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Value-at-Risk Models and Political Shocks: Empirical Evidence from UK Banks Pre and Post Brexit

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Abstract: *This study examines the effectiveness of Value-at-Risk (VaR) models in UK banks from 2015 to 2024, spanning pre- and post-Brexit periods. Brexit is conceptualised as a political shock with systemic effects comparable to financial crises. Guided by Extreme Value Theory (EVT), the study evaluates Parametric and Historical VaR models against four objectives: predictive accuracy, statistical adequacy, cross-firm variation, and practical implications. Using daily returns of nine FTSE 100 banks, VaR was estimated at the 95% confidence level and validated through Kupiec's Chi-Square backtesting. Findings reveal that Parametric VaR performed adequately in stable markets but underestimated tail risks post-Brexit due to Gaussian assumptions. Historical VaR more effectively captured fat-tailed volatility but varied by firm size and EU exposure. Larger internationally integrated banks faced greater exceedances, while domestically focused banks showed resilience. The study recommends hybrid frameworks integrating EVT-based approaches and urges regulators to embed multi-model validation into supervisory regimes.*

Keywords: Value-at-Risk, Brexit, UK banking, extreme value theory, risk management, political shocks.

INTRODUCTION

Value-at-Risk (VaR) has become a cornerstone of modern risk management, widely employed by banks and regulators to quantify the maximum expected loss of a portfolio over a given horizon at a specific confidence level. Its appeal lies in its simplicity and intuitive communication of downside risk, enabling institutions to integrate risk assessment across diverse portfolios while ensuring compliance with regulatory frameworks (Tsiotas, 2019). Beyond its practical utility, VaR also underpins capital allocation under the Basel Accords, where underestimation of risk may translate into systemic vulnerabilities. Despite its prominence, the validity of VaR is not uniform across contexts, as its performance depends heavily on model specification and prevailing market conditions.

The UK banking sector presents a compelling case for reassessment of VaR models following Brexit. The UK's exit from the European Union introduced structural uncertainty, regulatory divergence, and heightened volatility across financial markets (Oxford Analytical, 2016). Banks operating in this environment have faced disrupted capital flows, shifts in investor sentiment, and evolving supervisory standards. As James and Quaglia (2020) observe, Brexit created institutional and operational adjustments that challenge conventional models of financial stability. The compounded risks underscore the need for robust risk measurement tools that can capture not only average market behaviour but also extreme outcomes, which are more likely under political and economic dislocations.

While prior research has examined VaR performance during global crises such as 2008 or COVID-19, relatively little attention has been given to political shocks like Brexit. This gap is critical because political disruptions can generate tail risks analogous to financial crises, demanding a framework that accounts for rare but severe events. Extreme Value Theory (EVT) provides such a foundation by modelling the statistical behaviour of the tails of return distributions. EVT addresses the shortcomings of Gaussian-based approaches by explicitly accommodating fat tails and extreme volatility, offering a stronger theoretical rationale for evaluating VaR effectiveness in turbulent conditions (Omari, Mwita and Waititu, 2020; Wong *et al.*, 2016).

Against this backdrop, the core objective of this study is to rigorously evaluate the effectiveness of parametric (variance–covariance) and historical VaR models using empirical data from UK banks over the period 2014–2024. The specific aims are fourfold: first, to assess predictive accuracy during heightened volatility, particularly post-Brexit; second, to conduct backtesting and robustness checks using the Kupiec Chi-Square test; third, to compare model performance across banks, accounting for firm size and EU market exposure; and fourth, to derive practical implications for banks and regulators, including the Bank of England and the Prudential Regulation Authority. By situating Brexit within an EVT framework, this study contributes to the literature on risk measurement by reframing political shocks as tail events with systemic consequences.

LITERATURE AND THEORETICAL REVIEW

Value at Risk (VaR) Models in Financial Risk Management

Value at Risk (VaR) has become a cornerstone of financial risk management, providing banks and regulators with a standardised framework for quantifying potential losses. Defined as the maximum expected loss over a specified time horizon at a given confidence level, VaR translates uncertainty into a single, probabilistic measure that facilitates comparability across portfolios and institutions (Uylangco & Li, 2015). Its appeal lies in both its intuitive simplicity and regulatory endorsement, particularly under the Basel Accords, which have made VaR disclosures central to capital adequacy requirements (McAleer *et al.*, 2012).

The adoption of VaR intensified after the 2007–2008 global financial crisis, when weaknesses in risk management contributed to systemic instability. Regulators responded by embedding VaR into Basel II and III, emphasising accurate risk quantification and the integration of sophisticated methodologies into banks' internal systems (Dhawan, 2024; Papadamou *et al.*, 2021). These reforms sought to strengthen bank resilience by mandating rigorous VaR calculations and greater transparency. Ibrahim and Sufian (2014) highlight how Basel III encouraged banks to adopt models capable of incorporating time-varying volatility and rapid market shifts, thereby enhancing responsiveness to dynamic conditions.

Methodologically, VaR can be calculated using parametric (variance–covariance), Historical simulation, or more advanced models such as Monte Carlo simulation. The variance–covariance approach, widely used for its simplicity, assumes normally distributed returns and constant variance. By contrast, Historical simulation relies on empirical data, capturing non-linearities and volatility clustering more effectively. While both approaches are entrenched in practice, their effectiveness diverges under stress conditions, as assumptions of normality and historical stability often break down (Uylangco & Li, 2015).

Criticism of VaR has persisted, particularly concerning its reliability during crises. Degiannakis *et al.* (2012) note that VaR systematically underestimates losses in extreme market conditions, as it neglects the probability and magnitude of tail events. The 2008 crisis underscored this weakness, prompting calls for alternative measures such as Expected Shortfall (ES), which captures the average of losses beyond the VaR threshold and thus provides a more comprehensive view of downside risk (Hajihasani *et al.*, 2021; Das & Rout, 2022). Scholars argue that ES is especially valuable during systemic shocks, where VaR's focus on a single quantile offers limited guidance.

Beyond technical limitations, VaR has raised concerns about its application in practice. Nieto and Ruiz (2016) argue that model complexity, combined with managerial discretion, creates opportunities for underestimation or manipulation of risk. Pérignon and Smith (2009, 2010) further warn that banks' autonomy in setting capital charges may encourage regulatory arbitrage, undermining supervisory objectives. These risks emphasise the need for regulatory oversight not only of model choice but also of disclosure practices.

Despite these criticisms, VaR remains integral to modern financial regulation and banking practice. Its widespread adoption reflects both regulatory enforcement and its usefulness as a common risk metric. However, its shortcomings during periods of volatility highlight the necessity of complementary approaches, such as ES, stress testing, and scenario analysis, to strengthen resilience against systemic shocks. In this regard, VaR should be understood not as a standalone model but as part of a broader, multifaceted risk management toolkit.

Crisis Contexts

The adequacy of VaR has been stress-tested most extensively during financial crises, where volatility exposes its weaknesses. During the 2007–2008 crisis, VaR was criticised for failing to capture systemic tail risks, leading to significant underestimation of bank losses (Degiannakis *et al.*, 2012). Similarly, during COVID-19, Omari, Mwita and Waititu (2020) show that Gaussian-based VaR models systematically underestimated extreme downside risks, while Historical and EVT-based approaches more accurately reflected realised losses. Wong *et al.* (2016) further highlight that long-memory and fat-tailed models provide stronger predictive accuracy under crisis conditions than parametric VaR. These findings consistently show that systemic shocks undermine models based on normality assumptions.

Brexit and the UK Financial Landscape

Brexit represents one of the most significant political shocks in recent history, with systemic consequences for the UK financial system that parallel those of traditional financial crises. Unlike crises driven by structural imbalances within financial markets, Brexit originated as a political event but produced widespread economic and financial disruptions through uncertainty, regulatory divergence, and shifts in investor sentiment. The period leading up to and following the 2016 referendum was characterised by heightened volatility, with markets responding to fears of declining growth and diminished trade access. Wincott (2021) reports that expectations of lower UK GDP growth were directly tied to Brexit-related uncertainties, while Belke *et al.* (2018) demonstrate that economic policy uncertainty generated elevated stock market volatility. These findings highlight how political shocks can shape financial market dynamics in ways comparable to systemic crises.

The regulatory dimension of Brexit has been equally significant. As Mugarura (2016) observes, the UK's departure from the EU ended automatic market access, creating profound uncertainty for financial institutions reliant on cross-border operations. This compelled banks to adapt through new compliance and reporting frameworks, often at the cost of competitiveness and efficiency. Such regulatory realignment underscores the need for robust risk management systems capable of capturing emerging risks that fall outside the scope of historical experience.

At the institutional level, Brexit has demanded adjustments in accounting, fiscal, and risk practices. Heald and Wright (2019) emphasise that post-Brexit fiscal realignments required clearer financial reporting and stronger internal controls to sustain stability. Similarly, Boland and O'Riordan (2019) argue that the structural uncertainties created systemic vulnerabilities for UK firms, exposing weaknesses in conventional frameworks designed primarily for financial rather than political disruptions. Song (2024) further highlights that traditional risk measures, such as VaR, may not fully reflect the realities of a post-Brexit environment, where non-financial shocks exert financial consequences.

In synthesis, Brexit should be understood as a political shock with systemic effects analogous to financial crises. It produced volatility, regulatory fragmentation, and heightened systemic risk—conditions that mirror the stress experienced during crises such as 2008 or COVID-19. Yet, while the broader economic and regulatory consequences have been widely studied, there remains limited focus on how Brexit specifically challenges the adequacy of VaR models. This gap provides the rationale for evaluating VaR effectiveness in a post-Brexit context, where traditional assumptions of stability and normality are most likely to break down.

Gaps in Literature

While the literature on Value-at-Risk (VaR) is extensive, several important gaps remain. Much of the existing research has focused on the performance of VaR during financial crises, such as the 2007–2008 global financial crisis or the COVID-19 pandemic, where its limitations in capturing tail risks were well documented (Degiannakis *et al.*, 2012; Omari, Mwita and Waititu, 2020). However, less attention has been given to the effectiveness of VaR under political shocks, such as Brexit, which differ in origin but produce systemic consequences similar to financial crises through volatility, uncertainty, and regulatory fragmentation (Wincott, 2021; Belke *et al.*, 2018). This neglect leaves unanswered whether VaR models are robust enough to manage risks arising from political disruptions that reshape institutional and market environments.

Moreover, prior studies have largely assessed VaR performance at the aggregate market level, overlooking firm-specific differences. Given that UK banks vary in size, EU market exposure, and risk profiles, an institution-level comparison is essential for understanding how VaR effectiveness may differ across the sector. Finally, while critiques of VaR's underestimation of tail risk are widespread, few studies have explicitly adopted a theoretical framework suited to extremes. This study addresses these gaps by employing extreme value theory (EVT), which directly models tail behaviour and provides a stronger basis for assessing risk during shocks like Brexit.

Theoretical Framework

To address these gaps, this study applies extreme value theory (EVT) as its guiding framework. Unlike Modern Portfolio Theory or the Efficient Market Hypothesis, which assume normality or efficiency, EVT focuses explicitly on the statistical behaviour of the tails of distributions. This makes it especially relevant for shocks such as Brexit, which—although political—generated financial instability comparable to crises. By situating VaR evaluation within EVT, this study not only investigates the predictive accuracy of models across UK banks but also reframes Brexit as a "tail event" requiring risk frameworks that extend beyond average conditions.

The EVT focuses on modelling the statistical properties of the tails of return distributions, where extreme losses are most likely to occur. Unlike Parametric VaR, which relies on restrictive Gaussian assumptions, EVT explicitly accounts for fat tails and volatility clustering—features that are well documented in financial markets (Degiannakis et al, 2012). This makes it particularly suited to assessing model performance during systemic shocks such as Brexit, which triggered rare but severe market outcomes.

By concentrating on extreme rather than average events, EVT provides a robust explanation for the study's empirical finding that Parametric VaR underestimated risks in the post-Brexit period, while Historical VaR produced results more closely aligned with realised losses. Prior evidence reinforces this conclusion: Omari et al, (2020) show that EVT-based and Historical approaches outperformed Gaussian models during COVID-19, while Wong *et al.* (2016) highlight the importance of accounting for long memory and fat tails in volatility modelling.

Compared with alternative frameworks such as Modern Portfolio Theory or the Efficient Market Hypothesis, EVT is more relevant because it does not assume stability or efficiency. Instead, it directly models the risks arising from rare shocks, aligning with regulatory reforms under Basel III that emphasise tail-sensitive measures such as Expected Shortfall (Chang et al, 2011).

In this way, EVT offers the most appropriate theoretical basis for analysing VaR model effectiveness under Brexit, framing it as a tail event with significant implications for financial stability.

METHODOLOGY

This study aims to critically assess the effectiveness of Value at Risk (VaR) models in measuring financial risk within the UK banking sector following Brexit, specifically utilizing two predominant approaches: Parametric VaR and Historical VaR. The chosen methodologies are significant given their relevance to current regulatory frameworks, most notably Basel III, which emphasizes the need for sound risk management practices to enhance financial stability (Schwerter, 2011). Parametric VaR, being assumption-driven, aligns with the requirements of regulatory compliance, while Historical VaR, a data-driven approach, allows for an empirical perspective on market behaviour. It is essential to exclude Monte Carlo VaR from this analysis due to its computational complexity and the sufficiency of the selected methods for a retrospective evaluation based on historical data.

The methodology comprises several phases: data collection, pre-processing, VaR estimation, and backtesting, with the robustness of the statistical results being evaluated through the Kupiec Chi-Square Test. The implementation of calculations is conducted in Microsoft Excel, enabling the study's accessibility and reproducibility (Rosiggnolo, 2017).

Data Collection

Sample: The dataset comprises daily adjusted closing stock prices of 15 financial institutions listed on the FTSE 100 Index, including notable entities such as Barclays, HSBC, and Lloyds. These institutions are pivotal to the UK banking sector, ensuring the relevance of the analysis concerning the implications of Brexit on financial risk (Peters *et al.*, 2013).

Period: The data spans from January 1, 2015, to December 31, 2024, covering approximately 2,500 trading days that encompass both pre- and post-Brexit periods. This timeframe is critical for capturing structural shifts in market dynamics and assessing the impact of Brexit on risk profiles.

Source: Daily adjusted closing prices are sourced from Bloomberg Terminal, as it is widely utilized in academic research and provide reliable data for empirical analyses (Le, 2022).

Variable: Adjusted closing prices are employed to ensure consistency in return calculations, accounting for any corporate actions such as dividends and stock splits.

Data Pre-processing

Log Return Calculation: Daily logarithmic returns are computed using the formula:

$$\mathrm{R}_t = \ln \frac{P_t}{P_{t-1}}$$

where (P_t) and ($P_{\{t-1\}}$) represent the adjusted closing prices at time (t) and (t-1), respectively. This transformation standardizes price changes, making returns more amenable to risk modeling techniques (Schwerter, 2011).

Cleaning: Missing data points, potentially arising from market holidays, are addressed through a forward-fill approach, carrying forward the prior day's price. If gaps exceed one day, those entries are deleted to maintain data integrity. Additionally, trading days across all selected firms are aligned to ensure comparability within the dataset.

Value at Risk (VaR) Estimation

VaR is estimated on a daily basis for each institution at a 95% confidence level ($\alpha = 0.05$), employing a 250-day rolling window reflective of a full trading year. This window captures recent market conditions crucial for accurate risk assessment (Boora & Jangra, 2018).

Parametric (Variance-Covariance) VaR Approach

This approach assumes that returns follow a normal distribution, utilizing mean and variance for its calculations, thereby enhancing regulatory alignment. The VaR calculation is represented as:

$VaR_t^{PR} = \mu_t - Z_{0.95} * \sigma_t$

where:

μ_t: 250-day rolling mean of returns, calculated as

$$\mu_t = \sqrt{\frac{1}{249} \sum_{i=t-249}^{t} (R_i - \mu_t)^2}$$

where:

μ_t: the 250-day rolling mean of returns,

$Z_{0.95}$: Z-score corresponding to the 95% confidence level from the standard normal distribution.

Historical Simulation VaR Approach

This non-parametric method leverages the empirical distribution of past returns, making no assumptions about their distribution and directly capturing tail risks from historical data. The VaR is calculated as:

$$VaR_r^{hist} = 5th\ percentile\ of\ (R_{t-249}, R_{t-248}, \dots \dots \dots, R_t)$$

Backtesting

To evaluate the accuracy of the VaR estimates, backtesting is conducted by comparing actual returns against the predicted thresholds over the post-estimation period (Rows 252–2501), roughly encompassing 2,250 trading days. A breach in this context occurs when the actual return dips below the VaR estimate. The expected breach rate at the 95% confidence level is anticipated to align with a frequency of 5% (i.e., 112.5 breaches over 2,250 days).

The actual breach rate is computed using:

$$Breach\ rate\ = \frac{\sum_{t=252}^{2500} Breach_t}{T} * 100$$

where (T = 2,250) denotes the number of backtested days. The output will summarize for each institution and method: total breaches, expected breaches, and the respective breach rates. Additionally, visualizations, such as line charts, was used to illustrate returns versus VaR thresholds, with breaches clearly marked.

Robustness Testing: Kupiec Chi-Square Test

The accuracy of the models will be further tested using the Kupiec (1995) unconditional coverage test, examining whether the observed breach rate aligns with the predicted 5% threshold under the null hypothesis (H0): the model's breach rate equals 0.05. The test statistic is expressed as:

$$LR_{uc} = -2\ln[(1-\propto)^{T-N} \propto^N] + 2\ln[(1-\rho)^{T-N}\rho^N$$

where:

- T : Total observations (2,250).

-N: Number of breaches (e.g., 135 for Parametric).

- α: Expected breach probability (0.05).

- ρ: Observed breach probability (N / T, e.g., 135 / 2250 = 0.06).

For large samples, this approximates a chi-square distribution with 1 degree of freedom:

$$LR_{uc} \approx X^2(1)$$

If (p > 0.05), the null hypothesis is not rejected (indicating model accuracy).

If (p < 0.05), the null hypothesis is rejected (indicating significant deviation from expected breaches).

Cross-Firm Comparison Analysis

This study will engage in cross-firm comparisons of breach rates and Kupiec test results, facilitating:

Assessment of model consistency across different methodologies (Parametric vs. Historical).

Identification of firm-specific risk patterns, particularly among banks with high exposure to EU markets.

Evaluation of model robustness amid post-Brexit market conditions, characterized by increased volatility.

RESULTS PRESENTATION

4.1 VaR Estimates Across Models

Table 1: Average daily VaR estimates at a 95% confidence

Firm	PRE BREXIT		POST BREXIT	
	Avg Parametric VaR	Avg Historical VaR	Avg Parametric VaR	Avg Historical VaR
HSBA	-2.04%	-1.94%	-2.73%	-2.59%
Barclay	-3.03%	-2.75%	-3.44%	-3.31%
Llyod	-2.62%	2.19%	-3.08%	-3.11%
NWG	-3.18%	-2.84%	-3.30%	-3.16%
STAN	-3.13%	-3.09%	-3.53%	-3.26%
IVP	-2.95%	-2.83%	-3.44%	-3.30%
BGEO	-3.21%	-3.03%	-3.91%	-3.45%
CBG	-2.36%	-2.07%	-3.95%	-3.52%
STB	-2.91%	-2.72%	-3.91%	-3.50%
Mean	-2.83%	-2.12%	-3.48%	-3.24%

Table 1 reports average daily Value at Risk (VaR) estimates for nine UK banks at a 95% confidence level, contrasting Parametric and Historical models across pre- and post-Brexit periods. The results provide insight into the relative effectiveness of the two models in capturing risk exposure within the UK banking sector.

During the pre-Brexit period, Parametric VaR estimates ranged from –2.36% (CBG) to –3.21% (BGEO), with a mean of –2.83%. Historical VaR values were generally less conservative, ranging from –2.07% (CBG) to –3.09% (STAN), averaging –2.12%. This pattern indicates that the Parametric model systematically produced larger risk estimates, reflecting its variance–covariance assumptions. By comparison, the Historical model, which directly relies on past return distributions, appeared to understate risk during relatively stable conditions, raising concerns over its ability to anticipate potential shocks.

In the post-Brexit period, both models registered higher average losses, consistent with increased volatility in UK financial markets. The mean Parametric VaR rose to –3.48%, while Historical VaR increased to –3.24%. This upward shift underscores the responsiveness of both methods to structural uncertainty, with Parametric again demonstrating more conservative outputs. For instance, Barclays recorded –3.44% (Parametric) versus –3.31% (Historical), while CBG's estimates widened to –3.95% and –3.52% respectively. Such results suggest that while both models effectively captured heightened risk post-Brexit, Parametric VaR continued to emphasize more severe loss scenarios.

Firm-specific variations further enrich interpretation. Larger, internationally exposed institutions such as Barclays (–3.44% Parametric) and NatWest (–3.30% Parametric) registered comparatively higher post-Brexit VaR estimates, reflecting greater sensitivity to European market disruptions. By contrast, domestically focused banks such as Lloyds displayed relatively lower estimates (–3.08% Parametric, –3.11% Historical), suggesting reduced exposure to cross-border volatility. BGEO and CBG also showed elevated post-Brexit VaR, indicative of heightened risk perceptions surrounding institutions with structural or regional vulnerabilities.

In evaluating effectiveness, the Parametric model demonstrates conservatism across both timeframes, potentially serving as a safeguard against underestimation of extreme losses. However, its reliance on normality assumptions may limit accuracy during tail events. The Historical model, although less conservative, aligns more closely with observed market distributions, offering a realistic reflection of empirical volatility, particularly in crisis contexts.

Overall, Table 1 reveals that both models effectively identified shifts in the UK risk environment, though neither is wholly sufficient in isolation. The evidence suggests that a hybrid approach—leveraging Parametric VaR's prudence alongside Historical VaR's empirical accuracy—would enhance risk management effectiveness within UK banks navigating post-Brexit uncertainty.

4.2 Backtesting Outcomes

Table 2: Backtesting Outcomes: Comparing Actual Returns Against the Predicted Thresholds

Firm	PRE BREXIT				POST BREXIT			
	Param Breaches	Hist Breaches	Param Rate	Hist Rate	Param Breaches	Hist Breaches	Param Rate	Hist Rate
HSBC	52	58	4.93%	5.50%	44	47	4.17%	4.46%
Barclay	52	52	4.93%	4.93%	44	47	4.17%	4.36%
Llyod	48	62	4.55%	5.88%	38	36	3.61%	3.42%
NWG	47	54	4.46%	5.12%	39	43	3.70%	4.08%
STAN	52	53	4.93%	5.03%	32	39	3.03%	3.70%
IVP	50	55	4.74%	5.22%	43	48	4.08%	4.55%
BGEO	45	50	4.27%	4.74%	41	52	3.89%	4.93%
CBG	58	68	5.50%	6.45%	51	66	4.83%	6.26%
STB	62	75	5.88%	7.12%	42	51	3.98%	4.83%
Mean	52	59	4.91%	5.55%	42	48	3.94%	4.51%

Table 3: Robustness Test: Kupiec Chi-Square Test

Firm	PRE-BREXIT				POST BREXIT			
	Param LR_uc	Hist LR_uc	Param p-value	Hist p-value	Param LR_uc	Hist LR_uc	Param p-value	Hist p-value
HSBA	0.0098	0.5441	0.9210	0.4607	1.5979	0.672	0.2062	0.412
Barclay	0.0098	0.0098	0.9210	0.9210	1.6152	0.9485	0.2038	0.3301
Llyod	0.4542	1.6390	0.5003	0.2005	4.7605	6.2380	0.0291	0.0125
NWG	0.6724	0.0335	0.4122	0.8548	4.1316	2.0193	0.0421	0.1553
STAN	0.0098	0.0018	0.9210	0.9662	9.9377	4.1316	0.0016	0.0421
IVP	0.1480	0.1042	0.7004	0.7468	2.0193	0.4637	0.1553	0.4959
BGEO	1.2433	0.1480	0.2648	0.7004	2.9739	0.0113	0.0846	0.9154
CBG	0.5441	4.3003	0.4607	0.0381	0.0618	3.2560	0.8037	0.0712
STB	1.6390	8.8313	0.2005	0.0030	2.4718	0.0618	0.1159	0.8037
Mean	0.5256	1.7347	0.5891	0.5435	3.2855	1.9780	0.1825	0.3598

Objective 2 evaluates the predictive accuracy of Parametric and Historical Value at Risk (VaR) models using backtesting and robustness checks through the Kupiec Chi-Square test. Tables 2 and 3 provide evidence on whether the models' breach frequencies met statistical expectations across UK banks in pre- and post-Brexit periods.

Backtesting outcomes (Table 2) show that at a 95% confidence level, the expected breach frequency is 5%. Pre-Brexit, Parametric VaR produced a mean breach rate of 4.91%, slightly below expectation, while Historical VaR recorded 5.55%, marginally above the benchmark. This indicates that Parametric VaR was more conservative during stable conditions, whereas Historical VaR displayed heightened sensitivity to past data. Post-Brexit, both models underestimated breaches, with Parametric at 3.94% and Historical at 4.51%. These lower-than-expected rates suggest both models struggled to capture the magnitude of heightened volatility, though Historical VaR aligned more closely with the theoretical threshold.

Firm-level patterns reinforce these observations. For instance, Lloyds reported relatively low breach rates post-Brexit (Parametric 3.61%, Historical 3.42%), reflecting its domestic focus and reduced exposure to EU-related volatility. Conversely, CBG recorded elevated breach rates (Parametric 4.83%, Historical 6.26%), showing its greater vulnerability to post-Brexit shocks. Barclays and HSBC, as globally exposed banks, demonstrated stable breach rates around 4–4.5%, suggesting better resilience but still underestimating tail risks. Smaller firms like STB revealed persistent deviations, with Historical breaches as high as 7.12% pre-Brexit, signalling over-sensitivity to historical data.

The Kupiec Chi-Square test (Table 3) provides statistical validation. Pre-Brexit, most banks produced p-values above 0.05, indicating alignment with expected breach frequencies. For example, Barclays and HSBC both achieved p-values of 0.921, reflecting robust model accuracy in stable markets. Post-Brexit, however, differences emerged. Parametric VaR frequently returned p-values below 0.05—such as Lloyds (p = 0.029) and NatWest (p = 0.042)—indicating systematic underestimation of risk. By contrast, Historical VaR achieved higher p-values in several cases, including HSBC (p = 0.412) and IVP (p = 0.496), suggesting greater robustness under volatile conditions. Yet exceptions exist; CBG's Historical p-value (0.071) was borderline, reflecting inconsistent accuracy.

In summary, firm-specific evidence shows that Parametric VaR aligned well during pre-Brexit stability but underestimated risks post-Brexit, particularly for larger internationally exposed banks. Historical VaR, while sometimes overestimating breaches, proved more reliable in volatile contexts, capturing risk dynamics for banks most affected by Brexit. Thus, Historical VaR emerges as the more robust approach for the post-Brexit UK banking sector.

Cross-Firm Variations in Breach Frequency and Model Performance

Objective 3 seeks to compare the performance of Value at Risk (VaR) models across firms, highlighting how firm-specific factors influenced accuracy during pre- and post-Brexit periods. Tables 2 and 3 provide evidence of heterogeneous outcomes, reflecting variations in size, market exposure, and operational focus within the UK banking sector.

Pre-Brexit patterns reveal that most banks recorded breach rates near the expected 5%, though disparities emerged. Lloyds exhibited relatively low breach frequencies (Parametric 4.55%; Historical 5.88%), suggesting limited exposure to international volatility given its domestic orientation. Conversely, STB demonstrated pronounced exceedances under Historical VaR (7.12%), pointing to heightened model sensitivity to firm-specific return distributions. Large multinational banks such as Barclays and HSBC displayed stable breach rates around 4.9–5.5%, reflecting the capacity of both models to capture their diversified risk exposures under relatively calm conditions.

Post-Brexit comparisons underscore greater divergence. NatWest and CBG experienced elevated breach frequencies, with CBG's Historical VaR rising to 6.26%, well above the expected threshold. This suggests weaker alignment between model forecasts and realised volatility, likely linked to heightened sensitivity to European market dynamics and capital exposure. By contrast, HSBC and Barclays maintained relatively moderate breaches, with both models producing results between 4.1–4.5%, indicating greater resilience in absorbing Brexit-induced volatility. Lloyds, again, exhibited comparatively low rates (Parametric 3.61%; Historical 3.42%), consistent with its domestic risk profile. These findings illustrate that firm size and market orientation significantly shaped how effectively VaR models performed.

The Kupiec test results (Table 3) reinforce these cross-firm differences. Post-Brexit, Parametric VaR produced statistically significant underestimations for several firms, including Lloyds ($p = 0.029$), NatWest ($p = 0.042$), and Standard Chartered ($p = 0.002$). This indicates systematic failure of the Parametric model to capture extreme volatility for banks heavily engaged in international operations. Conversely, Historical VaR maintained robustness for many firms, such as HSBC ($p = 0.412$) and IVP ($p = 0.496$), suggesting stronger adaptability to empirical distributions. However, inconsistencies were evident for BGEO and STB, where Historical models also underperformed, highlighting limitations when firm-specific return distributions deviated significantly from broader sectoral patterns.

In synthesis, cross-firm analysis reveals that larger, globally integrated banks often challenged the assumptions of Parametric VaR post-Brexit, while Historical VaR demonstrated greater robustness in aligning with actual volatility. However, neither model performed uniformly well across all firms. These variations underscore the importance of tailoring risk measurement approaches to firm-specific characteristics, suggesting that a hybrid framework may better accommodate the diverse structures of UK banks in the post-Brexit landscape.

Discussion, Implications and Conclusion

This section interprets the findings in relation to the four study objectives, integrating Extreme Value Theory (EVT) and existing literature. It also highlights contributions, recommendations, and concluding remarks.

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5.1 Discussion

Objective 1: Predictive Accuracy of VaR Models

The first objective was to assess the predictive accuracy of Value-at-Risk (VaR) models in capturing realised market conditions during Brexit-related volatility. Results indicate that the Parametric (variance–covariance) VaR model generated conservative forecasts during the pre-Brexit period, where markets were relatively stable. This conservative tendency can be interpreted as a safeguard against underestimation, consistent with Degiannakis *et al.* (2012), who show that Gaussian-based models align more closely with reality under calm conditions. However, post-Brexit volatility exposed systematic weaknesses: Parametric VaR underestimated losses by relying on Gaussian assumptions of thin-tailed distributions and constant variance.

Historical VaR, by contrast, aligned more closely with realised outcomes during turbulent periods. Because it uses empirical data, Historical VaR is responsive to volatility clustering and non-normal distributions. This result is consistent with Wong *et al.* (2016), who emphasise that empirical simulation better accommodates shocks, and Omari et al, (2020), who found Gaussian VaR underestimated tail risks during COVID-19. Brexit therefore reinforces evidence that political shocks destabilise models reliant on normality assumptions.

Here, EVT provides theoretical clarity. EVT directly models the statistical behaviour of extreme tails, where losses beyond the VaR threshold occur (Geenens & Dunn, 2020). Parametric VaR failed precisely because it assumes returns approximate a normal distribution, while Historical VaR's closer alignment reflects empirical sensitivity to fat-tailed dynamics. EVT explains why tail-sensitive approaches capture volatility that Gaussian frameworks cannot. Thus, Objective 1 demonstrates that Brexit highlights the inadequacy of Gaussian VaR while affirming the relevance of EVT and Historical approaches.

Objective 2: Backtesting and Robustness Checks

The second objective focused on evaluating the statistical adequacy of VaR models using Kupiec's proportion-of-failures test. Pre-Brexit, both Parametric and Historical VaR produced breach frequencies close to the expected 5% threshold, suggesting statistical adequacy under tranquil conditions. Parametric VaR was slightly more conservative, while Historical VaR occasionally overstated breaches. This echoes Degiannakis *et al.* (2012), who found parametric models acceptable in low-volatility settings.

Post-Brexit results, however, were starkly different. Parametric VaR consistently failed Kupiec tests across multiple banks, producing breach frequencies well below expectations. Historical VaR, while not perfect, remained statistically valid for most institutions. These results mirror Geenens and Dunn (2020), who argue that nonparametric methods maintain robustness during structural breaks, and Omari *et al.* (2020), who show EVT and Historical models outperform Gaussian VaR under systemic shocks.

EVT provides the theoretical explanation for these rejections. Kupiec test failures stem from the breakdown of Gaussian assumptions under fat-tailed volatility. EVT explicitly accounts for extremes, quantifying exceedances that Gaussian VaR ignores. The Brexit context therefore validates EVT as a superior theoretical framework. Moreover, the results support Basel III's regulatory shift from VaR to Expected Shortfall (Dhawan, 2024), recognising that capital adequacy frameworks must incorporate tail risk. Objective 2 therefore highlights that Brexit demonstrates not only descriptive but statistical inadequacy of Gaussian-based VaR.

Objective 3: Cross-Firm Variation in Model Performance

The third objective examined whether model performance varied across banks based on firm size, EU exposure, and operational scope. The findings reveal significant heterogeneity. Large, internationally integrated institutions—Barclays, HSBC, and Standard Chartered—recorded higher exceedances under Parametric VaR post-Brexit. Their substantial EU market exposure amplified contagion effects and cross-border volatility, challenging Gaussian assumptions. Historical VaR fared better but still underperformed where portfolios were highly diversified and exposed to multiple jurisdictions.

By contrast, Lloyds exhibited consistently low breach rates (Parametric 3.61%; Historical 3.42%), reflecting resilience derived from its domestic orientation. Limited exposure to EU dynamics insulated Lloyds from Brexit-related shocks. Smaller institutions such as CBG and STB produced idiosyncratic patterns. Thin trading volumes and concentrated portfolios occasionally caused Historical VaR to overstate risks, underscoring the sensitivity of empirical models to data sparsity.

These results reinforce Al Janabi (2006), who argues that liquidity, size, and integration strongly influence VaR reliability. Boland and O'Riordan (2019) similarly highlight that Brexit exacerbated systemic risks for EU-exposed firms. Theoretically, EVT explains why large global banks fared worse: fat-tailed shocks are more prevalent in globally integrated portfolios subject to contagion, making Gaussian assumptions untenable. Domestically focused banks faced narrower exposures approximating normality, explaining their stronger alignment with Parametric VaR.

Objective 3 therefore contributes by showing that VaR model adequacy is contingent upon firm-specific factors. Brexit amplified this heterogeneity, confirming that risk management frameworks cannot adopt one-size-fits-all approaches. EVT strengthens this conclusion by explaining why cross-firm variation reflects the interaction between fat-tailed exposures and model assumptions.

Objective 4: Practical and Policy Implications

The fourth objective derived practical lessons for banks and regulatory bodies. For banks, results demonstrate that reliance on a single model is insufficient. Internationally exposed institutions should adopt hybrid frameworks that combine Parametric VaR for stability, Historical VaR for empirical adaptability, and EVT-based methods for tail sensitivity. Domestically focused banks may rely more on Parametric models during stable periods but must still integrate EVT-based stress testing to remain resilient.

For regulators such as the Prudential Regulation Authority (PRA) and Bank of England, two implications emerge. First, political shocks must be treated as systemic risks equivalent to financial crises. Brexit illustrates how political events destabilise models and amplify systemic vulnerabilities. Second, regulatory frameworks should embrace multi-model validation and scenario-based stress testing. This aligns with Basel III's emphasis on Expected Shortfall but extends it by recognising political shocks as systemic in origin (James & Quaglia, 2020).

Supporting literature reinforces these points. Heald and Wright (2019) stress that Brexit necessitated more rigorous accounting and risk frameworks. Song (2024) highlights that conventional VaR underestimates risks in the post-Brexit environment. Together, the findings emphasise that adaptive regulation must evolve to incorporate political as well as financial disruptions. Objective 4 therefore advances the literature by generating practical and policy insights directly applicable to banks and supervisors.

Implications to Research and Practice

The findings of this study carry important implications for both research and practice. From a research perspective, the results demonstrate that Brexit, as a political shock, generated volatility patterns similar to financial crises, highlighting the need for future studies to examine political disruptions within systemic risk analysis. By applying Extreme Value Theory (EVT), the study reinforces the value of tail-sensitive frameworks, suggesting that scholars should move beyond Gaussian assumptions when modelling risk in uncertain environments. This contributes to ongoing debates in financial econometrics and strengthens the theoretical foundation for stress testing under non-financial shocks.

From a practical standpoint, the evidence shows that reliance on a single VaR model is inadequate. For banks, hybrid risk frameworks that combine Parametric, Historical, and EVT-based approaches are essential to balance conservatism, adaptability, and tail sensitivity. For regulators such as the Prudential Regulation Authority and the Bank of England, the findings highlight the importance of embedding multi-model backtesting and scenario-based stress testing into supervisory practice. These measures will ensure greater resilience of the UK banking sector to political shocks, while aligning with evolving Basel III standards on Expected Shortfall.

CONCLUSION

This study examined VaR model performance in UK banks across 2014–2024, spanning pre- and post-Brexit periods. Results show that Parametric VaR was effective in tranquil markets but systematically underestimated risks during Brexit volatility. Historical VaR provided better adaptability but varied across firms depending on size and EU exposure. Large, internationally integrated banks experienced higher exceedances, while domestically oriented banks such as Lloyds showed resilience.

By framing Brexit as a political shock with systemic consequences akin to financial crises, the study extends risk management literature into new territory. EVT provides the theoretical foundation, explaining why Gaussian models failed and why tail-sensitive approaches are essential.

Practical recommendations: Banks should employ hybrid risk frameworks combining Parametric conservatism, Historical adaptability, and EVT-based tail modelling. Internationally exposed firms must prioritise EVT approaches to capture fat-tailed risks, while domestic banks should maintain multi-model resilience.

Policy recommendations: Regulators such as the PRA and Bank of England should treat political shocks as systemic threats, moving beyond Gaussian VaR toward multi-model validation and scenario-based stress testing. Basel III's move to expected shortfall is important but must be explicitly operationalised in relation to political disruptions.

Future Research

Future research should extend this study by examining the performance of Value-at-Risk (VaR) and Extreme Value Theory (EVT)-based models across other jurisdictions experiencing political shocks, such as the Eurozone debt crisis or U.S. trade policy disruptions. Comparative studies would provide deeper insights into whether Brexit's effects are unique or part of a broader pattern of politically induced systemic risks. Additionally, firm-level factors such as governance structures, risk culture, and capital resilience could be integrated to explain variations in model adequacy. Finally, exploring the integration of EVT-based Expected Shortfall into capital frameworks remains a promising avenue.

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