Academic Article

Understanding Market Risk in Banking: Analytics, Measurement Tools, and Financial Reporting Disclosures

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Received: *December 14, 2025*
Revised: *January 9, 2026*
Accepted: *January 20, 2025*

ABSTRACT

Market risk measurement is a central component of financial risk management and a critical element of the disclosures provided by financial institutions. This paper examines the conceptual foundations, computational approaches, and practical applications of key market-risk assessment tools, including Value-at-Risk (VaR), Scenario Analysis, and Stress Testing. It outlines the assumptions, strengths, and limitations of the three primary VaR methodologies——Variance-Covariance, Historical, and Monte Carlo simulation——and discusses the implications of model risk, distributional assumptions, correlation instability, and regulatory requirements. The analysis further evaluates real-world disclosures from major financial institutions to illustrate the disclosure practice and interpretation of market-risk exposures. Integrating theoretical frameworks with practical exemplars, the paper provides readers with the analytical foundation needed to interpret market-risk disclosures critically, recognize the limitations of standard risk metrics, and assess the resilience of financial institutions under normal and stressed market conditions.

Keywords: Market Risk, Banking, Analytics, Market Risk Measurement Tools, Financial Reporting Disclosure

การทำความเข้าใจความเสี่ยงด้านตลาดในธุรกิจธนาคาร : การวิเคราะห์ เครื่องมือการวัด และการเปิดเผยข้อมูลในรายงานทางการเงิน

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วันที่ตอบรับตีพิมพ์บทความ : *20 มกราคม 2569*

บทคัดย่อ

การวัดความเสี่ยงด้านตลาดเป็นองค์ประกอบหลักของการบริหารความเสี่ยงทางการเงิน และเป็นส่วนสำคัญสำหรับการเปิดเผยข้อมูลของสถาบันการเงิน บทความนี้ได้พิจารณ์รากฐานเชิงแนวคิด แนวทางการคำนวณ และการประยุกต์ในทางปฏิบัติของเครื่องมือสำคัญในการประเมินความเสี่ยงด้านตลาด รวมถึง Value-at-Risk (VaR) การวิเคราะห์สถานการณ์จำลอง และการทดสอบภาวะวิกฤต บทความนี้นำเสนอสมมติฐาน จุดแข็ง และข้อจำกัด สำหรับทั้ง 3 วิธีหลักของ VaR ได้แก่ ระเบียบวิธีความแปรปรวน-ความแปรปรวนร่วม ระเบียบวิธีแบบดั้งเดิม (Historical) และระเบียบวิธีจำลองมอนติคาร์โล (Monte Carlo Simulation) รวมทั้งทั้งอภิปรายถึงนัยสำคัญของความเสี่ยงจากแบบจำลอง (Model Risk) สมมติฐานของการแจกแจง (Distributional Assumptions) ความไม่เสถียรของสหสัมพันธ์ (Correlation Instability) และข้อกำหนดด้านกฎระเบียบ นอกจากนี้ การวิเคราะห์ได้ประเมินการเปิดเผยข้อมูลจากสถาบันการเงินชั้นนำ เพื่อแสดงถึงแนวปฏิบัติในการเปิดเผยข้อมูลและการตีความสำหรับความเสี่ยงด้านตลาด โดยการบูรณาการกรอบแนวคิดเชิงทฤษฎีกับตัวอย่างในเชิงปฏิบัติ บทความนี้จึงให้ข้อมูลพื้นฐานการวิเคราะห์ที่จำเป็นแก่ผู้อ่าน เพื่อให้สามารถตีความการเปิดเผยความเสี่ยงด้านตลาดได้อย่างมีวิจารณญาณ ตระหนักถึงข้อจำกัดของมาตรวัดความเสี่ยงมาตรฐาน และประเมินความสามารถในการปรับตัวของสถาบันการเงินภายใต้สภาวะตลาดปกติและภาวะวิกฤต

คำสำคัญ: ความเสี่ยงด้านการตลาด ธุรกิจธนาคาร การวิเคราะห์ เครื่องมือการวัดความเสี่ยงด้านการตลาด การเปิดเผยข้อมูลในรายงานทางการเงิน

INTRODUCTION

Market risk has long been one of the most scrutinized as well as mandatory dimensions of financial stability for financial services industry. Shareholders, regulators, and executive management regularly ask fundamental questions; How much can the bank lose? How can the risk management unit justify its market risk metrics? These questions, whilst simple on the surface, reveal the challenge of quantifying the potential impact of fluctuating market conditions on large and diversified portfolios. As financial institutions continue to expand their product offerings and global reach, the need for robust, transparent, and interpretable risk measures has become indispensable.

Due to regulators and stakeholders' pressure, financial institutions globally report and disclosure their market risk measures as a part of financial reporting (Jorion, 2002). Prior research examines the market risk disclosure practices, antecedents, informativeness, and various factors, such as, governance, corporate performance (Khandelwal, Kumar, Verma, & Singh, 2019; Al-Hadi, Hasan, & Habib, 2016). Particularly, disclosures of Value-at-Risk, a market risk measure, are informative and predictive for the variability of trading revenues (Jorion, 2002). The level of market risk disclosure positively associates with bank market capitalization (Savvides & Savvidou, 2012). The textual content of the disclosure relates to higher liquidity levels as well as lower liquidity uncertainty (Kohlbeck & Luo, 2024). Even though market risk disclosure practices among banks are diverse across countries (Savvides & Savvidou, 2012), the disclosures are beneficial if financial statements users want to compare the risk profiles of banks' trading portfolios (Jorion, 2002).

Contemporary risk management relies on several quantitative tools to measure and interpret market risk. Among these, Value-at-Risk (VaR), Scenario Analysis, and Stress Testing have become industry standards. While risk practitioners regularly work with these tools, financial statement users—particularly investors, analysts, and corporate decision-makers—struggle to interpret these disclosures. Understanding VaR tables, sensitivity measures, and interest-rate risk profiles requires foundational knowledge of how market risk is modeled and the assumptions on which these models are built. Equally important, users must understand the limitations of these techniques to avoid misinterpreting a firm's risk exposure.

The aim of this paper is to equip readers with the conceptual and analytical tools needed to comprehend market-risk disclosures critically. This paper, thus, provides a comprehensive overview of market risk concepts, VaR methodologies, scenario analysis, stress testing, and key considerations when interpreting market-risk disclosures in financial statements. Differing market risk reporting models are observed among empirical research (Savvides & Savvidou, 2012; Scannella & Polizzi, 2018). It,

therefore, evaluates examples from major financial institutions—Deutsche Bank, Goldman Sachs, and JPMorgan Chase—to illustrate how firms communicate their market-risk profile to stakeholders.

Practically, understanding market risk disclosure would help users of financial reports make informed resource allocation decisions, resulting in reduced uncertainty (Linsmeier, Thornton, Venkatachalam, & Welker, 2002). Policy setters as well as regulators then can encourage banks to improve their levels and quality of market risk disclosure. For banks themselves, improving quality of market risk disclosure should help reduce expectation gap from investors and creditors.

This main ideas in this paper may provoke the future research avenue. Prior research in market risk disclosure suggests that market risk measures are vital for financial services industry as well as global economy stability, this line of research is still limited and requires more academic attention as well as empirical research to better the disclosure practice (Savvides & Savvidou, 2012; Khandelwal, Kumar, Verma, & Singh, 2019) especially during the dynamic geopolitical uncertainties. Investigating market risk disclosure practices and regulatory framework differing in emerging market countries, e.g., banks in ASEAN countries, is of interest and relevant in contributing to the growing body of research as well.

MARKET RISK CONCEPT AND MEASUREMENTS

What is Market Risk?

Market risk refers to the risk that changes in market conditions may adversely affect the value of assets or liabilities due to fluctuations in several market variables, such as interest rates, foreign exchange rates, equity prices, commodity prices, implied volatilities, or credit spreads (Federal Reserve, 2025; Jorion, 2002). These adverse changes can also negatively impact current and future earnings as well as capital.

What is Value-at-Risk (VaR)?

Value-at-Risk (VaR) is one of the most widely used statistical measures of market risk and standard market risk measure (Pérignon & Smith, 2010). VaR estimates the potential future loss in value of a risky asset or portfolio over a defined period and confidence interval (Jorion, 2007a, 2007b). Under typical assumptions—usually a normal distribution—a one-week, 99% VaR of $100 means there is a 99% probability the portfolio will not lose more than $100 during any given week under normal market conditions.

The first concept of VaR emerged from the mathematics developed and formalized in the context of portfolio theory and early risk-quantification work by Harry Markowitz (1952) and others, aimed at constructing optimal portfolios with a focus on market risk and the effects of co-movements among asset classes (Glyn, 2022; Markowitz, 1952). In 1980, the U.S. Securities and Exchange Commission (SEC) required financial services firms to estimate a one-month 95% VaR using historical data and to hold sufficient capital to cover potential future losses.

The modern evolution of VaR accelerated in 1994 when JPMorgan publicly released its RiskMetrics system—a groundbreaking dataset and methodology for estimating market-risk parameters such as variances and covariances. RiskMetrics catalyzed the widespread adoption of VaR by providing standardized inputs and computational tools. The application and disclosure of VaR methodology for calculating capital charges in respect of financial risk has been global standards to promote banking sector stability. Since then, VaR has become a central element of market-risk management not only in banks but also in hedge funds, insurance companies, and non-financial corporations seeking to quantify financial exposures.

VaR is mostly used by commercial and investment banks to measure potential future loss in value of trading portfolios from adverse market fluctuation over a specified period. Banks rely on VaR values to determine capital or cash reserves needed to cover the risk of potential future losses under typical market conditions. Regulators, rating agencies, and investors also use VaR as an indicator of a firm's market-risk exposure.

VaR Computation Methods

VaR computation depends heavily on assumptions regarding return distributions and the variances and covariances among assets. There are three primary methods for estimating VaR: the Variance-Covariance approach, the Historical approach, and the Monte Carlo Simulation approach. Each method has strengths and limitations.

(1) Variance-Covariance (Parametric) Approach

This approach generally assumes that the return distributions of asset classes are normally distributed, and that the variances and covariances of returns among asset classes are used to compute the VaR of a portfolio that contains various asset classes. This approach is the most common practice for computing VaR used by investment banks and hedge fund managers. The strength of this approach is the simplicity of the calculation, and the input data are easy to obtain (e.g., variances and covariances across asset classes can be easily sourced from RiskMetrics). However, the major weakness of this method lies in its reliance

on normality assumptions. Financial returns frequently display "fat tails," meaning extreme losses occur far more frequently than a normal distribution predicts. Institutions such as Long-Term Capital Management (LTCM) failed in part because their models dramatically underestimated tail risks. In addition, correlations—especially across asset classes—tend to shift significantly during crises, reducing the reliability of these estimates during turbulent markets.

(2) Historical Approach

This approach is the easiest VaR computation because it ranks all historical returns from lowest to highest and then chooses the worst return according to the percentile corresponding to the chosen confidence level. The core assumption is that the past will repeat itself in the future and that return distributions are not needed for computation. In theory, this approach is better than the parametric approach if the historical data are large enough to cover major crisis events, changes in economic cycles, and periods of regime shifts. However, a major criticism of this approach is whether the past will correctly determine the future, and whether the historical dataset includes unusually extreme events that could make VaR overly conservative.

(3) Monte-Carlo Simulation Approach

This approach is the most flexible and is much more complex than other approaches. The Monte Carlo simulation aims to generate as many outcomes as possible for each market risk factor and to specify correlations among these market risk factors based on predefined statistical models in order to estimate a distribution of potential portfolio returns and calculate VaR. The strength of the Monte Carlo simulation approach is the flexibility it provides for modeling non-normal distributions, fat tails, skewness, and interactions among multiple risk factors. In addition, the Monte Carlo simulation approach is suitable for a portfolio containing nonlinear payoffs, such as derivatives, as the portfolio return distribution usually has positive or negative skewness or high or low kurtosis (i.e., not normally distributed). The primary drawback is the computational intensity and the sensitivity to model assumptions. If the underlying model is flawed, the results—even with extensive simulation—will be inaccurate.

Comparisons of VaR Approaches

The three VaR approaches aforementioned differ in complexity, required assumptions, adaptability to nonlinear products, and precision under extreme conditions (Jorion, 2007a, 2007b). Table 1 presents the key comparisons and features of three approaches in terms of positions, distributions and implementation. Parametric VaR is simple to compute but performs poorly when return distributions deviate from normality. Historical VaR reflects actual market behavior but depends heavily on the representativeness of historical data. Monte Carlo simulation offers flexibility but introduces model-risk concerns.

Table 1 Features and Comparisons of VaR Approaches

Features	Variance-Covariance	Historical	Monte-Carlo Simulation
Positions			
Valuation	Linear	Full	Full
Distribution			
Shape	Normal	Actual	General
Time varying	Yes	Possible	Yes
Implied data	Possible	No	Possible
Extreme events	Low probability	Depends on historical data	Possible
Correlation implication	Yes	Yes	Yes
VaR precision	Reasonably high under model assumptions	Poor with short window	Good with many iterations
Implementation			
Ease of computation	Yes	Yes	No
Pricing accuracy	Depends on portfolio	Yes	Yes
Communicability	Easy	Easy	Difficult
VaR analysis	Easy	Difficult	Difficult
Major pitfalls	Nonlinearities, fat tails	Time variation in risk, unusual events	Model risk

Key Considerations When Using VaR

Importantly, the usefulness of VaR relies on recognizing its assumptions and limitations as follows:

(1) Backward-Looking Data

Most banks use historical market data to calibrate VaR models. The use of backward-looking data may not be a good indicator of potential future events, particularly extreme events. This limitation can cause VaR to be underestimated (as in the 2008 financial crisis) or to overestimate risk. In addition, the correlation between risk factors may not hold true during extreme market events.

(2) Normal Market Conditions

Based on historical market data, VaR is most effective in estimating risk exposures in markets that have no sudden fundamental changes or shifts in market conditions (i.e., normal market conditions). During stress periods, return distributions tend to be skewed and exhibit extreme fat tails, reducing the predictive value of VaR.

(3) Holding Period Limitations

Most banks normally calculate VaR using a 99% confidence level and a 1-day holding period (i.e., a one-day forward-looking loss projection). However, a 1-day holding period does not fully capture transactions that cannot be closed out or hedged within one day (intraday transactions). Regulators often require banks to calculate VaR with a 10-day holding period to incorporate liquidity considerations and to overcome intraday transactions and settlement-period issues.

(4) Model Heterogeneity

There is no uniform industry methodology for estimating VaR. Different assumptions concerning the number of risk factors, the duration of the time series used and daily changes in these risk factors, as well as different methodologies, could produce materially different results, complicating comparisons, and therefore requiring caution when comparing VaR measures among comparable institutions (Lehman Brothers, 2007).

(5) Regulatory Requirements

According to Basel III, financial firms under this regulation are required to determine a regulatory VaR model framework which assumes a 10-business-day holding period at 99% confidence level for covered positions as defined by Basel III.

(6) Tail Risk

VaR does not indicate the potential loss beyond a predefined confidence level (e.g. 95%). Many academic researchers apply Conditional Value-at-Risk (CVaR) to help better assess the likelihood (at a predefined confidence level) that a specific loss will exceed VaR (see Figure 1). Conceptually, CVaR, also known as "Expected Shortfall", measures the average loss given that VaR has been breached and provides insight into tail-risk exposure.

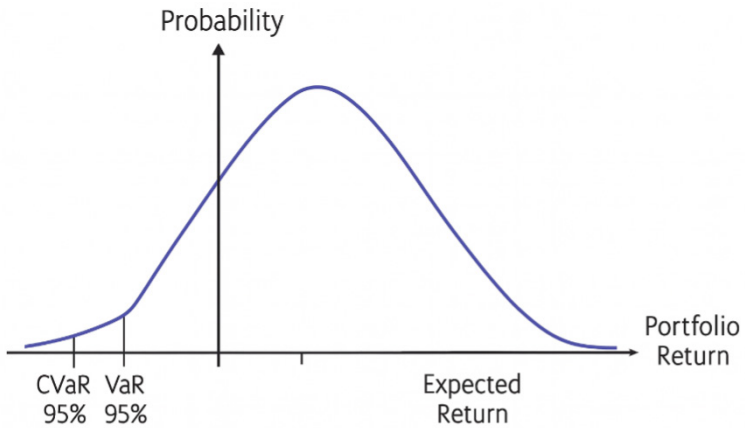


Figure 1: Illustration of CVaR and VaR with a 95% confidence level

(7) Stressed VaR

To better evaluate VaR during extreme events, Stressed VaR is another technique that utilizes the same systems, trade information, and processes as those used for the calculation of VaR. The only difference is that historical market data from a period of significant financial stress (i.e., characterized by high volatility) is used as an input for VaR computation. The time window selection process for the stressed VaR calculation is based on the identification of a time window characterized by high levels of volatility and extreme movements in the top VaR contributors.

(8) Blind Spots

There may be some risks, particularly in the trading book, that are partially captured or not captured by VaR. For example, intraday risks and other exposures may not appear in end-of-day VaR calculations.

These considerations underscore why VaR should never be used in isolation. It must be complemented by stress testing and scenario analysis discussed in the following sections.

Extensions of VaR

While VaR focuses on the value of a portfolio resulting from market price movements, another way to apply the VaR method is to measure operating cash flow for non-financial firms. Cash Flow at Risk (CFaR) evaluates the probability that operating cash flow will drop below a predefined level over a given horizon (e.g., quarterly or yearly). Firms use CFaR to assess liquidity risk and their ability to meet contractual obligations under adverse market conditions. For example, the annual CFaR at a 95% confidence level for a gold mining company is $-25 million. This means there is a 5% probability that operating cash flow will drop by more than $-25 million during the next 12 months. Non-financial firms can use CFaR to help evaluate a firm's ability to make contractual payments, such as, interest payments, debt payments, and lease expenses if a worst-case cash flow crisis occurs during a particular future period, putting the firm at risk of default. For readers who want to study more about CFaR, you can find further implementation details in Stein, Usher, LaGutta, & Yougen (2001).

What is Scenario Analysis?

Scenario analysis is a method that evaluates a portfolio under various extreme conditions but probable states of the world. The key point of scenario analysis involves large movements in key input variables to see how the portfolio will change according to changes in input variables. This method is also called "what-if analysis" or sensitivity testing. The major drawback of scenario analysis is its inability to incorporate joint correlations among input variables. Generally, real-world scenarios have joint movements among financial variables, and the correlations are crucial for modeling possible outcomes of the portfolio. Scenarios can be drawn from historical events or from prospective situations based on plausible business, economic, and political events. Analysts may shift yield curves, alter implied volatilities, adjust swap spreads, or simulate currency movements according to historical data. The scenarios that matter are those that generate extremely negative outcomes for the portfolio. Some guidelines for scenario tests are yield-curve shifting ±100 basis points, implied volatility changing by ±25% of current value, swap spread changing by ±20 basis points, or currency movements of ±10% of current value (Jorion, 2007a, 2007b).

What is Stress Testing?

Stress testing is a nonstatistical risk measure because it is not associated with a probability like VaR. Stress testing can be described as a process to identify and manage situations that could cause extreme negative returns for the portfolio. Whenever the stress tests reveal weaknesses, management must manage the identified risks that arise from the test. The goal of a stress test is to make sure

that the firm can survive the consequences of rare but catastrophic shocks—market crashes, sovereign defaults, liquidity freezes, or geopolitical crises.

Unlike VaR, stress testing is simple and meaningful. It begins with scenario analysis that analyzes the effect of simulated large movements of key financial variables on the portfolio. Some extreme scenarios (e.g., Black Monday on Wall Street, sovereign debt default, or the COVID-19 crisis) are considered forms of stress tests. Stress testing is a supplement to the VaR method because it allows users to include scenarios that do not occur in VaR computation (Jorion, 2007a, 2007b).

For the banking industry, the Bank for International Settlements (BIS) has issued principles for sound stress-testing practices and supervision[1], which were formulated with a view toward application to large, complex banks on a proportionate basis (Bank for International Settlements, 2009). A set of stress tests, categorized as either historical or hypothetical, should include shocks to underlying market risk factors that may be well beyond the shocks found in the historical data used to calculate VaR. Historical stress tests, which replicate past crises (e.g., the 2008 crisis or the Dot-Com crisis), simulate the impact of the market moves that occurred during a period of extended historical market stress. Hypothetical stress tests, which simulate forward-looking extreme scenarios, provide simulations of the estimated portfolio impact from potential future market stress events (Bank of America, 2015).

Excerpts of Market Risk Disclosures

Financial service firms normally discuss their market risk management and risk measurement in the Management Discussion and Analysis section published in their annual reports. The following exemplars illustrate how different financial institutions disclose market risk exposures, sensitivity analysis as well as our commentary to help users interpret such information.

Exemplar 1: Value-at-Risk Exposures

Figure 2 presents the VaR exposures extracted from Deutsche Bank's 2024 annual report (Deutsche Bank, 2024). The figure demonstrates that total VaR of Deutsche bank does not equal to the summation of Interest rate risk, Credit spread risk, Equity price risk, Foreign Exchange risk, and Commodity price risk; that is, [Total VaR ≠ (Interest rate risk + Credit spread risk + Equity price risk + Foreign Exchange risk + Commodity price risk)]. Due to the diversification effect arising from correlations among different asset classes, it helps reduce the total VaR of the portfolio.

[1] The document is available for download from http://www.bis.org/publ/bcbs155.pdf.

Trading Market Risk Exposures

Value-at-Risk Metrics of Trading Units of Deutsche Bank Group

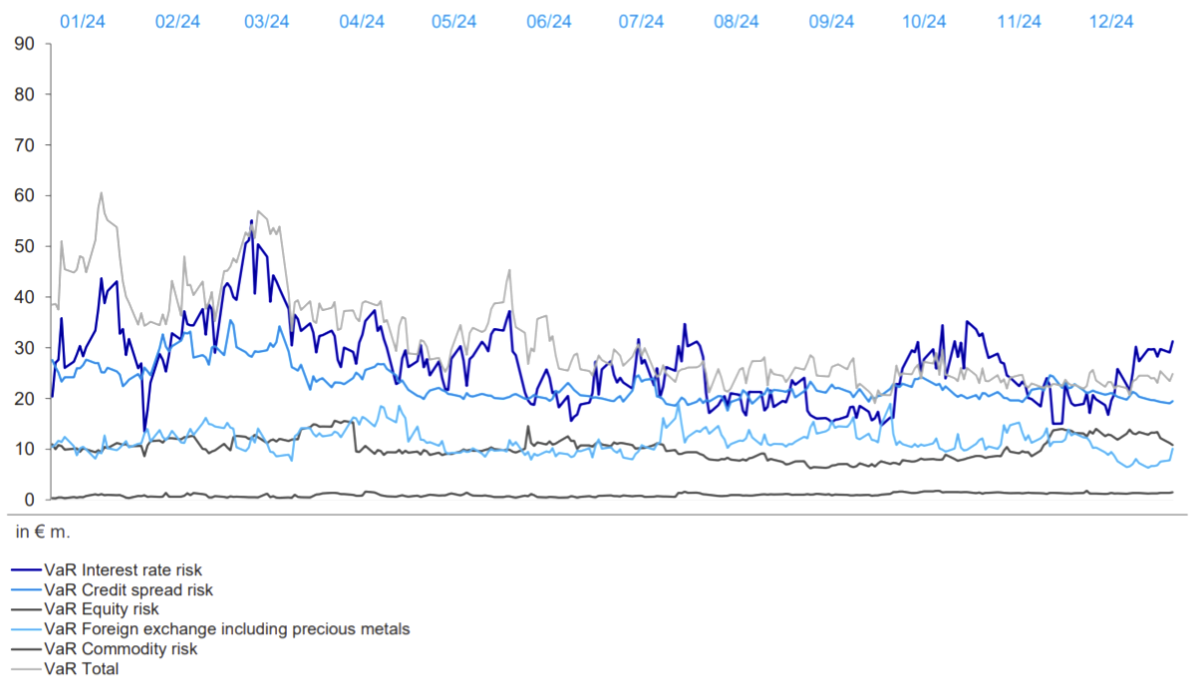
The tables and graph below present the Historic Simulation value-at-risk metrics calculated with a 99% confidence level and a one-day holding period for the Group's trading units.

Value-at-Risk of Trading Units by Risk Type[1]

	Total		Diversification effect		Interest rate risk		Credit spread risk		Equity price risk		Foreign exchange risk[2]		Commodity price risk	
in € m.	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023	2024	2023
Average	31.4	40.7	(41.2)	(46.3)	26.9	27.5	22.9	38.6	10.2	7.8	11.6	12.1	1.0	0.9
Maximum	60.6	74.3	(27.2)	(21.2)	55.1	40.1	35.5	68.4	15.6	14.9	19.0	17.4	1.8	2.8
Minimum	19.0	23.2	(56.2)	(64.9)	13.4	15.7	17.6	21.9	6.2	4.5	6.3	8.2	0.3	0.2
Period-end	24.9	39.0	(48.3)	(31.9)	31.3	20.3	19.5	28.4	10.8	11.0	10.1	10.9	1.5	0.3

[1] Figures for 2024 as of December 31, 2024. Figures for 2023 as of December 31, 2023
[2] Includes value-at-risk from gold and other precious metal positions

Development of historic simulation value-at-risk by risk types in 2024



The average 1d trading value-at-risk over 2024 was € 31 million, which decreased by € 9.2 million (-23%) compared to the average for 2023; this was primarily driven by roll-off of high market volatility period of H1 2023 from the historical VaR observation period and reduction in risk levels under Fixed Income and Currencies Trading business.

Figure 2: Excerpt of Value-at-Risk Metrics Disclosed by Deutsche Bank

Within trading units, Deutsche Bank is largely exposed to interest rate risk of fixed income held in the banking book. This risk category is closely associated with credit spread risk in the banking book. In addition, fixed income assets (e.g., treasuries, corporate bonds) generate the largest VaR in Deutsche Bank's portfolio.

Comparing 2024 to 2023, VaR from equity and commodity increased, whereas VaR from interest rate, credit spread, and foreign exchange decreased. This finding implicitly suggests that there was a portfolio reallocation during that period by reducing exposure to fixed income and foreign exchange and increasing exposure to equity and commodity.

Exemplar 2: Sensitivity Measures

Investment portfolios comprising individual positions included in "Financial instruments owned, at fair value" prefer to use sensitivity measures rather than VaR calculations. For example, real estate investments are not financial instruments and are therefore ill-suited for VaR calculation.

Figure 3 reprints how Goldman Sach, an investment bank, discussed its 10% Sensitivity Measures in 2024 annual report (Goldman Sachs, 2024). The market risk of these positions is determined by estimating the potential reduction in net revenues from a 10% decline in the underlying asset value. Unlike VaR, sensitivity measures do not reflect diversification benefits across asset categories or across other market risk measures.

Sensitivity Measures

Certain portfolios and individual positions are not included in VaR because VaR is not the most appropriate risk measure. Other sensitivity measures we use to analyze market risk are described below.

10% Sensitivity Measures. The table below presents our market risk by asset category for positions accounted for at fair value or accounted for at the lower of cost or fair value, that are not included in VaR.

	As of December	
$ in millions	**2024**	2023
Equity	**$ 1,567**	$ 1,562
Debt	**1,904**	2,446
Total	**$ 3,471**	$ 4,008

Figure 3: Sensitivity Measures Disclosed by Goldman Sach

Since VaR excludes the impact of changes in counterparty credit risk and changes in credit spreads, many investment banks opt for credit-spread sensitivity to help estimate the profit/loss in asset value resulting from basis-point changes in credit spreads (both counterparty and the firm's own). For example, Goldman Sachs further narrated in its annual report that the estimated sensitivity to a one-basis-point increase in credit spreads on derivatives was a loss of $2 million (including hedges) as of both December 2024 and December 2023. Such disclosures help users assess exposures not captured by VaR—especially credit-spread risk.

Exemplar 3: Net Interest Income Sensitivity

Investment banks generally have the largest portion of bonds in their portfolios. Interest income shares a large proportion of their revenue. As a result, changes in interest rates can have a significant impact on overall revenue. JPMorganChase stated in their Management Discussion and Analysis (JPMorganChase, 2024) that,

> "*The effect of interest rate exposure on the Firm's reported net income is important as interest rate risk represents one of the Firm's significant market risks. Interest rate risk arises not only from trading activities which are included in VaR, but also from the Firm's traditional banking activities, which include extension of loans and credit facilities, taking deposits, issuing debt, as well as the investment securities portfolio, and associated derivative instruments...* (JPMorganChase, 2024, p. 146)"

Computing VaR, sensitivity analysis, and stress tests do not focus solely on evaluating loss or downside risk. JPMorganChase applies earnings-at-risk scenarios to estimate the potential change in its net interest-income baseline. These scenarios may consider the impact on exposures as a result of changes in interest rates from baseline rates, as well as pricing sensitivities of deposits, optionality, and changes in product mix. The scenarios include forecasted balance-sheet changes, as well as modeled prepayment and reinvestment behavior, but do not include assumptions about actions that could be taken by the firm or its clients and customers in response to any such instantaneous rate changes.

Figure 4 reprints the pretax net interest income sensitivity profile extracted from JPMorganChase's 2024 annual report. Based on its sensitivity profile, rising interest rates are expected to benefit the firm's income. Once the Federal Reserve begins to raise interest rates, JPMorganChase's financial performance would be expected to outperform.

The Firm's sensitivities are presented in the table below.

December 31, (in billions)	2024[a]	2023[b]
Parallel shift:		
+100 bps shift in rates	**$ 2.3**	$ 3.1
-100 bps shift in rates	**(2.5)**	(2.8)
+200 bps shift in rates	**4.6**	6.2
-200 bps shift in rates	**(4.9)**	(6.1)
Steeper yield curve:		
+100 bps shift in long-term rates	**1.0**	0.6
-100 bps shift in short-term rates	**(1.4)**	(2.2)
Flatter yield curve:		
+100 bps shift in short-term rates	**1.2**	2.5
-100 bps shift in long-term rates	**(1.1)**	(0.6)

(a) Reflects the simultaneous shift of U.S. dollar and non-U.S. dollar rates, and the inclusion of the hedges of non-U.S. dollar capital investments. This inclusion had no impact on total sensitivities but increased U.S. dollar and decreased non-U.S. dollar sensitivities. Subsequent to this change, non-U.S. dollar sensitivities were insignificant.
(b) At December 31, 2023, represents the total of the Firm's U.S. dollar and non-U.S. dollar sensitivities as previously reported.

Figure 4: JPMorganChase Pretax Net Interest Income Sensitivity

Note that JPMorganChase did not provide any explicit justification for potential benefits from rising interest rates in its 2024 annual report. This deviates from its discussion in the 2015 annual report. The firm provided a positive outlook on rising interest rates, supported with rationale as reprinted in Figure 5. Specifically, higher U.S. interest rates are beneficial for JPMorganChase because the firm can reinvest its money at higher yields, and its assets adjust to the new, higher rates more quickly than its customer deposits (JPMorganChase, 2015). This demonstrates how interest-rate risk affects earnings rather than just asset valuations.

JPMorgan Chase's 12-month pretax net interest income sensitivity profiles
(Excludes the impact of CIB's markets-based activities and MSRs)

(in billions)	Instantaneous change in rates			
December 31, 2015	+200 bps	+100 bps	-100 bps	-200 bps
U.S. dollar	**$ 5.2**	**$ 3.1**	**NM** [(a)]	**NM** [(a)]

(a) Downward 100- and 200-basis-points parallel shocks result in a federal funds target rate of zero and negative three- and six-month U.S. Treasury rates. The earnings-at-risk results of such a low probability scenario are not meaningful.

The Firm's benefit to rising rates on U.S. dollar assets and liabilities is largely a result of reinvesting at higher yields and assets repricing at a faster pace than deposits. The Firm's net U.S. dollar sensitivity profile at December 31, 2015 was not materially different than December 31, 2014.

Figure 5: JPMorganChase Interest Income Sensitivity Profiles in 2015

CONCLUSION

Market risk measurement is fundamental to the stability and performance assessment of financial institutions. Risk management tools, i.e., VaR, Scenario Analysis, and Stress Testing provide essential insights into how portfolios respond to movements in market variables. Undeniably, market risk disclosure is empirically informative in market (Jorion, 2002). However, these tools must be interpreted with a clear understanding of their assumptions, limitations, and contexts.

VaR offers a probabilistic estimate of potential loss but can be misleading if users ignore distributional assumptions, correlation instability or tail risks. Scenario analysis expands understanding by modeling extreme yet plausible conditions, while stress testing pushes further by examining the consequences of rare but potentially devastating shocks. Each method contributes differently to a holistic view of market risk.

Financial statement users must interpret market-risk disclosures with caution. Disclosures from financial institutions, such as, Deutsche Bank, Goldman Sachs, and JPMorgan Chase, show how market risk metrics differ depending on portfolio composition, modeling choices, and regulatory requirements. Recognizing these factors enables a more informed assessment of a firm's vulnerability to market fluctuations.

Facing an increasingly interconnected global financial system, thoughtful analysis of market risk disclosures is essential. Equipped with the conceptual tools outlined in this paper, analysts and decision-makers can evaluate the stability, resilience, and strategic positioning of financial institutions navigating complex and volatile markets.

These dynamic changes call for more attention from policy setting and regulatory bodies to consider the reporting and disclosure requirements in order to mitigate potential adverse consequences. With informative disclosure required, market participants, investors, creditors and stakeholders will be able to make well-informed decisions. Further empirical research examining market risk disclosure, measurements and market reaction should benefit the academic advancements especially during the era of unsettling border disputes around the world.

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