Economic Journal of Emerging Markets, 17(2) 2025, 124-142

Check for updates

EJEM
Econ.J.Emerg.Mark.

Economic Journal of Emerging Markets
Available at https://journal.uii.ac.id/jep

Quantifying mark-to-market risk in Jamaica's banking sector

Kishan Clarke[1], Robert Stennett[2*]

[1]Phillips Academy, Andover, Massachusetts, United States of America
[2]Bank of Jamaica, Kingston, Jamaica
*Corresponding author: Robert.Stennett@boj.org.jm

Article Info

Article history:
Received 07 September 2025
Accepted 15 October 2025
Published 28 October 2025

JEL Classification Code:
C58, G17, G32

Author's email:
kishan.clarke@gmail.com

DOI:
10.20885/ejem.vol17.iss2.art2

Abstract

Purpose — This study evaluates how well parametric Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) models measure market risk from Jamaican banks' sovereign bond exposures.

Method — We calibrate VaR and CVaR models using banks' aggregate portfolio holdings across the entire financial system.

Findings — The parametric VaR model performs reliably, passing standard statistical tests for consistency, independence, and reliability.

Implications — The results suggest that these standard risk measures effectively capture Jamaican banks' market risk exposure to foreign currency-denominated sovereign bonds, which could serve as a helpful tool for regulators to monitor market risk and financial system stability.

Originality — This research applies VaR and CVaR to a novel dataset of Jamaica's entire financial system, demonstrating how regulators can transition from the currently prescribed methods. The findings indicate that these standard risk measures effectively capture risk charges for market risk assessment, as allowed under Basel II, and align with more modern Basel-style frameworks.

Keywords — Value-at-Risk, Conditional VaR, Gaussian distribution, Jamaican bonds, Back testing, Basel II.

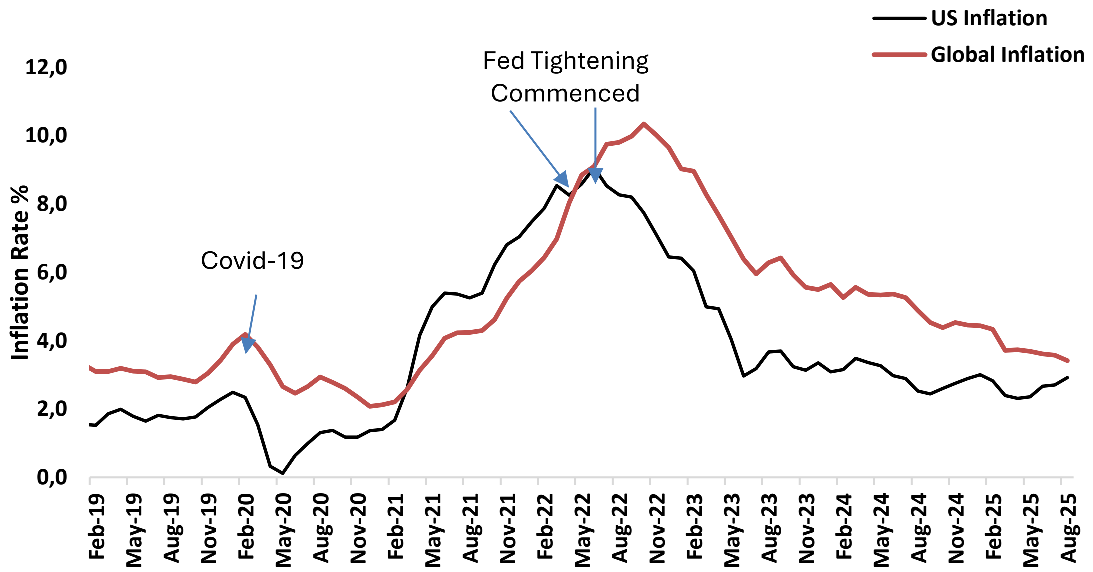
Introduction

With the implementation of IFRS 13 in 2013, central banks worldwide face the challenge of maintaining financial sector stability, especially as the country's sovereign bonds—fundamental assets of their banking systems—are prone to sudden, volatile price fluctuations (Bank for International Settlements, 2016). This risk materialised following the twin shocks of the Covid-19 pandemic and the Russia/Ukraine war, resulting in an unexpected surge in global inflation and a significant, synchronised monetary tightening globally. The sharp increases in interest rates worldwide, particularly in US financial markets, led to substantial drops in the prices of fixed-income securities. If not properly hedged, this type of volatility and the significant mark-to-market losses on financial institutions' balance sheets that it causes can also threaten their capital bases, weaken their liquidity, jeopardise their solvency, diminish confidence in the system, and, in the worst cases, trigger full-scale banking crises.

For established banks operating in Jamaica, sovereign Jamaican government bonds are the safest assets in terms of credit risk compared to other Jamaican assets. This creates a challenge. Banks need to hold these assets, but they can sometimes experience significant fluctuations in value. How should central banks evaluate the market risk to the financial system that comes from these bond holdings? Can they estimate the potential range and scale of system-wide mark-to-

P ISSN 2086-3128 | E ISSN 2502-180X

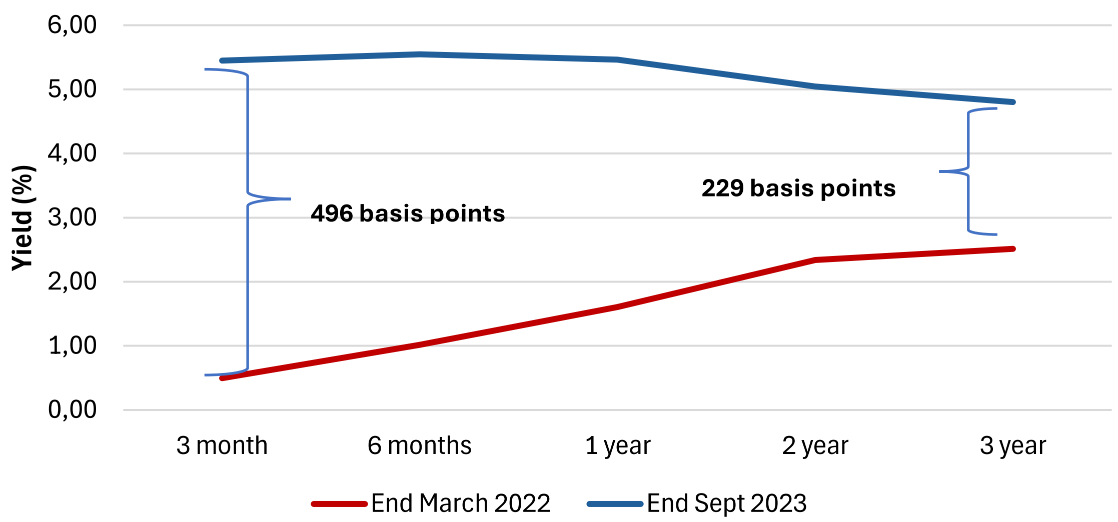
market losses in advance? Are banks sufficiently capitalised to handle this risk? Following the COVID-19 pandemic and the subsequent outbreak of war between Ukraine and Russia, the world experienced a period of high inflation, which prompted central banks around the globe to tighten monetary policy. Annual CPI inflation in the US peaked at 9.1% in June 2022, after gradually rising from 2.5% in January 2020. This pattern closely resembled that of global inflation but showed a slightly sharper increase. The causes of the inflation surge have been well documented (Barnichon et al., 2022; Prokopowicz, 2022).



Source: Bloomberg L.P. (2025).

Figure 1. Global vs US inflation rate (2019-2025)

Although the responses of central banks around the world to the inflation shock were delayed, they were profound. Most notably, the United States Federal Reserve (Fed) initiated an aggressive cycle of raising the target for the federal funds rate. Between March 2022 and July 2023, the Fed raised the federal funds rate by 525 basis points (International Monetary Fund, 2024). This was the fastest rate of interest rate increase since the early 1980s (Justiniano and Barlevy, 2023), and this significant shift affected many countries and regions. In the context of the Fed's policy actions, there was a proportional upward shift at the short end of the US Treasury bond yield curve of six months to three years, as captured in Figure 2.



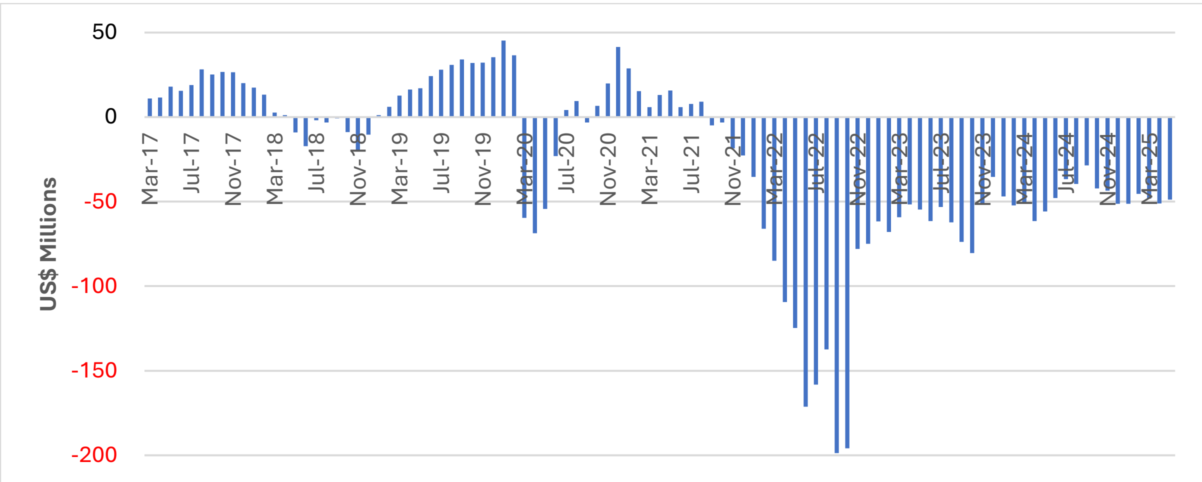
Source: Bloomberg L.P. (2025).

Figure 2. Shift in the US Treasury bill yield curve between March 2022 and September 2023

Before this tightening cycle, the Fed's Monetary Policy Committee began signalling upcoming monetary tightening through its forward guidance, providing a clear and vital signal to portfolio managers. As early as September 2021, the Fed began publicly communicating that future adjustments to the pace of its quantitative easing program were necessary and that it expected progressive interest rate hikes over the next three years (Ihrig & Waller, 2024; Peterson, 2021).

As market interest rates rose from pandemic lows during 2022, financial institutions worldwide recorded significant fair value losses on their balance sheets, the extent of which appeared unanticipated.[1]. For US banks, the value of their fixed-rate assets declined substantially. At the end of 2024, fair value losses, i.e., the value of their available-for-sale portfolios relative to their book values, amounted to US$297 billion, or just over 1.0% of US GDP.

The situation in Jamaica was similar. Jamaican banks hold a significant portion of foreign currency-denominated government bonds as part of their investment activities. In September 2021, six months before the Fed's tightening cycle began, the Jamaican banking system held nearly US$1 billion in USD- and euro-denominated bonds, about 6.8% of Jamaica's gross domestic product. From September 2021 to October 2022, monthly mark-to-market changes ranged from US$62 million in losses to US$13 million in gains, with an average monthly loss just under US$16 million. During this period, cumulative mark-to-market losses increased over the first nine months, reaching a peak of US$198 million in October 2022, equal to 1.0% of GDP or roughly 20.0% of the pre-crisis portfolio value. These banks also experienced mark-to-market losses on their Jamaican-dollar bond holdings, as referenced in the Bank of Jamaica's 2022-2023 report.



Source: Graphs generated by the author using data extracted from the Bank of Jamaica's internal database, which is not publicly available (Access date: July 2025).

Figure 3. Cumulative banking system mark-to-market gains/losses by month (2017-2025)

This level of mark-to-market loss on the safest assets poses a challenge to regulators, raising the question: Could the potential scale of these mark-to-market losses have been quantified in advance? VaR models have been used across various financial markets over the past 30 years for similar purposes, which became a fundamental risk metric (Jorion, 1996). Related papers,

[1] The IMF's Global Financial Stability Report in October 2021 (International Monetary Fund, 2021), for example, highlighted the risk of monetary easing for financial vulnerabilities more than the building market risks associated with monetary policy. Similarly, while US banks publish scenario analyses involving fair value shocks in their annual stress testing disclosures, these scenarios are guided by Supervisory Severely Adverse Scenarios (SSAC) disseminated to the system by the Federal Reserve (Board of Governors of the Federal Reserve System, 2021). The scenario assumptions that were prescribed in early 2021 highlighted the main risks as largely emanating from a protracted global recession (JP Morgan Chase & Co., 2021). The scenario featured economic slowdowns, starting in the first quarter of 2021 among the major developed economies, leading to recessions in the Euro area, the United Kingdom, and Japan (Board of Governors of the Federal Reserve System, 2021). In the context of stable inflation in the US, long-term Treasury rates were projected to rise gradually from 0.30% in the first quarter of 2021 to just 0.90% by the first quarter of 2023 (JP Morgan Chase & Co., 2021).

subsequently, bridged academic and practitioner views and introduced parametric, historical simulation, and Monte Carlo methods of VaR. In a series of papers, the Basel Committee on Banking Supervision enshrined VaR as the global standard for capital adequacy related to market risk, especially under the Internal Models Approach (IMA) (Basel Committee on Banking Supervision, 1996) and (Basel Committee on Banking Supervision, 2004). These papers had a profound influence on bank risk management practices.

Over time, improvements to the VaR framework have been suggested and incorporated into analytical toolkits (Barone-Adesi et al., 1999). In 2001, Danielsson et al. critiqued the VaR methodology, arguing that it can underestimate risk due to model risk, procyclicality, and the failure to capture systemic risk (Danielsson et al., 2001). This paper prompted the work by Acerbi, Carlo, and Tasche (2002), which provided formal proofs that the expected shortfall approach (or Conditional VaR, or CVaR for short) satisfies all coherence axioms and showed how to compute it under various distributional assumptions (Acerbi et al., 2002). In 2016, the Basel Committee on Banking Supervision officially replaced VAR with Expected Shortfall in regulatory capital calculations for market risk under the Fundamental Review of the Trading Book (Bank for International Settlements, 2016).

In the wake of the 2008 financial crisis, stress testing has become a core risk management and regulatory tool in global finance. It has now been formally adopted by the BIS, the IMF, the ECB, the US Federal Reserve, the BoE (with its Annual Stress Tests program), and the EBA (EU-wide stress tests). The first formal application of stress testing emerged when the Fed, in 2009, published its Supervisory Capital Assessment Program, a large-scale, top-down test applied to U.S. banks. Its introduction was novel at the time, as it used a standard set of macroeconomic scenarios and a common forward-looking conceptual framework. Other papers after that one extended the stress testing framework to include more formal transmission of macroeconomic shocks to the banking system (Jobst & Ong, 2016) and to systemically important institutions (Henry & Kok, 2013).

In research on Jamaican bonds, a VaR methodology was developed to identify uncorrelated market risk factors on which the VaR model would be based (Tracey, 2009). This approach eliminated the need to compute covariance matrices, simplifying the calculation of VaR for the portfolios involved. Aside from this paper and White (2009), there is little, if any, published work applying VaR methodologies to Jamaican bonds. This represents a gap that offers an opportunity for further research, including the work described here.

This paper employs parametric Value at Risk (VaR) and Conditional Value at Risk (CVaR) models to estimate the system-wide market risk inherent in the foreign currency-denominated Jamaican sovereign bond portfolio held by the Jamaican banking system prior to the tightening of global financial conditions in early 2022. It also back-tests the predictive power of the VaR models. Its main contribution to the literature is to demonstrate the ability of benchmark models to quantify market risk in the Jamaican setting reasonably. The paper suggests that Gaussian VaR and CVaR models can provide a customised view of market risk and, with further research, offer regulators the option to update the current fixed risk-weighting system to better reflect market dynamics.

Methods

Value-at-risk (VaR) models estimate the minimum potential loss in value over a fixed period that the owner of a financial asset should experience with a specified probability, assuming the asset is held over that period. It is crucial to bear in mind that VaR provides only an estimate, and VaR calculations say nothing about the distribution of potential losses when losses exceed the VaR estimate.

There are three types of VaR models: 1) parametric VaR where financial asset returns or changes in the financial assets' risk factors are assumed to follow a particular probability distribution function, 2) historical VaR, where the VaR model is estimated entirely from the actual historical distribution of actual past asset prices or risk factor behavior and does not assume that any particular parametric probability distribution can describe these asset prices or risk factors, and 3) simulation VaR where the model is computed by simulating asset price or risk factor behavior. The simulation is then run many times, and the distribution of simulated losses is used to estimate VaR.

Model Framework

We now set out, from first principles, the theoretical model framework used for the application of parametric multivariate Gaussian VaR and CVaR to our dataset. We begin with the assumption that the price of a bond, B, that matures at the time T is a function of its yield to maturity y. That is,

$$B \equiv B(y;T)\ y \geq 0, T > 0$$

We further assume that the bond pays an annual coupon C and at maturity pays the principal P. Then, the price of the bond can be calculated as

$$B(y;T) = \sum_{t=1}^{T} \frac{C}{(1+y)^t} + \frac{P}{(1+y)^T} \tag{1}$$

The Taylor series expansion of $B(y;T)$ gives

$$B(y+\Delta y) = B(y) + \frac{B'(y)\Delta y}{1!} + \frac{B''(y)(\Delta y)^2}{2!} + \cdots + \frac{B^n(y)(\Delta y)^n}{n!} + \cdots \tag{2}$$

Ignoring the terms in $(\nabla y)^n$, for $n \geq 2$, given that these terms will be small for small ∇y, we obtain a first-order Taylor expansion that approximates how $B(y;T)$ changes for small changes in y:

$$B(y+\nabla y) \approx B(y) + B'(y)\Delta y + \cdots \tag{3}$$

Where $B'(y)$ is the first derivative of B with respect to y and is given by

$$B'(y) = \sum_{t=1}^{T} -\frac{tC}{(1+y)^{t+1}} - \frac{TP}{(1+y)^{T+1}} \tag{4}$$

We can rearrange Equation (3) and divide both sides by $B(y)$ to yield the following first-order approximation:

$$\frac{B(y+\Delta y) - B(y)}{B(y)} \approx \frac{B'(y)}{B(y)}\Delta y \tag{5}$$

That is, we have an expression for the decimal form of the percentage change in bond price given slight changes in yield. The quantity $\frac{B'(y)}{B(y)}$ is known in the fixed income literature as the negative modified duration, D^*, of the bond B. That is,

$$D^* = -\frac{B'(y)}{B(y)} \tag{6}$$

Incorporating the definition of D^*, in Equation (5), allows us to express the following first-order approximations:

$$\frac{\Delta B(y)}{B(y)} \approx D^*\Delta y \tag{7}$$

$$\Delta B(y) \approx D^* B(y)\Delta y \tag{8}$$

as stated in (Jorion, 1996) where $\Delta B(y)$ is the change in bond price due to a slight change in yield, i.e. $\Delta B(y) = B(y+\Delta y) - B(y)$. By multiplying the result in Equation (7) by 100%, we obtain a first-order approximation for the percentage change in the price of a bond due to small changes in yield, expressed in terms of the modified duration of cap D to the asterisk operator. Similarly, Equation (8) gives us a first-order approximation for the dollar change in the price of a bond, ΔB *, due to small changes in yield cap delta y, where cap delta y* is expressed as a decimal. If, as is the practice case, Δy is expressed in units of basis points, and since one basis point = 0.0001, Equation (8), which provides the dollar change in the bond price, becomes:

$$\Delta B(y) \approx \left[\frac{-D^* B(y)}{10{,}000}\right] . \Delta y \tag{9}$$

The expression in square brackets is often referred to as the dollar value of a basis point (DV01) and represents the change in a bond's price for a one-basis-point change in its yield.

Estimating VaR for a single bond

Daily changes in Jamaican bond yields are influenced by many, small random events e.g. 1) perceptions of the creditworthiness of the issuer, 2) global events such as decisions of the Federal Reserve, oil price changes, geopolitical events 3) macro news such as inflation, unemployment and economic growth data and 4) events within local Jamaican and global financial markets relating to sentiment and liquidity among other factors. Each of these factors and their component sub-factors contributes a small part to the overall daily change in bond yield. These factors can be thought of as independent or weakly dependent random variables, and the daily change in bond yields is therefore a summation of these many small factors. The Central Limit Theorem informs us that when a variable is the sum of many independent random variables or weakly dependent factors, its distribution approximates the normal distribution.

This provides some basis for us to assume that actual daily changes in bond yields, ϵ, expressed in basis points (i.e., one basis point = 1/100th of a percentage point), are generally distributed with a mean μ_ϵ and variance σ_ϵ^2. That is,

$$\epsilon \sim N(\mu_\epsilon, \sigma_\epsilon^2) \tag{10}$$

We are therefore interested in leveraging this Gaussian assumption of daily bond yield changes to characterise daily changes in bond prices ΔB given changes in yield ϵ. Given the linear relationship between ΔB and small changes in yield in Equation (9), coupled with the Gaussian assumption in (10), we can deduce the variance (Var) of ΔB which we denote as σ_B^2:

$$\sigma_B^2 = Var[\Delta B(y)] \approx Var\left[\frac{-D^*B(y)}{10{,}000} . \epsilon\right] = \left[\frac{D^*B(y)}{10{,}000}\right]^2 \sigma_\epsilon^2 \tag{11}$$

The standard deviation of bond price changes is given by

$$\sigma_B = \left[\frac{D^*B(y)}{10{,}000}\right] \sigma_\epsilon \tag{12}$$

Providing a linear relationship between the standard deviation of daily bond price changes and the standard deviation of daily yield changes. Similarly, the expected daily bond price change, μ_B , is given by:

$$\mu_B = E[\Delta B(y)] \approx E\left[\frac{-D^*B(y)}{10{,}000} . \epsilon\right] = \left[\frac{-D^*B(y)}{10{,}000}\right] \mu_\epsilon \tag{13}$$

Therefore, from our assumption in (10), it follows that daily bond price changes would also be normally distributed with a mean μ_B and standard deviation σ_B. That is,

$$\Delta B \sim N(\mu_B, \sigma_B^2) \tag{14}$$

We further leverage the properties of the normal distribution, which imply that daily changes in the price of bonds ΔB should observe the probabilistic relationship

$$P(\Delta B \geq \mu_B + Z_{1-\alpha}\sigma_B) = \alpha \tag{15}$$

where $0 < \alpha < 1$ *and* $Z_{1-\alpha}$ is the $(1-\alpha)$ quantile of the standard normal distribution, and we refer to the quantity $\mu_B + Z_{1-\alpha}\sigma_B$ as the $VaR_{\alpha.100\%}$ estimate with respect to the bond.
From Equation (12), therefore, $VaR_{\alpha.100\%}$ is given by

$$VaR_{\alpha.100\%} = \left[\frac{-D^*.B(y)}{10{,}000}\right] \mu_\epsilon + Z_{1-\alpha}\left[\frac{D^*.B(y)}{10{,}000}\right] \sigma_\epsilon \tag{16}$$

Equation (16) gives us the daily Value at Risk at $\alpha.100\%$ confidence level. To obtain the corresponding Value at Risk for monthly, quarterly, semi-annual, and annual intervals, we use a property of the normal distribution, which states that if ϵ_i are independent and identically normally distributed random variables where $\epsilon_i \sim N(\mu, \sigma^2)$ *for* $i = 1, 2, \cdots, T$ then $\sum_{i=1}^{T} \epsilon_i \sim N(\mu, \sigma^2 T)$. We thereby scale the daily Value at Risk by $\sqrt{T}$ where T is now the number of trading days in the interval, we assume that there are, on average, 21 trading days in a month.

Estimating VaR for a portfolio of bonds

Now, assume we have a portfolio of n bonds $B_1, B_2, \cdots, B_n$ where each bond is a function of its yield y_i and matures at the time T_i. That is,

$B_i \equiv B_i(y_i; T_i)\ y_i \geq 0, T_i > 0$ for i = 1, 2, $\cdots, n$

Furthermore, assume each bond B_i pays the annual coupon C_i and at maturity pays the principal P_i. Then, from (1), the price of each bond B_i for $i = 1,2, \cdots, n$ can be calculated as

$$B_i(y_i; T_i) = \sum_{t=1}^{T_i} \frac{C_i}{(1+y)^t} + \frac{P_i}{(1+y)^{T_i}} \tag{17}$$

We further assume that k_i units of each bond B_i are held in the portfolio such that the value of the portfolio V is given by:

$$V = k_1 B_1(y_1) + k_2 B_2\,(y_2) + \cdots + k_n B_n\,(y_n) \tag{18}$$

where $V: \mathbb{R}^n \rightarrow \mathbb{R}$ is a multivariate function that takes the n-tuple $(y_1, y_2, \cdots, y_n)$ as input and returns the scalar value of the portfolio. We define

$$w_i = \frac{k_i B_i(y_i)}{V} \tag{19}$$

for $i = 1, 2, \cdots, n$ where each w_i represents the weight of the holdings of the bond B_i in the portfolio V and the matrix $\boldsymbol{W}$ is given by the diagonal matrix of the w_i:

$$\boldsymbol{W} = \begin{bmatrix} w_1 & & \\ & \ddots & \\ & & w_n \end{bmatrix} \tag{20}$$

Now, the first-order Taylor series expansion of $V(y_1, y_2, \cdots, y_n)$ yields:

$$V(y_1 + \Delta y_1, y_2 + \Delta y_2, \cdots, y_n + \Delta y_n) = V(y_1, y_2, \cdots, y_n) + \sum_{i=1}^{n} \frac{\partial V}{\partial y_i} \Delta y_i + \cdots \tag{21}$$

Where we ignore higher-order terms in $\Delta y_i^k, k > 1$, $\Delta y_i y_j$, and beyond. A rearrangement of Equation (21) gives us the first-order approximation of the change in V, denoted ΔV, that results from a change in yields $y_1, y_2, \cdots, y_n$ by the small amounts $\Delta y_1, \Delta y_2, \cdots, \Delta y_n$

$$\Delta V \approx \sum_{i=1}^{n} \frac{\partial V}{\partial y_i} \Delta y_i \tag{22}$$

From Equations (18), (6), and (19):

$$\frac{\partial V}{\partial y_i} = k_i B'(y_i) = -k_i D_i^* B(y_i) = -w_i D_i^* V \tag{23}$$

where D_i^* is the modified duration of the ith bond. So, again, if the changes in yield Δy_i are all measured in basis points, as opposed to decimals, ΔV will be given by:

$$\Delta V \approx \frac{V}{10{,}000} \sum_{i=1}^{n} -w_i D_i^* \Delta y_i \tag{24}$$

Like the previous section, we assume that actual changes in the column vector of bond yields.

$$\boldsymbol{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \tag{25}$$

are given by

$$\boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix} \tag{26}$$

which are characterised by a multivariate normal distribution of the mean $\boldsymbol{\mu}_{\epsilon}$ with a variance-covariance matrix $\boldsymbol{\Sigma}$

$$\boldsymbol{\mu}_{\epsilon} = \begin{bmatrix} \mu_{\epsilon_1} \\ \vdots \\ \mu_{\epsilon_n} \end{bmatrix} \tag{27}$$

and

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22}^2 & & \vdots \\ \vdots & \vdots & \ddots & \\ \sigma_{n1} & \cdots & & \sigma_{nn}^2 \end{bmatrix} \tag{28}$$

where σ_{ii}^2 represents the variance of the daily yield changes ϵ_i and σ_{ij} represents the covariance between daily yield changes ϵ_i and ϵ_j. Using equation (24) with ϵ_i substituted for Δy_i , we can now derive the expected value μ_V, variance σ_V^2, and standard deviations σ_V of daily portfolio changes as follows:

$$\mu_V = E[\Delta V] = \frac{V}{10{,}000} \sum_{i=1}^{n} -w_i D_i^* \mu_{\epsilon_i} \tag{29}$$

$$\sigma_V^2 = Var[\Delta V] = \left[\frac{V}{10{,}000}\right]^2 \left(\boldsymbol{D}^{*T} \boldsymbol{W}\right) \boldsymbol{\Sigma} \left(\boldsymbol{W}^T \boldsymbol{D}^*\right) \tag{30}$$

where $\boldsymbol{D}^*$ is the column vector of modified durations, D_i^*, of each bond. We can further deduce that, due to the properties of the normal distribution:

$$\Delta V \sim N(\mu_V, \sigma_V^2) \tag{31}$$

which allows us to express the daily Value at Risk for the change in portfolio value, ΔV, at $\alpha.100\%$ confidence, where $0 < \alpha < 1$, as

$$VaR_{\alpha.100\%} = \frac{V}{10{,}000} \left[-\left(\boldsymbol{D}^{*T} \boldsymbol{W} \boldsymbol{\mu}_{\epsilon}\right) + Z_{1-\alpha} \sqrt{\left(\boldsymbol{D}^{*T} \boldsymbol{W}\right) \boldsymbol{\Sigma} \left(\boldsymbol{W}^T \boldsymbol{D}^*\right)} \right] \tag{32}$$

Estimating CVaR for a portfolio of bonds

Value-at-risk models suffer from the inadequacy that, while they quantify a loss threshold below which losses should be confined with specific probability, they do not inform us of the expected value of losses should this threshold be breached (Rockafellar & Uryasev, 2000; Rockafellar & Uryasev, 2002). If a tail event occurs, we can lose more than the threshold itself; however, VaR does not provide guidance on the potential extent of this loss. Conditional Value at Risk (CVaR), which measures the average loss conditional on the loss threshold being breached, has been proposed as a solution to the VaR insufficiency. CVaR measures the magnitude of potential losses when the VaR loss threshold is breached (Rockafellar & Uryasev, 2000; Rockafellar & Uryasev, 2002).

We are interested in calculating the Conditional Value-at-Risk for the daily change in the value of our portfolio of bonds, that is $\Delta V \sim N(\mu_V, \sigma_V^2)$. We express the Conditional Value-at-Risk of the daily change in our portfolio's value, at the $\alpha.100\%$ confidence level, as:

$$CVaR_{\alpha.100\%} = E[\Delta V | \Delta V \geq VaR_{\alpha.100\%}] \tag{33}$$

The general closed-form solution for Conditional Value at Risk at the $\alpha.100\%$ confidence level under Gaussian assumptions is derived in (Khokhlov, 2016) given by:

$$CVaR_{\alpha.100\%} = \mu_V - \frac{e^{\frac{-Z_{(1-\alpha)}^2}{2}}}{\alpha\sqrt{2\pi}} \sigma_V \tag{34}$$

where $0 < \alpha < 1$ *and* $Z_{1-\alpha}$ is the $(1-\alpha)$ quantile of the standard normal distribution.

Data and Calculations

We used daily market price data from 28 July 2015 to 31 August 2021 for all of seven US$-denominated Jamaican sovereign bonds that were outstanding during this period. This represents the most extended period for which daily data are available for all seven bonds, since two of the bonds were issued at the beginning of this period, i.e., on 28 July 2015. The seven bonds had/have maturity dates of: 15 January 2022, 17 October 2025, 28 April 2028, 28 February 2036, 15 March 2039, and 28 July 2045. For each of the bonds, over the six years for which we gathered price data, we calculated daily bond yields, the daily changes in bond yields, the standard deviation of these daily changes, as well as the modified duration of each bond at September 2021, December 2021, and March 2022. We also calculated the variance-covariance matrix relating to the seven daily yield change data series.

From bank filings, we then calculated the amounts in which these sovereign dollar bonds were held, in aggregate, by the banking system as at September 2021, December 2021, and March 2022, as a proportion of the banking system's holdings of these bonds. This provided the entries for our diagonal matrix **W**, in equation (20), for each of these dates. One of the assumptions underlying the VaR methodology is that holdings remain constant throughout the forecast period. As would be expected, banks sometimes buy and sell these bonds in response to liquidity and other considerations. Therefore, a particular institution's holdings of these bonds will change over time. However, outside of a bond maturity, removing a bond entirely from the system, the deposit-taking financial system's aggregate holdings of US dollar-denominated sovereign Jamaican dollar bonds did not change significantly over the period.

We then employed Equation (32) to compute the daily VaR and the monthly VaR (by scaling the daily VaR as appropriate) at the 95% and 99% confidence levels, respectively, as of September 2021, December 2021, and March 2022. Using equation (34), we calculated the daily and monthly Conditional Value at Risk at the respective 95% and 99% confidence levels for September 2021, December 2021, and March 2022. All these VaR metrics were calculated using bond price data through August 31, 2021. This allows us to ascertain the risk of loss that could have been quantified in advance of the mark-to-market losses that eventually ensued.

The final element of our framework involved the generation of daily portfolio values. We have monthly changes in the value of the banking systems' portfolio of US dollar-denominated sovereign bonds as reported by the banks and aggregated by the central bank. However, this limits us to just 45 monthly observations in the out-of-sample period from October 2021 to May 2025. While banks do not report daily portfolio values, we can construct a close approximation of these values as we have the weights in which the bonds were held on three dates, we know the daily prices of the bonds, and we know the size of the overall portfolio at the beginning of the out-of-sample period. Therefore, to complement our analysis and mitigate concerns about small-sample bias, we construct daily portfolio values by assuming that the March 2022 weights in Table 2 hold through to the end of the period and use the historical bond price data to simulate the daily value of the financial system's portfolio of foreign currency denominated Jamaican sovereign bonds.

Backtesting

Backtesting is an essential step in validating the accuracy and reliability of VaR models. The three standard tests employed in the literature, and which are briefly reviewed below, are the Kupiec Test, Christoffersen's Markov Test, and Christoffersen's Conditional Convergence Test. The Kupiec Test, also called the Proportion of Failures Test or the Unconditional Coverage Test, is one of the most frequently used VaR backtesting techniques. It evaluates whether the observed frequency of VaR breaches is consistent with the model's expected frequency and uses a likelihood ratio to do so (Kupiec, 1995).

The Kupiec Test statistic is given by:

$$LR_{uc} = -2\ln\left[\frac{(1-p)^{N-x}p^{x}}{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}}\right] \tag{35}$$

where N is the number of observations, x is the number of exceptions where the loss exceeds the VaR estimate, and p is the VaR confidence level (e.g., 0.95). The test follows the $\chi 2(1)$ distribution under the null hypothesis that the observed exceptions are consistent with the model.

The Christoffersen's Markov Test examines whether VaR exceptions are independently distributed using a Markov framework. The test checks whether analysing sequences of exception clusters and evaluates whether an exception occurs in the current period, given what happened last period (Christoffersen, 1998). The Christoffersen's Markov test defines the following:

$$\pi_{01} = \frac{n_{01}}{n_{00}+n_{01}}, \pi_{11} = \frac{n_{11}}{n_{10}+n_{11}}, \pi = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}} \tag{36}$$

where 1) n_{00} is the number of times that a month, where the observed mark-to-market loss is less than the VaR threshold (i.e., no VaR exception), is followed by a similar month 2) n_{01} is the number of times that a month without a VaR exception is followed by a month with a VaR exception, 3) n_{10} is the number of times that a month with a VaR exception is followed by a month without a VaR exception, and 4) n_{11}. This refers to the number of consecutive months with a VaR exception.

Then the Likelihood under Markov is computed as

$$L_1 = (1-\pi_{01})^{n_{00}} \left(\pi_{01}^{n_{01}}\right)(1-\pi_{11})^{n_{10}} \left(\pi_{11}^{n_{11}}\right) \tag{37}$$

The Likelihood under independence is computed as:

$$L_0 = (1-\pi)^{(n_{00}+n_{10})}\left(\pi^{(n_{01}+n_{11})}\right) \tag{38}$$

The Christoffersen's Markov Test combines these likelihoods to compute:

$$LR_{ind} = -2\ln\left(\frac{L_0}{L_1}\right) \tag{39}$$

which follows the $\chi^2(1)$ distribution under the null hypothesis that the VaR exceptions are independent over time.

The Christoffersen's Conditional Convergence Test is a joint test, both that the observed VaR exceptions are consistent with model expectations and that VaR exceptions are independent (Christofferson, 1998). It combines the previous test statistics LR_{uc} and LR_{ind} as follows:

$$LR_{cc} = LR_{uc} + LR_{ind} \tag{40}$$

where $LR_{cc} \sim\chi^2(2)$ under the null hypothesis that the observed VaR exceptions are both model consistent and independent.

Results and Discussion

The primary objective of this paper is to use historical price data prior to September 2021 to assess the efficacy of multivariate Gaussian VaR and CVaR models in estimating the risk of loss due of the severe monetary tightening that followed in 2022/23. In this regard, this objective differs from that of other papers, such as Omari (2017), Swami (2016), Abad et al. (2013), Rossignolo, Duygun, & Shaban (2012), and Vlaar (2000), where the relative efficacy of competing VaR techniques is compared. It also differs from papers such as those by Obadović et al. (2016), which assess the accuracy of a particular method. However, the relative performance of a variety of VaR models was applied to emerging financial markets, and their performance was evaluated over the period of the global financial crisis (Miletic & Miletic, 2015; Živković & Aktan, 2009). The similarity in intent of these papers with ours lies in the assessment of the efficacy of a VaR methodology during a period of market distress. We have been motivated by the Jamaican experience and seek to answer the specific question of whether the heavy system-wide mark-to-market losses could have been anticipated using the Gaussian VaR/CVaR methodology, with the system-wide data available up to the end of August 2021.

The descriptive statistics of changes in daily bond yields, over the period 28 July 2015 to 31 August 2021, are shown in Table 1, and the corresponding frequency distribution is shown in

Figure 4. Of the 1,590 values of daily yield changes for each bond, 98% of these daily changes, i.e., everything between the 1st and 99th percentiles, lie well within -20 and 20 basis points. However, the daily yield changes for each bond are characterised by a few extreme movements, tens of standard deviations away from the mean, as indicated by the minimum and maximum daily yield changes for each bond. The extreme kurtosis and excess skew are clear signs of the non-normality of these daily bond yield changes. In Lau (2012), descriptive statistics are provided on sovereign bonds issued by 11 different European governments over the period 1999 - 2012. All these bond return series exhibit extreme kurtosis. Greek and Portuguese bonds exhibit kurtosis levels similar to those of Jamaican bonds. In addition, Omran & Semnkova (2019) examine returns on Russian government and corporate bond indices, finding excess kurtosis like the levels reported here, with conclusions of non-normality.

Table 1. Descriptive statistics of daily bond yield change by bond maturity (basis points)

Maturity	Jan'22	Jul '25	Oct '25	Apr '28	Feb '36	Mar'39	Jul '45
1st percentile	−7.87	−12.24	−17.63	−14.41	−14.19	−12.11	−12.28
5th percentile	−0.51	−5.67	−6.43	−7.08	−5.24	−5.73	−5.50
95th percentile	0.00	4.36	5.24	6.12	4.37	5.42	4.87
99th percentile	10.25	11.34	16.99	12.45	10.59	11.92	10.64
Minimum	−43.16	−34.06	−59.94	−108.11	−273.15	−36.59	−35.29
Maximum	24.02	86.57	296.37	98.93	508.40	88.92	76.81
Mean	−0.08	−0.15	−0.16	−0.18	−0.14	−0.14	−0.19
Std. Deviation	3.04	5.02	9.12	6.93	18.34	5.65	5.12
Skew	−3.51	6.24	21.42	1.14	11.30	5.64	5.56
Kurtosis	69.95	97.30	705.43	91.63	450.45	84.93	81.9

This aligns with the findings of Gabriel (2014) and Gabriel & Lau (2012), who found that European bond returns also exhibit excess skewness and kurtosis that are incompatible with the normal distribution. In (Bauer & Chernov, 2024), non-normality and skewness in US Treasury bond yields are well documented and explained in terms of risk premia. Much earlier, it was found that the distribution of daily changes in short-term interest rates in the United Kingdom also exhibited non-normal characteristics with high peaks and fat tails (Robinson & Taylor, 1993). Regarding Jamaican asset prices, White (2009) found that the distributions of the asset classes held by banks were non-normal.

Table 2. The proportion of US$-denominated sovereign Jamaican bonds held by the Jamaican deposit-taking institution

Bond	Sep-21	Dec-21	Mar-22
15-Jan-22	5.3%	5.5%	0.0%
9-Jul-25	13.1%	11.0%	11.7%
17-Oct-25	0.0%	1.0%	0.0%
28-Apr-28	30.8%	29.6%	31.2%
28-Feb-36	1.0%	1.6%	1.8%
15-Mar-39	18.8%	21.0%	22.2%
28-Jul-45	31.2%	30.3%	33.1%
Total	100.0%	100.0%	100.0%

Despite these shortcomings, the Gaussian assumption is attractive in its simplicity. Its invariance property makes it useful as a descriptor of risk factor behaviour when constructing Value-at-Risk models, allowing for analytic solutions for any holding period and parameters that can be easily estimated (Jorion, 1996; Vlaar, 2000). Furthermore, these classes of models can serve as a benchmark for the application of other Value-at-Risk techniques to understudied markets such as Jamaica's. Furthermore, Andersson (2021) shows that although individual bond returns may be non-Gaussian, when bonds are aggregated into bond portfolios, the normal distribution is adequate for modelling of portfolio returns for risk management purposes. So, the normal distribution continues to be used to model daily changes in bond yields in the context of building Value-at-Risk models (Pratiwi, 2024; Obadović et al., 2016).

The proportion in which the various bonds were held in Jamaica's banking system on the respective reporting dates is shown in Table 2. The composition of the banking system's aggregate bond portfolio did not change materially across these dates. The modest observed changes appeared to be related to the maturation of the Jan 2022 bond by March 2022.

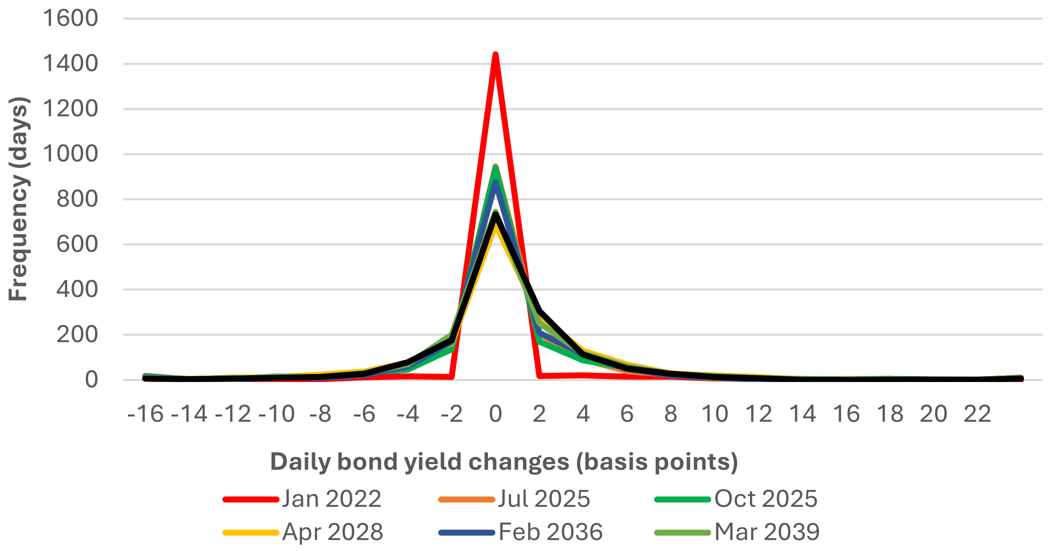


Figure 4. Frequency distribution of daily bond yield changes by bond

The system-wide VaR results at these reporting dates are shown in Table 3. In September 2021, with respect to the banking system's foreign currency-denominated Jamaican sovereign bond portfolio size of just under US$1 billion, the daily VaR was US$5.3 million, and the monthly VaR was US$24.4 million, both at the 95% confidence level. The corresponding VaRs at the 99% confidence level were US$7.5 million and US$34.4 million.

Table 3. Value at Risk (VaR) for the Jamaican banking system's sovereign bond portfolio (US$ '000)

Conf.	September 2021		December 2021		March 2022	
Level	Daily	Monthly	Daily	Monthly	Daily	Monthly
95%	(5,325)	(24,403)	(5,485)	(25,135)	(5,240)	(24,015)
99%	(7,511)	(34,418)	(7,735)	(35,447)	(7,391)	(33,868)

The system-wide CVaR results at the three reporting dates of September 2021, December 2021, and March 2022 are shown in Table 4. In September 2021, the banking system's foreign currency-denominated Jamaican sovereign bond portfolio was characterised by a CVaR of US$6.6 million and a monthly CVaR of US$30.2 million, both at the 95% confidence level. The corresponding CVaRs at the 99% confidence level were US$7.5 million and US$34.4 million.

Table 4. Conditional Value at Risk (CVaR) for the Jamaican banking system's sovereign bond portfolio (US$ '000)

Conf.	September 2021		December 2021		March 2022	
Level	Daily	Monthly	Daily	Monthly	Daily	Monthly
95%	(6,586)	(30,180)	(6,781)	(31,076)	(6,479)	(24,015)
99%	(7,511)	(34,418)	(7,735)	(35,447)	(7,391)	(33,868)

Figure 5 shows the observed monthly mark-to-market losses of the banking system from August 2021 to May 2025, along with a VaR estimate at the 95% confidence level, calibrated using data up to August 2021. This yields a Kupiec test statistic of $LR_{uc} = 1.176$ which supports the null hypothesis that the model is consistent with the observed outcomes. More generally, the VaR model passes all the backtesting procedures for consistency and independence, as shown in Table 5.

This is similar to the results in (Obadovic et al., 2016), where the parametric multivariate Gaussian VaR model applied to a Serbian government bond portfolio is shown to be effective at the 95% level using the Kupiec test. However, this contrasts with results in (Campbell & Smith, 2022), where VaR estimates produced by Australian banks are rejected by the standard backtesting procedures used here. Similarly, Omari (2017) finds that Gaussian VaR significantly underestimates risks on the Indian foreign exchange market. Also, in (Žiković & Aktan, 2009), all VaR models examined fail both the Kupiec and Independence tests when applied to Turkish and Croatian equity returns during the period of the Global Financial Crisis.

Table 5. Monthly VaR model backtesting results (95% confidence level)

Test	Test Statistic	Degrees of Freedom	Critical Value (5%)	p-value	Reject Null Hypothesis?
Unconditional Coverage	1.176	1	3.84	0.278	No
Independence	0.782	1	3.84	0.377	No
Conditional Coverage	1.957	2	5.99	0.376	No

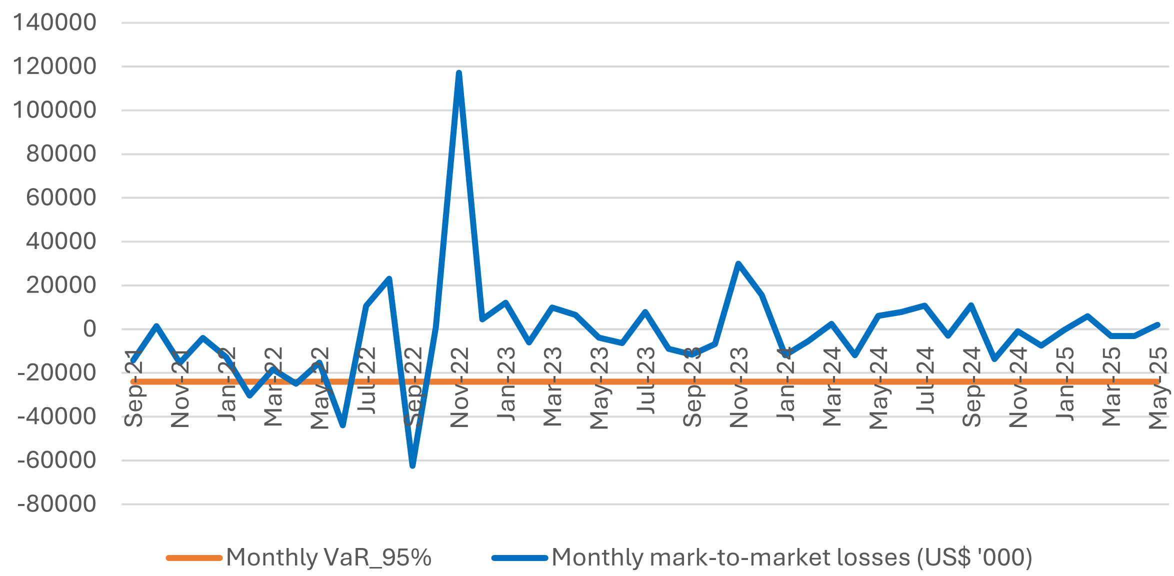


Figure 5. Monthly mark-to-market losses compared with Monthly $VaR_{95\%}$

The drawback of the above backtesting analysis is that it is applied to a financial dataset of only 45 monthly values covering a period of just under 4 years. By contrast, in (Obadovic et al., 2016), backtesting is applied to a bond portfolio with 1,262 daily values over five years, as well as to annual periods with approximately 250 daily values. To mitigate concerns of small-sample bias, as outlined in the Data and Calculations sub-section of this paper, we generate daily values of the aggregate banking system's foreign currency-denominated Jamaican sovereign bond portfolio over the period September 2021 to June 2025. This provides us with 1,000 daily portfolio values from which we calculate daily changes in the value of the portfolio.

Table 6 presents descriptive statistics on daily changes in portfolio value. Furthermore, Table 7 provides the frequency distribution of the daily changes in portfolio value. The distribution shows some asymmetry and is further characterised by fat tails with a notable concentration of daily portfolio changes near the centre. These observations are also evidence of non-normality. However, what both Table 6 and Table 7 show, interestingly, is that, while excess kurtosis rules out the normal distribution as a flawless theoretical descriptor, the empirical percentiles of the distribution of daily portfolio changes nevertheless mimic those of a standard normal distribution. Specifically, the 1st and 99th percentiles are approximately three standard deviations from the mean, while the 5th and 95th percentiles are approximately 1.6 standard deviations from the mean. Similarly, in (Li et al., 2025), descriptive statistics, inclusive of percentiles, are aggregated for thousands of emerging market bond returns, and it is shown that the 1st and 99th percentiles of these bond return distributions lie approximately three standard deviations from the mean bond return.

Table 6. Descriptive statistics of the daily portfolio changes

Statistic	US$ ('000)
Minimum	(23,268)
Maximum	16,174
Mean	(153)
Standard Deviation	3,336
1st percentile	(10,490)
5th percentile	(5,319)
95th percentile	4,652
99th percentile	9,534
Skew	-0.56
Kurtosis	6.43

Table 7. Frequency distribution of daily portfolio changes with corresponding Z Scores

Value Range (US$ '000)	Frequency	Cumulative Frequency	Midpoint	Z-Score
(10,000) and below	12	12	−10,000	−2.95
(9,000) to (10,000)	4	16	−9,500	−2.80
(8,000) to (9,000)	3	19	−8,500	−2.50
(7,000) to (8,000)	10	29	−7,500	−2.20
(6,000) to (7,000)	9	38	−6,500	−1.91
(5,000) to (6,000)	18	56	−5,500	−1.61
(4,000) to (5,000)	31	87	−4,500	−1.32
(3,000) to (4,000)	44	131	−3,500	−1.02
(2,000) to (3,000)	71	202	−2,500	−0.72
(1,000) to (2,000)	98	300	−1,500	−0.42
less than zero to (1,000)	263	563	0	0.05
0 to 1,000	140	703	500	0.20
1,000 to 2,000	112	815	1,500	0.50
2,000 to 3,000	76	891	2,500	0.80
3,000 to 4,000	41	932	3,500	1.10
4,000 to 5,000	24	956	4,500	1.39
5,000 to 6,000	15	971	5,500	1.69
6,000 to 7,000	9	980	6,500	1.98
7,000 to 8,000	5	985	7,500	2.28
8,000 to 9,000	3	988	8,500	2.58
9,000 to 10,000	3	991	9,500	2.87
10,000 and above	9	1,000	—	

Figure 6 shows the daily changes in the value of the aggregate banking system's Jamaican foreign currency-denominated sovereign bond portfolio over the period September 2021 to June 2025. It also shows the daily $VaR_{95\%}$ as calculated in Table 3. During the 1,000 days in this out-of-sample period, the $VaR_{95\%}$ threshold is breached 53 times. We apply the Kupiec Unconditional Coverage Test, yielding a test statistic of 0.18, which indicates that this exception rate is consistent with model expectations at the 95% confidence level.

Of these exceptions, there are six occurrences of breaches of the $VaR_{95\%}$ threshold on two consecutive days.[2] We apply Markov's Independence Test, which yields a test statistic of 3.15, indicating that these exceptions are not statistically clustered and, on the contrary, appear independent over time. Table 8 shows these back-testing results. These results mirror some of the findings of Watson & Rampersad (2011), who found that Kupiec Tests revealed that parametric VaR was most effective in assessing risk in the Barbadian, Eastern Caribbean, Jamaican, and Trinidadian equity markets. The results here also compare with (Fruzzetti et al., 2023), where Gaussian VaR passes backtesting procedures for consistency in an application of Gaussian VaR to Italy's foreign exchange reserves.

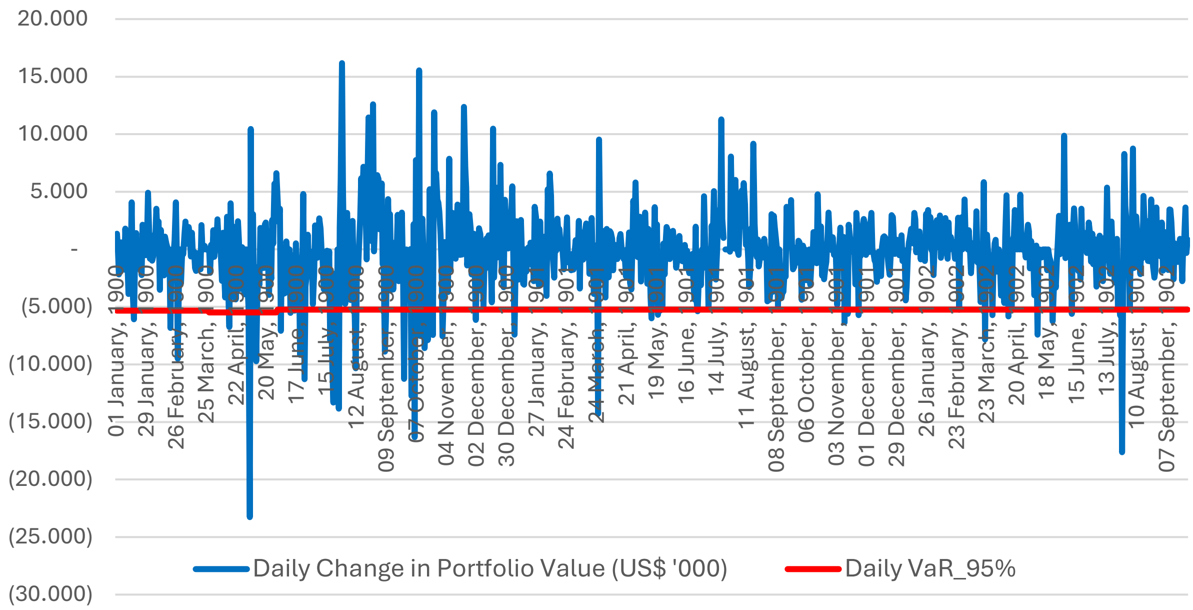


Figure 6. Daily portfolio changes compared with daily $VaR_{95\%}$

Table 8. Daily VaR model backtesting results (95% confidence level)

Test	Test Statistic	Degrees of Freedom	Critical Value (5%)	p-value	Reject Null Hypothesis?
Unconditional Coverage	0.180	1	3.84	0.6717	No
Independence	3.151	1	3.84	0.0759	No
Conditional Coverage	3.331	2	5.99	0.1892	No

Finally, in the case of comparing the banking system's monthly mark-to-market gains/losses on its foreign currency-denominated Jamaican sovereign bond portfolio, we observed that these losses exceeded the monthly $VaR_{95\%}$ threshold 4 times in this 45-month window. The average of these four losses that breached the monthly $VaR_{95\%}$ threshold is US$40.4 million, or approximately 4% of portfolio value, compared to a monthly CVaR estimate of US$30.2 million, or approximately 3% of portfolio value, at the 95% confidence level. Moreover, comparing the daily fluctuations in the value of the banking system's foreign-currency-denominated Jamaican sovereign bond portfolio, we observed that daily losses exceeded the $VaR_{95\%}$ threshold 53 times over the 1,000-day window. The average of these 53 losses that breached the daily $VaR_{95\%}$ threshold was US$8.5 million, or approximately 0.85% of portfolio value, compared to the daily CVaR estimate of US$6.6 million, or approximately 0.66% of portfolio value, at the 95% confidence level. Therefore, CVaR better captures extreme losses than VaR, both monthly and daily. CVaR also better describes extreme losses than VaR as conditional variance models of asset returns were used to generate VaR and CVaR estimates for the S&P 500, DAX, and Hang Seng stock indices (Du and Escanciano, 2016).

[2] These are difficult to see in Figure 6 as breaches, say seven days apart, appear close together in the figure.

Conclusion

This paper uses parametric VaR and CVaR models to measure the market risk from Jamaican banks' sovereign bond exposures before the surge in global interest rate volatility in 2022. The results, including backtesting, show that these standard risk measures effectively captured the Jamaican banking system's market risk exposure to Jamaican foreign currency-denominated sovereign bonds. Specifically, the calibrated parametric VaR and CVaR, based on data prior to the global interest rate increases, estimated much of the risk of mark-to-market losses that later impacted the Jamaican banking system's holdings of foreign currency-denominated Jamaican sovereign bonds. These findings also offer a helpful foundation for regulators, including those in Jamaica, to gradually adopt more current Basel frameworks and assist financial institutions in using these models to monitor market risk and determine their capital needs in response to these risks.

In the publication, the Basel Committee provides and describes two frameworks (Standardised Approach (SA) and Internal Models Approach (IMA)) for evaluating market risk and computing banks' capital requirements (Basel Committee on Banking Supervision, 2019). The capital requirement under Basel II's SA is the interest rate risk in the trading book (IRRTB), which is the sum of issuer-related risk (specific risk) and general market risk, applicable to all qualifying domestic and foreign currency-denominated positions. Under this approach, portfolio positions are grouped into maturity buckets involving a combination of specific risk weights depending on issuer quality, and general risk weights for yield curve risk are applied.

However, many central banks, including the Bank of Jamaica, still use this somewhat outdated Standardised Measurement Method (SMM) to determine capital requirements for banks' market risk. In this method, banks apply the regulator-defined risk weights to calculate their market risk-based capital needs. Although it is a more straightforward approach, it is less sensitive to risk when setting capital charges. The findings suggest that, on a systemic level, standard VaR and CVaR techniques can reasonably estimate the risk of Jamaican sovereign bonds. Therefore, these results offer a valuable example of how Jamaican regulators could enhance capital provisioning for the financial system.

Author contributions

Kishan Clarke: Methodology, Software, Validation, Formal analysis, Writing-original draft, Writing-review & editing.
Robert Stennett: Conceptualisation, Methodology, Validation, Writing-review & editing.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

Acknowledgments

Kishan Clarke wishes to thank Meghan Clarke (no relation) at Phillips Academy for helpful comments on earlier stages of this work.

References

Abad, P., Muela, S., & López, C. (2014). A comprehensive review of value at risk methodologies. *The Spanish Review of Financial Economics, 12*, 15–32. https://doi.org/10.1016/j.srfe.2013.06.001

Acerbi, C., & Tasche, D. (2002). Expected shortfall: A natural coherent alternative to value at risk. *Economic Notes, 31*(2), 379–388. https://doi.org/10.1111/1468-0300.00091

Andersson, S. (2021). *Bond portfolio optimization with term structure models* (Master's thesis). Uppsala University, School of Engineering Sciences. https://www.diva-portal.org

Bank for International Settlements. (2016). *Minimum capital requirements for market risk*. https://www.bis.org/bcbs/publ/d352.htm

Bank of Jamaica. (2022). *Financial stability report 2021*. https://www.boj.org.jm/uploads/pdf/financial_stability/financial_stability_report/financial_stability_report_2021.pdf

Bank of Jamaica. (2023). *Financial stability report 2022*. https://boj.org.jm/wp-content/uploads/2023/03/FinStab-Annual-Report-2022.pdf

Bank of Jamaica. (2025). *Financial stability report 2024*. https://boj.org.jm/wp-content/uploads/2025/03/Financial-Stability-Report-2024.pdf

Barnichon, R., & Shapiro, A. H. (2022). How much did supply constraints boost U.S. inflation? *Economic Letter*. Federal Reserve Bank of San Francisco, Economic Research Department. https://www.frbsf.org/wp-content/uploads/el2022-15.pdf

Barone-Adesi, G., Giannopoulos, K., & Vosper, L. (1999). VaR without correlations for nonlinear portfolios. *Journal of Futures Markets, 19*(5), 583–602. https://doi.org/10.1002/(SICI)1096-9934(199908)

Basel Committee on Banking Supervision. (1996). *Amendment to the capital accord to incorporate market risks*. Bank for International Settlements. https://www.bis.org/publ/bcbs24.htm

Basel Committee on Banking Supervision. (2004). *International convergence of capital measurement and capital standards: A revised framework*. Bank for International Settlements. https://www.bis.org/publ/bcbs107.htm

Basel Committee on Banking Supervision. (2019). *Minimum capital requirements for market risk*. Bank for International Settlements. https://www.bis.org/bcbs/publ/d457.htm

Bauer, M. D., & Chernov, M. (2024). Interest rate skewness and biased beliefs. *Journal of Finance, 79*(1), 173–217. https://doi.org/10.1111/jofi.13276

Board of Governors of the Federal Reserve System. (2021). *2021 stress test scenarios*. https://www.federalreserve.gov/publications/stress-test-scenarios-february-2021.htm

Board of Governors of the Federal Reserve System. (2025). *Financial stability report*. https://www.federalreserve.gov/publications/files/financial-stability-report-20250425.pdf

Bloomberg L.P. (2025). *Global and US inflation (WOININFL Index for global inflation, CPURNSA Index for US inflation)*. Retrieved September 15, 2025, from Bloomberg Terminal.

Bloomberg L.P. (2025). *US Treasury yields for 3-month, 6-month, 1-year, 2-year, and 3-year maturities (GB3 Govt, GB6 Govt, GB12 Govt, GT2 Govt, GT3 Govt)*. Retrieved July 29, 2025, from Bloomberg Terminal.

Campbell, A., & Smith, D. R. (2022). An empirical investigation of the quality of value-at-risk disclosure in Australia. *Accounting & Finance, 62*(1), 469–491. https://doi.org/10.1111/acfi.12795

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review, 39*(4), 841–862. https://doi.org/10.2307/2527341

Danielsson, J., Embrechts, P., Goodhart, C., Keating, C., Muennich, F., Renault, O., & Shin, H. S. (2001). *Value at risk: Dangerous for risk management?* Journal of Financial Econometrics, Special Report. London School of Economics.

Du, Z., & Escanciano, J. C. (2016). Backtesting expected shortfall: Accounting for tail risk. *Management Science, 63*. https://doi.org/10.1287/mnsc.2015.2342

Fruzzetti, M., Nasti, D., & Orlandi, M. (2023). The backtesting of value-at-risk and expected shortfall: Evidence from the Bank of Italy's foreign reserves portfolio. In *Evolving Practices in Public Investment Management (EPPIM) Conference Proceedings* (pp. 211–228).

Gabriel, C., & Lau, C. (2012). On the distribution of European government bond returns: Empirical evidence. Paper presented at EFMA Annual Meeting 2012. https://www.efmaefm.org/

Gabriel, C. L., & Lau, C. (2014). On the distribution of government bond returns: Evidence from the EMU. *Financial Markets and Portfolio Management, 28*, 181–203. https://doi.org/10.1007/s11408-014-0228-y

Henry, J., & Kok, C. (2013). *A macro stress testing framework for assessing systemic risks in the banking sector* (Occasional Paper No. 152). European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp152.pdf

Ihrig, J., & Waller, C. (2024). *The Federal Reserve's responses to the post-COVID period of high inflation.* FEDS Note, Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/

International Monetary Fund. (2021). *Global financial stability report: Pre-empting a legacy of vulnerabilities.* https://www.imf.org/en/Publications/GFSR

International Monetary Fund. (2024). *The US banking sector has been in turmoil since March 2023*. IMF Note. https://www.imf.org/

Jobst, A. A., & Ong, L. L. (2016). Assessing macro financial risks in the banking sector: The role of stress testing. *Journal of Financial Stability, 25*, 105–114.

Jorion, P. (1996). *Value at risk: The new benchmark for controlling derivatives risk.* McGraw-Hill.

JPMorgan Chase & Co. (2021). *Dodd-Frank Act stress test results and methodology disclosure.* https://www.jpmorganchase.com/

Justiniano, A., & Barlevy, G. (2023). How tight is U.S. monetary policy? *Chicago Fed Letter* (No. 476). https://www.chicagofed.org/

Khokhlov, V. (2016). Conditional value-at-risk for elliptical distributions. *European Journal of Economics and Management.* https://eujem.cz/wpcontent/uploads/2016/eujem_2016_2_6/12.pdf

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *Journal of Derivatives, 3*(2), 73–84. https://doi.org/10.3905/jod.1995.407942

Lau, C. (2012). *Non-normality in financial markets and the measurement of risk* (Doctoral dissertation). German National Library. https://d-nb.info/1078505004/

Li, D., Lu, L., Qi, Z., & Zhou, G. (2025). International corporate bond returns: Uncovering predictability using machine learning. *Journal of Financial Markets*, 101008. https://doi.org/10.1016/j.finmar.2025.101008

Miletic, M., & Miletic, S. (2015). Performance of value at risk models in the midst of the global financial crisis in selected CEE emerging capital markets. *Economic Research–Ekonomska Istraživanja, 28*, 132–166. https://doi.org/10.1080/1331677X.2015.1028243

Obadović, M., Petrović, E., Vunjak, N., & Ilić, M. (2016). Assessing the accuracy of delta-normal VaR evaluation for the Serbian government bond portfolio. *Economic Research–Ekonomska Istraživanja, 29*(1), 475–484. https://doi.org/10.1080/1331677X.2016.1174391

Omari, C. (2017). A comparative performance of conventional methods for estimating market risk using value at risk. *International Journal of Econometrics and Financial Management, 5*, 22–32. https://doi.org/10.12691/ijefm-5-2-1

Omran, S., & Semnkova, E. (2019). Bond market efficiency and volatility: Evidence from Russia. *Humanities and Social Sciences Reviews, 7*, 1389–1397. https://doi.org/10.18510/hssr.2019.74193

Peterson, D. (2021). Fed signals taper and hikes sooner — 5 takeaways and four more questions. *Global Economy Brief.* The Conference Board. https://www.conference-board.org/research/global-economy-briefs/FOMC-Sept-2021

Pratiwi, R. G. (2024). Analysis of value at risk measurement using the variance-covariance method in the securities portfolio. *Jurnal Indonesia Sosial Teknologi, 5*(1), 257–272.

Prokopowicz, D. (2022). The post-COVID rise in inflation: Coincidence or the result of misguided, excessively interventionist, and monetarist economic policies? *International Journal of New Economics and Social Sciences, 16*(2), 105–148. https://doi.org/10.5604/01.3001.0016.3409

Robinson, G., & Taylor, M. P. (1993). The statistical distribution of short-term LIBOR rates under two monetary regimes. *Working Paper.* Bank of England. https://www.bankofengland.co.uk/

Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *Journal of Risk, 2*(3), 21–41. https://doi.org/10.21314/JOR.2000.038

Rockafellar, R. T., & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking & Finance, 26*(7), 1443–1471. https://doi.org/10.1016/S0378-4266(02)00271-6

Rossignolo, A. F., Duygun Fethi, M., & Shaban, M. (2012). Value-at-Risk models and Basel capital charges: Evidence from Emerging and Frontier stock markets. Journal of Financial Stability, 8(4), 303–319. https://doi.org/10.1016/j.jfs.2011.11.003

Swami, O. (2016). Value-at-risk estimation of foreign exchange rate risk in India. *Asia-Pacific Journal of Management Research and Innovation, 12*, 1–10. https://doi.org/10.1177/2319510X16650057

Tracey, M. (2009). Principal component value at risk: An application to the measurement of the interest rate risk exposure of Jamaican banks to GOJ bonds. *Technical Report.* Bank of Jamaica, Financial Stability Department. https://www.boj.org.jm/uploads/pdf/

Vlaar, P. J. (2000). Value at risk models for Dutch bond portfolios. *Journal of Banking & Finance, 24*(7), 1131–1154. https://doi.org/10.1016/S0378-4266(99)00068-0

Watson, P. K., & Rampersad, R. (2011). The efficacy of value-at-risk models in Caribbean equity markets. *Technical Report.* CERT. https://www.cert-net.com/files/publications/conference/2011/6_1-Rampersad_Watson-p.pdf

White, O. B. (2009). Is the conventional value-at-risk (VaR) model an appropriate tool for estimating market risk? The case of an indicative Jamaican financial institution. *Journal of Business, Finance & Economics in Emerging Markets, 2*(4), 257–272.

Žiković, S., & Aktan, B. (2009). Global financial crisis and VaR performance in emerging markets: A case of EU candidate states, Turkey and Croatia. *Zbornik Radova Ekonomskog Fakulteta u Rijeci, 27*(1), 149–170. https://ssrn.com/abstract=2267751