented market risk internal models. Hence capital modeling method adopted and bank size are not correlated in Zimbabwean banks. This means banks in Zimbabwe are violating the proportionality philosophy.

4.1.3. Data & Skills Sufficiency

As a further follow up on bank size and capital methodology, respondents are asked questions that gauge their implementation of advanced capital modeling methods for credit, operational and market risk. These questions are intended to investigate data and skills sufficiency for Basel implementation in Zimbabwean banks. This is because the theoretical prerequisite for applying advanced financial modeling methods are huge databases and enough skills (Danielson et al.,2001; BCBS,2006; Zimbabwe Basel II Technical Guidance, 2011). Table 4 shows that Zimbabwean banks have implemented the Advanced Internal Ratings Approach for credit risk modeling with 96 percent confessing probability of default, 96 percent loss given default, 97 percent exposure at default, 84 percent maturity and 42 percent asset correlation estimation on their own.

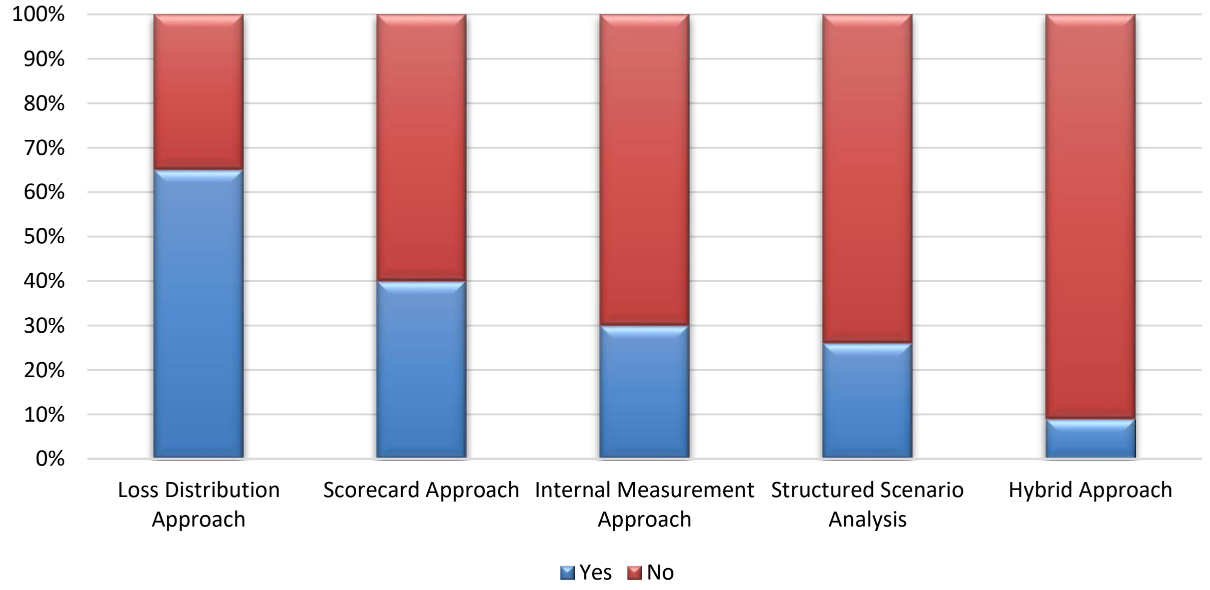
Table 4: Implementation of IRB for Credit Risk

Question 5: Basel credit risk parameters are used in advanced credit risk modeling approaches. Do you use these parameters to estimate regulatory and economic capital for credit risk?

Credit risk parameters	**Frequency**	
	Yes	**No**
Probability of default (PD)	115 (96%)	5 (4%)
Loss given default (LGD)	115 (96%)	5(4%)
Exposure at Default (EAD)	116 (97%)	4 (3%)
Maturity	101(84%)	19(16%)
Asset Correlation	50 (42%)	70 (58%)

However, 42% of the respondents reveal that banks apply the asset correlation provided by the supervisor, whilst 58% use their own estimates thus violating Basel II requirements. Compliance to Basel II/III four credit risk parameters validates that banks in Zimbabwe have enough data and expertise for credit risk modelling. Using a different asset correlation means regulatory and economic capital diverges. Figure 2 shows that Zimbabwean banks are compliant to AMA modelling with 65 percent adoption of Loss Distribution Approach, 40 percent Scorecard Approach, 30 percent Internal Measurement Approach, 26 percent Structured Scenario Analysis and 9 percent Hybrid Approach.

Figure 2: AMA Operational Risk Modeling Method Implementation
Question 7 Circle the AMA method your bank uses to calculate operational risk capital



Again, the results for AMA implementation validate that banks in Zimbabwe have adequate databases and skills for operational risk modelling. This is contrary to previous studies that cites inadequate data for operational risk modelling as a hindrance to Basel implementation (Danielson al.,2001; Dowd et al.,2011; Embrechts,2015). This study found that 72 percent of banks apply the VaR methodology, 23 percent both VaR and Expected shortfall and 5 percent Expected shortfall only. Banks calculated value at risk as a sum of traditional value at risk (VaR), stressed VaR and incremental VaR. Thus, banks in Zimbabwe are compliant to Basel 2.5.

Table 5: Internal Modeling Approach for Market Risks

Question 6: Indicate the statements that best describe the practice of measuring market risk capital in your bank			
Component	**Frequency**	**Computation Methodology**	**Frequency**
Value at Risk	72%	Traditional VaR	100%
		Stressed VaR	96%
		Incremental VaR	96%
Expected shortfall	5%		
Both	23%		

Banks in Zimbabwe have implemented the three market risk components. 100 percent calculate traditional VaR, 96 percent stressed VaR and 96 percent incremental VaR. These results are contrary to the regulator who reports adoption of simple capital modelling methods for market risk (Zimbabwe Basel II, Technical Guidance,2011). In summary empirical evidence from this study shows that there is sufficient databases and skills for Basel II/III capital modelling in Zimbabwean banks contrary to studies in least developing countries by Ward (2002); Powell (2004); Held and Young (2009); Muvingi (2011); Matanda (2015); Kasekende (2015); Gottschalk (2016); Jones and Zeitz (2017) and Jones and Knaack (2019).

4.1.4 State of Market Discipline and Supervision for Pillar 1

The results from thematic analysis using disclosure checklist are presented. Table 6 shows that they were 3003 phrases, with mean 601 and standard deviation 720 reported in annual audited financial statements from 2011-2020.

Table 6: Basel II/III Disclosure Results

Theme	Total Frequency	Percentage
Definitions of capital	1 885	63%
Capital adequacy	911	31%
Credit risk capital	70	2%
Market risk capital	69	2%
Operational risk capital	70	2%
Economic capital	-	-
Total	3003	
Mean	601	
Standard Deviation	720	

Banks comply to disclosure themes: 62 percent on definitions of capital and 31 percent on capital adequacy ratios because the regulator has strong focus on Pillar 1 adoption. However, they do not report methodologies they use for capital modeling as shown by results for credit risk (2%), market risk (2%) and operational risk (2%). These results indicates that banks report the implementation of simple methods to the central bank. The level of market discipline and supervision for Pillar 1 is concluded to be low.

4.2. Qualitative Results

As previously mentioned, the sample for qualitative design comprised 35 annual audited financial statements and 20 previous survey reports on Basel II/III in Zimbabwe. These were exposed to thematic analysis and repetitive reading.

Table 7: Summary of Qualitative Results

Theme	Modeling method	Question	Finding
Credit risk	MSA	What method is used in determining regulatory capital	High implementation in all types of banks
	FIRB		Not yet implemented but draft rules completed in 2011
	AIRB		Not yet implemented but draft rules completed in 2011
Operational Risk	ASA	Same as above	High implementation in all banks since 2011
	AMA		Not yet implemented but rules completed in 2011
Market risk	SA	Same as above	High implementation in all types of banks
	IMA		Nil but draft rules completed in 2011
Economic capital	What method is used to calculate economic capital		Nil reports and methods for economic capital modeling
Skills sufficiency	Are there sufficient skills for Basel II/III capital modeling		Yes, except in derivatives. Derivatives are not allowed in Zimbabwean financial market
Data sufficiency	Is there sufficient data for Basel II/III capital modeling		No clear results from reports
Pre-existing capital requirements	Are there any other capital requirements apart from Basel II/III		Yes, USD30 million minimum requirement for Tier 1 banks and USD 20 million for building societies

The results indicate that banks in Zimbabwe have high implementation of simple modeling methods, for example MSA for credit risk, ASA for operational risk and SA for market risk. Furthermore, banks are not reporting economic capital. It is not clear from the latent analysis whether Zimbabwean banks have collected sufficient data for capital modeling. However, both reports validate that skills for dealing with Basel II/III capital modeling are sufficient except in the derivatives area. Since there is no derivatives market in Zimbabwe, an absence of specialist skills in this area has zero effect on capital modeling. The usefulness of the Basel II/III is doubtful given the existence of higher pre-existing capital requirements rules for Zimbabwean banks (USD 30 million for Tier 1 banks and USD20 million for building societies). This support extant studies that have stated that the usefulness of Basel II/III capital modeling implementation is ambiguous in the presence of pre-existing higher capital requirements (Kasekende,2015; Jones and Knaack,2019).

4.3. Discussion

The fusion of the results indicates a concurrence by three research methods that there is deep Basel II/III capital modeling implementation, sufficient data and skills, violation of the proportionality principle and low levels of market discipline and supervision. The study indicates that there is no relationship between bank size and capital modeling method adopted. However, the survey and archival results show differences on type of capital modeling method adopted. The survey results indicate that banks are implementing advanced capital modeling regardless of size. These results represent the bank's view of Basel II/III capital modeling implementation. On the contrary archival data prepared mainly by the regulator or for the regulator reveal that that banks are implementing simple capital modeling methods. It is acknowledged that archival data reveal the regulator's view. Furthermore, survey indicates that banks in Zimbabwe have implemented Basel 2.5 whereas the results from archival study are contrary. These differences reveal the existence of information asymmetries between the regulator and banks. Banks are implementing advanced capital modeling methods regardless of size for their own internal purposes such as economic capital modeling whilst reporting simple methods for regulatory purposes. Furthermore, banks are adopting Basel II/III capital modeling methods at a faster pace than their regulator. From these results, the paper concludes that Basel capital modeling implementation in Zimbabwean banks is not hampered by data and skills insufficiency but by information asymmetries between banks and their central bank. Again, from a policy perspective, the usefulness of Basel II/III capital modeling in Zimbabwean banks remains ambiguous in the presence of other parallel high capital requirements rules enforced by the regulator.

5. CONCLUSION AND IMPLICATIONS

Basel II/III miinimum capital requirements are an important ingredient in mantaining financial stability and promoting resilience in banks. Following the adoption of Basel II/III by the Reserve Bank of Zimbabwe, this paper pioneers a holistic test and critical examination of usefulness of Basel capital modeling methods implementation in sixteen banks. Concurrent triangulation mixed methods were employed to achieve objectives of this study. This involved mixing survey and archival research methods in a quantitative and qualitative research designs. First, the paper finds deep implementation of Basel II/III capital modeling methods, sufficient data and skills, violation of the proportionality principle, existence of information asymmetries and low levels of market discipline and supervision in Zimbabwean banks. The violation of proportionality principle is shown by the fact that local banks are implementing advanced capital modeling methods at the same pace or even higher than internationally active banks. The implication is that adoption of Basel II/III in Zimbabwean banks is thus creating a level field of competition between the domestic, Pan African, and international banks. The existence of information asymmetries is shown by divergence of perspectives between regulator and banks. While the regulator is enforcing proportionality, banks are adopting advanced methods for their internal purposes regardless of size. Second, the usefulness of Basel II/III capital modeling in Zimbabwean banks as a tool for managing risk based minimum capital requirements is ambiguous given the violation of the proportionality principle by banks and existence of other parallel higher capital requirements enforced by the regulator. These results suggest as in Jones and Knaack (2019) that Basel II/III implementation in Zimbabwean banks may not be attributed to technical considerations but are a product of inward pressure to signify sophistication and competitive standing to international community. Furthermore, it is recommended that the central bank of Zimbabwe must choose one ideology either parallel minimum capital requirements or Basel II/III. Further research should address the effects of eliminating parallel minimum capital requirements and reasons for violation of proportionality principle by domestic banks.

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APPENDICES

A. Disclosure Checklist

Theme	Phrases
Definitions of capital	Tier 1 capital, Tier 2 capital, Tier 3 capital, Tier 1 ratio, Tier 2 ratio, Tier 3 ratio, core capital, supplementary capital
Capital adequacy	Risk weighted assets, capital adequacy ratio, regulatory capital
Credit risk capital	Standardised approach, foundation internal ratings approach, advanced internal ratings-based approach, probability of default, exposure at default, loss given default, maturity, credit scoring, ratings philosophy
Market risk capital	Standardised approach, Internal measurement approach, value at risk, expected shortfall, historical simulation, monte carlo simulation, variance covariance
Operational risk capital	Alternative standardised approach, basic indicator, advanced measurement approach, Loss distribution approach, internal measurement approach, scorecard approach

Source: Tepetepe et al.,2022

B. Structured Questionnaire

1. I work in my bank as ……… (*Please choose from the options provided below***)**

Position	Code	Indicate your choice by marking the appropriate selected blank block with an "X"
Quantitative Risk Manager (Financial Engineer, Actuary)	1	
Market Risk Manager	2	
Operational Risk Manager	3	
Credit Risk Manager	4	
Emerging Risk Manager e.g., Information Risk, Occupational Health and Safety Manager, Business Continuity Manager	5	
Asset and Liability Manager	6	
Capital Manager (Regulatory and Economic Capital)	7	

2. My highest qualification is …… (*Choose from the options provided*)

Qualification	Code
PhD	1
Master's Degree	2
First Degree	3
Postgraduate Diploma	4

3. My experience in dealing with Basel II/III capital modeling is …… (*Choose the options that best describe your level of experience from the ones below*).

Experience	Code	Indicate your choice by marking the appropriate selected blank block with an "X"
At most 2 years	1	
3-5 years	2	
6-10 years	3	
11-15 years	4	
Above 15 years	5	

4. To what extent have you have implemented the following Basel II/III methods for capital modeling. Choose the methods that best apply to your bank from the list below.

Method	Not to any extent	To a very little extent	To some extent	To a large extent	To a very large extent
Standardised approach for credit risk	1	2	3	4	5
Foundation internal ratings-based approach for credit risk	1	2	3	4	5
Modified standardised approach for credit risk	1	2	3	4	5
Advanced internal ratings-based approach for credit risk	1	2	3	4	5
Basic indicator approach for operational risk income	1	2	3	4	5
Standardised approach for operational risk	1	2	3	4	5
Advanced measurement approach for operational risk	1	2	3	4	5
Standardised Measurement approach for operational risk	1	2	3	4	5
Standardised Approach for market risks	1	2	3	4	5
Internal models approach for market risk	1	2	3	4	5

5. Basel risk parameters are used to estimate credit risk for advanced modeling methods. Do you use these parameters to estimate regulatory and economic capital for credit risk?

Risk parameter	Yes	No
Probability of default (PD)	1	2
Loss Given Default (LGD)	1	2
Exposure at default	1	2
Maturity	1	2
Asset correlations	1	2

6. Indicate the statements that best describe the practice of measuring market risk capital in your bank. Circle the appropriate boxes for each component of market risk.

Component	Method		
Value at Risk			
Expected Shortfall			
Both value at risk and expected shortfall			
In general value at risk is calculated using:	1 Traditional Value at Risk	2 Stressed Value at Risk	3 Incremental value at Risk

7. Circle the AMA method you use to calculate the operational risk capital in your bank.

Methods	Yes	No
Loss Distribution Approach	1	2
Structured Scenario Analysis	1	2
Internal Measurement Approach	1	2
Scorecard Approach	1	2
Hybrid Approach	1	2