Estimating the Regulatory Capital for Operational Risk Using Basel Approaches

Submitted by

Dr. Salah Ahmed Oraby

Associate Professor,
Accounting department,
Saudi Electronic University.

DOI:

https://doi.org/10.21608/ijaefs.2024.336966.1045

IJAEFS

International Journal of Administrative, Economic and Financial Sciences

Volume (4), Issue (12), January 2025

E-ISSN: 2812-6408 **P-ISSN: 2812-6394**

https://ijaefs.journals.ekb.eg/

Publisher

Association of Scientific Research Technology and the Arts

https://srtaeg.org/

Estimating the Regulatory Capital for Operational Risk Using Basel Approaches

Submitted by
Dr. Salah Ahmed Oraby
Associate Professor, Accounting department,
Saudi Electronic University

ABSTRACT

The study aimed to quantify the regulatory capital for the loan portfolio's operational risks, using Basel Committee approaches for a leading bank as a case study of Saudi Arabia.

The study used the statistical programming language R to identify the regulatory capital using a model based on loss distribution. The results indicated that the standardized income-based approach generated the lowest regulatory capital because it used a beta of 12% of the 3-year average total income. However, the model based on loss allocation under the advanced measurement method generatedthe largest regulatory operational risk capital for the credit portfolio at a confidence level of 99.9%.On the other hand, the income-based approach generated regulatory capital with a beta of 15% of the 3-year average gross income less than the capital estimated by the loss distribution-based model. The study's results confirmed that the regulatory capital estimated by income-based methods was less than the real exposure to operational risks estimated by the model using the distribution of losses. The results of the present study will be useful to regulatory authorities, bank managers, and investors in measuring operational risk. The present study contributes to the literature on estimating and comparing regulatory capital for operational risk. However, we expect banks to stop relying on Basel Committee income-based approaches, assuming one size fits all. The results indicate that these methods underestimate the regulatory capital assessment of the bank's operational risk under this study. In addition, the results of the current study can help academics and practitioners use real operational risk indicators rather than proxies such as cost-to-income ratios and operating expenses.

KEYWORDS: Basel Committee; Value at Risk; Regulatory Capital; Confidence Level; Loss Distribution

ملخص البحث :

تهدف الدراسة إلى تحديد رأس المال الرقابي للمخاطر التشغيلية لمحفظة القروض، وذلك باستخدام نماذج لجنة بازل للرقابة المصرفية بالتطبيق على أحد البنوك الكبرى بالمملكة العربية السعودية. استخدمت الدراسة لغة البرمجة الإحصائية R لتحديد رأس المال الرقابي باستخدام نموذج توزيع الخسارة. أشارت النتائج إلى أن النماذج المعيارية على أساس على الدخل تولد رأس مال رقابي منخفض لمخاطر التشغيل لمحفظة القروض –مقارنة بنماذج توزيع الخسائر - ويعزى ذلك الى ان نماذج الدخل المعيارية تستخدم بيتا بمعدل ١٢٪ من متوسط إجمالي الدخل لمدة ٣ سنوات. كما اشارت النتائج الى ان نماذج توزيع الخسائر تولد رأس مال رقابي لمخاطر التشغيل أكبر لمحفظة القروض –مقارنة بالمدخل المعياري- عند مستوى ثقة قدره ٩٩,٩٪. كما اشارت نتائج الدراسة لمدخل المؤشر الأساسي على أساس الدخل إلى ان هذا المدخل يولد رأس مال رقابي منخفض لمخاطر التشغيل لمحفظة القروض -مقارنة بنماذج توزيع الخسائر - باستخدام بيتا قدرها ١٥٪ من متوسط الدخل الإجمالي لمدة ٣ سنوات. كما اشارت نتائج الدراسة الى أن رأس المال الرقابي لمخاطر التشغيل لمحفظة القروض المحتسب باستخدام نماذج الدخل يعد أقل من التعرض الحقيقي للمخاطر التشغيلية المقدرة بالنموذج باستخدام توزيع الخسائر. ان نتائج هذه الدراسة مفيدة للسلطات

الرقابية ومديري البنوك والمستثمرين في قياس المخاطر التشغيلية. هذا، ونتوقع الدراسة أن تتوقف البنوك عن الاعتماد على مداخل لجنة بازل القائمة على الدخل، لأنها تفترض وجود مقياس واحد يناسب جميع البنوك رغم اختلاف هياكل مخاطرها، بالإضافة إلى ذلك، تساعد نتائج الدراسة الحالية في تحفيز الأكاديميين والممارسين على استخدام مؤشرات مخاطر تشغيلية حقيقية بدلاً من المؤشرات البديلة مثل نسب التكلفة إلى الدخل ونفقات التشغيل.

الكلمات المفتاحية: لجنة بازل- القيمة المعرضة للمخاطر- راس المال الرقابي-مستوى ثقة - توزيع الخسائر.

1. Introduction:

Multiple factors, such as new products, globalization, massive mergers and acquisitions, and the use of technologies, had enormous impacts on the risk management processes of banks, especiallyoperational risk, and became among the major financial risks along with credit and market risk. Operational risk has received less academic attention than credit, interest rate, liquidity, and leverage risks. This may be due to the difficulty of obtaining accurate and reliable data on losses and operational risks. On the other hand, many authors, such as (Velez, 2022), stated that operational risks are ad hoc and have limited systemic implications. However, (Elul,2013;Berger et al.,2022) reported that operational risk interferes with financial stability, as they reported that operational losses resulting from insufficient operational risk management in banks directly increase systemic risk by weakening the market value of banks. Recent global crises have contributed to increasing awareness of the significance of risk management in banks generally and of operational risks in particular. Banks face increasing operational risk because of the rapid development of financial markets and the widespread use of information technology; thus, operational risk measurement must be accurate and reliable. (Lu et al., 2013) stated that the definition of operational risk is challenging as it is correlated with all banking activities; it is also difficult to estimate it separatelyfrom other risks. Berger et al., 2020) criticized views of operational risk as idiosyncratic with limited systemic implications, as they noted that operational risk was no longer idiosyncratic but became systemic, affecting the banking system's integrity. According to (Basel Committee,2003), banks use descriptive and quantitative criteria to estimate operational risk, asbanks target profitability, and the going concern assumption can be achieved only when banks achieve targeted profits. However, (Hellbock & Wagner, 2006) stated that operational risk has become a major barrier to earnings sustainability; thus, stakeholders such as banks, regulators, auditors, and credit rating agencies have focused on operational risk separately from market and credit risk.

2. Study problem

The absence of empirical studies on measuring operational risk according to the Basel pillars prompted the researcher to perform the current study and compare the estimated results to determine whether the advanced approach provides less or more capital than income-based models. To the researcher's knowledge, no empirical study in the Kingdom of Saudi Arabia or outside has dealt with estimating operational risk by adopting an integrated approach under the Basel committee. Previous studies (Hamrit & Wael, 2020; Nifar & Al-Jarboui,2018; Al-Amer et al., 2020; Haddad & Allawi, 2022; Al-Majzoum et al., 2016) investigated the determinants of Saudi banks' disclosure of operational risk. The current study differs from previous studies in that it estimates the regulatory capital for the operational risks of the loan portfolio, as it is considered the largest source of operational risk. The credit portfolio has been chose because of the size and details of the disclosure of income and expenses in the bank's income statement related to the loan portfolio and the total losses of the loan portfolio.

(Currie, 2005) noted that, in contrast to Models used to estimate market risk and credit risk, the main problem with measuring the regulatory capital to absorb the operational risk of banks lies in the use of models that depend on a percentageof total income without considering the true structure of the operational risk for each bank. Based on the argument of (Mignola et al., 2016; Cristea, 2021), the study's main objective is to quantify the loan portfolio's regulatory capital for operational risk via the basic indicator approach (BIA), standardized approach (SA), and advanced measurement approach (AMA). Therefore, the study quantifies the following:

1. Loan Portfolio's Regulatory Capital for Operational Risk using (BIA)
2. Loan Portfolio's Regulatory Capital for Operational Risk using (SA)
3. Loan Portfolio's Regulatory Capital for Operational Risk using (AMA).

The study tries to compare the estimated regulatory capital using Basel's three approaches to test the argument's validity. Specifically, the estimated regulatory capital under income-based approaches developed by the Basel Committee is less than the capital derived fromthe advanced measurement approach.

3. Literature Review

(According to (Moosa, 2007), operational risk is a broad concept that includes chances of loss resulting from unexpected events such as failure of operations, mistakes,fraud, litigation, and data violations, which have a passive effect on the bank's operations. Previous researchers have attempted to measure operational risk from different perspectives but have yet to recognize the distinction between quantifiable risks and the uncertainty associated with daily operations. (Crouhy et al., 2001; Rao & Dev, 2006) defined operational risk as the residual of risks, including all risks except both market risk and credit risk. The bank under study defines operational risk as failing to achieve a bank’s strategic objectives because of insufficient internal control systems, deterioration of internal processes, individuals, and systems, or external factors. The operation risk becomes one of the elements of the risk management structure in banks under Basel II to enhance the stabilization of operations. Basel II defined operational risk as loss due to the collapse of internal processes, individuals, systems and external events. However, the definition ignores both strategic risks and reputational risks. Previous studies on operational risk can be classified into three categories: determinants of operational risk, the influence of operational risk on banks’ performance, and approaches to measuring operational risk.

3.1. Determinants of Operational Risk

(Khan et al., 2023) investigated the factors of credit risk and operational risk of (3) listed banks in Pakistan for the period 2000--2016. Using fixed-effect regression models, the results revealed apositive relationship between credit and operational risk with non-performing loans, financial leverage, and the cost-to-income ratio as a proxy for operational efficiency, whereas the results indicated a positive relationship between credit and operational risk. No statistically significant relationship with liquidity ratios was found. (AL-Din et al., 2023) investigated the impact of digital operations in banks on operational risk. The sample included (264) banks from (43) states for a period of 10 years. The study used the total income model as a proxy for operational risk as the dependent variable. However, the study used information technologies related to expenditures as an alternative to digitization, as an independent variable, along with other variables at the bank level, such as total assets, the liquidity ratio, the deposits-to-assets ratio, and the loans-to-assets ratio. Loan loss allocation, leverage, and interest margin. In addition, state-level independent variables such as the financial freedom index and GDP are used. The study used a fixed effect, with least squares regression models plus GMM, to measure the influence of digitalization on operational risk. The results indicated that digital operations increased operational risk, and banksresponded to security threats by increasing cyber spending. (Hermit & Wael, 2020) investigated methods of disclosing operational risk in Saudi banks and the impact of corporate governance and credit scoring on the informational substance of the disclosure of operational risk. The study used content analysis to collect data from banks' financial reports from 2008 to 2015. The results indicated that the number of branches, financial stability, frequency of board meetings, percentage of independent board members, and credit rating had an inverse relationshipwith enhanced operational risk disclosures.

3.2. The Impact of Operational Risk on the Performance of Banks

(Abu Bakr et al.,2023) investigated the influence of the risk management committee structure on the relationship between the operational risk and performance of (16) banks in Nigeria for the period of 2018--2022. The study used regression models with fixed and variable effects to test the study's hypotheses. The study used return on investment as a proxy for bank performance as the dependent variable. The study used the cost–to–income ratio as a proxy for operational risk and the risk committee structure as independent variables. The results indicated that operational risk had significant and negative impacts on the performance of banks and that the structure of the risk committee reduced the negative impact of operational risk on banks' performance. (Qabajeh et al., 2023) investigated the impact of operational risk on the performance of (20) Islamic banks operating in (12) countries in North Africa and the Middle East. The study used the cost-income ratio as a proxy for operational risk and as the independent variable. The study used the return oninvestment and equity as proxies for banks' performance and as the dependent variables.The results of the fixed-effect regression models indicated that operational risk negatively affected both return on assets and equity. (Bani Yousef et al., 2023) examined the effects ofoperational risk on banks' financial performance for (135) banks operating in (14) states in the Middle East and North Africa for the period 2005--2019. The results showed that operational risknegatively affects the financial performance of banks. (Aslam & Abadi, 2023) investigated the impact of credit risk, operational risk, and liquidity risk on the performance of six banks operatingin Indonesia for the period of 2018--2022. The study's results indicated that non-performing loans, as a proxy for credit risk, did not affect the return on assets. As a proxy for liquidity risk, the ratio of loans to deposits did not affect the return on assets. As a proxy for operational risk, the cost-to-income ratio had a statistically significant effect on the return on assets.

(Hunjra et al., 2022) investigated the impact of credit risk, operational risk, and liquidity risk on the performance of (76) commercial banks operating in India, Pakistan, Bangladesh, and Sri Lanka forthe period 2009--2018. The results indicated that nonperforming loans, as a proxy for credit risk, hurt bank performance. In addition, the Z score, as a proxy for operational risk,had a positive effect on bank performance, whereas the loan-to-deposit ratio, as a proxy for liquidity risk, hurt bank performance. (Suryaningsih & Sudirman, 2020) analyzed the impact of operational risk, credit risk, and liquidity risk on the profitability of (72) banks operating in Indonesia for the period of 2014--2018. The results indicated that the cost-to-income ratio as a proxy for operational risk and non-performing loans as a proxy for credit risk negatively affected returns on assets as a proxy for profitability. In contrast, liquidity risk quantified by the ratio of loans to deposits positively impacted asset returns. (Okeke et al., 2018) investigated the impact of operational risk on banks' performance in Ado State, Nigeria. The studyused the questionnaire method with a sample of (386) participants. The study used descriptive analysis to describe the variables under study and correlation analysis to support the results of the regression models. In addition, the study used least squares regression models to test the study's hypotheses. The study's results showed that personnel risk had strong and negative effects on the performance of banks. In contrast, systems and technology risk had significant and negative effects on the performance of banks, and the risk of external factors had weak and positive effects on theperformance of banks. (Saeed, 2015) analyzed the impact of operational, credit, and liquidity risks on the performance of (27) banks working in Malaysia for the period 2005--2013. The study used the return on assets and the return on equity as proxies for banks' financial performance and as the dependent variables. The study used the ratio of earnings before interest and taxes (EBIT) to total assets as the proxy for operational risk, the ratio of loans to total assets as the proxy for credit risk, and the ratio of net loans to deposits as a proxy for liquidity and deposit risk as the independent variables. The results showed that the three risks positively affected returns on equity, whereas both credit risk and operational risk positively affected asset returns. However, liquidity risk had no significant effect on the return on assets. (Allen & Bali, 2007) noted that 18% of bank returns on equity are explained by operational risk. In addition, operational risk factors cause catastrophic expected losses. These results were valid if catastrophic risks and operational risks were estimated via extreme value theory and skewed fat-tailed distribution.

3.3. Approaches to Measuring Operational Risk

(Xu, et al., 2019) Proposed (3) approaches to measuring capital for operational risk: basic indicator, standardized, and advanced measurement. The Advanced Measurement approach included five eligible versions: the Loss Distribution Approach, Extreme Value Theory, Bayesian Belief Networks, and the Score Card Approach. The operational risk measurement corresponds to the concept of value at risk, as with market and credit risks. The Bankof International Settlements (BIS) defines four main sources of operational risk: systems, operations, people, and external factors. However, new threats are related to operational risks proxied by digital banking and operations automation. The Basel Committee focused on measuring the capital required to absorb operational risk, whether regulatory capital according to risk weights determined by the regulatory authorities or the economic capital derived from banks' internal models. (Daryakin & Andriashina, 2015) suggested indicators for operational risks to absorb operational risks by net profit, equity, and total assets, as they set threshold values, as the equity-based index must be at least (10) times the total assets-based index. The net profit-basedindex must be at least (50) times the total assets-based index.

In 1998, the Basel Committee on Banking Supervision (BCBS) issued a document on operationalrisk, published in 2001 and entered into force in 2007. Therefore, when capital adequacy ratios were calculated, operational risks became part of the first pillar, along with credit and market risks. In 2004, the Basel Committee provided a narrow definition of operational risk for supervisory purposes by focusing on daily losses resulting from hardware and personnel failures while neglecting reputational losses resulting from strategic business errors (Allen & Bali, 2007). In 2004, Basel II proposed (3) approaches to measuring the regulatory capital for operational risk, varying in difficulty under the first pillar. The basic index approach, which isthe least difficult, requires banks to hold capital equal to 15% of the average annual positive grossincome over the past three years. The standard approach is the modified version of the fundamentalindicators approach because both are income statement-based. The standardized approach still relies on the total income index as a proxy for operational risk. Still, it divides banks' activitiesinto (8) business lines: commercial banking, asset management, retail brokerage, corporate finance, agency services, payment and transfer. Settlement, retail banking, corporate finance. These activities differ in risk structure and weights, ranging from 12% to 18% compared with 15% generally under the core indicator approach. The advanced measurement approach, known as the management accounting-based approach, relies on banks' internal models to measure operating risk capital. The approach allows banks to choose their income models if the safety criterion is met based on a one-year assumptionand a 99.9 confidence level. However, (Butler & Brooks, 2023) argues that the current income-based approach to measuring operational risk appears underdeveloped overall. Therefore, banks must track and categorize data loss by risk event type. Banks classify operational risk events such as internal cheating, external deceit, employment acts and work climate safety, customers, products,business acts, losses to tangible assets, business disturbances, system collapse, and process Management, delivery, execution, and process uncertainty. Basel III established a comprehensive framework for measuring operational risks linked to the volume of banks' business based on information derived from financial statements. (BCBS, 2011; Allen & Paley, 2007) explained that operational risk can be measuredeither from the perspective of costs or returns on equity. Measuring operational risk via the advanced or standard approach is difficult becausethe data required for measurement are internal data that researchers cannot access. In addition, the basic index approach used to measure operational risks, assuming that one size fits all, and it assumes that operational risk never exceeded 15% of the 3-year average gross income. Most previous studies have used non-Basel proxies for operational risk, such as the cost-income ratio, as a proxy for operational risk. For example, (Abu Bakr et al.,2023; Khan et al.,2023; Aslam & Ebadi,2023;

Suryaningsih & Sudirman,2020; Wang & Hsu,2013; Barakat& Hussein,2013; Bello Ahmadu,2013; Riaz et al.,2022) In addition, (Santika et al. ,2022) usedtotal operating expenses, operational efficiency expressed in net interest income, and assets turnover as proxies for operational risk.

(Chernobai et al. (2007) noted that banks can manage risks through the top-down and the bottom-up approaches. The top-down approach determines the probability and significance of potential losses and threats that may prevent banks from achieving their strategic goals. This approach easily enables the measurement of risk at the bank level, but itis difficult to measure operational risk at business line-wise levels. The top-down approach uses quantitative models such as capital asset pricing models, expense-based models, income-based models, scenario models, and stress testing models. On the other hand, the bottom-to-top approach focuses on the sources of risk: technology, procedures, people, products, and other internal and external factors. This approach enables banks to measure risks for each source separately and then sum all sources to estimate risks at the bank level. The approaches used were loss distribution-based, actuarial, and extreme value theory-based models. The Basel Committee (BCBS,2001; 2011) did not measure the operational risk directly,but it required banks to maintain capital to absorb the operational risk, as the Basel Committee determined three approaches to measuring operational risk: the basic indicator approach (BIA), standardized approach (SA) and advanced measurement approach (AMA). Banks should apply a beta of 15% of the 3-year average gross income under (BIA). The required capital is equivalent to the sum of the following items derived from banks' income statements: interest income and fixed income on securities, interest expenses and similar expenses, income from stocks and variable income on other securities, income from commissions, expenses from commissions, net income or loss from financial operations and other operating income. The regulatory capital equation for operational risk is $k = \alpha * GI$, where $\alpha = 15\%$ and GI stands for gross income.

(SA) is an improvement on (BIA), as capital estimation depends on the activity type. The standardized approach falls between the advanced approach and the basic indicators approach, as it is similar to the (AMA) in that it requires the same standards as the advanced approach. Still, the difference lies in calculating the required regulatory capital. The standardized approach is attractive for small traditional banks for retail banking activities, as it takes a weight of 12% when regulatory capital is calculated, compared with 15% under the basic indicator approach. (Mignola et al., 2016) noted that the standardized measurement approach to measuring regulatory capital for operational risk could not differentiate between banks' risk structures. In addition, it creates large fluctuations in regulatory capital compared with the advanced measurement method, which fails to find the relationship between management procedures and capital requirements for operational risks. The regulatory capital equation is $K = \Sigma\beta \times GI$, where GI = gross income and $\Sigma\beta$ = activities. The Basel Committee sets 12%, 15%, and 18% values. (BCBS, 2017) made revisions to Basel III, known as Basel 4, effective January 1, 2022, as (BCBS, 2017) revised Basel III to estimate capital for operational risk. On the other hand, the three approaches are replaced with a single risk-sensitive approach that all banks should use. The single risk-sensitive approach is estimated as the product of the basic indicator component and an internal loss multiplier. The main indicator element that acts as the bank's exposure to operational risk is computed as the sum of the average of the last three years' values for the three components of banks' financial statements: the interest, services, and financial components multiplied by a parameter. The BIA component measures the bank's exposure to operational risk and works as a proxy of the bank's business volume. The loss multiplier component is added to the formula because banks' operational risk depends not only on banks' business volume but also on banks' ability to control the risk and limit potential losses. The loss multiplier component is the average historical operational loss, which is 15x the average annual operational risk loss over the last 10 years.(Chernobai et al. ,2005) mentioned that under (AMA) banks could use theconcept of value at risk and the Monte Carlo method to identify the capital required to absorb operational risk. In addition, banks can use the loss distribution method, which requires historical loss data. (Nešlehová et al., 2006; El et al., 2014) mentioned that the advancedmeasurement approach requires calculating the expected losses or average losses for each categoryof activity separately as follows: $K = \gamma \times EL$ whereas EL= the average loss; γ = a scaling factor. The average loss is calculated via the following parameters: $EL = EI \times PE \times LGE$. where EL = the exposure indicator, PE = the probability of an event, and LGE = the loss given event. The Basel Committee did not provide a specific mathematical formulation for the value-at-risk method. (X u et al., 2019) used the loss distribution method to estimate capital for operational risk. The results indicate that the capital estimated by the double correlation model is less than that estimatedby other correlation models when the confidence level is less than 99%. However, the opposite istrue if the significance level increases to more than 99%.

(Peters et al., 2016) noted that the Basel Committee developed (SA) to measure operational risk. However, capital requirements for operational risk are still stable or even decreased despite the frequency and severity of operational risk events before or after financial crises. Dziwok (2018) reported that dividing operating losses from several perspectives is possible. Forexample, from the expectation perspective, losses are classified into expected operating losses andunexpected operating losses; from the severity perspective, operating losses are classified into high-severity losses and low-severity operating losses; and from the frequency perspective, operating losses are classified into high-frequency losses and low operating losses. (Mignola et al., 2016) reported that models for measuring operational risk based on a percentage of gross income do not respond appropriately to any changes in the risk structure of banks. In addition, these models could not recognize the variation in the extent of the risk structure between banks; they also failed to find any relationship between management actions and capital requirements to protect against operational risk. Therefore, using income-based models developed by Basel may lead to either overestimation or underestimation of capital to protect against operational risk.

(Cristea, 2021) stated that (AMAs) allow banks to use their internal models to measure the capital required to absorb operational risk. The estimated capital by the advanced measurement approach was greater than the capital estimated by the basic indicator approach, which indicates the importance of accurately measuring operational risk because banks offer diverse products and services that increase operational risk.

4. Methodology

In this section, the study identifies sample and data collection methods, estimates regulatory capital,and compares the results to test the argument's validity on Basel's income-based approaches to estimating regulatory capital for operational risk. The study used the case study method to obtainan in-depth understanding of approaches to estimating regulatory capital for loan portfolios' operational risk under the Basel Accord. The study is applied to a leading Bank in Saudi Arabia. All study data required to calculate gross income were collected from the additional disclosure of the published income statements of the bank under study for the years 2020, 2021, and 2022, and the regulatory income-based models were calculated. The study collected actual credit losses from published annual financial reports plus internal data on credit losses to determine the severity and the frequency of losses for 2020, 2021, and 2022 to quantify regulatory capital via a loss distribution-based model. The study used a quantitative method to calculate the loan portfolio's regulatory capital for operational risk, assuming a one-year holding period. The study used a top-down, income-based model to calculate the basic indicator and standardized approaches-based regulatory capital and a bottom-top model, which is a loss-based model, to calculate advanced measurement-based regulatory capital for loan portfolio operational risk.

5. Empirical Results

The study quantified the capital required to absorb the operational risk of the loan portfolio via (BIA, SA, and (AMA).

Income-Based Approaches

Income-based approaches include the basis indicator and standardized approaches, using a fixed beta of gross income.

Gross income for the loan portfolio = interest income + noninterest income – interest expense –noninterest expense. This approach used a beta of 15% of the 3-year average gross income.

Therefore, the regulatory equation equals:

$$C_{IBIA} = 0.15 * \frac{(7,549,176 + 7,666,138 + 9,143,166)}{3} = 1,217,923$$

The beta for the loan portfolio is equal to 12%; therefore, the regulatory capital used to absorb operational risk is as follows:

$$C_{STA} = 0.12 * \frac{(7,549,176 + 7,666,138 + 9,143,166)}{3} = 974,339$$

Loss Distribution -Based Model (AMA)

The study used the actual loss volumes for the 2020--2022 credit portfolios, which resulted from internal events such as system failure, weak credit policies, employee inefficiency, and external events such as Covid-19 and geopolitical events. Table (1) shows the gross losses for the period under study. In 2020, the bank experienced significant increases in losses because of Covid-19, meaning that External events constitute one of the main sources of operational risk.

Table (1) Gross losses on loan portfolio (Amounts in Thousands)

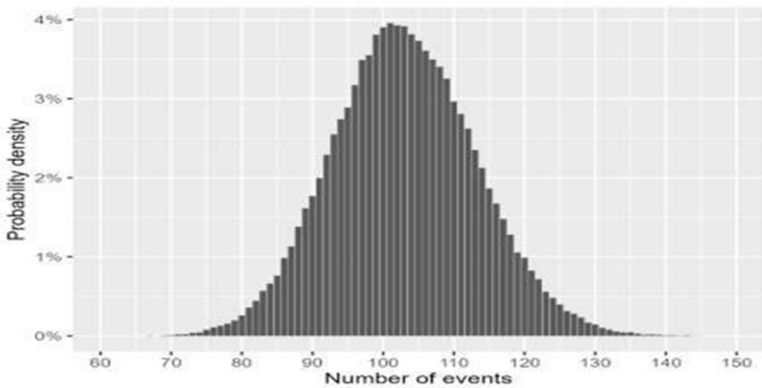
Years	LOAN Events Losses
2022	588997
2021	3020

Years	LOAN Events Losses
2020	2079802

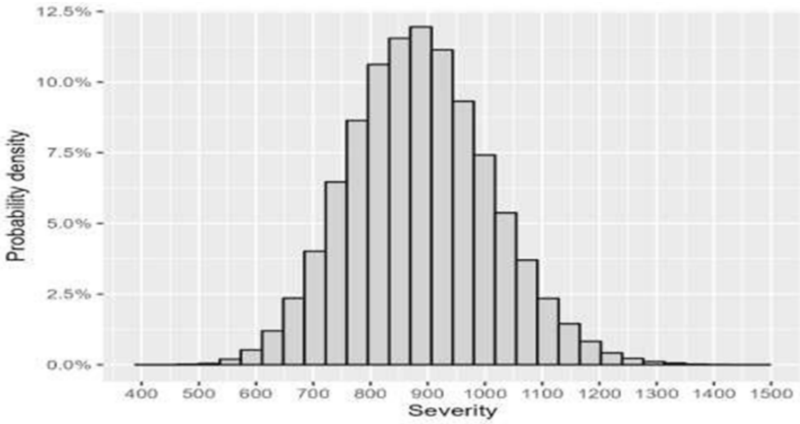
Under operational risk, regulatory capital absorbs both expected and unexpected losses. On the other hand, unexpected losses are absorbed only by capital under credit risk, and expected allowances for loan losses absorb credit losses. The current study uses the loss distribution approach to compute the value at risk (VaR) for operational risk. This methodology involves deriving the loss distribution through the convolution of two constituents: the frequency distribution of loss events, which indicates the number of events per unit of time, and the severity distribution, which identifies the monetary result (loss) associated with each action. The computation of the loss distribution relied on historical data and Monte Carlo simulations. This is accomplished by generating two random variables: the estimation of the loss frequency utilization of the Poisson distribution, with the parameter μ corresponding to the average number of losses within a given period, and the estimation of the losssize through an exponential distribution, with the parameter λ being the reciprocal of the average losses incurred during that period. The process was carried out via *R* (statistical programming language) as follows: 100,000 Poisson random variables representing the number of events for the 100,000 hypothetical periods were generated. For each period, the required number of severity (loss size) random variables is generated via the following steps:

If the simulated number of events for a period is "k" generate a k number of uniform random variables (p). The amount of loss for each event is estimated via the exponential distribution via

The following formula: $x = lnln(1-p)-\lambda$ Where $= 1/\mu$ and where μ is the average loss. The aggregated loss for the period is calculated by summing the amount of loss for each event in that period. The vector representing the aggregated loss of the 100,000 simulated periods is obtained, and the (VaR) is calculated for several confidence levels. The yearly frequency of operational loss events was derived via a Poisson distribution with a lambda parameter of 103 events. This procedure yielded 100,000 random variables indicating the frequency of events, denoting the potential number of losses during a hypothetical span of 100,000 years.



For each hypothetical year, the necessary quantity of severity random variables was equivalent to the previously determined frequency and was computed via an exponential distribution with a parameter $\lambda = 1/8.62$. These variables were subsequently aggregated through the application of Monte Carlo simulation; an aggregated loss distribution based on the frequency distribution of lossevents was presented.



The distribution of the aggregated losses indicated the possibility of identifying the necessarycapital by employing the VaR for various confidence levels.

Table (2) Capital requirements for the loan portfolio's operational risk at different confidence levels (in thousands of Riyals).

Confidence level	Regulatory capital (VaR)	Expected Loss	Unexpected loss
99.9%	1,308.298	887.122	421.176
99%	1,193.886	887.122	306.764
95%	1,097.607	887.122	210.485
90%	1,048.092	887.122	160.970

Regulatory capital absorbs the operational risks associated with the loan portfolio, which equals the value at risk (VaR) and encompasses expected and unexpected losses. Table (2) indicates a positive relationship between the confidence level and the value at risk. The confidence level is 99.9%, and the regulatory capital recorded a SAR of 1,308.298, whereas, at the confidence level of 90%, the regulatory capital recorded a SAR of 1,048.092. The income-based and loss distribution-based model results at the confidence level are 99.9%,whereas the regulatory capital values are 1,217,923, 974,339, and 1,308.298 for BIA (SA) (AMA). Each generated approach is a different method for estimating regulatory capital for operational risk. Therefore, the study's results proved that income-based approaches Developed by the Basel Committee underestimated regulatory capital for operational risk compared with the (AMA). Therefore, the assumption that the regulatory capital for operational risks using income-based approaches never exceeds a beta of gross income is invalid.

6. Discussion and Conclusions

The current study aimed to estimate the regulatory capital of the loan portfolio for operational riskvia Basel II approaches within the framework of the first and second pillars of Basel II. The BaselII agreement classified the approaches for estimating regulatory capital for operational risk into two categories. The first category is the income-based approach, which includes both (BIA) and (SA), and the second category is the (AMA). (BIA) uses the beta of 15% of the 3-year average of total income for all business lines. The (SA) uses the beta of 12% of the 3-year gross income average. Income-based approaches are top-down models, as they can estimate regulatory capital atthe bank level, assuming it is difficult to measure regulatory capital per bank business unit.In contrast to top-down models, the loss allocation approach allows banks to estimate regulatory capital for operational risk for each business line and then easily calculate regulatory capital for operational risk at the bank level. The empirical study conducted on a leading bank in Saudi Arabia, as the case study aiming obtaining in-depth understanding of methods for measuring regulatory capital for a loan portfolio for operational risk. In addition, compares the results to determine whether methods based on gross income generate sufficient regulatory capital to absorb operational risk. The R programminglanguage program was used to quantify the loss distribution-based model under the advanced scaling approach. However, this approach relies on the concept of value at risk, which includes both expected and unexpected losses during the study period. The results indicated that the loss distribution-based model provided the greatest regulatory capital at 99.9% confidence. In contrast, the standardized approach provided the least regulatory capital because it used a beta of 12% of the 3-year average of the total income. In addition, the results indicate a positive relationship between the confidence level and regulatory capital. Based on the study results, a fixed beta of 15% or 12% of the 3-year average total income generated less regulatory capital than the capital specified by the loss allocation model to absorb the credit portfolio's operational risk, reflecting the true operational risk exposure. The results of the present research confirmed the findings of (Mignola et al., 2016), who reported that income-based models did not respond adequately to any changes in the risk structure of banks. In addition, the present results confirmed the results of (Cristea, 2021), who confirmed that the capital estimated by internal models under (AMA) was greater thanthe capital estimated by (BIA). The current study attempts to add a contribution to the literature because it opens the way for researchers to use Basel-based operational risk proxies to investigate the impact of operational risk on bank performance instead of non-Basel indicators of operational risk

7. Research Limitations and recommendations

The research is confined to estimating the operational risks inherent in the loan portfolio due to the availability of the required data in the published financial statements. Therefore, the research did not estimate the operational risks for all sectors of the bank's business in this study because the required data are internal and are subject to confidentiality. In addition, the study used thecase study method on the largest bank in the Kingdom of Saudi Arabia, as the bank disclosed the data required to set the size of capital to absorb the operational risks of the portfolio of loans. The study recommends expanding the scope of the current study by conducting future studied using large samples. Based on the study results banks should abandon the income- based models as they generate less regulatory capital compared to non-income based models.

References

Abubakar, M.B.K, Mustapha, N. & Kambai, M.P. (2023). Operational Risk and Performance ofListed Deposit Money Banks in Nigeria: Moderating Effect of Risk Management CommitteeStructure. Nigerian Journal of Management SciencesVol. 24, Issue, 337-346. https://nigerianjournalofmanagementsciences.com/operational-risk-and-performance-of-listed- deposit-money-banks-in-nigeria-moderating-effect-of-risk-management-committee-structure/

Allen, L. & Bali, T.G. (2007). Cyclicality in Catastrophic and Operational Risk Measurements.Journal of Banking & Finance. Volume 31, Issue 4, 1191-1235.

Al-Maghzom, A., Hussainey, K. & Aly, D. (2016). Corporate Governance and Risk Disclosure: Evidence from Saudi Arabia. Corporate Ownership and Control Journal/Volume 13, Issue 2 145-166. https://doi.org/10.22495/cocv13i2p14.

Aslam, A.P. & Abadi, R.R. (2023). The Effect Of Liquidity Risk, Credit Risk, Operational Risk On Profitability In Companies In Indonesia –Case Study On Banking In Indonesia, International Journal Of Humanity Advance, Business & Science. Vol.1, Issue 1, 15-22. https://journals.indexcopernicus.com/api/file/viewByFileId/1879144

Bani Yousef, A., Taha, R., Muhmad, S.N, Abidin, A.F.Z. (2023). Operational Risk and Financial Performance of Banks in the Middle East and North Africa. Journal of International

Studies. Journal International Studies 19(2):93–118. DOI:10.32890/jis2023.19.2.4

Barakat, A., Hussainey, K. (2013). Bank Governance, Regulation, Supervision, And Risk Reporting: Evidence From Operational Risk Disclosures In European Banks. International Review of Financial Analysis, 30, 254–273. DOI:10.1016/j.irfa.2013.07.002

Basel Committee on Banking Supervision (2003).Sound Practices for the Management and Supervision of Operational Risk, Bank for International Settlements. https://www.bis.org/publ/bcbs96.htm

Basel Committee on Banking Supervision (2017) .Basel III monitoring report. The results of the cumulative quantitative impact.https://www.bis.org/bcbs/publ/d426.pdf

Basel Committee on Banking Supervision (BCBS) (2001), Working Paper on the Regulatory Treatment of Operational Risk, BIS. https://www.bis.org/publ/bcbs_wp8.pdf

Basel Committee on Banking Supervision (BCBS) (2004). Basel ii: International Convergence ofCapital Measurement and Capital Standards: A Revised Framework. Bank for International Settlements, Basel. https://www.bis.org/publ/bcbs107.pdf

Basel Committee on Banking Supervision (BCBS) (2011). Principles for the Sound Managementof Operational Risk, BIS. https://www.bis.org/publ/bcbs195.pdf

Bello, A. (2013). Corporate Governance and Risk Exposure of Banks in Nigeria. The Businessand Management Review, 3(2), 99-105.
https://www.researchgate.net/publication/363691819_Corporate_governance_and_risk_exposure
_of_banks_in_Nigeria

Berger, A.N., Curti, F., Mihov, A. Sedunov, J. (2022). Operational Risk is More Systemic than You Think: Evidence from U.S. Bank Holding Companies. Journal of Banking & Finance Volume143, 106619. https://doi.org/10.1016/j.jbankfin.2022.106619

Butler, T. & Brooks, R. (2023). Time For A Paradigm Change: Problems with the Financial Industry's Approach to Operational Risk. Risk Analysis, pp. 1–20. https://doi.org/10.1111/risa.14240

Chernobai A.S., Rachev S.T., Fabozzi F.J. (2007).Operational Risk. A Guide to Basel II Capital Requirements, Models, and Analysis. Wiley; [John Wiley, distributor], Hoboken, N.J., [Chichester]. https://search.worldcat.org/title/Operational-risk-:-a-guide-to-Basel-II-capital- requirements-models-and-analysis/oclc/166328312.

Chernobai, A., C., Menn, S. T, Rachev C. (2005). Estimation of Operational Value-at-Risk in thePresence of Minimum Collection Thresholds, Technical Report, University of California Santa Barbara, 1-62.

https://www.researchgate.net/publication/228946765_Estimation_of_operational_value-at-risk_in_the_presence_of_minimum_collection_thresholds

Currie, C. V., A (2005).Test of the Strategic Effect of Basel Ii Operational Risk Requirements on Banks. University of Technology, Sydney Working Paper No. 143, Available at SSRN: https://ssrn.com/abstract=831304 or http://dx.doi.org/10.2139/ssrn.831304

Dziwok, E. (2018). Methods Of Measuring Operational Risk And Their Influence On The Level Of Bank's Capital Adequacy. Prace Naukowe Uniwersytetu Ekonomicznego We Wrocławiu Nr 207 Research Papers Of Wrocław University of Economics NR, 519, ISSN 1899-3192 e-ISSN 2392-0041. DOI:10.15611/pn.2018.519.04

El Arif, F. Z. & Hinti, S. (2014). Methods of Quantifying Operational Risk in Banks: Theoretical Approaches. American Journal of Engineering Research (AJER) e-ISSN: pp. 2320-0847 p-ISSN: pp. 2320-0936 Volume-03, Issue-03, 238-244. https://www.ajer.org/papers/v3(3)/ZF33238244.pdf

Elamer, A.A., Ntim, C G., Abdou, H. A., Pyke, C. (2020). Sharia Supervisory Boards, Governance Structures and Operational Risk Disclosures: Evidence from Islamic Banks in MENA countries. Global Finance Journal. Volume 46, 100488. https://doi.org/10.1016/j.gfj.2019.100488

Ellul, A. and Yerramilli, V. (2013). Stronger Risk Controls, Lower Risk: Evidence from U.S. Bank Holding Companies. The Journal of Finance, 68, 1757-1803. http://dx.doi.org/10.1111/jofi.12057

Haddad, A.E. and Alali, H. (2022). Risk Disclosure and Financial Performance: The Case of Islamic and Conventional Banks in the GCC. Journal of Islamic Accounting and Business Research, Vol. 13 No. 1, 54-72. https://doi.org/10.1108/JIABR-11-2020-0343

Hermits, W. (2020). Difference between the determinants of operational risk reporting in Islamic and conventional banks: evidence from Saudi Arabia. The Journal of Operational Risk 15(1):1-38.DOI:10.21314/JOP.2019.235

Helbok, Guenther and Wagner, Christian (2006). Determinants of Operational Risk Reporting in the Banking Industry. Available at SSRN: https://SSRN.com/abstract=425720 or http://dx.doi.org/10.2139/ssrn.425720

Hunjra, A.I., Mehmood, A., Nguyen, H.P. & Tayachi, T. (2022). Do firm-specific risks affect bank performance https://doi.org/10.1108/IJOEM-04-2020-032?" .International Journal of Emerging Markets, Vol. 17 No. 3, pp. 664–682. https://doi.org/10.1108/IJOEM-04-2020-032

Khan, I. A., Akhter, S., Faiz, J., Khan, S., Amir, M., Shah, N. A., & Khan, M. S. (2023). Determinants of Credit Risk and Operational Risk in Banking Sector Evidence from Pakistani Banking Sector. Journal of Financial Risk Management, 12, 15-27. https://doi.org/10.4236/jfrm.2023.121002

Lu, J., Guo, L. &, Liu, X. (2013). Measuring the Operational Risk of Chinese Commercial Banks Using the Semi-Linear Credibility Model. The Journal of Operational Risk 8(2), 3-34 DOI:10.21314/JOP.2013.123.

Mignola, G., Ugoccioni R. & Eric Cope, E. (2016). Comments on the Basel Committee on BankingSupervision Proposal for a New Standardized Approach for Operational Risk. Journal of Operational Risk, Vol. 11, No. 3, 51-69. DOI: 10.21314/JOP.2016.184

Moosa, I. A. (2007) .Operational Risk: A Survey. Financial Market, Institutions andInstruments.Volume16, Issue 4, 167-200. https://pthistle.faculty.unlv.edu/FIN%20740_Spring2018/Week5/MoosaFMII2007.pdf

Neifar, S., Jarboui, A. (2018). Corporate Governance and Operational Risk Voluntary Disclosure:Evidence from Islamic Banks. Research in International Business and Finance. Volume 46, 43-54.https://doi.org/10.1016/j.ribaf.2017.09.006

Nešlehová, J., P. Embrechts, Chavez-Demoulin, (2006). Infinite mean models and the LDA for operational risk, Journal of Operational Risk, 1, (1) 3-25. DOI:10.21314/JOP.2006.001

Okeke, M.N, Ganske C.U. & Onuorah, A.N. (2018). Operational Risk Management and Organizational Performance of Banks in, Edo State. International Journal of Academic Research Economics and Management Sciences Vol. 7, No. 4, 103 – 120. DOI:10.6007/IJAREMS/v7- i4/5187

Peters, G. W., Shevchenko, P.V., Hassani, B., Chappelle, A. (2016). Should The Advanced Measurement Approach Be Replaced With The Standardized Measurement Approach For Operational Risk? Journal of Operational Risk, Vol. 11, Issue 3, 1-49, 2016. DOI: https://doi.org/10.21314/JOP.2016.177

Qabajeha, M., Almajalia, D., Al Natourc, A. R., Alqsassa, M. & Maalid, H. (2023). The Impact of Operational Risk on Profitability: Evidence from Banking Sector in the MENA region.Uncertain Supply Chain Management 11, 1459–1466. https://www.growingscience.com/uscm/Vol11/uscm_2023_139.pdf

Reyad, S., Chinnasamy, G. & Madbouly, A. (2022).Risk Management and Corporate Governance of Islamic Banks: Evidence from GCC countries. Corporate Governance, Vol. 22 No.7, 1425–1443. https://doi.org/10.1108/CG-08- 2020-0360

RIYADH h Bank https://www.RIYADH bank.com/documents/20121/0/Quarter%204-Disclosure.pdf P 72

Saeed, M. H. (2015). Examining the Relationship between Operational Risk, Credit Risk and Liquidity Risk with Performance of Malaysia Banks. Thesis Submitted to Othman Yeop AbdullahGraduate School of Business University Utara Malaysia. Examining the relationship between operational risk, credit risk and liquidity risk with performance of Malaysia Banks | Semantic Scholar. https://etd.uum.edu.my/4631/1/s814431.pdf

Suryaningsih, N.P.R. Sudirman, M.S. N. (2020). The Influence of Credit Risk, Liquidity Risk, and Operational Risk on Profitability in Rural Banks in Bali Province. American Journal of Humanities and Social Sciences Research (AJHSSR) e-ISSN: 2378-703X Volume-4, Issue-3, 258-265. https://www.ajhssr.com/wp-content/uploads/2020/03/ZI2043258265.pdf

Uddin, M. H., Mollah, S., Islam, N. and Ali, M. H. (2023). Does digital transformation matter for operational risk exposure? Technological Forecasting and Social Change. 197 (Art. 122919). https://doi.org/10.1016/j.techfore.2023.122919

Velez, S.B. (2022). Regulation of Operation Losses and Capital in Banks. Operational Risk Management in Banks and Idiosyncratic Loss Theory: A Leadership Perspective. Emerald Publishing Limited, Leeds, 23-36. https://doi.org/10.1108/978-1-80455-223-020221006

Wang, T., Hsu, C. (2013). Board Composition and Operational Risk Events of Financial Institutions. Journal of Banking and Finance, 37, 2042- 2051. DOI:10.1016/j.jbankfin.2013.01.027

Xu, C., Zheng, C. Wang, D. Ji, J., Wang, N. (2019). Double Correlation Model for Operational Risk: Evidence from Chinese Commercial Banks. Physical A: Statistical Mechanics and Its Applications. Volume 516, 327-339. https://doi.org/10.1016/j.physa.2018.10.031