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Risk Assessment and Management of a portfolio Value-at-Risk

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Master in Finance

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BUSINESS SCHOOL

Department of Finance

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Resumo

Esta dissertação examina a avaliação e a gestão do risco de mercado através da aplicação de metodologias de Value-at-Risk (VaR) a um portefólio diversificado composto por títulos de dívida e ações dos mercados dos Estados Unidos, Europa e Ásia. Este estudo teve dois objetivos principais, nomeadamente identificar o método de estimação mais fiável e avaliar se a gestão baseada nesta medida melhora a estabilidade e o desempenho de longo prazo do portefólio.

Foram consideradas várias metodologias, incluindo o modelo Normal, a Simulação Histórica, a Quantile Regression (QR) e o Skewed Generalized Student-t (SGSt). A análise demonstrou que modelos capazes de captar assimetrias e caudas pesadas (também designadas por caudas grossas) produzem estimativas mais robustas do que abordagens simplificadas. Os procedimentos de backtesting confirmaram a fiabilidade do modelo selecionado em diferentes condições de mercado. Quando aplicado à gestão do portefólio, no período de 2023 a 2024, o modelo revelou-se eficaz na identificação das principais fontes de risco e na orientação da implementação de uma estratégia dinâmica de cobertura que reduziu a volatilidade e melhorou os retornos ajustados ao risco.

Os resultados mostram que a diversificação, por si só, não é suficiente em períodos de turbulência, quando os mercados globais tendem a mover-se em conjunto. Sublinha-se assim a importância de combinar uma modelação rigorosa com ações de gestão oportunas para proteger o capital e sustentar um desempenho financeiro consistente.

Palavras-Chave: Value-at-Risk, Risco de mercado, Backtesting, Estratégia de Cobertura, Retornos Ajustados ao Risco, Gestão de Portefólio

Classificação JEL: G11, C58

Abstract

This thesis examines the measurement and management of market risk through the application of Value-at-Risk (VaR) methodologies to a diversified portfolio composed of fixed-income securities and equities from the United States, European, and Asian markets. The research pursued two main objectives, namely, to determine which estimation method provides the most reliable VaR and to assess whether a management framework based on this measure can enhance portfolio stability and long-term performance.

Several methodologies were considered, including the Normal model, Historical Simulation, Quantile Regression (QR), and the Skewed Generalized Student-t (SGSt) model. The analysis showed that models capable of capturing asymmetrical and heavy tails provide more robust estimates than simpler approaches. Backtesting procedures confirmed the reliability of the chosen model across different market conditions. When applied to portfolio management during 2023 to 2024, the chosen model proved effective in identifying the main sources of risk and guiding the implementation of a dynamic hedging strategy that reduced volatility and improved risk adjusted returns. The contribution of this research lies in its systematic comparison of parametric and non-parametric VaR models within a multi asset portfolio and in demonstrating the practical value of integrating VaR into active portfolio management.

The findings demonstrate that diversification on its own is not sufficient in periods of market turbulence, when global markets tend to move together. They underline the importance of combining accurate modelling with timely management actions in order to protect capital and to sustain consistent financial performance over time.

Keywords: Value-at-Risk, Market risk, Backtesting, Hedging Strategy, Risk-Adjusted Returns, Portfolio Management

JEL Classification: G11, C58

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List of Abbreviations

BCP	Berkowitz–Christoffersen–Pelletier test
CAC 40	Cotation Assistée en Continu 40 Index
EC	Economic Capital
EUR	Euro
EWMA	Exponentially Weighted Moving Average
FCHI	CAC 40 Index
FTSE 100	Financial Times Stock Exchange 100 Index
FX	Foreign Exchange
GBP	British Pound Sterling
GSPC	S&P 500 Index
HKD	Hong Kong Dollar
HSI	Hang Seng Index
JPY	Japanese Yen
N225	Nihon Keizai Shinbun 225 Index (Nikkei 225)
P&L	Profit and Loss
PV01	Price Value of a Basis Point
QR	Quantile Regression
RORAC	Return on Risk Adjusted Capital
S&P 500	Standard & Poor’s 500 Index
SGSt	Skewed Generalised Student-t
UC	Unconditional Coverage
USD	United States Dollar
VaR	Value-at-Risk

Chapter 1.
Introduction

In today's interconnected and volatile financial landscape, managing market risk has become a central priority for financial institutions, investors and regulators alike. As financial markets across the globe become more integrated, fluctuations in asset prices, driven by macroeconomic shifts, geopolitical uncertainty and changing monetary policies, can rapidly translate into significant portfolio losses. The recent context, marked by the COVID-19 pandemic, persistent inflationary pressures, rising interest rates and geopolitical tensions such as the war in Ukraine, has further reinforced the urgency of developing robust tools to monitor and mitigate risk. This evolving environment requires the use of quantitative frameworks that can anticipate, measure and manage exposure to market risk.

One of the most widely adopted tools for market risk assessment is Value-at-Risk (VaR), a statistical measure that estimates the maximum expected loss of a portfolio over a given time horizon and confidence level. Its relevance expanded significantly during the 1990s, as J.P. Morgan's RiskMetrics framework introduced VaR into mainstream practice by providing a clear methodology together with freely accessible estimates of volatility and correlation. This practical adoption was soon matched by regulatory recognition, when the 1996 Market Risk Amendment to the 1988 Basel Accord (Basel I) required banks to allocate capital against potential trading losses, thereby establishing VaR as the international standard for measuring market risk. Beyond its regulatory importance, VaR continues to play a central role in determining Economic Capital (EC), the amount of capital a firm must hold to absorb potential losses, which in turn guides investment choices and hedging strategies.

This dissertation contributes to the literature by systematically comparing parametric and non-parametric VaR methodologies in a multi asset portfolio and by assessing their effectiveness during a recent period of heightened volatility. The analysis focuses on a diversified portfolio composed of equities and fixed income securities from the United States and European markets, covering 2023 to 2024 which was characterized by considerable turbulence in financial markets, and the goal is to identify the most accurate and reliable VaR estimation methodology while also examining how actively managing the portfolio's VaR through a dynamic hedging strategy can influence overall risk adjusted performance.

To achieve this, four classes of VaR models are considered. These are the parametric Normal VaR, the Skewed Generalized Student-t model, the Historical Simulation approach and the Quantile Regression method. The dissertation highlights the importance of comparing these models in terms of their ability to capture asymmetry, fat tails and extreme losses, aspects that are often underestimated by simpler approaches, while the technical details are developed in the following chapters. Their performance is evaluated through a rigorous backtesting framework, which includes the Unconditional Coverage (UC) test and the Berkowitz-Christoffersen-Pelletier (BCP) test, both designed to assess the accuracy of risk forecasts and the presence of tail clustering.

Once the most effective model is identified, it is used to measure daily VaR over the study period under two scenarios. The first is an unmanaged portfolio where no action is taken to control risk. The second is a VaR managed portfolio where equity exposure is dynamically adjusted to ensure that the portfolio's EC does not exceed a predefined threshold. The performance of both strategies is evaluated using the Return on Risk Adjusted Capital (RORAC) metric, which allows for a meaningful comparison between profitability and risk containment.

The findings highlight that active risk management, supported by accurate VaR modelling, can limit exposure during stress periods and promote more stable outcomes. This reinforces the practical importance of not only measuring risk but also embedding responsive controls into the portfolio management process.

The structure of this dissertation is presented as follows. Chapter 2 reviews the relevant literature on market risk and VaR modelling. Chapter 3 outlines the portfolio composition and data sources. Chapter 4 describes the risk modelling and backtesting methodologies. Chapter 5 presents model validation results. Chapter 6 details the dynamic hedging strategy and analyses portfolio performance. Chapter 7 concludes with key takeaways and recommendations for risk management in institutional settings.

Chapter 2.
Literature Review

The management of financial risks has gained central importance, particularly following significant crises that affected both markets and the broader economy. Events such as the global financial crisis highlighted the vulnerability of financial systems to market shocks and reinforced the role of capital regulation in shaping how institutions measure and report market, credit and operational risks (Bank for International Settlements, 2009; Brunnermeier, 2009; Hoggarth et al., 2002). Within this context, market risk is the potential loss arising from adverse price movements across asset classes (Hull, 2015).

Value-at-Risk became a widely adopted benchmark for quantifying potential losses over a specified horizon and confidence level. Its popularization in practice is closely linked to J. P. Morgan's RiskMetrics framework in the mid-1990s, which provided a tractable parametric approach based on variance–covariance methods (J. P. Morgan, 1996; Jorion, 2007; Linsmeier & Pearson, 2000). However, the normality assumption underlying basic implementations is often violated, as financial returns display skewness and fat tails, prompting the use of more flexible distributions such as the Skewed Generalized Student-t (SGSt) (Cont, 2001; Theodossiou, 1998). This distinction is material for portfolio risk because mis specifying tails can bias capital allocation and weaken controls in stress periods (Kuester et al., 2006).

SGSt models increases flexibility by allowing asymmetry and heavy tails, thereby improving the fit to empirical return distributions (Theodossiou, 1998). Evidence suggests that fat-tailed specifications can yield more accurate tail-risk estimates than Gaussian models, especially at lower quantiles relevant for risk control (Haas et al., 2006; Lin & Shen, 2006; Theodossiou, 1998). Even so, SGSt performance can be sensitive to parameter stability and estimation choices, which is a practical limitation for consistent daily use in portfolio management and motivates comparative testing against simpler specifications. Alongside parametric approaches, non-parametric Historical Simulation remains attractive for its data-driven nature, yet it can overweight stale regimes and under-react to shifts in conditional risk, limitations documented in the literature (Boudoukh et al., 1998; Pritsker, 2006). This trade-off between flexibility and adaptability is central to model selection in applied settings.

An additional strand uses quantile-based methods. Quantile Regression-style VaR models the conditional quantile directly rather than the full return distribution, which can adapt better to changing conditions (Gaglianone et al., 2011; Koenker & Bassett, 1978). Comparative studies report that quantile approaches can outperform RiskMetrics and Historical Simulation in turbulent settings, reinforcing their practical relevance (Steen et al., 2015). Nevertheless, these models can be more demanding to calibrate and to communicate to non-technical stakeholders, which justifies balancing statistical gains with interpretability when selecting a benchmark.

Backtesting is essential to evaluate whether a VaR model delivers the intended coverage and responsiveness. The Unconditional Coverage (UC) test checks if the frequency of exceedances matches the nominal rate (Kupiec, 1995). Consistent with the empirical design of this study, the Berkowitz–Christoffersen–Pelletier (BCP) test, which expands upon the Conditional Coverage framework of Christoffersen (1998), is then applied to the full set of model configurations in order to assess calibration and the time series behaviour of exceedances, which complements the UC criterion in samples that include stress episodes (Berkowitz et al., 2011). For clarity, an exceedance occurs when the portfolio loss is greater than the estimated VaR at the chosen confidence level, and both tests are run on the daily evaluation window (Jorion, 2007). The joint use of UC and BCP provides a balanced diagnosis that covers hit-rate accuracy as well as dynamic adequacy, and the results are used to rank specifications before the portfolio application.

Performance assessment should consider risk and return jointly. Measures such as Return on Risk-Adjusted Capital (RORAC) relate profitability to economic capital, enabling comparable evaluations between unmanaged and actively hedged strategies and clarifying trade-offs between risk containment and performance (Crouhy et al., 2014; Hull, 2015). This aligns the statistical evaluation of VaR with managerial objectives, which is necessary for implementing actionable controls.

In sum, the literature supports comparing Normal, SGSt, Historical Simulation and Quantile-based VaR in a unified empirical setting. This review therefore motivates the design of this dissertation, which tests these four approaches on a diversified portfolio and evaluates them with UC and BCP backtests while relating outcomes to risk-adjusted performance, so that statistical accuracy and practical management can be assessed together.

Chapter 3.
Portfolio Composition

This chapter describes the portfolio used in the empirical analysis. The design seeks a balance between long term growth and capital stability through diversification across asset classes, regions and sectors. The allocation is approximately 53% in equities and 47% in fixed income. Although holdings span several currencies, all valuations and portfolio level results are expressed in EUR. Portfolio holdings, security characteristics and weights are measured at the reference date of 3 January 2023. Bond coupons are reinvested in the portfolio and equity dividends are not modelled, so equity returns use price series. For risk measurement, the portfolio is mapped to market risk factors as detailed in Chapter 4.

3.1. Equities

The equity component comprises 51 stocks across major developed markets, with regional representation benchmarked to widely followed indices such as the S&P 500, FTSE 100, CAC 40, Nikkei 225 and Hang Seng Index. The United States allocation focuses on large cap names in technology such as Apple, in financials including JPMorgan Chase, and in healthcare with Johnson and Johnson. The European allocation provides exposure to leaders in the United Kingdom and the Eurozone including BP in energy and L'Oréal in consumer. The Asia Pacific allocation broadens geographical coverage through Japanese and Hong Kong listings in automotive sector, suck as Toyota, and in infrastructure including CK Infrastructure Holdings. The portfolio also includes two short positions that complement the long book within the overall risk budget.

A compact view of the equity composition is shown in Table 3.1, which lists all positions with market code, quantity, value and portfolio weight. Appendix A.1 reports with more details including ticket reference, respective currency, share price and the exchange rate used for conversion.

Table 3.1. Equities portfolio composition, as of 3 January 2023

Stock	Ref Market	Quantity	Value	Allocation
Microsoft Corporation	GSPC	472	104 518.96 €	1.21%
JPMorgan Chase & Co.	GSPC	889	107 213.20 €	1.24%
NVIDIA Corporation	GSPC	13511	182 374.27 €	2.11%
Alphabet Inc.	GSPC	1214	100 402.16 €	1.16%
Apple Inc	GSPC	1457	172 272.70 €	1.99%
Pfizer Inc.	GSPC	2844	128 258.74 €	1.48%
Warner Bros. Discovery, Inc.	GSPC	-7305	-64 866.74 €	-0.75%
HP Inc.	GSPC	4253	101 010.82 €	1.17%
Citigroup Inc.	GSPC	1997	79 646.49 €	0.92%
Nike, Inc.	GSPC	815	87 901.98 €	1.01%
The Coca-Cola Company	GSPC	1587	89 486.58 €	1.03%
Johnson & Johnson	GSPC	455	72 022.99 €	0.83%
Advanced Micro Devices, Inc.	GSPC	2150	129 274.21 €	1.49%
First Energy Corp.	GSPC	2341	87 026.00 €	1.00%
eBay Inc.	GSPC	796	30 048.76 €	0.35%
Netflix, Inc.	GSPC	248	68 292.01 €	0.79%
Ralph Lauren Corporation	GSPC	308	30 018.90 €	0.35%
Mastercard Incorporated	GSPC	510	163 879.89 €	1.89%
Starbucks Corporation	GSPC	1772	161 111.87 €	1.86%
Exxon Mobil Corporation	GSPC	564	54 695.55 €	0.63%
Chevron Corporation	GSPC	612	96 129.62 €	1.11%
Intel Corporation	GSPC	5122	123 858.19 €	1.43%
Verizon Communications	GSPC	2724	91 170.52 €	1.05%
American Express Company	GSPC	930	125 367.35 €	1.45%
American Airlines Group Inc.	GSPC	11546	137 240.18 €	1.58%
Bank of America Corporation	GSPC	3430	102 130.89 €	1.18%
FedEx Corporation	GSPC	413	65 850.70 €	0.76%
The Goldam Sachs Group, Inc	GSPC	555	170 939.99 €	1.97%
Bio-Techne Corporation	GSPC	1792	137 619.95 €	1.59%
AstraZeneca PLC	FTSE	7	86 741.18 €	1.00%
Barclays PLC	FTSE	668	112 229.34 €	1.30%
BP p.l.c	FTSE	163	82 392.01 €	0.95%
easyJet plc	FTSE	236	86 540.12 €	1.00%
Vodafone Group Public Limited Company	FTSE	769	61 629.51 €	0.71%
Burberry Group plc	FTSE	36	80 563.00 €	0.93%
Legal & General Group Plc	FTSE	89	21 839.70 €	0.25%
BNP Paribas SA	FCHI	2239	107 719.12 €	1.24%
Engie SA	FCHI	13358	150 158.25 €	1.73%
L'Oréal S.A.	FCHI	361	118 186.86 €	1.36%
L'Air Liquide S.A.	FCHI	546	71 366.29 €	0.82%
Publicis Groupe S.A.	FCHI	1998	114 497.52 €	1.32%
Veolia Environnment SA	FCHI	2796	63 999.06 €	0.74%
Sony Group Corporation	N225	1517	107 910.76 €	1.25%
Canon Inc.	N225	2324	45 347.30 €	0.52%
CyberAgent, Inc.	N225	12459	101 621.23 €	1.17%
NTT DATA Group Corporation	N225	6539	88 242.93 €	1.02%
Nissui Corporation	N225	18924	70 292.26 €	0.81%
Obayashi Corporation	N225	8407	55 739.75 €	0.64%
ENN Energy Holdings Limited	HSI	-5321	-66 445.55 €	-0.77%
Alibaba Health Information Technology Limited	HSI	32644	25 969.81 €	0.30%
CK Infrastructure Holdings Limited	HSI	16220	72 019.41 €	0.83%
Total			4 593 456.62 €	53.02%

3.2. Fixed Income

The fixed income component consists of sovereign issues from the United States, Germany and the Netherlands, selected for liquidity and credit quality. Holdings include US Treasuries with maturities such as 2028 and 2041, German government bonds around 2031 and 2034, and a Dutch government bond maturing in 2044. Maturities are staggered to support income generation and a stable duration profile, and all valuations are reported in EUR.

Summary information for the bond allocation is presented in Table 3.2, which lists all sovereign positions with maturity, coupon frequency, fair value and portfolio weight, with face value and exchange rate reported in Appendix A.2.

Table 3.2. Fixed Income portfolio composition, as of 3 January 2023

Bonds	Maturity	Currency	Coupons/Year	Fair Value	Allocation
US912810FF04	15/11/2028	USD	2	451 729.29 €	5.21%
US912810QN19	15/02/2041	USD	2	677 806.09 €	7.82%
DE0001135176	04/01/2031	EUR	1	1 459 143.25 €	16.84%
DE0001135226	04/07/2034	EUR	1	620 216.11 €	7.16%
NL0015001RG8	15/01/2044	EUR	1	860 638.45 €	9.93%
Total				4 069 533.18 €	46.98%

Chapter 4.
Methodology

This dissertation aims to estimate and manage the Value-at-Risk of a diversified investment portfolio over the period from 3 January 2023 to 2 February 2024, ensuring that the portfolio's risk exposure remains within a pre-defined Economic Capital limit. The analysis is designed to provide effective risk control through a systematic evaluation of multiple VaR models and the implementation of a backtesting framework that is both comprehensive and robust. When necessary, a dynamic hedging strategy is considered to limit potential breaches of the established risk threshold.

The methodological framework begins with the identification and classification of the portfolio's key risk factors. Based on these exposures, a suitable volatility estimation model is selected to reflect the time-varying behaviour of financial markets. This provides the foundation for the specification and calibration of a range of VaR models, tailored to the underlying characteristics of the portfolio.

The analysis includes a comparative evaluation of various VaR modelling approaches, incorporating different estimation techniques and parameter configurations. For each model under consideration, a time series of daily VaR estimates is produced by applying the current portfolio structure to historical data, thereby simulating how the models would have performed under real market conditions. The dataset used for calibration and validation extends over a sufficiently long horizon, from 2013 to 2023, to support statistical reliability.

To assess model performance, a backtesting process is carried out. This involves the application of formal statistical tests to evaluate both the accuracy and reliability of the VaR forecasts. The outcomes of these tests provide the basis for identifying the most suitable model for ongoing risk management.

This chapter sets out the methodological structure that supports the analysis, explaining the rationale for model selection and for the choice of volatility modelling. Chapter 5 presents the results of the backtesting procedures and model chosen, while Chapter 6 compares the performance of the hedged and the unhedged portfolio, highlighting the effectiveness of risk mitigation strategies.

4.1. Risk Factor Mapping

An essential step in developing a Value-at-Risk framework is to identify and quantify the portfolio's exposure to the main sources of market risk. Before risk can be measured in a meaningful way, each asset needs to be connected to the market variables that drive its value. This process, often referred to as risk factor mapping, is the foundation of the modelling work that follows.

Risk factors are observable variables such as equity indices, interest rate curves, exchange rates or commodity prices that influence asset returns. By mapping each position to these factors, it becomes possible to obtain a consistent view of the overall risk of the portfolio.

This approach makes it possible to estimate the Value-at-Risk of the portfolio by linking asset positions to their underlying drivers. In doing so, it also highlights how sensitive the portfolio may become to broader market shocks, as correlations between markets often increase during periods of stress (Longin and Solnik, 2001).

All positions are translated into the portfolio's base currency, EUR, using spot Foreign Exchange (FX) rates at the valuation date to ensure consistency in valuation. This conversion does not eliminate currency risk, which is explicitly captured by mapping non-EUR exposures to exchange-rate factors such as EUR/USD, EUR/GBP or EUR/JPY. In line with standard practice (Hull, 2015), translation is an accounting step, while FX risk enters through the return series of the underlying drivers, ensuring comparability across assets without neglecting the contribution of currency movements to overall risk.

The portfolio Θ includes multiple positions, each exposed to one or more risk factors. The exposure to each risk is represented by θ_i and these exposures are grouped into a vector of risk factor loadings Θ:

$$\theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \tag{1}$$

This vector captures how the portfolio is exposed to its underlying risk factors. The method used to obtain these exposures varies depending on the asset class, reflecting the different ways each asset type responds to market movements.

4.1.1. Equity

The risk associated with equity positions is primarily driven by fluctuations in individual stock prices. To quantify this risk, the exposure for each stock is calculated as the total value invested, expressed in EUR to maintain a uniform currency basis. This follows the standard treatment in Hull (2015) and is obtained by multiplying the number of shares by the current stock price and by the relevant exchange rate:

$$M_{i,t} = \sum_{i\,=\,1}^{n} N_{i,t} \times P_{i,t} \times FX_{i,t} \tag{2}$$

where $M_{i,t}$ represents the position's value in EUR, $N_{i,t}$ the number of shares, $P_{i,t}$ the share price, and $FX_{i,t}$ the spot exchange rate converting the asset's currency into euros at time *t*.

The profit and loss (P&L) for each equity position is derived from the relative change in the associated risk factor, either the stock price or the index value, depending on the chosen framework. This allows for consistent return estimation across both individual holdings and the whole portfolio. Specifically, the P&L for stock i at time t can be expressed as:

$$P\&L_{i,t} = \theta_{i,t} \times \left(\frac{P_{i,t}}{P_{i,t-1}} - 1 \right) \tag{3}$$

This mapping process provides a solid foundation for measuring equity risk under both idiosyncratic and systematic perspectives. It gives sufficient detail to evaluate the risk of individual stocks with accuracy while remaining practical for assessing the overall portfolio through VaR.

4.1.2. Fixed Income

The valuation of bonds fundamentally depends on the present value of their expected future cash flows, which are discounted using current interest rates. As highlighted by Alexander (2008), the principal risk driver for fixed-income instruments is the sensitivity of these discounted cash flows to fluctuations in the yield curve. Unlike equities, whose value is linked to company earnings and market sentiment, bond prices react primarily to changes in interest rates, making interest rate risk the central focus of fixed-income risk management.

Mathematically, the present value PV_{CT,r_T} of a cash flow C_T payable at time T can be expressed as:

$$PV_{CT,r_T} = C_T \times e^{-r_T \times T} \times FX_t \tag{4}$$

where r_T is the continuously compounded zero-coupon rate for maturity T, and FX_t accounts for currency conversion if the cash flow is denominated in foreign currency.

To capture the sensitivity of bonds to interest rate movements, the Present Value of a Basis Point (PV01) is commonly used. PV01 measures how much the value of the bond changes when the entire yield curve shifts by one basis point. This sensitivity can be approximated using a first order Taylor expansion as follows:

$$PV01_{CT,r_T} \approx -\frac{\partial PV_{CT,r_T}}{\partial_{r_T}} \times 0.01\% = T \times PV_{CT,r_T} \times 0.01\% \tag{5}$$

When portfolios contain bonds with multiple cash flows spanning various maturities, direct risk factor exposure becomes complex, as each cash flow depends on a potentially unique point on the yield curve. Interest rate data is usually available only at standard maturities, known as vertices. To address this, the methodology introduced by Alexander (2008) and others employs a mapping process that projects cash flows with non-standard maturities onto adjacent standard maturities. This approach ensures both the total present value and the PV01 remain invariant, preserving the portfolio's overall interest rate sensitivity.

Formally, if a cash flow with maturity T is mapped to vertices T_1 and T_2 (where $T_1 < T < T_2$), the weights x_{T1} and x_{T2} are computed to satisfy:

$$\begin{cases} x_{T1} + x_{T2} = PV_{CT} \\ T_1 x_{T1} + T_2 x_{T2} = T \times PV_{CT} \end{cases} \tag{6}$$

This linear system guarantees that both present value and duration-weighted value (related to PV01) are maintained after mapping.

Finally, the portfolio's exposure to interest rate risk is summarized by aggregating the PV01 exposures across all vertices. Changes in interest rates at each vertex translate into changes in portfolio value, with profit and loss approximated as:

$$P\&L_t = -\sum_{i=1}^{n} PV01_{T_i} \times \frac{\Delta r_{T_i}}{0.01\%} \tag{7}$$

This framework provides a practical yet precise way of mapping fixed income exposures, supporting Value-at-Risk estimation while keeping a clear link between portfolio value and interest rate risk.

4.1.3. Currency

Currency risk arises from fluctuations in exchange rates, affecting the value of assets and liabilities denominated in foreign currencies. Unlike equity or fixed income instruments, where risk factors relate to prices or interest rates, currency exposure is determined mainly by changes in exchange rates relative to the portfolio's base currency, which in this study is the EUR, as noted by Hull (2015).

The exposure to each currency i at time t is quantified by converting the net position $V_{i,t}$ into the base currency using the spot exchange rate $FX_{i,t}$:

$$\theta_{i,t} = V_{i,t} \times FX_{i,t} \tag{8}$$

Daily profit and loss (P&L) attributable to currency movements is computed as the product of this exposure and the relative change in the exchange rate:

$$P\&L_{i,t} = \theta_{i,t} \times \left(\frac{FX_{i,t}}{FX_{i,t-1}} - 1\right) \tag{9}$$

This approach provides a consistent mapping of currency positions to their respective risk factors and allows their integration within the broader VaR framework, as also described by Jorion (2007). While volatility in foreign exchange markets can behave differently from that of other asset classes, accurately capturing currency exposures is crucial for effective risk management in internationally diversified portfolios.

4.1.4. Portfolio Exposure

A fundamental step in market risk analysis is the identification and quantification of the portfolio's exposure to underlying risk factors. This mapping provides a structured representation of how changes in market variables, such as stock prices, interest rates or exchange rates, impact portfolio valuation. They serve as the starting point for VaR models and other techniques of risk attribution.

Table 4.1. summarizes the mapped risk factor exposures as of the reference date, 3 January 2023. Each asset class is associated with its relevant set of risk factors, and exposures are obtained using the methodologies described in the previous sections. For equities, this typically involves measuring sensitivities to individual stock prices or representative indices. For fixed-income instruments, exposures are usually expressed as sensitivities to shifts in the yield curve across standard maturities. For currency, the exposures reflect the portfolio’s sensitivity to fluctuations in relevant foreign exchange rates.

The resulting exposure vector provides the aggregated impact of these risk factors on the portfolio’s value. This framework ensures that risk is measured consistently across asset classes, and it makes it possible to decompose VaR into contributions from each source of risk.

Table 4.1. Summary of portfolio exposures to Equity, Fixed-Income and Currency risk factors, as of 3 January 2023

Equity		Fixed-Income		Currency	
Risk factor	**Value**	**Risk factor**	**Value**	**Risk factor**	**Value**
MSFT	104 518.96 €	USD3M	-0.69 €	USDEUR	4 064 432.12 €
JPM	107 213.20 €	USD6M	-0.56 €	GBPEUR	531 934.87 €
NVDA	182 374.27 €	USD1Y	-3.62 €	JPYEUR	469 154.23 €
GOOGL	100 402.16 €	USD2Y	-9.34 €	HKDEUR	31 543.68 €
AAPL	172 272.70 €	USD3Y	-20.00 €		
PFE	128 258.74 €	USD5Y	-134.92 €		
WBD	-64 866.74 €	USD7Y	-143.72 €		
HPQ	101 010.82 €	USD10Y	-171.09 €		
C	79 646.49 €	USD20Y	-590.30 €		
NKE	87 901.98 €	EUR3M	-4.26 €		
KO	89 486.58 €	EUR6M	2.97 €		
JNJ	72 022.99 €	EUR1Y	-9.57 €		
AMD	129 274.21 €	EUR2Y	-21.16 €		
FE	87 026.00 €	EUR3Y	-46.13 €		
EBAY	30 048.76 €	EUR5Y	-98.53 €		
NFLX	68 292.01 €	EUR7Y	-589.45 €		
RL	30 018.90 €	EUR10Y	-727.16 €		
MA	163 879.89 €	EUR15Y	-162.12 €		
SBUX	161 111.87 €	EUR20Y	-1 198.72 €		
XOM	54 695.55 €				
CVX	96 129.62 €				
INTC	123 858.19 €				
VZ	91 170.52 €				
AXP	125 367.35 €				
AAL	137 240.18 €				
BAC	102 130.89 €				
FDX	65 850.70 €				
GS	170 939.99 €				
TECH	137 619.95 €				
AZN.L	86 741.18 €				
BARC.L	112 229.34 €				
BP.L	82 392.01 €				
EZJ.L	86 540.12 €				
VOD.L	61 629.51 €				
BRBY.L	80 563.00 €				
LGEN.L	21 839.70 €				
BNP.PA	107 719.12 €				
ENGI.PA	150 158.25 €				
OR.PA	118 186.86 €				
AI.PA	71 366.29 €				
PUB.PA	114 497.52 €				
VIE.PA	63 999.06 €				
6758.T	107 910.76 €				
7751.T	45 347.30 €				
4751.T	101 621.23 €				
9613.T	88 242.93 €				
1332.T	70 292.26 €				
1802.T	55 739.75 €				
2688.HK	-66 445.55 €				
0241.HK	25 969.81 €				
1038.HK	72 019.41 €				

4.2. Volatility

Accurate volatility estimation is fundamental to effective risk measurement, particularly in the computation of VaR. Traditional methods, such as the simple historical standard deviation, treat all past data points equally. This equal weighting can obscure recent changes in market dynamics, which are often the most relevant for forward-looking risk assessments.

To overcome this limitation, the Exponentially Weighted Moving Average (EWMA) method is adopted. This method assigns exponentially smaller weights to older observations and increases the importance of recent ones, which makes the estimates more responsive to changes in volatility. The EWMA variance estimate at time t is recursively defined as:

$$\hat{\sigma}_t^2 = (1-\lambda)\, r_{t-1}^2 + \lambda \hat{\sigma}_{t-1}^2 \tag{10}$$

where r_{t-1} denotes the return observed at time $t-1$, and $\lambda \in (0,1)$ is the smoothing parameter governing the rate at which past data loses influence.

The choice of λ plays a decisive role because it must balance the sensitivity to new information with the stability provided by historical data. The RiskMetrics framework (J.P. Morgan, 1996) recommends $\lambda = 0.94$ for daily data, which became widely adopted as a practical benchmark. Nevertheless, Alexander (2008) argues that the optimal parameter depends on factors such as asset class, volatility regime, and specific risk management objectives.

In this dissertation a range of λ values are systematically tested to identify the parameter best suited to the portfolio's characteristics. This selection is subsequently validated through backtesting, ensuring that volatility estimates, and the VaR measures derived from them, are both reliable and reflective of prevailing market conditions.

4.3. VaR Models

Value-at-Risk is one of the most widely used measures in financial risk management, providing a clear estimate of the maximum expected loss a portfolio could incur over a defined time horizon, at a given confidence level. In this study a one-day horizon is adopted (h = 1) together with a significance level of α = 1%, which corresponds to a 99% confidence level. This implies that under the assumption of a constant portfolio composition, the probability of a daily loss exceeding the VaR estimate is expected to be only one percent.

Formally, the one-day VaR at level α is defined as the negative α-quantile of the return distribution:

$$P\left(X < -VaR_{1,\alpha}\right) = \alpha \tag{11}$$

where X represents the portfolio's daily return. Equivalently, if the cumulative distribution function F of X_h is known, the VaR corresponds to:

$$VaR_{h,\alpha} = -F^{-1}(\alpha) \tag{12}$$

with $F^{-1}(\alpha)$ denoting the inverse cumulative distribution function evaluated at α.

Since financial return distributions often deviate from normality by displaying asymmetry, fat tails and time varying volatility, this dissertation evaluates four different Value at Risk methodologies. These are the Normal model, the Skewed Generalised Student-t (SGSt) distribution, the Historical Simulation and the Quantile Regression (QR) approach.

By analysing these models side-by-side, the study assesses their suitability for capturing the portfolio’s risk under different distributional assumptions. Each model is estimated using the same set of risk factor exposures and volatility forecasts to ensure a consistent comparison. The following subsections explain the methodology of each approach and prepare the ground for the backtesting analysis presented in Chapter 5.

4.3.1. Normal VaR

The Normal VaR model provides a foundational framework for quantifying potential losses in financial portfolios. It is built on the assumption that returns follow a normal distribution, a simplifying condition that allows for closed-form analytical solutions. Although this assumption does not fully capture the behaviour of financial markets, the Normal VaR remains widely applied because of its computational efficiency and the clarity with which its results can be interpreted (Jorion, 2007).

Let X_h represent the return of the portfolio over a holding period h, assumed to be normally distributed:

$$X_h \sim \mathcal{N}(\mu_h, \sigma_h^2) \tag{13}$$

where μ_h is the expected return and σ_h is the standard deviation over the horizon h. Under this assumption, the h-day VaR at a confidence level $1-\alpha$ can be expressed as the negative α-quantile of the return distribution:

$$VaR_{h,\alpha} = -\Phi^{-1}(\alpha) \times \sigma_h - \mu_h \tag{14}$$

Here, $\Phi^{-1}(\alpha)$ denotes the inverse cumulative distribution function (quantile function) of the standard normal distribution evaluated at level α. This represents the return threshold that the portfolio is expected to fall below with probability α.

For daily VaR estimation (h = 1), it is common practice to set μ_h = 0, as short-term expected returns are typically negligible and difficult to estimate accurately (Alexander, 2008). This assumption simplifies the expression to:

$$VaR_{1,\alpha} = -\Phi^{-1}(\alpha) \times \sigma \tag{15}$$

In this analysis, the volatility σ is estimated using the Exponentially Weighted Moving Average (EWMA) approach, as discussed in the previous chapter. This method prioritizes recent observations, allowing the model to better reflect current market conditions while preserving analytical tractability.

Despite its limitations, particularly the inability to account for fat tails or asymmetry in return distributions, the Normal VaR remains a consistent benchmark and a useful reference against which more sophisticated models such as those incorporating skewness or non-parametric techniques can be evaluated in the following sections.

4.3.2. SGSt

While the assumption of normally distributed returns facilitates analytical tractability, it often underestimates the probability of extreme losses due to its inability to capture skewness and heavy tails in financial return distributions. To address this, the Skewed Generalized Student-t (SGSt) distribution, introduced by Theodossiou (1998), provides a more flexible framework that incorporates both asymmetry and fat tails, which are frequently observed in empirical asset returns

The SGSt distribution is defined by five parameters: location (μ), scale ($\sigma > 0$), skewness ($\lambda \in (-1, 1)$), central shape ($p > 0$), and tail shape ($q > 0$). These are typically estimated via maximum likelihood over rolling windows of historical returns, allowing the distribution to adapt dynamically to changing market conditions.

Assuming the portfolio return over a horizon h, denoted X_h, follows a SGSt distribution:

$$X_h \sim SGSt(\mu_h, \sigma_h, \lambda, p, q) \tag{16}$$

and under this specification the VaR over horizon h at significance level α can be expressed as:

$$VaR_{h,\alpha} = -T^{-1}_{\mu,\sigma,\lambda,p,q}(\alpha) \tag{17}$$

Here, T^{-1} denotes the inverse cumulative distribution function of the SGSt distribution, which maps the chosen confidence level α to the corresponding quantile of returns.

In practice, following standard short-horizon assumptions, the mean return is set to zero (i.e., μ=0), and volatility σ_h is estimated using the exponentially weighted moving average (EWMA) model. This leads to the simplified expression:

$$VaR_{h,\alpha} = -T^{-1}_{0,1,\lambda,p,q}(\alpha) \times \sigma_h \tag{18}$$

This methodology extends the classical parametric VaR framework by explicitly modelling distributional characteristics that are critical in stress scenarios, thereby improving the reliability of risk estimates when returns are skewed and leptokurtic (Theodossiou, 1998).

4.3.3. Historical

Unlike parametric models that rely on distributional assumptions, the Historical Simulation approach provides a non-parametric framework that directly utilizes past market data. It estimates potential losses by constructing an empirical distribution of portfolio returns, requiring no explicit assumptions about the shape of the return distribution. This makes it especially relevant when asset returns exhibit skewness, excess kurtosis, or other deviations from normality (Jorion, 2007).

The methodology involves collecting a historical window of n past daily returns over a fixed time horizon h, assuming the portfolio's composition remains constant over that period. These returns are treated as hypothetical scenarios of how the current portfolio would have behaved under previously observed market conditions. Once ordered from worst to best, each observation is assigned equal probability $\frac{1}{n}$ and the VaR at confidence level α is obtained as the negative α-quantile of the empirical return distribution:

$$VaR_{h,\alpha} = -Quantile(r_{historical}) \tag{19}$$

While this method is simple and distribution-free, one of its limitations lies in its equal weighting of all observations. Older data may no longer reflect current market conditions, which reduces the method's responsiveness to changing volatility regimes. To address this, Hull and White (1998) proposed the volatility-adjusted Historical VaR, in which past returns are scaled to match current market volatility. This adjustment involves rescaling each historical return r_t by the ratio of current estimated volatility σ_T to the volatility at the time of the return σ_t, usually estimated via an EWMA model:

$$\hat{r}_t = r_t \times \frac{\hat{\sigma}_T}{\hat{\sigma}_t} \tag{20}$$

The empirical distribution is then re-computed using these adjusted returns, and the VaR is obtained as the negative quantile of this new distribution:

$$VaR_{h,\alpha}^{adj} = -Quantile_{\alpha} \times (\hat{r}_t) \tag{21}$$

This adjustment preserves the simplicity and distribution free nature of Historical VaR while improving its sensitivity to current volatility. The choice of sample size remains critical. A very short window may overlook important risk episodes, while a very long window may reduce responsiveness to recent changes. Finding the right balance is essential for effective risk measurement.

4.3.4. Quantile Regression

Quantile Regression (QR) VaR offers a non-parametric alternative to traditional risk models by estimating VaR as the conditional α-quantile of portfolio returns, based on observable risk factors. Rather than assuming a specific return distribution, this method provides greater flexibility because it captures asymmetry and fat tails directly from the data (Koenker and Bassett, 1978).

The standard form relates returns y_t to one or more explanatory variables, typically involving time-varying volatility estimates such as EWMA volatility σ_t. The α-quantile of the conditional return distribution is then modelled as:

$$VaR_{\alpha,t} = -\left(\hat{a} + \hat{b}x_t\right) \tag{22}$$

where x_t denotes the selected explanatory variable and $\hat{a}$,$\hat{b}$ are parameters estimated through quantile regression.

These parameters are obtained by solving the minimization problem (Koenker and Bassett Jr, 1978):

$$\left(\hat{a}, \hat{b}\right) = arg \min_{a,b} \sum_{i=1}^{n} [y_i - (a + bx_i)]\left(\alpha - I_{\{y_i-(a+bx_i)<0\}}\right) \tag{23}$$

with the indicator function defined as:

$$I_{\{y_i-(a+bx_i)<0\}} = \begin{cases} 1, & if \quad y_i - (a + bx_i) < 0 \\ 0, & otherwise \end{cases} \tag{24}$$

The regression is repeated over a rolling window to reflect changing market conditions. Further extensions may combine daily, short term and long-term volatility measures, which improves the model’s responsiveness to different temporal dynamics (Gaglianone et al., 2011).

By directly focusing on the lower tail of the return distribution, QR VaR provides a robust, data-driven estimate of downside risk that adapts naturally to volatility clustering and non-linear effects.

Chapter 5.
Backtesting

After introducing the methodology used to compute the four Value-at-Risk models in the previous chapter, this section turns to evaluating their performance through a formal backtesting process. A total of 320 model configurations were tested, combining variations in model specification, sample sizes of 200, 400, 600, 800 and 1000 observations, and EWMA smoothing parameters between 0.9 and 0.995. These configurations were applied to daily portfolio data over a ten-year period, with each model generating a series of one-day ahead VaR forecasts. Backtesting is carried out not only over the entire 2013 to 2023 period (referred to as the global period), but also annually, allowing for detailed performance tracking across different market conditions.

The purpose of backtesting is to verify how well each model predicts potential losses by comparing the estimated VaR with actual portfolio P&Ls. When a portfolio's daily loss exceeds the predicted VaR, we observe what is known as an exceedance. Both the frequency and timing of these exceedances are key indicators of model quality. A reliable model should generate a number of exceedances that is consistent with its confidence level, and these events should occur independently rather than in clusters.

To evaluate the adequacy of the VaR models, two complementary statistical tests are employed. The Unconditional Coverage (UC) test developed by Kupiec (1995) examines whether the proportion of exceedances aligns with the probability implied by the model's confidence level. The BCP test introduced by Berkowitz, Christoffersen and Pelletier (2011) builds on the Conditional Coverage framework of Christoffersen (1998) and extends it by modelling the time between exceedances. While the UC test provides a first indication of whether the number of violations is correct, the BCP test adds a richer perspective by assessing whether exceedances occur in a pattern consistent with independent risk events. Together these tests offer a more complete view of model performance and help to identify the specifications that deliver both accurate coverage and robust behaviour under different market conditions (Kupiec, 1995; Christoffersen, 1998; Berkowitz et al., 2011).

The next sections outline the methodology for each of these tests and present the results from both the annual and global evaluations. Taken together, these steps make it possible to identify the model that not only achieves accurate coverage but also demonstrates stable and reliable behaviour across the full period and under different market conditions.

5.1. Unconditional Coverage Test

The Unconditional Coverage (UC) test developed by Kupiec (1995) provides a clear way to verify whether a Value at Risk model generates the expected frequency of exceedances. In practice an exceedance occurs when the realised portfolio loss is greater than the VaR forecast for that day. If the model is correctly specified, the observed proportion of exceedances should be close to the theoretical probability defined by the chosen confidence level.

For the purposes of this dissertation the models are calibrated at a 99% confidence level. This implies that on average 1% of daily P&Ls should exceed the VaR threshold. With 2600 daily observations in the sample, this translates into an expectation of 26 exceedances over the entire period. The indicator function used to identify exceedances is defined as:

$$I_{\alpha,t} = \begin{cases} 1, & if \quad P\&L_t < -VaR_{\alpha,t} \\ 0, & otherwise \end{cases} \tag{25}$$

where $P\&L_t$ is the observed P&L on day t and $VaR_{\alpha,t}$ is the VaR estimate for that day at confidence level α.

The UC test then evaluates whether the observed proportion of exceedances, denoted π_{obs}, matches the expected rate α. This is formalised through the hypotheses:

$$H_0: \pi_{obs} = \alpha \tag{26}$$

$$H_1: \pi_{obs} \neq \alpha \tag{27}$$

The likelihood ratio statistic is then given by:

$$LR_{UC} = -2ln\left[\frac{(1-\alpha)^{n-n_1}\alpha^{n_1}}{(1-\ \pi_{obs})^{n-n_1}\ \pi_{obs}{}^{n_1}}\right] \tag{28}$$

where n is the total number of observations, and n_1 is the number of exceedances observed.

Under the null hypothesis this statistic follows a chi squared distribution with one degree of freedom:

$$LR_{UC} \sim x_1^2 \tag{29}$$

If the test statistic exceeds the critical value at the 5% significance level, the null hypothesis is rejected, which indicates that the model does not deliver the expected coverage.

The strength of the UC test lies in its clarity and interpretability. It directly reveals whether a model systematically underestimates or overestimates risk by producing too few or too many exceedances. At the same time, the test does not address the timing of exceedances, which is why it is complemented by other approaches. Despite this limitation the UC test remains an essential first step in any backtesting exercise, and in this dissertation, it is applied to both the full sample and annual subsamples in order to evaluate the consistency of model performance over time.

5.2. BCP test

The BCP test, developed by Berkowitz, Christoffersen and Pelletier (2011), provides a framework to evaluate whether exceedances generated by a Value at Risk model occur independently over time. Passing the UC test confirms that the overall frequency of exceedances is consistent with the model’s confidence level, yet this does not guarantee that violations are randomly distributed. If exceedances appear in clusters, the model may underestimate risk during periods of stress. A correctly specified model should therefore generate exceedances that are both consistent in number and independent in timing.

The test addresses this by analysing the autocorrelation of the exceedance indicator series. The hypotheses can be written as:

$$H_0: \rho_k = 0 \quad \text{for all } k = 1, \dots, K \tag{30}$$

$$H_1: \exists k \in (1, \dots, K) \quad \text{such that } \rho_k \neq 0 \tag{31}$$

where ρ_k denotes the autocorrelation of the exceedance indicator at lag k. The test statistic is:

$$BCP(K) = n(n+2) \sum_{k=1}^{K} \frac{\hat{\rho}_k^2}{n-k} \tag{32}$$

where n is the total number of observations and $\hat{\rho}_k$ is the sample autocorrelation at lag k. Under the null hypothesis, this statistic follows a chi-squared distribution with K degrees of freedom:

$$BCP(K) \sim x_K^2 \tag{33}$$

The choice of lag length K reflects a trade off in the way the test captures dependence. Larger values allow the detection of autocorrelation that persists over longer horizons, although this may reduce the ability to identify short term clustering. Smaller values focus on immediate autocorrelation, but they fail to detect longer range dynamics. In this dissertation the BCP test is applied with lag lengths between 1 and 10. This range provides a balanced compromise, making it possible to identify both short-term and medium-term clustering of exceedances while maintaining reliable statistical power.

By applying the BCP test alongside the UC test, the analysis evaluates not only whether the overall number of exceedances matches the confidence level but also whether these exceedances are randomly distributed through time. This two-step framework provides a more comprehensive and reliable assessment of VaR model performance.

5.3. Results and Model selection

To evaluate the performance and reliability of the Value-at-Risk models developed in this dissertation, a structured backtesting procedure was carried out combining the Unconditional Coverage (UC) test of Kupiec (1995) and the BCP test of Berkowitz, Christoffersen and Pelletier (2011). In total, 320 model configurations were estimated, varying across distributional assumptions, sample sizes and EWMA smoothing parameters. The complete list of these models is reported in Appendix B.

The first step in the model evaluation process consisted of applying the UC test over the full evaluation period, from 2013 to 2023. This test verified whether the number of exceedances produced by each configuration aligned with the theoretical one percent probability implied by the chosen confidence level. Out of the 320 configurations, 176 models passed this test, indicating statistical consistency in terms of unconditional coverage. A breakdown of these results by model class reveals that none of the Normal specifications (20 models) passed the UC test, confirming their inability to capture the heavy-tailed nature of financial return distributions, as anticipated in the literature. For the remaining 300 models analysed, distributed equally across SGSt, Historical Simulation and Quantile Regression, the results were more balanced. A total of 63 SGSt models satisfied the unconditional coverage criterion, while 46 Historical Simulation models and 67 Quantile Regression models also achieved this standard. The detailed list of configurations that satisfied this first criterion is reported in Appendix C (from Appendices C.1 to C.4).

Following this first filter, the BCP test was applied to the same set of models. However, none of the 320 configurations passed the BCP test over the full period, as reported in Appendix C (from C.5 to C.8). Berkowitz et al. (2011) emphasize that even well specified models can fail independence checks in the presence of market turbulence or structural breaks, which provides a plausible explanation for the systematic rejection observed in this study. For these reasons, and in line with practices documented in the literature on risk model validation, the UC test was retained as the primary criterion for model selection.

Among the 176 models that passed the overall UC test, the analysis then turned to annual evaluations from 2013 to 2023, as showed in Appendix C (from Appendices C.9 to C.11). This step aimed to test the year-by-year consistency of each configuration. After applying the UC test on an annual basis, 60 models continued to display satisfactory statistical performance. The results are reported in Appendix C.12.

To further improve the selection, the exceedance rates of the 60 shortlisted models were compared to the target significance level. From this group, only three models consistently maintained an average exceedance rate of 1% over the ten-year period. These configurations are presented in Table 5.1.

Table 5.1. Comparison of the three shortlisted models with an average exceedance rate of 1%

Model Number	Model	Sample Size	EWMA Smoothing Factor	Exceedance rate
92	SGSt	800	0.955	1.00%
93	SGSt	800	0.96	1.00%
112	SGSt	1000	0.955	1.00%

To determine the most suitable model for the portfolio, these three candidates were then evaluated in greater detail. The three shortlisted models were then compared in more detail through a year-by-year analysis of UC test, for p-values and exceedance rates. Tables 5.2 and 5.3 report these results. While the differences between the models were subtle, Model 93 displayed the most consistent alignment with the one percent exceedance rate and the most stable pattern of p-values across the ten-year period.

Table 5.2. UC year-by-year test comparison of the exceedances rates

Model Number	13/14	14/15	15/16	16/17	17/18	18/19	19/20	20/21	21/22	22/23
92	0.38%	1.54%	1.54%	0.77%	0.38%	1.15%	1.15%	2.31%	0.38%	0.38%
93	0.38%	1.54%	1.54%	0.77%	0.38%	1.15%	1.15%	1.92%	0.38%	0.77%
112	0.38%	1.54%	1.92%	0.77%	0.38%	1.15%	1.15%	1.92%	0.38%	0.38%

Table 5.3. UC year-by-year test comparison of the p-values

Model Number	13/14	14/15	15/16	16/17	17/18	18/19	19/20	20/21	21/22	22/23
92	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	25.44%	25.44%
93	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	69.67%
112	25.44%	41.87%	18..44%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	25.44%

The analysis ultimately highlighted Model 93 as the most robust and consistent. Based on the SGSt distribution with a sample size of 800 observations and an EWMA smoothing factor of 0.96, this model not only achieved the expected number of exceedances at the aggregate level but also maintained stable performance across individual years. When comparing the three shortlisted models in detail, Model 92 showed weaknesses during 2020/21, when it recorded more exceedances than expected, and again in 2022/23, when the coverage was insufficient. Model 112 presented similar limitations, with an excess of exceedances in 2015/16 and too few in 2022/23. Model 93 displayed a more balanced pattern across the entire horizon, avoiding the most pronounced deviations observed in the other two configurations. Although these differences were relatively small, they consistently pointed to Model 93 as the specification with the most reliable alignment to the theoretical 1% exceedance rate. In total, Model 93 produced 26 exceedances over 2600 daily observations, exactly in line with the theoretical value implied by the 99% confidence level.

This multi-step evaluation, combining UC tests with annual consistency checks, ensures that the chosen model performs well both in aggregate and through time. Although none of the configurations satisfied the BCP independence criterion, the stability and accuracy demonstrated by Model 93 under the UC test provide strong evidence for its suitability in practical risk management applications, consistent with the arguments advanced by Christoffersen (1998) and Berkowitz et al. (2011).

Chapter 6.
VaR Management

Following the statistical validation carried out in the previous chapter, the Value-at-Risk model selected for ongoing risk management is Model 93. As discussed in detail in Chapter 5.3, this specification is based on a Skewed Generalized Student-t distribution, employs an Exponentially Weighted Moving Average volatility forecast with a smoothing parameter of 0.96, and uses a rolling sample of 800 observations. Among the 320 models tested, Model 93 consistently achieved the most reliable performance under the Unconditional Coverage test, which supports its adoption as the core tool for risk monitoring and capital allocation in this portfolio.

As of 3 January 2023, the portfolio held a total market value of 8 662 989.81€. From this date through 2 February 2024, it was actively monitored and managed using the selected VaR model, which provided daily risk estimates reflecting the evolving market conditions and the portfolio's exposure to them.

To establish a clear threshold for daily risk control, the methodology relied on the average of the lower and upper terciles of the ordered distribution of VaR estimates, from 3 January 2023 to 2 February 2024. This choice avoids distortions caused by extreme values and provides a more representative measure of the portfolio’s typical risk profile. In this case, the lower tercile corresponded to approximately 133 168.78€, the upper tercile to 146 633.31€, and the resulting average to 139 901.04€, which was rounded to 140 000.00€ for communication and operational purposes.

This threshold functions as a dynamic risk control mechanism throughout the management period. When the estimated VaR remains below it, the portfolio is left unchanged, ensuring stability in exposures. If the VaR exceeds the limit, a hedging strategy is activated. This strategy identifies the risk factors that contribute most to the portfolio’s risk and reduces their impact either by adjusting positions or by offsetting exposures through derivatives such as futures. In this way the portfolio is brought back within its defined risk boundaries while preserving its strategic allocation as closely as possible. This approach provides consistent oversight while maintaining the flexibility required to respond effectively to changing market conditions.

To maintain internal consistency, any cash flows such as bond coupon payments are reinvested according to the portfolio's existing allocation. This prevents distortions in exposures and ensures that the VaR model continues to represent the actual risk profile accurately.

The remainder of this chapter explores in detail how the selected VaR model is used to monitor and manage portfolio risk. It begins by introducing the methodology for decomposing VaR into its component sources, which makes it possible to understand which assets or risk factors are driving overall exposure. It then explains the procedures that govern the implementation of the hedging strategy whenever the VaR limit is breached. Finally, the chapter compares the risk and performance characteristics of the portfolio under both managed and unmanaged conditions, assessing the effect of the risk control framework on portfolio outcomes over time.

By applying a statistically supported VaR model in a real-time risk management setting, this chapter demonstrates how theoretical risk measures can be transformed into a practical, disciplined and adaptive tool for investment management.

6.1. VaR Decomposition

To support a more targeted and transparent approach to portfolio risk management, the total Value-at-Risk is decomposed into individual contributions associated with specific risk factors. This decomposition clarifies which exposures drive portfolio risk, helping to design allocation decisions and targeted interventions.

The methodology employed relies on the concept of Marginal VaR, which quantifies the sensitivity of the portfolio's VaR to marginal changes in its underlying exposures. In practice, it measures the extent to which a marginal increase in each factor affects overall risk, assuming all other exposures remain constant.

Formally, let Θ represent the full vector of portfolio exposures and Θ_s a selected subset of those exposures. The Marginal VaR of that subset can be approximated by the following expression:

$$Marginal\ VaR_{\Theta_s} = \nabla f(\Theta)^T \times \Theta_s = \sum_{i=1}^{n} \left(\frac{\partial VaR}{\partial \theta_i} \times \theta_i^{(s)} \right) \tag{34}$$

This expression decomposes the portfolio VaR into a weighted sum of marginal contributions. The gradient vector $\nabla f(\Theta)$ contains the partial derivatives of the VaR with respect to each risk factor, showing how much total risk would change if that factor increased slightly, while the exposure $\theta_i^{(s)}$, represents how much of that risk factor is present in the portfolio. indicates the size of the position. Multiplying them gives the contribution of each factor, and summing across all exposures yields the overall VaR.

This decomposition transforms VaR from a single aggregate number into an interpretable map of its underlying sources. By identifying the most influential exposures, the framework becomes both a diagnostic tool and a practical guide for ongoing risk supervision.

In the practical application of this thesis, on 3 January 2023, the total one-day VaR of the portfolio was estimated at 197 134.75 €. Table 6.1 presents the marginal contributions of each risk factor group on that date, expressed in both monetary terms and as percentages of VaR.

Table 6.1. Marginal VaR decomposition by risk factor, as of 3 January 2023

Decomposition by risk factor group	Marginal VaR		Decomposition by risk factor type	Marginal VaR	
USDEUR	20 185.00 €	10.24%	Currency	24 940.70 €	12.65%
GBPEUR	1 358.32 €	0.69%			
JPYEUR	3 245.57 €	1.65%			
HKDEUR	151.80 €	0.08%			
GSPC	110 326.22 €	55.96%	Equity	131 979.20 €	66.95%
FTSE	7 625.43 €	3.87%			
FCHI	12 600.32 €	6.39%			
N225	705.00 €	0.36%			
HSI	722.23 €	0.37%			
IR_USD	8 812.98 €	4.47%	Interest Rate	40 214.86 €	20.40%
IR_EUR	31 401.88 €	15.93%			

The results show that equity is the dominant source of portfolio risk, accounting for 66.95% of VaR. Within this group, the S&P 500 (GSPC) is by far the most significant contributor at 55.96%, while the CAC 40 (FCHI) and the FTSE 100 (FTSE) contribute 6.39% and 3.87%, respectively. The contributions of the Nikkei 225 (N225) and the Hang Seng Index (HSI) are very small, at 0.36% and 0.37%, respectively.

Interest rate exposures together account for 20.40%, with the euro curve (IR_EUR) alone responsible for 15.93% and the U.S. dollar curve (IR_USD) for 4.47%. Currency risk represents 12.65% of VaR, primarily driven by the USD/EUR pair at 10.24%, while the GBP/EUR and JPY/EUR pairs contribute only 0.69% and 1.65%, respectively. The HKD/EUR pair is negligible at 0.08%.

Although currencies and interest rates contribute to risk, the hedging strategy focuses on equity indices. As illustrated in Figure 6.1, equities not only represent the largest share of portfolio allocation but also consistently dominate the decomposition of VaR. Index derivatives further reinforce this choice, as they provide highly liquid and cost-efficient instruments for hedging. By contrast, hedges in currencies and rates are often more costly, less precise, and less impactful on overall portfolio risk.

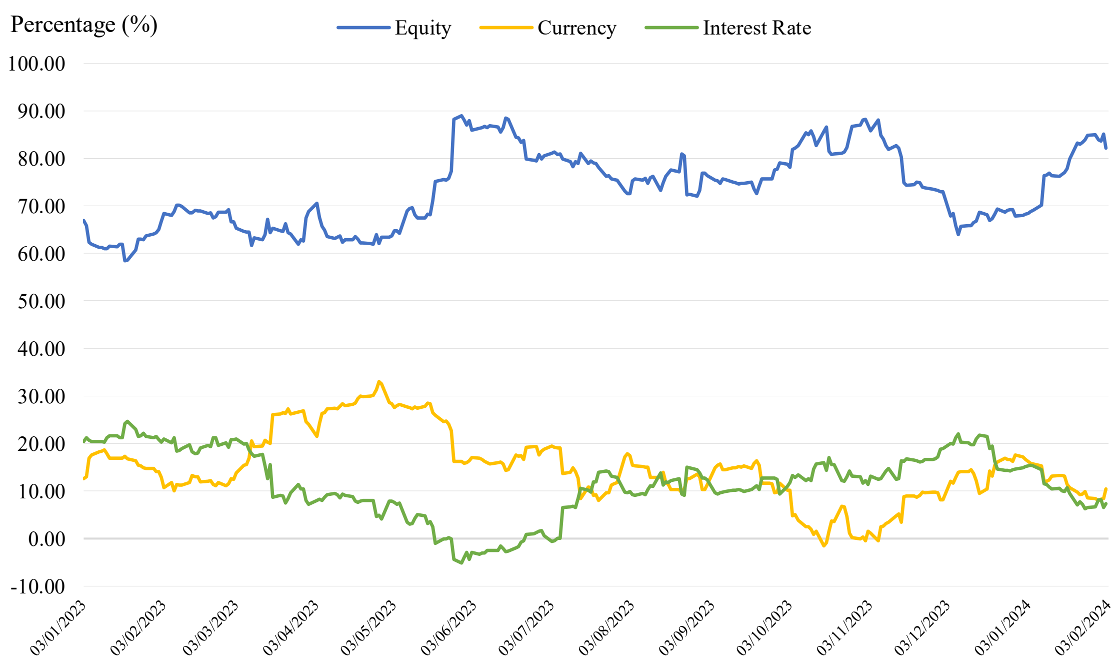

Figure 6.1. Evolution of Portfolio VaR decomposition by risk factor type for unhedged portfolio, during the observation period

Figure 6.2 shows the evolution of the marginal contributions of equity indices to overall equity VaR, highlighting how the importance of each index within equity risk changed over the observation period.

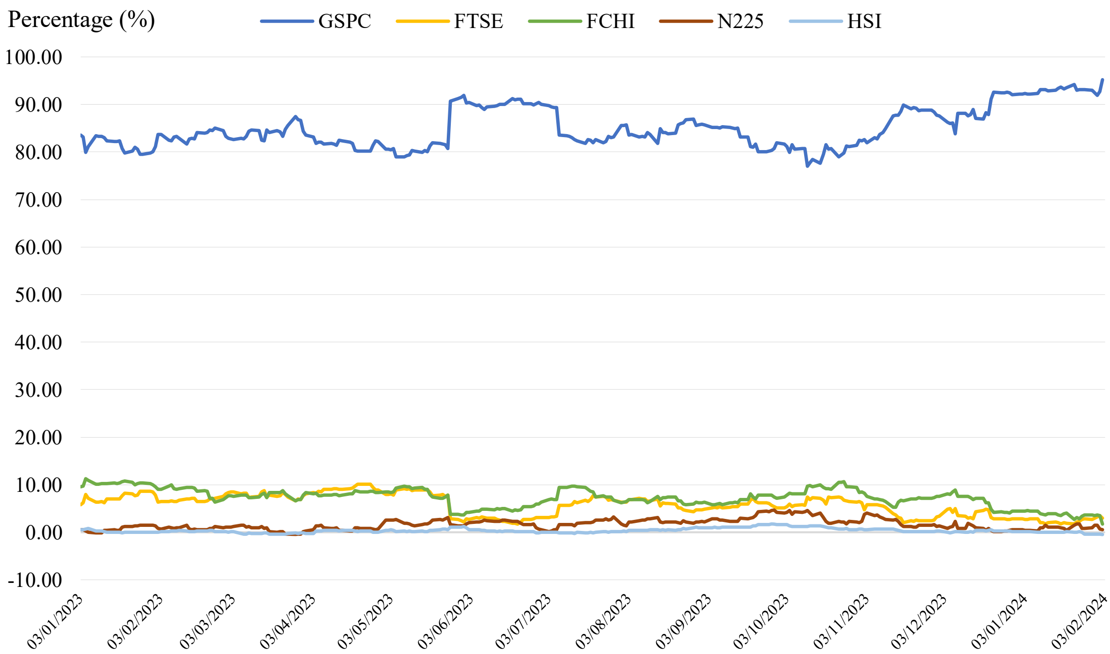

Figure 6.2. Evolution of equity indices' relative marginal contributions to equity VaR for unhedged portfolio, during the observation period

The figure confirms the persistent dominance of the S&P 500, which consistently accounts for the largest share of portfolio risk, while also displaying the most pronounced volatility over time. A notable increase is observed in late May, early June of 2023, coinciding with U.S. debt ceiling negotiations and heightened equity volatility, particularly in the technology sector. A second significant spike occurs in late October 2023, reflecting global equity market corrections linked to surging bond yields, before stabilising towards the end of the year.

Taken together, the decomposition highlights equity indices as the main drivers of portfolio risk and provides the rationale for focusing the hedging strategy on this segment, rather than on currencies or interest rates, thereby linking directly to the management approach outlined earlier in this chapter.

6.2. Comparative Analysis of Unhedged and Hedged Portfolios

The comparative analysis of the unhedged and hedged portfolios provides an opportunity to assess the extent to which active risk management can shape both performance outcomes and risk exposures.

As a first step, it is instructive to consider the evolution of the portfolio's value over the observation period. Between 3 January 2023 and 2 February 2024, the portfolio increased from 8 662 989.81€ to 10 636 504.60€, representing a cumulative return of 22.78%. While the long-term trajectory was clearly positive, the progression was not entirely linear. A sharp drawdown in late October 2023, linked to global equity market corrections caused by rising bond yields, highlighted the portfolio's sensitivity to episodes of market stress. This evolution, illustrated in Figure 6.3, reflects the progression of the portfolio in its unhedged form.

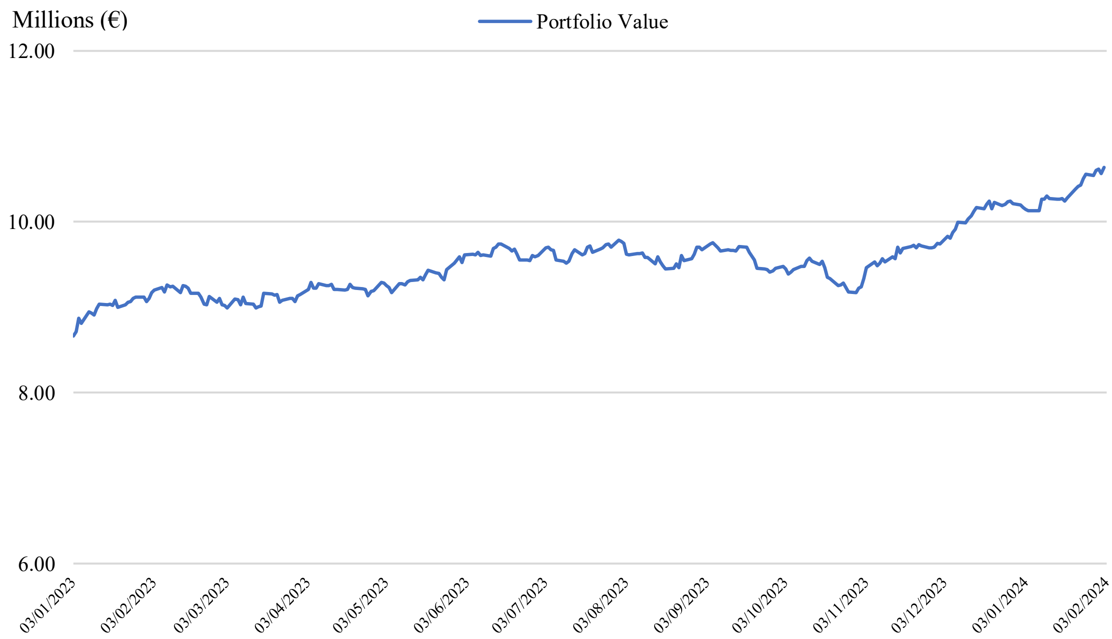

Figure 6.3. Evolution of unhedged portfolio value, during the observation period

6.2.1. Hedging Strategy

As established in Section 6.1, equity indices were identified as the main drivers of portfolio risk, with the S&P 500 standing out as the most significant single contributor. This observation provided the basis for directing the hedging strategy towards equity markets rather than currencies or interest rates, whose contributions were comparatively limited. To implement the strategy, equity index futures were chosen because of their high liquidity, transparency and cost efficiency.

The hedging mechanism was designed to translate the decomposition of VaR into concrete positions in a systematic and adaptive way. For each equity index, the gradient was first combined with the gradient of its corresponding currency pair, thereby capturing the joint sensitivity of the portfolio to both equity and currency risk. The only exception was the CAC 40, which is denominated in euros and thus required no currency adjustment. These adjusted gradients were then weighted by the relative marginal contributions of each index to overall equity risk. On 3 January 2023, for example, the S&P 500 accounted for 83.59% of equity VaR, compared with 9.55% for the CAC 40, 5.78% for the FTSE 100, and less than 1% each for the Nikkei 225 and Hang Seng Index, as shown in Figure 6.2 for the observation period.

Multiplying each adjusted gradient by its corresponding weight yielded a single aggregate gradient, which represented the overall hedging requirement for the portfolio. On 3 January 2023, this procedure resulted in a total hedging short position of 1 704 238.39€. This aggregate position was then distributed back across indices in proportion to their marginal contributions, ensuring that hedge allocations directly reflected the structure of equity risk. The S&P 500 therefore absorbed the largest share of the hedge, while the other indices received proportionally smaller allocations.

Figure 6.4 illustrates how these hedging positions evolved over the full observation period. The S&P 500 consistently dominated the hedge allocations, reflecting its central role in portfolio risk, while the FTSE 100 and CAC 40 played smaller but still relevant roles. The Nikkei 225 and HSI, though much smaller, were included to maintain coverage of all relevant exposures. The variation in hedge sizes over time highlights the adaptive nature of the approach, with adjustments reflecting changes in market conditions and in the relative contributions of each index to equity risk.

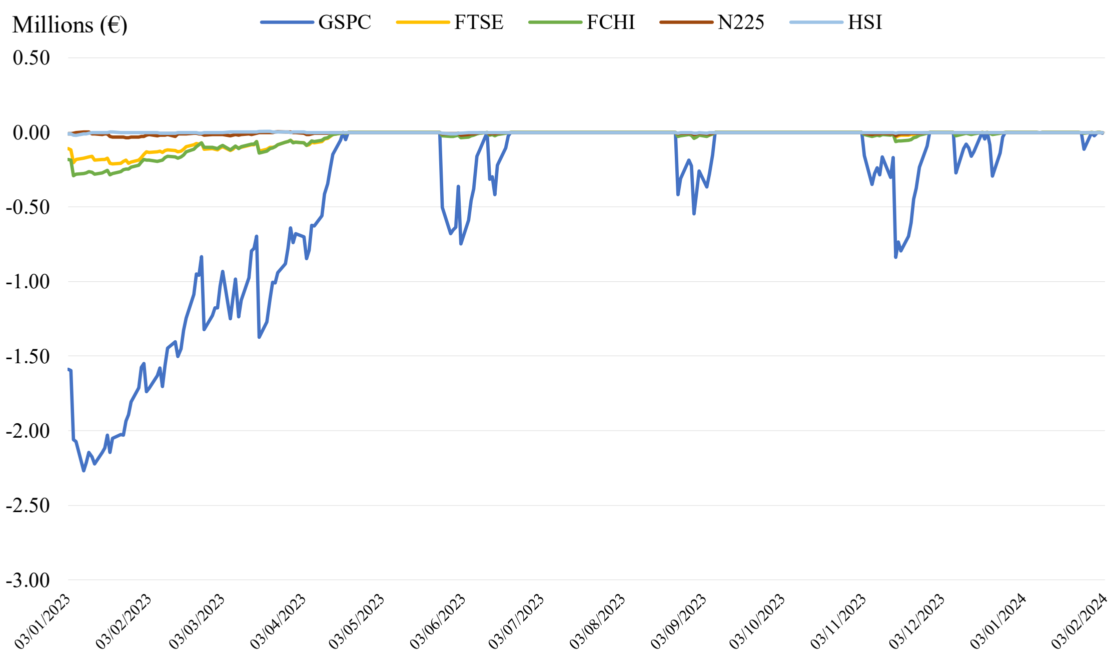

Figure 6.4. Progression of hedge positions, during the observation period

This gradient-based framework thus provided a transparent and rule-driven method for aligning hedge positions with the evolving sources of risk in the portfolio. By integrating equity and currency sensitivities and scaling allocations to marginal contributions, the strategy ensured that hedging remained consistent with the decomposition of VaR presented earlier in this chapter.

6.2.2. Value-at-Risk Progression

The comparison of Value-at-Risk across the unhedged and hedged portfolios highlights the direct impact of the hedging framework on overall risk levels. As shown in Figure 6.8, daily VaR for the unhedged portfolio remained elevated during the first months of 2023 with values consistently above the Economic Capital (EC) threshold of 140 000.00 € and reaching a maximum of 229 440.63 € on 9 January 2023. This behaviour reflects the concentration of risk identified in Section 6.1, particularly the dominant influence of the S&P 500 index. Although VaR gradually declined in the following months, the portfolio still experienced long periods above the capital tolerance. Out of the 284 trading days analysed, 136 recorded a VaR higher than the limit, most of them concentrated in the first four months of the year.

By contrast, the hedged portfolio displayed a clear reduction in overall VaR. Once the hedge was introduced, daily values were initially anchored at the 140 000.00€ threshold, creating extended periods of stability. From April 2023 onwards such episodes became less frequent, since risk levels increasingly remained below the threshold without requiring additional intervention. This pattern highlights the effectiveness of the framework in aligning risk with predefined tolerance levels while preserving the portfolio's core structure.

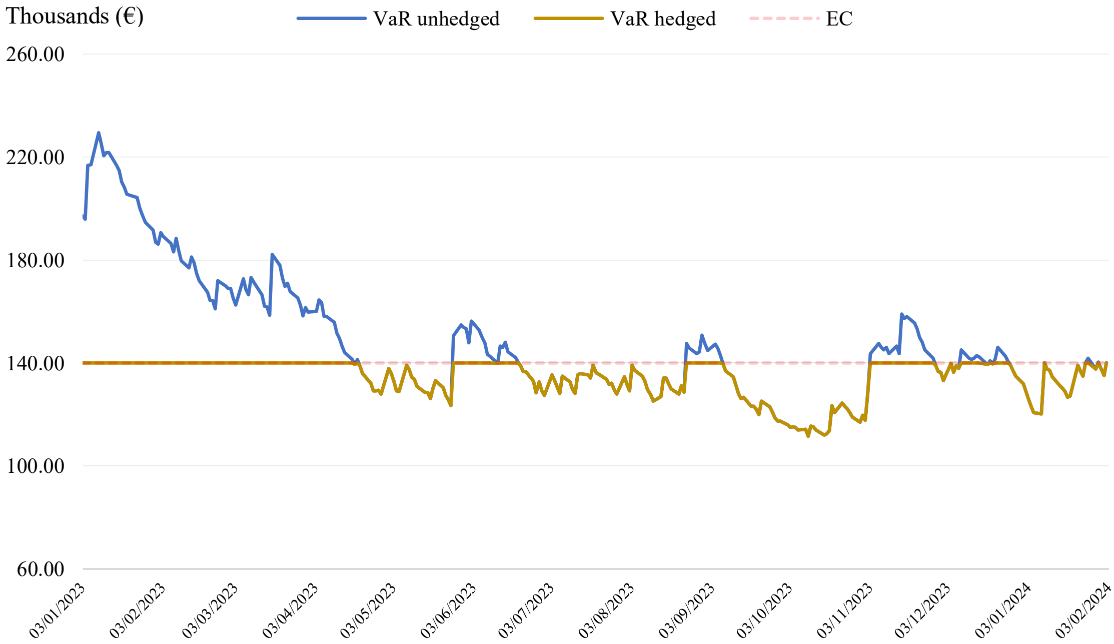

Figure 6.5. VaR progression of the unhedged and hedged portfolios, during the observation period

Taken together, these results show that hedging not only reduced the absolute level of risk but also enhanced the reliability of the risk management process by containing VaR within the boundaries set by EC. This outcome underlines the practical relevance of targeting equity indices, as identified in Section 6.1, since they were the primary drivers of the portfolio's risk.

6.2.3. Exceedances

For both the unhedged and hedged portfolios two exceedances were observed during the period of analysis. The first occurred on 2 August 2023 when portfolio losses reached 133 137.83€ against a VaR of 129 107.80€. The second was on 18 October 2023 with losses of 117 043.36€ compared with a VaR of 113 764.10.€. In both cases the VaR estimate was below the economic capital threshold of 140 000.00€, which indicates that the breaches reflected isolated tail events rather than a structural excess of risk and were consistent with the frequency expected under a 99% confidence level.

Figures 6.9 and 6.10 show these exceedances for the unhedged and hedged portfolios. The fact that the same breaches occurred in both cases illustrates two key points. First, hedging is effective in lowering overall risk, but it cannot shield the portfolio from rare extreme shocks. Second, Value-at-Risk itself has a structural limitation, as it identifies when a breach occurs but gives no indication of the possible magnitude of losses beyond the threshold.

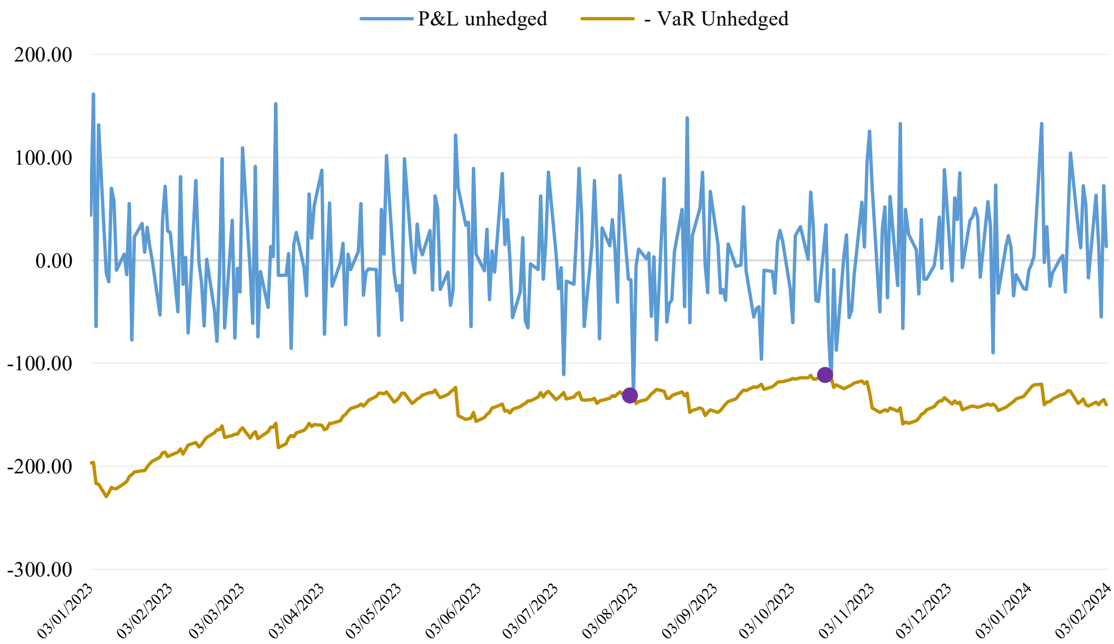

Figure 6.6. Exceedances in the unhedged portfolio, during the observation period

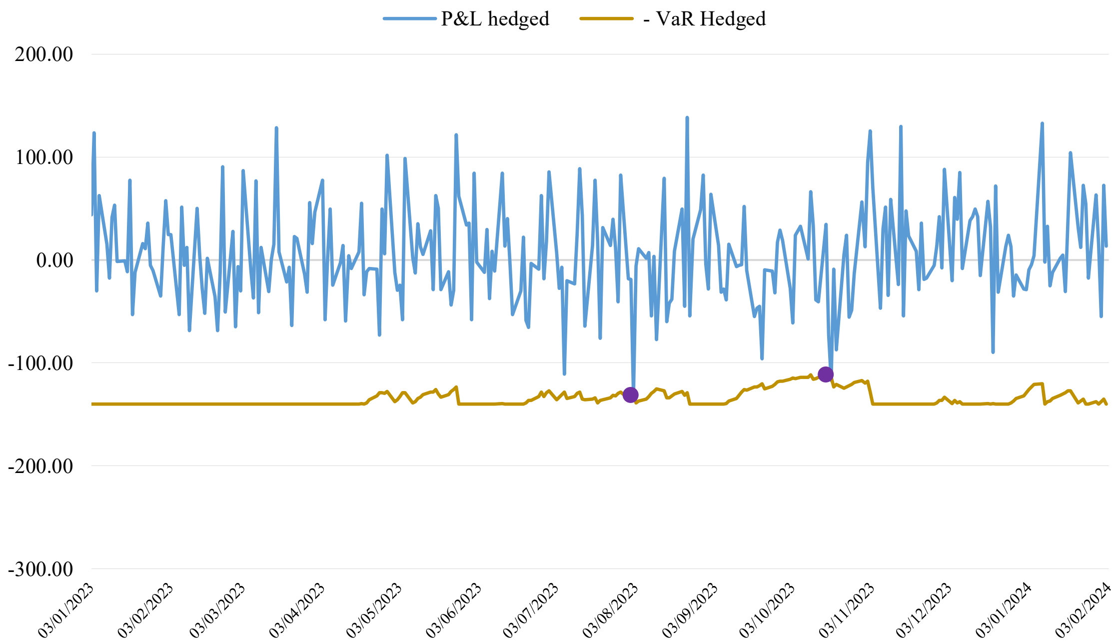

Figure 6.7. Exceedances in the hedged portfolio, during the observation period

6.2.4. Profit and Loss Dynamics

The analysis of profit and loss (P&L) dynamics provides a direct measure of the portfolio's sensitivity to market fluctuations and the practical effect of the hedging strategy. Observing the daily P&L series of both the unhedged and hedged portfolios highlights that the overall profiles follow a broadly similar trajectory, with the hedge serving to smooth out extreme variations rather than altering the fundamental trend. As shown in Figure 6.5 the unhedged portfolio recorded a maximum daily profit of 161 473.71€ on 4 January 2023 while the hedged portfolio peaked at 138 580.57€ on 23 August 2023. Both portfolios experienced their lowest daily result on 2 August 2023 with losses of 133 137.83€. These observations confirm that hedging dampened the scale of exceptional gains while offering comparable protection in adverse conditions.

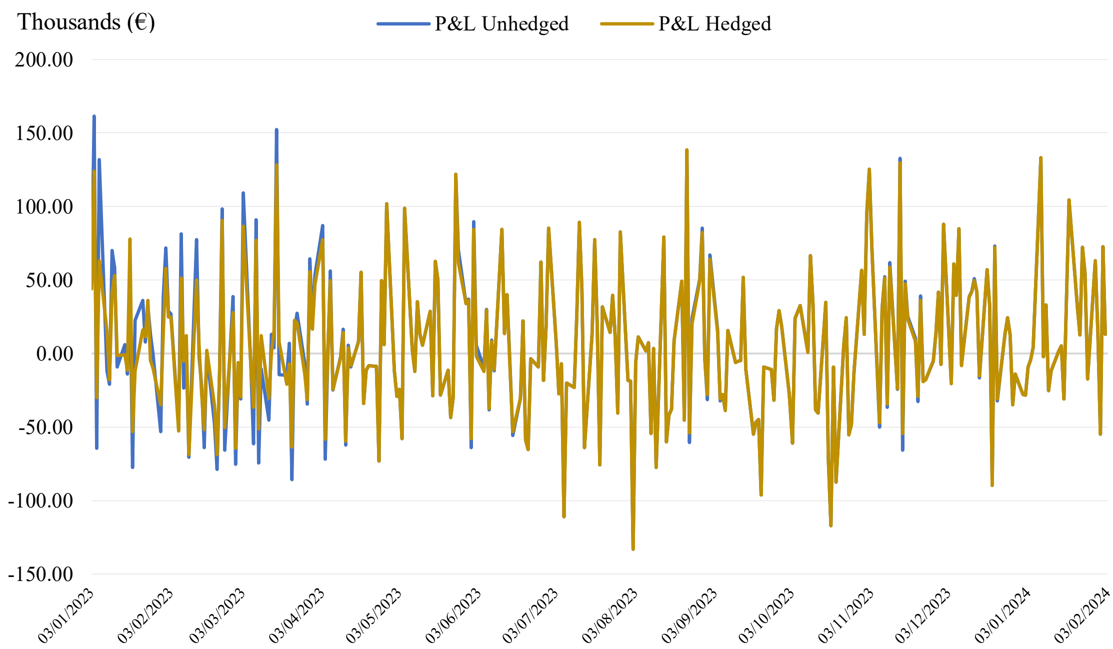

Figure 6.8. Daily P&L comparison between unhedged and hedged portfolios, during the observation period

The distribution of daily results presented in Table 6.2 reinforces this conclusion. Both the average and the median of profitable days were higher in the unhedged portfolio which reflects the hedge's role in capping gains. Conversely losses were less pronounced in the hedged portfolio which shows its function as a downside protection tool. Although the absolute effect on profitability was limited the greater balance between gains and losses indicates a more stable risk–return profile.

Table 6.2. Comparative distribution of daily P&L between unhedged and hedged portfolios

	P&L Unhedged			**P&L Hedged**		
	Positive	Negative	Total	Positive	Negative	Total
Average	44 490.89 €	-34 931.08 €	6 457.84 €	41 746.65 €	-32 714.66 €	6 089.12 €
Median	35 583.13 €	-28 581.12 €	3 169.38 €	34 389.01 €	-28 545.67 €	2 312.53 €

A complementary perspective is provided in Figure 6.6 which depicts the direct difference between the two portfolios. Over the hedging period, the largest positive difference was 34 506.87€ on 5 January 2023, while the largest negative difference reached 68 974.43€ on 6 January 2023. This shows the dual effect of hedging as it reduced profits on particularly favourable days but mitigated losses during adverse ones. The summary statistics in Table 6.3 confirm this pattern.

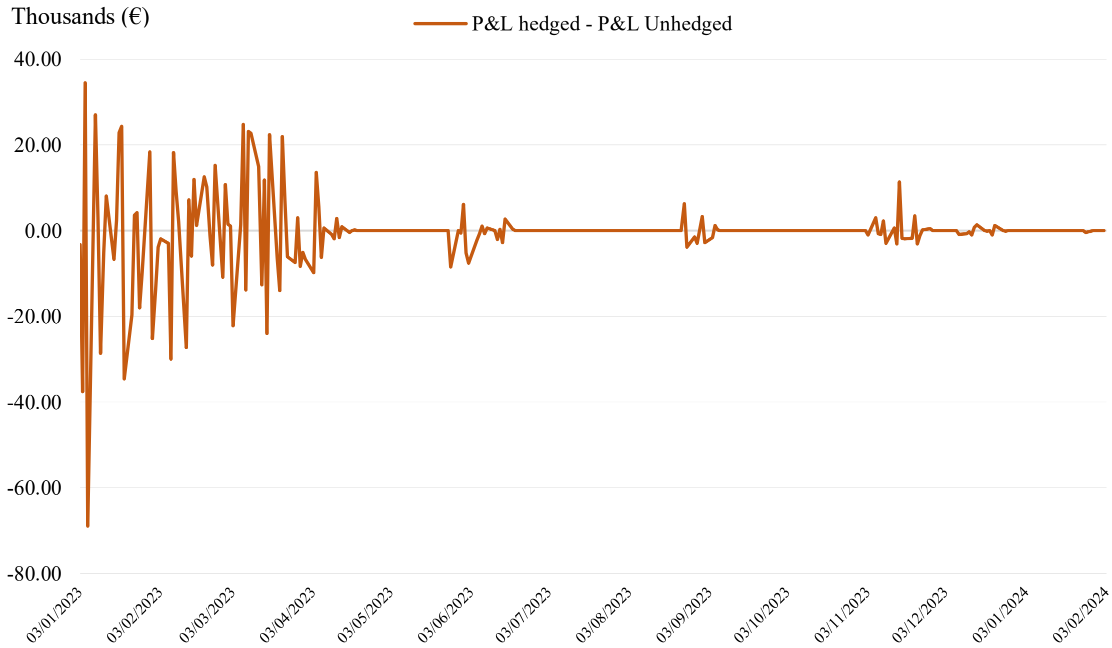

Figure 6.9. Daily P&L progression of the difference between hedged and unhedged portfolios, during the observation period

Table 6.3. Summary statistics of the difference between hedged and unhedged portfolios

	P&L positive	**P&L negative**	**Total**
Number of Occurrences	62	74	136
Average	7 642.20 €	-7 818.00 €	-769.97 €
Median	3 160.53 €	-3 061.00 €	-244.18 €
Positive difference	17.74%	68.92%	45.59%

Across the 136 hedging days analysed, the difference between the hedged and unhedged portfolios was positive on 62 days and negative on 74 days. This asymmetry shows that the hedge was not uniformly advantageous and depended on prevailing market conditions. Specifically, when the unhedged portfolio generated profits the hedge enhanced results in only 17.74% of cases. In contrast when losses occurred the hedge reduced their magnitude in 68.92% of cases. Overall, the cumulative impact was slightly negative which reflects the inherent trade-off of hedging as gains are occasionally sacrificed in exchange for protection against substantial losses.

Finally Figure 6.7 illustrates the cumulative P&L trajectories of the two portfolios and highlights this trade off. The unhedged portfolio captured stronger gains during market rallies although this came at the cost of more pronounced drawdowns during adverse periods. The hedged portfolio on the other hand displayed a smoother evolution with lower exposure to abrupt declines and ended the period with only a slightly lower cumulative result compared with the unhedged portfolio. This modest difference underscores that the primary value of the hedge lies in stabilising outcomes rather than maximising returns. Such stability is particularly valuable in risk management contexts where predictability and resilience are often prioritised over short term gains. While these observations highlight the trade-off between absolute profitability and stability a more precise assessment of the risk profile requires turning to Value at Risk and related indicators which are examined in the following sections.

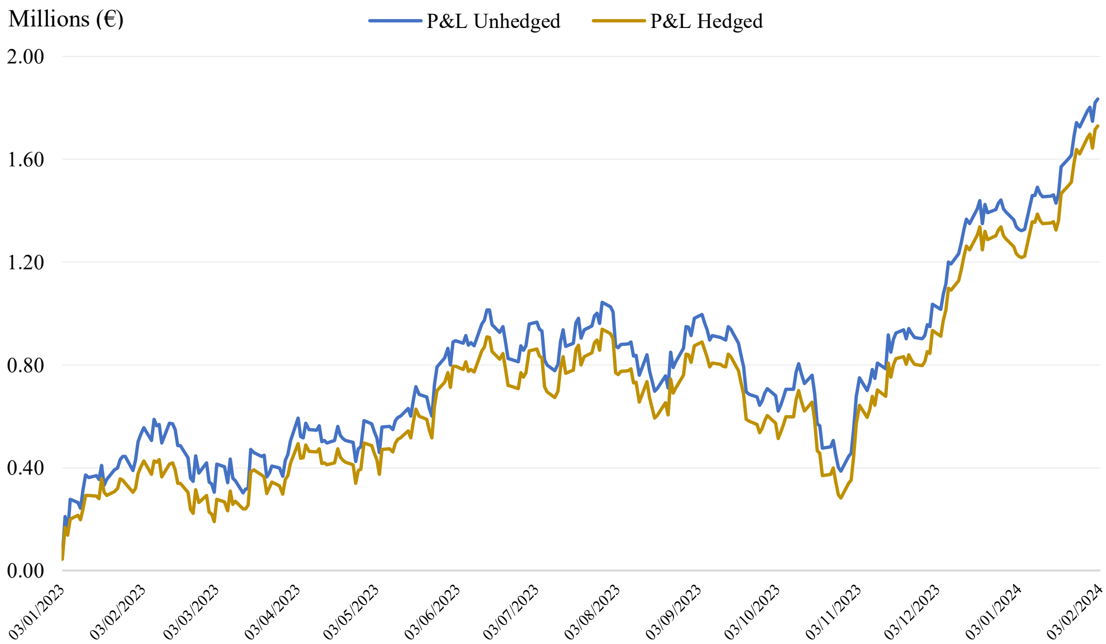

Figure 6.10. Cumulative P&L progression of unhedged and hedged portfolios, during the observation period

6.2.5. Return on Risk-Adjusted Capital

The Return on Risk-Adjusted Capital (RORAC) provides a way of assessing profitability relative to the amount of risk capital required. It shows how efficiently the portfolio generates returns for each unit of risk absorbed. Formally, it can be expressed as:

$$RORAC = \frac{P\&L}{VaR} \tag{35}$$

where $P\&L$ represents cumulative profits and losses, and VaR denotes the cumulative risk capital over the observation period. This approach allows for a direct comparison between portfolios, since it measures performance on a risk-adjusted basis rather than in absolute terms.

Table 6.4 presents the results for the unhedged and hedged portfolios. The unhedged portfolio recorded a RORAC of 4.41%, while the hedged portfolio achieved slightly higher value of 4.53%. Although the difference appears modest, it reflects a genuine improvement in efficiency since the hedge reduced the level of risk capital required without materially diminishing returns.

These findings indicate that the hedged strategy provided a more favorable balance between risk and profitability, reinforcing the role of hedging as a valuable component of portfolio management.

Table 6.4. Comparative of RORAC between unhedged and hedged portfolios, during observation period

	Unhedged	**Hedged**
P&L	1 830 766.05 €	1 729 309.74 €
VaR	41 535 467.04 €	38 193 792.14 €
RORAC	4.41%	4.53%

Chapter 7.
Conclusion

The purpose of this dissertation was to evaluate the market risk of a diversified portfolio and to understand the extent to which different Value-at-Risk methodologies can support the active management of that risk. To address this question four distinct models were considered namely the Normal model, Historical Simulation, Quantile Regression and the Skewed Generalized Student-t distribution, applied to a portfolio comprising equities and bonds from multiple regions. The analysis was carried out over a specific period, between 2013 and 2024, and structured in two stages. The first stage, from 2013 to 2023, focused on the testing and backtesting of the different models considered, while the second stage, from 2023 to 2024, was dedicated to the application of the selected SGSt model in the management of the portfolio. The results showed that approaches capable of capturing asymmetry and fat tails produced more consistent outcomes than simplified alternatives, with the SGSt proving to be the most reliable. In this final stage, the SGSt model helped identify risks and supported the adoption of hedging strategies that improved risk-adjusted results.

The findings contribute to the comparison between parametric and non-parametric VaR models in multi-asset portfolios and demonstrate that flexible approaches are especially valuable in unstable market conditions. They further reveal that diversification, although essential, does not by itself ensure a meaningful reduction of risk when markets move together, highlighting the importance of complementary tools.

Although diversified, the portfolio excluded alternative asset classes and complex instruments that could have altered the perception of overall exposure, such as commodities, real estate, derivatives and cryptocurrencies. In addition, methodological choices, including sample size, horizon of analysis and smoothing parameters, had a direct influence on the results and condition their generalisation. These constraints suggest relevant avenues for future research. Extending the analysis to longer horizons would allow for an assessment of the stability of results across different market regimes. Broadening the range of assets considered could also provide a deeper understanding of financial interconnections and emerging sources of risk. The use of methods based on artificial intelligence and machine learning offers further potential to design risk models that are more adaptive and responsive to rapidly changing conditions.

The conclusions reached emphasise that risk management should be treated as an integral part of investment strategy rather than only as a regulatory compliance exercise. The comparative use of VaR methodologies confirmed that more advanced quantitative tools not only anticipate potential losses but also provide tangible support for risk mitigation. In a financial environment defined by uncertainty and increasing interdependence, combining rigorous modelling with proactive management emerges as indispensable for ensuring stability and resilience. This dissertation therefore delivers both an academic contribution and practical insights, reinforcing the case for integrating more sophisticated VaR methodologies within modern risk management practice.

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Appendicies

Appendix A. Portfolio Composition and Data

Appendix A.1. Equities portfolio composition with complete details, as of 3 January 2025

Stock	Ticker	Currency	Ref Market	Quantity	Share Price	Exchange rate	Value	Allocation
Microsoft Corporation	MSFT	USD	GSPC	472	237.15	0.93373	104 518.96 €	1.21%
JPMorgan Chase & Co.	JPM	USD	GSPC	889	129.16	0.93373	107 213.20 €	1.24%
NVIDIA Corporation	NVDA	USD	GSPC	13511	14.46	0.93373	182 374.27 €	2.11%
Alphabet Inc.	GOOGL	USD	GSPC	1214	88.57	0.93373	100 402.16 €	1.16%
Apple Inc	AAPL	USD	GSPC	1457	126.63	0.93373	172 272.70 €	1.99%
Pfizer Inc.	PFE	USD	GSPC	2844	48.30	0.93373	128 258.74 €	1.48%
Warner Bros. Discovery, Inc.	WBD	USD	GSPC	-7305	9.51	0.93373	-64 866.74 €	-0.75%
HP Inc.	HPQ	USD	GSPC	4253	25.44	0.93373	101 010.82 €	1.17%
Citigroup Inc.	C	USD	GSPC	1997	42.71	0.93373	79 646.49 €	0.92%
Nike, Inc.	NKE	USD	GSPC	815	115.51	0.93373	87 901.98 €	1.01%
The Coca-Cola Company	KO	USD	GSPC	1587	60.39	0.93373	89 486.58 €	1.03%
Johnson & Johnson	JNJ	USD	GSPC	455	169.53	0.93373	72 022.99 €	0.83%
Advanced Micro Devices, Inc.	AMD	USD	GSPC	2150	64.39	0.93373	129 274.21 €	1.49%
First Energy Corp.	FE	USD	GSPC	2341	39.81	0.93373	87 026.00 €	1.00%
eBay Inc.	EBAY	USD	GSPC	796	40.43	0.93373	30 048.76 €	0.35%
Netflix, Inc.	NFLX	USD	GSPC	248	294.92	0.93373	68 292.01 €	0.79%
Ralph Lauren Corporation	RL	USD	GSPC	308	104.38	0.93373	30 018.90 €	0.35%
Mastercard Incorporated	MA	USD	GSPC	510	344.14	0.93373	163 879.89 €	1.89%
Starbucks Corporation	SBUX	USD	GSPC	1772	97.37	0.93373	161 111.87 €	1.86%
Exxon Mobil Corporation	XOM	USD	GSPC	564	103.86	0.93373	54 695.55 €	0.63%
Chevron Corporation	CVX	USD	GSPC	612	168.22	0.93373	96 129.62 €	1.11%
Intel Corporation	INTC	USD	GSPC	5122	25.90	0.93373	123 858.19 €	1.43%
Verizon Communications	VZ	USD	GSPC	2724	35.84	0.93373	91 170.52 €	1.05%
American Express Company	AXP	USD	GSPC	930	144.37	0.93373	125 367.35 €	1.45%
American Airlines Group Inc.	AAL	USD	GSPC	11546	12.73	0.93373	137 240.18 €	1.58%
Bank of America Corporation	BAC	USD	GSPC	3430	31.89	0.93373	102 130.89 €	1.18%
FedEx Corporation	FDX	USD	GSPC	413	170.76	0.93373	65 850.70 €	0.76%
The Goldam Sachs Group, Inc	GS	USD	GSPC	555	329.86	0.93373	170 939.99 €	1.97%
Bio-Techne Corporation	TECH	USD	GSPC	1792	82.25	0.93373	137 619.95 €	1.59%
AstraZeneca PLC	AZN.L	GBP	FTSE	7	10970.87	1.1295	86 741.18 €	1.00%
Barclays PLC	BARC.L	GBP	FTSE	668	148.75	1.1295	112 229.34 €	1.30%
BP p.l.c	BP.L	GBP	FTSE	163	447.52	1.1295	82 392.01 €	0.95%
easyJet plc	EZJ.L	GBP	FTSE	236	324.65	1.1295	86 540.12 €	1.00%
Vodafone Group Public Limited Company	VOD.L	GBP	FTSE	769	70.95	1.1295	61 629.51 €	0.71%
Burberry Group plc	BRBY.L	GBP	FTSE	36	1981.28	1.1295	80 563.00 €	0.93%
Legal & General Group Plc	LGEN.L	GBP	FTSE	89	217.26	1.1295	21 839.70 €	0.25%
BNP Paribas SA	BNP.PA	EUR	FCHI	2239	48.11	1	107 719.12 €	1.24%
Engie SA	ENGI.PA	EUR	FCHI	13358	11.24	1	150 158.25 €	1.73%
L'Oréal S.A.	OR.PA	EUR	FCHI	361	327.39	1	118 186.86 €	1.36%
L'Air Liquide S.A.	AI.PA	EUR	FCHI	546	130.71	1	71 366.29 €	0.82%
Publicis Groupe S.A.	PUB.PA	EUR	FCHI	1998	57.31	1	114 497.52 €	1.32%
Veolia Environnment SA	VIE.PA	EUR	FCHI	2796	22.89	1	63 999.06 €	0.74%
Sony Group Corporation	6758.T	JPY	N225	1517	9976.76	0.00713	107 910.76 €	1.25%
Canon Inc.	7751.T	JPY	N225	2324	2736.69	0.00713	45 347.30 €	0.52%
CyberAgent, Inc.	4751.T	JPY	N225	12459	1143.96	0.00713	101 621.23 €	1.17%
NTT DATA Group Corporation	9613.T	JPY	N225	6539	1892.69	0.00713	88 242.93 €	1.02%
Nissui Corporation	1332.T	JPY	N225	18924	520.96	0.00713	70 292.26 €	0.81%
Obayashi Corporation	1802.T	JPY	N225	8407	929.90	0.00713	55 739.75 €	0.64%
ENN Energy Holdings Limited	2688.HK	HKD	HSI	-5321	104.38	0.119631	-66 445.55 €	-0.77%
Alibaba Health Information Technology Limited	0241.HK	HKD	HSI	32644	6.65	0.119631	25 969.81 €	0.30%
CK Infrastructure Holdings Limited	1038.HK	HKD	HSI	16220	37.12	0.119631	72 019.41 €	0.83%
Total							**4 593 456.62 €**	**53.02%**

Appendix A.2. Fixed income portfolio composition with complete details, as of 3 January 2025

Bonds	Maturity	Coupons/Year	Currency	Exchange Rate	Face Value	Fair Value	Allocation
US912810FF04	15/11/2028	2	USD	0.93373	420 178.50 €	451 729.29 €	5.21%
US912810QN19	15/02/2041	2	USD	0.93373	606 924.50 €	677 806.09 €	7.82%
DE0001135176	04/01/2031	1	EUR	1	1 150 000.00 €	1 459 143.25 €	16.84%
DE0001135226	04/07/2034	1	EUR	1	500 000.00 €	620 216.11 €	7.16%
NL0015001RG8	15/01/2044	1	EUR	1	750 000.00 €	860 638.45 €	9.93%
Total						**4 069 533.18 €**	**46.98%**

Appendix B. VaR Models tested

Appendix B.1. Normal VaR Model configurations

Model Number	Model Class	EWMA Smoothing Factor
1	Normal	0.9
2	Normal	0.905
3	Normal	0.91
4	Normal	0.915
5	Normal	0.92
6	Normal	0.925
7	Normal	0.93
8	Normal	0.935
9	Normal	0.94
10	Normal	0.945
11	Normal	0.95
12	Normal	0.955
13	Normal	0.96
14	Normal	0.965
15	Normal	0.97
16	Normal	0.975
17	Normal	0.98
18	Normal	0.985
19	Normal	0.99
20	Normal	0.995

Appendix B.2. SGSt VaR Model configurations

Model Number	Model	Sample Size	EWMA Smoothing Factor
21	SGSt	200	0.9
22	SGSt	200	0.905
23	SGSt	200	0.91
24	SGSt	200	0.915
25	SGSt	200	0.92
26	SGSt	200	0.925
27	SGSt	200	0.93
28	SGSt	200	0.935
29	SGSt	200	0.94
30	SGSt	200	0.945
31	SGSt	200	0.95
32	SGSt	200	0.955
33	SGSt	200	0.96
34	SGSt	200	0.965
35	SGSt	200	0.97
36	SGSt	200	0.975
37	SGSt	200	0.98
38	SGSt	200	0.985
39	SGSt	200	0.99
40	SGSt	200	0.995
41	SGSt	400	0.9
42	SGSt	400	0.905
43	SGSt	400	0.91
44	SGSt	400	0.915
45	SGSt	400	0.92
46	SGSt	400	0.925
47	SGSt	400	0.93
48	SGSt	400	0.935
49	SGSt	400	0.94
50	SGSt	400	0.945
51	SGSt	400	0.95
52	SGSt	400	0.955
53	SGSt	400	0.96
54	SGSt	400	0.965
55	SGSt	400	0.97
56	SGSt	400	0.975
57	SGSt	400	0.98
58	SGSt	400	0.985
59	SGSt	400	0.99
60	SGSt	400	0.995
61	SGSt	600	0.9
62	SGSt	600	0.905
63	SGSt	600	0.91
64	SGSt	600	0.915
65	SGSt	600	0.92
66	SGSt	600	0.925
67	SGSt	600	0.93
68	SGSt	600	0.935
69	SGSt	600	0.94
70	SGSt	600	0.945

Remain of table continues next page.

Model Number	Model	Sample Size	EWMA Smoothing Factor
71	SGSt	600	0.95
72	SGSt	600	0.955
73	SGSt	600	0.96
74	SGSt	600	0.965
75	SGSt	600	0.97
76	SGSt	600	0.975
77	SGSt	600	0.98
78	SGSt	600	0.985
79	SGSt	600	0.99
80	SGSt	600	0.995
81	SGSt	800	0.9
82	SGSt	800	0.905
83	SGSt	800	0.91
84	SGSt	800	0.915
85	SGSt	800	0.92
86	SGSt	800	0.925
87	SGSt	800	0.93
88	SGSt	800	0.935
89	SGSt	800	0.94
90	SGSt	800	0.945
91	SGSt	800	0.95
92	SGSt	800	0.955
93	SGSt	800	0.96
94	SGSt	800	0.965
95	SGSt	800	0.97
96	SGSt	800	0.975
97	SGSt	800	0.98
98	SGSt	800	0.985
99	SGSt	800	0.99
100	SGSt	800	0.995
101	SGSt	1000	0.9
102	SGSt	1000	0.905
103	SGSt	1000	0.91
104	SGSt	1000	0.915
105	SGSt	1000	0.92
106	SGSt	1000	0.925
107	SGSt	1000	0.93
108	SGSt	1000	0.935
109	SGSt	1000	0.94
110	SGSt	1000	0.945
111	SGSt	1000	0.95
112	SGSt	1000	0.955
113	SGSt	1000	0.96
114	SGSt	1000	0.965
115	SGSt	1000	0.97
116	SGSt	1000	0.975
117	SGSt	1000	0.98
118	SGSt	1000	0.985
119	SGSt	1000	0.99
120	SGSt	1000	0.995

Appendix B.3. Historical VaR Model configurations

Model Number	Model	Sample Size	EWMA Smoothing Factor
121	Historical	200	0.9
122	Historical	200	0.905
123	Historical	200	0.91
124	Historical	200	0.915
125	Historical	200	0.92
126	Historical	200	0.925
127	Historical	200	0.93
128	Historical	200	0.935
129	Historical	200	0.94
130	Historical	200	0.945
131	Historical	200	0.95
132	Historical	200	0.955
133	Historical	200	0.96
134	Historical	200	0.965
135	Historical	200	0.97
136	Historical	200	0.975
137	Historical	200	0.98
138	Historical	200	0.985
139	Historical	200	0.99
140	Historical	200	0.995
141	Historical	400	0.9
142	Historical	400	0.905
143	Historical	400	0.91
144	Historical	400	0.915
145	Historical	400	0.92
146	Historical	400	0.925
147	Historical	400	0.93
148	Historical	400	0.935
149	Historical	400	0.94
150	Historical	400	0.945
151	Historical	400	0.95
152	Historical	400	0.955
153	Historical	400	0.96
154	Historical	400	0.965
155	Historical	400	0.97
156	Historical	400	0.975
157	Historical	400	0.98
158	Historical	400	0.985
159	Historical	400	0.99
160	Historical	400	0.995
161	Historical	600	0.9
162	Historical	600	0.905
163	Historical	600	0.91
164	Historical	600	0.915
165	Historical	600	0.92
166	Historical	600	0.925
167	Historical	600	0.93
168	Historical	600	0.935
169	Historical	600	0.94
170	Historical	600	0.945

Remain of table continues next page.

Model Number	Model	Sample Size	EWMA Smoothing Factor
171	Historical	600	0.95
172	Historical	600	0.955
173	Historical	600	0.96
174	Historical	600	0.965
175	Historical	600	0.97
176	Historical	600	0.975
177	Historical	600	0.98
178	Historical	600	0.985
179	Historical	600	0.99
180	Historical	600	0.995
181	Historical	800	0.9
182	Historical	800	0.905
183	Historical	800	0.91
184	Historical	800	0.915
185	Historical	800	0.92
186	Historical	800	0.925
187	Historical	800	0.93
188	Historical	800	0.935
189	Historical	800	0.94
190	Historical	800	0.945
191	Historical	800	0.95
192	Historical	800	0.955
193	Historical	800	0.96
194	Historical	800	0.965
195	Historical	800	0.97
196	Historical	800	0.975
197	Historical	800	0.98
198	Historical	800	0.985
199	Historical	800	0.99
200	Historical	800	0.995
201	Historical	1000	0.9
202	Historical	1000	0.905
203	Historical	1000	0.91
204	Historical	1000	0.915
205	Historical	1000	0.92
206	Historical	1000	0.925
207	Historical	1000	0.93
208	Historical	1000	0.935
209	Historical	1000	0.94
210	Historical	1000	0.945
211	Historical	1000	0.95
212	Historical	1000	0.955
213	Historical	1000	0.96
214	Historical	1000	0.965
215	Historical	1000	0.97
216	Historical	1000	0.975
217	Historical	1000	0.98
218	Historical	1000	0.985
219	Historical	1000	0.99
220	Historical	1000	0.995

Appendix B.4. QR VaR Model configurations

Model Number	Model	Sample Size	EWMA Smoothing Factor
221	QR	200	0.9
222	QR	200	0.905
223	QR	200	0.91
224	QR	200	0.915
225	QR	200	0.92
226	QR	200	0.925
227	QR	200	0.93
228	QR	200	0.935
229	QR	200	0.94
230	QR	200	0.945
231	QR	200	0.95
232	QR	200	0.955
233	QR	200	0.96
234	QR	200	0.965
235	QR	200	0.97
236	QR	200	0.975
237	QR	200	0.98
238	QR	200	0.985
239	QR	200	0.99
240	QR	200	0.995
241	QR	400	0.9
242	QR	400	0.905
243	QR	400	0.91
244	QR	400	0.915
245	QR	400	0.92
246	QR	400	0.925
247	QR	400	0.93
248	QR	400	0.935
249	QR	400	0.94
250	QR	400	0.945
251	QR	400	0.95
252	QR	400	0.955
253	QR	400	0.96
254	QR	400	0.965
255	QR	400	0.97
256	QR	400	0.975
257	QR	400	0.98
258	QR	400	0.985
259	QR	400	0.99
260	QR	400	0.995
261	QR	600	0.9
262	QR	600	0.905
263	QR	600	0.91
264	QR	600	0.915
265	QR	600	0.92
266	QR	600	0.925
267	QR	600	0.93
268	QR	600	0.935
269	QR	600	0.94
270	QR	600	0.945

Remain of table continues next page.

Model Number	Model	Sample Size	EWMA Smoothing Factor
271	QR	600	0.95
272	QR	600	0.955
273	QR	600	0.96
274	QR	600	0.965
275	QR	600	0.97
276	QR	600	0.975
277	QR	600	0.98
278	QR	600	0.985
279	QR	600	0.99
280	QR	600	0.995
281	QR	800	0.9
282	QR	800	0.905
283	QR	800	0.91
284	QR	800	0.915
285	QR	800	0.92
286	QR	800	0.925
287	QR	800	0.93
288	QR	800	0.935
289	QR	800	0.94
290	QR	800	0.945
291	QR	800	0.95
292	QR	800	0.955
293	QR	800	0.96
294	QR	800	0.965
295	QR	800	0.97
296	QR	800	0.975
297	QR	800	0.98
298	QR	800	0.985
299	QR	800	0.99
300	QR	800	0.995
301	QR	1000	0.9
302	QR	1000	0.905
303	QR	1000	0.91
304	QR	1000	0.915
305	QR	1000	0.92
306	QR	1000	0.925
307	QR	1000	0.93
308	QR	1000	0.935
309	QR	1000	0.94
310	QR	1000	0.945
311	QR	1000	0.95
312	QR	1000	0.955
313	QR	1000	0.96
314	QR	1000	0.965
315	QR	1000	0.97
316	QR	1000	0.975
317	QR	1000	0.98
318	QR	1000	0.985
319	QR	1000	0.99
320	QR	1000	0.995

Appendix C. Backtesting Results

Appendix C.1. UC tests for the Normal VaR Models

Model Number	Model	Number of Exceedances	Exceedance rate (%)	P-value (%)
1	Normal	54	2.08%	0.00%
2	Normal	54	2.08%	0.00%
3	Normal	52	2.00%	0.00%
4	Normal	52	2.00%	0.00%
5	Normal	53	2.04%	0.00%
6	Normal	51	1.96%	0.00%
7	Normal	52	2.00%	0.00%
8	Normal	51	1.96%	0.00%
9	Normal	49	1.88%	0.00%
10	Normal	50	1.92%	0.00%
11	Normal	49	1.88%	0.00%
12	Normal	48	1.85%	0.00%
13	Normal	48	1.85%	0.00%
14	Normal	47	1.81%	0.00%
15	Normal	48	1.85%	0.00%
16	Normal	45	1.73%	0.10%
17	Normal	47	1.81%	0.00%
18	Normal	49	1.88%	0.00%
19	Normal	51	1.96%	0.00%
20	Normal	57	2.19%	0.00%

Appendix C.2. UC tests for the SGSt VaR Models

Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
21	SGSt	200	49	1.88%	0.01%
22	SGSt	200	48	1.85%	0.01%
23	SGSt	200	49	1.88%	0.01%
24	SGSt	200	48	1.85%	0.01%
25	SGSt	200	47	1.81%	0.02%
26	SGSt	200	45	1.73%	0.07%
27	SGSt	200	45	1.73%	0.07%
28	SGSt	200	46	1.69%	0.12%
29	SGSt	200	44	1.69%	0.12%
30	SGSt	200	45	1.73%	0.07%
31	SGSt	200	43	1.65%	0.22%
32	SGSt	200	42	1.62%	0.38%
33	SGSt	200	41	1.58%	0.64%
34	SGSt	200	40	1.54%	1.06%
35	SGSt	200	40	1.54%	1.06%
36	SGSt	200	39	1.50%	1.70%
37	SGSt	200	37	1.42%	4.15%
38	SGSt	200	40	1.54%	1.06%
39	SGSt	200	40	1.54%	1.06%
40	SGSt	200	43	1.65%	0.22%
41	SGSt	400	42	1.62%	0.38%
42	SGSt	400	42	1.62%	0.38%
43	SGSt	400	41	1.58%	0.64%
44	SGSt	400	40	1.54%	1.06%
45	SGSt	400	39	1.50%	1.70%
46	SGSt	400	38	1.46%	2.69%
47	SGSt	400	36	1.38%	6.25%
48	SGSt	400	38	1.46%	2.69%
49	SGSt	400	37	1.42%	4.15%
50	SGSt	400	37	1.42%	4.15%
51	SGSt	400	37	1.42%	4.15%
52	SGSt	400	35	1.35%	9.20%
53	SGSt	400	33	1.27%	18.54%
54	SGSt	400	33	1.27%	18.54%
55	SGSt	400	33	1.27%	18.54%
56	SGSt	400	32	1.23%	25.37%
57	SGSt	400	29	1.12%	56.15%
58	SGSt	400	30	1.15%	44.15%
59	SGSt	400	33	1.27%	18.54%
60	SGSt	400	37	1.42%	4.15%
61	SGSt	600	37	1.42%	4.15%
62	SGSt	600	37	1.42%	4.15%
63	SGSt	600	38	1.46%	2.69%
64	SGSt	600	37	1.42%	4.15%
65	SGSt	600	36	1.38%	6.25%
66	SGSt	600	35	1.35%	9.20%
67	SGSt	600	35	1.35%	9.20%
68	SGSt	600	35	1.35%	9.20%
69	SGSt	600	34	1.31%	13.22%
70	SGSt	600	33	1.27%	18.54%

Remain of table continues next page.

Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
71	SGSt	600	33	1.27%	18.54%
72	SGSt	600	31	1.19%	33.88%
73	SGSt	600	32	1.23%	25.37%
74	SGSt	600	30	1.15%	44.15%
75	SGSt	600	30	1.15%	44.15%
76	SGSt	600	31	1.19%	33.88%
77	SGSt	600	29	1.12%	56.15%
78	SGSt	600	30	1.15%	44.15%
79	SGSt	600	34	1.31%	13.22%
80	SGSt	600	35	1.35%	9.20%
81	SGSt	800	37	1.42%	4.15%
82	SGSt	800	37	1.42%	4.15%
83	SGSt	800	36	1.38%	6.25%
84	SGSt	800	33	1.27%	18.54%
85	SGSt	800	32	1.23%	25.37%
86	SGSt	800	32	1.23%	25.37%
87	SGSt	800	30	1.15%	44.15%
88	SGSt	800	30	1.15%	44.15%
89	SGSt	800	29	1.12%	56.15%
90	SGSt	800	28	1.08%	69.70%
91	SGSt	800	27	1.04%	84.47%
92	SGSt	800	26	1.00%	100.00%
93	SGSt	800	26	1.00%	100.00%
94	SGSt	800	28	1.08%	69.70%
95	SGSt	800	28	1.08%	69.70%
96	SGSt	800	28	1.08%	69.70%
97	SGSt	800	27	1.04%	84.47%
98	SGSt	800	27	1.04%	84.47%
99	SGSt	800	34	1.31%	13.22%
100	SGSt	800	36	1.38%	6.25%
101	SGSt	1000	34	1.31%	13.22%
102	SGSt	1000	34	1.31%	13.22%
103	SGSt	1000	30	1.15%	44.15%
104	SGSt	1000	29	1.12%	56.15%
105	SGSt	1000	30	1.15%	44.15%
106	SGSt	1000	29	1.35%	9.20%
107	SGSt	1000	29	1.12%	56.15%
108	SGSt	1000	29	1.12%	56.15%
109	SGSt	1000	29	1.12%	56.15%
110	SGSt	1000	31	1.19%	33.88%
111	SGSt	1000	28	1.08%	69.70%
112	SGSt	1000	26	1.00%	100.00%
113	SGSt	1000	25	0.96%	84.28%
114	SGSt	1000	25	0.96%	84.28%
115	SGSt	1000	25	0.96%	84.28%
116	SGSt	1000	26	1.00%	100.00%
117	SGSt	1000	25	0.96%	84.28%
118	SGSt	1000	27	1.04%	84.47%
119	SGSt	1000	27	1.04%	84.47%
120	SGSt	1000	34	1.31%	13.22%

Appendix C.3. UC tests for the Historical VaR Models

Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
121	Historical	200	42	1.62%	0.38%
122	Historical	200	40	1.54%	1.06%
123	Historical	200	40	1.54%	1.06%
124	Historical	200	40	1.54%	1.06%
125	Historical	200	40	1.54%	1.06%
126	Historical	200	40	1.54%	1.06%
127	Historical	200	38	1.46%	2.69%
128	Historical	200	37	1.42%	4.15%
129	Historical	200	37	1.42%	4.15%
130	Historical	200	37	1.42%	4.15%
131	Historical	200	36	1.38%	6.25%
132	Historical	200	35	1.35%	9.20%
133	Historical	200	37	1.42%	4.15%
134	Historical	200	37	1.42%	4.15%
135	Historical	200	37	1.42%	4.15%
136	Historical	200	36	1.38%	6.25%
137	Historical	200	36	1.38%	6.25%
138	Historical	200	37	1.42%	4.15%
139	Historical	200	38	1.46%	2.69%
140	Historical	200	48	1.85%	0.01%
141	Historical	400	38	1.46%	2.69%
142	Historical	400	37	1.42%	4.15%
143	Historical	400	37	1.42%	4.15%
144	Historical	400	37	1.42%	4.15%
145	Historical	400	37	1.42%	4.15%
146	Historical	400	37	1.42%	4.15%
147	Historical	400	34	1.31%	13.22%
148	Historical	400	34	1.31%	13.22%
149	Historical	400	33	1.27%	18.54%
150	Historical	400	34	1.31%	13.22%
151	Historical	400	33	1.27%	18.54%
152	Historical	400	33	1.27%	18.54%
153	Historical	400	34	1.31%	13.22%
154	Historical	400	34	1.31%	13.22%
155	Historical	400	36	1.38%	6.25%
156	Historical	400	36	1.38%	6.25%
157	Historical	400	43	1.65%	0.22%
158	Historical	400	46	1.77%	0.04%
159	Historical	400	50	1.92%	0.00%
160	Historical	400	48	1.85%	0.01%
161	Historical	600	33	1.27%	18.54%
162	Historical	600	32	1.23%	25.37%
163	Historical	600	31	1.19%	33.88%
164	Historical	600	32	1.23%	25.37%
165	Historical	600	32	1.23%	25.37%
166	Historical	600	33	1.27%	18.54%
167	Historical	600	32	1.23%	25.37%
168	Historical	600	30	1.15%	44.15%
169	Historical	600	29	1.12%	56.15%
170	Historical	600	31	1.19%	33.88%

Remain of table continues next page.

Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
171	Historical	600	31	1.19%	33.88%
172	Historical	600	31	1.19%	33.88%
173	Historical	600	30	1.15%	44.15%
174	Historical	600	29	1.12%	56.15%
175	Historical	600	29	1.12%	56.15%
176	Historical	600	29	1.12%	56.15%
177	Historical	600	31	1.19%	33.88%
178	Historical	600	32	1.23%	25.37%
179	Historical	600	33	1.27%	18.54%
180	Historical	600	36	1.38%	6.25%
181	Historical	800	66	2.54%	0.00%
182	Historical	800	63	2.42%	0.00%
183	Historical	800	59	2.27%	0.00%
184	Historical	800	58	2.23%	0.00%
185	Historical	800	54	2.08%	0.00%
186	Historical	800	53	2.04%	0.00%
187	Historical	800	51	1.96%	0.00%
188	Historical	800	51	1.96%	0.00%
189	Historical	800	50	1.92%	0.00%
190	Historical	800	48	1.85%	0.01%
191	Historical	800	46	1.77%	0.04%
192	Historical	800	46	1.77%	0.04%
193	Historical	800	44	1.69%	0.12%
194	Historical	800	39	1.50%	1.70%
195	Historical	800	34	1.31%	13.22%
196	Historical	800	33	1.27%	18.54%
197	Historical	800	32	1.23%	25.37%
198	Historical	800	32	1.23%	25.37%
199	Historical	800	31	1.19%	33.88%
200	Historical	800	35	1.35%	9.20%
201	Historical	1000	68	2.62%	0.00%
202	Historical	1000	65	2.50%	0.00%
203	Historical	1000	60	2.31%	0.00%
204	Historical	1000	58	2.23%	0.00%
205	Historical	1000	58	2.23%	0.00%
206	Historical	1000	53	2.04%	0.00%
207	Historical	1000	53	2.04%	0.00%
208	Historical	1000	52	2.00%	0.00%
209	Historical	1000	51	1.96%	0.00%
210	Historical	1000	48	1.85%	0.01%
211	Historical	1000	47	1.81%	0.02%
212	Historical	1000	46	1.77%	0.04%
213	Historical	1000	42	1.62%	0.38%
214	Historical	1000	40	1.54%	1.06%
215	Historical	1000	35	1.35%	9.20%
216	Historical	1000	34	1.31%	13.22%
217	Historical	1000	32	1.23%	25.37%
218	Historical	1000	33	1.27%	18.54%
219	Historical	1000	34	1.31%	13.22%
220	Historical	1000	35	1.35%	9.20%

Appendix C.4. UC tests for the QR VaR Models

Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
221	QR	200	43	1.65%	0.22%
222	QR	200	40	1.54%	1.06%
223	QR	200	40	1.54%	1.06%
224	QR	200	41	1.58%	0.64%
225	QR	200	41	1.58%	0.64%
226	QR	200	41	1.58%	0.64%
227	QR	200	40	1.54%	1.06%
228	QR	200	39	1.50%	1.70%
229	QR	200	40	1.54%	1.06%
230	QR	200	41	1.58%	0.64%
231	QR	200	40	1.54%	1.06%
232	QR	200	38	1.46%	2.69%
233	QR	200	39	1.50%	1.70%
234	QR	200	39	1.50%	1.70%
235	QR	200	41	1.58%	0.64%
236	QR	200	39	1.50%	1.70%
237	QR	200	39	1.50%	1.70%
238	QR	200	40	1.54%	1.06%
239	QR	200	43	1.65%	0.22%
240	QR	200	54	2.08%	0.00%
241	QR	400	37	1.42%	4.15%
242	QR	400	37	1.42%	4.15%
243	QR	400	37	1.42%	4.15%
244	QR	400	36	1.38%	6.25%
245	QR	400	36	1.38%	6.25%
246	QR	400	36	1.38%	6.25%
247	QR	400	35	1.35%	9.20%
248	QR	400	34	1.31%	13.22%
249	QR	400	34	1.31%	13.22%
250	QR	400	34	1.31%	13.22%
251	QR	400	34	1.31%	13.22%
252	QR	400	33	1.27%	18.54%
253	QR	400	33	1.27%	18.54%
254	QR	400	35	1.35%	9.20%
255	QR	400	38	1.46%	2.69%
256	QR	400	40	1.54%	1.06%
257	QR	400	47	1.81%	0.02%
258	QR	400	48	1.85%	0.01%
259	QR	400	52	2.00%	0.00%
260	QR	400	49	1.88%	0.01%
261	QR	600	34	1.31%	13.22%
262	QR	600	35	1.35%	9.20%
263	QR	600	33	1.27%	18.54%
264	QR	600	34	1.31%	13.22%
265	QR	600	33	1.27%	18.54%
266	QR	600	34	1.31%	13.22%
267	QR	600	33	1.27%	18.54%
268	QR	600	31	1.19%	33.88%
269	QR	600	31	1.19%	33.88%
270	QR	600	31	1.19%	33.88%

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Model Number	Model	Sample Size	Number of Exceedances	Exceedance rate (%)	P-value (%)
271	QR	600	31	1.19%	33.88%
272	QR	600	31	1.19%	33.88%
273	QR	600	30	1.15%	44.15%
274	QR	600	30	1.15%	44.15%
275	QR	600	31	1.19%	33.88%
276	QR	600	32	1.23%	25.37%
277	QR	600	34	1.31%	13.22%
278	QR	600	33	1.27%	18.54%
279	QR	600	35	1.35%	9.20%
280	QR	600	38	1.46%	2.69%
281	QR	800	33	1.27%	18.54%
282	QR	800	34	1.31%	13.22%
283	QR	800	33	1.27%	18.54%
284	QR	800	33	1.27%	18.54%
285	QR	800	33	1.27%	18.54%
286	QR	800	32	1.23%	25.37%
287	QR	800	34	1.31%	13.22%
288	QR	800	34	1.31%	13.22%
289	QR	800	33	1.27%	18.54%
290	QR	800	33	1.27%	18.54%
291	QR	800	31	1.19%	33.88%
292	QR	800	31	1.19%	33.88%
293	QR	800	29	1.12%	56.15%
294	QR	800	30	1.15%	44.15%
295	QR	800	30	1.15%	44.15%
296	QR	800	30	1.15%	44.15%
297	QR	800	33	1.27%	18.54%
298	QR	800	33	1.27%	18.54%
299	QR	800	37	1.42%	4.15%
300	QR	800	39	1.50%	1.70%
301	QR	1000	31	1.19%	33.88%
302	QR	1000	31	1.19%	33.88%
303	QR	1000	31	1.19%	33.88%
304	QR	1000	31	1.19%	33.88%
305	QR	1000	31	1.19%	33.88%
306	QR	1000	32	1.23%	25.37%
307	QR	1000	32	1.23%	25.37%
308	QR	1000	32	1.23%	25.37%
309	QR	1000	33	1.27%	18.54%
310	QR	1000	33	1.27%	18.54%
311	QR	1000	33	1.27%	18.54%
312	QR	1000	32	1.23%	25.37%
313	QR	1000	31	1.19%	33.88%
314	QR	1000	31	1.19%	33.88%
315	QR	1000	30	1.15%	44.15%
316	QR	1000	31	1.19%	33.88%
317	QR	1000	33	1.27%	18.54%
318	QR	1000	33	1.27%	18.54%
319	QR	1000	38	1.46%	2.69%
320	QR	1000	36	1.38%	6.25%

Appendix C.5. BCP tests for the Normal VaR Models

Model Number	Model	Worst p-value (%)	Lags
1	Normal	0.00%	3
2	Normal	0.00%	3
3	Normal	0.00%	3
4	Normal	0.00%	3
5	Normal	0.00%	3
6	Normal	0.00%	3
7	Normal	0.00%	3
8	Normal	0.00%	3
9	Normal	0.00%	3
10	Normal	0.00%	3
11	Normal	0.00%	3
12	Normal	0.00%	3
13	Normal	0.00%	3
14	Normal	0.00%	3
15	Normal	0.00%	5
16	Normal	0.10%	10
17	Normal	0.00%	10
18	Normal	0.00%	10
19	Normal	0.00%	10
20	Normal	0.00%	10

Appendix C.6. BCP tests for the SGSt VaR Models

Model Number	Model	Worst p-value (%)	Lags
21	SGSt	0.78%	2
22	SGSt	0.53%	2
23	SGSt	0.04%	2
24	SGSt	0.02%	2
25	SGSt	0.01%	2
26	SGSt	0.00%	2
27	SGSt	0.00%	2
28	SGSt	0.00%	2
29	SGSt	0.00%	2
30	SGSt	0.00%	2
31	SGSt	0.00%	2
32	SGSt	0.00%	2
33	SGSt	0.00%	2
34	SGSt	0.00%	2
35	SGSt	0.00%	2
36	SGSt	0.00%	3
37	SGSt	0.00%	10
38	SGSt	0.00%	10
39	SGSt	0.00%	10
40	SGSt	0.00%	10
41	SGSt	0.42%	1
42	SGSt	0.42%	1
43	SGSt	0.28%	2
44	SGSt	0.17%	2
45	SGSt	0.10%	2
46	SGSt	0.06%	2
47	SGSt	3.10%	1
48	SGSt	0.06%	2
49	SGSt	0.03%	2
50	SGSt	0.03%	2
51	SGSt	0.01%	3
52	SGSt	0.00%	3
53	SGSt	0.00%	3
54	SGSt	0.00%	3
55	SGSt	0.00%	10
56	SGSt	0.00%	10
57	SGSt	0.00%	10
58	SGSt	0.00%	10
59	SGSt	0.00%	10
60	SGSt	0.00%	10
61	SGSt	0.05%	1
62	SGSt	0.05%	1
63	SGSt	0.09%	1
64	SGSt	0.05%	1
65	SGSt	0.03%	1
66	SGSt	0.01%	2
67	SGSt	0.01%	2
68	SGSt	0.00%	2
69	SGSt	0.00%	2
70	SGSt	0.00%	3

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Model Number	Model	Worst p-value (%)	Lags
71	SGSt	0.00%	3
72	SGSt	0.00%	3
73	SGSt	0.00%	10
74	SGSt	0.00%	10
75	SGSt	0.00%	10
76	SGSt	0.00%	10
77	SGSt	0.00%	10
78	SGSt	0.00%	10
79	SGSt	0.00%	10
80	SGSt	0.00%	10
81	SGSt	3.93%	1
82	SGSt	3.93%	1
83	SGSt	3.10%	1
84	SGSt	1.33%	1
85	SGSt	0.95%	1
86	SGSt	0.95%	1
87	SGSt	0.44%	1
88	SGSt	0.03%	2
89	SGSt	0.00%	2
90	SGSt	0.00%	3
91	SGSt	0.00%	3
92	SGSt	0.00%	10
93	SGSt	0.00%	10
94	SGSt	0.00%	10
95	SGSt	0.00%	10
96	SGSt	0.00%	10
97	SGSt	0.00%	10
98	SGSt	0.00%	10
99	SGSt	0.00%	10
100	SGSt	0.00%	10
101	SGSt	1.80%	1
102	SGSt	1.80%	1
103	SGSt	0.44%	1
104	SGSt	0.29%	1
105	SGSt	0.44%	1
106	SGSt	0.01%	2
107	SGSt	0.29%	1
108	SGSt	0.29%	1
109	SGSt	0.00%	1
110	SGSt	0.00%	3
111	SGSt	0.00%	3
112	SGSt	0.00%	3
113	SGSt	0.00%	10
114	SGSt	0.00%	10
115	SGSt	0.00%	10
116	SGSt	0.00%	10
117	SGSt	0.00%	10
118	SGSt	0.00%	10
119	SGSt	0.00%	10
120	SGSt	0.00%	10

Appendix C.7. BCP tests for the Historical VaR Models

Model Number	Model	Worst p-value (%)	Lags
121	Historical	0.42%	1
122	Historical	0.17%	2
123	Historical	0.17%	2
124	Historical	0.17%	2
125	Historical	0.17%	2
126	Historical	0.00%	1
127	Historical	0.00%	2
128	Historical	0.00%	2
129	Historical	0.00%	2
130	Historical	0.00%	2
131	Historical	0.00%	2
132	Historical	0.00%	2
133	Historical	0.00%	2
134	Historical	0.00%	2
135	Historical	0.00%	2
136	Historical	0.00%	2
137	Historical	0.00%	2
138	Historical	0.00%	3
139	Historical	0.00%	3
140	Historical	0.00%	9
141	Historical	0.06%	2
142	Historical	0.03%	2
143	Historical	0.03%	2
144	Historical	0.00%	2
145	Historical	0.00%	2
146	Historical	0.00%	2
147	Historical	0.00%	2
148	Historical	0.00%	2
149	Historical	0.00%	2
150	Historical	0.00%	2
151	Historical	0.00%	2
152	Historical	0.00%	2
153	Historical	0.00%	3
154	Historical	0.00%	3
155	Historical	0.01%	3
156	Historical	0.03%	1
157	Historical	0.00%	10
158	Historical	0.00%	9
159	Historical	0.00%	9
160	Historical	0.00%	9
161	Historical	0.01%	1
162	Historical	0.00%	1
163	Historical	0.00%	1
164	Historical	0.00%	1
165	Historical	0.00%	1
166	Historical	0.00%	2
167	Historical	0.00%	2
168	Historical	0.00%	2
169	Historical	0.00%	2
170	Historical	0.00%	3

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Model Number	Model	Worst p-value (%)	Lags
171	Historical	0.00%	3
172	Historical	0.00%	3
173	Historical	0.00%	3
174	Historical	0.00%	10
175	Historical	0.00%	10
176	Historical	0.00%	10
177	Historical	0.00%	10
178	Historical	0.00%	10
179	Historical	0.00%	10
180	Historical	0.00%	10
181	Historical	0.33%	3
182	Historical	0.08%	3
183	Historical	0.01%	3
184	Historical	0.00%	3
185	Historical	0.00%	3
186	Historical	0.00%	3
187	Historical	0.00%	3
188	Historical	0.00%	3
189	Historical	0.00%	3
190	Historical	0.00%	3
191	Historical	0.00%	3
192	Historical	0.00%	3
193	Historical	0.00%	3
194	Historical	0.00%	3
195	Historical	0.00%	10
196	Historical	0.00%	10
197	Historical	0.00%	10
198	Historical	0.00%	10
199	Historical	0.00%	10
200	Historical	0.00%	10
201	Historical	0.73%	3
202	Historical	0.21%	3
203	Historical	0.01%	3
204	Historical	0.02%	2
205	Historical	0.02%	2
206	Historical	0.00%	3
207	Historical	0.00%	3
208	Historical	0.00%	3
209	Historical	0.00%	3
210	Historical	0.00%	3
211	Historical	0.00%	3
212	Historical	0.00%	3
213	Historical	0.00%	3
214	Historical	0.00%	3
215	Historical	0.00%	3
216	Historical	0.00%	3
217	Historical	0.00%	7
218	Historical	0.00%	10
219	Historical	0.00%	10
220	Historical	0.00%	10

Appendix C.8. BCP tests for the QR VaR Models

Model Number	Model	Worst p-value (%)	Lags
221	QR	0.05%	2
222	QR	0.01%	2
223	QR	0.01%	2
224	QR	0.00%	2
225	QR	0.00%	2
226	QR	0.00%	2
227	QR	0.00%	2
228	QR	0.00%	2
229	QR	0.00%	2
230	QR	0.00%	2
231	QR	0.00%	2
232	QR	0.00%	2
233	QR	0.00%	3
234	QR	0.00%	3
235	QR	0.00%	3
236	QR	0.00%	3
237	QR	0.00%	2
238	QR	0.00%	3
239	QR	0.00%	3
240	QR	0.00%	9
241	QR	0.03%	2
242	QR	0.00%	2
243	QR	0.00%	2
244	QR	0.00%	2
245	QR	0.00%	2
246	QR	0.00%	2
247	QR	0.00%	2
248	QR	0.00%	2
249	QR	0.00%	3
250	QR	0.00%	3
251	QR	0.00%	3
252	QR	0.00%	3
253	QR	0.00%	3
254	QR	0.00%	3
255	QR	0.00%	3
256	QR	0.00%	3
257	QR	0.00%	10
258	QR	0.00%	9
259	QR	0.00%	10
260	QR	0.00%	9
261	QR	0.01%	3
262	QR	0.00%	3
263	QR	0.00%	3
264	QR	0.00%	3
265	QR	0.00%	1
266	QR	0.00%	3
267	QR	0.00%	3
268	QR	0.00%	3
269	QR	0.00%	3
270	QR	0.00%	3

Remain of table continues next page.

Model Number	Model	Worst p-value (%)	Lags
271	QR	0.00%	3
272	QR	0.00%	3
273	QR	0.00%	3
274	QR	0.00%	10
275	QR	0.00%	10
276	QR	0.00%	10
277	QR	0.00%	10
278	QR	0.00%	10
279	QR	0.00%	10
280	QR	0.00%	10
281	QR	1.33%	1
282	QR	0.37%	2
283	QR	0.00%	2
284	QR	0.00%	2
285	QR	0.00%	2
286	QR	0.00%	2
287	QR	0.00%	3
288	QR	0.00%	3
289	QR	0.00%	3
290	QR	0.00%	3
291	QR	0.00%	3
292	QR	0.00%	3
293	QR	0.00%	3
294	QR	0.00%	3
295	QR	0.00%	10
296	QR	0.00%	10
297	QR	0.00%	10
298	QR	0.00%	10
299	QR	0.00%	10
300	QR	0.00%	10
301	QR	0.66%	1
302	QR	0.66%	1
303	QR	0.00%	1
304	QR	0.00%	1
305	QR	0.00%	1
306	QR	0.00%	2
307	QR	0.00%	2
308	QR	0.00%	2
309	QR	0.00%	3
310	QR	0.00%	3
311	QR	0.00%	3
312	QR	0.00%	3
313	QR	0.00%	3
314	QR	0.00%	3
315	QR	0.00%	3
316	QR	0.00%	7
317	QR	0.00%	10
318	QR	0.00%	10
319	QR	0.00%	10
320	QR	0.00%	7

Appendix C.9. UC year-by-year tests for the SGSt VaR Models

Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
47	SGSt	80.77%	41.87%	41.87%	69.67%	25.44%	80.77%	41.87%	18.44%	2.34%	80.77%	9
52	SGSt	80.77%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	18.44%	80.77%	10
53	SGSt	69.67%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	18.44%	80.77%	10
54	SGSt	69.67%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	41.87%	80.77%	10
55	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	41.87%	80.77%	10
56	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	41.87%	80.77%	10
57	SGSt	25.44%	7.01%	80.77%	69.67%	25.44%	80.77%	80.77%	7.01%	25.44%	80.77%	10
58	SGSt	25.44%	7.01%	80.77%	69.67%	25.44%	41.87%	69.67%	7.01%	2.22%	18.44%	9
59	SGSt	25.44%	41.87%	80.77%	69.67%	25.44%	18.44%	69.67%	2.34%	2.22%	0.69%	7
65	SGSt	69.67%	41.87%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	41.87%	41.87%	10
66	SGSt	25.44%	18.44%	18.44%	69.67%	25.44%	80.77%	18.44%	18.44%	41.87%	41.87%	10
67	SGSt	25.44%	18.44%	18.44%	69.67%	25.44%	80.77%	18.44%	18.44%	41.87%	41.87%	10
68	SGSt	25.44%	18.44%	18.44%	69.67%	25.44%	41.87%	41.87%	18.44%	41.87%	41.87%	10
69	SGSt	25.44%	18.44%	18.44%	69.67%	25.44%	41.87%	41.87%	18.44%	80.77%	41.87%	10
70	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	41.87%	80.77%	7.01%	80.77%	41.87%	10
71	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	41.87%	80.77%	7.01%	80.77%	41.87%	10
72	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	41.87%	80.77%	7.01%	69.67%	80.77%	10
73	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	41.87%	80.77%	7.01%	69.67%	80.77%	10
74	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	69.67%	80.77%	10
75	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	69.67%	80.77%	10
76	SGSt	25.44%	7.01%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	69.67%	80.77%	10
77	SGSt	25.44%	7.01%	80.77%	69.67%	25.44%	80.77%	69.67%	7.01%	69.67%	80.77%	10
78	SGSt	25.44%	7.01%	80.77%	69.67%	25.44%	41.87%	69.67%	2.34%	25.44%	80.77%	9
79	SGSt	25.44%	18.44%	80.77%	69.67%	25.44%	18.44%	69.67%	2.34%	2.22%	0.69%	7
80	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	41.87%	25.44%	0.04%	2.22%	2.34%	7
83	SGSt	80.77%	80.77%	2.34%	69.67%	69.67%	80.77%	18.44%	18.44%	41.87%	69.67%	9
84	SGSt	80.77%	80.77%	2.34%	69.67%	25.44%	80.77%	18.44%	18.44%	80.77%	25.44%	9
85	SGSt	69.67%	80.77%	2.34%	69.67%	25.44%	80.77%	18.44%	18.44%	80.77%	25.44%	9
86	SGSt	69.67%	80.77%	2.34%	69.67%	25.44%	80.77%	18.44%	18.44%	80.77%	25.44%	9
87	SGSt	69.67%	80.77%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	69.67%	25.44%	10
88	SGSt	25.44%	41.87%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	69.67%	25.44%	10
89	SGSt	25.44%	41.87%	7.01%	69.67%	25.44%	80.77%	41.87%	18.44%	69.67%	25.44%	10

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Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
90	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	80.77%	80.77%	7.01%	69.67%	25.44%	10
91	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	80.77%	80.77%	7.01%	25.44%	25.44%	10
92	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	25.44%	25.44%	10
93	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	69.67%	10
94	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	80.77%	10
95	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	80.77%	10
96	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	2.22%	80.77%	9
97	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	2.22%	80.77%	9
98	SGSt	25.44%	41.87%	80.77%	69.67%	25.44%	41.87%	69.67%	2.34%	2.22%	80.77%	8
99	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	18.44%	69.67%	2.34%	2.22%	0.69%	7
100	SGSt	25.44%	80.77%	2.34%	69.67%	25.44%	41.87%	69.67%	0.04%	2.22%	7.01%	7
101	SGSt	69.67%	80.77%	0.69%	69.67%	69.67%	80.77%	18.44%	18.44%	80.77%	25.44%	9
102	SGSt	69.67%	80.77%	0.69%	69.67%	69.67%	80.77%	18.44%	18.44%	80.77%	25.44%	9
103	SGSt	69.67%	80.77%	7.01%	69.67%	69.67%	80.77%	18.44%	18.44%	25.44%	25.44%	10
104	SGSt	69.67%	80.77%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	25.44%	25.44%	10
105	SGSt	69.67%	80.77%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	69.67%	25.44%	10
106	SGSt	25.44%	18.44%	18.44%	69.67%	25.44%	80.77%	18.44%	18.44%	41.87%	41.87%	10
107	SGSt	25.44%	80.77%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	69.67%	25.44%	10
108	SGSt	25.44%	80.77%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	69.67%	25.44%	10
109	SGSt	25.44%	80.77%	7.01%	69.67%	25.44%	41.87%	41.87%	18.44%	69.67%	25.44%	10
110	SGSt	25.44%	41.87%	7.01%	69.67%	25.44%	41.87%	41.87%	7.01%	69.67%	25.44%	10
111	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	80.77%	80.77%	7.01%	69.67%	25.44%	10
112	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	25.44%	10
113	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	25.44%	10
114	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	25.44%	25.44%	10
115	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	80.77%	80.77%	18.44%	2.22%	69.67%	9
116	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	80.77%	80.77%	7.01%	2.22%	25.44%	9
117	SGSt	25.44%	18.44%	41.87%	69.67%	25.44%	80.77%	69.67%	7.01%	2.22%	25.44%	9
118	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	41.87%	69.67%	2.34%	2.22%	69.67%	8
119	SGSt	25.44%	41.87%	41.87%	69.67%	25.44%	41.87%	69.67%	2.34%	2.22%	69.67%	8
120	SGSt	25.44%	41.87%	7.01%	69.67%	25.44%	41.87%	25.44%	0.18%	2.22%	7.01%	8
90	SGSt	25.44%	41.87%	18.44%	69.67%	25.44%	80.77%	80.77%	7.01%	69.67%	25.44%	10

Appendix C.10. UC year-by-year tests for the Historical VaR Models

Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
131	Historical	18.44%	41.87%	18.44%	80.77%	80.77%	41.87%	80.77%	69.67%	80.77%	41.87%	10
132	Historical	41.87%	41.87%	18.44%	80.77%	80.77%	41.87%	80.77%	69.67%	80.77%	41.87%	10
136	Historical	41.87%	18.44%	41.87%	80.77%	80.77%	18.44%	80.77%	80.77%	69.67%	41.87%	10
137	Historical	41.87%	18.44%	41.87%	80.77%	80.77%	18.44%	80.77%	41.87%	69.67%	80.77%	10
147	Historical	7.01%	41.87%	18.44%	69.67%	80.77%	41.87%	80.77%	80.77%	69.67%	69.67%	10
148	Historical	7.01%	18.44%	18.44%	69.67%	80.77%	41.87%	80.77%	69.67%	25.44%	80.77%	10
149	Historical	18.44%	18.44%	18.44%	69.67%	80.77%	41.87%	80.77%	69.67%	25.44%	80.77%	10
150	Historical	7.01%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	80.77%	25.44%	80.77%	10
151	Historical	18.44%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	80.77%	25.44%	80.77%	10
152	Historical	18.44%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	80.77%	25.44%	80.77%	10
153	Historical	18.44%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	41.87%	25.44%	80.77%	10
154	Historical	18.44%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	41.87%	25.44%	80.77%	10
155	Historical	18.44%	18.44%	41.87%	69.67%	80.77%	41.87%	80.77%	41.87%	69.67%	41.87%	10
156	Historical	41.87%	7.01%	80.77%	69.67%	69.67%	18.44%	80.77%	41.87%	69.67%	18.44%	10
161	Historical	80.77%	41.87%	2.34%	69.67%	25.44%	41.87%	7.01%	80.77%	25.44%	69.67%	9
162	Historical	80.77%	41.87%	7.01%	69.67%	25.44%	41.87%	7.01%	80.77%	25.44%	69.67%	10
163	Historical	80.77%	41.87%	2.34%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	69.67%	8
164	Historical	80.77%	41.87%	2.34%	69.67%	25.44%	18.44%	18.44%	80.77%	2.22%	69.67%	8
165	Historical	80.77%	41.87%	2.34%	69.67%	25.44%	18.44%	18.44%	80.77%	2.22%	69.67%	8
166	Historical	80.77%	18.44%	2.34%	69.67%	25.44%	18.44%	18.44%	80.77%	2.22%	69.67%	8
167	Historical	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	18.44%	80.77%	2.22%	69.67%	9
168	Historical	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	41.87%	69.67%	2.22%	69.67%	9
169	Historical	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	80.77%	69.67%	2.22%	69.67%	9

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Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
170	Historical	41.87%	18.44%	18.44%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
171	Historical	41.87%	18.44%	18.44%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
172	Historical	41.87%	7.01%	18.44%	69.67%	25.44%	41.87%	80.77%	41.87%	2.22%	69.67%	9
173	Historical	80.77%	7.01%	18.44%	69.67%	25.44%	41.87%	80.77%	41.87%	2.22%	69.67%	9
174	Historical	69.67%	7.01%	41.87%	69.67%	25.44%	41.87%	80.77%	18.44%	2.22%	69.67%	9
175	Historical	69.67%	7.01%	41.87%	69.67%	25.44%	41.87%	80.77%	18.44%	2.22%	69.67%	9
176	Historical	69.67%	7.01%	41.87%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
177	Historical	69.67%	2.34%	80.77%	69.67%	25.44%	7.01%	80.77%	18.44%	2.22%	69.67%	8
178	Historical	69.67%	2.34%	80.77%	69.67%	25.44%	2.34%	69.67%	7.01%	2.22%	69.67%	7
179	Historical	25.44%	0.69%	41.87%	69.67%	25.44%	2.34%	69.67%	7.01%	2.22%	69.67%	7
180	Historical	69.67%	2.34%	2.34%	25.44%	25.44%	2.34%	69.67%	2.34%	2.22%	69.67%	5
195	Historical	69.67%	7.01%	18.44%	69.67%	25.44%	18.44%	18.44%	7.01%	2.22%	69.67%	9
196	Historical	69.67%	7.01%	18.44%	69.67%	25.44%	18.44%	41.87%	7.01%	2.22%	69.67%	9
197	Historical	69.67%	2.34%	41.87%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	69.67%	8
198	Historical	69.67%	2.34%	41.87%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	69.67%	8
199	Historical	25.44%	2.34%	18.44%	69.67%	25.44%	18.44%	69.67%	2.34%	2.22%	25.44%	7
200	Historical	25.44%	2.34%	0.18%	69.67%	25.44%	18.44%	69.67%	0.69%	2.22%	2.22%	5
215	Historical	41.87%	7.01%	7.01%	69.67%	25.44%	80.77%	18.44%	7.01%	2.22%	69.67%	9
216	Historical	41.87%	7.01%	7.01%	69.67%	25.44%	80.77%	41.87%	7.01%	2.22%	69.67%	9
217	Historical	69.67%	7.01%	7.01%	69.67%	25.44%	41.87%	80.77%	7.01%	2.22%	69.67%	9
218	Historical	69.67%	7.01%	7.01%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	69.67%	9
219	Historical	69.67%	2.34%	2.34%	69.67%	25.44%	41.87%	69.67%	2.34%	2.22%	69.67%	6
220	Historical	69.67%	7.01%	0.18%	69.67%	25.44%	41.87%	69.67%	0.69%	2.22%	25.44%	7

Appendix C.11. UC year-by-year tests for the QR VaR Models

Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
244	QR	2.31%	1.54%	2.31%	0.77%	1.15%	1.92%	1.15%	1.15%	0.38%	1.15%	0
245	QR	2.31%	1.54%	2.31%	0.77%	1.15%	1.92%	1.15%	1.15%	0.38%	1.15%	0
246	QR	2.31%	1.54%	2.31%	0.77%	1.15%	1.92%	1.15%	1.15%	0.38%	1.15%	0
247	QR	2.31%	1.92%	1.92%	0.77%	1.15%	1.54%	1.15%	1.54%	0.38%	0.77%	0
248	QR	2.31%	1.92%	1.92%	0.77%	1.15%	1.54%	1.15%	1.15%	0.00%	1.15%	0
249	QR	1.92%	1.92%	1.92%	0.77%	1.15%	1.54%	1.15%	1.54%	0.00%	1.15%	0
250	QR	2.31%	1.92%	1.54%	0.77%	1.15%	1.54%	1.15%	1.54%	0.00%	1.15%	0
251	QR	1.92%	1.92%	1.54%	0.77%	1.15%	1.92%	1.15%	1.54%	0.00%	1.15%	0
252	QR	1.92%	1.92%	1.54%	0.77%	1.15%	1.54%	1.15%	1.54%	0.00%	1.15%	0
253	QR	1.92%	1.92%	1.54%	0.77%	1.15%	1.54%	1.15%	1.54%	0.00%	1.15%	0
254	QR	1.92%	1.92%	1.54%	0.77%	1.15%	1.92%	1.15%	1.92%	0.00%	1.15%	0
261	QR	80.77%	41.87%	2.34%	69.67%	25.44%	41.87%	7.01%	41.87%	25.44%	69.67%	9
262	QR	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	7.01%	41.87%	25.44%	69.67%	10
263	QR	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	69.67%	9
264	QR	80.77%	18.44%	2.34%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	69.67%	8
265	QR	80.77%	41.87%	2.34%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	69.67%	8
266	QR	80.77%	18.44%	2.34%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	69.67%	8
267	QR	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	69.67%	9
268	QR	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	41.87%	80.77%	2.22%	69.67%	9
269	QR	80.77%	18.44%	7.01%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
270	QR	41.87%	18.44%	18.44%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
271	QR	41.87%	18.44%	18.44%	69.67%	25.44%	18.44%	80.77%	41.87%	2.22%	69.67%	9
272	QR	41.87%	7.01%	18.44%	69.67%	25.44%	41.87%	80.77%	41.87%	2.22%	69.67%	9
273	QR	80.77%	7.01%	18.44%	69.67%	25.44%	41.87%	80.77%	41.87%	2.22%	69.67%	9
274	QR	69.67%	7.01%	41.87%	69.67%	25.44%	41.87%	80.77%	7.01%	2.22%	69.67%	9
275	QR	69.67%	7.01%	41.87%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	69.67%	9
276	QR	69.67%	7.01%	41.87%	69.67%	25.44%	7.01%	80.77%	7.01%	2.22%	69.67%	9
277	QR	69.67%	2.34%	80.77%	69.67%	25.44%	2.34%	80.77%	2.34%	2.22%	69.67%	6
278	QR	69.67%	2.34%	80.77%	69.67%	25.44%	2.34%	69.67%	2.34%	2.22%	69.67%	6
279	QR	25.44%	0.69%	41.87%	69.67%	25.44%	2.34%	69.67%	2.34%	2.22%	80.77%	6
281	QR	80.77%	41.87%	0.69%	69.67%	25.44%	41.87%	7.01%	80.77%	25.44%	25.44%	9
282	QR	80.77%	18.44%	0.69%	69.67%	25.44%	41.87%	7.01%	80.77%	25.44%	25.44%	9
283	QR	80.77%	7.01%	0.69%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	25.44%	8

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Model Number	Model	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	Years Passed
284	QR	80.77%	7.01%	0.69%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	25.44%	8
285	QR	80.77%	7.01%	0.69%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	25.44%	8
286	QR	80.77%	7.01%	2.34%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	25.44%	8
287	QR	80.77%	7.01%	0.69%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	8
288	QR	80.77%	7.01%	0.69%	69.67%	25.44%	18.44%	18.44%	80.77%	2.22%	25.44%	8
289	QR	80.77%	18.44%	0.69%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	8
290	QR	80.77%	7.01%	2.34%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	8
291	QR	80.77%	7.01%	18.44%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	9
292	QR	80.77%	7.01%	18.44%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	9
293	QR	69.67%	7.01%	18.44%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	2.22%	8
294	QR	25.44%	7.01%	18.44%	69.67%	25.44%	41.87%	18.44%	18.44%	2.22%	25.44%	9
295	QR	69.67%	7.01%	18.44%	69.67%	25.44%	18.44%	80.77%	18.44%	2.22%	25.44%	9
296	QR	69.67%	7.01%	18.44%	69.67%	25.44%	18.44%	80.77%	18.44%	2.22%	25.44%	9
297	QR	69.67%	2.34%	7.01%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	25.44%	8
298	QR	25.44%	2.34%	18.44%	69.67%	25.44%	7.01%	69.67%	2.34%	2.22%	69.67%	7
301	QR	80.77%	80.77%	0.69%	69.67%	69.67%	80.77%	18.44%	80.77%	25.44%	25.44%	9
302	QR	80.77%	41.87%	0.69%	69.67%	25.44%	80.77%	18.44%	80.77%	25.44%	25.44%	9
303	QR	80.77%	41.87%	0.69%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
304	QR	80.77%	41.87%	0.69%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
305	QR	80.77%	41.87%	0.69%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
306	QR	80.77%	18.44%	0.69%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
307	QR	80.77%	18.44%	0.69%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
308	QR	80.77%	18.44%	0.69%	69.67%	25.44%	41.87%	18.44%	80.77%	2.22%	25.44%	8
309	QR	80.77%	18.44%	0.69%	69.67%	25.44%	41.87%	18.44%	41.87%	2.22%	25.44%	8
310	QR	80.77%	18.44%	2.34%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	25.44%	8
311	QR	80.77%	18.44%	2.34%	69.67%	25.44%	18.44%	18.44%	41.87%	2.22%	25.44%	8
312	QR	80.77%	7.01%	2.34%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	8
313	QR	80.77%	7.01%	7.01%	69.67%	25.44%	80.77%	18.44%	41.87%	2.22%	25.44%	9
314	QR	69.67%	7.01%	7.01%	69.67%	25.44%	80.77%	18.44%	18.44%	2.22%	25.44%	9
315	QR	69.67%	7.01%	7.01%	69.67%	25.44%	80.77%	41.87%	18.44%	2.22%	25.44%	9
316	QR	69.67%	7.01%	7.01%	69.67%	25.44%	41.87%	80.77%	7.01%	2.22%	25.44%	9
317	QR	69.67%	7.01%	7.01%	69.67%	25.44%	18.44%	80.77%	7.01%	2.22%	69.67%	9
318	QR	69.67%	7.01%	2.34%	69.67%	25.44%	41.87%	69.67%	2.34%	2.22%	69.67%	7

Appendix C.12. List of models that went through the UC year-by-year tests and comparison of their exceedances rates

Model Number	Model	Sample Size	EWMA	Exceedance rate
52	SGSt	400	0.955	1.35%
53	SGSt	400	0.96	1.27%
54	SGSt	400	0.965	1.27%
55	SGSt	400	0.97	1.27%
56	SGSt	400	0.975	1.23%
57	SGSt	400	0.98	1.12%
65	SGSt	600	0.92	1.38%
66	SGSt	600	0.925	1.35%
67	SGSt	600	0.93	1.35%
68	SGSt	600	0.935	1.35%
69	SGSt	600	0.94	1.31%
70	SGSt	600	0.945	1.27%
71	SGSt	600	0.95	1.27%
72	SGSt	600	0.955	1.19%
73	SGSt	600	0.96	1.23%
74	SGSt	600	0.965	1.15%
75	SGSt	600	0.97	1.15%
76	SGSt	600	0.975	1.19%
77	SGSt	600	0.98	1.12%
87	SGSt	800	0.93	1.15%
88	SGSt	800	0.935	1.15%
89	SGSt	800	0.94	1.12%
90	SGSt	800	0.945	1.19%
91	SGSt	800	0.95	1.04%
92	SGSt	800	0.955	1.00%
93	SGSt	800	0.96	1.00%
94	SGSt	800	0.965	1.08%
95	SGSt	800	0.97	1.08%
103	SGSt	1000	0.91	1.15%
104	SGSt	1000	0.915	1.12%
105	SGSt	1000	0.92	1.15%
106	SGSt	1000	0.925	1.35%
107	SGSt	1000	0.93	1.12%
108	SGSt	1000	0.935	1.12%
109	SGSt	1000	0.94	1.12%
110	SGSt	1000	0.945	1.19%
111	SGSt	1000	0.95	1.08%
112	SGSt	1000	0.955	1.00%
113	SGSt	1000	0.96	0.96%
114	SGSt	1000	0.965	0.96%
131	Historical	200	0.95	1.38%
132	Historical	200	0.955	1.35%
136	Historical	200	0.975	1.38%
137	Historical	200	0.98	1.38%
147	Historical	400	0.93	1.31%
148	Historical	400	0.935	1.31%
149	Historical	400	0.94	1.27%
150	Historical	400	0.945	1.31%
151	Historical	400	0.95	1.27%
152	Historical	400	0.955	1.27%
153	Historical	400	0.96	1.31%
154	Historical	400	0.965	1.31%
155	Historical	400	0.97	1.38%
156	Historical	400	0.975	1.38%
162	Historical	600	0.905	1.23%
244	QR	400	0.915	1.38%
245	QR	400	0.92	1.38%
246	QR	400	0.925	1.38%
247	QR	400	0.93	1.35%
262	QR	600	0.905	1.35%