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Equity implied volatility-return correlation in the High Yield and Investment Grade corporate bond markets

A quantile regression analysis

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Abstract:

Tämä tutkielmaa tutkii osakkeiden implisiittisen volatiliteetin ja yrityslainojen tuottojen välistä suhdetta. Osakkeiden implisiittisen volatiliteetin ja tuottojen välisestä suhteesta on olemassa runsaasti kirjallisuutta, ja suurin osa tutkimuksista viittaa negatiiviseen suhteeseen: implisiittisen volatiliteetin kasvaessa, osakekurssit laskevat. Sen sijaan aiempaa tutkimusta implisiittisen volatiliteetin ja yrityslainojen tuottojen välisestä suhteesta on vähän, erityisesti tutkimusta, joka tarkastelisi, miten suhde muuttuu volatiliteetin kasvaessa ja onko eroa korkean luottoluokituksen Investment Grade ja matalan luottoluokituksen High Yield -lainojen välillä. Tämän tutkielman menetelmä perustuu OLS-regressioon keskimääräisen korrelaation selvittämiseksi sekä kvantiiliregressioon, jolla tarkastellaan suhdetta koko volatiliteettijakaumaa pitkin. Tulokset osoittavat, että korkean luottoluokituksen lainojen indeksi korreloi positiivisesti osakkeiden implisiittisen volatiliteetin kanssa matalan korkotason ympäristössä. Tämä suhde kääntyy negatiiviseksi korkotason noustessa. High Yield -lainat ovat negatiivisessa korrelaatiossa osakkeiden implisiittisen volatiliteetin kanssa, muistuttaen samanlaista mutta heikompaa korrelaatiota mikä osakkeilla oli. Korkopolitiikan muutoksilla on pieni vaikutus HY-lainoihin, mutta ei yhtä merkittävä kuin IG-lainoihin. Tämä tutkielma täydentää olemassa olevaa kirjallisuutta tukemalla käsitystä siitä, että HY-lainat käyttäytyvät hyvin samankaltaisesti kuin osakkeet. Tuloksilla on hyödyllisiä sovelluksia salkun allokoinnissa ja riskienhallinnassa, sillä ne tukevat IG lainojen turvasatamaominaisuutta korkean volatiliteetin, matalan korkotason ympäristöissä.

KEYWORDS: Implied volatility, VIX, corporate bonds, quantile regression, OLS, high yield, investment grade, interest rate policy

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1 Introduction

The study of the relationship between returns in the equity and bond markets has long been an important theme in financial research, since empirical correlations between asset returns provide strategic information for guiding dynamic asset allocation, portfolio selection, and risk management (Chiang, Li & Yang, 2015). Bonds provide investors with fixed incomes, while stocks represent compensation for bearing higher levels of uncertainty. Holding a combined allocation of both equity and fixed asset instruments helps spread risk within an investor's portfolio. This is especially true if the two assets do not move in tandem, whereby the offset creates a diversification benefit (Menounos et al., 2017). As the market dynamic is ever-changing, exposing the portfolio to different risks at different times, it is not desirable to hold a constant proportion of stocks and bonds in investors' portfolios (Chiang, Li & Yang, 2015).

Strategically, investors are advised to continually assess market information and adjust their portfolios in response to emerging market indicators (Chiang, Li & Yang, 2015). One of the most well-known market indicators is the Chicago Board Options Exchange's Volatility Index, the VIX, which measures the stock market's expectation of volatility based on S&P500's index options. The relation between VIX and equity returns is repeatedly found to be a negative one, meaning when market volatility increases, stock market value decreases (Harvey & Whaley, 1991; Christensen & Prabhala, 1998). This paper studies the relation between the VIX index and corporate bond returns using both OLS regression and quantile regression, to get a deeper understanding of how the variance in equity markets spills over into the corporate bond markets at different levels of volatility, which provides information for future applications of asset allocation in volatile markets. This thesis also studies if a change in interest rate policy causes a shift in this relation.

1.1 Purpose of the paper

The purpose of this study is to investigate the contemporaneous relationship between equity implied volatility and corporate bond returns. This research aims to bridge the gap between traditional financial theories and practical applications in portfolio allocation, particularly under volatile and extreme market conditions.

Historically, bonds with lower risk profiles, which include Treasury bonds and investment grade (IG) corporate bonds, have shown a negative correlation with equity returns. During periods of market distress, investors often engage in *flight-to-safety*, reallocating capital from equities into the safer aforementioned fixed-income assets, which in turn drives their prices up (Brixton et al., 2023). However, this negative correlation does not hold uniformly across all market regimes; Ilmanen (2003) notes that during high inflationary periods, the stock-bond return correlation often turns positive. Bansal, Connolly & Stivers (2014) find that the negative stock-bond correlation is explained by the joint risk-return pricing dynamics, and that it largely disappears when controlling for asset-class risk changes.

While most studies on equity-bond relation have focused on sovereign debt, corporate bonds remain relatively overlooked. Comer and Rodriguez (2013) find that the risk-adjusted performance of corporate bonds often exceeds that of government bonds. If IG bonds combine superior returns with safe haven characteristics, they warrant deeper exploration in asset allocation models. This insight motivates the current study's focus on corporate bonds and supports the use of quantile regression to analyze how the equity volatility-bond return relationship shifts under different market conditions, especially during extreme volatility.

Several studies highlight the evolving dynamics of the equity implied volatility-bond relationship. Connolly et al. (2005) find that the comovement between stock and Treasury bond returns is negatively associated with stock market risk, as proxied by the VIX. This supports the *flight-to-safety* hypothesis, wherein rising market uncertainty prompts investors to shift into bonds. Similarly, Chiang, Li & Yang (2015) show that stock-bond correlations weaken during heightened uncertainty, with VIX capturing this fear-driven behavior. These relationships are not only statistically significant but also persistent over time.

Campbell and Taksler (2003) examine the impact of equity volatility on corporate bond yields and find that rising idiosyncratic volatility in equity markets leads to wider yield spreads, reflecting increased borrowing costs for firms. Their findings demonstrate that equity volatility can influence both the short-term dynamics and the long-term trends in corporate bond spreads.

Demirovic et al. (2017) identify a positive correlation between corporate equity returns and corporate bond returns, suggesting a close relationship between a firm's equity and debt performance. Building on this, this thesis extends the literature by investigating whether equity market volatility is contemporaneously related to corporate bond performance. While the relationship between VIX and sovereign bond returns is well documented, relatively few studies directly examine the link between VIX and corporate bond returns, particularly across two distinct interest rate environments.

Recent research underscores that traditional safe haven assets, such as gold, may have lost some of their protective features during recent market turmoils (Ciner, Gurdgiev & Lucey, 2013; Flavin & Sheenan, 2024). However, Cheema, Faff & Szulcyk (2022) note that high-rated corporate bonds regained safe haven characteristics during the COVID-19 pandemic, and Wang, Yang & Chong (2025) even propose that corporate bonds of high credit rating may emerge as a substitute for gold in this role. Understanding the spillover effects from equity market volatility into corporate bond returns, especially for IG bonds in the upper quantiles of VIX, may therefore have significant implications for future portfolio strategies.

High yield (HY) bonds present a distinct dynamic. Unlike IG bonds, HY bonds display weaker sensitivity to interest rate movements and a stronger correlation with equity market performance (Menounos, Alexiou & Vogiazas, 2019). Guo, Kontonikas & Maio (2020) find that aggressive monetary policy actions tend to affect IG bond returns more strongly, while HY bonds are more influenced by inflation uncertainty. Kim & Stock (2014) find that interest rate uncertainty has a more drastic effect on HY yield spreads due to their elevated credit risk.

Finally, interest rate environments can significantly modulate these relationships. Li (2002) finds that real interest rate uncertainty increases stock-bond comovement. Following this line of research, this thesis divides the sample into two subperiods: (1) a low or zero interest rate environment and (2) the period following the Federal Reserve's aggressive rate hikes post-2022. This segmentation allows for a deeper examination of how the VIX–bond return relationship varies under different monetary regimes.

1.2 Hypothesis

This study seeks to examine the contemporaneous relationship between bond returns and implied volatility. Building on existing literature the following hypotheses are proposed to guide the analysis:

> *H_1:* A statistically significant contemporaneous relationship exists between implied volatility index returns and the corporate bond index returns.

Demirovic et al. (2017) find that there exists a positive correlation between corporate equity returns and corporate bond returns. I extend this literature by proposing that there is correlation with the volatility of the corporate equity and the returns of the corporate bonds. Whether the relation is positive or negative is contingent on which type of bond is in question: for the more equity-like high yield bonds the relation is expected to be negative, for the more risk-free investment grade bonds the relation is expected to be positive. To test this, I will run an OLS regression with the corresponding corporate bond index returns as the dependent variable and VIX returns as the independent variable.

> *$H_{1.1}$:* If H1 holds true, then the correlation becomes stronger during particularly high implied volatility.

This hypothesis extends H1 by suggesting that when market volatility increases, the markets experience a risk-off sentiment (Erdemlioglu & Joliet, 2019), resulting in investors fleeing to safer assets, in this case investment grade bonds, from the riskier equities and high yield bonds. In this case, investment grade bonds should experience a more positive correlation in the upper echelons of volatility. If we assume that there are strong similarities in the behaviour of high yield bonds and equities (Menounos, Alexiou & Vogiazas, 2019), the coefficients of high yield bonds should grow more negative the higher the volatility becomes, as it would with equities (Fleming, Ostdiek & Whaley, 1995). Following Badshah (2013), I utilize quantile regressions, which helps determine if the relationship is more pronounced in different parts of the bond return distribution.

> *H_2:* The negative return-volatility relationship is stronger in high-yield bonds, than in investment-grade bonds.

Following Reilly et al. (2010), who suggest that lower-grade high yield bonds behave similarly to small cap stocks, I hypothesize that there will be significantly more spillover from equity market volatility into the HY bond returns, than into IG bonds. This will be apparent if there is a significant negative contemporaneous correlation between VIX and HY bond index, similar as the one observed to appear between VIX and equities (Fleming, Ostdiek & Whaley, 1995).

> *H_3:* The negative correlation between VIX and corporate bond returns strengthens in high-interest rate environment.

Following Li (2002), who observed that with rising interest rates, the comovement between stocks and bonds strengthens, which in this situation will be observable as the correlation becoming more negative in the post-interest rate hike period.

1.3 Structure of the paper

The remaining of the paper is organized as follows. Section 2 introduces the theoretical background relevant to the topic. Section 3 discusses the relevant literature on the topic. The fourth section goes over the methodology employed for this research. The fifth section describes the data sources used for this research. Section 6 presents the empirical results. We conclude in section 7.

2 Theoretical background

This section includes the theoretical background for implied and realized volatility, along with their differences. Since volatility is derived from option prices, option valuation methods are the starting point of this section. Following this, we different volatility measures, after which we move to describing the differently rated bonds, and how they behave in relation to equity. The section concludes by describing portfolio management, as this frames the topic of this thesis into a wider context.

2.1 Option valuation

According to Hull (2021), derivatives valuation is based on the assumption of risk-neutrality: when investors do not increase the expected return, they require from an investment to compensate for increased risk. Although the Hull (2021) specifies that risk-neutrality does not apply to the real world, applying the risk-neutral assumption gives us the right option price in both a risk-neutral world and the real world. This is because when pricing the derivative in terms of the price of the underlying asset, the risk preferences become unimportant. Hull (2021) also presents two features of a risk-neutral world that simplify the pricing of derivatives; that the expected return on the asset is the risk-free rate, and that the discount rate used for the expected payoff of an option is the risk-free rate. Hull (2021) presents the two most-often used options pricing models: the binomial pricing model and the Black-Scholes-Merton model. Both of the pricing models will be discussed further in this section.

2.1.1 Binomial pricing model

The binomial model, as explained by Hull (2021) is a technique that utilizes a binomial tree; a diagram representing a range of possible paths for the probable price movements of the underlying asset throughout the life of the option, with the assumption that the price movements of the underlying follow a random walk. The model assigns a certain probability of moving up or down with a certain percentage.

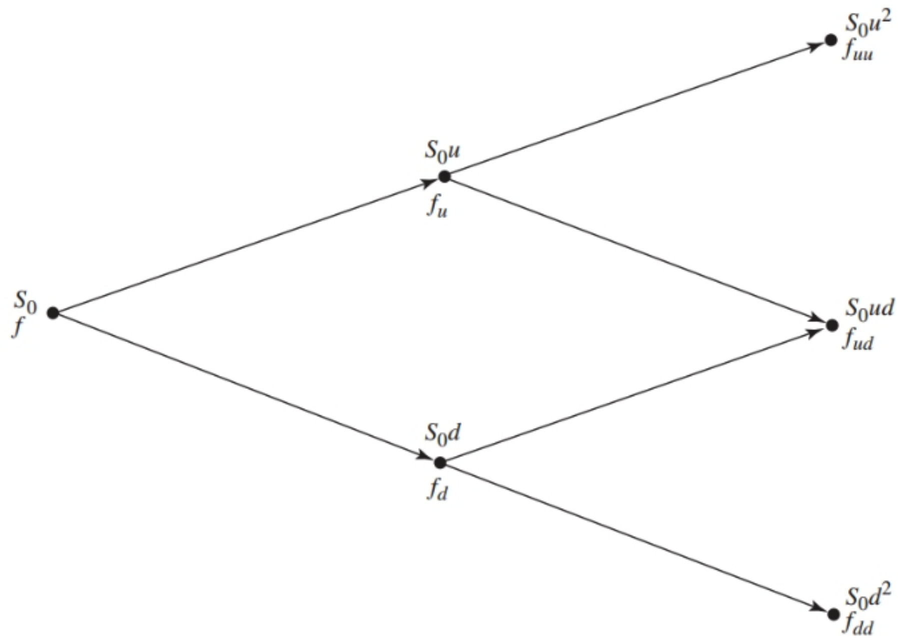

Figure 1 Stock and option prices in a general two-step tree (Hull, 2021).

Where S_0 is the stock price, *u* and *d* are the proportional upward and downward price movements respectively, and *f* is the price of the option. Hull (2021) shows that a European option price given by the binomial tree converges to the Black–Scholes price as the time steps becomes smaller, e.g. approach infinity. The binomial tree is often used for valuing American-style option.

2.1.2 Black-Scholes model

The Black-Scholes-Merton, or simply the Black-Scholes model, is a popular option valuation model, which assumes that percentage changes in the stock in a very short period of time are normally distributed (Hull, 2021). As opposed to binomial trees, the Black-Scholes model is used for valuing European-style options. The formula for calculating options using the Black-Scholes formula is:

For the call option:

$$c = S_0 N(d_1) - Ke^{-rT} N(d_2)$$

And for the put option:

$$p = Ke^{-rT} N(-d_2) - S_0 N(-d_1)$$

Where

$$d_1 = \frac{\ln \frac{S_0}{K} + (r + \sigma^2 /2)T}{\sigma\sqrt{T}}$$

and

$$d_2 = \frac{\ln \frac{S_0}{K} + (r + \sigma^2 /2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

where *c* and *p* are the European call and European put price, S_0 is the stock price at time zero, *K* is the strike price, r is the continuously compounded risk-free rate, *s* is the stock price volatility, and *T* is the time to maturity of the option (Hull, 2021).

2.2 Volatility

Volatility describes the uncertainty about the future stock price movements (Hull, 2021). It measures how much and how quickly prices change, often driven by factors like economic data, company performance, geopolitical events, or market sentiment. Higher volatility means prices fluctuate dramatically, often within a short period, while lower volatility indicates more stable price movements (Hull, 2021). Volatility is one of the most relevant measures for investors, as it affects risk and potential returns. When the market is volatile, prices can swing dramatically in either direction over a short time, which can be both an opportunity and a risk for investors. Volatility is often quantified using standard deviation, which measures the dispersion of stock returns from the average; beta, which indicates how much a stock fluctuates in relation to the overall market and volatility indices, such as VIX. When speaking of volatility in relation to options, people often refer to either realized volatility and implied volatility. According to Hull (2021), the volatility, σ, of a stock is a measure of the uncertainty about the returns provided by the stock. Volatility estimates based on historical data are used extensively in risk management (Hull, 2021).

According to Andersen & Teräsvirta (2009), realized volatility is a nonparametric ex-post estimate of the return variation. In other words, it measures the actual price fluctuations of a stock or market index over a specific past period. It is calculated by analyzing historical price data, typically using the standard deviation of daily returns

2.3 Implied volatility

Whereas realized volatility was backward-looking volatility, implied volatility is the market’s prediction of future volatility, derived from option market prices. While realized volatility is most often used for hedging, implied volatility is most often used by traders (Hull, 2021).

The original volatility index in popular use, the VXO, was calculated using Black-Scholes implied volatilities derived from at-the-money options on the S&P 100 (Whaley, 2000). The methodology for this calculation is detailed in the works of Whaley (1993, 2000) and Fleming et al. (1995). In 2003, the CBOE introduced an updated version of the VIX, built on the concept of fair value of future variance valuation proposed by Demeterfi et al. (1999), replacing the Black-Scholes model for calculating VIX (Jiang & Tian, 2007).

The currently in-use VIX is calculated directly from observable market data, such as the prices of call and put options and prevailing interest rates, without relying on any specific pricing model (Cboe Global Index, 2024).. Additionally, the underlying index was changed from the S&P 100 to the S&P 500. Although the updated VIX is variance-based, it continues to be quoted as the square root of variance to maintain comparability with implied volatility measures Whaley (Cboe Global Index, 2024).

In 2014, the CBOE further enhanced the VIX Index by incorporating SPX Weeklys, which includes weekly expirations into the S&P 500 Index options. This adjustment improved the representation of the fixed 30-day timeframe that the VIX aims to measure (Cboe Global Index, 2024).

Implied volatility indices have practical applications in risk management, product development, and sentiment analysis. For instance, they are crucial inputs for Value-at-Risk (VaR) calculations and portfolio optimization (Slim, Dahmene, & Boughrara, 2020). Additionally, indices like VIX and VVIX have become underlying assets for derivative products, enabling investors to directly trade or hedge volatility (Alexander et al., 2015).

2.4 Corporate bonds

Corporate bonds are debt securities issued by companies to raise capital. The corporate bond issuer promises to pay a specified percentage value on designated dates, and to repay the principal value at maturity (Fabozzi, 2012). Corporate bonds, along with equity, are a way for businesses to finance expansions, acquisitions, or general operations while offering investors opportunities for fixed-income returns (Fabozzi, 2012).

2.4.1 Bond pricing

The price of a corporate bond depends on several factors, including interest rates, credit risk, and time to maturity. A bond's price is determined by discounting its future cash flows, coupon payments and the principal repayment, back to the present using an appropriate discount rate (Veronesi, 2016). The bond pricing formula is:

$$P = \sum_{t=1}^{T} \frac{C}{(1+r)} + \frac{F}{(1+r)^T}$$

where P is the price of the bond, C is the coupon payment per period, F is the face value (par value) of the bond, r is the discount rate, and T is the number of periods until maturity. When market interest rates rise, bond prices typically fall, and vice versa. This inverse relationship arises because existing bonds with fixed coupons become less attractive compared to new bonds issued at higher rates (Mishkin, 2019).

2.4.2 Bond yields

Bond yields measure the return an investor earns from holding a bond. The most commonly used yield metrics include Current Yield, Yield to Maturity, Yield to Call and Spread to Treasury, to name a few. The Current Yield measures the annual coupon payment relative to the bond's current market price (Bodie, Kane, & Marcus, 2023).

Yield to Maturity (YTM), as described by Bodie, Kane, & Marcus (2023), represents the total return an investor can expect if the bond is held until maturity, accounting for all coupon payments and any capital gain or loss. Yield to Call (YTC), which is only applicable to callable bonds, it measures the yield assuming the bond is redeemed before maturity at the call price (Bodie, Kane, & Marcus, 2023). Spread to Treasury, is the difference between the yield on a corporate bond and the yield on a risk-free Treasury bond of similar maturity, which reflects the credit risk premium (Mishkin, 2019).

2.4.3 Investment-grade bonds

Corporate bonds are classified based on their credit ratings, which assess the issuer's ability to meet its debt obligations. Investment-grade bonds are issued by companies with strong creditworthiness and are considered lower risk. These bonds are rated BBB- or higher by Standard & Poor's and Baa3 or higher by Moody's (Veronesi, 2016). Key characteristics include lower yields due to lower default risk, higher demand from institutional investors, greater liquidity in the market, and often being issued by well-established companies with stable financials (Veronesi, 2016).

2.4.4 High-yield bonds

High-yield bonds, also known as *junk bonds*, are issued by companies with weaker credit profiles and carry higher default risk. These bonds are rated BB+ or lower by Standard & Poor’s and Ba1 or lower by Moody’s. Key characteristics include higher yields to compensate for increased risk, greater price volatility compared to investment-grade bonds, and more sensitivity to economic conditions and market sentiment (Bodie, Kane, & Marcus, 2023). High-yield bonds are typically issued by companies with higher leverage or uncertain earnings (Bodie, Kane, & Marcus, 2023).

2.4.5 Relationship Between Corporate Bonds and Equities

Corporate bonds and equities represent two primary ways for companies to raise capital, but they differ in structure, risk, and return characteristics. In terms of risk and return, equities generally offer higher potential returns but come with greater risk, as shareholders are residual claimants in case of liquidation. Bondholders, on the other hand, receive fixed interest payments and have priority over shareholders in the event of bankruptcy (Fabozzi, 2012). Bonds are part of a company’s debt financing, while equities represent ownership stakes. A firm’s capital structure affects both its financial stability and cost of capital (Bodie, Kane, & Marcus, 2023).

Bonds and equities tend to react differently to market conditions. In economic downturns, equities often experience significant losses, whereas investment-grade bonds may hold their value better due to their fixed income nature, which is why they are often considered a safe haven asset in times of market crises. High-yield bonds, on the other hand, can behave more like equities due to their increased credit risk (Mishkin, 2019).

Bonds are more sensitive to interest rate changes than equities. When interest rates rise, bond prices generally fall, whereas equity valuations depend on factors such as corporate earnings, economic growth, and investor sentiment (Fabozzi, 2012). Due to the different reaction to interest rates and other external factors, investors often use bonds and equities together to diversify their portfolios. Investors often have a varying allocation of the two asset classes, based on their risk tolerance as well as the market outlook (Bodie, Kane, & Marcus, 2023).

The verdict on the extent of how much the behaviour of corporate bonds is similar to stocks is conflicted. Van Zundert & Driessen (2022), who study a cross-sectional relation between corporate bonds and stocks by taking stock prices from the markets and using them to calculate an implied, market efficient corporate bond value for the corresponding company. The market price of the stock is then compared to the efficiently derived implied bond value. The empirical findings exhibit a negative relation between the realized stock and implied bonds, which suggests a mispricing between stocks and corporate bonds. This negative relation, suggesting mispricing, is most prevalent in high-risk firms and liquid stocks.

Low-credit High Yield bonds are often compared to be very similar in behaviour to equity, with drastically conflicting research for (Fridson, 1994) and against (Christensen & Faria, 1994) this notion. Fridson (1994) argues that the price progression in low-grade high yield bonds is similar to equity. Christensen & Faria (1994) noted that the behaviour of stocks and high yield bonds diverges in so that in the case the company announces the issuance of more stock or convertible securities, the price of the stock decreases, as this dilutes the outstanding shares. In contrast, the issuance of debt on the other hand, has no significant negative impact on stock price Christensen & Faria (1994).

2.5 Portfolio Management

Portfolio management is a fundamental discipline within finance that focuses on the strategic allocation and management of assets to achieve specific investment objectives under varying levels of risk tolerance. At its core, portfolio management seeks to optimize the trade-off between risk and return by the allocation of the overall portfolio to safe versus risky assets, and the determination of the composition of the risky portion of the portfolio (Bodie, Kane & Marcus, 2023). By combining a mixture of assets that move in separate directions, the offsetting price movements create a diversification benefit for portfolios (Menounos et al., 2019).

The modern portfolio management theory is attributed to Markowitz (1952), who introduced Modern Portfolio Theory (MPT). Markowitz (1952) demonstrated that investors can achieve optimal portfolios, those that offer the highest expected return for a given level of risk, by diversifying across assets with convergently correlated returns. Markowitz's (1952) theory introduced the concept of the efficient frontier, which represents the set of optimal portfolios that offer the maximum expected return for each level of risk. Investors, based on their risk aversion, choose their preferred position along this frontier. The theory also implies that holding a diversified portfolio can significantly reduce unsystematic risk, though it cannot eliminate systematic risk, which is inherent to the market.

Building on MPT, the Capital Asset Pricing Model (CAPM), published by Sharpe (1964), Lintner (1965), and Mossin (1966), provided a model to price individual securities and relate them to portfolio theory (Bodie, Kane & Marcus, 2023). The CAPM is predicated on two sets of assumptions: one pertaining to the rationality of investors, the second to market efficiency. Despite its simplifying assumptions, CAPM remains a widely used model used in asset pricing and portfolio management. CAPM posits a linear relationship between expected return and systematic risk, as captured by the beta (Bodie, Kane & Marcus, 2023). The CAPM equation is given by:

$$E(r_i) = R_f + \beta_i(E(R_m) - R_f)$$

While CAPM considers a single market factor, subsequent models such as Arbitrage Pricing Theory (APT) by Ross (1976) and multifactor models, including the Fama-French three-factor model (Fama & French, 1993), extended the theoretical foundation by incorporating multiple sources of risk. These models argue that asset returns are influenced by various macroeconomic and firm-specific factors beyond market beta, such as size, value, momentum, and quality (Bodie, Kane & Marcus, 2023). Multifactor models allow portfolio managers to construct factor-based strategies, enabling targeted exposures to specific risk premiums while controlling for unintended factor risks (Bodie, Kane & Marcus, 2023).

Alongside maximizing return, a major component of portfolio management is managing risk. Various risk optimization techniques exist, one which is the widely used Black and Litterman model, which proposes an approach that uses past data, equilibrium considerations, and the private views of the portfolio manager about the near future to construct the optimal portfolio (Bodie, Kane & Marcus, 2023). Risk management involves not only ex-ante portfolio construction but also ex-post monitoring using metrics such as Value-at-Risk (VaR), tracking error, maximum drawdown, and stress testing (Bodie, Kane & Marcus, 2023). Diversification remains a key tool, but portfolio managers also employ dynamic rebalancing, hedging, and scenario analysis to mitigate risks and adapt to changing market conditions (Bodie, Kane & Marcus, 2023).

3 Literature review

Following the introduction of the Black Scholes model (Black & Scholes, 1973), the topic of implied volatility has been extensively researched. This part covers the relevant literature on the relationship between implied volatility and asset returns, focusing on literature from the equity market, but also includes some papers from different asset classes, such as foreign exchange. This section also covers papers that examine the functionality of corporate bonds as safe haven assets.

The implied volatility-return relationship has been researched for decades. One of the first papers on the topic was conducted in 1995 by Fleming, Ostdiek & Whaley, who found a strong, negative contemporaneous correlation between VIX changes and S&P100 index returns, suggesting a now well-established inverse relationship between the two. Even then asymmetric behaviour in the correlation was noted; stock returns react more strongly to negative changes in implied volatility than positive ones. Since the introduction of the first volatility index, the VIX by Whaley (1993), the scope of volatility indices has expanded to cover multiple asset classes, methodologies, and geographic markets. This review compiles the literature on implied volatility indices, exploring their relationships to returns across geographical settings and asset classes, as well as other implied volatilities.

Diavatopolous, Doran & Peterson (2010) study whether implied idiosyncratic volatility, which reflects market expectations about a firm's unique risks, is related to future stock returns. It also compares the predictive power of this measure to historical volatility measures. Their findings show that implied idiosyncratic volatility is a better measure of future risk than historical measures. Stocks with higher implied idiosyncratic volatility tend to deliver higher returns, especially among smaller firms and those with high book-to-market ratio.

Banerjee, Doran & Peterson (2007) study whether implied volatility, proxied by the VIX index, can predict excess stock returns. They investigate, if the role of both the current levels of implied volatility and unexpected changes in these levels, referred to as innovations, on future returns. The study also examines how different types of portfolios, sorted by factors like size, B/M ratio, and beta respond to VIX. It also adjust for well-known factors to determine whether VIX adds any unique predictive power. The empirical results suggest that high B/M firms have larger returns than low B/M firms. The effect of volatility-excess return is stronger for high beta firms. The effect is strongest for 60-day portfolios, because the VIX takes approximately 60 days to revert to the mean.

Bekaert & Wu (2000) study the relationship between stock market returns and volatility, with a specific focus on asymmetric volatility. The authors posit two potential reasons for the asymmetry; the leverage effect, the tendency of negative returns for high-leverage companies to increase leverage, expressed by the debt-to-equity ratio, making the firm riskier, and the time-varying risk premium (sometimes called the volatility effect), the anticipation of higher volatility increasing the required return, lowering stock prices and reinforcing the volatility response. The paper, using weekly observations from 1985 to 1994, finds that volatility is persistent and asymmetric at both market and firm levels. Covariance in the asymmetry is observed, suggesting that the relationship between firm-specific returns and market changes more drastically after negative shocks. High-leverage portfolios are also the ones with the strongest volatility asymmetry.

Badshah (2013) also studies the relationship between stock index returns and changes in implied volatility using quantile regression. The study uses daily data from four major stock market indices S&P 500, NASDAQ 100, DAX, and EURO STOXX 50, and their corresponding implied volatility indices VIX, VXN, VDAX, and VSTOXX. The findings suggest that negative stock returns lead to a larger increase in volatility than positive returns of the same magnitude. Unlike Bekaert & Wu (2000), Badshah (2013) highlights that this asymmetry may be better explained by behavioral heuristics, like emotions and biases in decision-making, rather than traditional finance theories like the leverage or feedback effects.

Conrad, Dittmar & Ghysels (2009) further explore the relationship between implied volatility and returns by examining the relationship between higher moments of stock return distributions (volatility, skewness, and kurtosis) and subsequent stock returns, using data derived from option prices from 1996 to 2005. Adjustments are made for firm-specific characteristics, including size, value, and established risk factors introduced by Fama & French (1993). The findings suggest that stocks with higher volatility have lower subsequent returns, stocks with more negative skewness tend to have higher subsequent returns, and fat tails in the return distribution is associated with higher future returns. These relationships persist even after controlling for traditional risk factors and co-moments with the market.

The relationship between volatility and returns in the options market is studied by Kelly, Pastor & Veronesi (2014). Instead of proxying uncertainty using the VIX, they opt for analyzing political uncertainty, where prominent political events introduce risks that investors want to hedge against. The phenomenon is studied across 20 countries, spanning equity index options and ETFs. The events include national elections, such as presidential and parliamentary, and global economic summits, for example G8, G20, and the European summits. The analysis includes about 64 election events and 216 summit events. Variables such as GDP growth, stock market returns, and leading economic indicators are used to measure the state of the economy. Uncertainty is measured using poll spreads for elections as proxies for uncertainty about outcomes. The key findings of this paper suggest that the option premiums spanning elections or summits are more expensive due to the additional risks these events present. The pricing effect is more pronounced during weak economic conditions - higher uncertainty about election outcomes or summit decisions leads to more expensive options, and that political uncertainty in one country can affect option pricing in other countries, especially during economic crises.

Other studies showing evidence from the options market include Atilgan, Bali & Demirtas (2011), who study whether the difference between the implied volatilities of out-of-the-money put options and at-the-money call options (volatility spreads) can predict future returns on the S&P 500 index. They argue that option prices carry information about market expectations, potentially offering insights that are not immediately reflected in stock prices. The implied volatilities are derived from S&P 500 index options, specifically focusing on out-of-the-money puts and at-the-money calls. Other factors, such as macroeconomic indicators like default spreads, term spreads, and consumer sentiment indexes are taken into account. According to the paper, a significant negative relationship exists between volatility spreads and expected market returns for up to one week long horizons - this relationship is stronger during periods of high information flow, such as company earnings announcements or when consumer sentiment reaches extreme levels. A trading strategy based on this relationship yields higher risk-adjusted returns (0,032% with a Sharpe ratio of 0,036) than simply investing in the S&P 500.

The topic has also been studied using other asset classes. Kaurijoki, Nikkinen & Äijö (2015) study the relationship between currency returns and implied volatility for high-yielding (investment) and low-yielding (funding) currencies, focusing on six major currencies: Australian dollar (AUD), Canadian dollar (CAD), Euro (EUR), British pound (GBP), Japanese yen (JPY), and Swiss franc (CHF), all quoted against the U.S. dollar (USD). It studies how currency futures returns influence implied volatilities, particularly before and during the 2008 financial crisis. High-yielding currencies tend to exhibit a negative relationship between returns and implied volatility during volatile periods, while low-yielding currencies exhibiting an opposite pattern, with a positive relationship between returns and implied volatility. This behaviour is somewhat similar to equities during market downturns.

The relationship of implied volatility with commodity prices is studied by Padungsaksawasdi & Daigler (2014), specifically for gold, oil and the Euro. ETFs for the corresponding commodities are used as proxies for the commodity assets. Unlike stocks, price changes in commodity ETFs have a much weaker connection to changes in implied volatility, though for gold the relationship is similar to what Kaurijoki, Nikkinen & Äijö

(2015) found with foreign exchange currencies; when gold prices increase, implied volatility also tends to rise, opposite than with equity prices. The researchers assign behavioral explanations to this phenomenon: fear and speculation during volatile markets drives investors towards flight-to-safety assets, while the return-volatility relation remains negative.

In more recent studies, Cao, Chen & Hull (2019) use sophisticated neural network models to study the movements in the implied volatility surfaces in relation to equity returns. As opposed to statistical model, machine learning models, including neural networks, are exceptional at revealing non-linear relationships, finding what would otherwise not been found with traditional statistical models. Cao, Chen & Hull's (2019) findings are similar to what was discussed here before with the exception that when volatilities are low and index returns particularly high, volatility tends to increase.

While not directly studying the effect of implied volatility and returns, Lopez (2015) does study how implied volatility from equity markets effects treasury bond implied volatilities/the main drivers in the Treasury bond implied volatilities. The study was conducted by creating three Treasury bond volatility indices (TBVIXs) using a model-free approach,

then analyzing how TBVIXs move in relation to changes in Treasury yield rates. The calculation involves option prices on Treasury futures, specifically focusing on 5-year, 10-year, and 30-year maturities. Both TBVIX (10y) and TBVIX (30y) are positively correlated with VIX, EVZ (euro), GVZ (gold), and OVX (crude oil). This means that when volatility increases in one market, such as equities, volatility tends to increase in the Treasury market as well, especially during periods of market uncertainty. This correlation reduces the potential for diversification benefits when using volatility products across these asset classes. The study finds that these correlations are stronger in the post-crisis period (after July 2009) compared to during the financial crisis (June 2008 to June 2009). Lopez (2015) also studies how implied volatility of Treasury bonds is affected by scheduled economic announcements. The signifiers for economic announcements were consumer price index (CPI), gross domestic product (GDP), non-perform payrolls (NFP), producer price index (PPI), consumer confidence index (CCI), and federal open market committee (FOMC) meetings. Generally, the TBVIX (5-year, 10-year, and 30-year) significantly decreases following the release of these economic reports. This drop suggests that once the data becomes public, uncertainty diminishes because investors no longer need to speculate on the outcome. The largest reductions in TBVIX occur after the NFP report, indicating that employment data has the strongest impact on resolving uncertainty in the Treasury market. Other significant announcements include the CPI, GDP, and FOMC policy decisions. The paper by Lopez (2015) highlights the spillover effect between implied volatilities across asset classes.

A similar study was conducted by Markellos & Psychoyios (2018), who also construct a model-free fixed income asset implied volatility index using 5-year, 10-year and 30-year Treasury futures. While the premise and framework being similar to Lopez (2015), the findings are significantly different from each other: Markellos & Psychoyios (2018) find that interest rate volatility is negatively correlated with both interest rate levels and equity volatility, making it useful for diversification. The study also finds that interest rate volatility is substantial and changes significantly over time. For medium-term instruments, volatility is especially high. For example, implied volatility for the 5-year instrument is almost double that of the equity volatility index. The effect is significantly more pronounced during economic crises. Similar to Lopez (2015), Markellos & Psychoyioc (2018) also study how interest rate volatility is affected by scheduled economic announcements, using the same institutional announcements, add to Lopez's (2015) findings that the effect is most pronounced in the long-term 30-year Treasury bonds. The paper finds that interest rate volatility isn't fully explained by the yield curve. This concept is called *unspanned stochastic volatility*.

Cao et al. (2023) are one of the only ones who have researched the relation of implied volatility specifically to corporate bonds. Corporate bonds from firms with the largest increases in implied volatility underperform those with the largest decreases by 0.6%

per month on average, with the highest underperformers being ones with longer maturities, below investment-grade credit ratings and lower liquidities. Adjusting for the aforementioned risk factors, the underperformance increases to 0.98% per month, highlighting that the spread is not due to conventional risk compensation. The study contrasts its findings with prior research on stock markets, finding that stock market reactions to changes in IV are different because stocks and bonds have distinct payoff structures. Due to the high transaction costs, among other factors, the bond market also underreacts to information from the options market, which leads to predictable patterns in bond returns following IV changes. The underperformance of bonds with increasing IV highlights inefficiencies in how the corporate bond market processes risk information, which presents opportunities for informed investors.

Another research studying the effect of equity market volatility on bond markets was conducted by Jubinski & Lipton (2012), who studied how fluctuations in the stock market effects treasury bond yields, corporate bond yields, and yield spreads. They explore whether investors react to implicit or realized volatility, and how these reactions influence their behaviour in the bond markets. The bonds used in the research belong to different credit ratings, from AAA to B. The findings show that, when equity market volatility increases, investors expectedly shift money into the safer Treasury bonds, which in turn causes Treasury yields to fall and yield spreads to widen. The effect on the yields spread is most notable in lower-rated corporate bonds. Realized volatility has more effect on investor behaviour, meaning that investors are more influenced by current market activity than expectations of future volatility. High equity market volatility also causes a flattening of the yield curve, so the difference between short-term and long-term yields decreases.

Busch, Christensen & Nielsen (2011) conduct a multi-asset research, studying the effect of implied volatility on the foreign exchange, equity, and bond markets. They also separate the effect of continuous volatility (small, daily fluctuations in volatility) and jump volatility (sudden large movements in volatility). Implied volatility from options provides significant additional information for predicting future volatility across all the studied asset classes: in the foreign exchange market, implied volatility fully captures the information in past realized volatility and its components, but for equity and bond markets, the researchers advice for using implied volatility in combination with some component of past realized volatility for better forecasting performance. Surprisingly, the jump component of volatility, which is usually harder to predict, shows some predictability, and implied volatility reflects this information, suggesting that option market participants to some extent base their trading behaviour on information about future price jumps in stock and bond prices, as well as foreign exchange rates.

Ciner, Gurdgiev & Lucey (2013) investigate how different financial asset classes, such as stocks, bonds, gold, oil, and exchange rates, are related to each other in terms of their functionality as a safe haven for each corresponding asset. As the paper aims to study the interdependency of these assets, both in normal market conditions but also in more volatile environments, the study applies both a Dynamic Conditional Correlation (DCC) GARCH Model and a Quantile regression analysis. The findings show that gold does not act as a strong safe haven for stocks, but it does for exchange rates, both US Dollar and British Pound. Bonds remain a traditional safe haven against equities; when stocks drop significantly, bond returns tend to be positive. However, the bond market does not serve as a hedge against gold. Oil is not a consistently reliable safe haven asset for equity, though in specific market periods, such as the 1990 Gulf War and the 2008 financial crisis, it does act as a safe haven. Rolling regression analysis shows that oil's safe haven role is event-driven rather than permanent.

Cheema, Faff & Szulcyk (2022) study the performance of safe haven assets during the 2008 financial crisis, as well as the COVID-19 pandemic market crash. Similarly to Ciner, Gurdgiev & Lucey (2013), Cheema, Faff & Szulcyk (2022) study the performance of the precious metals gold and silver, currencies US Dollar and Swiss Franc, as well as US Treasury bills, Treasury bonds and AAA-rated corporate bonds during market crises. During the 2008 financial crisis, U.S. Dollar, the Swiss Franc and Treasury bonds serves as intermediary safe havens, while gold, silver and Treasury bills performed poorly as a safe haven assets. During the COVID-19, precious metals performed poorly, in some instances having become even riskier than stock holdings, while AAA-grade corporate bonds have strengthened as a safe haven from 2008. This paper highlights that there is no one-size-fits-all hedge solution for market crises: the nature of the crash matters, as 2008 was a financial systemic collapse of the financial system, while the other was an economic shock resulting from a health-driven panic.

Flavin & Sheenan (2024) investigate whether green bonds can serve as a safe-haven asset for equity investors. The study also compares green bonds to traditional safe-haven assets like sovereign bonds and gold. The study uses daily data from January 2012 to December 2022 on four asset classes; the S&P 500 index, 10-year U.S. sovereign bond and gold prices as benchmarks, as well as S&P Dow Jones Green Bond Index. The paper employs two main econometric approaches: Marginal Expected Shortfall (MES) and Markov-switching VAR (MS-VAR). MES findings show show that green bonds are not a safe haven for equity positions; in the 5% tail events, green bonds move in conjunction with equities, while 10-year sovereign bonds and gold yield positive returns. In 1% tail events, sovereign bond returns remain positive, while gold becomes negative and green bond returns remain negative but in a larger magnitude than in 5% tail events. MS-VAR findings show that there is a bi-directional contagion between green bonds and stocks during turbulent periods, meaning they reinforce each other’s price movements. Sovereign bonds are the most consistent safe-haven asset, they exhibit negative correlation with equities in all market conditions, meaning they provide diversification benefits when most needed. Gold acts as a safe haven in most cases, but not always; it provides protection in regular crises but loses this role during extreme financial turbulence, and in the paper’s case, during COVID-19 market crash and the Russia’s invasion of Ukraine.

Wang, Yang & Chong (2025) study the performance of investment grade corporate bonds during the COVID-19 pandemic, and how they performed compared to stocks and other asset, such as gold, oil and the USD. The bond returns were benchmarked against the equity indices S&P500, FTSE, NIKKEI 225 and the Shanghai Composite, and the time period covered was from 2018 to 2022, and the comparison period was the 2008 financial crisis. The study uses statistical methods to compare the returns, risks, and correlations of stocks and bonds during different phases of COVID-19. The daily returns and risk-adjusted performance were comparatively measured using the Sharpe ratio. The safe haven functionality was conducted using dynamic conditional correlations and Pearson correlations. The study also examines how interest rate hikes and relief programs influence asset prices. The findings show that during the pandemic, the high-yield bonds provided better risk-adjusted returns than stocks during crisis periods. The Sharpe ratios of the high-grade bonds (DAAA) and lower investment-grade bonds (DBAA) throughout the entire COVID-19 cycle (2020-2022) were 3,39 and 6,06, respectively, whereas the Sharpe ratios for the indices were 0,0232 for the S&P500; 0,0040 for FTSE; 0,0168 for NIKKEI 225; and 0,00006 for Shanghai Composite. The effect of the governmental and monetary policies was as follows: the relief policies initially helped stocks, but the effect was short-lived as the stock indices started descending after the first year of the relief policies, whereas the interest rate hikes had a positive effect on bond yields but did not significantly impact stock prices. The paper also noted that while gold initially did provide protection in the early 2020, it lost its safe havens status throughout the pandemic; prior to the pandemic, the correlation between gold and the stock indices was negative, while mid mid-pandemic the correlation between the two assets became positive. The reasoning behind this is the liquidity crisis in the early 2020's: investors liquidated their gold holdings, weakening the hedging quality of gold. Also, the hiked interest rated made bonds a more attractive investment than gold.

4 Methodology

This section outlines the methodological framework employed to examine the asymmetric relationship between stock returns and implied volatility, and its implications for corporate bond returns. The VIX index is used as an estimate of implied volatility to control for measurement errors. Since I want to analyze both the overall trend, as well as the relationship across the whole of the dependant variable's implied volatility distribution, I will utilize both OLS regression and quantile regression models in this paper. Following Padungsaksawasdi & Daigler (2014), Kaurijoki, Nikkinen & Äijö (2015) and Badshah (2013), to name a few, this paper will explore the relationship using both OLS regressions to analyze the conditional mean, and quantile regression to measure across the entire volatility correlation spectrum.

4.1 OLS regression

Ordinary least square (OLS) regressions are used to provide an analysis of the general, average relationship, which is useful for understanding overall trends. For my subject, OLS provides a straightforward way to quantify how changes in implied volatility are associated with changes in the mean of equity returns, making it suitable for assessing the central tendency of their relationship. Running an OLS regression assumes that the distribution of equity returns is approximately symmetric and homoscedastic. If these conditions hold, the OLS regression yields unbiased and efficient estimates of the effect of implied volatility.

Following Padungsaksawasdi & Daigler (2014), the baseline measure of the average relationship between equity returns an changes in implied volatility is tested by running an OLS regression of the following VIX values:

$$\Delta IVt = \beta 0 + \beta Rt + \varepsilon t$$

where ΔIVt is the daily log-normal change in the implied volatility and Rt is the log-normal change of the daily return. The errors, ε, are assumed to be independent.

4.2 Quantile regression

According to Koenker and Bassett (1978), quantile regression well-suited for studying the relationship between implied volatility and corporate returns, because it provides a more nuanced understanding of their interaction than other regression models. Unlike the OLS regression, which estimates the average relationship between the dependent and independent variables based on conditional means, quantile regressions allow for the examination of how the relationship varies across the conditional distribution of the dependant variable. For example, the effect might differ during periods of extreme losses to periods of substantial gains. This is highlighted in financial markets, where tail events, such as the 2008 financial crisis, are extremely consequential.

According to the hypothesis, implied volatility has varying effects in returns depending on the level of returns. For example, small changes in implied volatility might have a larger effect during periods of market stress. Quantile regression captures these non-linear effects, offering a robust examination of how the relationship changes under different market conditions. Following Badshah (2013), to estimate the relationship between corporate bond returns and VIX, the quantile regression is constructed in the following quantiles $(\tau) \in$ (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9):

$$Q_\tau(\tau|\Delta\mathrm{VI}) = \alpha + \sum \beta \Delta VI + \sum \gamma_{(\tau)} R + \varepsilon$$

where $Q_\tau(\tau|\Delta\mathrm{VI})$is the τ-th conditional quantile of the implied volatility index. α is the intercept. β is the coefficients for the log-normal change ΔVI in a volatility index. $\gamma_{(\tau)}$ is the coefficients for the log-normal change in asset returns. The errors, ε, are assumed to be independent and derived from the distribution $\phi(\varepsilon)$ with a qth quantile equal to zero.

5 Data

The data used for examining equity market volatility, equity returns and bond returns are described here. All data is sourced either from Datastream or directly from Standard & Poor’s website. The section concludes by presenting the descriptive statistics for the data.

5.1 Data collection

The dataset for this study comprises of daily closing data on stock market and corporate bond indices, as well as the daily high values on the CBOE VIX index. The dataset was sourced from the reliable financial market data provider Datastream and Standard & Poor’s website, ensuring comprehensive coverage of the variables under consideration. The time period for the analysis spans 2015-2025, providing sufficient observations to analyze both relatively low-interest rate market conditions from 2015-2022, and aggressive interest-rate hike market conditions from 2022-2025.

The stock market indices selected for this study include the S&P Investment Grade Corporate Bond Index, the S&P High Yield Corporate Bond Index, as well as S&P500 for the comparison equity index. Since this paper studies how equity market implied volatility affects the corporate bond markets, the VIX index serves as a measure of equity market implied volatility.

5.2 Descriptive statistics

Tables 1 and 2 presents the descriptive statistics for the key variables, including stock index returns, implied volatility indices, and bond data for their respective time periods. The results provide insights into the data distribution, including mean, standard deviation, skewness, kurtosis, and stationarity properties.

Table 1 Descriptive statistics for daily VIX high values, S&P Investment Grade and High Yield ETFs, as well as S&P500 stock index for the pre-interest rate hike period from 19.3.2015 to 16.3.2022

	VIX	*S&P 500*	*S&P Investment Grade*	*S&P High Yield*
Mean	0,000	0,000	0,000	0,000
Standard Error	0,002	0,000	0,000	0,000
Median	-0,005	0,001	0,000	0,000
Mode	0,000	0,000	0,000	0,000
Standard Deviation	0,089	0,012	0,003	0,003
Sample Variance	0,008	0,000	0,000	0,000
Kurtosis	6,705	19,933	12,947	46,775
Skewness	1,102	-0,997	-1,241	-0,845
Range	1,239	0,217	0,047	0,075
Minimum	-0,464	-0,128	-0,028	-0,036
Maximum	0,776	0,090	0,019	0,039
Sum	0,604	0,730	0,187	0,378
Count	1762	1762	1762	1762

During the pre-hike period, the VIX exhibited a slightly positive average return (0,0003), with a noticeably negative median (-0,0055), indicating a distribution skewed to the right. This positive skewness (1,10) reflects the inherent nature of volatility indices to experience occasional large upward movements during market stress. In contrast, the S&P500 showed a higher mean return (0,0004), with a median of 0,0007, suggesting relatively stable equity performance. The distribution was negatively skewed (-0,99), pointing to a higher likelihood of extreme negative returns, which is a common feature in equity markets. Fixed income indices demonstrated much lower mean returns: 0,0001 for investment grade bonds and 0,0002 for high yield bonds. Both bond series were also negatively skewed, with higher downside tail risk.

Volatility, as indicated by standard deviation, was highest for the VIX (0,0891). The S&P 500 displayed moderate volatility (0,0115), while investment grade and high yield bonds were far less volatile (0,0031 and 0,0030, respectively). All asset classes exhibited high kurtosis, particularly the S&P 500 (19,93) and high yield bonds (46,78), indicating high amount of tail behaviour and the presence of outliers, which is more than what would be expected from a normally distributed dataset.

Table 2 Descriptive statistics for daily VIX high values, S&P's Investment Grade and High Yield ETFs, as well as the S&P500 stock index for post-hike period from 17.3.2022 to 14.3.2025

	VIX	*S&P 500*	*S&P Investment Grade*	*S&P High Yield*
Mean	0,000	0,000	0,000	0,000
Standard Error	0,003	0,000	0,000	0,000
Median	-0,003	0,000	0,000	0,000
Mode	-0,021	0,000	0,000	0,000
Standard Deviation	0,078	0,011	0,004	0,003
Sample Variance	0,006	0,000	0,000	0,000
Kurtosis	25,555	2,234	0,777	5,194
Skewness	1,697	-0,265	0,051	-0,299
Range	1,433	0,098	0,038	0,041
Minimum	-0,637	-0,044	-0,019	-0,025
Maximum	0,796	0,054	0,018	0,016
Sum	-0,202	0,258	0,039	0,126
Count	773	773	773	773

In the post-hike period, notable changes in distributional properties occurred. The VIX mean turned negative (-0,0002), and its skewness increased further (1,70), indicating that while average daily changes in implied volatility declined, the index remained vulnerable to sharp spikes. Interestingly, despite a decrease in standard deviation (0,0776), VIX kurtosis surged to 25,55, reflecting a heavier concentration of extreme events, more than in the pre-hike period.

For the S&P500, the mean return remained positive (0,0003) but declined slightly compared to the earlier period. Skewness moderated to -0,26, and kurtosis fell significantly to 2,23, suggesting that post-hike equity returns became more symmetrically distributed with fewer extreme events. Investment grade and high yield bonds also showed marked changes. Investment grade bonds moved from a negatively skewed and leptokurtic profile (-1,24 skewness, 12,95 kurtosis) to a distribution that was nearly symmetrical (0,05 skewness) and platykurtic (0,78 kurtosis), indicating stabilization. High yield bonds still displayed negative skewness and leptokurtosis (-0,29 and 5,19, respectively), but both measures were significantly reduced from the pre-hike period.

Overall, the post-hike environment is characterized by lower average volatility but heightened tail risk in volatility indices, while equities and bonds have shifted toward more normal distributions with less extreme behavior. The tightening of the return distribution for equities and bonds suggests that monetary policy may have had a stabilizing effect on these markets.

6 Empirical results

This section examines how the VIX affects the returns of the S&P 500, investment grade bonds, and high-yield bonds, both before and after the U.S. Federal Reserve's aggressive interest rate hiking cycle that began in 2022. The regression framework includes both Ordinary Least Squares (OLS) and quantile regression models, allowing for the analysis of the average effects as well as the distributional impacts across different return quantiles.

6.1 The relation between VIX and corporate bond returns

Tables 3 and 4 present the empirical results of both the OLS and quantile regressions for the contemporaneous implied volatility-return relation for equities, investment grade and high yield bonds:

Table 3 OLS and quantile regression results for VIX and the respective asset. Data for the pre-hike period 2015-2022

	Pre-FED hikes									
	OLS	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
S&P500										
Coefficient	-0,547	-0,074	-0,067	-0,064	-0,061	-0,061	-0,063	-0,064	-0,065	-0,064
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,002	-0,007	-0,004	-0,002	-0,001	0,001	0,002	0,003	0,005	0,009
Intercept p-value	0,239	0,000	0,000	0,000	0,000	0,001	0,000	0,000	0,000	0,000
INVESTMENT GRADE										
Coefficient	0,094	0,001	0,002	0,004	0,004	0,005	0,005	0,004	0,006	0,008
Coefficient p-value	0,000	0,533	0,075	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,000	-0,003	-0,002	-0,001	0,000	0,000	0,001	0,001	0,002	0,003
Intercept p-value	0,978	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000
HIGH YIELD										
Coefficient	-0,324	-0,013	-0,010	-0,009	-0,008	-0,008	-0,007	-0,007	-0,008	-0,009
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,002	-0,002	-0,001	-0,001	0,000	0,000	0,001	0,001	0,001	0,002
Intercept p-value	0,241	0,000	0,000	0,000	0,222	0,000	0,000	0,000	0,000	0,000

During the pre-hike period, the regression results indicate a strong and statistically significant negative relationship between the VIX and S&P 500 returns, which is consistent with previous literature on the topic (Badshah, 2013). The OLS coefficient is -0,547 ($p < 0,001$), suggesting that an increase in implied volatility tends to significantly depress equity returns on average. The quantile regression estimates further reinforce this finding. Coefficients are negative across all deciles, ranging from -0,074 at the 1st quantile to -0,064 at the 9th quantile, with all p-values below 0,001. This consistency across the distribution indicates that heightened volatility dampens equity returns not only during downturns but also in more favorable market conditions.

Investment grade bonds display a positive and significant relationship with the VIX in the pre-hike period. The OLS coefficient is 0,094 ($p < 0,001$), and quantile regression coefficients become increasingly positive at higher quantiles: from 0,001 at the 1st quantile to 0,008 at the 9th quantile. All coefficients from the 3rd quantile onward are statistically significant at the 1% level. These findings suggest that IG bonds serve as a safe haven asset in low-interest rate environments, benefiting from risk-off sentiment when volatility spikes.

The high yield bond market exhibits a negative contemporaneous relation to VIX, which is weaker than the one with equities. The OLS coefficient is -0,324 ($p < 0,001$), with quantile coefficients ranging from -0,013 to -0,009. The distribution suggests that HY bonds benefitted from rising volatility, as the correlation grows weaker at the mid-high (6th – 7th) quantiles, before going back up at the last two quantiles. This suggests that while investors fled away from equity at times of heightened volatility, they were still willing to bear the risk of the HY bonds, until the upper levels of volatility forced them to sell off their HY holdings.

Table 4 OLS and quantile regression results for VIX and the respective asset. Data for the post-hike period 2022-2025

	Post-FED hikes									
	OLS	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
S&P500										
Coefficient	-0,506	-0,073	-0,076	-0,065	-0,066	-0,067	-0,072	-0,077	-0,074	-0,064
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,001	-0,010	-0,006	-0,003	-0,001	0,000	0,002	0,004	0,007	0,011
Intercept p-value	0,686	0,000	0,000	0,000	0,000	0,713	0,000	0,000	0,000	0,000
INVESTMENT GRADE										
Coefficient	-0,080	-0,004	-0,007	-0,008	-0,008	-0,003	-0,004	-0,002	0,001	-0,004
Coefficient p-value	0,027	0,408	0,043	0,002	0,002	0,266	0,139	0,409	0,780	0,386
Intercept	0,000	-0,006	-0,003	-0,002	-0,001	0,000	0,001	0,002	0,004	0,005
Intercept p-value	0,946	0,000	0,000	0,000	0,000	0,944	0,000	0,000	0,000	0,000
HIGH YIELD										
Coefficient	-0,298	-0,017	-0,016	-0,015	-0,011	-0,011	-0,009	-0,008	-0,010	-0,011
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,018
Intercept	0,001	-0,004	-0,002	-0,001	0,000	0,000	0,001	0,002	0,002	0,004
Intercept p-value	0,754	0,000	0,000	0,000	0,002	0,156	0,000	0,000	0,000	0,000

In the post-hike period, the negative relationship between VIX and S&P500 returns remains statistically significant. The OLS coefficient is -0,506 ($p < 0,001$), slightly smaller than in the pre-hike period. Quantile regression coefficients are again negative across all quantiles, with slightly larger magnitudes in the upper quantiles (for example, -0,077 at the $0,7^{th}$ quantile), while remaining relatively similar in lower quantiles. This indicates that while the average impact of volatility on equities has very lightly, if at all, softened, the S&P 500 remains broadly sensitive to increases in implied volatility across all market conditions.

The most notable shift post-hike occurs in the investment grade bond segment. The OLS coefficient flips to -0,080 ($p = 0,027$), suggesting that IG bonds no longer offer the same protection during volatility spikes than they did in pre-hike environment. Quantile regression results are mixed: coefficients are generally negative in the lower and mid quantiles, with significance varying across quantiles. For example, the coefficients at the 0,2 and 0,3 quantiles are -0,007 and -0,008, respectively, and both are significant at the 5% level. However, in the upper 8th and 9th quantiles, the coefficients become statistically insignificant. This shift indicates that investment grade bonds have lost their pre-hike safe-haven characteristics, likely due to increased duration risk and sensitivity to rising yields.

High yield bonds continue to display a significant negative relationship with the VIX in the post-hike period, although the magnitude of the effect has slightly diminished. The OLS coefficient is -0,298 ($p < 0{,}001$), compared to -0,324 in the pre-hike period. Quantile regression coefficients remain negative and significant throughout, with stronger effects in lower quantiles (e.g. -0,018 at 0,1, -0,015 at 0,3), and a slight tapering off at higher quantiles. This confirms the findings in the pre-hike period, whereby the relation grows weaker in the mid-high (6th – 8th quantiles), before going back up at the highest quantile, which highly suggests that investors are willing to hold onto their riskier bonds despite relatively higher market uncertainty. The coefficients are statistically significant throughout the distribution.

Since the correlation coefficients are in most part statistically significant, we can confirm hypothesis 1. Hypothesis 1.1 is partially confirmed, as the coefficients for investment grade bonds increase with higher quantiles of volatility in the pre-hike period. However, the coefficients for the high yield bonds do not strengthen in the higher quantiles, so we can only partially confirm hypothesis 1.1. Hypothesis 2 can be confirmed, as the coefficients for high yield bonds are closer to the ones with equities than to investment grade bonds. This is also confirmed by the fact they don’t change as drastically between periods as investment grade ones do. We can confirm hypothesis 3, as the change in periods from low-interest rate environment into the post-hike era, significantly altering the implied volatility-return dynamics of investment grade bonds.

6.2 Comparison to previous literature

The empirical results in this thesis are consistent with equity volatility spillover in bond markets (Jubinski & Lipton, 2012; Merkellos & Psychoioyios, 2018; The results support Jubinski & Lipton (2012), who observed that a rise in equity market volatility leads to a *flight-to-quality* effect in Treasury bonds and investment grade corporate bonds, as the implied volatility-return coefficients in investment grade bonds in this thesis increase with VIX in the pre-hike period. Expanding on these findings, this thesis suggests that this dynamic dissipates in an environment with aggressive monetary policies, e.g. interest rate hikes, as this positive relation turns negative in the 2022-2025 era.

While not directly studying the safe haven properties of investment grade corporate bonds, this thesis supports Cheema, Faff & Szulcyk's (2022) findings, who observed that high rated corporate bonds acted as safe haven during COVID-19, by demonstrating that investment grade corporate bonds had an increasing implied volatility-return coefficient the higher the levels of VIX were. This indicates that rising volatility indeed guided investors to reallocate their holdings in safer corporate bonds of higher credit ratings.

These findings also imply that high yield bonds display a weaker sensitivity to interest rate movements than investment grade bonds (Menounos, Alexiou & Vogiazas, 2019), as the variation in the coefficients between the two periods is not as drastic in high yield bonds as it is in investment grade bonds. Instead, high yield bonds tend to move in a similar pattern alongside the VIX distribution as equities are, if not more skewed to the upper quantiles, supporting the findings of Menounos, Alexiou & Vogiazas (2019), whereby high yield bonds are more influenced by equity market fluctuation than interest rate environment.

This thesis also supports studies on the effects of interest rate uncertainty on the equity-corporate bond comovement (Li, 2002) and corporate bond returns (Guo, Kontonikas & Maio, 2020). As Table 4 shows, the VIX-return coefficients of both the high yield and investment grade bonds grew closer to those of equities across all quantiles, indicating that the return patterns of corporate bonds and equities indeed do converge in environments of high-interest rate uncertainty, supporting Li's (2002) findings. The more negative coefficients for both high yield and investment grade bonds also support Guo, Kontonikas & Maio's (2020) findings, as the decreasing implied volatility-return coefficients in the post-hike period is an indication of lower level of returns in the post-hike period.

6.3 Limitations

This paper studies the effect of high-interest rate environment by dividing the dataset into two periods; 2015-2022 and 2022-2025. Since the years prior to this period were also a time of exceptionally high inflation (Ha et al., 2023), this thesis does not have control for a direct effect of either inflation or interest rates, so it fails to differentiate if the changed implied volatility-return dynamic in corporate bonds is because of inflation uncertainty or high interest rates. In the real world, it is difficult to differentiate the two, since interest rate hikes are usually a reaction to rising inflation. Still, future studies could study this relation more directly, to resolve if the interest rate hikes themselves cause the shift in dynamics or is it more-so caused by inflation uncertainty.

7 Conclusion

This study examines the relationship between implied market volatility, as measured by the VIX, and the returns of three key asset classes; equity, investment-grade corporate bonds, and high-yield corporate bonds, using both ordinary least squares and quantile regression to analyze the correlation across different points of the return distribution. Additionally, the analysis divides the dataset into two distinct periods: before the aggressive interest rate hikes initiated by the U.S. Federal Reserve in 2022, and the period following those hikes. The findings help support prior literature on VIX-corporate bond relation (Jubinski & Lipton, 2012; Merkellos & Psychoioyios, 2018), equity-corporate bond comovement (Li, 2002) and corporate bond returns in a high interest-rate environment (Guo, Kontonikas & Maio, 2020).

As expected, based on prior literature, the VIX exhibits a consistently strong and statistically significant negative relationship with S&P 500 returns in both pre- and post-hike period. This inverse relationship is evident in the OLS estimates and remains remarkably stable across quantiles, highlighting the broad impact of volatility expectations on equity market performance. Notably, the magnitude of the VIX's impact appears somewhat more negative in the post-hike period, particularly in the upper quantiles, suggesting that heightened volatility has had an increasingly adverse effect even on stronger equity return realizations. This reflects a shift in market sentiment, where even relatively favorable return scenarios are more vulnerable to volatility shocks in a higher-rate environment.

The results for investment-grade bonds reveal a notable regime shift in their sensitivity to VIX across the two periods. Prior to the rate hikes, IG bond returns had a positive and statistically significant relationship with VIX across nearly all quantiles, indicating a potential *flight-to-quality* behavior during periods of elevated uncertainty in the equity markets. However, in the post-hike period, this relationship turns negative, particularly at the lower and middle quantiles. The OLS coefficient also turns significantly negative. This suggests that the protective, risk-off characteristics of IG bonds weakened in the higher rate environment, possibly due to rising interest rate sensitivity increasing the duration risk and diminished safe haven appeal in the face of persistent inflation and macroeconomic stress.

High yield bonds maintained a strong and consistently negative relationship with VIX across both periods. Interestingly, high yield bonds experience their weakest coefficients in their 6th and 7th quantiles, as opposed to equities, which in both periods experienced their weakest coefficient in the middle 4th, 5th and 6th quantiles. This suggests that holders of high yield bonds are not so hasty at selling off their holdings at the same magnitudes of volatility they would offload their equity holdings.

The findings offer several key implications for investors and policymakers in the area of portfolio construction, risk management and monetary policy. For portfolio construction, rising VIX adversely impacts equities and HY bonds in both periods, but the loss of positive correlation between VIX and IG bond returns post-hikes suggests a reduction in diversification benefits traditionally offered by investment-grade credit, allowing the portfolio manager to reallocate their stock-bond positions according to the monetary environment and VIX expectations. Since quantile regression results reveal that tail risks are significantly affected by volatility, especially for HY bonds and equities, portfolio stress testing and downside risk management should consider quantile-specific dynamics. The post-hike shift in return sensitivities underscores how monetary tightening reshapes asset pricing dynamics. Asset classes respond not only to current volatility but also to broader macro-financial regimes shaped by central bank policy. When making drastic monetary policy changes, the policymakers should consider these results with the investors in mind.

While this thesis has focused on broad asset class indices such as the S&P 500, investment grade bonds, and high yield bonds, future studies could involve decomposing the broad asset classes into finer sectors or industry segments. For fixed income, differentiation between credit quality buckets within investment grade (e.g. AAA vs.

BBB-rated bonds) or high yield sectors (e.g. distressed vs. near-investment grade) could reveal unique sensitivities to market uncertainty. Since different sectors exhibit distinct exposure to macroeconomic variables such as interest rates, inflation, or growth expectations, it is plausible that their sensitivity to the VIX varies accordingly. Building on the periodical segmentation approach used in this thesis, further research could also explore how the sensitivity of fixed income asset returns to VIX evolves continuously over time. Employing time-varying coefficient models, such as rolling window regressions, would allow researchers to identify structural changes in the VIX-return relationship across different market regimes. For instance, the reaction of high yield bonds to volatility might intensify during credit crunches but remain moderate during stable growth periods.

In addition to the direct impact of implied volatility on asset returns, future research could also include control variables, for example, bond market liquidity and credit spreads. During periods of heightened volatility, liquidity in the bond market can deteriorate rapidly, exacerbating price movements and magnifying return sensitivity to risk sentiment. By incorporating bond market liquidity variables, such as bid-ask spreads or trading volumes, researchers can assess whether changes in liquidity conditions amplify the relationship between VIX and bond returns. Similarly, credit spreads, which reflect investors’ compensation for default risk, are likely to widen in response to rising volatility, especially in riskier segments of the fixed income market. This approach would be particularly valuable in distinguishing whether returns are driven more by changing risk appetite or by fundamental shifts in credit quality and market functioning.

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Appendices

Appendix 1. Regression results for the pre-hike period

	Pre-FED hikes									
	OLS	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
S&P500										
Coefficient	-0,547	-0,074	-0,067	-0,064	-0,061	-0,061	-0,063	-0,064	-0,065	-0,064
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,002	-0,007	-0,004	-0,002	-0,001	0,001	0,002	0,003	0,005	0,009
Intercept p-value	0,239	0,000	0,000	0,000	0,000	0,001	0,000	0,000	0,000	0,000
INVESTMENT GRADE										
Coefficient	0,094	0,001	0,002	0,004	0,004	0,005	0,005	0,004	0,006	0,008
Coefficient p-value	0,000	0,533	0,075	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,000	-0,003	-0,002	-0,001	0,000	0,000	0,001	0,001	0,002	0,003
Intercept p-value	0,978	0,000	0,000	0,000	0,000	0,003	0,000	0,000	0,000	0,000
HIGH YIELD										
Coefficient	-0,324	-0,013	-0,010	-0,009	-0,008	-0,008	-0,007	-0,007	-0,008	-0,009
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,002	-0,002	-0,001	-0,001	0,000	0,000	0,001	0,001	0,001	0,002
Intercept p-value	0,241	0,000	0,000	0,000	0,222	0,000	0,000	0,000	0,000	0,000

Appendix 2. Regression results for the post-hike period

	Post-FED hikes									
	OLS	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
S&P500										
Coefficient	-0,506	-0,073	-0,076	-0,065	-0,066	-0,067	-0,072	-0,077	-0,074	-0,064
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Intercept	0,001	-0,010	-0,006	-0,003	-0,001	0,000	0,002	0,004	0,007	0,011
Intercept p-value	0,686	0,000	0,000	0,000	0,000	0,713	0,000	0,000	0,000	0,000
INVESTMENT GRADE										
Coefficient	-0,080	-0,004	-0,007	-0,008	-0,008	-0,003	-0,004	-0,002	0,001	-0,004
Coefficient p-value	0,027	0,408	0,043	0,002	0,002	0,266	0,139	0,409	0,780	0,386
Intercept	0,000	-0,006	-0,003	-0,002	-0,001	0,000	0,001	0,002	0,004	0,005
Intercept p-value	0,946	0,000	0,000	0,000	0,000	0,944	0,000	0,000	0,000	0,000
HIGH YIELD										
Coefficient	-0,298	-0,017	-0,016	-0,015	-0,011	-0,011	-0,009	-0,008	-0,010	-0,011
Coefficient p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,018
Intercept	0,001	-0,004	-0,002	-0,001	0,000	0,000	0,001	0,002	0,002	0,004
Intercept p-value	0,754	0,000	0,000	0,000	0,002	0,156	0,000	0,000	0,000	0,000