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Predicting Value at Risk in Investment Portfolio Using Monte Carlo Simulation: The Case of The Syrian Internasional Islamic Bank

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ABSTRACT

This study applies a Monte Carlo simulation model to estimate the value at risk (VaR) for the Syrian International Islamic Bank's investment portfolio, aiming to assess potential risks and Information is provided for investment decisions making. Using 2024 portfolio data, the simulation, conducted with R-Studio, calculates the VaR to identify credit risks and guide strategic decision-making. The results indicate that the potential future loss for the portfolio may exceed the projected losses from individual loans. Based on these findings, the study recommends that the Bank reduce its funding in the near term to mitigate the identified risks. The research also emphasizes the importance of continuous monitoring of the portfolio to improve risk assessment practices over time. Furthermore, the study advocates for the integration of advanced modeling techniques and real-time data to strengthen the Bank's analytical capabilities. This would improve forecasting accuracy and enable more effective loan repricing strategies in response to changing financial conditions. The proactive adoption of these risk management tools is essential for the Bank to navigate the evolving financial landscape and remain resilient against market volatility. This research contributes to the broader discourse on financial risk management by providing actionable insights that can enhance the Bank's performance.

Keywords: *monte carlo simulation; value at risk; kmv model; expected loss*

A. INTRODUCTION

Banks operate in dynamic and unpredictable economic environments, where exposure to various risks is inevitable (Mashamba et al.,2024). Among these, credit risk stands as one of the most significant challenges faced by financial institutions. As banks grant credit, the potential for defaults introduces a critical need for innovative risk management strategies that minimize risk while optimizing returns (Alzoubi,2020, Mulyadi, 2023) . Accurately predicting credit risk within a loan portfolio is not just important—it is essential. This prediction allows banks to estimate their value at risk (VaR) and prepare for potential financial losses in the event of defaults, providing a strategic edge in managing risk.

Researchers (see for example, Antony , 2011) in this field have employed a variety of analytical models and statistical techniques to estimate VaR, one of the most prominent being Monte Carlo simulation. This method generates a broad range of potential outcomes by simulating portfolio behavior over a specified period, allowing for the assessment of default probabilities and the estimation of maximum potential loss within a given time frame. By providing detailed insights into the likelihood and magnitude of potential losses, Monte Carlo simulation offers valuable information for strategic decision-making, enabling banks to effectively manage credit risk; and this in turn contributes to achieving financial stability and realizing the desired financial objectives.

In this study, we employed Monte Carlo simulation models to estimate the VaR for an investment portfolio, with the primary objective of assessing the potential risks associated with financing strategies. Our aim was to provide valuable insights into risk management and to support more informed decision-making processes within a financial context.

Our research methodology involved analyzing financial data and applying Monte Carlo simulations to model various potential outcomes and estimate the portfolio's VaR. By incorporating factors such as market volatility, asset correlations, and other relevant risk parameters, we were able to offer a comprehensive analysis of the risks inherent in the portfolio. The simulations enabled us to explore a wide range of scenarios, giving a detailed perspective on the downside risk exposure within the portfolio.

Our findings demonstrated that the Monte Carlo models effectively predicted the VaR, highlighting the portfolio's exposure to potential downside risks. The analysis revealed that projected losses at specified confidence levels could surpass expected losses from individual assets, underscoring the need for robust risk management strategies. Additionally, we identified areas where adjustments in funding levels and asset allocation could help mitigate these risks and enhance the overall risk-return profile of the portfolio.

We further emphasize the importance of continuous monitoring of market conditions and portfolio performance to adapt to evolving risk factors and optimize decision-making processes. This study contributes to the broader understanding of risk management in financial portfolios and offers practical strategies for minimizing risk in a dynamic market environment.

This study makes several key contributions to the field of financial risk management, specifically in the context of credit risk assessment using advanced simulation techniques. First, it expands the theoretical understanding of credit risk by offering a comprehensive framework for measuring and managing risk within investment portfolios. Through the application of Monte Carlo simulations, this research demonstrates how banks can accurately estimate VaR, providing a more dynamic and precise method than traditional models. Second, the study bridges the gap between theory and practice by applying these advanced techniques to a real-world case, focusing on the Syrian International Islamic Bank.

This practical application highlights the effectiveness of Monte Carlo simulations in predicting maximum potential losses and enables decision-makers to strategically manage credit risks and portfolio exposure. Finally, the research provides actionable insights for enhancing financial stability and risk management practices within banks. It underscores the importance of continuously monitoring investment portfolios and using data-driven tools to adjust funding strategies and improve resilience to economic fluctuations. By integrating advanced analytical techniques, this study advances both the academic literature and practical application of credit risk management, offering a refined approach to estimating VaR and enabling better-informed strategic decisions in the banking sector.

The remainder of the paper is organized as follows. Section 2 present the theoretical framework and the development of the research hypotheses. Section 3 discusses the concept of credit risk and the various methodologies for its measurement. Section 4 provides an in-depth discussion of Monte Carlo simulation techniques and their application in predicting VaR. We present the results in Section 5. Section 6 concludes the paper.

B. LITERATURE REVIEW

1. VaR in Investment Portofolio

Banks must evaluate the potential maximum loss within their portfolios, giving rise to the widespread application of the Value at Risk (VaR) framework. VaR is defined as a statistical metric used to quantify portfolio risk by estimating the potential loss in portfolio value resulting from adverse market conditions over a specified time horizon and at a designated confidence level (Qandouz, 2020; Alexander, 2003; Harmantzis et al, 2005; Manganelli, 2001). Fundamentally, VaR provides an estimate of the maximum expected loss a portfolio could incur during unfavorable market circumstances.

Scholarly research aimed at predicting VaR in investment portfolios can be classified into three principal streams. The first stream, the classical approach, focuses on the application of traditional financial theories, such as investment theory and financial analysis, to estimate VaR. The second stream, rooted in behavioral finance, examines the psychological and behavioral factors that affect financial decision-making and the estimation of risk. The third, modern approach, integrates both traditional financial theories and behavioral finance principles, while incorporating contemporary technological innovations to enhance VaR estimation models.

Several foundational theories inform the practical analysis of risk and return. Among the most influential is Modern Portfolio Theory, introduced by Markowitz (1952) and later expanded by William Sharpe (1964) and John Lintner, culminating in the development of the Capital Asset Pricing Model (CAPM) (Fama & French, 2004). CAPM remains a critical tool for estimating the expected return on financial assets based on the risks inherent in the assets. During the 1970s, Fama further contributed to risk-return theory through the formulation of the Efficient Market Hypothesis (EMH), which asserts that asset prices incorporate all available information, rendering future price movements unpredictable (Fama, 1991).

Concurrently, the introduction of Prospect Theory by Amos Tversky and Daniel Kahneman (1979, further developed in 1992) brought a behavioral dimension to risk analysis. Prospect Theory examines how individuals make decisions under risk and uncertainty, particularly when faced with probabilistic alternatives and varying levels of uncertainty (Rubin, Estevez, & Chen, 2024).

The estimation of VaR has undergone considerable refinement, with key contributions from Richard Thaler (1988) advancing the understanding of how behavioral and psychological factors influence financial decision-making. Thaler's work has indirectly improved VaR forecasting by illuminating the complex interplay between cognitive biases and financial behavior, thereby fostering a more nuanced approach to risk estimation.

Various analytical techniques have been employed to predict VaR, including the Parametric VaR method (analytical approach) and Historical Simulation. Danielsson et al. (1997) compared semi-parametric methods with historical simulation and J.P. Morgan's RiskMetrics technique, highlighting that while historical simulations tend to overestimate losses in extreme scenarios, risk metrics models tend to underestimate them. The Monte Carlo Simulation method has also been widely adopted, providing a robust means of addressing uncertainty and generating more reliable risk estimates (Antony, 2011). Furthermore, Gunay (2017) explored the application of fat-tailed distributions by analyzing several VaR models designed to measure the risk of passive investment portfolios. His research encompassed various VaR methodologies, including Parametric VaR, Historical VaR, and Monte Carlo Simulation, to assess the risk profiles of single assets and diversified portfolios.

The evolution of VaR estimation methodologies reflects the integration of traditional financial theory, behavioral economics, and advanced statistical techniques. This comprehensive approach has enhanced the ability of financial institutions to assess and manage potential losses under adverse market conditions, thereby improving risk management practices.

Further advancements, such as those demonstrated by Gunay (2017), analyzed various VaR models, including parametric VaR, historical VaR, historical simulation, and Monte Carlo VaR, using unnatural (fat-tailed) distributions. Gunay's research applied these models to both single-asset and virtual portfolios, revealing the effectiveness of Monte Carlo simulations in predicting risks across varying investment strategies. Monte Carlo methods, by simulating a range of potential outcomes, offer a flexible tool for estimating risk under complex, uncertain market conditions.

2. The Concept And Measurement of Credit Risk

Risk is generally conceptualized as a potential situation, event, or problem that has not yet materialized but may arise in the future (Platona,2014). Credit risk, more specifically, is defined as the risk stemming from a borrower's inability to fulfill payment obligations or reschedule debt and is intricately tied to changes in the borrower's credit quality, known as credit migration (Oorato, 2005). This form of risk is associated with unforeseen losses that may result in economic detriment to the lender (Schroeck, 2002), including counterparty losses.

Effective management of credit risk necessitates the calculation of potential portfolio losses, which are categorized into expected and unexpected losses. The actual realization of credit losses may, in some cases, be mitigated by the liquidation of collateral, which can serve to offset part of the losses (Banks, 2003). Furthermore, lending institutions may leverage certain adverse events, such as borrower distress, as opportunities to renegotiate the terms of the loan agreement (Fight, 2004). Additionally, default probabilities have a significant influence on the market value of financial contracts by impacting credit ratings and discounting through credit spreads (Stagars & Kkizidis, 2016).

To manage and mitigate credit risk effectively, banks frequently employ simulations that model the evolution of market and credit risk factors in order to respond to potential future changes. These simulations are based on models that utilize historical data to anticipate market developments and evaluate their implications for credit risk. Such simulations aim to assess how credit costs are influenced by value-at-risk (VaR) estimates and other market-related variables, and to determine their impact on the bank's credit risk exposure.

Many financial institutions adopt sophisticated simulation models to estimate value-at-risk, assess potential credit risks, and evaluate their effects on credit portfolios. These models typically rely on a detailed analysis of historical data and the application of advanced statistical and financial modeling techniques to construct realistic scenarios of future market developments. Such simulations enable organizations to analyze the potential impact of various risk factors on their credit portfolios, allowing for a more informed and proactive approach to risk management.

a. Losses Arising From Credit Risk

1) Expected Loss (EL)

The Basel II framework defines expected loss (EL) as e*xpected losses (El) as losses that can and cannot occur*. Expected loss is derived from the average value of the probability distribution of potential future losses. In practice, the lender estimates the expected loss in advance, allowing for risk hedging by incorporating an appropriate risk premium into the required return on the loan. In the event of a default, the lender receives the expected net return (Gerhard, 2002). Estimating expected loss when issuing a loan involves three critical components:

a) Exposure at Default (EAD):

EAD is a random variable representing the total exposure at the time of default. This includes the current exposure as well as potential variations in the loan size between the current time and the default event. Estimating the total loss exposure can be challenging, and decision-makers often employ Monte Carlo Simulation techniques to estimate this value (Gerhard, 2002).

b) Probability of Default (PD):

PD refers to the likelihood that a borrower will fail to meet their repayment obligations before the end of a specified time horizon, which is typically one year. It is important to note that PD differs from a credit score, which is a classification of the borrower's creditworthiness. While credit scores can be positive or negative, the probability of default is expressed as a value between 0 and 1. A key challenge is the conversion of a credit score into a probability of default (Joseph, 2013; Gerhard, 2002).

c) Loss Given Default (LGD):

LGD represents the percentage of the total exposure that the lender expects to lose after accounting for recoverable amounts, such as collateral. It is calculated as LGD = 1– RR, where RR is the Recovery Rate. LGD can range from 0% to 100% (Resti, 2007).

The expected loss (EL) can be calculated using the following formulas:

$EL = \mathbb{E} (\widetilde{L_n})$ EAD. PD. LGD……(1)

$EL_P = \mathbb{E} (\widetilde{L_n}) = \sum_{i=1}^{N} EAD_i . PD_i . LGD_i$ ………(2)

The expected loss of the credit portfolio is generated by the sum of the expected losses of the assets EBF (2016).

$\mathbf{EAD}_i$ **:** Credit exposure upon default of the borrower(i)

$\mathbf{PD}_i$: Borrower's probability of default (i)

$\mathbf{EAD}_i$: Loss of exposure to the borrower (i)

Hypothesis (H0): At a 99% confidence level, the maximum expected loss of the investment portfolio will not exceed the total projected losses from individual loans within the portfolio, assuming no changes in the portfolio composition.

2) **Unexpected Loss (UL**) is defined as loss arising from unexpected deviations in credit loss levels. They are potential losses that is, they exist but are not enabled /possible for any risk factor to do/both are calculated using a 12-month time horizon.

Table 1. summarizes the two types of losses that the investment portfolio is exposed to (Gerhard,2002., EBF,2016)

Table1. Types of losses that an investment portfolio is exposed to

• Probable financial loss over a 12-month time horizon at a specified confidence level	(EL) Expected Loss
• Potential financial loss over a 12-month time horizon at a specified confidence level.	(UL) Un Expected Loss

Source: (Gerhard,2002)

b. Credit risk Measurement methods

There are several credit risk measurement techniques available to measure the risk of default to a bank using market information, including distance to default and bond prices practically market-based indicators are more accurate than accounting indicators and more useful in predicting bank failure.

1) Credit risk+^{TM}Model

Known as the actuarial credit model, which Credit Suisse Financial Products worked on in 1997 and was an approach derived from the insurance business and applied to credit risk Bessis(2015) as it relied on tools used in the mathematics of insurance (actuarial mathematics) and specifies that credit losses stem from two main variables: 1) Repetition of the event. 2) The amount to be paid when the event occurs (severity of loss). Losses depend on the frequency of default events and the rate of loss in case of default, and on this measurement, it is possible to use insurance-derived models to estimate credit losses.

Repayment risk and recovery risk will be treated as inevitable and therefore neither default nor recovery risk can be estimated. CreditRisk+^{TM}Model (unlike structural models) does not seek to explain the cause of default; on the contrary, it assumes that debtors default odds and repayment rates for their loans have already been estimated by other tools (such as the bank's internal rating system: it is a system used by banks and financial institutions to classify credit risk for current and potential bank customers or studies produced by rating agencies (as Standard & poor's and Moody's and Fitch Ratings).

2) Merton Model

a) Calculation of the probability of Default in Banking This most common credit risk measurement model assesses the probability of a company defaulting at a given time and, based on Merton's approach, the borrower defaults when the market value of its assets falls below the book value of its obligations O'Kane (2006). to estimate the probability of default, subtract the face value of the company's debt from the estimated market value of the company and divide the difference by the estimated volatility of the company, resulting in a/ Z-score/ often referred to as the default distance degree (DD), and the Merton model assumes that the company's equity is equivalent to the option to purchase the company's assets. Since shareholders are the remaining claimants to the assets of the company after all obligations have been fulfilled. Merton's model is based on an important assumption that the total market value of a company's underlying assets follows a geometric Brownian movement.

$dV_A = \mu V_A \, dt + \sigma_A V_A dW$..........(3)

Where $\mathbf{V_A}$: The value of a company's assets, $\boldsymbol{\mu}$ Is the expected immediate periodic rate of $\boldsymbol{\sigma_A}$return on an asset, the immediate standard deviation of the rate of return on an asset, or the fluctuation of An asset dW is the standard winner process.

b) **Distance-to-default Probability in Banking**: To estimate the probability of default, the Merton model proposes to view the value of the borrowing company's equity as a purchase option relative to assets, with the Merton method based on the following idea: When a loan is due or its interest if the borrowed company's assets are less than the value of its liabilities. It will not be able to repay this loan and therefore will default in this case the value of equity subs equity will fall to zero, and if the value of its assets V_A is greater than the value of its liabilities then it will be able to repay the loans and the market value of the equity of the company will equal the difference between the value of its assets and the value of its liabilities. The present market value of a stock can be expanded V_E , assuming that the value of the company's assets at the moment **t** is the logarithm of the normal distribution, and that the loans the company has received are insured, the Merton model shows that using the Black and Scholes formula for purchase options the initial price of its equity is Gerhard (2002):

$$V_E = V_A N(d_1) - X_e^{-rT} N(d_2) \ldots..(4)$$

$$d_1 = \frac{\ln(\frac{V_A}{x}) + (r + 0.5\,\sigma_A{}^2)T}{\sigma A\sqrt{T}} \ldots\ldots(5)$$

$$d_2 = d_1 \text{-} \sigma_A\sqrt{T} \ldots\ldots(6)$$

$$d_2 = \frac{\ln(\frac{V_A}{x}) + (r + 0.5\,\sigma_A{}^2)T}{\sigma A\sqrt{T}} = d_1 - \sigma_A\sqrt{T} \ldots..(7)$$

Where r: Is the risk-free interest rate, σ_A Is the instantaneous standard deviation of the rate of return on the value of an asset (volatility of assets) and N is the cumulative rate of the standard normal distribution density function and x is the value of a company's liabilities.

Distance-to-default :is the distance between a company's expected asset value in the horizontal analysis and the default point, the calculation of the probability dimension DD requires two equations Resti (2007): The first is the equation that V_E States that the value of a company's equity is a function of the value of the company, the second relates to the volatility of the company.

$$DD_t = \frac{\ln\left(\frac{V_{A,t}}{x_t}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \quad \ldots\ldots(8)$$

V_A: value of assets*,* σ_A: volatility of assetsx_t: total liabilities*,* T: time period . Therefore, is calculated *the* probability of default with the following relationship: PD= N(-DD)

PD: the probability of default

N: cumulative probability distribution

3) KMV Model

This model was developed by Moody's KMV in 1993 where, based on a sample of several hundred companies, KMV noted that companies are more likely to default when their asset values reach a certain critical level somewhere in between total value obligations and the value of short-term obligations. KMV implements an additional step; (Saunders 2010; Zieliński, 2009) that refers *to the* critical default threshold as the default point /default threshold/, for the KMV model the default point is rounded (DPT) approximately by the sum of all short term debt (STD) and half of the long-term liabilities:(TD)

$$DPT = STD + 0.5LTD \quad \ldots\ldots(9)$$

The KMV approach calculates the known Distance to Default(DD) Kimber (2004) index is defined as the distance between a company's projected asset value in the horizontal analysis and the default point that is settled by the standard deviation of future asset returns. The absolute probability of default DD ′ Is expressed (in expected asset percentages) as the distance between the expected asset and the default point (DPT).

$$DD' = \ln\left(\frac{A_0}{DPT}\right) + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T \quad \ldots(10)$$

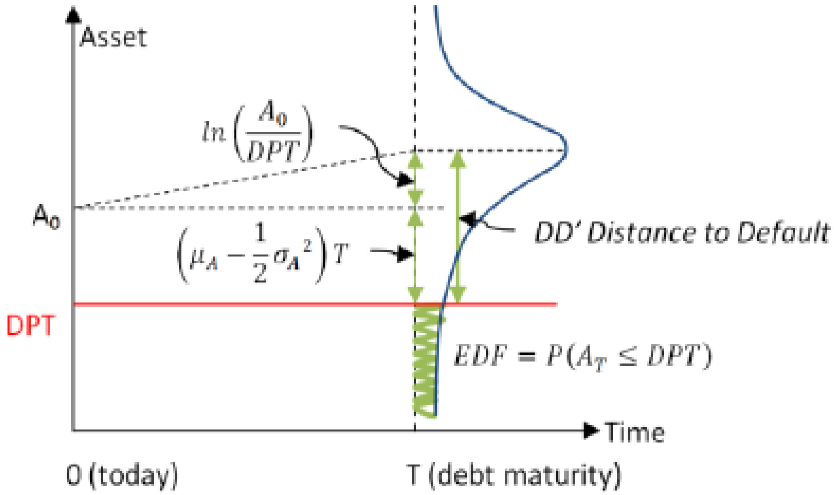
$$DD = \frac{E(A_T) - DPT}{\sigma} \quad \ldots\ldots(11)$$

In the KMV model, μ_A it is no longer risk-free but the expected rate of return of the company's assets and DPT is the point of default rather than debt (face value of debt), the expected growth Is equal $\left(\mu_A - \frac{1}{2}\sigma_A^2\right)$ of the asset instead of μ_A, Whereas the rate of return is normally distributed as the future value of the investment (or actual return of the return). $\mu_A$logarithmic distribution, which is the rate of deviation (expected rate of return)

.Ln $\left(\frac{S_T}{S}\right) \sim N\left(\left(\mu_A - \frac{1}{2}\sigma_A^2\right)\sigma_A\sqrt{T}\right)$ By dividing the absolute value DD′ With the volatility of the asset (according to /T/period, usually one year) we can calculate DD in relative terms as a multiplier of the standard deviation.

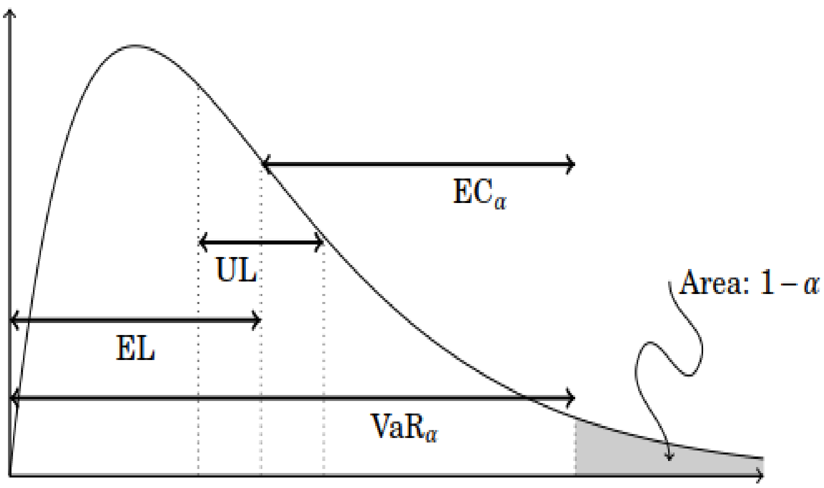
$$DD = d_2 = \frac{\ln\left(\frac{A_0}{DPT}\right) + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \text{.....(12)}$$

Figure1.Distribution of the value of the company's assets when the loan is due



Source: (Zieliński ,2009).

DD Similar to d_2 (with the replacement of r *with* μ_A *and* x_t with DPT) Similarity is the result of the relationship between risk-free probability and actual probability, the actual



Source: Leeuwarden, (2011).

a) EL: Expected Loss EL: = $\widetilde{\mathbf{L_n}}$

b) UL: Unexpected loss can be defined as the standard deviation of a portfolio loss Ul $= \sqrt{Var\ [\ \widetilde{\boldsymbol{L_n}}]}$Unexpected loss captures deviations away from the expected value of the loss that exceeds expectations.

c) Var: Value at risk it means determining the expected value of the risk based on the specified level of confidence. Nawlo (2022)

$$VaR_a = \inf\left\{x \geq 0: \mathbb{P}\left(\widetilde{L_n} \leq x\right) \geq \alpha\right\} \text{ where } \quad \alpha(0{,}1)$$

d) EC Economic capital $\mathrm{EC}_a = \mathrm{VaR_a} - \mathrm{EL}$ This is called capital cushion the risk value can be used as a method of selecting the appropriate capital cushion Gerhard (2002*)*, for example, if the capital cushion is chosen by the amount of the one-year risk value at the level of α, the capital cushion is expected to be sufficient at) 100* (1-α %) of years. So if the value of α = 0.998, the portfolio loss is expected to exceed the capital cushion only twice in 1000 years Bessis (2015) What makes distribution analysis $\widetilde{\boldsymbol{L_n}}$ Interesting is that variables $\mathbf{I}_{(\boldsymbol{D_i})}$Are usually related to each other.

C. RESEARCH METHODOLOGY AND HYPOTHESES TEST

The study was based on the analytical descriptive approach through reference to many books, references, and scientific journals, both Arab and foreign, and the study also used the case study method through the study of the investment portfolio at the Syrian International Islamic Bank in Aleppo.

The study community is considered one of the main sectors affecting the Syrian economy and is one of the leading Syrian Islamic private banks operating in the Syrian Arab Republic, and the sample of the study was derived from the previous society through the selection of the Syrian International Islamic Bank in Aleppo for the availability of data related to the Islamic portfolio of the branch of Aleppo.

For this study, it was first: necessary to determine the probability of stumbling in the investment portfolio of the Syrian International Islamic Bank in Aleppo, where the study was based on the model KMV (the model of the KMV was relied on in the probability of stumbling because it is a model developed from the Merton model. this takes into account the multiple default probability values between 0 and 1 that fit the requirements of the study as well as being a model approved by Basel).

By applying relevant relationships to calculate the probability of default:

DPT = STD + 0.5 LTD……….(25)

Table 3. Involves calculating the expected loss value for each fund in the investment portfolio Based on data from the Islamic Bank's loan portfolio.

PD	DD	σ_A	*T*	DPT	STD	μ_A	A_0	Value of funding	*N*
0.056146093	1.58797414	0.075	1	6750000	6,750,000	23.38%	42,900,000	18,300,000	**1**
0.01	-26.066	0.522	1	6300000	6,300000	1%	48,870000	24,000000	**2**
-	-	-	-	-		-	-	-	-
0.00451	0.122583972	0.0154	2	88,250,000	88,250,000	22.6%	798,250,000	49,000,000	**3**

Source: (created by the authors).

$$DD = d_2 = \frac{\ln\left(\frac{A_0}{DPT}\right) + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \text{........(26)}$$

$$PD = N(-DD)\text{......(27)}$$

Second: after reaching the probability of default PD through the previous step, we must determine the amount of loss resulting from the probability of default for each loan by determining the value of each EAD and LGD and the following equation to calculate the expected loss value for each loan.

$$EL = \mathbb{E}(\widetilde{L_n})\ EAD.\ PD.\ LGD$$

To determine the value of LGD = 1-RR you must calculate the value of both alpha and beta transactions and rely on the table in the appendix by applying the following equations:

$$\alpha = \frac{M}{Max}.\left[\frac{\mu.(Max-\mu}{Max-\sigma^2} - 1\right] \text{....}(28) \quad و \quad \beta = \alpha.\left[\frac{Max}{\mu} - 1\right] \text{....}(29)$$

The default value is defined.. Max as 1 and the value of RR by the following equation: $RR = \frac{\alpha}{\alpha+\beta}.Max$

Table 4. Includes data relating to the calculation of the probability of default Based on data from the Islamic Bank's loan portfolio.

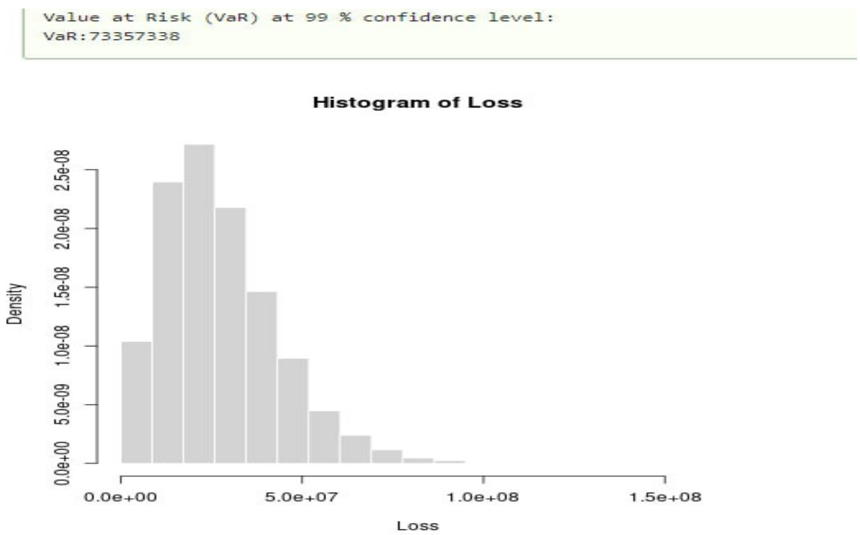
EL	EAD	LGD	RR	β	α	M ax	σ	μ	PD	N
516380.95	19489500.00	0.4719	0.5281	112.250	125.618	1	3.23%	53%	0.05614	1
9283700	21590000	0.43	0.57	973.9875	129.0997	1	1.04%	57%	0.01	2
-	-	-	-	-	-	-	-	-	-	-
123116.07	57820000	0.4719	0.5281	112.25	125.618999	1	3.23%	53%	0.00451	3

Source: (created by the authors).

Third: conducting a Monte Carlo simulation to estimate the maximum loss that can be experienced by the investment portfolio:

1- We generate the random variable $Y_i \sim N(0,1)$ by generating random numbers for each debtor in the wallet where the portion of the granted loan is represented idiosyncratic part to reflect individual differences in behavior or performance.

Figure3.The graph shows the distribution of losses in the portfolio as a result of the simulation process



Source: (from the output of the R-Studio programming language)

2- We calculate the probability of default and the amount of expected loss corresponding to each loan within the portfolio.

3- We perform a simulation of (N) a borrower within the portfolio to obtain the distribution of the expected losses within the portfolio, based on the ***R-Studio*** program.

Fourth: Forecasting the future value at risk based on the outputs of the Monte Carlo simulation.

To estimate the value at risk we assume thatL_i And i=1,2,....n are independent values from the simulation output. $\widetilde{L_n}$

N is the number of attempts, where L_i statistical commands are indicated in the same sequence but in ascending order

$$L_{(1)} \leq L_{(2)} \leq \cdots \leq L_{(n)}$$

Thus, we obtain the value at risk programmatically through :

$$\frac{j}{N} \leq \alpha < \frac{j+1}{N}$$

Fifth: Hypothesis testing: We will test the null hypothesis against the alternative hypothesis which states that

H0: At a 99% confidence level, the maximum expected loss of the investment portfolio will not exceed the total projected losses from individual loans within the portfolio, assuming no changes in the portfolio composition.

The total projected losses for individual loans in the portfolio were 99923197, while the maximum projected loss was 73357338, so we reject the null hypothesis and accept the alternative hypothesis.

D. RESULT AND DISCUUSION

Monte Carlo simulation: The name of this method dates back to the French city of Monaco, where the Monte Carlo simulation opened the door to solving complex problems Mun (2006) where the Monte Carlo simulation generates random numbers Barrailler (2014) useful in prediction and statistical inference, where real data is collected for three funding applicants. A random number generator is then used to generate hundreds or perhaps tens of thousands of hypothetical changes to predict the value at risk, the Monte Carlo simulation imposes the risk structure that Pallotta (2000) is supposed to look at.

Monte Carlo simulation of portfolio risk is carried out according to scientific studies using two basic types of simulation through which the distribution of portfolio losses is modeled:

1) Simulation of Times To Default: along the lines of the “reduced form” model of default (Bessis,2015; Roszbach,2003) This enables analysts to assess potential risks in the portfolio and make smarter investment decisions.

Simulations of dependent default event with the asset model: This technique is used by Moody's KMV Model and Credit risk+^{TM}.Based on the "structural default model", where default under this model occurs when the value of the assets is lower or equal to the threshold corresponding to the probability of default for each borrower. Simulations of default events are generated using a standardized model of asset value, where all factors affecting the general borrower are included to determine its probability of default this model assumes that the value of the asset follows the normal distribution and therefore the default point is a function of the probability of default for each borrower Bessis (2015). Then default occurs when the value of the assets owned by the borrower is less or equal to a certain level of probability of default, and when simulation is performed within the investment portfolio the number of stumbles within the portfolio equals the sum of the imaginary variables that represent the default for one borrower with a Probability of default: **D** and the default point: $\boldsymbol{A_d}$ For the value of random assets A**.**

$$A_d = \Phi^{-1}(d) \qquad \text{or} \qquad d = \Phi(A_d)$$

WhereΦ: Is the standard cumulative normal distribution. For example, with d=1%, the default point is $A_d = \Phi^{-1}(1\%) = -2.33$ and so on. If the standard model of asset value for a single borrower is based on the common factor Z where the common factor is used to represent systemic changes or general factors that affect multiple values in the model or system, helps in understanding the interconnectedness of variables and analyzing how the common factor affects the associated outcomes or phenomena and assumes the value of the borrower's assets i, Y has the following formula Bessis (2015): $Y_i = \rho Z + \sqrt{1-\rho^2}\, X_i$ In this case, we consider the constant correlation with the common factor is also the correlation between all dependent variables. The common probability of default is d=5%, and the default threshold corresponds to the asset value. $\Phi^{-1}(d) = 1.6449$ other For more than one borrower, y: a variable that follows the normal distribution, calculated by the association of P with Z:

$y = p\,\Phi^{-1}(U_1) + \sqrt{1-\rho^2}\,\Phi^{-1}(U_2)$ where $u_1 = 0.5$ $Z = \Phi^{-1}(U_1) = 0$ and

U_2: It is an intermediate variable.

$$\text{Cov}(Y_i, Y_j) = \text{Cov}\{\rho Z + \sqrt{1-\rho^2}\, X_i, \rho Z + \sqrt{1-\rho^2}\, X_i,\} = \rho^2\Phi^2 + \text{Cov}((X_i, X_j)$$

Since U_1 represents the cumulative probability of a standard normal random variable, the value 0.5 corresponds to the arithmetic mean 0 of the standard normal random variable.

We can summarize the simulation process according to the following steps: First, Derive the value of the assets. Second, the variable y_i is compared to The default threshold where the default occurs when the value of the asset reaches the default point. It goes on to compare the value of the asset to the default point to derive the default variable of the default from the value of the asset, which is equal to 1 when the value of the asset is less or equal to the default point and equal to 0 if the value of the asset is greater than the default point. Third, Determine the distribution of alpha and beta in this step the default values are studied based on the coefficients of alpha and beta using the coefficient of beta the default values are converted to a dependent variable following a normal distribution, where the beta distribution is limited by upper and lower limits ranging from zero to one.

This means that the resulting beta distribution falls between these two values and that the form coefficients (alpha) and (beta): determine the form of the beta distribution. The alpha coefficient affects the shape of the top and the distribution in the right part of the chart, while the beta coefficient affects the shape of the top and the distribution in the left part of the chart. Fourth, Recovery values that follow the beta distribution are converted to a dependent variable that follows a normal distribution, which is explicitly defined as follows Servies (2002):

$$\text{Dependent Variable} = y_i = N^{-1}\,[\text{Betadist}(\text{RecovRt}_i, \alpha_d, \beta_d, \text{Min}, \text{Max}_d)]$$

$$\text{RecovRT}_i = \min(\text{Max} - \varepsilon, \text{observed recovdry rate}) \qquad \varepsilon = \text{some small value}$$

$$\alpha_d = \text{The Beta Distribution's center parameter}$$

$$\beta_d = \text{The Beta Distribution's shape parameter}$$

Min=Set to zero for all cases

Max_d=Set to 1.1 for bonds, but otherwise is 1.0

d= {loans, bonds, preferred stock}

"d" corresponds to each type of debt. Distributions of three different asset classes can be calculated by specifying two values for the alpha and beta form coefficient. For each beta distribution, many of these distributions can be captured, and it is possible, through the algebraic coefficient, to determine the beta distribution that simply corresponds to the mean and the mathematical standard deviation, as the beta distribution is a function of the gamma distributions when the minimum is set to zero, the distribution can be described as follows.

$$\beta\text{eta}(x,\alpha,\beta,\text{Min}=0,\text{Max}) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left[\frac{x}{\text{Max}}\right]^{\alpha-1}\left[1-\frac{x}{\text{Max}}\right]^{\beta-1}\left[\frac{1}{\text{Max}}\right] \ldots\ldots(19)$$

The coefficients of the beta distribution form can be extrapolated in several ways, for example, they can be converted to an average or standard deviation:

$$\alpha = \frac{M}{\text{Max}}.\left[\frac{\mu.(\text{Max}-\mu}{\text{Max}-\sigma^2} - 1\right] \ldots(20) \quad \text{and} \quad \beta = \alpha.\left[\frac{Max}{\mu} - 1\right] \ldots(21)$$

On the contrary, given the beta distribution parameters, the average and standard deviation can be easily calculated.

$$\mu = \frac{\alpha}{\alpha+\beta}.\text{Max} \ldots(22) \quad \text{and} \quad \sigma = \sqrt{\frac{\alpha.\beta}{(\alpha+\beta)^2 + (1+\alpha+\beta)}}.\text{Max} \ldots(23)$$

Fifth, Estimating the value at risk: The value at risk is α-quantile, meaning that it divides the data into two parts; if the value α is 0.05, then 0.05-quantile ratio represents the value in which 5% of the data is in the lower tail (the lower part) of the distribution, and therefore 95% of the data in the upper tail (the upper part) of the distribution. Assuming L_i And i=1,2....n is an independent value for estimating the risk value (simulation output. $\widetilde{L_n}$).

N is the number of attempts, where L_i Statistical commands are indicated in the same sequence but in ascending order.

$$L_{(1)} \leq L_{(2)} \leq \cdots \leq L_{(n)} \qquad \ldots\ldots(24) \qquad \frac{j}{N} \leq \alpha < \frac{j+1}{N}$$

$L_{(J)}$Is approximation (1-α)-quantile of the loss distribution.

About the Syrian International Islamic Bank: The Syrian International Islamic Bank was established in the form of an anonymous Syrian joint stock company on 07/09/2006, with a capital of fifteen billion Syrian pounds distributed over 150.000.000 shares worth 100 Syrian pounds per share, and on 02/06/2009 it was listed on the stock market. The bank continued to expand with the opening of branches in the provinces and major cities until the bank branches had 26 branches and offices in various cities SIIB (2014).

The Bank obtained the ISO certificate in 19/11/2015, the Bank prepared to implement the requirements of Basel III after the completion of the application of the requirements plan for compatibility with Basel II, each year, the Bank prepares stress tests on the investment portfolio to study its impact on the allocations to be hedged, based on the directives of the Central Bank of Syria, by preparing the effort tests in a quarterly manner according to previously defined scenarios.

Table 2. Includes information about SIIB

Number of shares in millions	Capital in 2011 in millions	Date of listing on the stock exchange	Date of direct	Date of establishment	Symbol	Name of the bank
10	5000	02/06/2009	15/09/2007	07/09/2006	SIIB	Syrian International Islamic Bank

Source: (created by the authors).

E. CONCLUSION

This study employed a Monte Carlo simulation model to estimate the Value at Risk (VaR) for the investment portfolio of the Syrian International Islamic Bank, aiming to provide a comprehensive assessment of potential risks and enhance investment decision-making through a detailed analysis of risk and return. The results demonstrated that the Monte Carlo simulation effectively estimated VaR, revealing that future losses could exceed the expected losses of individual loans in the portfolio. These findings underscore the critical importance of proactive and dynamic risk management strategies within the bank's operations.

In addition, the study suggests that adjusting funding levels in the near term could help the Syrian International Islamic Bank mitigate the identified risks. Continuous monitoring and evaluation of the portfolio’s performance are essential for improving risk assessment and management capabilities over time. By integrating advanced analytical tools and modern risk management techniques, the bank could enhance its forecasting accuracy and optimize loan repricing strategies to better respond to evolving market conditions. Moreover, the study emphasizes the need to assess appropriate levels of economic capital to cover potential losses, particularly in light of potential future market fluctuations.

Theoretically, this study contributes to the broader understanding of how quantitative risk management models, such as Monte Carlo simulations, can be applied in diverse environments, including emerging markets or regions facing specific economic challenges, such as Aleppo. It highlights the unique characteristics of local markets in such regions, offering insights into how quantitative techniques can be leveraged for risk identification and prediction in these contexts. The study advances the theoretical discourse on the critical role of quantitative methods in modern risk management.

However, this study also recognizes its limitations. One key challenge is the difficulty in accurately modeling unexpected risks in regions impacted by unstable geopolitical or economic conditions, such as Aleppo, where traditional Monte Carlo simulations may not fully account for unpredictable events. Moreover, interpreting the simulation results can be complex, particularly for decision-makers who may have limited expertise in quantitative modeling and risk management, posing a potential barrier to the practical application of the findings.

In conclusion, this study underscores the importance of employing robust risk management frameworks, while also advocating for the continuous refinement of simulation models and risk assessment tools to better address the dynamic and unpredictable nature of financial markets, particularly in volatile economic environments.

REFERENCES

Akkizidis, I.& Stagars, M. (2016). Marketplace Lending, Financial Analysis, And The Future Of Credit. Wiley & Sons,125.

Alexander,G. j.,& Baptista,A..M. (2003), CVAR as a Measure of Risk: Implication forPortfolio Sel ection. UCAL and University of Minnesota and Arizona, 3.

Alzoubi, T. (2020). How size influences the credit risk in Islamic banks. Cogent Economic &Finance,7(1),2.

Anthony,J.B.(2011). Risk Management Monte Carlo Simulation in cost estimating. Project Management Institute.

Banks, E., & Dunn, R. (2003). Practical Risk Management. John Wiley & Sons, Ltd, West Sussex, England, 19.Available

Barrailler, M., & Dufour,Th.(2014). Value At Risk And Expected Shortfall. NicSophi Polytech,6.

Bessis, J. (2015). Risk management in banking, fourth edition. John Wiley & Sones, Ltd, 287- 300.

Danielsson.J.,& de Vries.C,G.(1997). Value-at-Risk and Extreme Returns.London School of Economics and Institute of Economic Studies at University of Iceland,1 Available at https://papers.tinbergen.nl/98017.pdf

EBF. (2016).Interaction between the prudential and accounting framework Expected losses EBF Netherlands EBF 2.

Fama, E,F; & French,K,R. (2004). The Capital Asset Pricing Model: Theory and Evidence.Journal of Economic Perspectives, 18(3),43.

Fama,E,F.(1991). Efficient Capital Markets: II. The Journal Of Finance, XLVI(5), 1576.Available at https://www.bu.edu/econ/files/2011/01/Fama2.pdf

Fight,A. (2004).Credit Risk Management. Elsevier's in Oxford,212.

Gunay,S.(2017).Value at risk (VaR) analysis for fat tails and long memory in returns. Finance Department, American University of the Middle East, Eqaila.

Harmantzis et al. (2005). Empirical Study of Value at Risk an Expected shortfall Models with Heavy Tails. Stevens Institute of Technology, 2.

Joseph,C.(2013). Advanced Credit Analysis and Management. Wiley & Sons,164.

Kimber, A.(2004). Credit Risk From Transaction To Portofolio Management.Elsevier Finance,82.

Leeuwaarden, J,V.(2011). Monte Carlo Simulation with Applications to Mathematical Finance. Ein dhoven University of Technology, 55 - 57. Available at https://resing.win.tue.nl/2DF11/sim.pdf

Manganell, S,. Engel, R, F. (2001).Value at Risk Models in Finance, European Central Bank, Frank furt, Working paper (75), 5.

Markowitz,H,M. (1991). Foundations Of Portfolio Theory. Journal of Finance, 46(2), 470.

Mashamba, T & Gani, Sh .(2024) . Upstarts vs incumbents: the interaction between fintech credit and bank lending in Sub-Saharan Africa. Cogent Economic &Finance 12(1),2 .

Mulyadi, S.(2023). Contributions of Internal and External Variables in Non-Performing Financing Bank Muamalat for the Period of 2005-2021. el-Jizya: Jurnal Ekonomi Islam.

Mun, J.(2006). Modeling Risk: Applying Monte Carlo Simulation, Real Options Analysis, Stochasti c Forecasting, and Optimization. John Wiley &Sons, New Jersey, United States of America, 73.

Nawlo M.A.(2022). Financial and banking risk management between theory and practice,University of Aleppo,401401.Available at https://www.academia.edu/66848109/

Onorato, M.(2005). Essays on Credit Risk, Risk Adjustwd Performance and EconomicCapital in Fi nancial Capital In Finacial Instrtutions, PHD Kingston University, London.

O'kane, D.(2008). Modeling Single-name and Multi- Name Credit Derivatives. Wiley &Sons,38. Available at.https://www.amazon.co.uk/Modelling-Single-name-Multi-name-Derivatives-Finance-ebook/dp/B004S82S00

Platona,V,.&Comstantinescu,A.(2014).MonteCarlo Method in risk analysis for investments Projects, Procedia Economics and Finance, 394.

Pallotta,M., &Zenti,R. (2000), Risk Analysis for Asset Managers: Historical Simulationthe Bootstrap Approach and Value at Risk Calculation. Efma 2001 lugano Meeting, 4.

Qandouz, A,K,A.(2020). Banking Risks and Measurement Methods. Issue 5, Arab Monetary Fund, 64_65.Available at https://www.amf.org.ae/sites/default/files/publications/2022-01/banking-risks-and-ways-to-measure-them.pdf

Resti, A., & Sironi,, A. (2007). Risk Management And Shareholders Value In Banking. John Wiley & Sons, 279.

Rubin,D; et al.(2024). Prospect Theory: What It Is and How It Works, With.Instopedia.

Saunders,A., &Allen, L.(2010). Credit Risk Measurement In and Out Of The FinancialCrisis,3rd ed. Wiley & Sons,92.

Schroeck, G. (2002). Risk Management and Value Creation in Financial Institutions John Wiley & Sons, Ltd, 2nd Ed,170.

Gupton, G,M.,& Stein;R.M. (2002). LosssCalc^{TM}: Moody's Model For Predicting

Loss Given Default(LGD), Global Credit Research,25. Available at http://www.rogermstein.com/wp-content/uploads/losscalc.pdf

SIIB.(2014). Consolidated Financial Statements, Syria,53.Available at https://www.siib.sy/images/reports/30-06-2024.pdf

Thaler, R. (1988). Anomalies The Winner's Curse. Journal of Economic Perspective, 2(1),193.

Zieliński,T.(2009). Merton’s and KMV Models In Credit Risk Management.University of Economics in Katowice, 131- 133.