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Impact of macroeconomic shocks on extreme stock returns: a quantile approach

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Abstract:

This thesis investigates how key macro-financial variables, including market volatility (VIX), credit spreads (BAA–10Y) and interest rate changes (10Y–3M), affect stock returns across six major equity indices: the S&P 500, NASDAQ 100, CAC 40, DAX 30, Nikkei 225 and Hang Seng. Covering the period from January 2000 to January 2024, the analysis uses a variety of econometric methods such as Ordinary Least Squares (OLS), Quantile Regression (QR), Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF) to explore how these relationships vary across different market environments and segments of the return distribution.

The results show that the effects of macro-financial variables on returns vary depending on market conditions. Volatility, as measured by the VIX, has a consistently negative impact, particularly in the lower quantiles, which suggests that uncertainty affects returns most strongly during periods of market stress. Credit spreads display a more nuanced pattern, showing a positive relationship with returns during bearish conditions. This counterintuitive finding may reflect a shift toward riskier assets in down markets, although it might also result from model limitations or unobserved factors. Interest rate changes, on the other hand, have weak and inconsistent effects, with no clear link to stock returns.

By comparing the four models, the study highlights the value of quantile-based and nonlinear approaches in capturing the asymmetric and context-specific behaviour of financial markets. These findings provide valuable insights for investors who seek to manage risk under different market conditions, but also for policymakers who monitor volatility and credit dynamics to support financial stability. The thesis adds to the literature on the predictability of returns and highlights the limitations of traditional mean-based models.

Keywords:

Quantile regression, tail risk, stock returns, macro-financial variables, market volatility, credit spreads, yield curve, nonlinear model, risk management

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Signed in Ottignies on May 22, 2025

Julien Dupont

Dupont

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I would like to express my deepest gratitude to Professor Leonardo Iania for his exceptional guidance, constant support, and constructive feedback throughout this thesis. His expertise and encouragement have been invaluable.

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Contents

List of Tables

List of Figures

1 Introduction

Understanding the behaviour of stock market returns is a central issue in financial economics, with important implications for asset pricing, portfolio strategy, risk assessment and economic policy. For a long time, researchers have used linear models such as Ordinary Least Squares (OLS) to study how returns react to macroeconomic factors. These methods are useful for identifying average trends, but they are often insufficient when it comes to capture the full complexity of financial markets, particularly during periods of volatility, when economic shocks can have much larger and asymmetric effects.

During financial crises and episodes of heightened volatility, stock return distributions deviate substantially from normality, displaying characteristics such as fat tails, skewness, and volatility clustering (Barro, 2006; Bollerslev & Todorov, 2011). Relying exclusively on mean-based estimations in such contexts risks overlooking crucial dynamics that are highly relevant to risk managers, policymakers, and market participants. Understanding how markets react not only in stable conditions but also in extreme states (such as severe downturns or speculative surges) is critical for effective financial decision-making (Kelly & Jiang, 2014).

To address these limitations, this thesis adopts a quantile regression framework, originally introduced by Koenker and Bassett (1978) , to provide a more nuanced analysis of stock return predictability. Unlike traditional models that focus solely on central tendencies, quantile regression and its nonlinear extensions such as Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF) allow for a deeper and more flexible exploration of how macro-financial variables impact stock returns across different parts of the distribution. This approach is particularly valuable to assess tail behavior, which represent rare but consequential market events (Chernozhukov & Hansen, 2007; White & al., 2015).

By estimating coefficients at different points in the return distribution, this method reveals whether macroeconomic factors have a greater impact during times of extreme pessimism (at the 5th percentile of returns) or during periods of strong optimism (at the 95th percentile). These insights, which are hidden in conventional OLS models, offer a more complete comprehension of how markets behave in various scenarios.

This analysis covers six major stock market indices: the S&P 500, the NASDAQ 100, the CAC 40, the DAX 30, the Nikkei 225 and the Hang Seng. It provides a broad and cross-market perspective that takes into account variations in local monetary policies, investor behaviour and economic structures. Major macro-financial events like the Dot-com crash, the 2008 Global Financial Crisis, the European sovereign debt crisis and the COVID-19 pandemic are covered by the study which is based on monthly data from January 2000 to January 2024. These events provide real-world examples of how different macro-financial shocks affect equity markets in diverse settings.

To comprehensively capture systemic and macroeconomic risks, this study incorporates three key predictors: the slope of the yield curve (10-Year Treasury minus 3-Month Treasury, in first difference), the VIX index (in levels), and the BAA-10Y corporate credit spread (in levels). These choices preserve their economic interpretability, in line with (Whaley, 2000; Gilchrist & Zakrajšek, 2012). The yield curve slope is widely recognized as a leading indicator of economic cycles (Parker & Schularick, 2021; Campbell & Shiller, 1991) with inverted curves often signaling signalling the likelihood of an imminent recession. The VIX reflects market-implied volatility and investor sentiment, particularly during periods of financial stress (Whaley, 2000; Liu et al., 2022). The BAA-10Y spread, representing corporate credit risk, captures the differential between risky corporate bonds and safer government bonds making it a critical measure of market-perceived credit conditions and liquidity. (Gilchrist & Zakrajšek, 2012; Faust et al., 2013). Together, these predictors capture three critical dimensions of the macro-financial environment, monetary policy, market uncertainty and credit risk, each of which can significantly influence investor behavior and asset returns.

By analyzing key quantiles (specifically the 5th, 25th, 50th (median), 75th, and 95th percentiles), this study offers a comprehensive perspective on how shocks to these macro-financial variables impact both median returns and the extremes of the distribution. This approach facilitates the identification of asymmetries, such as whether an increase in market volatility disproportionately affects negative returns compared to positive ones, and uncovers state-dependent sensitivities that remain undetected in traditional mean-based models.

This thesis is guided by the following research questions:

- **How do macro-financial predictors influence stock returns in the tails of the return distribution?**
- **Do these effects differ significantly from their behavior at the median?**
- **To what extent can quantile regression improve the modeling of extreme return outcomes compared to traditional mean-based methods?**

This thesis aims to address three key objectives:

- First, to determine whether macro-financial variables exhibit statistically significant effects across different segments of the return distribution, capturing the dynamics of extreme losses and gains.
- Second, to evaluate the performance of quantile regression and its nonlinear extensions (QGAM and QRF) in capturing these effects, relative to traditional OLS models.
- Third, to assess the consistency of these relationships across six major international equity markets, offering insights into regional market behavior.

While exploratory in nature, the findings of this research may offer valuable insights for practitioners focused on managing tail risks, as well as for researchers seeking to refine financial modeling techniques during periods of macroeconomic stress. Additionally, the cross-sectional analysis of major stock indices provides a foundation for discussions on financial integration and the global transmission of macro-financial shocks.

The rest of this thesis is organized to offer a thorough understanding of how macro-financial variables influence stock returns. Section 2 provides a review of the academic literature, focusing on return predictability, tail risks and the use of quantile regression in financial econometrics. Section 3 explains the methodological approach, including the data used, how the variables were transformed, the estimation strategy and the reasons for choosing quantile regression along with its nonlinear extensions (QGAM and QRF). Section 4 presents the main empirical results, starting with OLS regressions, then moving to linear quantile regression and expanding with the results from QGAM and QRF models. This section also includes a detailed look at each index, a comparison across markets, a discussion of the key findings and a review of the research hypotheses. Finally, Section 5 wraps up the thesis by summarizing the main takeaways, reflecting on their theoretical and practical significance and offering ideas for future research.

2 Literature review

The predictability of stock returns using macro-financial variables has been a cornerstone of empirical finance for decades, shaping investment strategies, risk management practices and financial policymaking. Traditional approaches have predominantly relied on mean-based linear regressions, typically estimated using Ordinary Least Squares (OLS), to link macroeconomic factors to asset returns (Yang, 2024). However, their effectiveness is often challenged during periods of heightened market volatility and macroeconomic disruptions. Under such conditions, stock returns frequently exhibit characteristics such as fat tails, volatility clustering and asymmetric distributions, phenomena collectively known as "stylized facts" of financial markets (Cont, 2001).

Recent advances in empirical finance emphasize distribution-sensitive techniques that capture both central and extreme outcomes. Among these, quantile regression (QR), first introduced by Koenker and Bassett (1978), has gained prominence as a flexible and robust approach to analyze return predictability across different market conditions. Unlike traditional mean-based models, which focus solely on average effects, QR estimates the conditional quantiles of the response variable, providing insights into how macro-financial variables impact both typical and extreme outcomes (Chernozhukov & Hansen, 2007; White et al., 2015). This feature is particularly valuable in financial markets where rare but impactful events can lead to substantial portfolio losses.

Empirical studies have documented the shortcomings of mean-based approaches. Traditional models, which assume symmetric behavior and constant variance, often fail to capture the complex, dynamic nature of financial markets where extreme events can lead to severe financial instability. These limitations are most evident during episodes of systemic stress such as the 2008 Global Financial Crisis and the COVID-19 pandemic where standard risk assessment models struggled to capture the magnitude and persistence of losses (Danielsson et al., 2001; Taleb, 2007).

As a response, modern financial research has increasingly turned to quantile regression and other distribution-sensitive methodologies. Quantile regression provides a comprehensive view of how macro-financial variables affect different segments of the return distribution, from extreme losses (e.g., 5th percentile) to extreme gains (e.g., 95th percentile). This capability has made it a valuable tool for assessing tail risks, designing robust stress-testing frameworks and improving portfolio risk management.

This literature review traces the evolution of empirical methods in stock return modeling, critically examines the limitations of traditional mean-based techniques, highlights the significance of tail risks and extreme events and introduces quantile regression as a powerful alternative to capture the asymmetric and nonlinear dynamics inherent in financial markets.

2.1 Traditional models of return predictability and their limitations

Traditional empirical studies of stock return predictability have long relied on OLS regression, which estimates the conditional mean of stock returns based on a set of macro-financial predictors. Seminal works by Fama and Schwert (1977) and Chen et al. (1986) demonstrated that economic indicators, such as interest rates, inflation, industrial production and default spreads, possess significant explanatory power over stock returns. These early contributions provided a foundational understanding of how macroeconomic conditions influence asset prices.

Subsequent research expanded this framework, testing a broader set of predictive variables. Welch and Goyal (2008) conducted a comprehensive evaluation of numerous financial predictors, including the dividend-price ratio, earnings-price ratio, term spreads and interest rates. However, their findings revealed that many of these variables struggled to outperform simple historical averages in out-of-sample forecasting. This result raised questions about the robustness and reliability of mean-based predictive models, particularly during periods of heightened market volatility or economic uncertainty.

Despite their widespread use, OLS-based models are fundamentally limited. They inherently assume a constant, linear and symmetric relationship between predictors and returns, capturing only the average effect of each predictor. In reality, financial markets are characterized by complexity, nonlinearity and volatility clustering, where extreme losses or gains are more common than predicted by a normal distribution (Cont, 2001). OLS compresses these extreme dynamics into a single average relationship, overlooking the heightened sensitivity of returns to macro-financial shocks, particularly during periods of financial stress.

Moreover, OLS relies on the assumption of homoscedasticity (constant variance of residuals), an assumption that is frequently violated in financial data. Financial markets often experience heteroscedasticity, where periods of elevated uncertainty lead to clusters of large returns, followed by calmer periods. This time-varying nature of volatility undermines the accuracy of standard errors and confidence intervals in OLS models, making statistical inference unreliable.

Another critical limitation is that OLS is fundamentally a static model, providing a single estimated relationship that applies uniformly across the entire sample period. This is problematic because financial markets are inherently dynamic, influenced by evolving macroeconomic conditions, shifts in monetary policy, regulatory changes and changing investor sentiment. As a result, the predictive power of macro-financial variables can vary significantly across different economic regimes. Static OLS models fail to account for these evolving dynamics, leading to models that may be accurate in one period but misleading in another.

The inability of OLS to capture asymmetric, nonlinear and state-dependent relationships has led to the development of more flexible, distribution-sensitive methodologies. Among these, quantile regression has gained prominence as a robust alternative. Introduced by Koenker and Bassett (1978), quantile regression provides a more nuanced analysis of stock return predictability by estimating the conditional quantiles of the response variable. Unlike OLS, which focuses solely on average effects, quantile regression captures the full distribution of returns, allowing for the analysis of both central tendencies and extreme outcomes (Chernozhukov & Hansen, 2007; White et al., 2015).

Quantile regression is particularly valuable in financial markets, where tail risks and nonlinear relationships often dominate. By estimating the conditional quantiles of stock returns, it reveals how macro-financial variables influence not only median returns but also extreme outcomes such as the 5th or 95th percentiles. This capability is crucial for assessing tail risks, understanding the dynamics of extreme losses or gains and designing robust risk management strategies. As subsequent sections will demonstrate, quantile regression provides a richer understanding of how macro-financial variables influence returns across different market conditions, offering valuable insights for risk management, asset allocation and financial policy analysis.

2.2 Tail risk and the importance of extreme events

Recent financial crises such as the 2008 Global Financial Crisis and the COVID-19 pandemic have highlighted just how important tail risks are in financial markets. These events exposed major weaknesses in traditional risk assessment methods, especially those based on Value-at-Risk (VaR) models that assume returns follow a normal distribution (Danielsson et al., 2001). By underestimating both how likely and how severe extreme losses can be, these models missed the complex and nonlinear patterns that often emerge during periods of market stress. As a result, they led to serious misjudgments in assessing risk and allocating capital.

Traditional models often fail to capture extreme events, which is a problem that relates to the idea of “Black Swan” events described by Taleb (2007). These are rare and unexpected events that have a big impact, but they are hard to predict using models that rely on average results and assume returns are normally distributed. Because Black Swans fall in the extreme ends of the distribution, they are often missed by standard forecasting tools. In this thesis, these events show why it is important to go beyond models that only look at average outcomes. To better understand how markets behave during times of stress, we need methods that focus on what happens in the tails of the distribution, where the most severe market movements occur.

Although tail events are infrequent, they generate disproportionate fluctuations in portfolio values and systemic stability. As highlighted by Barro (2006) but also by Bollerslev and Todorov (2011), extreme market movements are often triggered by rare economic disasters, volatility shocks or abrupt liquidity crises. These kinds of events have a strong impact on asset pricing, risk management and overall financial stability. They show how important it is to take tail risks into account when studying how returns can be predicted. Traditional models often focus on average patterns and tend to miss how sensitive financial markets can be to extreme losses especially during periods of stress.

Given the limits of traditional models, researchers have increasingly turned to methods that are better at capturing risks in the tails of the distribution. For example, the CoVaR model developed by Adrian and Brunnermeier (2016) goes beyond standard risk measures by showing how financial distress can spread across the system. Other models, like the spline-GARCH model by Engle and Rangel (2008), are designed to handle extreme situations by adjusting to changing risk levels over time. These approaches help capture the way volatility tends to persist and cluster during market turbulence. Overall, they highlight that financial relationships are often nonlinear and behave differently during crises, when traditional forecasting models tend to fall short.

Recognizing and properly modeling tail risks is not just a theoretical issue, it is a practical priority for financial institutions, portfolio managers and central banks. A solid understanding of how extreme events spread through financial markets is essential to design effective risk management strategies, run reliable stress tests and monitor systemic risk.

Building on this idea, the thesis uses a quantile regression approach to better reflect the asymmetric and nonlinear nature of tail risks in financial markets. It explores how macro-financial factors, such as market volatility, credit spreads and interest rate dynamics, influence the full distribution of stock returns under different market conditions. By applying quantile regression along with its nonlinear extensions, the analysis captures how these effects vary depending on the state of the market, with a special focus on extreme outcomes. The goal is to offer a deeper understanding of how macroeconomic shocks shape both downside and upside return patterns across major global stock indices, providing useful insights for managing portfolio risk, designing stress testing frameworks and building more resilient investment strategies.

2.3 Introduction to quantile regression in finance

Quantile regression, first introduced by Koenker and Bassett (1978), provides a flexible approach to estimate the conditional quantiles of a response variable given a set of predictors. Unlike OLS, which focuses on the conditional mean, quantile regression models the full distribution of the dependent variable making it particularly valuable in finance, where return distributions often exhibit asymmetries, volatility clustering and extreme events (Koenker & Hallock, 2001). This capacity to capture heterogeneous effects across quantiles is very important to understand how macro-financial variables influence returns in both normal and extreme market conditions.

Quantile regression has become a widely used tool in financial risk analysis. For example, Engle and Manganelli (2004) applied it to Value-at-Risk (VaR) estimation, showing how well it captures extreme losses. Bloom (2009) also demonstrated that uncertainty shocks affect asset returns differently depending on the stage of the economic cycle. More recent developments have extended quantile regression to panel data (Galvão, 2011) and dynamic financial time series (White et al., 2015), further increasing its relevance for practical applications.

Building on these insights, this thesis applies quantile regression and its nonlinear extensions to six major stock indices. This approach helps to better understand how returns behave across the distribution and provides a solid framework to evaluate downside risk and compare how different markets respond to macro-financial factors.

2.4 Summary and positioning of this study

This thesis tackles the key limitations of models that focus only on average outcomes which often overlook the complex behavior of stock returns. By using a quantile regression approach, it captures the asymmetric, nonlinear and state-dependent effects that macro-financial variables can have on returns. This method is especially relevant in financial markets, where extreme events, periods of high volatility and tail risks are common and can significantly influence market dynamics.

This study focuses on three key macro-financial indicators. The first is the VIX, a widely used measure of market-implied volatility that reflects investor sentiment and perceived risk. The second is the credit spread, specifically the difference between BAA-rated corporate bonds and 10-year U.S. Treasury bonds. This spread provides insight into how investors view corporate credit risk and overall market liquidity (Gilchrist & Zakrajšek, 2012). The third is the slope of the yield curve, measured as the difference between 10-year and 3-month interest rates. This indicator is often used to predict economic cycles, as an inverted yield curve has frequently preceded recessions (Parker & Schularick, 2021). Together, these variables offer a broad perspective on monetary policy, market uncertainty and credit conditions, factors that play a central role in shaping investor decisions and asset returns.

By examining these indicators across six major international stock indices, the S&P 500, NASDAQ 100, CAC 40, DAX 30, Nikkei 225 and Hang Seng, this thesis offers a broad and cross-market perspective. It investigates how macro-financial variables affect stock returns across different parts of the distribution, specifically at the 5th, 25th, 50th, 75th and 95th percentiles. This approach captures not only average trends but also extreme outcomes on both ends of the return spectrum.

In addition to standard quantile regression, the study uses two advanced nonlinear models: Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF).

QGAM estimates smooth, nonlinear relationships between variables, making it possible to detect threshold effects and more subtle patterns across the distribution (Fasiolo et al., 2020). QRF, a fully nonparametric method based on random forests, captures complex interactions and nonlinearities without assuming a specific functional form (Meinshausen, 2006). These models deepen the analysis by uncovering patterns that traditional methods might miss.

This thesis addresses the limitations of traditional models and makes three main contributions. First, it shows that macro-financial variables affect stock returns in ways that are both asymmetric and dependent on the broader market context, especially at the extremes of the distribution. Second, it uses more advanced quantile-based methods (QGAM and QRF) to uncover complex and nonlinear patterns that standard approaches often miss. Third, it compares results across major global stock indices to reveal how different markets respond to macro-financial shocks.

At the crossroads of quantile econometrics and financial risk analysis, this study offers useful insights for portfolio managers, risk professionals, policymakers and researchers. It adds to the growing research on tail-risk modeling and return prediction, while also offering practical guidance on how macroeconomic shocks can affect financial markets.

3 Methodology and data

3.1 Introduction

This chapter presents the methodological framework and empirical procedures used to examine the impact of macroeconomic shocks on the distribution of stock returns. The primary objective is to investigate how variables such as interest rate changes, credit spreads and market volatility influence returns across the entire distribution, rather than focusing solely on the mean. Given the limitations of traditional linear models in capturing tail behavior, this study adopts a quantile-based approach to provide a more comprehensive understanding of return dynamics under both normal and extreme market conditions.

The empirical strategy is structured in several stages. It begins with standard Ordinary Least Squares (OLS) regressions which serve as a benchmark for assessing the average effect of macro-financial variables on stock returns. This is followed by classical Quantile Regression (QR) which extends the analysis by estimating predictor effects at various quantiles of the return distribution, capturing asymmetric and heterogeneous impacts. To further account for potential nonlinearities and complex interactions, the study employs two advanced, nonparametric extensions: Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF). These methods provide additional flexibility in modeling the relationships between macro-financial variables and stock returns, accommodating both smooth nonlinear effects and complex dependencies.

The analysis is conducted across a panel of major equity indices. This cross-market perspective enables a comparative assessment of how macro-financial shocks propagate across different regions, each with its own economic structure, regulatory environment and investor behavior. Special attention is paid to downside risks, reflecting the critical importance of tail-risk management in financial markets.

By combining linear (OLS), quantile-based (QR) and nonlinear quantile methods (QGAM and QRF), this study offers a robust and flexible analytical framework. This multi-method approach enhances the reliability of the findings, providing a detailed understanding of how macroeconomic shocks shape stock returns under varying market conditions.

3.2 Data and variables

3.2.1 Description of indices and sources

This study analyzes monthly return data from six major stock market indices, representing a diverse range of developed and international financial markets: the S&P 500 and NASDAQ 100 (United States), CAC 40 (France), DAX 30 (Germany), Nikkei 225 (Japan) and Hang Seng

Index (Hong Kong). These indices collectively capture distinct macroeconomic and regional dynamics, offering a comprehensive view of global equity market behavior.

The financial data for the indices are obtained from Investing.com. Stock returns are computed using the log-difference method, calculated as the first difference of the natural logarithm of prices:

$$r_t = \log(P_t) - \log(P_{t-1})$$

where r_t denotes the return at time t, P_t is the closing price of the index at time t and P_{t-1} is the closing price at the previous period. This method is widely used in financial econometrics due to its desirable statistical properties, including normality under certain conditions and its ability to capture continuously compounded returns.

The sample period extends from January 2000 to January 2024, covering multiple market regimes, including the Dot-com bubble burst, the 2008 Global Financial Crisis, the European Sovereign Debt Crisis, the COVID-19 pandemic and recent monetary policy tightening cycles. These episodes provide a robust context for examining how macro-financial shocks propagate through global stock markets under varying economic conditions.

3.2.2 Macroeconomic variables

To capture macro-financial shocks and investor sentiment, three explanatory variables are selected based on their theoretical relevance and empirical support in the literature:

VIX: The CBOE Volatility Index serves as a proxy for market-implied volatility and risk aversion. It reflects investors' expectations of near-term volatility and tends to spike during periods of financial stress. The VIX is widely recognized as a reliable indicator of market uncertainty and is frequently used in financial research to measure risk sentiment (Whaley, 2000; Liu et al., 2022).

Credit spread (BAA10Y): Measured as the spread between Moody's BAA-rated corporate bond yields and the 10-year U.S. Treasury yield, this variable captures credit risk premia and broader financing conditions. Credit spreads are a well-established proxy for perceived credit risk, liquidity conditions and economic stress, making them a critical predictor of financial market dynamics (Gilchrist & Zakrajšek, 2012; Faust et al., 2013).

Yield curve slope change: Defined as the monthly change in the difference between the 10-year and 3-month U.S. Treasury yields, this variable reflects shifts in expectations regarding economic growth and monetary policy. A declining or inverted slope has historically been associated with increased recession risk (Estrella & Hardouvelis, 1991; Shiller, 1991).

All macroeconomic variables are sourced from the Federal Reserve Economic Data (FRED) database and are aligned temporally with the stock return series.

3.2.3 Data transformations

Before estimation, several transformations are applied to ensure that the return series are appropriately scaled and comparable. Stock returns for each index are computed using log-differences, defined as the difference between the natural logarithm of consecutive monthly prices. This transformation captures continuously compounded returns, which are commonly used in financial analysis due to their statistical properties.

Unlike in some prior studies, the macro-financial variables are treated differently to preserve their economic interpretability. Specifically, the VIX and the BAA10Y credit spread are included in their original levels, maintaining their direct economic meaning. This allows the estimated coefficients to reflect the impact of a one-point change in these variables on different parts of the return distribution, which is particularly useful for policy and risk management interpretation. This approach is consistent with previous studies that include credit spreads and volatility indices in levels, allowing for direct interpretation of their effects on asset prices and economic conditions (Gilchrist & Zakrajšek, 2012; Stock & Watson, 2012). While these studies do not explicitly argue for level usage on methodological grounds, they reflect a common practice aimed at preserving the structural and economic meaning of such indicators in financial models.

In contrast, the interest rate variable (10Y–3M) is expressed as the first difference, capturing monthly changes in the yield curve slope. This transformation reflects the dynamic nature of interest rate shifts while avoiding issues related to non-stationarity. This methodological choice aligns with the study's objective of capturing the asymmetric and nonlinear effects of macro-financial variables across the distribution of stock returns.

3.3 Preliminary diagnostics

3.3.1 Stationarity tests

Before performing any regression analysis, either linear or quantile-based, it is crucial to assess the stationarity properties of the variables to avoid spurious relationships and invalid inference. Stationarity ensures that a time series exhibits consistent statistical behavior over time, which is a key requirement for reliable estimation and hypothesis testing.

To this end, Augmented Dickey-Fuller (ADF) tests were applied to both the price and return series of all six stock indices. As expected, price levels were found to be non-stationary, while the log return series (calculated as first differences of log prices) were confirmed to be stationary, justifying their use as the dependent variable in the analysis.

Macro-financial variables were similarly examined. The term spread (10Y–3M) was transformed into first differences to ensure stationarity, while the VIX and BAA–10Y credit spread were used in levels to retain economic interpretability. Although the VIX was found to be stationary, the BAA–10Y spread did not reject the unit root hypothesis. Nevertheless, it was retained in levels given its theoretical significance in capturing credit risk premia. All ADF test results are detailed in the Appendix, from Figures 16 to 30.

3.3.2 Multicollinearity

To ensure the reliability of regression coefficient estimates, it is essential to assess the potential presence of multicollinearity among the explanatory variables. Multicollinearity can inflate standard errors, reduce statistical power and lead to misleading inference.

To this end, both a correlation matrix and a Variance Inflation Factor (VIF) analysis were conducted on the three predictors. The correlation matrix reveals that the BAA–10Y credit spread and the VIX exhibit a moderate correlation ($\rho \approx 0.72$), while the other pairwise correlations remain low. The VIF values for all predictors were well below the conventional threshold of 5, ranging from approximately 1.01 to 2.11, indicating that multicollinearity is not a serious concern in the model (Figures 31 to 32).

3.3.3 Heteroscedasticity tests

To assess the presence of heteroscedasticity (non-constant variance of residuals) in the error terms of the linear regressions, Breusch–Pagan tests were performed on the residuals for each stock index. As shown in Table 3, the null hypothesis of homoscedasticity is rejected at the 1% significance level across all indices. This consistent detection of heteroscedasticity indicates that the variance of residuals is not constant, violating one of the key assumptions of Ordinary Least Squares (OLS).

This finding implies that standard OLS inference may be unreliable, particularly for hypothesis testing and confidence intervals based on conventional standard errors. It further underscores the need for more robust estimation techniques, such as quantile regression, which do not rely on the assumption of homoscedasticity.

To mitigate the impact of heteroscedasticity within the OLS framework, robust standard errors were calculated using heteroscedasticity-consistent estimators (HC1), following the method introduced by White (1980). HC1 was chosen because it provides a simple yet effective correction for heteroscedasticity, even in moderate sample sizes like those used in this study (approximately 288 observations per index). This adjustment ensures the validity of inference for the coefficient estimates, providing reliable p-values and t-statistics.

3.4 Estimation strategy

3.4.1 OLS baseline model

As a preliminary benchmark, the analysis begins with a standard OLS regression model to estimate the conditional mean of stock index returns based on macro-financial variables. The dependent variable is the monthly return of each index and the explanatory variables include the first difference of the 10Y–3M yield curve slope, the level of the VIX and the level of the BAA–10Y credit spread. This baseline model serves as a reference point for assessing the average relationship between macro-financial conditions and equity returns, against which distributional methods such as quantile regression can be compared.

To address the presence of heteroscedasticity detected through Breusch–Pagan tests, robust standard errors are employed. This correction ensures consistent inference even in the presence of non-constant variance in the error terms.

The OLS and robust OLS results are presented in Figures 33 to 38 in the Appendix, highlighting differences in significance levels under standard and heteroscedasticity-consistent specifications.

3.4.2 Quantile regression (QR)

To assess how macro-financial variables influence different parts of the return distribution, this thesis applies the quantile regression (QR) framework introduced by Koenker and Bassett (1978). Unlike OLS, which estimates the conditional mean of the dependent variable, QR estimates conditional quantiles, providing a more comprehensive view of the distribution of stock returns. This approach is particularly valuable in financial markets, where extreme losses or gains can significantly influence portfolio performance.

For a given quantile $\tau \in (0, 1)$, the conditional τ-th quantile function of stock returns R_t, given macro-financial predictors X_t, is defined as:

$$Q_\tau(R_t \mid X_t) = \beta_0(\tau) + \beta_1(\tau) \cdot YC_t + \beta_2(\tau) \cdot VIX_t + \beta_3(\tau) \cdot CS_t + \varepsilon_t(\tau),$$

where:

- $Q_\tau(R_t \mid X_t)$ is the conditional quantile of monthly returns at level τ.
- YC_t represents the first difference of the 10Y–3M term spread.
- VIX_t is the volatility index in levels.
- CS_t denotes the BAA–10Y credit spread in levels.
- $\beta_i(\tau)$ are quantile-specific coefficients for each predictor.

- $\varepsilon_t(\tau)$ is the quantile-specific residual.

Quantile regression is estimated by minimizing an asymmetric loss function:

$$\min_{\beta} \sum_{t=1}^{T} \rho_\tau(R_t - X_t^\top \beta),$$

where $\rho_\tau(u) = u \cdot (\tau - \mathbb{I}_{\{u<0\}})$ is the check function and $\mathbb{I}_{\{u<0\}}$ is an indicator function. This function applies different penalties to over-predictions and under-predictions, making QR sensitive to asymmetric risks.

Estimation is performed using the `rq()` function from the `quantreg` package in R. Standard errors are calculated using the kernel density method (`se = “ker”`), which provides robust and asymptotically valid inference without assuming constant variance. This approach provides robust inference without assuming homoscedasticity, making it preferable for this dataset.

The model is estimated at five quantiles (5%, 25%, 50%, 75% and 95%), capturing a wide range of market conditions. The 5% quantile, which is directly related to the concept of Value-at-Risk (VaR), focuses on extreme negative outcomes, revealing how variables impact returns during severe downturns. At the 25% quantile, the analysis reflects moderately stressed conditions, providing early warning signals. The median (50%) offers insights into the central tendency of returns, serving as a robust measure unaffected by extreme values. The 75% quantile highlights moderate positive return dynamics, while the 95% quantile explores how macro-financial variables influence large positive returns, shedding light on exuberant market phases.

This multi-quantile strategy provides a nuanced understanding of return dynamics. It captures asymmetric effects, revealing how macro-financial variables influence returns differently during downturns and upswings. By modeling predictor effects across varying market conditions, it uncovers state-dependent relationships, such as heightened volatility impacts during crises. Moreover, it offers a clear view of tail risks, directly informing risk management and policy decisions by explicitly quantifying extreme outcomes.

By extending beyond mean-based models, quantile regression offers a more comprehensive view of how macroeconomic shocks influence return dynamics, particularly under extreme market conditions. This approach is essential for accurately assessing downside risks and designing robust risk management strategies.

3.5 Nonlinear quantile methods

While standard quantile regression effectively captures distributional asymmetries, it relies on a linear specification for the relationship between predictors and responses at each quantile.

However, financial variables often exhibit nonlinear and state-dependent behaviors, which cannot be fully captured by linear models. To overcome this limitation, this study extends the quantile regression framework with two advanced, nonlinear methods: Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF). These models offer greater functional flexibility, enabling the detection of complex, nonlinear relationships that would otherwise remain obscured under linearity assumptions.

3.5.1 Quantile generalized additive models (QGAM)

To capture potential nonlinearities in the relationship between macro-financial variables and stock returns across different parts of the distribution, this study employs Quantile Generalized Additive Models (QGAM), following the framework introduced by Fasiolo et al. (2020). QGAMs extend classical quantile regression by allowing covariates to enter the model as smooth functions rather than being restricted to linear effects, leveraging the theoretical foundation of Generalized Additive Models (GAMs) as described by Wood (2017).

The conditional quantile function at level $\tau \in (0, 1)$ is modeled as:

$$Q_\tau(R_t \mid X_t) = \beta_0(\tau) + s_1(\mathrm{IR}_t) + s_2(\mathrm{VIX}_t) + s_3(\mathrm{CS}_t),$$

where R_t is the monthly return of a stock index and $s_j(\cdot)$ are smooth, nonparametric functions of the predictors: the interest rate slope change (IR_t), the VIX index (VIX_t) and the BAA–10Y credit spread (CS_t).
The smooth terms $s_j(\cdot)$ are constructed using penalized regression splines, a flexible technique that balances model complexity with overfitting control. Specifically, each $s_j(\cdot)$ is defined as a weighted sum of basis functions:

$$s_j(x) = \sum_{k=1}^{K} b_k B_k(x)$$

where: $B_k(x)$ are basis functions (typically cubic splines or thin-plate splines), b_k are coefficients to be estimated and K is the number of basis functions, chosen based on the complexity of the relationship.

To prevent overfitting, a penalty is applied to the smooth terms, defined as:

$$\lambda \int [s_j''(x)]^2 dx$$

where λ is a smoothing parameter that controls the trade-off between model flexibility and smoothness:

- A high value of λ leads to a smoother curve (less flexible).

- A low value of λ allows the curve to follow the data more closely (more flexible).

The optimal value of λ is determined using Restricted Maximum Likelihood (REML), a data-driven method that balances model fit and smoothness (Wood, 2017). This approach is particularly well-suited for time series data exhibiting structural nonlinearities.

For estimation, the `qgam()` function from the `qgam` package in R (Fasiolo et al., 2020) is employed. This function allows for efficient estimation of quantile GAMs using a fast algorithm optimized for quantile regression with smooth terms. In this study, separate QGAM models are fitted for each quantile of interest, providing a detailed picture of how the effects of predictors vary from extreme downside risk to extreme upside gains.

The graphical diagnostics, generated using the `draw()` function, provide visual insights into the estimated smooth effects across quantiles. These visualizations are particularly useful for identifying nonlinear relationships that may not be captured by standard quantile regression or OLS models.

By adopting QGAM, this study is able to flexibly model nonlinear and asymmetric effects of macro-financial shocks on stock returns while still preserving the quantile-based framework essential for tail risk analysis. This approach aligns with the growing recognition of the importance of nonlinear modeling in financial econometrics, particularly to understand tail risks and extreme market behaviors (Fasiolo et al., 2020; Fasiolo et al., 2021; Wood, 2017).

3.5.2 Quantile regression forest (QRF)

Quantile Regression Forests (QRF), introduced by Meinshausen (2006), provide a nonparametric method to estimate the full conditional distribution of a response variable. As an extension of the Random Forest framework, QRF captures complex interactions, nonlinearities and structural breaks without imposing a predefined functional form.

The QRF algorithm builds an ensemble of decision trees, each trained on a bootstrapped sample of the dataset. Each tree is constructed by recursively partitioning the data based on predictor values forming a series of decision nodes. Unlike standard regression trees, where each terminal node (leaf) provides a single average prediction, QRF retains the full distribution of the response variable at each leaf. This enables the model to directly calculate conditional quantiles from the empirical distribution of values in each leaf. Specifically, the predicted τ-th quantile for an observation is determined as:

$$\hat{Q}_\tau(R_t \mid X_t) = \text{Quantile}_\tau\{R_i : X_i \in \text{leaf}_j\}$$

where R_t denotes stock returns, X_t represents the macro-financial predictors and τ is the target quantile. This design allows QRF to capture distributional features such as fat tails, heteroscedasticity and asymmetric effects which are common in financial data.

In this study, QRF is implemented using the `quantregForest()` function in R, trained on an ensemble of 5,000 trees. This configuration balances stability in quantile estimates with computational efficiency. The model's nonparametric nature avoids restrictive linear assumptions enabling it to uncover complex and data-driven relationships between macro-financial variables and stock returns.

QRF offers significant advantages over traditional regression models. It provides nonparametric flexibility, capturing complex interactions and nonlinear effects among predictors without requiring a predefined functional form. By directly estimating conditional quantiles, QRF effectively assesses tail risks (e.g., the 5th percentile as Value-at-Risk and the 95th percentile for upside risks). Additionally, it generates variable importance metrics, identifying the relative influence of each predictor on the distribution of returns. These metrics are derived using a permutation-based approach, where the importance of a variable is determined by the reduction in prediction accuracy when its values are randomly shuffled.

In this thesis, QRF serves two key purposes. First, it provides a robust, flexible benchmark for validating the findings of other quantile-based models (QR and QGAM). Second, it enriches the analysis by capturing complex and nonlinear interactions among macro-financial variables, offering insights that may not be evident in linear or additive models.

The combination of QRF and QGAM extends the analytical depth of this study. While QGAM models smooth nonlinear relationships, QRF captures sharp interactions and distributional shifts, ensuring a comprehensive understanding of how macro-financial variables impact stock returns. This multi-method approach enhances the robustness and reliability of the findings.

3.6 Index-by-Index comparative framework

This thesis adopts an index-by-index modeling strategy, separately estimating each model specification for six major equity indices: the S&P 500, NASDAQ 100, CAC 40, DAX 30, Nikkei 225 and Hang Seng Index. This disaggregated approach avoids the restrictive assumptions of pooled models, enabling a detailed exploration of how macro-financial shocks affect returns in each market.

Each index operates under distinct monetary policies, investor compositions and economic conditions which may alter the sensitivity of returns to macroeconomic shocks. For example, volatility shocks may have a stronger impact in U.S. markets with high institutional participation, while interest rate changes could be more influential in Japan's Nikkei 225, where central bank policies are more active. Such differences justify a region-specific analysis.

Applying a consistent set of models, including OLS, QR, QGAM and QRF, to each index ensures methodological coherence while preserving flexibility. This design allows for a clear comparison of coefficient patterns, nonlinearities and tail sensitivities, highlighting how macro-financial variables impact returns across diverse markets.

3.7 Summary and research hypotheses

This study employs a comprehensive methodological framework that integrates both linear and nonlinear quantile regression techniques to examine how macro-financial shocks influence equity returns across the entire distribution. By combining standard QR with advanced extensions like QGAM and QRF, the analysis captures a wide range of effects, including asymmetries, nonlinearities and state-dependent behaviors across each index. The analysis is guided by the following research hypotheses:

- **H1:** Increases in market volatility (VIX) are associated with significant declines in stock returns with stronger effects observed in the lower quantiles of the distribution.
- **H2:** Widening credit spreads (BAA–10Y) negatively impact returns, especially during downturns, reflecting heightened risk aversion and tighter financial conditions.
- **H3:** The effects of macro-financial variables are asymmetric across the return distribution, being more pronounced in the tails (5th and 95th percentiles) than at the center (median).

These hypotheses are tested across models and indices using a consistent set of predictors: interest rate changes, credit spreads and market volatility. This approach ensures that the analysis captures robust patterns of tail sensitivity, providing insights relevant for asset allocation, policy design and systemic risk monitoring.

4 Results and analysis

4.1 Overview of analytical strategy

This section presents the empirical findings of the study, analyzing how macro-financial variables, including interest rate changes (10Y–3M), market volatility (VIX), and the credit spread (BAA–10Y), affect stock market returns across various market conditions. The analysis covers six major equity indices, providing a global perspective.

The empirical approach begins with Ordinary Least Squares (OLS) regressions, establishing a baseline for the average relationship between predictors and returns. Quantile Regression (QR) extends this analysis by revealing how these effects vary across the return distribution, highlighting tail risks and asymmetric impacts. To account for potential nonlinearities, the study applies Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF), which provide a flexible view of predictor effects under different market states.

This multi-method approach ensures a robust exploration of macro-financial influences on equity returns, offering a detailed understanding of both central and extreme market behaviors. By systematically comparing the results across OLS, QR, QGAM, and QRF, the analysis captures the complexity of return dynamics under varying economic conditions.

4.2 OLS regression

This section presents the results of OLS regressions and their robust counterparts (Robust OLS with heteroscedasticity-consistent standard errors) for the six stock indices. The objective is to assess the average impact of the three macro-financial variables while accounting for potential heteroscedasticity in the residuals.

Why robust OLS?

The decision to include robust OLS alongside standard OLS was driven by evidence of heteroscedasticity, as confirmed by Breusch-Pagan tests (Table 3). Heteroscedasticity indicates that the variance of residuals is not constant, violating a key OLS assumption. This issue can lead to unreliable standard errors misleading p-values and incorrect significance levels.

Robust OLS corrects for this by applying heteroscedasticity-consistent (HC) standard errors which provide valid inference (standard errors, t-values, and p-values) without altering the coefficient estimates. This analysis uses the HC1 method, a commonly applied correction in empirical research, ensuring that results remain reliable even under heteroscedasticity.

4.2.1 Presentation of results

Table 1 provides a comparative overview of the OLS and Robust OLS regression results for all indices. For each model, coefficients and significance levels are reported. Complete regression results can be found in Figures 33 to 38.

Table 1: Comparative summary of OLS and robust OLS regression results

Index	Variable	OLS Coeff.	Robust OLS Coeff.
S&P 500	Intercept	0.0201 *	0.0201
	Diff_InterestRate_Change	-0.0014	-0.0014
	VIX	-0.0028 ***	-0.0028 ***
	BAA10Y_Spread	0.0154 **	0.0154 **
NASDAQ 100	Intercept	0.0316 **	0.0316 **
	Diff_InterestRate_Change	-0.0010	-0.0010
	VIX	-0.0039 ***	-0.0039 ***
	BAA10Y_Spread	0.0203 ***	0.0203 **
CAC 40	Intercept	0.0293 **	0.0293 *
	Diff_InterestRate_Change	0.0078	0.0078
	VIX	-0.0027 ***	-0.0027 ***
	BAA10Y_Spread	0.0105 .	0.0105
DAX 30	Intercept	0.0295 *	0.0295 *
	Diff_InterestRate_Change	0.0193	0.0193
	VIX	-0.0033 ***	-0.0033 ***
	BAA10Y_Spread	0.0159 *	0.0159 *
Nikkei 225	Intercept	0.0238 *	0.0238 .
	Diff_InterestRate_Change	0.0112	0.0112
	VIX	-0.0035 ***	-0.0035 ***
	BAA10Y_Spread	0.0190 **	0.0190 **
Hang Seng	Intercept	0.0137	0.0137
	Diff_InterestRate_Change	0.0080	0.0080
	VIX	-0.0026 ***	-0.0026 **
	BAA10Y_Spread	0.0148 *	0.0148

*Note: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1*

4.2.2 Analysis of results

The OLS and Robust OLS results provide several important insights into how macro-financial variables influence stock returns across the six indices.

First, VIX consistently shows a significant negative impact on stock returns, aligning with Whaley (2000) and Bloom (2009) who demonstrated that rising market volatility leads to lower asset prices. This effect is most pronounced for the NASDAQ 100 and Nikkei 225 which is consistent with the findings of Liu et al. (2022) who demonstrated the strong influence of volatility on stock returns. The heightened sensitivity of these indices may be attributed to their exposure to technology sectors and global markets where investor sentiment and volatility have a pronounced impact.

Second, credit spreads (BAA–10Y) generally exhibit a positive impact on stock returns, especially for the NASDAQ 100 and Nikkei 225. While this finding contrasts with traditional theories (Fama & French, 1989) which associate wider credit spreads with higher perceived risk and lower asset prices, it aligns with the interpretation of Gertler and Lown (1999). They argue that credit spreads can act as indicators of financial conditions and broader macroeconomic dynamics. In this context, a widening spread may reflect shifts in investor expectations or changing monetary conditions, which, under certain circumstances, can coincide with increased equity investment despite elevated credit risk.

Third, interest rate changes (10Y–3M) show limited and insignificant effects across the indices. This finding aligns with Adrian et al. (2019) who observed that the predictive power of the yield curve has diminished in recent years, particularly in persistently low-interest-rate environments.

These findings reveal that the sensitivity of stock returns to macro-financial variables is not uniform, varying by index. This heterogeneity highlights the importance of considering regional and sectoral differences in financial analysis.

4.2.3 Implications for further analysis

The OLS and Robust OLS results provide a useful benchmark for assessing the average effects of macro-financial variables on stock returns. However, the R^2 values of these models are relatively low across all indices, ranging from approximately 0.05 to 0.17. This outcome is common in financial econometrics, where stock returns are influenced by a wide range of unpredictable factors, including investor sentiment, geopolitical events, and macroeconomic shocks that are difficult to fully capture with a limited set of predictors.

Importantly, the low R^2 values do not invalidate the analysis but rather highlight the inherent difficulty of explaining return variability using a small set of macro-financial variables. This result is consistent with the findings of Welch and Goyal (2008) who demonstrated that many traditional predictors struggle to deliver consistent explanatory power for stock returns.

These observations underscore the need for more sophisticated techniques capable of capturing nonlinear and asymmetric relationships which are often present in financial data. In the following sections, the analysis moves beyond the linear structure of OLS by employing quantile regression and its nonlinear extensions (QGAM and QRF). These methods allow for a more nuanced analysis by revealing how the effects of interest rate changes, VIX, and credit spreads vary across different parts of the return distribution, particularly in the tails, where risks are most pronounced.

4.3 Quantile regressions

4.3.1 Linear quantile regression (QR)

This section presents the results of the linear quantile regression (QR) models applied to each of the six equity indices. The primary objective is to assess how the sensitivity of stock returns to key macro-financial variables varies across the distribution of returns, from the lower tail (5th percentile) to the upper tail (95th percentile). Complete regression tables are provided in the Appendix, from Table 4 to Table 9.

Market volatility (VIX)

The VIX index, a widely recognized measure of market volatility, consistently displays a negative and highly significant impact on stock returns across all indices. This finding aligns with the literature which identifies the VIX as a “fear gauge” (Whaley, 2000), where rising volatility is directly associated with falling stock returns. The magnitude of the effect varies, with the NASDAQ 100 and Nikkei 225 showing the strongest sensitivity, reflecting their high exposure to technology and globally-oriented sectors, consistent with Liu et al. (2022).

Interestingly, the VIX is most significantly negative at lower quantiles, amplifying losses during downturns. However, at higher quantiles, the coefficients are positive (though often weaker or less significant), suggesting that in bullish conditions, rising volatility may not necessarily depress returns and might even reflect increased risk appetite or speculative dynamics. This asymmetry highlights that the impact of volatility on returns is context-dependent, with stronger negative effects during downturns and more ambiguous signals during market upswings.

Credit spreads (BAA–10Y spread)

The effect of credit spreads which capture perceptions of corporate credit risk, exhibits a generally positive relationship with stock returns at lower quantiles for some indices. For the S&P 500 and NASDAQ 100, wider credit spreads are associated with higher stock returns at the 5th and 25th quantiles, a finding that contrasts with traditional theories (Fama & French, 1989) which view widening spreads as signals of increased financial risk and lower expected returns. These counterintuitive results may reflect risk-taking behavior during stress periods or model limitations. The Nikkei 225 presents a notable exception, where credit spreads are significant at the median and upper quantiles. This suggests that Japanese investors may interpret widening spreads as part of a broader shift in financial conditions, possibly related to sectoral rotation or expectations of macroeconomic normalization. This pattern is consistent with Gertler and Lown (1999) who emphasize that credit spreads can reflect evolving financial conditions beyond pure default risk, particularly in the context of business cycle dynamics.

Interest rate changes (10Y–3M term spread)

The impact of interest rate changes on stock returns is highly heterogeneous across indices. For the S&P 500 and NASDAQ 100, the coefficients are generally insignificant across all quantiles, suggesting that these US indices are less directly affected by short-term rate fluctuations. This aligns with Adrian et al. (2019) who highlighted the declining predictive power of the yield curve in recent years. In contrast, European markets display more significant effects. The DAX 30 exhibits a positive coefficient at the 5th quantile, suggesting that higher interest rates may be associated with increased returns during severe downturns. This unexpected result could be linked to the resilience of financial and industrial sectors within the DAX, which may benefit from higher rates. For the CAC 40, the relationship is generally positive but lacks statistical significance.

In Asia, the Nikkei 225 presents a positive and significant coefficient at the 5th quantile, a finding that appears contradictory to conventional expectations where rising interest rates typically depress stock returns. However, this result may reflect Japan's unique monetary environment where higher rates can be seen as a signal of economic normalization rather than a tightening measure. Finally, the Hang Seng Index shows no significant relationship between interest rate changes and returns, suggesting that this market is more influenced by other factors.

4.3.2 Nonlinear quantile regression with QGAM

This section presents the results of the Quantile Generalized Additive Models (QGAM) applied to the six stock indices, offering a flexible framework to capture nonlinear relationships between macro-financial variables and stock returns across different quantiles. By modeling each predictor as a smooth function, QGAM allows for the detection of nonlinear and state-dependent effects, revealing how these variables shape return dynamics beyond the linear assumptions of standard quantile regression. Complete QGAM regression results, including the graphical representations of smooth effects, are provided in the Appendix, from Figure 39 to Figure 50.

Overall model performance

The QGAM models demonstrate strong explanatory power across indices, particularly in the tails of the return distribution where risk management is most critical. The explained deviance at the 5th and 95th quantiles is consistently high, reflecting the models' ability to capture the nonlinear dynamics of stock returns in extreme scenarios.

For the S&P 500, the explained deviance reaches 87.6% at the 5th quantile and 86.8% at the 95th quantile, indicating a strong fit in both the lower and upper tails. The NASDAQ 100 shows even higher performance, with 87.6% at the 5th quantile and 89.1% at the 95th quantile, reflecting its high sensitivity to volatility and macro-financial shocks. In European markets, the CAC 40 achieves an explained deviance of 86.1% at the 5th quantile and 85.4% at the 95th quantile, while the DAX 30 demonstrates slightly higher values, with 87.1% and 84.7%, respectively. These results highlight the models' robustness in capturing the heterogeneous responses of European indices to macroeconomic variables. The performance of the QGAM models in Asian markets is similarly strong. For the Nikkei 225, the explained deviance is 85.4% at the 5th quantile and 86.4% at the 95th quantile, reflecting the index's sensitivity to macro-financial factors, including interest rates and credit spreads. The Hang Seng also shows high explanatory power, with 86.9% at the 5th quantile and 86.4% at the 95th quantile, underscoring the models' ability to capture volatility-driven dynamics in this market.

Overall, these high values confirm that the QGAM models effectively capture the nonlinear and asymmetric dynamics of stock returns, particularly in the extreme tails where traditional models often struggle. This strong performance reinforces the importance of adopting flexible, nonlinear methods when analyzing return distributions in global equity markets.

Smooth effect visualization and interpretation

The QGAM results reveal several important insights into the nonlinear effects of macro-financial variables across different indices and quantiles, providing a clearer understanding of how these factors shape stock returns. By leveraging QGAM, the analysis captures complex relationships that standard linear models cannot fully address.

For market volatility, the QGAM results consistently show a negative impact across all indices, particularly at lower quantiles. This pattern is most pronounced in the S&P 500 and NASDAQ 100 where rising volatility significantly erodes returns, consistent with the role of VIX as a "fear gauge." These findings align with Liu et al. (2022) who show that technology and growth-oriented stocks are particularly vulnerable to volatility shocks, especially in bearish market conditions.

The relationship between credit spreads (BAA–10Y Spread) and returns appears more complex and somewhat counterintuitive. Across all indices credit spreads exhibit generally positive relationship, even at lower quantiles. This suggests that rising credit spreads, typically associated with increased financial risk, may, in certain contexts, coincide with higher stock returns. Such a pattern could reflect investor demand for risk premiums or monetary policy expectations that offset risk aversion.

The impact of interest rate changes (10Y–3M Term Spread) on stock returns is generally weak and nonlinear across all indices. Most coefficients are statistically insignificant, indicating limited explanatory power. While isolated effects appear at specific quantiles for certain indices, no consistent pattern emerges. This suggests that stock markets may be relatively insensitive to term spread fluctuations in the short term or that the effects of interest rates are masked by other macro-financial variables. These findings support the view that the influence of interest rates on equity returns is both state-dependent and context-specific, potentially shaped by regional monetary policy regimes and investor expectations.

The QGAM smooth effect visualizations provide a clear illustration of the nonlinear relationships between macro-financial variables and stock returns. Volatility consistently shows a strong negative effect, particularly at lower quantiles, where rising uncertainty amplifies downside risk. This pattern supports the role of the VIX as a "fear gauge" and highlights its disproportionate impact during bearish market conditions. Credit spreads (BAA–10Y Spread) reveal a generally positive, nonlinear relationship with returns across quantiles. Although counterintuitive, this may reflect investor search-for-yield behavior or the influence of monetary policy expectations during periods of financial stress. Interest rate changes (10Y–3M Term Spread) exhibit weak and inconsistent effects. The smooth curves tend to be relatively flat or weakly nonlinear across most quantiles, with no robust or systematic patterns. This suggests that the influence of interest rates on stock returns is limited in the short term and likely shaped by broader macro-financial dynamics.

These visualizations confirm the asymmetric nature of macro-financial effects on stock returns, highlighting significant variations across regions and quantiles. By capturing these nonlinear dynamics, QGAM provides a more nuanced understanding of how interest rates, volatility, and credit conditions influence global equity markets, underscoring the importance of flexible, data-driven methods in financial analysis.

4.3.3 Nonlinear quantile regression with QRF

The analysis of nonlinear effects using Quantile Regression Forests (QRF) reveals consistent patterns across the six stock indices. The VIX consistently shows a negative relationship with stock returns across all indices. This effect is most pronounced for the NASDAQ 100 and S&P 500 where increases in VIX are associated with sharper declines in returns. These findings align with the interpretation of VIX as a “fear gauge,” where rising volatility signals market stress, leading to lower returns.

Credit spreads generally exhibit a positive relationship with stock returns. This effect is visible across all indices, though it is more pronounced in the NASDAQ 100 and Nikkei 225. These findings may reflect a “reach for yield” behavior where investors shift toward higher-risk assets in search of better returns even as credit risk rises. This interpretation is broadly consistent with Gertler and Lown (1999) who show that credit spreads can provide early signals about changes in financial conditions and investor sentiment.

The impact of interest rate changes is generally weak across all indices, with no clear or consistent pattern emerging. Although slight nonlinearities are observed, these effects are surrounded by wide confidence intervals, indicating high uncertainty. This result aligns with the literature which suggests that the predictive power of interest rates has diminished in recent years, especially in low-rate environments (Adrian et al., 2019).

Overall, the QRF results confirm the asymmetric and nonlinear nature of the relationships between macro-financial variables and stock returns. The patterns are broadly consistent across indices, with minor variations in sensitivity and magnitude. These findings support the view that while global markets share common risk factors, regional characteristics may slightly alter their impact. The complete visualization of the QRF model results, illustrating the variable effects across quantiles, are provided in the Appendix, from Figure 51 to Figure 58.

4.4 Synthesis and comparative insights

4.4.1 Cross-model comparative analysis

This section compares the findings of the four estimation methods to highlight the strengths and limitations of each approach. While OLS provides a baseline estimate of average effects, QR captures heterogeneity across the distribution. QGAM introduces nonlinearities through smooth effects, and QRF offers a fully nonparametric alternative capable of uncovering complex interactions.

Table 2: Comparative summary of effects across models

Variable	OLS	QR	QGAM	QRF
VIX	Negative, significant	Negative, stronger in lower quantiles	Nonlinear, negative slope	Dominant predictor
Credit spread	Positive, mostly significant	Positive when significant	Nonlinear, generally positive	Moderate impact
Interest rate change	Insignificant	Weak, occasional significance at tails	Nonlinear, weak effects, index-specific	Low impact

VIX across models. The VIX shows consistent negative effects across all models, reinforcing its role as a reliable proxy for investor fear and market volatility. OLS captures a significant negative average effect, while QR confirms that this effect intensifies in the lower quantiles. QGAM further refines this insight by revealing nonlinear and asymmetric impacts. QRF supports these findings, confirming the robustness of the VIX effect across model specifications and highlighting its relevance for both downside and upside tail risks.

Credit spreads across models. The behavior of credit spreads shows heterogeneity across models and quantiles. OLS results reveal a generally positive and mostly significant relationship between credit spreads and stock returns. This association becomes more nuanced in quantile-based approaches. QR indicates that the relationship varies across the return distribution, with some evidence of positive effects at both lower and upper quantiles, though statistical significance is less consistent. QGAM uncovers nonlinear patterns that suggest a generally positive but heterogeneous effect, with the strength and shape of the relationship varying across quantiles. QRF confirms the moderate but asymmetric influence of credit spreads on returns, further emphasizing the context-dependent nature of how markets respond to changes in perceived credit risk. These results support the idea that credit spreads can reflect a broad set of financial conditions, as suggested by Gertler and Lown (1999), beyond their traditional role as pure risk indicators.

Interest rate changes across models. The effect of interest rate changes (10Y–3M) is relatively weak across all models. OLS results are mostly insignificant, a finding echoed in the QR estimates, where only a few indices show significant effects in the lower or upper quantiles. QGAM reveals some nonlinearities suggesting that the yield curve's predictive power may be regime-dependent, consistent with recent findings in the literature (Adrian et al., 2019). QRF generally corroborates the limited role of interest rates, although it highlights marginal effects in specific quantile ranges for select indices.

Overall, this comparative analysis illustrates the added value of using quantile and nonlinear models in financial econometrics. While OLS offers a convenient summary of average relationships, it fails to capture important distributional dynamics. QR, QGAM, and QRF extend this framework, each adding layers of insight into how macro-financial variables influence returns under varying market conditions.

4.4.2 Cross-market comparison

This section provides a comparative analysis of the effects of macro-financial variables on stock returns across six major equity indices. By estimating each model separately, this study uncovers region-specific sensitivities to macroeconomic shocks, allowing for a more nuanced interpretation of cross-market dynamics. For detailed index-by-index results, see Appendix 7.5.

In U.S. markets, the VIX emerges as the most consistently significant predictor across all models and quantiles. Its negative effect is strongest at the lower quantiles, suggesting heightened vulnerability to volatility shocks during downturns. This pattern supports findings from Liu et al. (2022) who emphasized the sensitivity of technology-heavy and globally exposed indices to volatility. Credit spreads in U.S. markets also show a generally positive relationship with returns at lower quantiles, although the effects are not consistently significant. This counterintuitive pattern may reflect investor demand for higher risk premiums during stress periods or shifts in monetary policy expectations. It also aligns with Gertler and Lown (1999) who highlight the role of credit spreads as indicators of changing financial conditions rather than pure default risk. Interest rate changes, by contrast, show weak and generally insignificant effects, confirming prior evidence from Adrian et al. (2019) that the predictive power of the yield curve has diminished in recent years.

In European markets, the VIX remains negatively associated with returns, though the effects are slightly weaker than in the U.S., possibly reflecting differences in market structure or investor behavior. Credit spreads, by contrast, show generally weak and statistically insignificant effects across quantiles, suggesting a limited role in explaining return dynamics within these markets. This may reflect regional differences in credit transmission mechanisms or the relative importance of credit-sensitive sectors. Interest rate changes also remain mostly insignificant across models, with only minor nonlinear patterns observed in QGAM. These findings suggest that, in European contexts, volatility plays a more prominent role than credit or interest rate indicators in shaping stock return behavior.

Asian markets present the least consistent patterns. The VIX retains a generally negative relationship with returns, though the magnitude varies. Credit spreads exhibit unexpected positive effects at higher quantiles, which may indicate that investors interpret widening spreads as signals of improving growth prospects or sectoral rotation in certain contexts. This finding diverges from classical theory (Fama & French, 1989), suggesting that local market features or model-specific dynamics may be at play. Interest rate changes remain largely insignificant, although QGAM reveals some nonlinear behavior that may reflect context-dependent influences.

In summary, VIX consistently dominates as the most influential predictor across regions, especially in U.S. markets where investor sentiment and uncertainty have immediate effects on equity returns. Credit spreads exhibit a generally positive but heterogeneous relationship with returns, with effects that vary by region and quantile, and are often not statistically significant. Interest rate changes show limited explanatory power overall, though some nonlinear effects hint at more complex underlying dynamics.

4.4.3 Discussion of main findings

The empirical results confirm that macro-financial variables exert heterogeneous effects across the return distribution, with notable differences in strength, direction, and nonlinearity. This section interprets the key findings through three main dimensions: volatility, credit risk, and interest rates while connecting them to existing literature.

Volatility as a universal predictor. Across all indices and models, the VIX consistently emerges as the most reliable predictor of stock returns. Its effect is particularly strong in the lower quantiles, reaffirming its role as a proxy for investor fear during downturns (Whaley, 2000; Bollerslev & Todorov, 2011). These results align with Andersen et al. (2003) who emphasize the strong link between volatility spikes and return declines. Nonlinear models further reveal threshold effects: VIX impacts are steeply negative in bear markets and tend to flatten in neutral or bullish phases. This asymmetry highlights the state-dependent nature of volatility shocks.

Credit spreads as context-dependent. The influence of the BAA–10Y credit spread appears more complex and context-dependent. While traditional theory (Fama & French, 1989) associates wider spreads with increased risk and lower returns, this study finds generally positive coefficients across models, though these effects are not consistently significant. In certain contexts, such as stress periods in U.S. markets, this pattern may reflect investor demand for risk premiums or the influence of accommodative monetary policy. Gertler and Lown (1999) argue that credit spreads can reflect broader financial conditions beyond default risk, including shifts in credit supply and macroeconomic expectations. However, the relationship is far from uniform. QGAM and QRF results suggest that the influence of credit spreads varies across market states and regions, underscoring their role as a context-sensitive signal shaped by local dynamics and investor perception.

Interest rates as weak but occasionally nonlinear. The impact of the term spread (10Y–3M) on stock returns appears generally limited, consistent with the view that the yield curve is more indicative of macroeconomic trends than short-term equity performance (Estrella & Hardouvelis, 1991). However, QR and QGAM reveal occasional nonlinear effects, particularly at the tails of the return distribution, suggesting regime-specific sensitivities in certain markets. These findings align with Adrian et al. (2019) who argue that the predictive power of the yield curve depends on broader economic conditions and prevailing monetary policy regimes.

Cross-model synthesis. The integration of OLS, QR, QGAM, and QRF confirms the added value of distribution-sensitive and nonlinear approaches. While OLS provides a useful average benchmark, it overlooks tail dynamics that are critical for understanding risk. QR reveals asymmetric and state-dependent effects, consistent with findings from Chen et al. (2001). QGAM captures smooth nonlinearities and threshold behaviors (Fasiolo et al., 2020), while QRF reinforces these insights within a flexible, nonparametric framework, further highlighting the VIX as a dominant driver of return asymmetries (Meinshausen, 2006). Collectively, these models provide a richer and more robust understanding of how macro-financial shocks propagate across global equity markets.

4.4.4 Implications for practice and policy

The findings of this study carry important implications for both investors and policymakers. For investors, the strong and consistently negative influence of the VIX across quantiles and indices reinforces its role as a key barometer of market sentiment and risk. Monitoring volatility is particularly critical during periods of financial stress when its predictive power is most pronounced. Furthermore, the nuanced relationship between credit spreads and stock returns, especially the counterintuitive positive effects observed in some contexts, suggests that credit risk metrics should be interpreted with caution. Rising spreads do not uniformly indicate deteriorating conditions and may, in certain environments, reflect shifts in investor behavior, risk appetite or structural market features.

For policymakers, the state-dependent and asymmetric effects identified across quantiles underscore the need for more flexible and responsive financial stability tools. Models based on average relationships may fail to capture how shocks propagate under extreme market conditions. As demonstrated in this study, the impact of volatility, credit risk and interest rate changes varies significantly between calm and turbulent regimes. Recognizing these nonlinearities is very important to design interventions that mitigate systemic risk without overreacting to routine fluctuations.

Overall, this research advocates for the broader adoption of quantile-based methods in both financial analysis and policy modeling. By moving beyond mean-based frameworks, approaches such as quantile regression and its extensions allow for a more accurate assessment of tail risks and market vulnerabilities, critical dimensions in today's increasingly uncertain global financial landscape.

4.5 Revisiting the research hypotheses

This section revisits the initial research hypotheses in light of the empirical results from the four models applied across the six equity indices.

The first hypothesis, that increases in market volatility are associated with significant declines in stock returns, particularly in the lower quantiles, is strongly supported. Across all models and indices, VIX consistently exhibits a negative impact, with the effect being most pronounced in the tails of the return distribution. This confirms the heightened sensitivity of equity markets to volatility during downturns, a pattern well-documented in the literature.

The second hypothesis anticipated a negative effect of widening credit spreads on stock returns, especially during market downturns. However, the findings frequently contradict this expectation. Across models and quantiles, credit spreads often display a positive relationship with returns, even in lower quantiles where negative effects were expected. This counterintuitive result may reflect investor demand for higher risk premiums during periods of financial stress, or the influence of monetary policy environments that encourage risk-taking. It may also stem from model limitations such as omitted variable bias or the complex, context-dependent nature of credit risk. These findings align more closely with the view of Gertler and Lown (1999) who argue that credit spreads reflect evolving financial conditions beyond simple default risk.

The third hypothesis, which posits that the effects of macro-financial variables are asymmetric across quantiles and more pronounced in the tails than at the median, is strongly supported. Both the QR and QGAM results reveal substantial heterogeneity in the magnitude and direction of predictor effects depending on market conditions. Volatility exhibits a consistently strong negative influence in the lower quantiles, highlighting its role in amplifying downside risk. In contrast, the effects of credit spreads and interest rate changes are weaker and more variable across quantiles, underscoring the importance of modeling return dynamics in a distribution-sensitive and nonlinear framework.

Overall, the results reinforce the central role of volatility in shaping tail risk while challenging conventional expectations regarding credit spreads. These findings highlight the value of quantile-based approaches in uncovering asymmetric relationships and suggest several avenues for refining empirical models of macro-financial transmission.

4.6 Limitations and directions for future research

While this study provides valuable insights into how macro-financial variables impact stock returns across quantiles, several limitations should be acknowledged, pointing to avenues for future research.

First, the choice of macro-financial variables, VIX, credit spreads (BAA–10Y) and interest rate changes, was based on their theoretical relevance and prominence in the literature. However, omitting other potentially influential factors such as exchange rates, commodity prices or sector-specific indicators, may have limited the scope of the analysis. Future studies could incorporate a broader range of predictors to offer a more comprehensive understanding of market dynamics.

Second, using VIX and credit spreads in levels enhanced interpretability but may have introduced non-stationarity into the models. Although stationarity was confirmed for most series, the high persistence of some variables could have influenced estimation. Future research could test alternative transformations such as logarithmic differences or de-trended series to balance economic interpretability with statistical robustness.

Third, while this study employed both linear quantile regression and nonlinear approaches (QGAM and QRF), it focused on a fixed set of quantiles (5th, 25th, 50th, 75th, and 95th). A more flexible design could involve dynamic quantile models that adapt to evolving market regimes. Future research might also explore deep learning-based quantile estimators or hybrid models that integrate linear and nonlinear components.

Fourth, the cross-market analysis revealed regional differences in macro-financial sensitivities but did not account for interdependencies such as contagion or global spillovers. Further studies could adopt multivariate quantile frameworks or network-based approaches to better capture cross-market linkages and transmission channels.

Fifth, the models used in this study are fundamentally predictive, not causal. Therefore, the relationships identified should not be interpreted as evidence of causality. For example, a positive relationship between credit spreads and returns might reflect reverse causality where falling equity prices lead to wider spreads. Future research could apply instrumental variable quantile regression or Granger causality testing to address this limitation.

Finally, the analysis spans January 2000 to January 2024, covering key events such as the 2008 Global Financial Crisis and the COVID-19 pandemic. However, including earlier periods of financial stress such as the 1997 Asian Financial Crisis or the initial phase of the Dot-com bubble could provide additional historical context. Moreover, while monthly data are appropriate for medium-term analysis, higher-frequency data could uncover short-term dynamics that this study may have missed.

4.7 Future research directions

Building on these limitations, several avenues for future research can be identified.

First, expanding the set of macro-financial variables to include global factors such as oil prices, geopolitical risk indices or sector-specific indicators could provide a more comprehensive view of market dynamics.

Second, future work could explore dynamic quantile models that adapt to evolving market regimes or incorporate time-varying parameters, allowing for greater flexibility in capturing structural changes over time.

Third, investigate the influence of market structure, including liquidity, market microstructure features or investor sentiment, may reveal important drivers of quantile-dependent return behavior.

Fourth, to address concerns of endogeneity and improve causal interpretation, future research could apply techniques such as Instrumental Variable Quantile Regression.

Finally, extending the analysis to higher-frequency data or to other asset classes, including bonds, commodities or cryptocurrencies, would allow for a broader understanding of how macro-financial shocks propagate across different segments of the financial system. Together, these directions offer promising paths for refining and extending the findings of this study and deepening our understanding of risk transmission, asset pricing and financial stability.

5 General conclusion

This thesis investigated how macro-financial variables, specifically market volatility, credit spreads, and interest rate changes, affect stock returns across six major indices (S&P 500, NASDAQ 100, CAC 40, DAX 30, Nikkei 225, and Hang Seng) from 2000 to 2024. Using OLS, Quantile Regression (QR), Quantile Generalized Additive Models (QGAM) and Quantile Regression Forests (QRF), it offered a detailed and distribution-sensitive understanding of these relationships.

The results reveal that these variables exert asymmetric and context-dependent effects on stock returns. Volatility consistently displayed a strong negative impact, particularly at lower quantiles, where rising uncertainty led to disproportionately negative returns, especially in U.S. markets. Nonlinear methods (QGAM and QRF) further highlighted that the influence of VIX is not constant but varies across the return distribution, revealing threshold effects and nonlinearities that are missed by traditional linear models.

Credit spreads exhibited a more nuanced behavior. While traditional theories suggest that widening credit spreads should be associated with declining stock returns due to heightened credit risk, the results indicated a more complex picture. At lower quantiles, credit spreads generally had a positive impact, suggesting that during bearish conditions, rising credit risk may coincide with higher returns. This counterintuitive result may reflect a shift towards riskier assets in adverse conditions where investors seek higher potential returns. Alternatively, it may be a consequence of model limitations such as the choice of explanatory variables or the specific sample period used.

Interest rate changes displayed the weakest and most inconsistent effects across the indices. While they were significant at lower quantiles in some markets, their impact was generally weak or statistically insignificant in other contexts. These results suggest that the direct effect of interest rate changes on stock returns may be limited, with other macroeconomic factors exerting a more dominant influence. Nonlinear models highlighted that even where interest rate effects were present, they were highly context-specific and nonlinear. The impact of these variables was not uniform across indices, highlighting differences in investor behavior, economic structures, and market sensitivities.

Methodologically, this thesis demonstrated the value of quantile-based approaches, capturing complex, asymmetric, and nonlinear relationships. QR highlighted tail effects while QGAM and QRF revealed hidden nonlinearities, enhancing the analysis beyond traditional OLS. This multi-method approach enhanced the robustness and depth of the analysis, providing a clearer understanding of how market conditions shape stock returns.

These findings offer useful insights for both investors and policymakers. For investors, they underscore the need for dynamic risk management strategies that account for the varying effects of financial indicators under different market conditions. Understanding that volatility has a stronger impact during downturns or that credit spreads can exhibit counterintuitive effects in bearish markets, can help design more resilient portfolios. For policymakers, the results emphasize the critical role of market volatility and credit conditions in shaping investor behavior, particularly during periods of financial stress. Monitoring these indicators may improve early warning systems for financial instability and help guide policy decisions aimed at preserving financial stability.

Despite its contributions, this thesis is not without limitations. The analysis was restricted to six major stock indices which may limit the generalizability of the findings. Moreover, the choice of explanatory variables was deliberately limited to three key macro-financial indicators which may overlook other important factors such as exchange rates, global liquidity or geopolitical risks. The use of monthly data, while providing a long-term perspective, may miss short-term market dynamics. Additionally, while quantile-based models provide valuable insights, they are fundamentally predictive rather than causal. The observed relationships should not be interpreted as direct causal effects. In particular, the counterintuitive positive impact of credit spreads in some cases may reflect model limitations, omitted variable bias or the influence of unobserved factors.

Future research could address these limitations by exploring additional financial variables, incorporating higher-frequency data and employing advanced causal inference techniques such as Instrumental Variable Quantile Regression (IVQR) or Granger causality tests. Moreover, extending the analysis to other asset classes such as commodities or foreign exchange could provide a more comprehensive view of the drivers of financial market dynamics.

In conclusion, this thesis has provided a deeper understanding of how financial indicators such as volatility, credit spreads and interest rates shape stock returns under varying market conditions. By combining linear, quantile-based and nonparametric approaches, it demonstrates the analytical value of distribution-sensitive methods in capturing asymmetric and nonlinear effects often missed by traditional models. The findings contribute meaningfully to both academic and applied finance, offering new insights into risk assessment, asset allocation and financial regulation. As global markets remain shaped by uncertainty and tail risk, improving the way we model these effects is not only a research priority but also a practical necessity for navigating the future of finance.

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7 Appendix

7.1 Analysis of time-series data

Time-series plots of indices and their returns

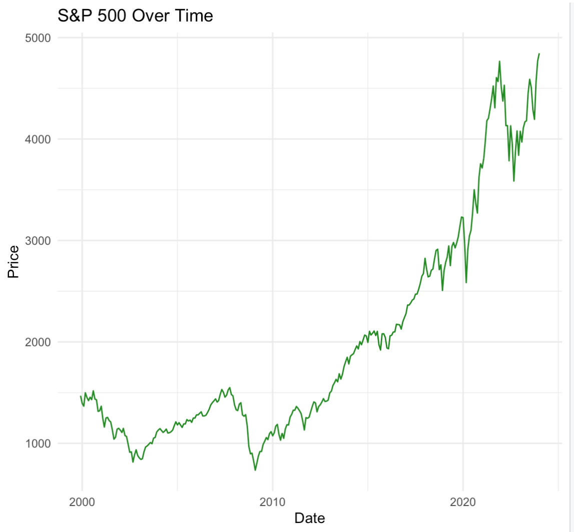


Figure 1: S&P 500 Index over time

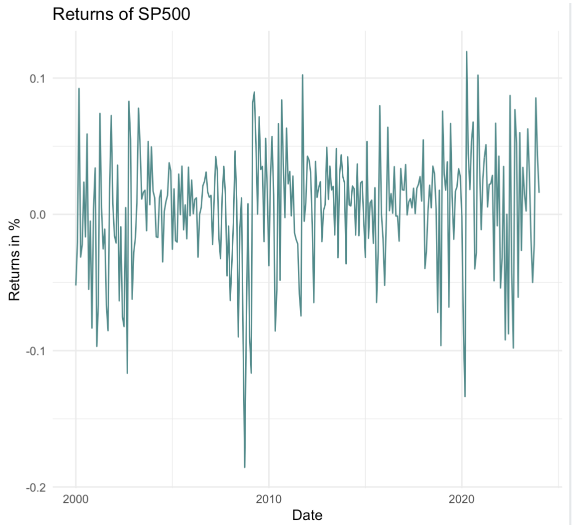


Figure 2: S&P 500 Monthly returns

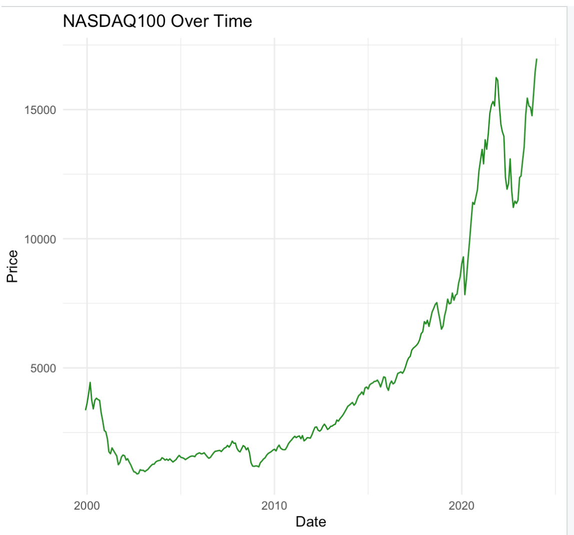


Figure 3: NASDAQ 100 Index over time

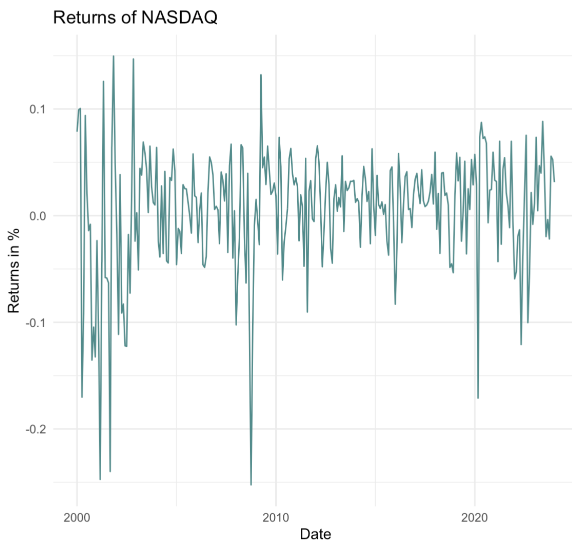


Figure 4: NASDAQ 100 Monthly returns

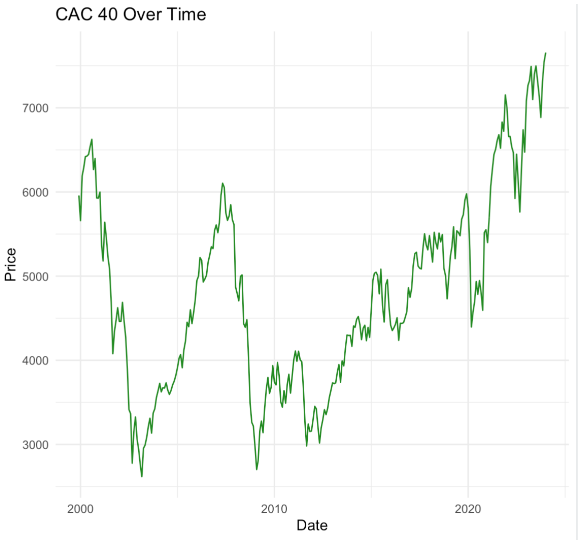


Figure 5: CAC 40 Index over time

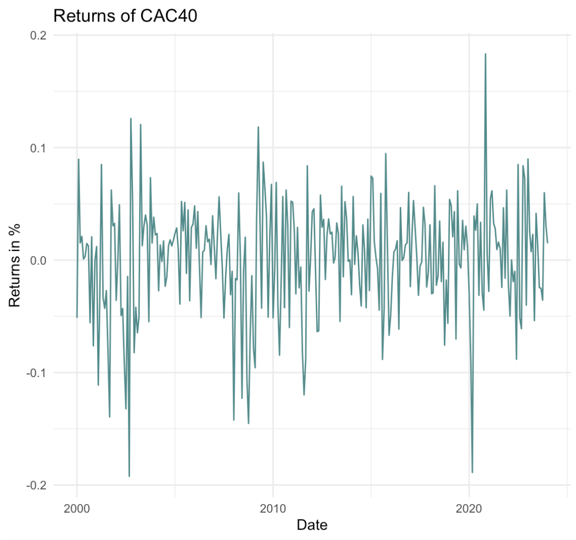


Figure 6: CAC 40 Monthly returns

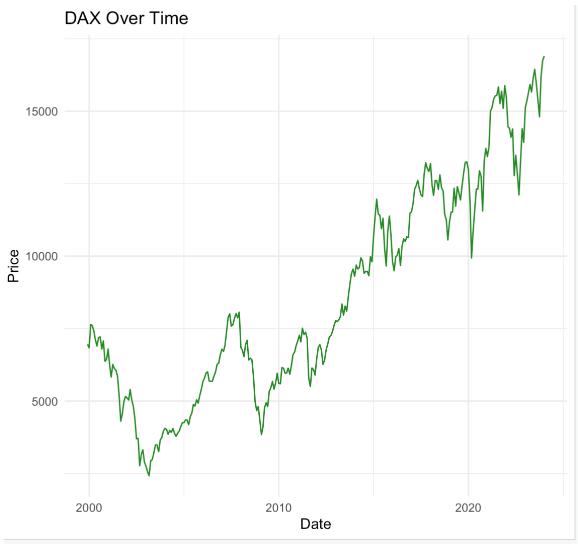


Figure 7: DAX 30 Index over time

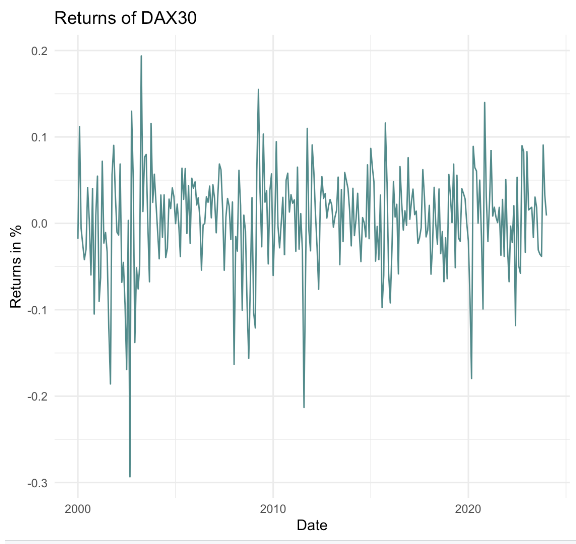


Figure 8: DAX 30 Monthly returns

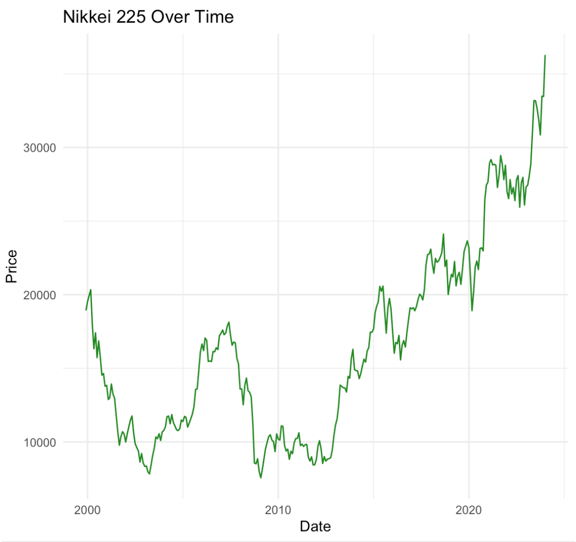


Figure 9: Nikkei 225 Index over time

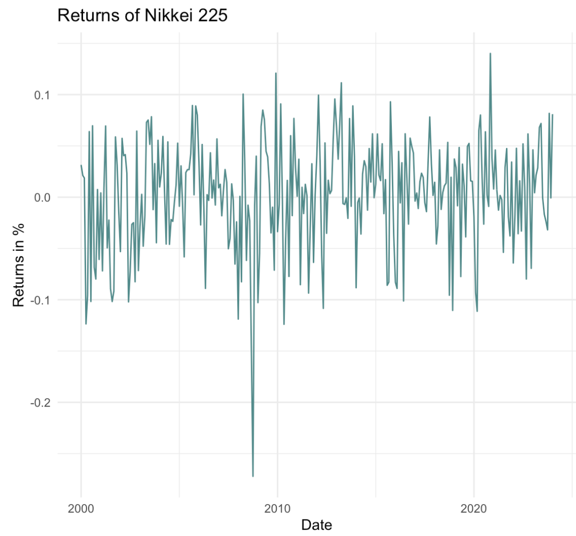


Figure 10: Nikkei 225 Monthly returns

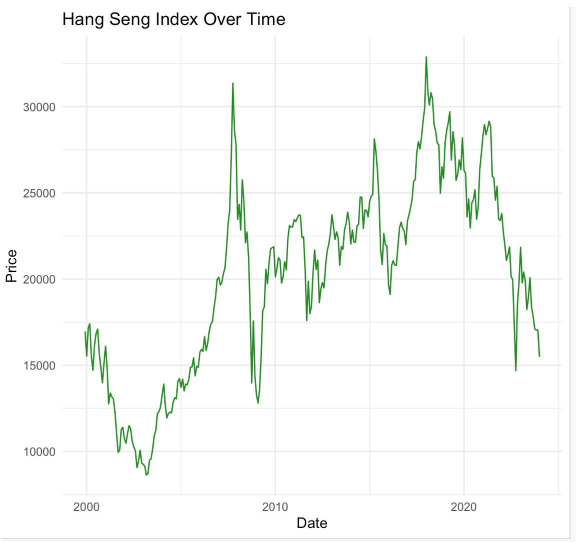


Figure 11: Hang Seng Index over time

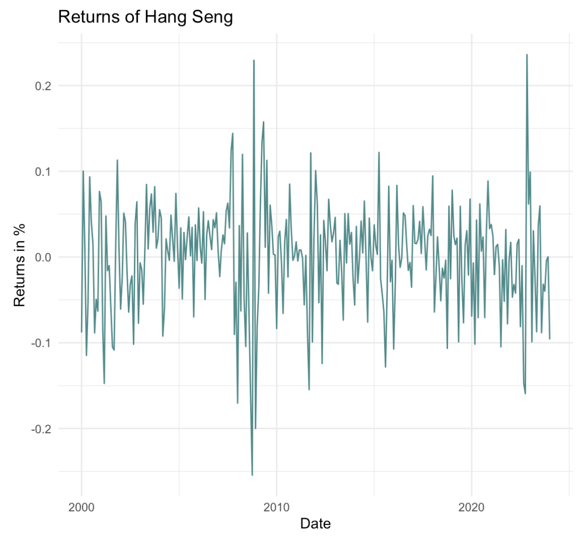


Figure 12: Hang Seng Monthly returns

Time-series plots of the variables

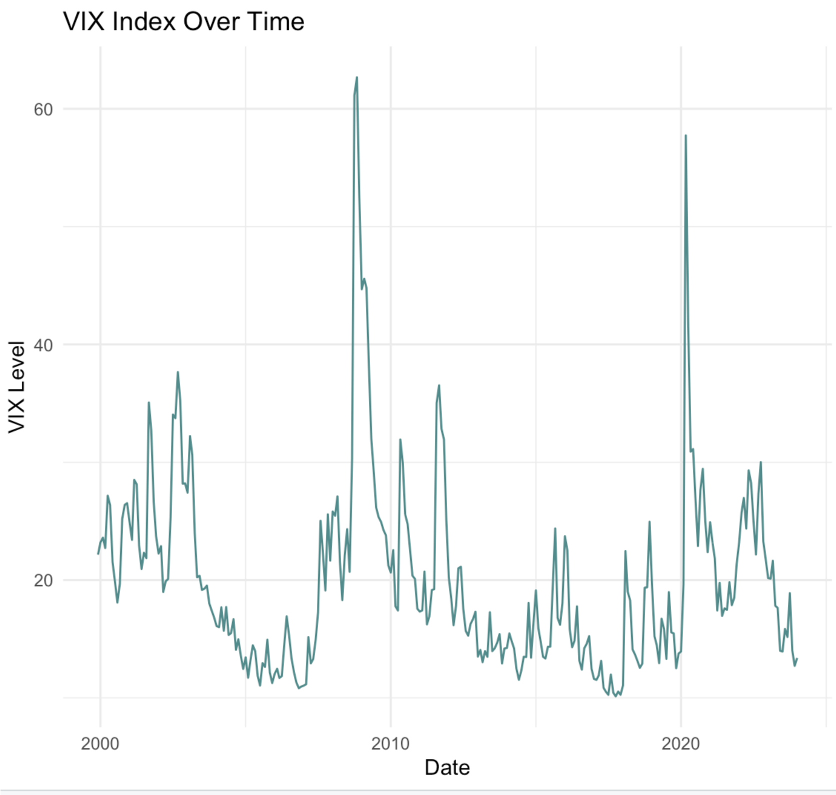


Figure 13: VIX Index Over Time

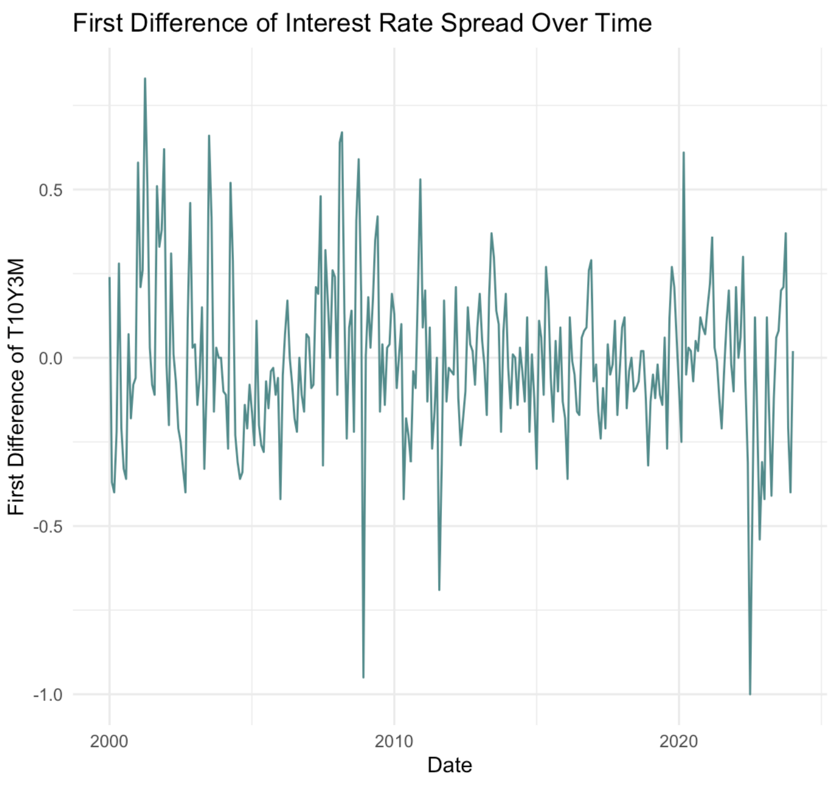


Figure 14: First Difference of Interest Rate Slope (10Y–3M)

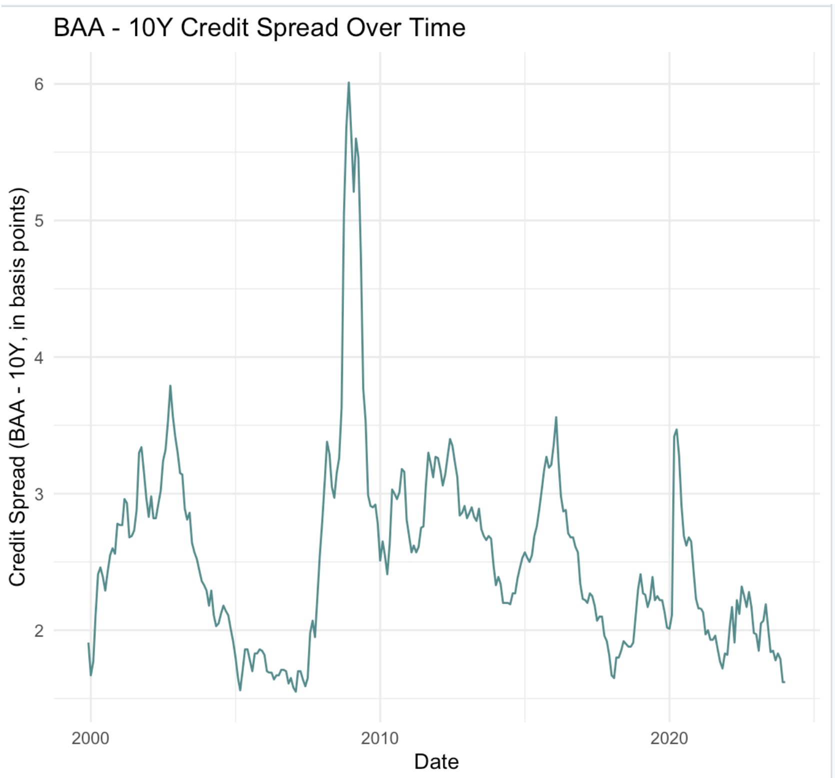


Figure 15: BAA–10Y Credit Spread Over Time

7.2 Statistical diagnostics

Stationarity tests

Indices

```
> adf_sp500    <- adf_test(master_sp500$SP500_Price, "S&P 500 Price") # NOT STATIONARY

--- ADF Test for S&P 500 Price ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -1.147, Lag order = 6, p-value = 0.9136
alternative hypothesis: stationary
```

Figure 16: ADF Test on S&P 500 Prices

```
> adf_returns_sp500    <- adf_test(master_sp500$Returns, "S&P 500 Returns") # STATIONARY

--- ADF Test for S&P 500 Returns ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -5.9276, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 17: ADF Test on S&P 500 Returns

```
> adf_nasdaq  <- adf_test(master_nasdaq$NASDAQ100_Price, "NASDAQ 100 Price") # NOT STATIONARY

--- ADF Test for NASDAQ 100 Price ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -1.2477, Lag order = 6, p-value = 0.8932
alternative hypothesis: stationary
```

Figure 18: ADF Test on NASDAQ 100 Prices

```
> adf_returns_nasdaq   <- adf_test(master_nasdaq$Returns, "NASDAQ 100 Returns") # STATIONARY

--- ADF Test for NASDAQ 100 Returns ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -5.5537, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 19: ADF Test on NASDAQ 100 Returns

```
> adf_cac40    <- adf_test(master_cac40$CAC40_Price, "CAC 40 Price") # NOT STATIONARY

--- ADF Test for CAC 40 Price ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -2.8497, Lag order = 6, p-value = 0.2181
alternative hypothesis: stationary
```

Figure 20: ADF Test on CAC 40 Prices

```
> adf_returns_cac40    <- adf_test(master_cac40$Returns, "CAC 40 Returns") # STATIONARY

--- ADF Test for CAC 40 Returns ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -5.9717, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 21: ADF Test on CAC 40 Returns

```
> adf_dax      <- adf_test(master_dax$DAX_Price, "DAX Price") # NOT STATIONARY

--- ADF Test for DAX Price ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -3.254, Lag order = 6, p-value = 0.07923
alternative hypothesis: stationary
```

Figure 22: ADF Test on DAX 30 Prices

```
> adf_returns_dax      <- adf_test(master_dax$Returns, "DAX Returns") # STATIONARY

--- ADF Test for DAX Returns ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -6.1106, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 23: ADF Test on DAX 30 Returns

```
> adf_nikkei   <- adf_test(master_nikkei$Nikkei_Price, "Nikkei 225 Price") # NOT STATIONARY

--- ADF Test for Nikkei 225 Price ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -1.4196, Lag order = 6, p-value = 0.8208
alternative hypothesis: stationary
```

Figure 24: ADF Test on Nikkei 225 Prices

```
> adf_returns_nikkei   <- adf_test(master_nikkei$Returns, "Nikkei 225 Returns") # STATIONARY

--- ADF Test for Nikkei 225 Returns ---

	Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -6.0984, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 25: ADF Test on Nikkei 225 Returns

```
> adf_hangseng <- adf_test(master_hangseng$HangSeng_Price, "Hang Seng Price") # NOT STATIONARY

--- ADF Test for Hang Seng Price ---

        Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -2.2227, Lag order = 6, p-value = 0.4823
alternative hypothesis: stationary
```

Figure 26: ADF Test on Hang Seng Prices

```
> adf_returns_hangseng <- adf_test(master_hangseng$Returns, "Hang Seng Returns") # STATIONARY

--- ADF Test for Hang Seng Returns ---

        Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -6.0558, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 27: ADF Test on Hang Seng Returns

Variables

```
> adf_interest <- adf_test(master_sp500$Diff_InterestRate_Change, "Interest Rate Change")  #STATIONARY

--- ADF Test for Interest Rate Change ---

        Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -5.4209, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(series, alternative = "stationary") :
  p-value smaller than printed p-value
```

Figure 28: ADF Test for Interest Rate Spread (10Y–3M)

```
> adf_vix <- adf_test(master_sp500$VIX, "VIX (Level)")  # STATIONARY

--- ADF Test for VIX (Level) ---

        Augmented Dickey-Fuller Test

data:  series
Dickey-Fuller = -3.4706, Lag order = 6, p-value = 0.04595
alternative hypothesis: stationary
```

Figure 29: ADF Test for VIX Index

```
> adf_baa <- adf.test(master_sp500$BAA10Y_Spread,  alternative = "stationary")  #  NON-STATIONARY
> adf_baa

        Augmented Dickey-Fuller Test

data:  master_sp500$BAA10Y_Spread
Dickey-Fuller = -3.377, Lag order = 6, p-value = 0.05863
alternative hypothesis: stationary
```

Figure 30: ADF Test for BAA–10Y Credit Spread

Multicollinearity diagnostics

```
> # Variance Inflation Factor test
> model <- lm(Returns ~ Diff_InterestRate_Change +  BAA10Y_Spread + VIX , data = master_sp500)
> vif_values <- vif(model)
> print(vif_values)
Diff_InterestRate_Change            BAA10Y_Spread                      VIX 
                1.014673                 2.106097                 2.095096 
```

Figure 31: Variance Inflation Factor (VIF) results

```
> # Correlation matrix
> cor_matrix <- cor(master_sp500[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")])
> print(cor_matrix)
                         Diff_InterestRate_Change        VIX BAA10Y_Spread
Diff_InterestRate_Change               1.00000000 0.09546635     0.1195398
VIX                                    0.09546635 1.00000000     0.7229190
BAA10Y_Spread                          0.11953984 0.72291895     1.0000000
```

Figure 32: Correlation matrix of predictors

To assess potential multicollinearity issues among the explanatory variables, both a correlation matrix and a Variance Inflation Factor (VIF) analysis were conducted. The correlation matrix confirms moderate correlation between the BAA-10Y spread and the VIX, while correlations between other pairs of predictors remain low. The VIF values, all well below the conventional threshold of 5, indicate that multicollinearity is not a major concern in the model. It is important to note that the VIF calculation examines only the relationships among the independent variables (Diff_InterestRate_Change, VIX, and BAA10Y_Spread) and does not depend on the specific dependent variable (S&P 500 returns) used for estimation. Therefore, the multicollinearity diagnostics based on the master_sp500 dataset are applicable for the broader model structure.

Breusch-Pagan tests for heteroscedasticity

To assess whether heteroscedasticity is present in the OLS residuals for each stock index, I conducted Breusch-Pagan tests. The results are summarized below:

Index	Test Statistic (BP)	p-value
S&P 500	71.024	< 0.001
NASDAQ 100	44.233	< 0.001
CAC 40	40.313	< 0.001
DAX 30	55.307	< 0.001
Nikkei 225	51.593	< 0.001
Hang Seng	64.737	< 0.001

Table 3: Breusch-Pagan test results for heteroscedasticity

The Breusch-Pagan test rejects the null hypothesis of homoscedasticity at the 1% significance level for all indices. This indicates the presence of heteroscedasticity in the OLS residuals, suggesting that the variance of errors is not constant across observations. Consequently, standard OLS inference may be unreliable, which further justifies the use of quantile regression methods that are more robust to such distributional issues. Given the presence of heteroscedasticity detected by the Breusch-Pagan test, standard errors are corrected using heteroskedasticity-consistent (HC1) estimators to ensure valid inference.Standard errors are corrected for heteroscedasticity using the HC1 method. Reported p-values and t-statistics are based on robust estimates. Model fit statistics such as R^2 and adjusted R^2 are computed based on the original OLS estimation.

7.3 OLS regressions

Figure 33: OLS vs. Robust OLS Regression for S&P 500

```
> run_ols_regression(master_sp500, "S&P 500")

--- OLS Regression for S&P 500 ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.114519 -0.024022 -0.001626  0.022063  0.159850

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.020088   0.009077   2.213   0.0277 *
Diff_InterestRate_Change -0.001375  0.010261  -0.134   0.8935
VIX                      -0.002754  0.000439  -6.272 1.32e-09 ***
BAA10Y_Spread            0.015435   0.004948   3.119   0.0020 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04206 on 285 degrees of freedom
Multiple R-squared:  0.1327,    Adjusted R-squared:  0.1236
F-statistic: 14.53 on 3 and 285 DF,  p-value: 7.787e-09
```

(a) Classical OLS

```
> robust_summary(lm_sp500, "S&P 500")

--- Robust OLS Summary for S&P 500 ---

t test of coefficients:

                           Estimate  Std. Error t value  Pr(>|t|)
(Intercept)              0.02008778  0.01149278  1.7479   0.08157 .
Diff_InterestRate_Change -0.00137473 0.01245264 -0.1104   0.91217
VIX                      -0.00275379 0.00056421 -4.8808 1.761e-06 ***
BAA10Y_Spread            0.01543474  0.00581379  2.6549   0.00838 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

(b) Robust OLS (HC errors)

Figure 34: OLS vs. Robust OLS Regression for NASDAQ 100

```
> run_ols_regression(master_nasdaq, "NASDAQ 100")

--- OLS Regression for NASDAQ 100 ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max
-0.228402 -0.025682 -0.000021  0.027411  0.157358

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.0315511  0.0111678   2.825 0.005059 **
Diff_InterestRate_Change -0.0010946 0.0126239  -0.087 0.930963
VIX                      -0.0038692 0.0005402  -7.163 6.74e-12 ***
BAA10Y_Spread            0.0203026  0.0060879   3.335 0.000966 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05174 on 285 degrees of freedom
Multiple R-squared:  0.1702,    Adjusted R-squared:  0.1615
F-statistic: 19.48 on 3 and 285 DF,  p-value: 1.612e-11
```

(a) Classical OLS

```
> robust_summary(lm_nasdaq, "NASDAQ 100")

--- Robust OLS Summary for NASDAQ 100 ---

t test of coefficients:

                           Estimate  Std. Error t value  Pr(>|t|)
(Intercept)              0.03155106  0.01160022  2.7199  0.006932 **
Diff_InterestRate_Change -0.00109463 0.01462207 -0.0749  0.940378
VIX                      -0.00386925 0.00065526 -5.9049 1.002e-08 ***
BAA10Y_Spread            0.02030263  0.00629136  3.2271  0.001397 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

(b) Robust OLS (HC errors)

Figure 35: OLS vs. Robust OLS Regression for CAC 40

```
> run_ols_regression(master_cac40, "CAC 40")

--- OLS Regression for CAC 40 ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.152131 -0.031151  0.001593  0.026407  0.196450 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              0.0292576  0.0105111   2.784  0.00574 ** 
Diff_InterestRate_Change 0.0077948  0.0118815   0.656  0.51233    
VIX                     -0.0027422  0.0005084  -5.394 1.45e-07 ***
BAA10Y_Spread            0.0104764  0.0057299   1.828  0.06854 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0487 on 285 degrees of freedom
Multiple R-squared:  0.1174,	Adjusted R-squared:  0.1081 
F-statistic: 12.64 on 3 and 285 DF,  p-value: 8.842e-08
```

(a) Classical OLS

```
> robust_summary(lm_cac40, "CAC 40")

--- Robust OLS Summary for CAC 40 ---

t test of coefficients:

                            Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)               0.02925759  0.01145067  2.5551   0.01114 *  
Diff_InterestRate_Change  0.00779482  0.01454386  0.5360   0.59241    
VIX                      -0.00274222  0.00063707 -4.3044 2.305e-05 ***
BAA10Y_Spread             0.01047642  0.00667708  1.5690   0.11775    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(b) Robust OLS (HC errors)

Figure 36: OLS vs. Robust OLS Regression for DAX 30

```
> run_ols_regression(master_dax, "DAX")

--- OLS Regression for DAX ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.246012 -0.032020  0.001696  0.027642  0.195214 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)               0.029504   0.012136   2.431   0.0157 *  
Diff_InterestRate_Change  0.019259   0.013718   1.404   0.1614    
VIX                      -0.003324   0.000587  -5.663 3.63e-08 ***
BAA10Y_Spread             0.015873   0.006616   2.399   0.0171 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05623 on 285 degrees of freedom
Multiple R-squared:  0.1204,	Adjusted R-squared:  0.1111 
F-statistic:    13 on 3 and 285 DF,  p-value: 5.53e-08
```

(a) Classical OLS

```
> robust_summary(lm_dax, "DAX 30")

--- Robust OLS Summary for DAX 30 ---

t test of coefficients:

                            Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)               0.02950364  0.01489402  1.9809   0.04856 *  
Diff_InterestRate_Change  0.01925873  0.01780375  1.0817   0.28029    
VIX                      -0.00332393  0.00073134 -4.5450 8.126e-06 ***
BAA10Y_Spread             0.01587271  0.00773238  2.0528   0.04101 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(b) Robust OLS (HC errors)

Figure 37: OLS vs. Robust OLS Regression for Nikkei 225

```
> run_ols_regression(master_nikkei, "Nikkei 225")

--- OLS Regression for Nikkei 225 ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.185735 -0.029835 -0.000278  0.035826  0.156167 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              0.0238227  0.0110289   2.160  0.03160 *  
Diff_InterestRate_Change 0.0111669  0.0124669   0.896  0.37116    
VIX                     -0.0034816  0.0005334  -6.527 3.07e-10 ***
BAA10Y_Spread            0.0190052  0.0060122   3.161  0.00174 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0511 on 285 degrees of freedom
Multiple R-squared:  0.1437,	Adjusted R-squared:  0.1346 
F-statistic: 15.94 on 3 and 285 DF,  p-value: 1.32e-09
```

(a) Classical OLS

```
> robust_summary(lm_nikkei, "Nikkei 225")

--- Robust OLS Summary for Nikkei 225 ---

t test of coefficients:

                           Estimate  Std. Error t value  Pr(>|t|)    
(Intercept)              0.02382272  0.01427831  1.6685   0.09632 .  
Diff_InterestRate_Change 0.01116689  0.01491809  0.7485   0.45475    
VIX                     -0.00348160  0.00066526 -5.2335 3.231e-07 ***
BAA10Y_Spread            0.01900519  0.00676831  2.8080   0.00533 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

(b) Robust OLS (HC errors)

Figure 38: OLS vs. Robust OLS Regression for Hang Seng Index

```
> run_ols_regression(master_hangseng, "Hang Seng")

--- OLS Regression for Hang Seng ---

Call:
lm(formula = formula, data = data)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.190458 -0.037070  0.001715  0.035718  0.291147 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)               0.013722   0.013603   1.009 0.313957    
Diff_InterestRate_Change  0.008028   0.015377   0.522 0.602043    
VIX                      -0.002568   0.000658  -3.904 0.000118 ***
BAA10Y_Spread             0.014758   0.007416   1.990 0.047533 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06303 on 285 degrees of freedom
Multiple R-squared:  0.05549,	Adjusted R-squared:  0.04555 
F-statistic: 5.581 on 3 and 285 DF,  p-value: 0.0009847
```

(a) Classical OLS

```
> robust_summary(lm_hangseng, "Hang Seng")

--- Robust OLS Summary for Hang Seng ---

t test of coefficients:

                           Estimate  Std. Error t value Pr(>|t|)   
(Intercept)              0.01372239  0.02265858  0.6056 0.545252   
Diff_InterestRate_Change 0.00802764  0.01978883  0.4057 0.685293   
VIX                     -0.00256835  0.00093296 -2.7529 0.006286 **
BAA10Y_Spread            0.01475809  0.00906938  1.6272 0.104790   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

(b) Robust OLS (HC errors)

7.4 Quantile regressions

Linear quantile regressions

Table 4: Quantile Regression Results for S&P 500 with Significance Levels

Quantile	Variable	Coefficient	P-value	Signif.
0.05	(Intercept)	0.0117277267	4.906000e-01	
0.05	Diff_InterestRate_Change	0.0010608187	9.543648e-01	
0.05	BAA10Y_Spread	0.0173003835	1.406238e-02	*
0.05	VIX	-0.0056096462	5.233591e-13	***
0.25	(Intercept)	0.0284482059	2.584116e-02	*
0.25	Diff_InterestRate_Change	0.0089909547	5.728500e-01	
0.25	BAA10Y_Spread	0.0169284401	1.153162e-02	*
0.25	VIX	-0.0047870102	6.039613e-14	***
0.50	(Intercept)	0.0297634535	8.500666e-02	
0.50	Diff_InterestRate_Change	0.0129699348	4.710220e-01	
0.50	BAA10Y_Spread	0.0102027456	2.320125e-01	
0.50	VIX	-0.0026585587	5.762670e-04	***
0.75	(Intercept)	0.0109119823	5.023513e-01	
0.75	Diff_InterestRate_Change	0.0009043299	9.619535e-01	
0.75	BAA10Y_Spread	0.0098637370	2.124849e-01	
0.75	VIX	-0.0001898582	8.586098e-01	
0.95	(Intercept)	0.0315305835	1.131026e-02	*
0.95	Diff_InterestRate_Change	0.0041491572	7.579046e-01	
0.95	BAA10Y_Spread	-0.0060017955	8.393255e-01	
0.95	VIX	0.0026178308	1.182090e-03	**

Note: *** p<0.001, ** p<0.01, * p<0.05

Table 5: Quantile Regression Results for NASDAQ 100 with Significance Levels

Quantile	Variable	Coefficient	P-value	Signif.
0.05	(Intercept)	0.0672159538	1.895021e-02	*
0.05	Diff_InterestRate_Change	-0.0098329185	7.302209e-01	
0.05	BAA10Y_Spread	0.0245603809	2.763591e-02	*
0.05	VIX	-0.0106207821	2.204836e-10	***
0.25	(Intercept)	0.0284926238	2.351605e-01	
0.25	Diff_InterestRate_Change	0.0133160661	4.362761e-01	
0.25	BAA10Y_Spread	0.0177509448	7.081461e-02	
0.25	VIX	-0.0048118608	2.534994e-10	***
0.50	(Intercept)	0.0341373191	2.250913e-02	*
0.50	Diff_InterestRate_Change	0.0021129114	9.087778e-01	
0.50	BAA10Y_Spread	0.0141639306	4.437442e-02	*
0.50	VIX	-0.0031395064	4.136649e-04	***
0.75	(Intercept)	0.0406757766	6.140448e-03	**
0.75	Diff_InterestRate_Change	0.0135996040	4.551175e-01	
0.75	BAA10Y_Spread	0.0059036714	5.068581e-01	
0.75	VIX	-0.0008942196	3.917572e-01	
0.95	(Intercept)	0.0317928907	6.518605e-02	
0.95	Diff_InterestRate_Change	0.0169858364	5.909843e-01	
0.95	BAA10Y_Spread	-0.0045286988	5.364410e-01	
0.95	VIX	0.0027462470	9.570787e-03	**

Note: *** p<0.001, ** p<0.01, * p<0.05

Table 6: Quantile Regression Results for CAC 40 with Significance Levels

Quantile	Variable	Coefficient	P-value	Signif.
0.05	(Intercept)	0.069216299	1.457291e-03	**
0.05	Diff_InterestRate_Change	0.039800758	5.554370e-02	
0.05	BAA10Y_Spread	-0.019004242	5.713420e-02	
0.05	VIX	-0.004740113	3.038481e-08	***
0.25	(Intercept)	0.022433943	1.471074e-01	
0.25	Diff_InterestRate_Change	0.022682155	2.402563e-01	
0.25	BAA10Y_Spread	0.008052150	3.197329e-01	
0.25	VIX	-0.003625135	1.345871e-07	***
0.50	(Intercept)	0.033913930	4.330780e-02	*
0.50	Diff_InterestRate_Change	-0.010832125	5.929088e-01	
0.50	BAA10Y_Spread	0.012717130	1.775629e-01	
0.50	VIX	-0.003151195	3.376232e-04	***
0.75	(Intercept)	0.025580481	1.251440e-01	
0.75	Diff_InterestRate_Change	0.009052528	6.165115e-01	
0.75	BAA10Y_Spread	0.012283292	1.716889e-01	
0.75	VIX	-0.001260361	2.507896e-01	
0.95	(Intercept)	0.025255159	1.296337e-01	
0.95	Diff_InterestRate_Change	-0.004688114	7.414588e-01	
0.95	BAA10Y_Spread	0.001569943	5.167155e-01	
0.95	VIX	0.001723623	9.844765e-02	

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 7: Quantile Regression Results for DAX 30 with Significance Levels

Quantile	Variable	Coefficient	P-value	Signif.
0.05	(Intercept)	0.073818702	3.010573e-03	**
0.05	Diff_InterestRate_Change	0.048668250	2.884129e-02	*
0.05	BAA10Y_Spread	-0.010657793	3.337670e-01	
0.05	VIX	-0.006030900	5.814031e-09	***
0.25	(Intercept)	0.028236048	1.120891e-01	
0.25	Diff_InterestRate_Change	0.031933767	1.861998e-01	
0.25	BAA10Y_Spread	0.014057731	1.094442e-01	
0.25	VIX	-0.004769169	3.955680e-09	***
0.50	(Intercept)	0.025127732	2.380573e-01	
0.50	Diff_InterestRate_Change	0.006622825	7.758380e-01	
0.50	BAA10Y_Spread	0.016395238	1.070985e-01	
0.50	VIX	-0.003097694	1.376495e-03	**
0.75	(Intercept)	0.019590472	2.551606e-01	
0.75	Diff_InterestRate_Change	0.007939348	6.669486e-01	
0.75	BAA10Y_Spread	0.017632299	5.997152e-02	
0.75	VIX	-0.001289116	2.629823e-01	
0.95	(Intercept)	0.018262693	3.313855e-01	
0.95	Diff_InterestRate_Change	-0.005717524	7.719944e-01	
0.95	BAA10Y_Spread	0.011556398	2.126149e-01	
0.95	VIX	0.001940096	9.032798e-02	

Note: *** p<0.001, ** p<0.01, * p<0.05

Table 8: Quantile Regression Results for Nikkei 225 with Significance Levels

Quantile	**Variable**	**Coefficient**	**P-value**	**Signif.**
0.05	(Intercept)	0.040157520	3.818879e-02	*
0.05	Diff_InterestRate_Change	0.068515208	4.748684e-04	***
0.05	BAA10Y_Spread	0.001013211	9.169510e-01	
0.05	VIX	-0.005976107	1.683107e-10	***
0.25	(Intercept)	0.026185505	2.185300e-01	
0.25	Diff_InterestRate_Change	0.025543208	2.564892e-01	
0.25	BAA10Y_Spread	0.015312115	1.375152e-01	
0.25	VIX	-0.004822017	8.405523e-06	***
0.50	(Intercept)	0.009251430	6.761444e-01	
0.50	Diff_InterestRate_Change	0.003846102	8.600385e-01	
0.50	BAA10Y_Spread	0.025835944	1.844888e-02	*
0.50	VIX	-0.003565206	3.202525e-05	***
0.75	(Intercept)	0.022440350	8.869085e-02	
0.75	Diff_InterestRate_Change	0.007395146	6.708862e-01	
0.75	BAA10Y_Spread	0.028243035	9.226791e-04	***
0.75	VIX	-0.002769837	2.303057e-03	**
0.95	(Intercept)	0.062274997	3.228372e-05	***
0.95	Diff_InterestRate_Change	-0.006314953	6.973569e-01	
0.95	BAA10Y_Spread	0.018345857	1.588028e-02	*
0.95	VIX	-0.001470258	9.014412e-02	

Note: *** p<0.001, ** p<0.01, * p<0.05

Table 9: Quantile Regression Results for Hang Seng Index with Significance Levels

Quantile	**Variable**	**Coefficient**	**P-value**	**Signif.**
0.05	(Intercept)	-0.0289736981	1.866321e-01	
0.05	Diff_InterestRate_Change	0.0021339680	2.98864e-01	
0.05	BAA10Y_Spread	0.0166686649	1.529311e-01	
0.05	VIX	-0.0056571588	4.425926e-08	***
0.25	(Intercept)	0.0300664247	2.144061e-01	
0.25	Diff_InterestRate_Change	-0.0178802072	4.494957e-01	
0.25	BAA10Y_Spread	0.0080107409	5.128198e-01	
0.25	VIX	-0.0044433175	2.981990e-05	***
0.50	(Intercept)	0.0254835312	3.358844e-01	
0.50	Diff_InterestRate_Change	0.0075977283	7.673487e-01	
0.50	BAA10Y_Spread	0.0130742690	2.080628e-01	
0.50	VIX	-0.0028690748	8.899938e-03	**
0.75	(Intercept)	0.0216199919	3.782271e-01	
0.75	Diff_InterestRate_Change	0.0131398093	5.950376e-01	
0.75	BAA10Y_Spread	0.0139644709	2.409414e-01	
0.75	VIX	-0.0009410288	4.446828e-01	
0.95	(Intercept)	0.01006227499	5.363622e-01	
0.95	Diff_InterestRate_Change	-0.0206602278	2.112553e-01	
0.95	BAA10Y_Spread	0.0109778396	2.664175e-01	
0.95	VIX	0.0025877714	1.823372e-02	*

Note: *** p<0.001, ** p<0.01, * p<0.05

Nonlinear Quantile Methods – QGAM and QRF

QGAM model

Figure 39: Summary outputs of the QGAM models across five quantiles for SP500

```
> summary(qgam_model_5_SP500)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.06256    0.00257  -24.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df  Chi.sq p-value
s(Diff_InterestRate_Change) 2.591  3.308   2.557  0.5297
s(VIX)                      2.454  2.988 109.525  <2e-16 ***
s(BAA10Y_Spread)            1.005  1.008   6.509  0.0108 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.0375   Deviance explained =    87%
-REML = -417.15  Scale est. = 1          n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_SP500)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.025086   0.002164  -11.59   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 3.93  4.917  10.40  0.0460 *
s(VIX)                      1.00  1.001 106.91  <2e-16 ***
s(BAA10Y_Spread)            1.00  1.001  11.24  0.0008 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0558   Deviance explained =   39%
-REML = -491.07  Scale est. = 1          n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_SP500)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.003240   0.002339   1.385    0.166

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 3.342  4.176   5.80 0.21959
s(VIX)                      2.280  2.799  55.67 < 2e-16 ***
s(BAA10Y_Spread)            1.900  2.373  11.71 0.00525 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.155   Deviance explained = 13.8%
-REML = -494.02  Scale est. = 1          n = 289
```

(c) QGAM – 50th percentile

```
> summary(qgam_model_75_SP500)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.033064   0.002594   12.74   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.898  2.464  0.536   0.708
s(VIX)                      3.177  3.854 35.243 4.9e-07 ***
s(BAA10Y_Spread)            1.829  2.264  8.941   0.016 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0807   Deviance explained = 36.2%
-REML = -474.96  Scale est. = 1          n = 289
```

(d) QGAM – 75th percentile

```
> summary(qgam_model_95_SP500)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.073906   0.002323   31.82   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.000    1.0  1.362    0.243
s(VIX)                      3.242    4.1 28.787 1.83e-05 ***
s(BAA10Y_Spread)            1.000    1.0  0.041    0.839
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.154   Deviance explained = 86.8%
-REML = -438.52  Scale est. = 1          n = 289
```

(e) QGAM – 95th percentile

Figure 40: Summary outputs of the QGAM models across five quantiles for NASDAQ

```
> summary(qgam_model_5_nasdaq)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.081589   0.003072  -26.56   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df  Chi.sq p-value
s(Diff_InterestRate_Change) 3.404  4.210   4.976   0.285
s(VIX)                      2.988  3.643 144.339  <2e-16 ***
s(BAA10Y_Spread)            4.552  5.480  56.322  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.22   Deviance explained = 87.6%
-REML = -367.11  Scale est. = 1         n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_nasdaq)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.027295   0.003168  -8.616   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 3.198  4.025  6.602    0.156
s(VIX)                      1.805  2.275 77.091  < 2e-16 ***
s(BAA10Y_Spread)            3.485  4.238 26.547 3.36e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.154   Deviance explained = 36.3%
-REML = -424.17  Scale est. = 1         n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_nasdaq)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.006992   0.002549   2.742   0.0061 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 2.524  3.222  2.859    0.497
s(VIX)                      2.664  3.314 76.798  < 2e-16 ***
s(BAA10Y_Spread)            2.690  3.326 25.612 2.43e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.197   Deviance explained = 15.4%
-REML = -444.17  Scale est. = 1         n = 289
```

(c) QGAM – 50th percentile

```
> summary(qgam_model_75_nasdaq)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.039565   0.002454   16.12   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.000  1.001  0.197   0.6576
s(VIX)                      3.512  4.323 35.485 1.33e-06 ***
s(BAA10Y_Spread)            2.630  3.304  8.797   0.0443 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.135   Deviance explained = 39.6%
-REML = -440.77  Scale est. = 1         n = 289
```

(d) QGAM – 75th percentile

```
> summary(qgam_model_95_nasdaq)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.08554    0.00230    37.2   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 6.405  7.336  35.02 1.23e-05 ***
s(VIX)                      3.988  4.841  51.68  < 2e-16 ***
s(BAA10Y_Spread)            2.597  3.153  11.37   0.0119 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.0575   Deviance explained = 89.1%
-REML = -411.7  Scale est. = 1         n = 289
```

(e) QGAM – 95th percentile

Figure 41: Summary outputs of the QGAM models across five quantiles for CAC 40

```
> summary(qgam_model_5_CAC40)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.076940   0.003178  -24.21   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.851  2.383  7.287   0.0379 *
s(VIX)                      1.000  1.000 45.344  < 2e-16 ***
s(BAA10Y_Spread)            3.074  3.766 29.924 5.78e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  -0.0121   Deviance explained = 86.1%
-REML = -364.2  Scale est. = 1         n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_CAC40)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.03327    0.00280  -11.88   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.353  1.635  3.961  0.0759 .
s(VIX)                      1.606  1.960 78.033  <2e-16 ***
s(BAA10Y_Spread)            2.658  3.262  9.279  0.0346 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.0851   Deviance explained = 36.8%
-REML = -438.61  Scale est. = 1         n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_CAC40)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 5.046e-05  2.628e-03   0.019    0.985

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.875  2.401  1.764 0.42894
s(VIX)                      2.440  3.018 58.398 < 2e-16 ***
s(BAA10Y_Spread)            2.633  3.277 15.064 0.00247 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.141   Deviance explained =    13%
-REML = -452.51  Scale est. = 1         n = 289
```

(c) QGAM – 50th percentile

```
> summary(qgam_model_75_CAC40)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.034506   0.003127   11.04   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.846  2.374  0.680 0.65054
s(VIX)                      2.254  2.766 13.308 0.00231 **
s(BAA10Y_Spread)            1.008  1.014  3.864 0.05038 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.0766   Deviance explained = 35.1%
-REML = -426.66  Scale est. = 1         n = 289
```

(d) QGAM – 75th percentile

```
> summary(qgam_model_95_CAC40)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.079497   0.002517   31.59   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.001  1.002  0.756   0.385
s(VIX)                      3.838  4.621 68.854  <2e-16 ***
s(BAA10Y_Spread)            1.313  1.534  3.290   0.127
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  -0.13   Deviance explained = 85.4%
-REML = -391.04  Scale est. = 1         n = 289
```

(e) QGAM – 95th percentile

Figure 42: Summary outputs of the QGAM models across five quantiles for DAX 30

```
> summary(qgam_model_5_DAX30)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.082708   0.002987  -27.69   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 2.205  2.850  22.63 0.000103 ***
s(VIX)                      4.543  5.340 105.02  < 2e-16 ***
s(BAA10Y_Spread)            3.767  4.544  33.09 3.61e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.138   Deviance explained = 87.1%
-REML = -354.9  Scale est. = 1         n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_DAX30)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.035078   0.003376  -10.39   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.002  1.003  7.767 0.00535 **
s(VIX)                      3.317  4.027 51.994 < 2e-16 ***
s(BAA10Y_Spread)            2.719  3.372  5.652 0.17672
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0483   Deviance explained = 34.2%
-REML = -397.81  Scale est. = 1         n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_DAX30)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.003236   0.002937   1.102    0.271

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 2.388  3.061  4.384 0.22178
s(VIX)                      2.061  2.549 46.281 < 2e-16 ***
s(BAA10Y_Spread)            2.168  2.697 12.834 0.00411 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.131   Deviance explained = 10.7%
-REML = -416.45  Scale est. = 1         n = 289
```

(c) QGAM – 50th percentile

```
> summary(qgam_model_75_DAX30)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.039622   0.003086   12.84   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.605  2.014  1.413 0.486789
s(VIX)                      3.271  3.967 21.322 0.000186 ***
s(BAA10Y_Spread)            2.064  2.561  8.930 0.019180 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.051   Deviance explained = 34.2%
-REML = -401.19  Scale est. = 1         n = 289
```

(d) QGAM – 75th percentile

```
> summary(qgam_model_95_DAX30)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.093348   0.003583   26.05   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.000  1.000  0.028  0.8683
s(VIX)                      2.506  3.177  9.295  0.0230 *
s(BAA10Y_Spread)            1.115  1.216  5.609  0.0334 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.124   Deviance explained = 84.7%
-REML = -328.33  Scale est. = 1         n = 289
```

(e) QGAM – 95th percentile

Figure 43: Summary outputs of the QGAM models across five quantiles for Nikkei 225

```
> summary(qgam_model_5_Nikkei)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.079472   0.003298   -24.1   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 3.049  3.851 11.795  0.0148 *
s(VIX)                      3.080  3.696 83.909  <2e-16 ***
s(BAA10Y_Spread)            1.002  1.003  0.521  0.4714
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0257   Deviance explained = 85.4%
-REML = -335.79  Scale est. = 1         n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_Nikkei)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.036383   0.003476  -10.47   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 3.032  3.865  8.808  0.0892 .
s(VIX)                      2.869  3.604 50.177  <2e-16 ***
s(BAA10Y_Spread)            1.001  1.002  1.523  0.2175
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.118   Deviance explained = 36.5%
-REML = -407.23  Scale est. = 1         n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_Nikkei)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.003250   0.002927    1.11    0.267

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 2.877  3.652  5.192  0.1950
s(VIX)                      1.000  1.001 40.549  <2e-16 ***
s(BAA10Y_Spread)            1.895  2.330 12.337  0.0031 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.155   Deviance explained = 13.5%
-REML = -433.28  Scale est. = 1         n = 289
```

(c) QGAM – 50th percentile

```
> summary(qgam_model_75_Nikkei)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.040314   0.002954   13.65   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.761  2.254   0.52    0.731
s(VIX)                      1.000  1.001  19.38 1.03e-05 ***
s(BAA10Y_Spread)            1.100  1.192  18.63 3.82e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.098   Deviance explained =   38%
-REML = -422.3  Scale est. = 1         n = 289
```

(d) QGAM – 75th percentile

```
> summary(qgam_model_95_Nikkei)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.082621   0.002631    31.4   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                              edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 1.000  1.000  0.236 0.627089
s(VIX)                      1.000  1.001 16.127 5.98e-05 ***
s(BAA10Y_Spread)            1.006  1.012 14.646 0.000132 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0681   Deviance explained = 84.6%
-REML = -376.03  Scale est. = 1         n = 289
```

(e) QGAM – 95th percentile

Figure 44: Summary outputs of the QGAM models across five quantiles for Hang Seng

```
> summary(qgam_model_5_HangSeng)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.11160    0.00396  -28.18   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.000  1.000  0.017   0.898
s(VIX)                      1.079  1.154 52.151  <2e-16 ***
s(BAA10Y_Spread)            1.000  1.001  1.979   0.160
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.106   Deviance explained = 86.9%
-REML = -306.14  Scale est. = 1          n = 289
```

(a) QGAM – 5th percentile

```
> summary(qgam_model_25_HangSeng)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.044125   0.003909  -11.29   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.833  2.344  1.151   0.780
s(VIX)                      1.000  1.001 35.022  <2e-16 ***
s(BAA10Y_Spread)            1.000  1.000  1.460   0.227
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.0371   Deviance explained = 32.5%
-REML = -360.63  Scale est. = 1          n = 289
```

(b) QGAM – 25th percentile

```
> summary(qgam_model_50_HangSeng)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.0004707  0.0033746  -0.139    0.889

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq  p-value
s(Diff_InterestRate_Change) 2.632  3.383  3.390    0.346
s(VIX)                      1.007  1.013 18.054 2.37e-05 ***
s(BAA10Y_Spread)            1.399  1.695  3.938    0.151
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.0526   Deviance explained = 6.67%
-REML = -380.55  Scale est. = 1          n = 289
```

(c) QGAM – 50th percentile

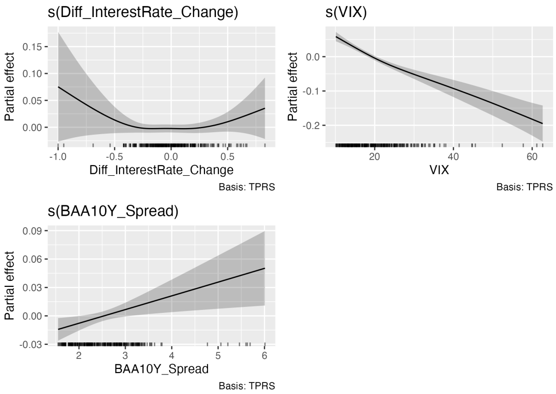
```
> summary(qgam_model_75_HangSeng)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.042928   0.003645   11.78   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 1.001  1.003  0.215  0.6436
s(VIX)                      2.791  3.598  5.687  0.2180
s(BAA10Y_Spread)            2.831  3.494 15.655  0.0024 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.0233   Deviance explained = 35.4%
-REML = -371.43  Scale est. = 1          n = 289
```

(d) QGAM – 75th percentile

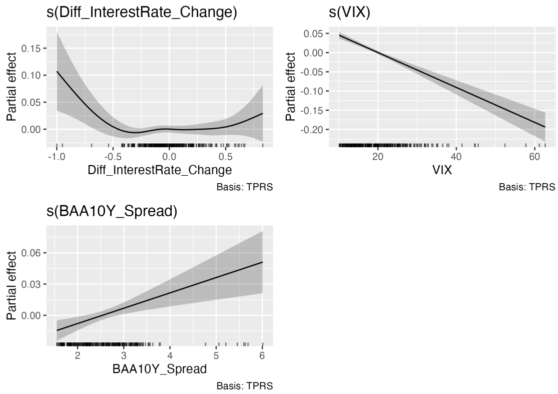
```
> summary(qgam_model_95_HangSeng)

Family: elf
Link function: identity

Formula:
Returns ~ s(Diff_InterestRate_Change) + s(VIX) + s(BAA10Y_Spread)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.103044   0.004215   24.44   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                             edf Ref.df Chi.sq p-value
s(Diff_InterestRate_Change) 5.895  6.966 22.469 0.00209 **
s(VIX)                      1.000  1.001  1.066 0.30198
s(BAA10Y_Spread)            2.157  2.650  6.775 0.06704 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  -0.235   Deviance explained = 86.4%
-REML = -288.98  Scale est. = 1          n = 289
```

(e) QGAM – 95th percentile

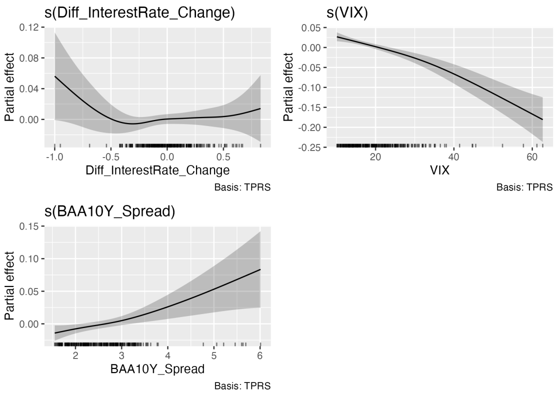
Figure 45: Visualization of smoothed QGAM effects across five quantiles for S&P 500



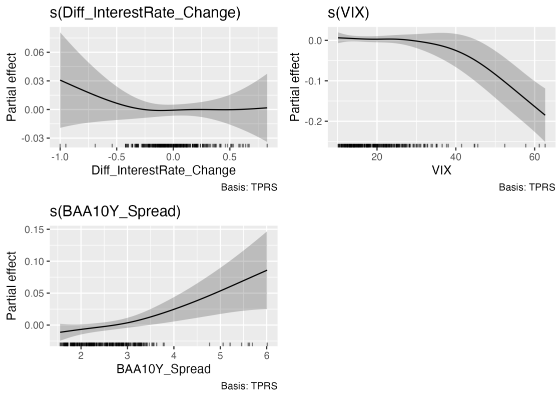
(a) Smoothed Effects – 5th percentile



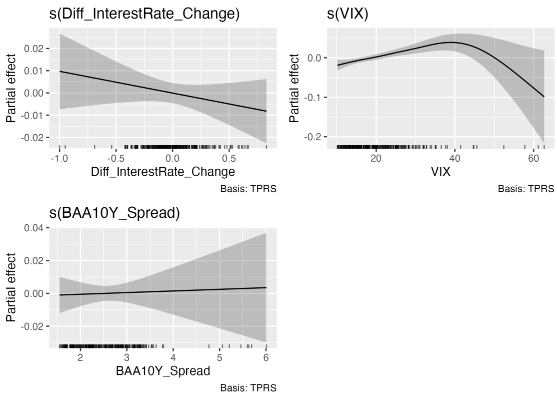
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile

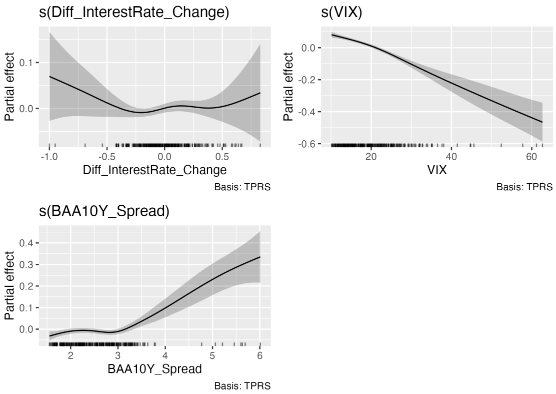


(d) Smoothed Effects – 75th percentile

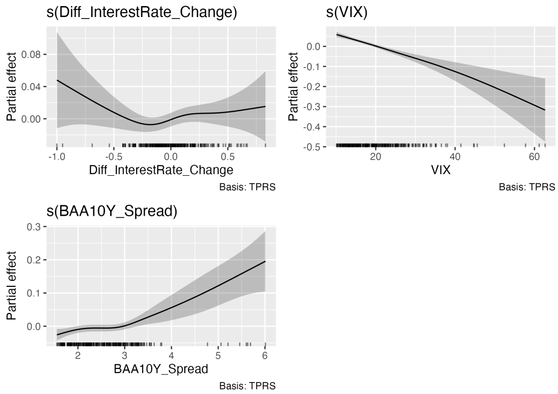


(e) Smoothed Effects – 95th percentile

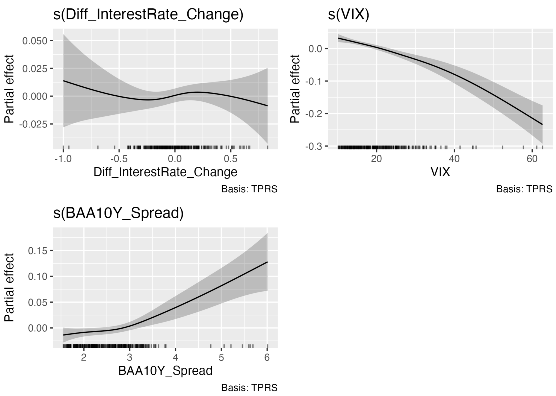
Figure 46: Visualization of smoothed QGAM effects across five quantiles for NASDAQ 100



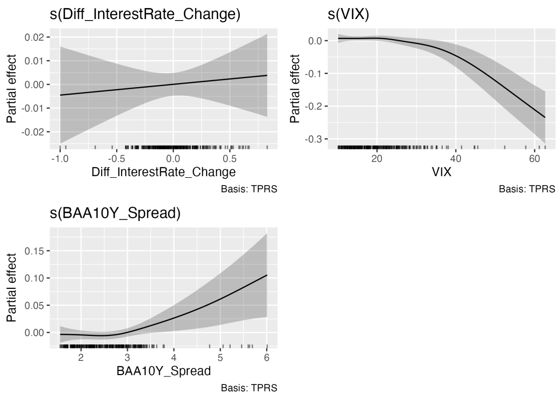
(a) Smoothed Effects – 5th percentile



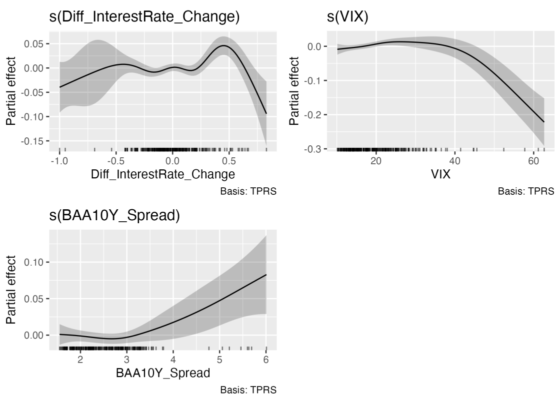
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile

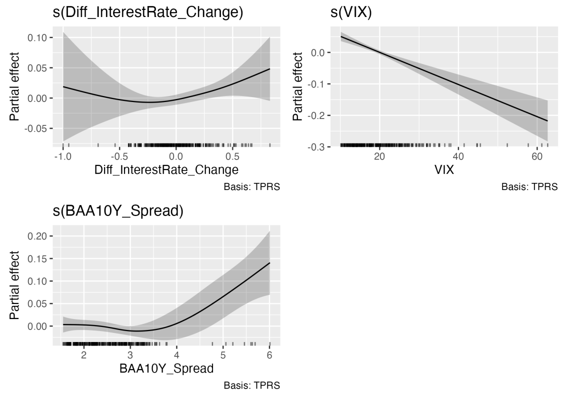


(d) Smoothed Effects – 75th percentile

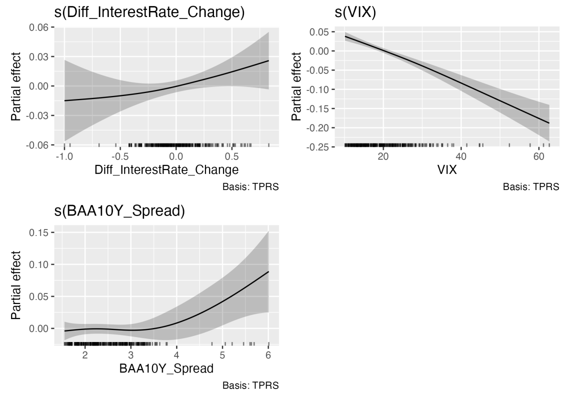


(e) Smoothed Effects – 95th percentile

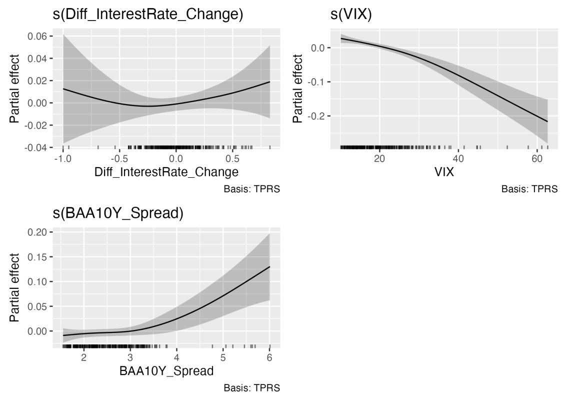
Figure 47: Visualization of smoothed QGAM effects across five quantiles for CAC 40



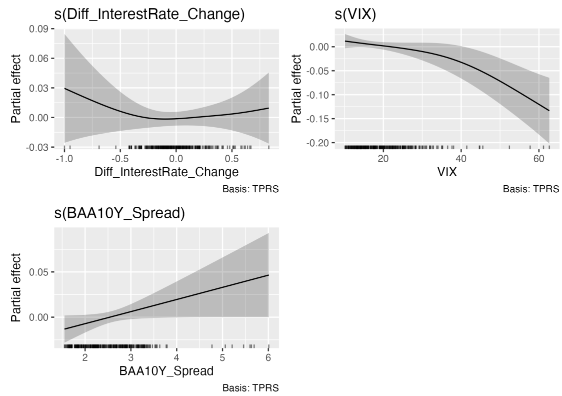
(a) Smoothed Effects – 5th percentile



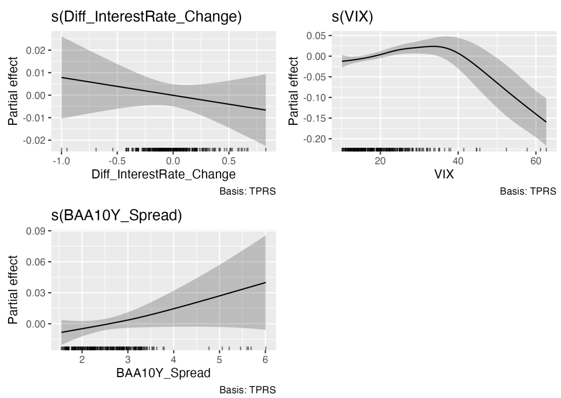
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile

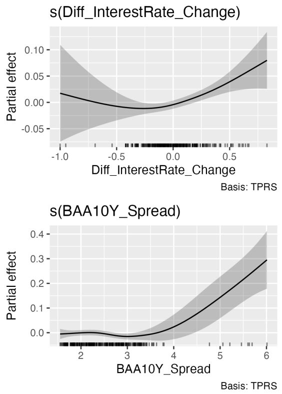


(d) Smoothed Effects – 75th percentile

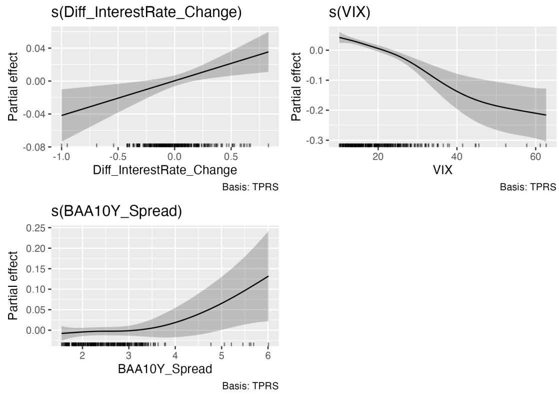


(e) Smoothed Effects – 95th percentile

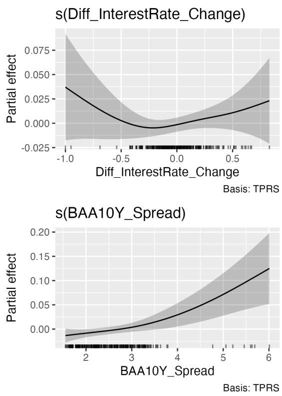
Figure 48: Visualization of smoothed QGAM effects across five quantiles for DAX 30



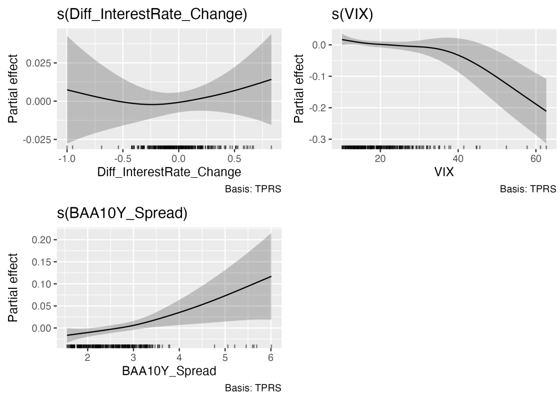
(a) Smoothed Effects – 5th percentile



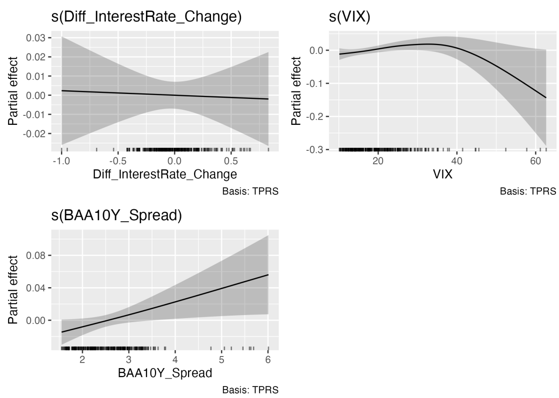
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile

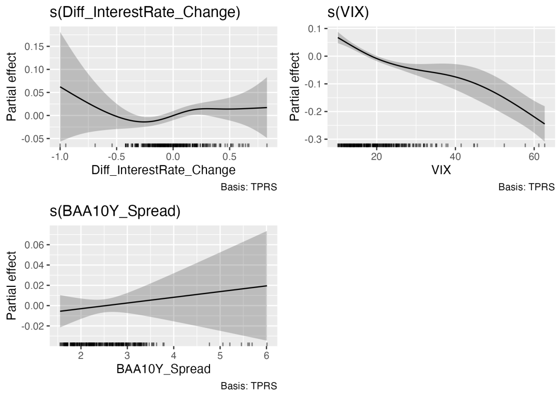


(d) Smoothed Effects – 75th percentile

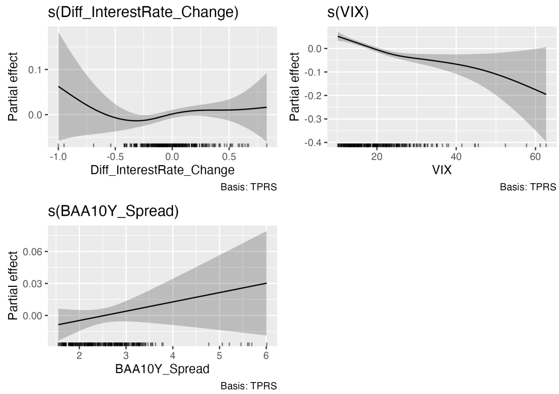


(e) Smoothed Effects – 95th percentile

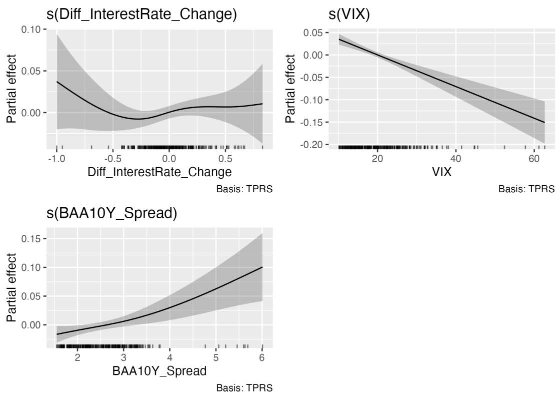
Figure 49: Visualization of smoothed QGAM effects across five quantiles for Nikkei 225



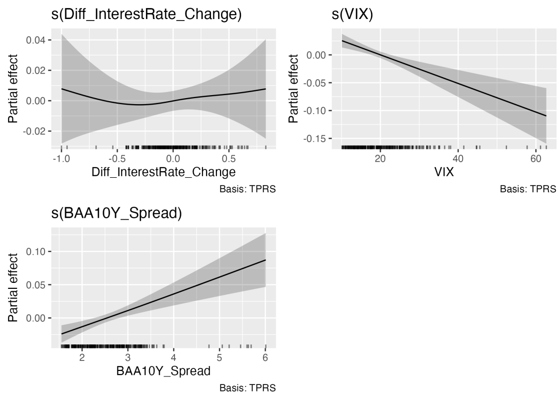
(a) Smoothed Effects – 5th percentile



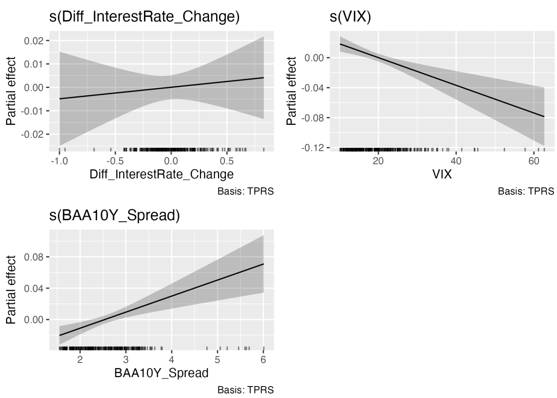
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile

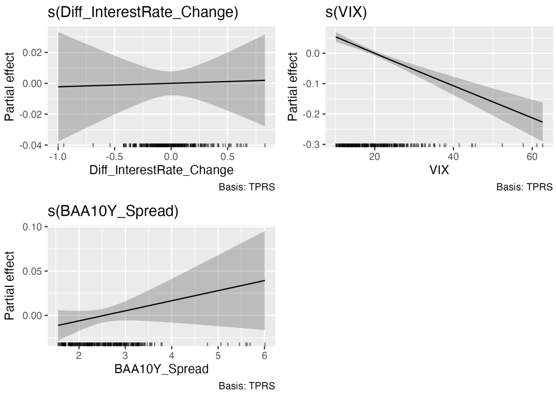


(d) Smoothed Effects – 75th percentile

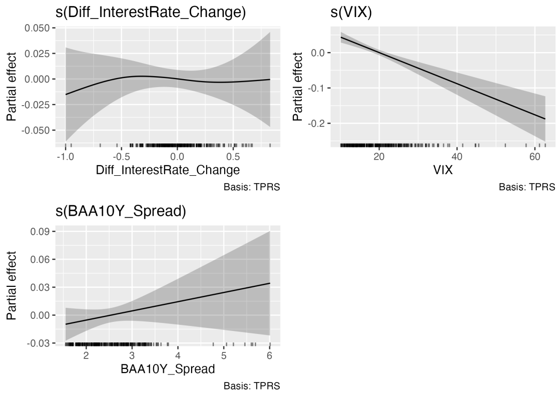


(e) Smoothed Effects – 95th percentile

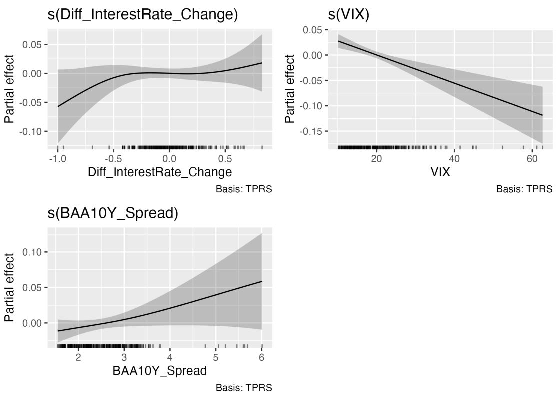
Figure 50: Visualization of smoothed QGAM effects across five quantiles for Hang Seng



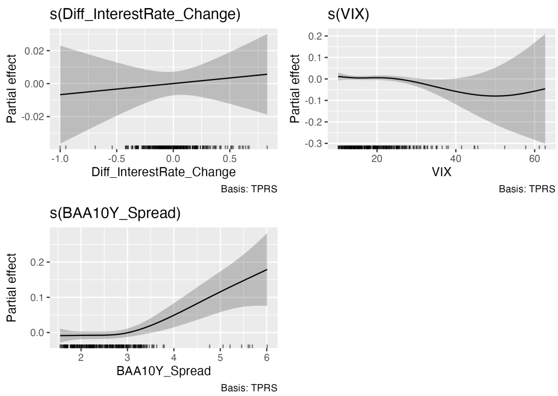
(a) Smoothed Effects – 5th percentile



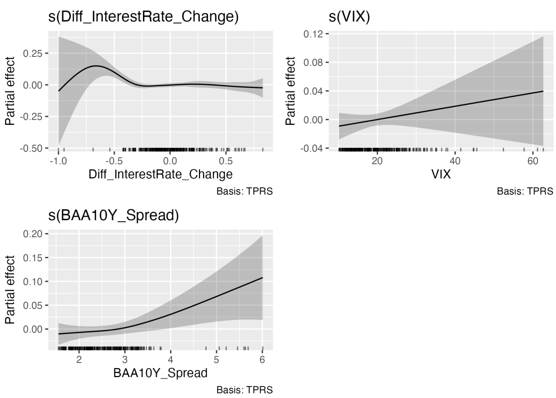
(b) Smoothed Effects – 25th percentile



(c) Smoothed Effects – 50th percentile



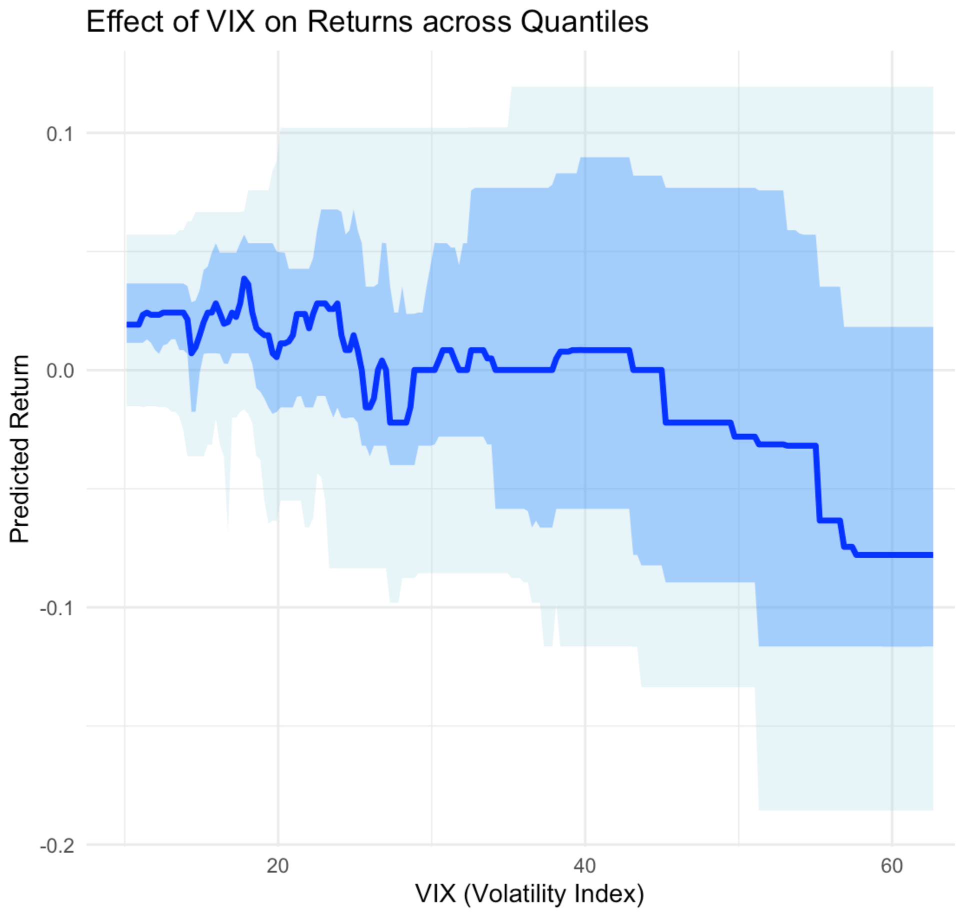
(d) Smoothed Effects – 75th percentile



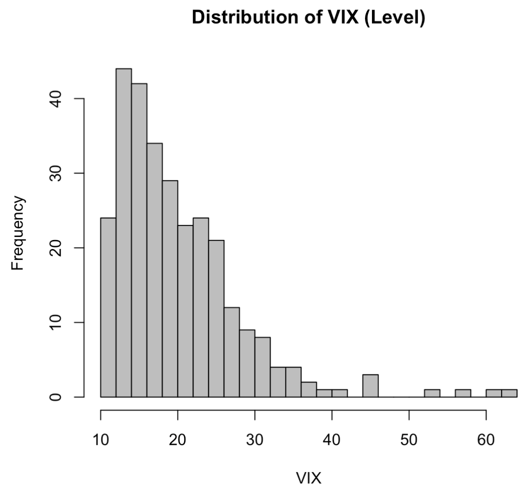
(e) Smoothed Effects – 95th percentile

QRF Model

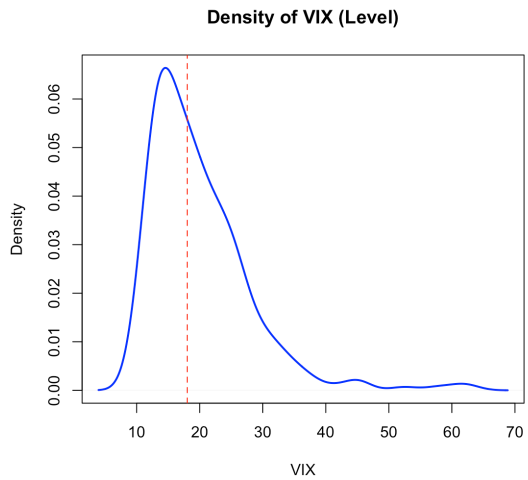
Figure 51: Analysis of VIX (in levels): Non-linear effect on returns and distributional properties for SP500



(a) Effect of VIX on returns across quantiles

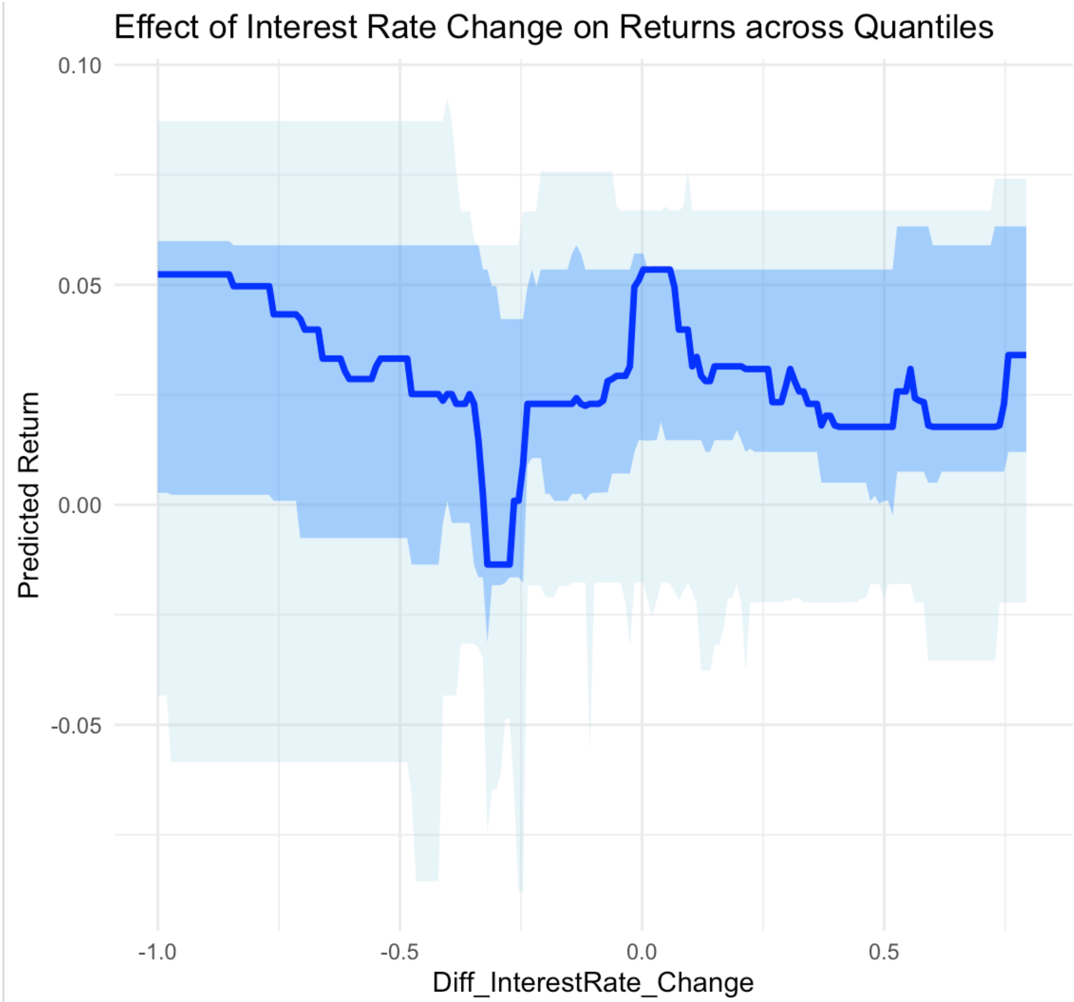


(b) Histogram of VIX (levels)

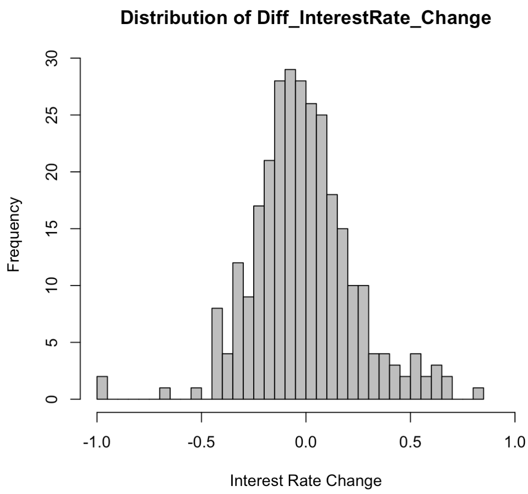


(c) Kernel density of VIX (levels)

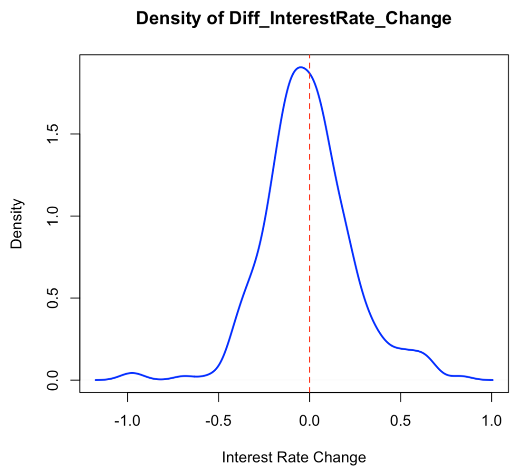
Figure 52: Analysis of Diff_InterestRate_Change: Non-linear effect on returns and distributional properties for SP500



(a) Effect of Diff_InterestRate_Change on returns across quantiles

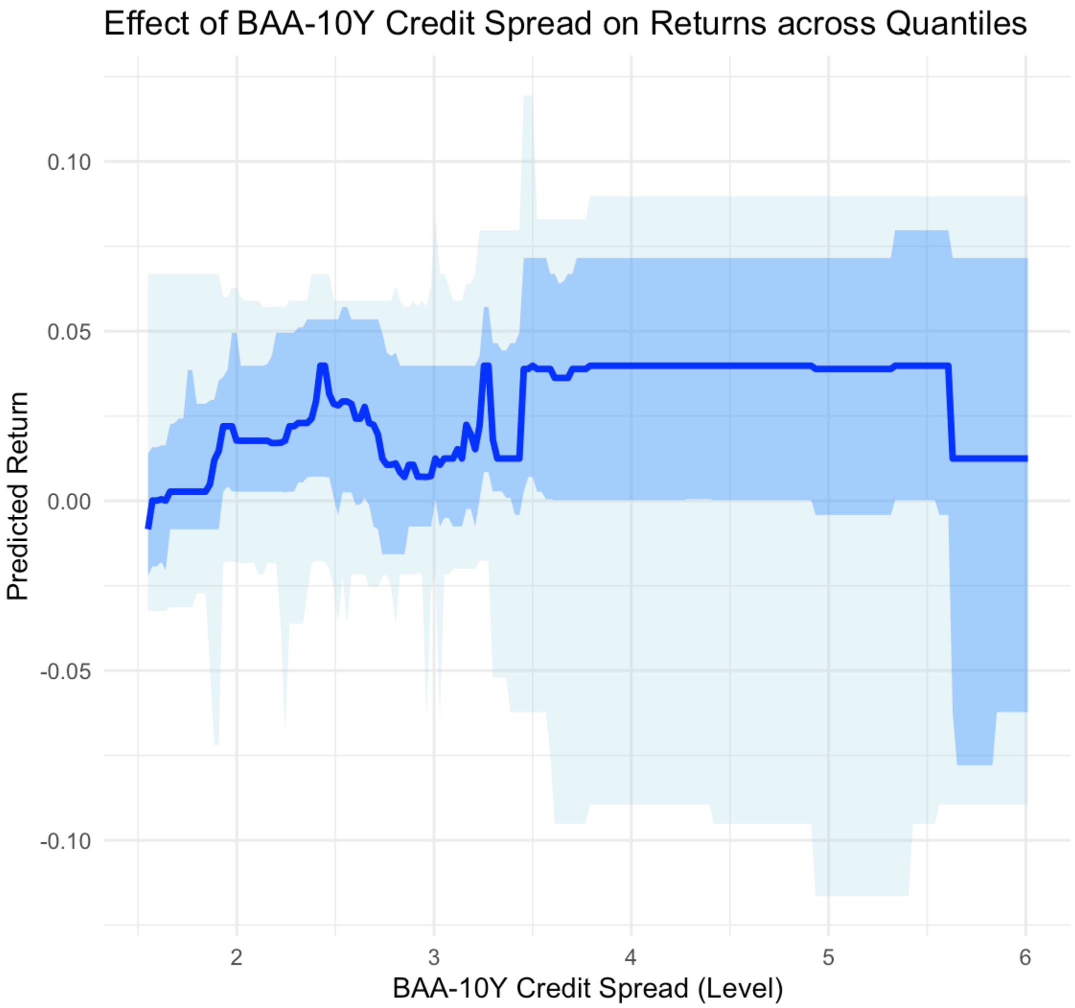


(b) Histogram of Diff_InterestRate_Change

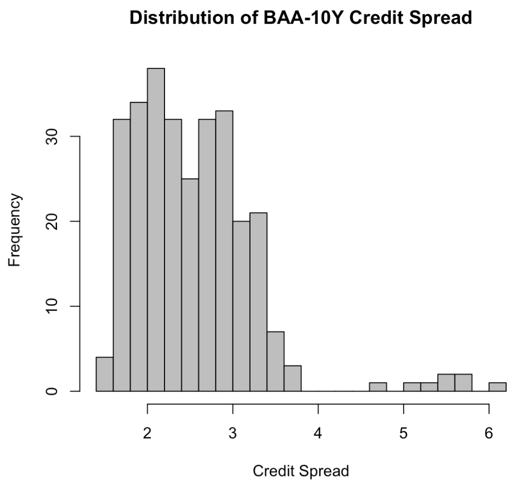


(c) Kernel density of Diff_InterestRate_Change

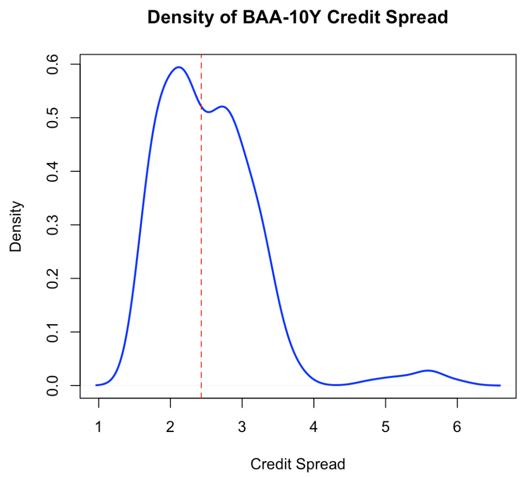
Figure 53: Analysis of BAA10Y credit spread (in levels): Non-linear effect on returns and distributional properties for SP500



(a) Effect of BAA10Y spread on returns across quantiles

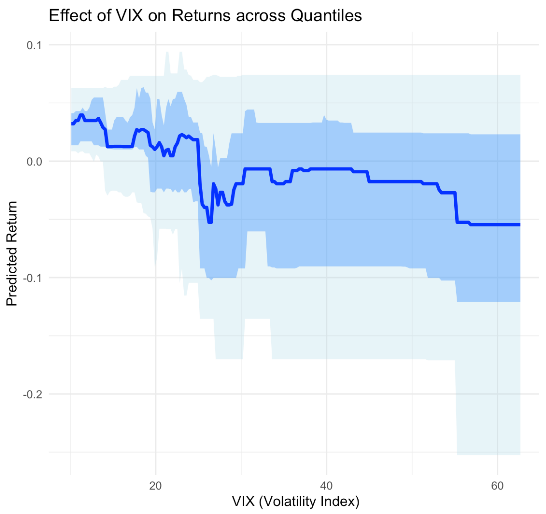


(b) Histogram of BAA10Y spread (levels)

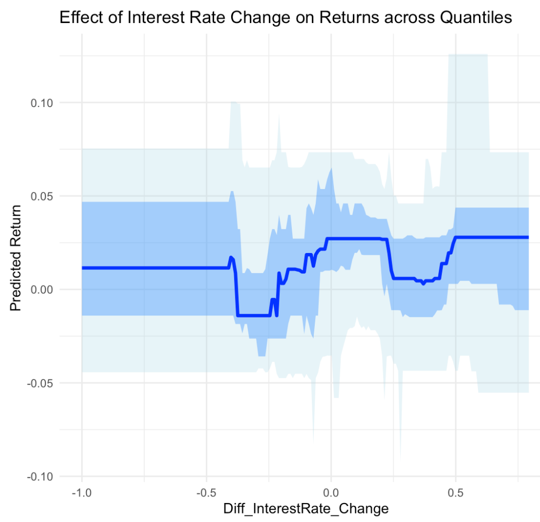


(c) Kernel density of BAA10Y spread (levels)

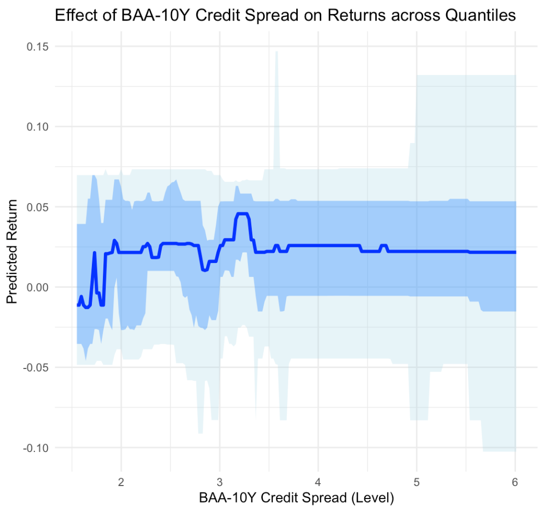
Figure 54: Effect of macro-financial variables on NASDAQ returns across quantiles



(a) Effect of VIX

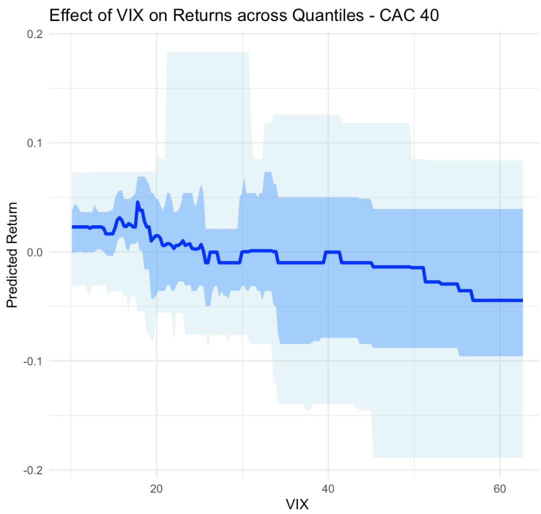


(b) Effect of Interest Rate Change

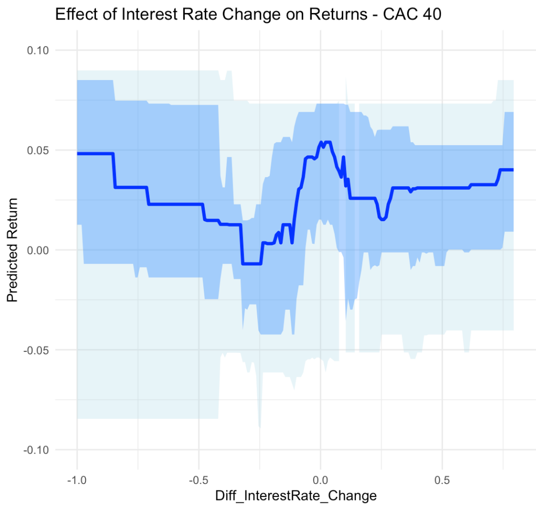


(c) Effect of BAA-10Y Credit Spread

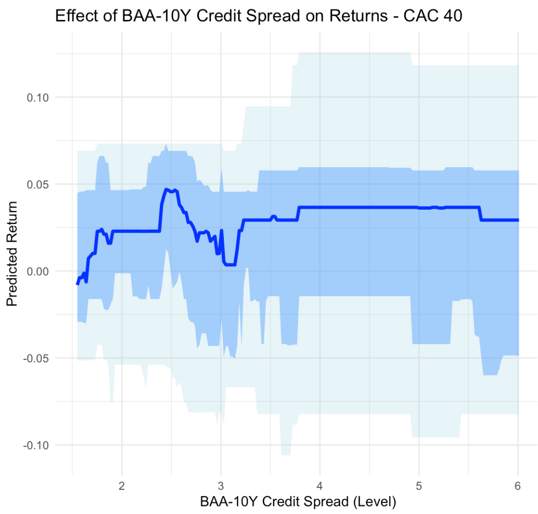
Figure 55: Effect of macro-financial variables on CAC 40 returns across quantiles



(a) Effect of VIX

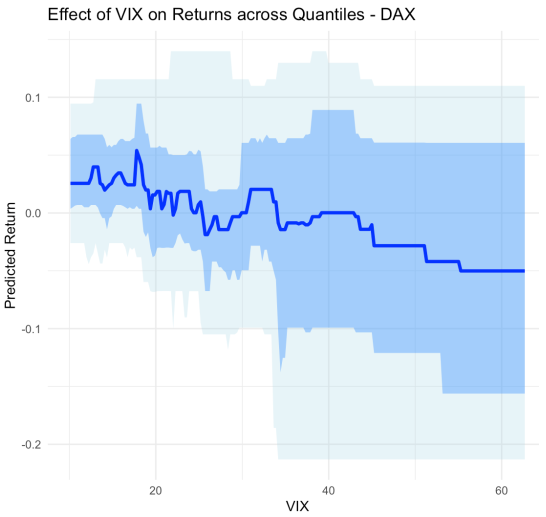


(b) Effect of Interest Rate Change

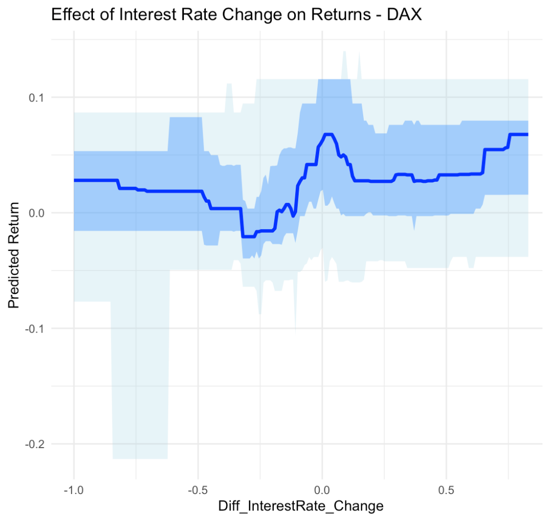


(c) Effect of BAA-10Y Credit Spread

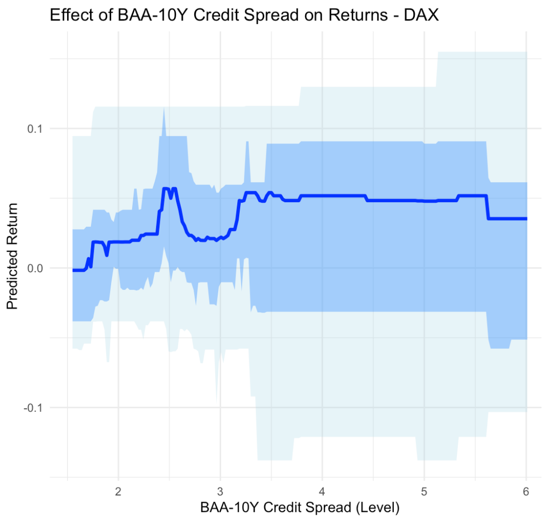
Figure 56: Effect of macro-financial variables on DAX 30 returns across quantiles



(a) Effect of VIX

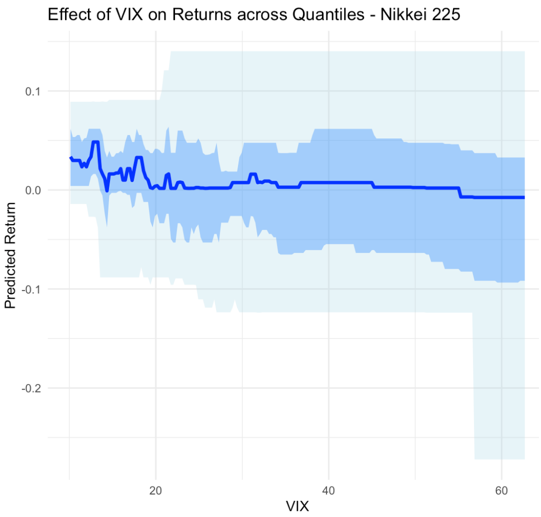


(b) Effect of Interest Rate Change

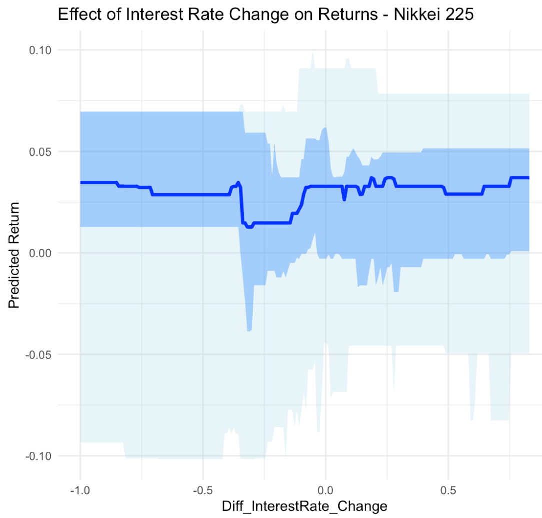


(c) Effect of BAA-10Y Credit Spread

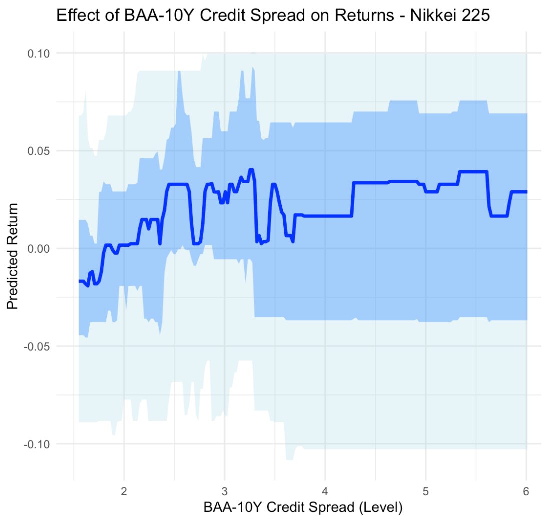
Figure 57: Effect of macro-financial variables on Nikkei 225 returns across quantiles



(a) Effect of VIX

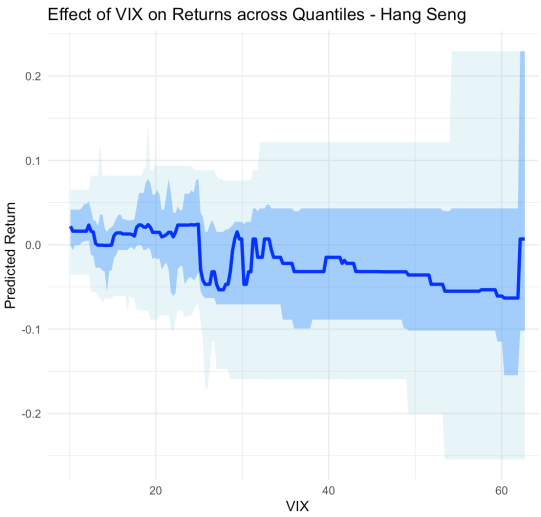


(b) Effect of Interest Rate Change

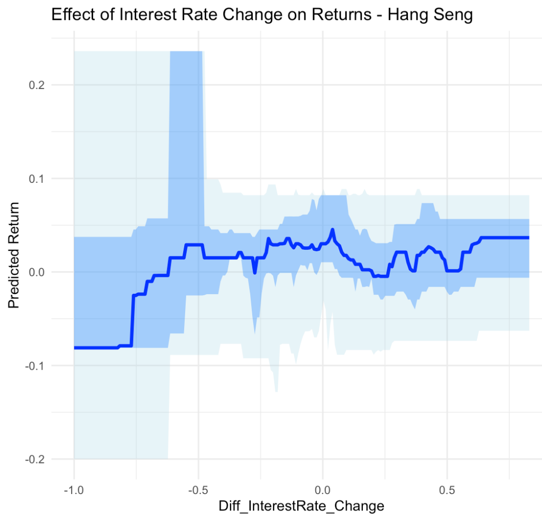


(c) Effect of BAA-10Y Credit Spread

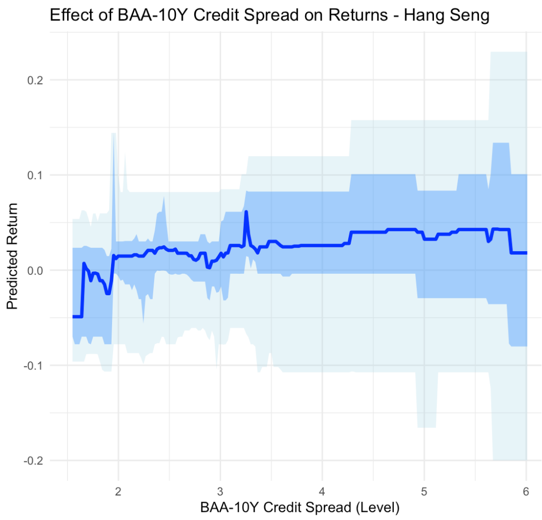
Figure 58: Effect of macro-financial variables on Hang Seng returns across quantiles



(a) Effect of VIX



(b) Effect of Interest Rate Change



(c) Effect of BAA-10Y Credit Spread

7.5 Index-level analysis

This section provides a detailed analysis of each stock market index examined in this study. The analysis for each index includes an overview of the index's performance over time, the results of OLS and Robust OLS regressions, insights from Quantile Regression (QR), and nonlinear effects captured through Quantile Generalized Additive Models (QGAM). This approach ensures a consistent, in-depth exploration of the effects of macro-financial variables across different market environments.

7.5.1 S&P 500

Overview of S&P 500 performance

The S&P 500 index has experienced substantial growth over the study period, punctuated by periods of significant volatility, particularly during major market events such as the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic. The monthly return series reveals sharp fluctuations, reflecting the inherent risk of this major U.S. stock index. (Figures 1 & 2)

OLS and robust OLS results

The OLS and Robust OLS regression results for the S&P 500 reveal the following key insights:
VIX: The effect of VIX is consistently negative and statistically significant, indicating that rising volatility is associated with lower stock returns. This relationship is robust across both classical and robust OLS models (see Figures 33a & 33b).
Credit Spread (BAA10Y Spread): Credit spreads exhibit a positive effect in the OLS models, suggesting that widening spreads are associated with higher stock returns.
Interest Rate Changes: The coefficient for interest rate changes is generally insignificant, implying that fluctuations in the yield curve slope do not have a substantial direct impact on average S&P 500 returns.

Quantile regression results

The quantile regression analysis provides a more granular view of these relationships across different parts of the return distribution (see Table 4):
VIX: The negative impact is most pronounced at lower quantiles (5th and 25th), underscoring the heightened sensitivity of the S&P 500 to volatility during downturns.
Credit Spread: The effect of credit spreads is generally positive at lower quantiles, which is counterintuitive as rising credit risk is typically expected to depress stock returns. This unexpected relationship may be due to the influence of specific market conditions, such as central bank interventions, or could reflect the model's limitations. The positive coefficient indicates that during bearish periods, rising credit spreads may coincide with a shift toward riskier equity investments rather than a flight to safety.

Interest Rate Changes: The effect remains largely insignificant across quantiles, confirming the findings from the OLS models.

Nonlinear analysis with QGAM

The QGAM results provide further insights into the nonlinear dynamics of these variables (see Figure 39):
VIX: The impact of VIX is consistently negative across all quantiles, with a sharper decline at lower quantiles, highlighting the asymmetric nature of volatility effects.
Credit Spread: The smooth effects of credit spreads reveal a positive relationship at lower quantiles, indicating that rising credit spreads are associated with higher returns under bearish conditions. This effect gradually diminishes or reverses at higher quantiles.
Interest Rate Changes: Although the linear effect of interest rates was generally insignificant, QGAM reveals some nonlinear patterns, suggesting that the relationship may be more complex.

Distributional Analysis of Key Variables

The distributional analysis of the key variables (VIX, Credit Spread, and Interest Rate Change) helps to contextualize the regression results:
VIX: The distribution is right-skewed, with the majority of observations clustered at lower levels, while extreme values are associated with crisis periods (see Figure 51).
Credit Spread: Primarily concentrated between 1 and 4, with a few observations at higher levels, likely reflecting periods of heightened credit risk.
Interest Rate Changes: Display a roughly symmetric distribution centered around zero, consistent with a stable yield curve environment.

Key insights and implications for S&P 500

The dominant role of VIX as a predictor highlights the importance of volatility as a leading indicator of market risk for the S&P 500.
The positive coefficients of credit spreads at lower quantiles suggest that rising credit spreads are associated with higher stock returns during downturns. This may reflect a situation where riskier assets, including equities, offer higher potential returns to compensate for increased perceived credit risk. Conversely, this effect diminishes or disappears at higher quantiles, where market conditions are more favorable.
The absence of a consistent effect for interest rate changes suggests that other macroeconomic factors may have a more direct impact on equity returns.
This structured analysis provides a comprehensive view of the S&P 500, leveraging both linear and nonlinear models to capture the complex dynamics of macro-financial variables across different market conditions.

7.5.2 NASDAQ 100

Overview of NASDAQ 100 performance

The NASDAQ 100 index, known for its technology-heavy composition, has exhibited substantial growth over the study period, characterized by pronounced volatility, particularly during the Dot-com bubble, the 2008 Global Financial Crisis, and the COVID-19 pandemic. The monthly return series also demonstrates sharp fluctuations, reflecting the index's sensitivity to global economic and technological developments (Figures 3 & 4).

OLS and robust OLS results

The OLS and Robust OLS regression results for the NASDAQ 100 reveal the following key insights (Figures 34a & 34b):
VIX: The impact of VIX is consistently negative and highly significant, underscoring the strong inverse relationship between market volatility and NASDAQ 100 returns. This effect is robust across both classical and robust OLS models.
Credit Spread (BAA10Y Spread): Credit spreads exhibit a positive effect, which is statistically significant. This positive coefficient suggests that rising credit spreads, which typically signal higher credit risk, may be associated with higher NASDAQ 100 returns. This may indicate a risk-on behavior in the tech-heavy NASDAQ during periods of credit stress.
Interest Rate Changes: The coefficient for interest rate changes is generally insignificant in both models, suggesting that fluctuations in the yield curve slope do not have a substantial direct impact on average NASDAQ 100 returns.

Quantile regression results

The quantile regression analysis provides a more detailed view of the relationships across the return distribution (see Table 5):
VIX: The negative impact of VIX is most pronounced at lower quantiles (5th and 25th), indicating that NASDAQ 100 returns are particularly sensitive to volatility during downturns.
Credit Spread: The effect of credit spreads is generally positive at lower quantiles, which may be counterintuitive. This finding suggests that rising credit spreads could coincide with higher returns, possibly reflecting a shift toward riskier assets or the influence of monetary policy measures.
Interest Rate Changes: The effect remains largely insignificant across quantiles, confirming the results of the OLS models.

Nonlinear analysis with QGAM

The QGAM results reveal important nonlinear dynamics for the NASDAQ 100 (see Figure 40):

VIX: The impact of VIX is consistently negative across all quantiles, with a stronger effect at lower quantiles, highlighting the asymmetric impact of volatility on NASDAQ 100 returns.
Credit Spread: The smooth effects of credit spreads reveal a positive relationship at lower quantiles, which diminishes at higher quantiles.
Interest Rate Changes: Although the linear effect of interest rates was generally insignificant, QGAM reveals some nonlinear patterns, particularly at the tails, suggesting that the relationship may be more complex.

Key insights and implications for NASDAQ 100

The consistent negative effect of VIX highlights the vulnerability of the NASDAQ 100 to volatility, especially during periods of market stress.
The positive coefficients of credit spreads at lower quantiles suggest that rising credit spreads may be associated with higher NASDAQ 100 returns during downturns, potentially reflecting a shift toward riskier technology stocks in times of credit stress.
The lack of a clear effect for interest rate changes suggests that other macroeconomic factors, such as technological innovation and global demand for technology, may play a more significant role in driving NASDAQ 100 returns.

7.5.3 CAC 40

Overview of CAC 40 performance

The CAC 40 index has experienced substantial growth over the study period, marked by periods of significant volatility. The monthly return series reveals sharp fluctuations, reflecting the inherent risk of this major French stock index. (Figures 5 & 6)

OLS and robust OLS results

The OLS and Robust OLS regression results for the CAC 40 reveal the following key insights:
VIX: The effect of VIX is consistently negative and statistically significant, indicating that rising volatility is associated with lower stock returns. This relationship is robust across both classical and robust OLS models (see Figures 35a & 35b).
Credit Spread (BAA10Y Spread): The coefficient for credit spreads is positive but not statistically significant, implying that variations in credit risk do not have a clear or consistent effect on average CAC 40 returns.
Interest Rate Changes: The coefficient for interest rate changes is insignificant, implying that fluctuations in the yield curve slope do not have a substantial direct impact on average CAC 40 returns.

Quantile regression results

The quantile regression analysis provides a more granular view of these relationships across different parts of the return distribution (see Table 6):
VIX: The negative impact is most pronounced at lower quantiles (5th and 25th), underscoring the heightened sensitivity of the CAC 40 to volatility during downturns.
Credit Spread: The coefficients are not statistically significant across the distribution, indicating that changes in credit spreads do not exhibit a consistent or robust relationship with CAC 40 returns under different market conditions.
Interest Rate Changes: The effect remains statistically insignificant across all quantiles, confirming the findings from the OLS models and suggesting that fluctuations in the yield curve slope do not have a substantial or systematic impact on CAC 40 returns.

Nonlinear analysis with QGAM

The QGAM results provide further insights into the nonlinear dynamics of these variables (see Figure 41):
VIX: The impact of VIX is consistently negative across all quantiles, with a sharper decline at lower quantiles, highlighting the asymmetric nature of volatility effects.
Credit Spread: The smooth effects of credit spreads reveal a generally positive relationship.
Interest Rate Changes: Although the linear effect of interest rates was generally insignificant, QGAM reveals some nonlinear patterns, suggesting that the relationship may be more complex.

Key insights and implications for CAC 40

The dominant role of VIX as a predictor highlights the importance of volatility as a leading indicator of market risk for the CAC 40.
The generally negative coefficients of credit spreads at lower quantiles suggest that rising credit risk is most damaging during downturns. However, the reversal at higher quantiles suggests that credit spreads may have a different impact in bullish market conditions.
The absence of a consistent effect for interest rate changes suggests that other macroeconomic factors may have a more direct impact on equity returns.

7.5.4 DAX 30

Overview of DAX 30 performance

The DAX 30 index, representing the 30 largest companies listed on the Frankfurt Stock Exchange, has shown substantial growth over the study period, with notable periods of volatility. The monthly return series exhibits significant fluctuations, reflecting the inherent risks in this major European stock index (Figures 7 & 8).

OLS and robust OLS results

The OLS and Robust OLS regression results for the DAX 30 present the following insights:
VIX: The effect of VIX is consistently negative and statistically significant, indicating that rising volatility is associated with lower stock returns. This relationship is robust across both classical and robust OLS models (see Figures 36a & 36b).
Credit Spread (BAA10Y Spread): The effect of credit spreads is positive in the OLS models, suggesting that widening spreads are associated with higher stock returns. This counterintuitive finding may reflect investor risk appetite, monetary policy effects, or sample-specific dynamics during periods of market stress.
Interest Rate Changes: The coefficient for interest rate changes is not statistically significant in the OLS model. This suggests that interest rate changes do not exert a consistent or robust influence on stock returns.

Quantile regression results

The quantile regression analysis for the DAX 30 provides further insights across different parts of the return distribution (see Table 7):
VIX: The negative impact of VIX is most pronounced at lower quantiles (5th and 25th), highlighting the heightened sensitivity of the DAX 30 to volatility during bearish conditions.
Credit Spread: The coefficients for credit spreads are generally positive across quantiles but not statistically significant. This indicates that there is no robust evidence of a consistent relationship between credit spreads and returns, and any apparent association should be interpreted with caution.
Interest Rate Changes: The impact of interest rate changes is significant and positive at the 5th quantile, indicating that rising rates may be associated with higher returns under extreme negative conditions.

Nonlinear analysis with QGAM

The QGAM results reveal more complex nonlinear relationships for the DAX 30 (see Figure 42):
VIX: The negative impact is consistent across quantiles, but the magnitude of the effect is stronger at lower quantiles, further confirming the heightened sensitivity of the DAX to volatility during market downturns.
Credit Spread: The smooth effects of credit spreads show a positive relationship.
Interest Rate Changes: Although the linear effect of interest rates was positive in some cases, the QGAM results reveal that this relationship is more complex, with non-linear patterns indicating that the impact of interest rate changes varies depending on market conditions.

Key insights and implications for DAX 30

The strong negative relationship between VIX and returns, particularly at lower quantiles, emphasizes the critical role of volatility in influencing the DAX 30.
The consistent positive effect of credit spreads across quantiles suggests that rising credit risk is generally associated with higher DAX 30 returns, possibly reflecting investor risk appetite or unconventional market dynamics.
The mixed effects of interest rate changes highlight the importance of considering non-linear models to capture the full range of dynamics affecting stock returns.

7.5.5 Nikkei 225

Overview of Nikkei 225 performance

The Nikkei 225 index has demonstrated substantial growth over the study period, characterized by notable volatility. Major events such as the 2008 Global Financial Crisis and the COVID-19 pandemic in 2020 are clearly reflected in the time series of the index, which exhibits sharp declines followed by rapid recoveries. The monthly return series further emphasizes the index's volatility, with frequent sharp fluctuations (Figures 9 & 10).

OLS and robust OLS results

The OLS and Robust OLS regression results for the Nikkei 225 reveal the following insights:
VIX: The coefficient of VIX is consistently negative and statistically significant, confirming that rising volatility is associated with declining stock returns for the Nikkei 225. This relationship is robust across both classical and robust OLS models (see Figures 37a & 37b).
Credit Spread (BAA10Y Spread): The effect of credit spreads is significant and positive in the OLS models, suggesting that higher credit spreads are associated with higher returns. This is a somewhat counterintuitive finding, potentially reflecting the unique dynamics of the Japanese market, where higher credit spreads might coincide with periods of higher equity returns.
Interest Rate Changes: The coefficient for interest rate changes is insignificant, suggesting that variations in interest rates do not have a clear linear effect on average returns for the Nikkei 225.

Quantile regression results

The quantile regression analysis provides a more nuanced view of these relationships across different parts of the return distribution (see Table 8):
VIX: The negative impact of VIX is most pronounced at lower quantiles (5th and 25th), highlighting that the Nikkei 225 is particularly sensitive to rising volatility during downturns.

Credit Spread: The effect of credit spreads is positive but not statistically significant at lower quantiles. However, it becomes significant and remains positive at the 50th, 75th, and 95th quantiles, suggesting that rising credit spreads are more strongly associated with higher returns under neutral to bullish market conditions.
Interest Rate Changes: The effect of interest rate changes on returns is statistically significant only at the 5th quantile, where the positive coefficient suggests that, in bearish market conditions, rising interest rates may be interpreted as a sign of economic recovery or normalization, particularly relevant for Japan, where interest rates have remained ultra-low for decades.

Nonlinear analysis with QGAM

The QGAM results further capture the nonlinear dynamics of these variables (see Figure 43):
VIX: The impact of VIX is consistently negative across all quantiles, with a sharper decline at lower quantiles, reinforcing its role as a key indicator of market risk.
Credit Spread: The smooth effects of credit spreads reveal a positive relationship at lower quantiles, which gradually diminishes as returns increase. This suggests that during market downturns, rising credit spreads may coincide with higher equity returns.
Interest Rate Changes: The nonlinear analysis reveals a mixed relationship, with positive effects at lower quantiles, potentially reflecting market perceptions of economic recovery during periods of rising rates.

Key insights and implications for Nikkei 225

The dominant role of VIX highlights the sensitivity of the Nikkei 225 to global volatility, particularly during downturns.
The positive impact of credit spreads at lower quantiles suggests that rising credit spreads may be associated with higher equity returns during downturns. This may reflect a market dynamic where investors seek higher potential returns in equities to offset credit risk.
The absence of a consistent effect for interest rate changes suggests that other macroeconomic factors, such as exchange rates or government policy, may have a more direct impact on the Nikkei 225.

7.5.6 Hang Seng

Overview of Hang Seng performance

The Hang Seng index has shown notable fluctuations over the study period, reflecting the volatility inherent in the Hong Kong stock market. The monthly return series captures these variations, highlighting periods of both strong gains and sharp losses (Figures 11 & 12).

OLS and robust OLS results

The OLS and Robust OLS regression results for the Hang Seng index are summarized below:
VIX: The effect of VIX is consistently negative and statistically significant, indicating that rising volatility is associated with lower Hang Seng returns. This relationship is robust across both classical and robust OLS models (see Figures 38a & 38b).
Credit Spread (BAA10Y Spread): Credit spreads exhibit a positive effect in the OLS model, suggesting that widening spreads are associated with higher Hang Seng returns. This positive effect may be counterintuitive, as rising credit risk is generally expected to reduce equity returns. This result could be influenced by specific market conditions or model limitations.
Interest Rate Changes: The coefficient for interest rate changes is insignificant, implying that fluctuations in interest rates do not have a substantial direct impact on average Hang Seng returns.

Quantile regression results

The quantile regression analysis provides a more granular view of these relationships across different parts of the return distribution (see Table 9):
VIX: The negative impact is most pronounced at lower quantiles (5th and 25th), reflecting the heightened sensitivity of the Hang Seng to volatility during bearish periods.
Credit Spread: The effect of credit spreads is positive across all quantiles, but not statistically significant. This suggests that there is no robust evidence of a consistent relationship between credit spreads and returns across market conditions, and any apparent pattern should be interpreted with caution.
Interest Rate Changes: The effect remains largely insignificant across quantiles, consistent with the OLS findings.

Nonlinear analysis with QGAM

The QGAM results provide further insights into the nonlinear dynamics of these variables (see Figure 50):
VIX: The impact of VIX is consistently negative across all quantiles, with a sharper decline at lower quantiles, highlighting the asymmetric nature of volatility effects.
Credit Spread: The smooth effects of credit spreads reveal a positive relationship, particularly at lower quantiles. This suggests that rising credit spreads may be associated with higher returns during bearish conditions, possibly due to risk premiums.
Interest Rate Changes: Although the linear effect of interest rates was generally insignificant, QGAM reveals some nonlinear patterns, indicating that the relationship may be more complex than captured by the linear model.

Key insights and implications for Hang Seng

The dominant role of VIX as a predictor highlights the importance of volatility as a leading indicator of market risk for the Hang Seng index.

The positive coefficients of credit spreads at lower quantiles suggest that rising credit spreads are associated with higher stock returns during downturns. This may reflect a situation where riskier assets, including equities, offer higher potential returns to compensate for increased perceived credit risk. Conversely, this effect diminishes or disappears at higher quantiles, where market conditions are more favorable.

The absence of a consistent effect for interest rate changes suggests that other macroeconomic factors may have a more direct impact on equity returns.

7.6 R Code

```r

# 0. Setup Environment ---------------------------------------------------------
if (!require("pacman")) install.packages("pacman")
pacman::p_load(
  quantreg, tidyverse, ggplot2, quantregForest,
  bayesQR, rqPen, qgam, gratia, robustbase, lmtest, car, tseries,sandwich)

# 1. Define file Paths ---------------------------------------------------------
sp500_path       <- "/Users/julien/Desktop/MA 2/Master thesis/data/S&P 500 Historical Data.csv"
nasdaq100_path   <- "/Users/julien/Desktop/MA 2/Master thesis/data/NASDAQ100.csv"
cac40_path   <- "/Users/julien/Desktop/MA 2/Master thesis/data/CAC 40 Historical Data.csv"
dax_path   <- "/Users/julien/Desktop/MA 2/Master thesis/data/DAX Historical Data.csv"
nikkei_path   <- "/Users/julien/Desktop/MA 2/Master thesis/data/Nikkei 225 Historical Data.csv"
hangseng_path   <- "/Users/julien/Desktop/MA 2/Master thesis/data/Hang Seng Historical Data.csv"

interest_10Y3M_path <- "/Users/julien/Desktop/MA 2/Master thesis/data/T10Y3M.csv"
vix_path          <- "/Users/julien/Desktop/MA 2/Master thesis/data/VIXCLS.csv"
BAA_path <- "/Users/julien/Desktop/MA 2/Master thesis/data/BAA10Y.csv"


# 2. Load and prepare the data ------------------------------------------------
## 2.1 Indices -----------------------------------------------------------------
### 2.1.1 USA ------------------------------------------------------------------
sp500_data <- read_csv(sp500_path) %>%
  select(1:2) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date) %>%
  rename(SP500_Price = Price)
ggplot(sp500_data, aes(x = Date, y = SP500_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "S&P 500 Over Time", x = "Date", y = "Price") +
  theme_minimal()
```

```r
nasdaq_data <- read_csv(nasdaq100_path) %>%
  select(1:2) %>%
  rename(Date = observation_date) %>%
  rename(NASDAQ100_Price = NASDAQ100) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date)
ggplot(nasdaq_data, aes(x = Date, y = NASDAQ100_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "NASDAQ100 Over Time", x = "Date", y = "Price") +
  theme_minimal()

### 2.1.2 Europe ---------------------------------------------------------------
cac40_data <- read_csv(cac40_path) %>%
  select(1:2) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date) %>%
  rename(CAC40_Price = Price)
ggplot(cac40_data, aes(x = Date, y = CAC40_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "CAC 40 Over Time", x = "Date", y = "Price") +
  theme_minimal()
dax_data <- read_csv(dax_path) %>%
  select(1:2) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date) %>%
  rename(DAX_Price = Price)
ggplot(dax_data, aes(x = Date, y = DAX_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "DAX Over Time", x = "Date", y = "Price") +
  theme_minimal()

### 2.1.3 Asia -----------------------------------------------------------------
nikkei_data <- read_csv(nikkei_path) %>%
  select(1:2) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date) %>%
  rename(Nikkei_Price = Price)
ggplot(nikkei_data, aes(x = Date, y = Nikkei_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "Nikkei 225 Over Time", x = "Date", y = "Price") +
  theme_minimal()
hangseng_data <- read_csv(hangseng_path) %>%
  select(1:2) %>%
  mutate(Date = as.Date(Date, format = "%m/%d/%Y")) %>%
  arrange(Date) %>%
```

```
  rename(HangSeng_Price = Price)
ggplot(hangseng_data, aes(x = Date, y = HangSeng_Price)) +
  geom_line(color = "forestgreen") +
  labs(title = "Hang Seng Index Over Time", x = "Date", y = "Price") +
  theme_minimal()

## 2.2 Variables
   ---------------------------------------------------------------
vix_data <- read_csv(vix_path) %>%
  rename(Date = observation_date, VIX = VIXCLS) %>%
  drop_na()
ggplot(vix_data, aes(x = Date, y = VIX)) +
  geom_line(color = "darkslategray4") +
  labs(title = "VIX Index Over Time", x = "Date", y = "VIX Level") +
  theme_minimal()

interest_rate_10Y3M_data <- read_csv(interest_10Y3M_path) %>%
  rename(Date = observation_date,
         InterestRate_Change = T10Y3M) %>%
  arrange(Date) %>%  # Ensure data is sorted by date
  mutate(Diff_InterestRate_Change = InterestRate_Change - lag(InterestRate
   _Change))
  drop_na()
ggplot(interest_rate_10Y3M_data, aes(x = Date, y = Diff_InterestRate_
   Change)) +
  geom_line(color = "darkslategray4") +
  labs(title = "First Difference of Interest Rate Spread Over Time",
       x = "Date",
       y = "First Difference of T10Y3M") +
  theme_minimal()

BAA_data <- read_csv(BAA_path) %>%
  rename(Date = observation_date,
         BAA10Y_Spread = BAA10Y) %>%
  arrange(Date) %>%
  drop_na()
ggplot(BAA_data, aes(x = Date, y = BAA10Y_Spread)) +
  geom_line(color = "darkslategray4") +
  labs(title = "BAA - 10Y Credit Spread Over Time",
       x = "Date",
       y = "Credit Spread (BAA - 10Y, in basis points)") +
  theme_minimal()

## 2.3 Create master dataset for each index
   ------------------------------------
master_sp500 <- sp500_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
```

```
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(SP500_Price) - lag(log(SP500_Price))) %>%
  drop_na(Returns)
ggplot(master_sp500, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of SP500",
       x = "Date",
       y = "Returns in %") +
  theme_minimal()

master_nasdaq <- nasdaq_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(NASDAQ100_Price) - lag(log(NASDAQ100_Price))) %>%
  drop_na(Returns)
ggplot(master_nasdaq, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of NASDAQ",
       x = "Date",
       y = "Returns in %") +
  theme_minimal()

master_cac40 <- cac40_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(CAC40_Price) - lag(log(CAC40_Price))) %>%
  drop_na(Returns)
ggplot(master_cac40, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of CAC40",
       x = "Date",
       y = "Returns in %") +
  theme_minimal()

master_dax <- dax_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(DAX_Price) - lag(log(DAX_Price))) %>%
  drop_na(Returns)
ggplot(master_dax, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of DAX30",
       x = "Date",
```

```
      y = "Returns in %") +
  theme_minimal()

master_nikkei <- nikkei_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(Nikkei_Price) - lag(log(Nikkei_Price))) %>%
  drop_na(Returns)
ggplot(master_nikkei, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of Nikkei 225",
       x = "Date",
       y = "Returns in %") +
  theme_minimal()

master_hangseng <- hangseng_data %>%
  left_join(interest_rate_10Y3M_data, by = "Date") %>%
  left_join(vix_data, by = "Date") %>%
  left_join(BAA_data, by = "Date") %>%
  mutate(Returns = log(HangSeng_Price) - lag(log(HangSeng_Price))) %>%
  drop_na(Returns)
ggplot(master_hangseng, aes(x = Date, y = Returns)) +
  geom_line(color = "darkslategray4") +
  labs(title = "Returns of Hang Seng",
       x = "Date",
       y = "Returns in %") +
  theme_minimal()

### 2.3.1 Display structure and summary statistics for each master dataset
    -----
str(master_sp500)
summary(master_sp500)

str(master_nasdaq)
summary(master_nasdaq)

str(master_cac40)
summary(master_cac40)

str(master_dax)
summary(master_dax)

str(master_nikkei)
summary(master_nikkei)

str(master_hangseng)
```

```r
summary(master_hangseng)

# 3. Diagnostics and Preliminary Tests
    -----------------------------------------
## 3.1 Heteroscedasticity Tests
    -----------------------------------------------
# Linear regression models for each index
lm_sp500 <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread,
    data = master_sp500)
lm_nasdaq <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread,
    data = master_nasdaq)
lm_cac40 <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread,
    data = master_cac40)
lm_dax <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread,
    data = master_dax)
lm_nikkei <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread,
    data = master_nikkei)
lm_hangseng <- lm(Returns ~ Diff_InterestRate_Change + VIX + BAA10Y_Spread
    , data = master_hangseng)

summary(lm_sp500)
summary(lm_nasdaq)
summary(lm_cac40)
summary(lm_dax)
summary(lm_nikkei)
summary(lm_hangseng)

diagnostic_analysis <- function(model, model_name) {
  cat("\n--- Diagnostics for", model_name, "---\n")

  bp_test <- bptest(model)
  print(bp_test)
}
diagnostic_analysis(lm_sp500, "S&P 500")
diagnostic_analysis(lm_nasdaq, "NASDAQ 100")
diagnostic_analysis(lm_cac40, "CAC 40")
diagnostic_analysis(lm_dax, "DAX")
diagnostic_analysis(lm_nikkei, "Nikkei 225")
diagnostic_analysis(lm_hangseng, "Hang Seng")

robust_summary <- function(model, model_name) {
  cat("\n--- Robust OLS Summary for", model_name, "---\n")
  print(coeftest(model, vcov = vcovHC(model, type = "HC1")))
}
robust_summary(lm_sp500, "S&P 500")
robust_summary(lm_nasdaq, "NASDAQ 100")
robust_summary(lm_cac40, "CAC 40")
```

```r
robust_summary(lm_dax, "DAX 30")
robust_summary(lm_nikkei, "Nikkei 225")
robust_summary(lm_hangseng, "Hang Seng")

## 3.2 Stationarity Tests -----------------------------------------------------
adf_test <- function(series, name) {
  cat("\n--- ADF Test for", name, "---\n")
  test_result <- adf.test(series, alternative = "stationary")
  print(test_result)
}
adf_sp500    <- adf_test(master_sp500$SP500_Price, "S&P 500 Price") # NOT STATIONARY
adf_nasdaq   <- adf_test(master_nasdaq$NASDAQ100_Price, "NASDAQ 100 Price") # NOT STATIONARY
adf_cac40    <- adf_test(master_cac40$CAC40_Price, "CAC 40 Price") # NOT STATIONARY
adf_dax      <- adf_test(master_dax$DAX_Price, "DAX Price") # NOT STATIONARY
adf_nikkei   <- adf_test(master_nikkei$Nikkei_Price, "Nikkei 225 Price") # NOT STATIONARY
adf_hangseng <- adf_test(master_hangseng$HangSeng_Price, "Hang Seng Price") # NOT STATIONARY

adf_interest <- adf_test(master_sp500$Diff_InterestRate_Change, "Interest Rate Change")  #STATIONARY
adf_vix <- adf_test(master_sp500$VIX, "VIX (Level)")  # STATIONARY
adf_baa <- adf.test(master_sp500$BAA10Y_Spread,  alternative = "stationary")  #  NON-STATIONARY
adf_baa

adf_returns_sp500     <- adf_test(master_sp500$Returns, "S&P 500 Returns") # STATIONARY
adf_returns_nasdaq    <- adf_test(master_nasdaq$Returns, "NASDAQ 100 Returns") # STATIONARY
adf_returns_cac40     <- adf_test(master_cac40$Returns, "CAC 40 Returns") # STATIONARY
adf_returns_dax       <- adf_test(master_dax$Returns, "DAX Returns") # STATIONARY
adf_returns_nikkei    <- adf_test(master_nikkei$Returns, "Nikkei 225 Returns") # STATIONARY
adf_returns_hangseng <- adf_test(master_hangseng$Returns, "Hang Seng Returns") # STATIONARY

## 3.3 Multicolinearity ---------------------------------------------------------
# Variance Inflation Factor test
```

```
model <- lm(Returns ~ Diff_InterestRate_Change +  BAA10Y_Spread + VIX ,
    data = master_sp500)
vif_values <- vif(model)
print(vif_values)

# Correlation matrix
cor_matrix <- cor(master_sp500[, c("Diff_InterestRate_Change", "VIX", "
    BAA10Y_Spread")])
print(cor_matrix)

# 4. Modeling
    -----------------------------------------------------------------
## 4.1 OLS Regression
    ---------------------------------------------------------
formula <- Returns ~ Diff_InterestRate_Change + VIX +  BAA10Y_Spread
run_ols_regression <- function(data, index_name) {
  cat("\n--- OLS Regression for", index_name, "---\n")
  model <- lm(formula, data = data)
  print(summary(model))
}
run_ols_regression(master_sp500, "S&P 500")
run_ols_regression(master_nasdaq, "NASDAQ 100")
run_ols_regression(master_cac40, "CAC 40")
run_ols_regression(master_dax, "DAX")
run_ols_regression(master_nikkei, "Nikkei 225")
run_ols_regression(master_hangseng, "Hang Seng")

## 4.2 Quantile Regression Approaches
    -----------------------------------------
### 4.2.1 Standard Quantile Regression with rq()
    ------------------------------
formula <- Returns ~ Diff_InterestRate_Change +  BAA10Y_Spread + VIX
run_quantile_regression <- function(data, index_name, quantiles = c(0.05,
    0.25, 0.5, 0.75, 0.95)) {
  cat("\n--- Quantile Regression for", index_name, "---\n")
  for (tau in quantiles) {
    cat("\nQuantile:", tau, "\n")
    model <- rq(formula, data = data, tau = tau)
    print(summary(model))
  }
}
run_quantile_regression(master_sp500, "S&P 500")
run_quantile_regression(master_nasdaq, "NASDAQ 100")
run_quantile_regression(master_cac40, "CAC 40")
run_quantile_regression(master_dax, "DAX")
run_quantile_regression(master_nikkei, "Nikkei 225")
run_quantile_regression(master_hangseng, "Hang Seng")
```

```r
### 4.2.2 Quantile regression : significance test
    ------------------------------
formula <- Returns ~ Diff_InterestRate_Change +  BAA10Y_Spread + VIX
run_quantile_significance_test <- function(data, index_name, quantiles = c
    (0.05, 0.25, 0.5, 0.75, 0.95)) {
  cat("\n--- Quantile Regression Significance Test for", index_name, "---\
    n")
  # Create a results data frame to store p-values
  results <- data.frame(Quantile = numeric(),
                        Variable = character(),
                        Coefficient = numeric(),
                        P_Value = numeric(),
                        Significant = character(),
                        stringsAsFactors = FALSE)
  for (tau in quantiles) {
    cat("\nQuantile:", tau, "\n")
    # Fit quantile regression model
    model <- rq(formula, data = data, tau = tau)
    model_summary <- summary(model, se = "ker")
    # Extract coefficient estimates and p-values
    coefs <- coef(model_summary)
    p_values <- coefs[, "Pr(>|t|)"]
    # Check if variables are significant (p < 0.05)
    significance <- ifelse(p_values < 0.05, "Yes", "No")
    # Store results in a dataframe
    temp_results <- data.frame(Quantile = rep(tau, length(p_values)),
                               Variable = names(p_values),
                               Coefficient = coefs[, "Value"],
                               P_Value = p_values,
                               Significant = significance,
                               stringsAsFactors = FALSE)
    # Append to results dataframe
    results <- rbind(results, temp_results)
  }
  print(results)
}
run_quantile_significance_test(master_sp500, "S&P 500")
run_quantile_significance_test(master_nasdaq, "NASDAQ 100")
run_quantile_significance_test(master_cac40, "CAC 40")
run_quantile_significance_test(master_dax, "DAX")
run_quantile_significance_test(master_nikkei, "Nikkei 225")
run_quantile_significance_test(master_hangseng, "Hang Seng")

# 7. Other method
    -----------------------------------------------------------------
## 7.1 Quantile Generalized Additive Model (qGAM)
```

```
    ------------------------------
### 7.1.1 SP500
    ----------------------------------------------------------------
qgam_model_5_SP500  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
     + s(BAA10Y_Spread), qu = 0.05, data = master_sp500)
qgam_model_25_SP500 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
     + s(BAA10Y_Spread), qu = 0.25, data = master_sp500)
qgam_model_50_SP500 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
     + s(BAA10Y_Spread), qu = 0.50, data = master_sp500)
qgam_model_75_SP500 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
     + s(BAA10Y_Spread), qu = 0.75, data = master_sp500)
qgam_model_95_SP500 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
     + s(BAA10Y_Spread), qu = 0.95, data = master_sp500)

summary(qgam_model_5_SP500)
summary(qgam_model_25_SP500)
summary(qgam_model_50_SP500)
summary(qgam_model_75_SP500)
summary(qgam_model_95_SP500)

draw(qgam_model_5_SP500)
draw(qgam_model_25_SP500)
draw(qgam_model_50_SP500)
draw(qgam_model_75_SP500)
draw(qgam_model_95_SP500)

### 7.1.2 NASDAQ
    ----------------------------------------------------------------
qgam_model_5_nasdaq  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.05, data = master_nasdaq)
qgam_model_25_nasdaq <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.25, data = master_nasdaq)
qgam_model_50_nasdaq <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.50, data = master_nasdaq)
qgam_model_75_nasdaq <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.75, data = master_nasdaq)
qgam_model_95_nasdaq <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.95, data = master_nasdaq)

summary(qgam_model_5_nasdaq)
summary(qgam_model_25_nasdaq)
summary(qgam_model_50_nasdaq)
summary(qgam_model_75_nasdaq)
summary(qgam_model_95_nasdaq)

draw(qgam_model_5_nasdaq)
draw(qgam_model_25_nasdaq)
```

```
draw(qgam_model_50_nasdaq)
draw(qgam_model_75_nasdaq)
draw(qgam_model_95_nasdaq)

### 7.1.3 CAC40 ------------------------------------------------------------------
qgam_model_5_CAC40  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.05, data = master_cac40)
qgam_model_25_CAC40 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.25, data = master_cac40)
qgam_model_50_CAC40 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.50, data = master_cac40)
qgam_model_75_CAC40 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.75, data = master_cac40)
qgam_model_95_CAC40 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.95, data = master_cac40)

summary(qgam_model_5_CAC40)
summary(qgam_model_25_CAC40)
summary(qgam_model_50_CAC40)
summary(qgam_model_75_CAC40)
summary(qgam_model_95_CAC40)

draw(qgam_model_5_CAC40)
draw(qgam_model_25_CAC40)
draw(qgam_model_50_CAC40)
draw(qgam_model_75_CAC40)
draw(qgam_model_95_CAC40)

### 7.1.4 DAX30 ------------------------------------------------------------------
qgam_model_5_DAX30  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.05, data = master_dax)
qgam_model_25_DAX30 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.25, data = master_dax)
qgam_model_50_DAX30 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.50, data = master_dax)
qgam_model_75_DAX30 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.75, data = master_dax)
qgam_model_95_DAX30 <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX)
    + s(BAA10Y_Spread), qu = 0.95, data = master_dax)

summary(qgam_model_5_DAX30)
summary(qgam_model_25_DAX30)
summary(qgam_model_50_DAX30)
summary(qgam_model_75_DAX30)
summary(qgam_model_95_DAX30)
```

```

draw(qgam_model_5_DAX30)
draw(qgam_model_25_DAX30)
draw(qgam_model_50_DAX30)
draw(qgam_model_75_DAX30)
draw(qgam_model_95_DAX30)

### 7.1.5 Nikkei225
    ------------------------------------------------------------------
qgam_model_5_Nikkei  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.05, data = master_nikkei)
qgam_model_25_Nikkei <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.25, data = master_nikkei)
qgam_model_50_Nikkei <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.50, data = master_nikkei)
qgam_model_75_Nikkei <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.75, data = master_nikkei)
qgam_model_95_Nikkei <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(VIX
    ) + s(BAA10Y_Spread), qu = 0.95, data = master_nikkei)

summary(qgam_model_5_Nikkei)
summary(qgam_model_25_Nikkei)
summary(qgam_model_50_Nikkei)
summary(qgam_model_75_Nikkei)
summary(qgam_model_95_Nikkei)

draw(qgam_model_5_Nikkei)
draw(qgam_model_25_Nikkei)
draw(qgam_model_50_Nikkei)
draw(qgam_model_75_Nikkei)
draw(qgam_model_95_Nikkei)

### 7.1.6 HangSeng
    ------------------------------------------------------------------
qgam_model_5_HangSeng  <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(
    VIX) + s(BAA10Y_Spread), qu = 0.05, data = master_hangseng)
qgam_model_25_HangSeng <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(
    VIX) + s(BAA10Y_Spread), qu = 0.25, data = master_hangseng)
qgam_model_50_HangSeng <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(
    VIX) + s(BAA10Y_Spread), qu = 0.50, data = master_hangseng)
qgam_model_75_HangSeng <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(
    VIX) + s(BAA10Y_Spread), qu = 0.75, data = master_hangseng)
qgam_model_95_HangSeng <- qgam(Returns ~ s(Diff_InterestRate_Change) + s(
    VIX) + s(BAA10Y_Spread), qu = 0.95, data = master_hangseng)

summary(qgam_model_5_HangSeng)
summary(qgam_model_25_HangSeng)
```

```r
summary(qgam_model_50_HangSeng)
summary(qgam_model_75_HangSeng)
summary(qgam_model_95_HangSeng)

draw(qgam_model_5_HangSeng)
draw(qgam_model_25_HangSeng)
draw(qgam_model_50_HangSeng)
draw(qgam_model_75_HangSeng)
draw(qgam_model_95_HangSeng)

## 7.2 quantregForest (qrF)
    ----------------------------------------------------
X <- master_sp500[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")]
Y <- master_sp500$Returns
set.seed(123)  # for reproducibility
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)

### 7.2.1 VIX ------------------------------------------------------------
# Create a grid of values for VIX (in levels now)
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
# Fix the other variables at median
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
# Predict quantiles
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25,
     0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
```

```r
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +   # 90% band
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) + # interquartile range
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +       # median
  labs(title = "Effect of VIX on Returns across Quantiles",
       x = "VIX (Volatility Index)",
       y = "Predicted Return") +
  theme_minimal()
# Histogram and density for VIX in levels
hist(master_sp500$VIX,
     breaks = 30,
     col = "grey",
     main = "Distribution of VIX (Level)",
     xlab = "VIX")
plot(density(master_sp500$VIX),
     main = "Density of VIX (Level)",
     xlab = "VIX",
     col = "blue", lwd = 2)
abline(v = median(master_sp500$VIX), col = "red", lty = 2)  # Median reference line

### 7.2.2 Diff_InterestRate_Change ------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
```

```
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  scale_x_continuous(limits = c(-1, 0.8)) +
  labs(title = "Effect of Interest Rate Change on Returns across Quantiles",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()
hist(master_sp500$Diff_InterestRate_Change,
     breaks = 30,
     xlim = c(-1, 1),
     col = "grey",
     main = "Distribution of Diff_InterestRate_Change",
     xlab = "Interest Rate Change")
plot(density(master_sp500$Diff_InterestRate_Change),
     main = "Density of Diff_InterestRate_Change",
     xlab = "Interest Rate Change",
     col = "blue", lwd = 2)
abline(v = 0, col = "red", lty = 2)

### 7.2.2 BAA10Y ------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out = 200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c(0.05, 0.25, 0.5, 0.75, 0.95))

plot_data_baa <- data.frame(
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns across Quantiles",
```

```r
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()
hist(master_sp500$BAA10Y_Spread,
     breaks = 30,
     col = "grey",
     main = "Distribution of BAA-10Y Credit Spread",
     xlab = "Credit Spread")
plot(density(master_sp500$BAA10Y_Spread),
     main = "Density of BAA-10Y Credit Spread",
     xlab = "Credit Spread",
     col = "blue", lwd = 2)
abline(v = median(master_sp500$BAA10Y_Spread), col = "red", lty = 2)


## 7.3 quantregForest (qrF) - Nasdaq
    ---------------------------------------------------
X <- master_nasdaq[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")
    ]
Y <- master_nasdaq$Returns
set.seed(123)  # for reproducibility
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)

### 7.3.1 VIX ----------------------------------------------------------
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25,
     0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
```

```
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +    # 90% band
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) + # interquartile range
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
          # median
  labs(title = "Effect of VIX on Returns across Quantiles",
       x = "VIX (Volatility Index)",
       y = "Predicted Return") +
  theme_minimal()

### 7.3.2 Diff_InterestRate_Change
    ------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_
    Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05,
     0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  scale_x_continuous(limits = c(-1, 0.8)) +
  labs(title = "Effect of Interest Rate Change on Returns across Quantiles
    ",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()

### 7.3.2 BAA10Y
```

```
------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out = 200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c(0.05, 0.25, 0.5, 0.75, 0.95))

plot_data_baa <- data.frame(
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns across Quantiles",
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()

## 7.4 quantregForest (qrF) - CAC40 ---------------------------------------------------
X <- master_cac40[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")]
Y <- master_cac40$Returns
set.seed(123)
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)
```

```
### 7.4.1 VIX -----------------------------------------------------------
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of VIX on Returns across Quantiles - CAC 40",
       x = "VIX",
       y = "Predicted Return") +
  theme_minimal()

### 7.4.2 Diff_InterestRate_Change ------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
```

```
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  scale_x_continuous(limits = c(-1, 0.8)) +
  scale_y_continuous(limits = c(-0.1, 0.1)) +
  labs(title = "Effect of Interest Rate Change on Returns - CAC 40",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()

### 7.3.3 BAA10Y ------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out = 200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_baa <- data.frame(
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns - CAC 40",
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()


## 7.5 quantregForest (qrF) - DAX ---------------------------------------------------
X <- master_dax[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")]
```

```
Y <- master_dax$Returns
set.seed(123)
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)

### 7.5.1 VIX ------------------------------------------------------------
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25,
     0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of VIX on Returns across Quantiles - DAX",
       x = "VIX",
       y = "Predicted Return") +
  theme_minimal()

### 7.5.2 Diff_InterestRate_Change
    ------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_
    Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
```

```
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05,
    0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of Interest Rate Change on Returns - DAX",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()

### 7.4.3 BAA10Y
    -------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out =
    200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c
    (0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_baa <- data.frame(
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
```

```
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns - DAX",
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()

## 7.6 quantregForest (qrF) - Nikkei
    ----------------------------------------------------
X <- master_nikkei[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")
    ]
Y <- master_nikkei$Returns
set.seed(123)
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)

### 7.6.1 VIX ------------------------------------------------------------
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25,
     0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
```

```
  labs(title = "Effect of VIX on Returns across Quantiles - Nikkei 225",
       x = "VIX",
       y = "Predicted Return") +
  theme_minimal()

### 7.6.2 Diff_InterestRate_Change
    ------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_
    Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05,
     0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of Interest Rate Change on Returns - Nikkei 225",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()

### 7.6.3 BAA10Y
    ------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out =
    200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c
    (0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_baa <- data.frame(
```

```r
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns - Nikkei 225",
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()


## 7.7 quantregForest (qrF) - Hang Seng ----------------------------------------------------
X <- master_hangseng[, c("Diff_InterestRate_Change", "VIX", "BAA10Y_Spread")]
Y <- master_hangseng$Returns
set.seed(123)
qrf_model <- quantregForest(x = X, y = Y, ntree = 5000, keep.inbag = TRUE)
qrf_preds <- predict(qrf_model, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
qrf_results <- data.frame(
  Q05 = qrf_preds[, 1],
  Q25 = qrf_preds[, 2],
  Q50 = qrf_preds[, 3],
  Q75 = qrf_preds[, 4],
  Q95 = qrf_preds[, 5]
)
importance(qrf_model)

### 7.7.1 VIX -----------------------------------------------------------
vix_seq <- seq(min(X$VIX), max(X$VIX), length.out = 200)
grid_data <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = vix_seq,
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds <- predict(qrf_model, newdata = grid_data, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data <- data.frame(
  VIX = vix_seq,
```

```
  Q05 = grid_preds[,1],
  Q25 = grid_preds[,2],
  Q50 = grid_preds[,3],
  Q75 = grid_preds[,4],
  Q95 = grid_preds[,5]
)
ggplot(plot_data, aes(x = VIX)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of VIX on Returns across Quantiles - Hang Seng",
       x = "VIX",
       y = "Predicted Return") +
  theme_minimal()

### 7.7.2 Diff_InterestRate_Change
    --------------------------------------------------------------
ir_seq <- seq(min(X$Diff_InterestRate_Change), max(X$Diff_InterestRate_
    Change), length.out = 200)
grid_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  VIX = median(X$VIX),
  BAA10Y_Spread = median(X$BAA10Y_Spread)
)
grid_preds_ir <- predict(qrf_model, newdata = grid_data_ir, what = c(0.05,
     0.25, 0.5, 0.75, 0.95))
plot_data_ir <- data.frame(
  Diff_InterestRate_Change = ir_seq,
  Q05 = grid_preds_ir[,1],
  Q25 = grid_preds_ir[,2],
  Q50 = grid_preds_ir[,3],
  Q75 = grid_preds_ir[,4],
  Q95 = grid_preds_ir[,5]
)
ggplot(plot_data_ir, aes(x = Diff_InterestRate_Change)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha =
    0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha =
    0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of Interest Rate Change on Returns - Hang Seng",
       x = "Diff_InterestRate_Change",
       y = "Predicted Return") +
  theme_minimal()

```

```r
### 7.7.3 BAA10Y ------------------------------------------------------------
baa_seq <- seq(min(X$BAA10Y_Spread), max(X$BAA10Y_Spread), length.out = 200)
grid_data_baa <- data.frame(
  Diff_InterestRate_Change = median(X$Diff_InterestRate_Change),
  VIX = median(X$VIX),
  BAA10Y_Spread = baa_seq
)
grid_preds_baa <- predict(qrf_model, newdata = grid_data_baa, what = c(0.05, 0.25, 0.5, 0.75, 0.95))
plot_data_baa <- data.frame(
  BAA10Y_Spread = baa_seq,
  Q05 = grid_preds_baa[,1],
  Q25 = grid_preds_baa[,2],
  Q50 = grid_preds_baa[,3],
  Q75 = grid_preds_baa[,4],
  Q95 = grid_preds_baa[,5]
)
ggplot(plot_data_baa, aes(x = BAA10Y_Spread)) +
  geom_ribbon(aes(ymin = Q05, ymax = Q95), fill = "lightblue", alpha = 0.3) +
  geom_ribbon(aes(ymin = Q25, ymax = Q75), fill = "dodgerblue", alpha = 0.4) +
  geom_line(aes(y = Q50), color = "blue", size = 1.2) +
  labs(title = "Effect of BAA-10Y Credit Spread on Returns - Hang Seng",
       x = "BAA-10Y Credit Spread (Level)",
       y = "Predicted Return") +
  theme_minimal()
```

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