Fixed Income Factors and the Implication's for Option Prices

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Zásady pro vypracování

Introduction

Define the objectives and the application methods used in the Master thesis.

I) Theoretical part

- Literature review on the relationship between fixed income factors and implied volatility index in the Bund Futures market, and an overview of existing option volatility strategies.

II) Practical part

- Identify the top 5 fixed income factors impacting IVI using Light GBM by collecting and pre-processing data, conducting feature engineering, training a model, ranking feature importance, and selecting the top 5 factors.
- Develop and evaluate trading strategy based on these factors against Short Condor Strategy.
- Test trading strategy using out-of-sample data from 2014-2023.

Conclusion

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ABSTRAKT

Cílem této práce je zjistit, jak faktory s pevným výnosem ovlivňují index implikované volatility na trhu s futures na dluhopisy, což může následně ovlivnit ceny opcí. Vysvětlující faktory indexu implikované volatility jsou odhadnuty s využitím rizikových faktorů fixního příjmu a jejich významnost je vyhodnocena s využitím strategie Short Condor jako referenční opční strategie volatility. Analýzy mimo vzorek jsou prováděny s využitím dat z období od března 2014 do červenec 2023. která byla rozdělena na trénovací a testovací soubor, a pro vyhodnocení výkonnosti strategie Short Condor jsou zvažovány všechny faktory trhu s pevným výnosem. Model Light GBM identifikuje pět nejvýznamnějších faktorů trhu s pevným výnosem na základě jejich relativní důležitosti. Předpovědi Light GBM týkající se těchto faktorů jsou pak využity ke konstrukci obchodní strategie založené na indikátorech. Tento výzkum přispívá k lepšímu pochopení vlivu faktorů pevného příjmu na index implikované volatility a může pomoci při vývoji efektivnějších opčních strategií na volatilitu.

Klíčová slova: Index implikované volatility, trh s dluhopisovými futures, ceny opcí, rizikové faktory s pevným výnosem, short Condor strategie, strategie volatility, Light GBM model.

ABSTRACT

The purpose of this thesis is to investigate how fixed income factors influence the implied volatility index of the Bond Futures market, which in turn can affect option prices. The explanatory factors of the Implied Volatility Index are estimated utilizing Fixed Income Risk Factors, and their significance is evaluated utilizing the Short Condor Strategy as the benchmark option volatility strategy. Out-of-sample analyses are conducted using data from March 2014 to July 2023, which was divided into a training set and a test set, and all fixed income market factors are considered to evaluate the performance of the short condor strategy. The Light GBM Model identifies the top five fixed income market factors based on their relative importance. The Light GBM predictions on these factors are then utilized to construct an indicator-based trading strategy. This research contributes to a greater comprehension of the impact of fixed income factors on the Implied Volatility Index and can aid in the development of more effective volatility option strategies.

Key words: Implied volatility index, bond futures market, option prices, fixed income risk factors, short Condor strategy, volatility strategy, Light GBM model.

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Motto: "Knowledge Explored, Wisdom Attained."

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Declaration of Honor:

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By submitting this thesis, I pledge my commitment to upholding the highest standards of academic ethics, honesty, and integrity in all my future academic and professional endeavors.

Signed: ____________________

Nirav Vyas

Date: 01.08.2023

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INTRODUCTION

When you acquire an asset, such as stocks or bonds, you become its proprietor. A substantial change in asset prices could affect investor returns. The fluctuation of an asset's valuation over time is known as its volatility. The annualized price fluctuations of an asset are known as realized volatility. Derivative products, such as options, are not linearly related to the underlying asset price and can be profitable in a variety of market conditions, such as during a crisis when most assets decline in value; an options-based derivative strategy can be uncorrelated to such a crisis. Options can contribute to achieving the investment objective because they have the potential to generate income, reduce risk, or profit from your favorable or bearish price prediction for the underlying asset. When you buy or sell an option, you obtain the right to acquire or dispose of the underlying asset. Unlike American options, which can be exercised at any time before the expiration date, European options can only be executed on the maturity day.

Figure below depicts how the master's thesis would be divided into five sections. The first topic would be the thesis' preface. The second topic is subdivided into subsections discussing the literature pertaining to bond futures, bond futures options, implied volatility of bond futures, fixed income risk factors and their implications, the significance of employing the options volatility strategy, and a summary of the literature review. The third topic describes the data set and presents data collection and summary statistics; the fourth topic is devoted to data analysis, including the results of quantitative methods such as PSL Regression, the Granger Causality test, and the Light GBM; and the final topic discusses the conclusions.

1. Introduction

2. Literature Review

3. Research Design and Methodology

3.1 Data Preprocessing – Collection of Data from 2012 to 2023.

3.2 Feature Variables- Factors from literature in general.

3.3 Target Variable- Bond Futures Implied Volatility Index.

3.4 Description of Model Used

3.4.1 **Regression**

PLS Regression analysis to determine the explanatory factors of implied volatility, taking into account numerous factors that could affect the implied volatility dynamics

3.4.2 **Statistical Linkage**

Granger Causality Test the statistical hypothesis method is used to check if any statistically significant between explanatory factors and short condor strategy performance.

3.4.3 **Factors significance out of sample forecast**

The Light GBM machine learning-based classification technique, to model factor based short condor strategy and forecasting the out of sample performance.

4. Findings and their implication on volatility strategy.

4.1 Result from Regression.

4.2 Result of Factors Significance Strategy.

4.3 Results of Out of Sample Forecast.

4.3.1 In Sample Test

4.3.2 Out of Sample Test

4.3.3 Performance comparison using trading signals

5. Conclusions

OBJECTIVE

This paper's primary objective will be to identify explanatory factors of implied Bond futures volatility, considering risk factors in the fixed income market. Bond futures are derivative products based on the fundamental asset of the 10-year German government bond, and Bond futures options derive their values from Bond futures. Fricke et al. (2011, p. 15) found that Bond futures are a key asset in the euro area for setting prices in terms of interest rate risk. The implied volatility derived from Bond futures options would be of great assistance in comprehending the European Futures Market. Sundaresan (2009, p. 14) and Fabozzi (2007, p. 17) discuss global fixed income market risk factors. Included are interest rate risk, credit risk, liquidity risk, yield curve risk, inflation risk, event risk, foreign exchange risk, volatility risk, and sovereign risk. We also investigate whether explanatory factors for implied volatility exist. Subsequently develop a model for out-of- sample data to determine whether the factor-based options short condor strategy outperforms the buy-and-hold options short condor strategy.

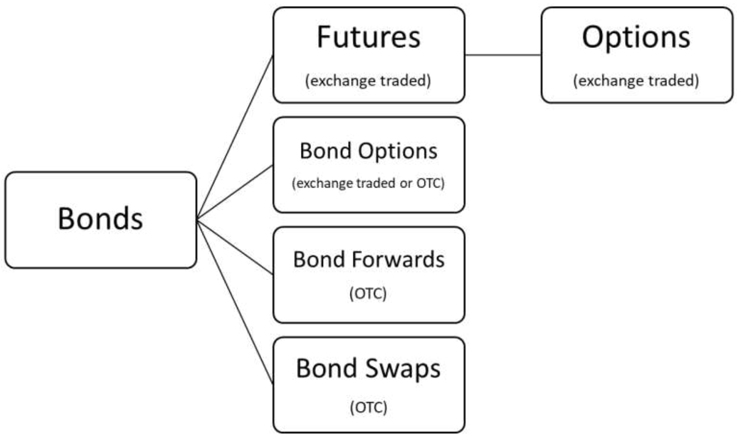


Figure 1: Bond Derivatives (own processing)

METHODOLOGY

This thesis investigates the explanatory factors of implied volatility while taking risk factors in the fixed income market into account, as well as their statistical significance and their ability to predict the performance of an options volatility strategy using out-of-sample data. To determine the significance of out-of-sample data forecasts, a statistically significant test of option volatility strategy factors is conducted by constructing an option volatility portfolio that profits from changes in volatility. Predictions for out-of-sample data are determined by constructing a factor-based model. Traders and investors who use options to make nonlinear profits, reduce risk, or hedge against a linear underlying would be able to manage their portfolios more effectively if they knew the explanatory implied volatility factors that would result from my thesis, as well as how portfolio performance would change as factors changed. Our factor-based model, which appears to operate as simplified versions compared to complex models by leveraging predictability, can support risk management and portfolio decisions and enhance option volatility trading performance.

As depicted in Figure 2, this is addressed by the primary research question "What are the Factors of Bond Implied Volatility and Implications for Volatility Strategy?"”. The following supplementary research queries will help fill the void left by a broader perspective.

R.1.1 Which variables explain the present dynamics of implied Bond volatility?

R.1.2 Does Granger causality exist between factors and the option volatility strategy?

R.1.3 Are factors significant in the out-of-sample forecasts of the option volatility strategy?

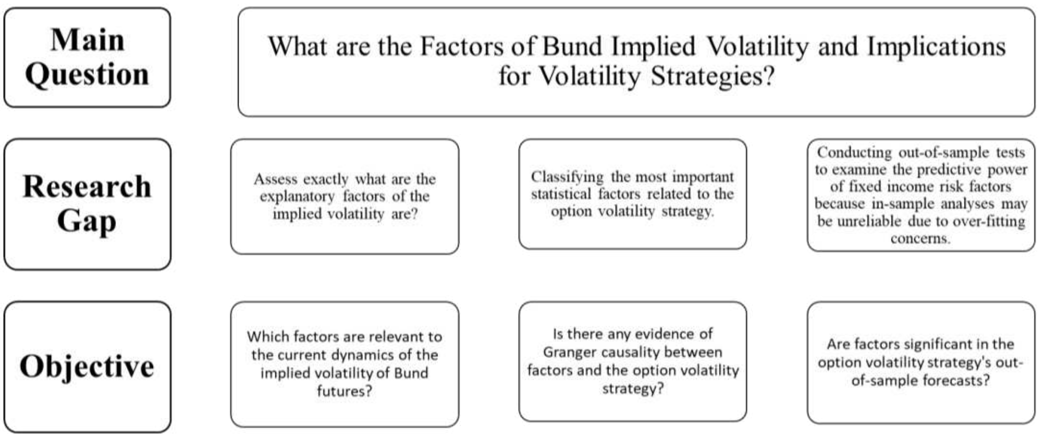


Figure 2: Main Research Question (own processing)

To begin answering these questions, we employ the implied at-the-money (ATM) 1 Month forward volatility index (RX 1M 50D VOL- Bloomberg Ticker) as a surrogate for Bond Futures Implied Volatility. The majority of the factors we consider are derived from the academic literature. We first use partial least squares (PLS) regression to examine the explanatory factors of the implied volatility, followed by a multivariate Granger-causality test between explanatory factors from PLS regression and the option volatility strategy, and then out-of-sample tests-Light Gradient Boosting Machine (GBM) to examine the predictive power of factors from the fixed income market on the option volatility strategy using out-of-sample data.

I.Theory

1. LITERATURE REVIEW

This topic discusses previous studies on government futures, government futures options, implied volatility, fixed income risk factors and their implications for bond futures, the importance of employing the options volatility strategy, and a summary of the relevant literature. It begins by attempting to define some characteristics of implied volatility in bond futures. Following a discussion of the used factors as part of the theoretical foundation, the chapter concludes.

1.1 Government Bond Futures

Futures are a type of derivative whose value is derived from the value of the fundamental asset. The most active trading occurs on futures markets, and investors discount their cash flow based on future expectations. Futures markets convey more information about risk premiums than spot markets. During difficult economic times, the futures market contains crucial information that the current market does not. During certain time periods, the future price can be defined as the sum of the spot price and the positive carry earned through market financing and lending. However, Upper et al. (2002, p. 1) express doubts that futures markets should not contain information that is distinct from spot markets. They explain that differences in risk premium between the spot market and a futures market may be subject to a number of risks, such as the absence of an opposite position to close or buy a position in different markets, increased financing needs for brokers due to increased market volatility, and adjustments to the cheapest to deliver bond (Upper & Werner, 2002, p. 9) The term cheapest to deliver bond refers to the least expensive bond that the futures vendor can deliver to fulfill their contractual obligation.

According to Yadav et al. (2003, p. 1876) the ability to take more calculated risks is facilitated by the order flow of specific assets in various markets, such as spot and futures markets, which varies with information content. These distinctions in the information evaluation performed by each market can be used to defend against various risks present in fixed income markets, such as interest rate risks. Futures markets have a greater likelihood of price discovery than spot markets due to the costs associated with transacting in spot markets (Brandt, 2007, p. 1049). The derivative market is utilized to generate carry-returns from interest differentials on positions held in various markets and to safeguard the underlying asset in the spot market.

Both the spot and derivative markets are influenced by the supply and demand of cash securities and derivative securities. Economic factor data announcements influence the "information shares" of derivative markets in the hour following the announcement, but the effect is diminished during and after central bank statements. It is crucial to make well- informed judgments based on futures market data, as changes in position can otherwise result in ambiguous changes in profits (Bruce Mizrach, 2008, p. 1230).

According to Ahn et al. (2002, p. 680) Bond Futures have become one of the most tradable financial assets. Bond Futures are derivative products based on the Bond, the 10- year German government bond. In 2021, Bond Futures trading volume reached 203 million contracts, with a market notional value of €35 Trillion (Futures Market, 2021) In the Eurozone, Bond futures have a long history as a benchmark derivative instrument, extending back to before their 1997 listing on the Eurex exchange. According to Fricke et al. (2011, p. 1071) as the most active derivative product in the euro area, the Bond Future conceals information faster than any other asset. Fricke et al. (2011, p. 1057) list some of the most important aspects of Bond Futures, such as a competent government with no recent default history, the significance of the futures market relative to the cash market, and the order flow of the futures market relative to the cash market. Fricke et al. (2011, p. 1071) demonstrate that Bond Futures play a significant role in price discovery for eurozone interest rate risk. Futures contracts for German government bonds are subdivided into four sections based on their remaining term (maturity), with the following names:

A. Futures on the Euro-Schatz are among the contracts with maturities between 1.75 and 2.25 years.

B. Euro-Bobl Futures are among the contracts with 4.5 to 5.5 year maturities.

C. Futures on the Euro-Bond have maturities ranging from 8.5 to 10.5 years.

D. Futures on the Euro-Buxl are among the contracts with maturities ranging from 24 to 35 years.

According to Fricke et al., the most readily available tradeable futures with highly rated underlying bonds are "Euro-Schatz Futures, Euro-Bobl Futures, and Euro-Bond Futures." (2011, p. 1058).

1.1 Options on government bond futures

Options are a type of derivative financial instrument that entitles the possessor to exercise it on the underlying assets at a future date. Future-related volatility influences the price of options, which is determined by the Black-Scholes equation.

According to Wilkens et al. (2006, p. 51) the Black-Scholes equation can be solved backwards to determine the future volatility of the underlying instrument. This market- priced future price fluctuation, derived from the prices of options quoted by market participants, can be used to forecast the future price range of the underlying asset. The future distribution of the underlying asset can also be approximated using the implied volatility for various strike prices derived from the underlying asset's options.

According to Dunis et al. (2004, p. 197) investors who have a solid grasp of implied volatility through options have an advantage over their competitors during the decision-making process. Using implied volatility to estimate the expected price range of the underlying asset's price enables investors to assess the potential risks of an option strategy, such as the maximum loss that could be sustained, and make informed decisions about when to close positions to protect their investment. According to Baran et al. (2020, p. 1) the market value of an option incorporates future uncertainties. Using various expectations derived from these option prices can provide a reliable indicator of future underlying asset prices. Baran et al. (2020, p. 2) construct a variety of volatility indices based on government bond futures that can integrate future uncertainties and forecast the volatility of the underlying asset. This market's volatility can be analyzed using a volatility index comprised of options derived from bond futures in multiple countries. Mismatches in the volatility index can be utilized for trading or safeguarding portfolios and underlying assets from risk. Option prices can provide key moments such as variability, asymmetry, and tail thickness, which can aid in portfolio repositioning and risk management. Chatterjee (2014, p. 121) states on page 121 that Risk management and trading strategies rely heavily on the term structure of statistically significant moments.

In academia, implied volatility, which is derived from option prices, is one of the most frequently discussed terms. In the section that follows, we will investigate the concept of implied volatility and whether it can produce accurate forecasts. We intend to concentrate on futures based on German government bonds (Bond Futures). Our goal is to analyze the factors influencing the implied volatility of Bond Futures and to comprehend the risk premium reflected in option prices. Understanding the factors that affect implied volatility can aid in predicting future unpredictability and enable better portfolio positioning in preparation for a variety of potential future outcomes. The Bond Futures Options that trade on the Eurex Exchange describe the options that are transacted on the market.

1.2 Implied Volatility

There are options for various time periods, including weekly, monthly, and quarterly. The implied volatility of an option can be used to determine how much the underlying asset will change in the future, because the price of an option includes an estimate of the underlying asset's volatility. For instance, if a central bank meeting is approaching in 10 weeks, the monthly options would account for the potential volatility induced by the central bank's decision, whereas the weekly options would not. Different maturity options entail distinct future hazards or uncertainties.

Three types of volatility are defined by Szakmary et al. (2003, p. 2152) historical volatility, realized volatility, and implied volatility. They define realized volatility, for example, if the Black Scholes equation is solved backwards using available historical call/put prices, the realized volatility is the result. According to Szakmary et al.'s (2003, p. 2173) analysis of various futures markets, implied volatility is an effective indicator for estimating future actual volatility, which can be defined as the fluctuation of the underlying price until the option expires. According to Wang (2009, p. 218), research has demonstrated that the implied volatility in various markets, such as the equity, money, and bond markets, possesses "information linkage" and "market volatility" that can be used to assess various future uncertainties. The implied volatility of various assets can be correlated, allowing for repositioning. If the contagion is observed in some assets but not others, portfolios may be affected. Nonetheless, this informational linkage can also reduce asset diversification.

According to Simon's (1997, p. 1) analysis of the relationship between the change in the price of US Treasury bond futures and implied volatility, the positive and negative link between the two impact the buying and selling of options differently. During a decline in bond futures prices, trading volume increases, resulting in an asymmetry in implied volatility. Asymmetry is greater when bond futures prices decline compared to when bond futures prices rise. Due to greater asymmetry during the decline of bond futures prices, it is more likely that implied volatility will increase. Simon (1997, p. 12) suggests purchasing puts instead of selling the futures contract during a decline in the price of bonds, as you would profit from a change in implied volatility. Option prices increase proportionally to implied volatility. According to Oozeer et al. . (2002, p. 114), options with various strike prices may have varying degrees of sensitivity to asset price changes, causing option prices for different strikes to respond differently to changes in the direction of asset price changes.

Scholes et al. (1973) developed the Black-Scholes option pricing model, which assumes that the implied volatility of various strike prices for the same underlying asset remains constant. After the 1987 market crash in the United States, it was observed that the market began to price the implied volatility of options differently for various strike prices, giving rise to the concept of the "volatility smile." When the strike price is plotted against the implied volatility, a smile-shaped curve results, with higher prices for out-of-the-money (OTM) put and call options. (i.e., options with strike prices higher than the current underlying price). According to Ignacio Pea et al. (2001), the existence of volatility smile due to the rise in value of OTM and ITM options in comparison to ATM options is brought on by "excess kurtosis in the distribution of returns on the underlying asset." The plot seems to lean more to one side than the other as a result of the imbalance in the US economy. Chen et al. (2022, p. 1) note that an increase in implied volatility causes an increase in option prices, resulting in "one of the most well-known financial anomalies" (option implied volatility grin). Chen et al. (2022, p. 16) discover that different moments of implied volatility smile, such as levels, slopes, and curvatures, have implications for trading. They also assert that the market utilizes the correct side of the volatility grin, i.e., the right side of the smile. OTM Telephone Call option to speculate on the fundamental asset's direction. Chen et al. (2022, p. 16) examine the spillover effect of implied volatility across various markets and find that implied volatility "smiles together" with countries with the same macrostructure, such as the United States and the European Union.

Volatility smirk is defined by Pathak et al. (2018, p. 64) as the disparity between an out-of-the-money put option and an in-the-money call option for the same underlying asset. During a crisis market, participants/investors are willing to pay more for OTM put options compared to Call Options due to the payoff structure of the put options, which protects investors during a market decline, resulting in a volatility smirk structure of implied volatility relative to the strike price. Pathak et al. (2018, p. 65) state that through volatility smirk, investors can reduce their future prospective losses due to volatility smirk's directional indication. When volatility is high and uncertainty is high, option traders can profit from short volatility strategies by selling options. These strategies capitalize on the volatility decline from its apex, allowing traders to profit from the volatility decline. According to Pathak et al. . (2018, p. 69) , volatility smirk can serve as a reliable indicator of the "marginal return" of the underlying asset upon which options are priced. In other words, you can profit during a market decline if you are on the correct side of the transaction and have correctly predicted the market's direction from its peak to its low.

The volatility smirk is defined by Silverio et al. (2005, p. 11) as the market's willingness to pay more for an asset's downside than its potential. During uncertain periods, market demand for put options increases relative to call options, resulting in fewer opportunities to hedge against a market crash. Figure 3 depicts the volatility smirk for Bond Futures Options, followed by plots for option expiration months including August 2022, September 2022, and October 2022. The graph illustrates how the market has valued various options regarding strike price for various maturities. The implied volatility for Bond Futures is obtained from Bloomberg for options with varying maturities.

Figure 3 demonstrates that implied volatility smile and smirk are also apparent in Bond Futures, with implied volatility smiling for August options' maturities and smirking for September and October maturities. It would be beneficial to comprehend the factors that impact implied volatility, notably when risk factors from the fixed income market are considered. Why do various factors cause investors' perceptions of future uncertainty to fluctuate? What factors are considered, and how do they influence the probability that the option will expire? This master's thesis will identify, based on option prices, the factors that influence implied volatility to fill knowledge gaps and enhance understanding of the major factors influencing implied volatility.

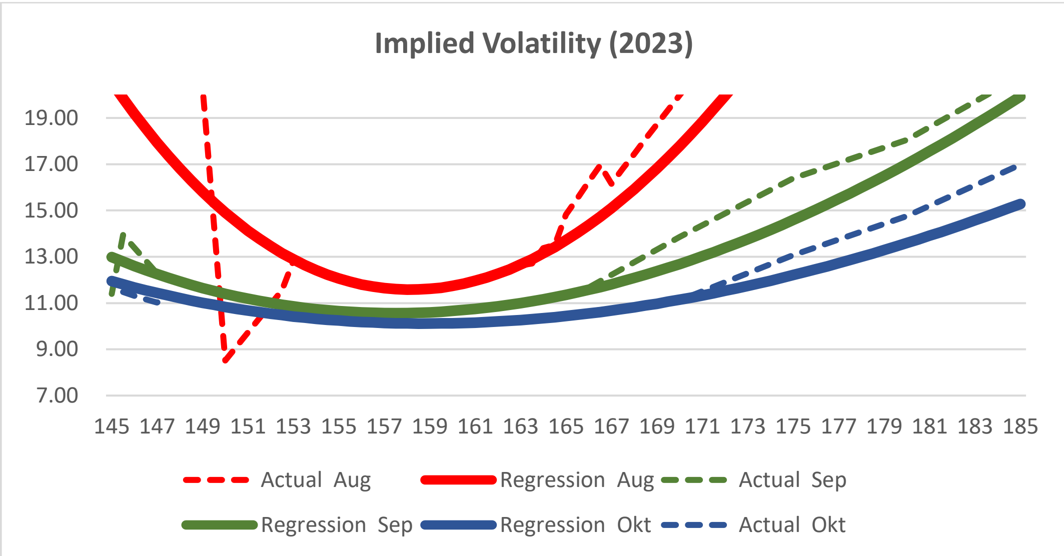


Figure 3: Volatility Smirk of Bond Futures (own processing)

1.3 Examining the factors that influence volatility outside of bond risk factors.

According to Singh et al. (2019, p. 321), oil is frequently blamed for global market volatility because it serves as a barometer of global economic trends and an indicator of developed economies. Oil is a commodity traded between many countries around the world, with some countries with excess oil reserves exporting oil to countries with fewer oil reserves. Changes in global oil prices can influence revenues and assets linked to oil, causing volatility to spread to other assets in oil exporting nations. As most oil expenses are paid in U.S. dollars, an increase in oil prices would also have a negative effect on the capital reserves of oil-importing nations, as they would be required to pay higher prices per barrel. Mensi et al. (2021, p. 15) note that Oil Futures serve as a significant indicator of financial market volatility via their inflation expectation-measuring components. A rise in oil prices increases future inflation expectations and bond yields, causing bond prices to decrease. The population consumes less because of higher crude prices, which reduces national income. The rise in oil prices because of the falling stock market, the depreciating value of the dollar, and low bond returns can explain market volatility (Amir Saadaoui, 2020, p. 1242).

According to a study by Prasad et al. (2022, p. 2), various economic factors such as the USD, gold price, and crude oil price can influence the VIX Index, a measure of stock market anxiety. Using machine learning techniques, they determined that these variables are reliable predictors of the VIX Index. Le et al. (2019, p. 28) found in a separate study that the stock price index in Vietnam is influenced by the price of gold, exchange rate, crude oil, M2 supply, and interest rates. Given the connection between the stock and bond markets, it would be fascinating to see how these factors affect bond market volatility and how they can impact the implied volatility of bond futures during times of market volatility.

1.4 Implementing a Volatility Strategy to Improve Portfolio Performance

Economic data announcements can affect market prices and volatility (Monroe, 1992). Profits are possible if a trader employs "Unexpected Volatility" as a strategy prior to data release. Volatility increases the cost of a call and puts options and the slope of the profit-and- loss curve. Participants in the market employ volatility strategies to speculate on market direction, generate risk-free profits, and safeguard underlying assets (Felix Goltz, 2012, p. 7) .When volatility is anticipated to increase, hedge funds implement long volatility exposure and when volatility is anticipated to decrease, they implement short volatility exposure (Srikant Dash, 2005, p. 77).As volatility returns to normal levels, the difference between 1-month and 3-month implied volatility can benefit risk-free profit producers (Felix Goltz, 2012, p. 4) . Options spread transactions, in which both calls and puts are held, can be used as bullish or bearish wagers with varying payouts based on the market cycle (McKeon, 2016, p. 422). Using a long call spread on index options, McKeon's research demonstrates that purchasing volatility yields favorable returns while selling volatility yields poor returns (McKeon, 2016, p. 432) To generate higher expected returns, it is essential to comprehend option payoffs and to know when to employ different strategies during various volatility regimes.

Brière et al. (2010, p. 3) discovered that purchasing volatility reduces market uncertainty more than traditional portfolios such as balanced portfolios or portfolios with a 100 percent allocation to fixed income. Doran explains that the average volatility has a left-skewed reward (2020, p. 842). Combining long implied volatility and long volatility risk premium strategies reduces extreme risk.

Moreover, both strategies protect investments during uncertain periods. According to Brenner et al., those who trade options using a directional neutral strategy are exposed to volatility risk, and a significant change in either direction can affect their positions (2006, p. 814). The ATMF strategy, in which call and put prices are predicated on the forward rate, entails volatility risk. Brenner et al. . (2006, p. 814) provide an illustration of the ATMF strategy and explain that the call and put prices reflect the risk of volatility with respect to the underlying asset.

During the 2008 financial crisis, some hedge fund and commodity indexes performed better than equity indexes, according to Szado (2009, p. 68).Szado utilized the implied volatility equity index as a risk-mitigating diversification asset. According to Szado (2009, p. 68) purchasing implied volatility can increase the diversification of an equity portfolio. Due to a negative risk premium, long-term investments in volatility strategies have been found to underperform the market. On the other hand, it has been demonstrated that shorting volatility generates an excess risk premium.

Numerous risk indicators affect option prices, including second moments of sensitivity such as charm and vanga and first moments such as delta, vega, theta, gamma, and rho. Chaput et. al (Option Spread and Combination Trading, 2003) noted that portfolio strategies could be developed based on sensitivity to underlying prices, volatility, time to expiration, or interest rates by employing a portfolio of options sensitive to some factors and neutral to others. The majority of spread strategies are more sensitive to the volatility of the underlying than to its prices. Combinations of options spreads can be utilized to both maximize exposure and mitigate certain risks.

Vertical spreads, including Call Spread and Put Spread, are employed to generate profits (Scott J Chaput, Vertical Spread Design, 2005). Most studies have concentrated on interest rate futures options, where vertical trades were executed to increase profits via extensive vertical spreads rather than to reduce losses by liquidating positions. Traders favor out-of-the-money (OTM) options because they are less expensive than other options under the spread payment structure. Spreads on ratios are regarded as "more versatile options trading strategies" (Scott J Chaput, Ratio Spreads, 2008). In ratio spreads, extra calls or puts are sold at varying prices. strikes were purchased for a solitary strike. If more options are sold than purchased, gains will be limited and losses will be unlimited, according to this theory. Nevertheless, Scott J. Chaput et. al (Ratio Spreads, 2008) noted that the use of ratio spreads as a volatility spread is still ambiguous, as their sensitivity to the various risk variables for volatility and directional change is too low to be considered for the volatility strategy. Most traders prefer a spread ratio of 2-1 because it balances the directional variations of the underlying.

Niblock (2017, p. 40) analyzed several variations of the iron condor strategy, such as the "long call, short call, long put, short put" and the iron condor, which consists of four legs comprised of both calls and puts. According to the results of their analysis, the short volatility strategy has weak skew returns, whereas volatility would be the primary factor driving the returns of the spread strategy. Statistics from Niblock (2017, p. 49) indicate that not all condor strategies perform well in terms of risk-return profiles, but these strategies can be advantageous for certain investors and market conditions. For instance, a strategy of selling volatility would generate cash flows without reducing the value of the capital retained for prospective future gains. According to Niblock (2017, p. 49) , a selling volatility strategy can generate cash flows without reducing the value of capital held for potential future gains, but it is only advantageous for investors with a moderate risk tolerance who can tolerate the risk-return tradeoff. According to Dziawgo, developing options strategies based on various strike prices and option maturities can result in effective risk management and have a substantial effect on the underlying price (2020, p. 34) . The iron condor strategy, consisting of a bear call spread and a bull put spread, has been proven successful (Dziawgo, 2020, p. 35) .

2. Options

2.1 Definition of Options

Options are financial contracts that grant the buyer the right, but not the obligation, to purchase (in the case of a call option) or sell (in the case of a put option) an underlying asset at a specified price (known as the exercise price or strike price) within a specified time frame (known as the expiration date). The fundamental asset can be anything with a market price, including stocks, commodities, and currencies. Option valuation is the process of determining an option's reasonable value. The most prevalent option pricing model is the Black-Scholes model, which considers the underlying asset price, the exercise price, the time to expiration, the risk-free interest rate, and the underlying asset's volatility. The intrinsic value and time value are the two primary components of an option's price (2008). A calculation of an option's profitability based on the strike price and market value of the underlying asset is its intrinsic value.

The time value of an option is determined by the expected volatility of the underlying asset and the time remaining before expiration. The time value of an option describes the probability that its price will fluctuate as the underlying asset's price changes up until the option's expiration date. The call option price for an out-of-the-money (OTM) option, whose strike price is greater than the price of the underlying asset, incorporates only time value (Bondarenko, 2003). The Out-of-the-Money (OTM) call option has time remaining before expiration, so there is a possibility that it will become In-the-Money (ITM), which means that the price of the underlying asset will exceed the option's exercise price, allowing investors to profit from a rise in the option's price. The price of an OTM call option maintains its time value until the option expires, but if the exercise price is higher than the underlying price at expiration, the option expires void and the investor loses the premium paid to acquire it (Khorana, 1999).

Even if the price of the underlying asset has no impact on option prices, macroeconomic, monetary, fiscal, and geopolitical information will impact the time value component of option prices. As the probability of being "In the Money" fluctuates, so does the time value component of the option price until it expires. If the price of the underlying asset moves in the anticipated direction or if the implied volatility changes as a result of new information that can affect option prices, option trading is likely to generate profits.

2.2 Black-Scholes model

The Black-Scholes model implies that the price of the underlying asset follows a random walk, which means that it fluctuates randomly over time. Based on the supposition that the underlying asset's price will follow a log-normal distribution, the model computes the expected value of the option at expiration (Merton, 1973).

Two components comprise the value of an option: intrinsic value and time value. The intrinsic value is the sum of the current market value of the underlying asset and the exercise price of the option. The intrinsic value of a call option is positive when the underlying asset price is greater than the exercise price, and the intrinsic value of a put option is positive when the underlying asset price is less than the exercise price.

The time value of an option is its value in excess of its intrinsic value, which is determined by the time remaining until expiration, the volatility of the underlying asset, and the risk- free interest rate. Time value is the possibility that an option's intrinsic value will increase before expiration.

Options may be in-the-money (ITM), at-the-money (ATM), or out-of-the-money (OTM). An ITM option has intrinsic value, whereas an ATM option lacks intrinsic value but has time value, and an OTM option has neither intrinsic nor time value (White, 1987).

In practice, the price of an option is determined by the market forces of supply and demand. The implied volatility of the underlying asset is reflected in the prices set by market participants for options, and the Black-Scholes model can be used to calculate an option's implied volatility given its market price and other inputs. The prices of options can also be affected by macroeconomic, monetary, fiscal, and geopolitical information. Understanding options and their value is crucial for investors and speculators seeking to mitigate risk and generate profits in the financial markets.

Options are valued using the Black Scholes equations, with inputs including underlying assets, time until maturity, option type, interest rates, volatility, and strike price. Black- Scholes's equation would yield the option prices as its ultimate output. When using the Black- Scholes formula to compute the price of a future-expiring option, we are unaware of two components: the option price itself and the volatility leading up to the option's expiration. The value of At the Money (strike price of option equal to underlying asset price) options is determined by market makers based on the demand and supply of ATM options (Madan, 1999). Since the price of an ATM option is determined by supply and demand, the only variable that remains unknown is the implied volatility of ATM options, which is determined by the Black Scholes equation using all known parameters and lasts until the option expires. The implied volatility of the underlying asset is reflected in the prices set by market participants for options. In other words, the implied volatility is used to represent volatility in Black's formula, which recreates the market-quoted price for an option. The option price or implied volatility may be quoted by the market (Schwartz, 1978).

2.3 Short Condor Strategy

The Short Condor is a complex options trading strategy that entails the simultaneous purchase and sale of four option contracts with, typically, the same expiration date. The objective of the strategy is to generate a profit by exploiting a restricted price range for the underlying asset. The Short Condor is a variation of the Condor spread, which is a limited-risk, limited-reward option trading strategy involving the purchase and sale of multiple option contracts with varying strike prices (Zaremba, 2019). In a Condor spread, the trader simultaneously sells two options contracts at one strike price, buys two options contracts at a higher strike price, and simultaneously buys and sells two options contracts at an even higher strike price. If the price of the underlying asset remains within a narrow range between the lower and upper strike prices, the result is a profit.

This strategy's Short Condor variation entails selling options contracts at two different strike prices rather than purchasing them. In particular, the trader sells two options contracts at a lower strike price, purchases one option contract at an intermediate strike price, and sells two options contracts at an even higher strike price (Klein, 2012). The result is a profit if the price of the underlying asset remains within a limited range between the lower and upper strike prices, and if the middle strike price remains higher than the price of the sold options.

2.4 Option Strategy

A combination of one or more option contracts that can be used to attain specific investment objectives or mitigate potential risks constitutes an option strategy. There are a variety of option strategies available to investors, each with their own advantages and disadvantages. These are some frequent option strategies:

Covered call: entails purchasing the underlying asset and selling the corresponding call option (Wang J. , 1995). This strategy can generate income from the sale of the call option premium while limiting potential losses should the price of the underlying asset decline.

Protective put entails purchasing both the underlying asset and a put option on that asset. This strategy can protect against potential losses if the price of the underlying asset declines, while also permitting potential gains if the price rises.

Long Straddle: A long straddle entails purchasing a call option and a put option with the same strike price and expiration date on the same underlying asset. This strategy can profit from large price movements in either direction, while limiting losses when the price does not move substantially.

Short Straddle: Selling a call option and a put option on the same underlying asset with the same strike price and expiration date is known as a short straddle. This strategy has the potential to generate income from the sale of options but entails the risk of substantial losses if the price moves too far in either direction.

Iron Condor: An iron condor entails buying and selling multiple calls and put options with different strike prices and expiration dates on the same underlying asset. This strategy can generate income from the sale of options while limiting potential losses if the price stays within a predetermined range (Paras, 1996).

These are only a handful of the numerous option strategies available to investors. The strategy chosen by an investor will depend on his or her individual objectives, risk tolerance, and market outlook.

2.5 Risks of the Fixed Income Market

If an investor or trader understands the variables that affect the implied volatility of Bond Futures, which already accounts for the risk premium for future uncertainties, they would have an advantage when predicting the direction of the underlying asset and repositioning their portfolio. Various risk factors could influence the underlying asset and, in turn, the implied volatility and option prices. Understanding these factors can provide an investor with a competitive advantage in various market conditions. Risk factors can influence implied volatility and option prices via their relationship to the underlying asset or via a spillover effect from another asset class. As a result of globalization, most nations respond to the flow of information from one central bank decision to another, which can impact the underlying assets and derivatives that depend on it. Due to the structure of financial markets and their participants, each asset is likely to be influenced by a multitude of risk factors. The primary aim of this thesis would be to be to categorize the factors that influence the implied volatility of Bond futures, considering risk factors in the fixed income market, with the ultimate objective of enhancing understanding of the European Futures market using implied volatility derived from Bond futures options, which are based on Germany's 10-year government bond.

Portfolios managed by investors and portfolio managers who limit the amount of potential profits through investment risk must take volatility into account (2003, p. 478). Since the implementation of the Basel accord in 1996, for instance, banks have been required to maintain three times the amount of capital as hazardous assets. Volatility is a crucial factor in calculating Value at Risk.

When determining monetary policy, the Bank of England (Central Bank of the United Kingdom) considers the implied volatility distributions of options (2003, p. 479).

Given the structure of the various fixed income securities, Sundaresan (2009, p. 14) and Fabozzi (2007, p. 17) outline numerous risk considerations for the fixed income market as a whole. In general, Sundaresan (2009, p. 14) and Fabozzi (2007, p. 17) provide the following list of hazards for the fixed income markets:

- Interest Rate Risk
- Credit Risk
- Liquidity Risk
- Inflation Risk
- Event Risk
- FX Risk
- Yield Curve Risk
- Volatility Risk
- Sovereign Risk

2.5.1 Interest Rate Risk

As interest rates rise, the value of an asset increases due to their inverse relationship, the price of these securities falls and vice versa. The only variable in fixed income securities such as government bonds that is subject to change based on macroeconomic conditions is the discount rate. (2006, p. 1998) . Understanding the relationship between monetary policy and asset prices is essential for understanding how policy changes can affect asset prices, such as fixed income securities, via interest rates, anticipated revenue flows, and excess yield (Kuttner, 2005, p. 1253) . Central bank policy decisions can affect fixed income securities and other assets and are typically announced every eight weeks based on the bank's assessment of the economy. Bonds have a higher correlation with future interest rate expectations than equities, but a lower risk premium (Ivan Indriawan, 2021, p. 2). The bond market is also influenced by the ad hoc interest rates set by the U.S. central bank.

Risk appetite and ambiguity are two factors that can influence the implied volatility of an asset (2013, p. 787). When the Federal Reserve lowers the fed funds rate, it reduces uncertainty and makes investors more risk-tolerant. Studies by Vahamaa et al. (2010, p. 1008) have also demonstrated that decisions made by the US central bank can influence the VIX index, which measures equity market uncertainty. The relationship between central bank decisions and implied volatility is variable, and implied volatility may decrease when central banks are "dovish" and support economic development by lowering interest rates. Bond risk premiums may also decline because of dovish central bank policy. The market may react fiercely to policy surprises when central banks are "hawkish" and advocate for a tighter monetary policy through an increase in interest rates. Additionally, asset prices can fluctuate in response to new information, resulting in heightened market volatility (Rohan Christie-David, 2003).

Unannounced meetings between central bankers have a discernible impact on future uncertainty. When central bankers convene unannounced meetings, market uncertainty increases, leading to greater implied volatility (2021, p. 20). In addition, Smales's research indicates that Treasury auctions contribute to increased market volatility. During an auction, the increase in supply of the underlying financial instrument causes a decline in future prices and an increase in futures price volatility (Markus K. Brunnermeier, 2017). The findings demonstrate the impact of central bank meetings and Treasury auctions on implied volatility in the fixed income market.

2.5.2 Credit Risk

Credit risk is an essential consideration when purchasing bonds. When market conditions are unfavorable and the bond issuer struggles to meet payment obligations, the risk of default rises. This can be attributed to the tightening of monetary policy in the global economy. Depending on the issuer, the sensitivity of debt securities to these adjustments can vary. For instance, low-yielding corporate bonds may be less correlated with monetary policy than high-yielding corporate bonds, as issuers of low-yielding corporate bonds may be able to issue new debt at higher interest rates (Nina Boyarchenko R. C., 2022).

When analyzing the factors that influence the implied volatility of currency options, Bhat (2018, p. 1804) employs the spread between local government 10-year bonds and US Treasury 10-year bonds as a proxy for "default spread." The spread can be affected by a country's capital inflows and outflows, which can influence the demand for certain options that are further out-of-the-money. (OTM). If the risk of default or credit risk increases, foreign investors may sell their securities and domestic investors may attempt to hedge their downside risk with OTM put options, leading to an increase in volatility. As an indicator of default risk, Mixon (2002, p. 934) employs the spread between corporate and government yields for the same maturity. According to the findings of Mixon (2002, p. 934), options with shorter maturities are affected by short-term interest rates, whereas the implied volatility curve for various maturities is affected by the difference between corporate and government bond yields. As a change in the slope of implied volatility smile for short-term options would increase the cumulative default spread, determined that the slope of implied volatility smile explains the cumulative default spread (2008, p. 727). Default spread is a significant determinant of ATM volatility. They also mention that the increasing number of international trades has made default spread a suspect of returns correlation, volatility spillover, and risk contagion. (2016, p. 819). As the likelihood of default increased during the European Government Crisis of 2013, capital fled a number of countries, including Greece, Italy, and others (Qian Han, 2016, p. 830) .

2.5.3 Liquidity Risk

Ability of issuers to issue new debt in the primary market and the ability of market participants to purchase and trade securities in the secondary market Boyarchenko et al. (2021). If market liquidity declines, it can impact the capacity of issuers to issue new debt securities, as well as the secondary market, which frequently uses the primary market as a benchmark for comparable bonds (Nina Boyarchenko A. K., 2020). In the secondary market, a wider bid-ask spread - the difference between the price at which a bond is offered for sale and the price at which it is purchased - may indicate less liquidity in the market for that security (2005, p. 85).

Liquidity is defined as the ease and low cost of purchasing and selling assets. In addition, they observe that when the Federal Reserve reduces interest rates or engages in quantitative easing, it can increase the flow of money into financial markets, thereby impacting the liquidity of both equity and fixed income markets (August 2021, p. 16). Discovered no correlation between reduced short-term interest rates (repo rates) and greater liquidity in emerging markets and found a correlation between liquidity and volatility in the stock and bond markets (2005, p. 85).

During recent financial crises, such as the Financial Crisis (2007-2009) (2020, p. 207),the "taper tantrum" of 2013, and the flash rally of 2014, market liquidity decreased and volatile Treasury bond prices rose. These occurrences had a substantial effect on both volatility and liquidity (2020, p. 2) .

Lower market liquidity results in less trading activity and higher margin requirements because there is less available funding. This means that investors must provide more collateral to trade certain assets, particularly more volatile ones (2020, p. 2). As a consequence, volatile assets are traded less frequently than less volatile ones, and there is a positive correlation between volatility and low market liquidity. An increase in implied volatility (VIX Index) correlates positively with low market liquidity. The MOVE Index reflects not only investor risk aversion but also future bond price uncertainty (2017, p. 1) . If investors anticipate greater risk, they may settle for lower bond prices(higher yields). However, if the market is insufficiently liquid, active managers may be forced to reduce their bond investments due to the danger of being unable to sell the bonds without difficulty (2020, p. 207).

2.5.4 Inflation Risk

Inflation risk premium for longer-term bonds tends to be higher. During periods of procyclical inflation and active monetary policies, non-inflation-adjusted bonds have a negative correlation with the price stability premium and the downward-sloping nominal yield curve (1998) . Changes in central bank policy can have an effect on deflationary inflation and alter market participants' views of the inflation premium. Non-inflation-adjusted bonds can offer protection during procyclical inflation in the United States (2017, p. 2761).

The breakeven inflation rate is the difference between the yields on US Treasury bonds and TIPS (Treasury Inflation-Protected Securities) with the same maturity. TIPS bonds are linked to inflation, whereas Treasury bonds are nominal (2012, p. 634). This difference is utilized by central banks to gauge inflation expectations over the life of the bond, which includes the liquidity premium and the inflation risk premium, this difference is an estimator of expected inflation that is biased because it incorporates both the inflation risk premium and the liquidity premium (2014, p. 91). The presence of an inflation risk premium may be influenced by a rise in the risk premium or investor aversion to assuming the risk. Variations in long-term inflation are directly related to changes in the output gap, the Central Bank's inflation objective, and, to a lesser extent, the short-term nominal interest rate . (2012, p. 636) .

Price stability is characterized by consistent and predictable price fluctuations over time. Inflation risk premium can vary based on the investment in question and the economy's overall price stability (2010, p. 18) . The inflation risk premium is a measure of the expected return on an investment that accounts for the possibility of inflation-related price fluctuations.

The impact of macroeconomic data on the performance of government debt securities is substantial (Sami Vähämaa S. W., 2005, p. 818). The prices of these securities tend to fluctuate before and after the release of inflation and unemployment data, depending on whether the data exceeds or falls short of market expectations. If the data meets market expectations, bond market implied volatility may change. The market reacts differently to unexpected data than to expected data (Sami Vähämaa S. W., 2005, p. 819).

Bond futures can provide additional information for assessing inflation risk, according to research. Numerous covariance assets, such as bond futures, exhibited an average inflation risk premium of 87 bps (Kanas, 2014, p. 97). Based on the type of macroeconomic data disclosed, the option-implied distribution of bond returns becomes more skewed toward negative returns and less skewed toward positive returns (Sami Vähämaa S. W., 2005, p. 822) In other words, the moments of the return distribution are susceptible to change based on the market's interpretation of the data and its implications for future interest rate changes.

Foreign exchange options, which are a forward-looking indicator, provide an unbiased estimate of the inflation risk premium. (2014, p. 92). This implies that the inflation risk premium can be predicted by analyzing bond futures options, which can influence bond futures volatility. Research has also demonstrated that economic data from the United States and the Euro Area can influence the implied price distribution of German government bond futures (Sami Vähämaa S. W., 2005, p. 841).

The release of macroeconomic data, particularly inflation and unemployment data, has significant effects on the bond market and can influence the volatility of bond futures. Understanding the relationship between the inflation risk premium and macroeconomic data can provide invaluable insight into the performance of government debt securities.

2.5.5 Event Risk

Event risk refers to the potential impact of unanticipated events, such as announcements by central banks or government agencies, on financial markets. These occurrences can lead to abrupt shifts in the supply of securities or interest rates, thereby increasing market volatility. Disruptive events are rare but can have significant economic consequences, creating unique challenges for future economic conditions. This can influence bond prices and create uncertainty regarding the economy and interest rates. Several asset classes, including bond futures, are susceptible to event risk. For example, Bond futures prices can be affected by the publication of macroeconomic data such as government accounts, employment data, and retail sales. There may be a positive relationship between bond futures and unemployment rates, but a negative relationship between bond futures and certain news releases. According to, new information can rapidly affect the price of bond futures, often within 60 seconds (Suk-Joong Kim, 2001, p. 135) . Due to its direct relationship with the flow of money in the economy, the market continuously reacts to central bank policy news. A rise in the central bank's money supply results in an excess supply on lower-level financial markets, which propels the demand for assets (1986). An unanticipated policy announcement could lead market participants to assume that inflation forecasts have changed and that additional rate hikes are planned, impacting on market liquidity and the pricing of financial assets. Prior to the financial crisis, the loosening policies of central banks, such as lowering interest rates and increasing financial flexibility, had a positive influence on economic growth. However, this effect has since diminished. (2017, p. 16) .

The probability function of an option, which depicts the likelihood of various outcomes for the price of the underlying asset, can be used to forecast the expected return on a bond future during the release of significant macroeconomic data. Indicators related to the economy, such as growth, unemployment, and price stability, are included in macroeconomic data, which provide information about the overall health and performance of an economy. By analyzing the probability function of options in conjunction with the release of relevant macroeconomic data, it is possible to make informed estimates regarding the likely performance of bond futures during events such as the release of GDP, unemployment rates, or inflation data (Sami Vähämaa S. W., 2005, p. 818).

2.5.6 FX Risk

The decision to issue debt securities in domestic or foreign currencies, such as the US Dollar or Euro, can affect the pricing and liquidity of these securities. The pricing of a bond on the domestic market may differ from its pricing in a foreign currency due to differences in the yields offered to investors, as well as differences in the trading of these securities due to their liquidity. Providing a pledge in the domestic market can eradicate currency volatility risk. If the Chinese government were to issue a bond denominated in US dollars, for instance, it would be exposed to the risk of fluctuations in the value of the US dollar (Ofek, 2001). However, the Chinese government may choose to issue a bond in US dollars for a variety of reasons, including attracting investors to invest in China, diversifying risk for the issuer, and gaining access to a more liquid market. Bonds issued in a foreign currency can expose the issuer to foreign exchange risk, as fluctuations in the value of the foreign currency can have an impact on the coupon payments received by investors and the principal amount to be repaid (Brown, 2007).

Foreign currency risk for bond issuers in the Euro area has decreased since the introduction of the Euro, and bond trading has increased due to the use of a single currency throughout the Euro area. Historically, investors could conceivably earn a positive carry (the difference in interest rates caused by different currencies) by purchasing bonds denominated in different currencies. However, following the introduction of the Euro (€), investors were required to forego returns associated with foreign exchange differentials (Blanco, 2002, p. 66) (2002, p. 70). Before the adoption of a single currency, the primary factor affecting yield differentials (the difference in yield between two bond securities of the same maturity) in the Euro area was the difference in currency values between countries and the ratings of those countries based on their debt and economic stability. As an illustration, he notes that the yield differential (the difference in yield) of German government bonds decreased after the adoption of a single currency because foreign currency risk decreased. Adoption of a single currency also decreased the yield disparity between various Eurozone nations (Juha Kilponen, 2015, p. 1) .

The "foreign risk premium" refers to the difference between two countries' expected prospective short-term interest rates, which is affected by the exchange rate between their currencies. For instance, if the expected future short-term interest rates for German bonds are higher than those for US bonds, this disparity in interest rates may be partially attributable to the exchange rate between the US Dollar and the Euro. The European Central Bank (ECB) has a greater impact on the Euro than the US Dollar. Changes in the ECB's forward guidance on short-term interest rates are one example the gap between German and American short-term interest rates could broaden, influencing the foreign risk premium between the two currencies.

Central bankers make monetary policy decisions based on their specific mandates and the condition of their economies, and these decisions can affect the exchange rate premium (John H. Rogers, 2018, p. 1846). Domestic risk factors, such as "conditional volatilities," can impact the foreign exchange premium. These domestic risk factors, which can influence bond yields, also influence the foreign risk premium, which fluctuates in tandem with bond yield risk premiums. This is because bond yield risk premiums consider variables such as a country's inflation rate, economic status, and changes in monetary policy short-term interest rates, all of which can impact foreign currency risk. Changes in short-term interest rates, for instance, can affect interest rate volatility, which in turn can impact bond yields and the foreign risk premium. (Andrew Ang, 2010, p. 1). The spread between lending and funding will broaden if the US interest rate falls. Due to cross-border obligations and the financial system of the receiving nation, this imbalance will influence global financial conditions, but especially on those of the receiving nation. (2015, p. 120),. By minimizing the risk of volatility, a reduction in the cost of US dollar funding results in a rise in bank leverage. The leverage in the banking sector is correlated with the implied volatility of the S&P 500 as a risk indicator.

Emerging market central bankers' interventions on the foreign exchange market have the potential to increase market volatility. This is because these interventions can affect the supply and demand for various currencies, thereby influencing their exchange rates. Changes in exchange rates can affect the value of assets denominated in foreign currencies or traded internationally. If a central bank weakens its own currency, for instance, export costs denominated in that currency may increase, but the value of assets denominated in that currency may decrease. Because of central bank efforts to strengthen a currency, the price of exports denominated in that currency may decline, but the value of assets held in that currency may increase. Foreign exchange interventions can generate market uncertainty and volatility, which can affect the value of other assets (Mohanty, 2013, p. 4) .

2.5.7 Yield Curve Risk

A yield curve shows the result of debt securities with varying maturities, such as 1 year, 2 years, 5 years, 10 years, 20 years, and 30 years. Typically, this curve has an upward inclined shape. This is due to the term premium that long-term debt security holders demand to mitigate anticipated inflation and economic uncertainty. Due to the inverse relationship between bond prices and interest rates, the central bank's control over short- term interest rates and their impact on long-term rates can also impact bond prices. An upward sloping yield curve is the consequence of anticipated inflation and economic uncertainty in the future (Ulrich, 2013, p. 295). A decrease in bond market price volatility can increase investor confidence in purchasing assets, resulting in a rise in trading volume and a reduction in the yield spread between various maturity debt securities (Rui Chen) (2023, p. 9). Inversely, a rise in expected volatility results in a higher yield for longer-term debt securities than for short-term debt securities. The yield curve's profile can be correlated with the business cycle. (2023, p. 9) For example, an increase in the short-term interest rate can cause the yield curve to invert and the shorter end to reflect lower economic growth and a greater likelihood of a recession, which is defined as a half-year of negative economic growth. The actions of the central bank, such as lowering interest rates or purchasing bonds on the open market, can have an effect on the premium associated with holding long-term bonds. These actions can increase the yield on long-term bonds relative to short-term bonds and reduce market volatility by altering investor perceptions of risk. Reducing interest rates may alter future price stability expectations, which could increase market volatility. (2023, p. 9) An increase in equity market volatility may prompt investors to transfer from riskier assets to safer alternatives, resulting in a reduction in the term premium. In contrast, a shock to the bond market's volatility may result in an increase in the term premium, potentially due to economic factors.

The bond yield can be used as an indicator of a nation's economic health (2008, p. 724). The spread between future interest rates influences the yield curve's slope, which in turn influences the uncertainty grin (2008, p. 716). The market's supply and demand for options will increase the prices If the lengthier end of the yield curve steepens, indicating an increase in future interest rates and inflation expectations, the prices of out-of-the-money (OTM) options will increase.

Different curve shapes will influence option prices and volatility. A flattening of the yield curve, where long-term and short-term maturities coincide, could cause market uncertainty regarding future guidance from central bankers. Resulting from changes in interest rates, uncertainty regarding future inflation expectations can cause fluctuations on the spot market and influence option prices (Piazzesi, 2006). During periods of rising interest rates, OTM options with shorter maturities are more expensive than during periods of stable or declining interest rates. The correlation between the slope of implied volatility and the yield curve varies according to the maturity of options, with extended maturity options exhibiting a negative correlation with the yield curve also imply that the yield curve can predict the time-varying smile of volatility (2008, p. 727) (Niu, 2010).

2.5.8 Volatility Risk

The risk-free debt market functions as a standard and collateral for pledging loans, as well as a reserve on bank balance sheets. It is also utilized by central banks to make economic decisions. Changes in this market's prices can provide insight into the macroeconomy and financial markets (Pan, 2018). A 10-year debt security, such as a bond, has a fair value equal to the present value of its future financial flows, including interest payments. When the asset's fair value fluctuates, it can cause market fluctuations. For example, the 10-year US Treasury bond is frequently used as a benchmark for assessing the risk of corporate bonds, valuing stocks, and pricing derivatives. However, if there is uncertainty regarding the price of the 10-year US Treasury bond, it can lead to market instability, not only in the

bond market but also in the broader market. Changes in bond prices may indicate economic uncertainty and investor ambiguity about the returns associated with assets, which will increase market volatility (Craig S. Hakkio, 2009, p. 7). Financial market fluctuations can have a cascading effect on the economy as a whole. For instance, volatility may result in shifts in asset prices and have an impact on the stock prices of companies. Due to uncertainty regarding future prosperity, households may also reduce their spending the effect of the link between equities and bonds would be distinct during "high risk" and "low risk" economic meltdowns or shifts in volatility (Bollerslev, 1998). Short-term migration to protective resources is a phenomenon that occurs in environments with significant risk. During challenging times, it would be prudent to diversify your investments if you were aware of the increased volatility associated with high-risk environments. However, given that bonds are dependent on long-term interest rates and depend on negative interest rates in low risk regimes, there is a negative correlation between implied bond volatility and high risk environments. the relationship between implied volatility of equities and bonds is a two-way phenomenon that also depends on the described volatility regimes (2014, p. 217).

There is a distinction between market price volatility and financial ambiguity. There may be a connection between the two, but they are not identical. For instance, when new information becomes available on the market, price volatility and uncertainty may increase (2010, p. 5). On the other hand, low market liquidity can result in low price volatility but high financial uncertainty, which can lead to wider spreads and a decrease in the volume of assets traded.

Central banks and market participants should use implied volatility in options to evaluate market uncertainty when making monetary decisions. Pricing and volatility of options should reflect uncertainty about the future (2005, p. 24). The distributions of implied volatility can influence the monetary policy decisions of central banks. Prior to the implementation of monetary policies, market sentiments are not uniform, particularly regarding fixed-income market expectations. This disparity is attributable to the actions of central banks during different monetary policy administrations, such as when they loosen or tighten policy. During the implementation of ECB policy, bond market expectations are inconsistent, with hawkish periods displaying a positive bias in the implied yield distribution and dovish periods displaying a negative skew in the implied volatility distribution. This asymmetry prior to policy implementation can be utilized by the European Central Bank as a decision-making indicator once the ECB policy is in place, as it minimizes the disparity between implied distributions of option prices.

Longer-term implied volatility correlates with interest rate risk, but is not a factor of longer-term interest rates. (2021, p. 597). Longer-term implied volatility for the 5-year, 10-year, and 15-year periods is more stable than short-term implied volatility. Long-term implied volatility is strongly correlated with interest rate risk, whereas short-term implied volatility is more strongly correlated with equity volatility.

2.5.9 Sovereign Risk

Sovereign risk is the risk an investor assumes when holding a bond issued by a foreign government. The value and volatility of the bond could be affected if the government defaults on its payment obligations due to domestic economic conditions. Changes in the domestic government that result in a refusal to pay bond payments can also cause sovereign risk, which can impact the price and increase market volatility (Fabozzi, 2007, p. 36). The sovereign risk an investor assumes can vary based on the bond's denominated currency. For instance, a foreign investor holding a Chinese government-issued bond denominated in Chinese Yuan may be exposed to both sovereign risk (credit risk) and foreign exchange risk. If the government defaults on its payments or the country's credit rating changes, it could impact bond prices and increase market volatility. Additionally, issuance of bonds in domestic or foreign currency can result in distinct sovereign risks.

In general, domestic bonds issued by emerging market governments rarely default on their obligations and are rated higher than foreign currency bonds because the government can generate tax revenue from its own population to pay the obligation (Amsta Marlene, 2020).

Sovereign risk can influence the duration of bonds with various credit ratings. Bond duration indicates the degree to which bond prices are sensitive to changes in interest rates. The researchers examined Asian countries that issue sovereign bonds denominated in U.S. dollars and discovered that sovereign risk reduces the sensitivity of bond prices to interest rate changes (2011, p. 450). Due to the European Union's adoption of a single currency, the yields on government bonds have contracted as a result of reduced exposure to currency risk and price stability concerns. During periods of crisis, sovereign risk can vary across nations. After the 2007-2009 financial crisis, for instance, many nations provided economic support through financial aid, which rendered them vulnerable due to certain fundamental variables. Greece was incapable of maintaining this whereas other countries with robust fundamentals, such as Germany, were less affected by the debt crisis in 2013. During the crisis, investors favored stable government bonds, resulting in lower yields and higher prices as a result of increased demand for these instruments (Juha Kilponen, 2015, p. 1).

Economic factors can influence the sovereign risk of a bond, as measured by variations in its yields. Changes in these variables can influence sovereign yields and increase sovereign risk (2007, p. 236). Greater sovereign risk increases the probability that a government will fail to meet its payment obligations on a bond contract. Sovereign risk in Eurozone nations can be linked to the banking sector. Large banks in a country can prosper and generate tax revenue for the government during prosperous economic times, while also lending to many investors and earning profits. During a crisis, however, these institutions can become a financial risk for the government, causing fluctuations in the yields on government bonds (2010, p. 2).

II.ANALYSIS

1. Data Pre-processing

Daily Change of Bond Futures Options' Implied Volatility This chapter describes the research methodology that will be applied to the thesis. The implied volatility index's daily data will be downloaded from the Bloomberg database from January 2009 to July 2023. RX 1M 50D VOL BVOL (Bloomberg Ticker) is an implied at-the-money (ATM) 1 Month forward volatility index that will serve as a proxy for Bond Futures Implied Volatility, henceforth known as the Implied Volatility Index. Figures 4 and 5 depict the implied volatility of Bond Futures Options and the day-to-day variation in the implied volatility series over the analyzed time frame. (January 2009–July 2023). The graph depicts several significant surges where implied volatility increased substantially. This could occur during periods of increased market volatility or a crisis.

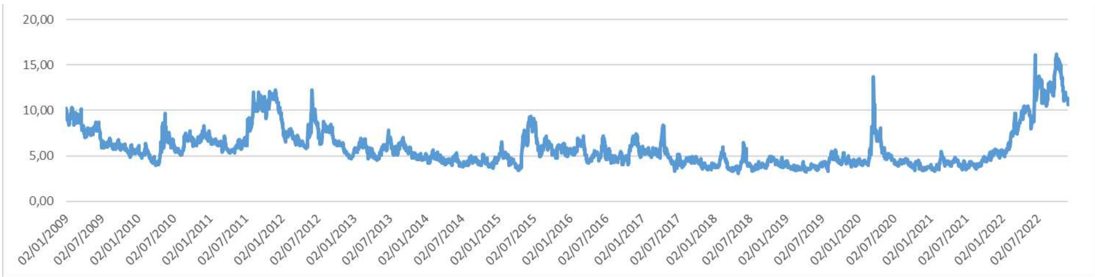


Figure 4: Bond Futures Options' Implied Volatility (own processing)

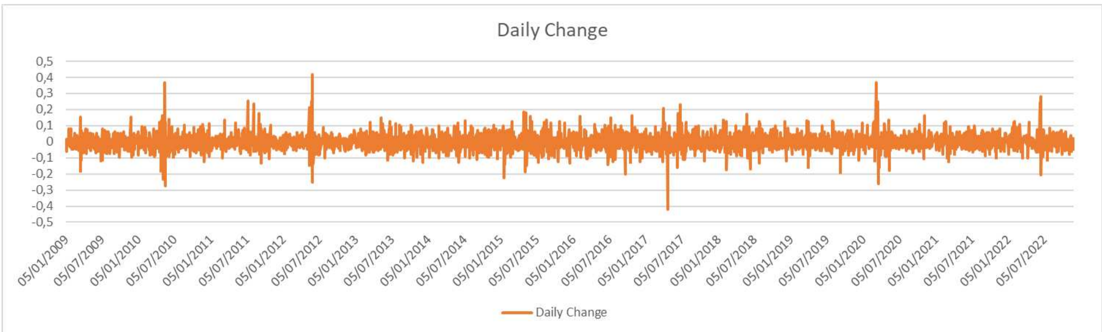


Figure 5: Daily Change of Bond Futures Options' Implied Volatility (own processing)

Table 1 displays some preliminary results of the data analysis. The results show that implied volatilities for the entire 13-year period have a mean value of 5.86437 and a standard deviation of 2.17124. The data is skewed toward greater values, and the kurtosis test suggests there may be indications of extreme events. The daily change in implied volatility series has a mean of

0.000011 and a standard deviation of 0.04985. The daily volatility series has less variation than the implied volatility series. The daily change series is positively skewed and has a larger probability of extreme events.

Table 1: Summary Statistics of Implied Volatility (own processing)

	Implied Volatility	*Daily Change of Implied Volatility*
Mean	5,86437	1,18671E-05
Standard Error	0,03643	0,000836501
Median	5,25000	-0,001440983
Mode	3,85000	0
Standard Deviation	2,17124	0,04985432
Sample Variance	4,71428	0,002485453
Kurtosis	3,05427	7,025995725
Skewness	1,68045	0,438589861
Range	13,15000	0,83833909
Minimum	3,07000	-0,418806725
Maximum	16,22000	0,419532365
Sum	20836,09680	0,042151834
Count	3553	3552

Notes: Skewness at Significant at the 5% level.

1.1 Variable Proxies

The majority of the fixed income market risk factors we evaluate are derived from literature. We will examine interest rate risk, credit risk, liquidity risk, yield curve risk, inflation risk, event risk, foreign exchange risk, volatility risk, and sovereign risk among the fixed income risk factors. Risk factors associated with central bank reports, macroeconomic factors, or financial factors may be hampered by reporting delays or a dearth of direct market indices for measuring their impacts. As a factor in addressing this issue, numerous proxies would be considered. From January 2009 to July 2023, data will be downloaded daily from the Bloomberg database for proxy factors.

1.2 Option Contract with Rolling Options.

To ascertain if explanatory factors identified through regression analysis can aid in the development of optimal trading strategies for options, a continuous option rolling contract based on Bond Futures options was constructed. The specified options are monthly options that expire on the fourth Friday of every month. Options are rolled seven days before expiration. This seven-day run is not being performed for research purposes, rather, as expiration approaches, options lose their time value component and liquidity issues may arise. Option Contract Expiry Specifications, for example (also viewed on Bloomberg RXA Comdty DES Go).

Jan –F	May-K	Sept-U
Feb-G	Jun-M	Oct-V
Marc-H	Jul-N	Nov-X
Apr-J	Aug- Q	Dec-Z

Option expires on 4th Friday of Each month.

RXX2C

Futures (RX) Option Expiry Initials(X) Year(2012) Option type(Call)

Note: option expiry initials states Nov but option expires in Oct, named 1m forward.
Option maturity date (RXX2C) on 26.10.2012 but we roll 7 days before that is on 19.10.2012 according to our rolling procedure.

By constructing this continuous rolling option contract based on Bund Futures, we are able to analyse data from March 2014 to July 2023. The option prices for each leg and the monthly contract were obtained from Bloomberg database. Data prior to 2014 is unavailable from Bloomberg. This continuous rolling option strategy allows us to answer the second question of our thesis, which is to understand the implications of factors on option volatility strategies.

1.3 Option Volatility Strategy-Short Condor Strategy

Volatility can be used to speculate on market direction, generate risk-free profits, and secure the underlying asset (Felix Goltz, 2012, p. 7). "Long volatility when volatility is expected to increase and short volatility when volatility is expected to decrease" is a common strategy employed by hedge funds (Srikant Dash, 2005, p. 77). Depending on the market cycle, option spread trades can be used as bullish or bearish wagers with variable payouts. Buying volatility as a strategy can mitigate extreme market volatility relative to traditional portfolios (Marie Brière, 2010, p. 3). In uncertain times, extreme risk can be mitigated by holding long positions in both implied volatility and volatility risk premium. Volatility risk can also have an impact on directionless and at-the-money forward strategies (Menachem Brenner, 2006, p. 814). Using implied volatility in the equity index as a diversification asset during a financial crisis, enhances portfolio diversification. Long-term, a negative risk premium may result in suboptimal returns for long volatility strategies, whereas investors can generate excess risk premium by shorting volatility (2009, p. 68). Option selling strategies involving the sale of options can generate a positive risk premium, but also carry the risk of unlimited loss (Dziawgo, 2020, p. 34).

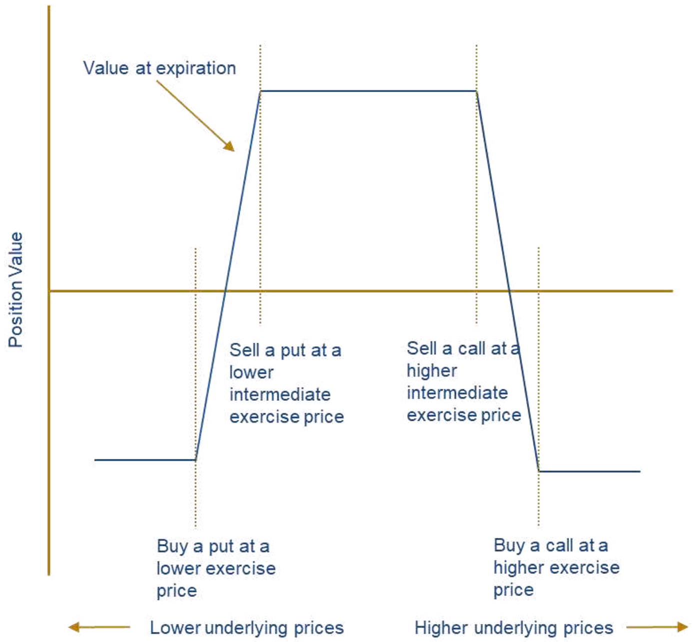


Figure 6: Payoff Structure of Short Condor Strategy (own processing)

The construction of an option volatility strategy consists of a short condor strategy consisting of options based on Bond Futures that are rolled again seven days prior to options expiration to construct a continuous short condor strategy from March 2014 to July 2023. The short condor strategy is a form of options trading strategy that employs four options. It includes being long a call option with a strike price higher than the current market price and short an out-of-the-money call option, as well as being long a put option with a strike price higher than the current market price and short an out-of-the- money put option. The objective of the short condor strategy is to have no direction risk, a limited profit, and a limited loss. In stationary market conditions, it will perform consistently, but in extreme conditions it may experience significant drawdowns. We will assess the statistical significance of the relationship between the explanatory factors from PLS regression and the performance of option volatility strategies. Then, we will develop a factors-based option volatility strategy to determine whether the factor-based short condor strategy outperforms the buy-and-hold short condor strategy in out-of-sample data. Figure 7 depicts the performance of a straightforward buy-and-hold short condor.

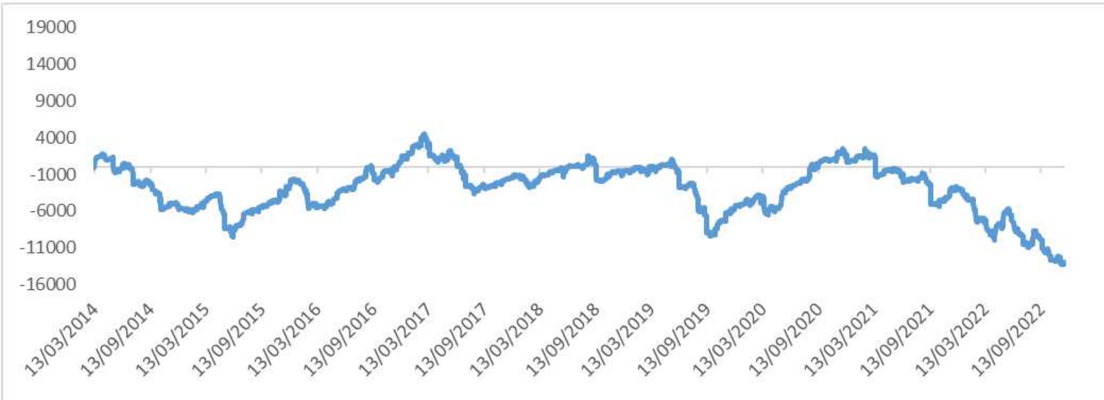
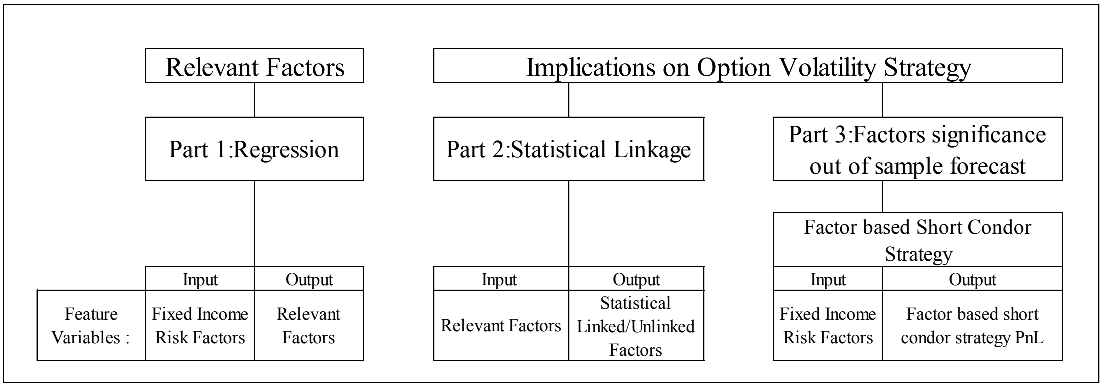


Figure 7: Simple Buy and Hold Short Condor Strategy Performance (PNL) (own processing)

2. Feature Variables- Factors from literature in general.

Table 2: Feature Variables for Analysis (own processing)



As shown in Table 2, the variable characteristics for three distinct quantitative analyses will vary.

Initially, fixed income risk factors will serve as feature variables for the analysis of the Implied Volatility Index's components. Below is a list of considered factors, and market-based indicator data from January 2009 to July 2023 will be downloaded from the Bloomberg Database. We will select daily, high-quality, economically relevant data. After identifying the explanatory variables, their statistical significance in relation to the performance of the brief condor strategy will be evaluated. The primary objective is to examine the possibility of a causal relationship between the factors that explain implied volatility and the option volatility strategy. After this is completed, all the factors will be used for out-of-sample testing, which involves dividing the dataset into a training set and a test set.

For the Statistical Linkage and Out of Sample analyses, where the target variable is the performance of the short condor strategy, data will be collected from March 2014 to July 2023, as no continuous data is available prior to that date to construct the rolling option contract. The training data set will consist of the first six years of data, whereas the test data set will consist of two years of data for out-of-sample testing.

Following is a summary and additional information regarding the motivation behind factor proxies, while Table 3 provides descriptive statistics regarding the factors.

2.1 Interest Rate Risk

This financial instrument is used to measure interest rate risk. The Eonia rate is based on the European Central Bank's (ECB) short-term interest rate. Due to anticipated future interest rate changes, inflation, and economic growth, the forward market valuation of the Eonia rate may differ from the spot rate. Forward swap prices based on the Eonia rate can reflect the anticipated future path of interest rates. It should be noted, however, that these market prices are not always realized, but the central bank can use them as a basis for decision making.

When interest rates rise, borrowing becomes less appealing, which can impact all forms of borrowing, including personal loans, mortgages, and credit card interest rates. In addition, the central bank could use instruments such as increasing reserve requirements or selling EU government bonds to reduce the money supply and slow inflation, which could lead to declining bond prices, rising yields, and poor market liquidity. Quantitative tightening (QT) seeks to reduce demand and ultimately slow inflation.

2.2 Credit Risk

Investors use derivatives such as credit default swaps to mitigate the risk of a creditor defaulting on a loan. When the probability of default increases, the price of credit default swaps increases.

These swaps are utilized to mitigate against credit risk, but do not account for interest rate risk (Byström, 2006, p. 65). The credit derivatives market brings together investors who wish to reduce their credit risk with those who wish to increase their credit risk. The iTraxx Europe Credit Default Swap Index is used as a benchmark in European markets and consists of 125 equally weighted European Investment Grade bonds that are rebalanced every six months based on a survey. As a means of measuring the credit risk on European markets, we will employ the "iTraxx Europe CDS Index with a 5-year maturity." This is due to the fact that 5-year CDS are the most actively traded securities and offer a more accurate representation of credit risk (Carol Alexander, 2008, p. 1010). There is a correlation between the "credit default swap index" and the "implied volatility index" in the equity market (2013, p. 497). In addition, the study by Bystrom (2008, p. 10) discovered that the credit default swap is associated with equity market uncertainty on the European market.

2.3 Liquidity Risk

Liquidity Funding liquidity risk is the possibility that a bank will be unable to borrow money from its counterparties when necessary. During the financial crisis, many banks were reluctant to lend to one another, resulting in a severe lack of market liquidity. The Federal Reserve had to intervene by purchasing US Treasuries and lowering interest rates, which increased market liquidity (Patrick McGuire, 2012, p. 1). Market liquidity risk can be characterized by the simplicity with which a security can be purchased or sold on the market. Typically, it is "determined by the bid-ask spread of the security." During difficult economic times, market liquidity risk and funding liquidity risk, which concerns the availability of funding for the purchase or sale of securities, are closely related. Due to a decline in "the number of buyers and sellers" and a widening of the bid-ask spread, market liquidity risk typically increases as the economy deteriorates. This can make purchasing and selling securities more difficult and costly (Cho-Hoi Hui, 2011, p. 308).

Using a proxy such as the EUR Swap spread is one method for measuring liquidity risk in the market. This spread indicates the cost of acquiring funds by calculating the difference between the swap rate and the variable rate in a swap contract. The Euro Swap 10-year spread can be utilized as an alternative measure of market funding liquidity risk. It is the risk of defaulting on debt obligations and the difference between the buy and sell spread risks (Jun Liu, 2006, p. 2338). It can represent the cost of obtaining money and the risk of not meeting financial obligations. When the spread is high, it indicates that funding liquidity risk is elevated. This is due to the fact that a wider spread indicates a higher cost of acquiring funds, indicating that investors are demanding a higher return to lend money, which is a sign of diminished market liquidity (Cho-Hoi Hui, 2011, p. 308).

2.4 Inflation Risk

Inflation risk refers to the potential for investments to lose value due to unanticipated price increases. Examining the spread between forward inflation swap rates and forward interest swap rates is one method to measure inflation risk. This differential, also known as the Forward Inflation Risk Index, represents the difference between the anticipated future interest rate and the anticipated future inflation rate.

Changes in the market's inflation expectations can influence bond prices, which are inversely correlated with inflation expectations. In order to compensate investors for the rise in product and service prices, bond prices will decrease, and bond yields will increase when inflation expectations rise. Central bankers closely monitor this to evaluate the efficacy of their monetary policy and the condition of the economy (Joshua C.C. Chan, 2018, p. 1139). Inflation risk can also be measured by comparing the yields of conventional government bonds to those of inflation-linked bonds with comparable maturities. Comparing conventional swap rates to inflation-linked swap rates is another method. Inflation swap rates are regarded as a more accurate indicator of inflation risk than bond inflation rates due to their lower liquidity risk and superior performance (Joseph Haubrich, 2012, p. 1590) (Will Devlin, 2012, p. 11). They are traded over the counter and have a wider variety of maturities. This thesis utilizes the Forward Inflation Risk Index, which is the difference between the forward interest swap rate and the forward Eur inflation swap rate, as an indicator of inflation risk. It represents the difference between the expected future inflation rate and the expected future interest rate, and variations in this spread can indicate changes in inflation expectations.

2.5 Event Risk

The Fear Barometer from Credit Suisse is a proxy index that measures event risk. It is derived from the Standard & Poor 500 Index options and is used as a global equity market growth indicator. The Fear Index is constructed using a zero-cost option strategy by selling OTM call options on the Standard & Poor's 500 Index and reinvesting the premium received to purchase OTM put options. The purchased and sold options are 3-month forward options, so the Fear Index reflects the sentiment of investors three months in advance. The Fear is the difference between the price received by shorting the call option and the price of an out-of-the-money put option that can be purchased with the same premium. Due to the unpredictability of the future, it is observed that buying and selling options on the market can reflect the sentiment of investors

(2021, p. 1). In addition, they note that "CSFB measures the option premium, which fluctuates based on the supply and demand for that option." As the CSFB rises, the market's perception of panic increases. Events such as COVID-19, the Financial Crisis of 2008, and the EU Debt Crisis of 2013 increase uncertainty about economic conditions and cause rapid fluctuations in market expectations of asset values, resulting in increased volatility and decreased liquidity (Akhilesh Prasad, 2022).

2.6 FX Risk

FX risk is the risk associated with fluctuations in currency value, and it can be measured using currency indices such as the US Dollar and Euro Currency Indices. Changes in the value of a currency may affect assets denominated in that currency. During times of crisis, for instance, investors tend to favor safe assets such as US Treasuries and German Bonds, which can lead to an increase in the demand for assets guaranteed by that currency and a rise in the value of the dollar or euro. Additionally, interest differentials resulting from domestic economic conditions can affect currency value, such as the difference in borrowing costs between Japan and the United States, which can increase demand for the currency of the country with reduced borrowing costs (Stefan Avdjiev, 2019, p. 2) (Boris Hofmann & Ilhyock Shim, 2016, p. 1) (Robert N McCauley, 2012, p. 92).

Due to globalization, the dominance of the US dollar has increased in recent years, which can have an effect on prices, assets, and liabilities. This can also reflect the sentiments of investors, such as an increase in remittances into emerging markets denominated in US dollars and euros due to a shift in risk-taking for higher yields in emerging markets by foreign investors. Foreign currency reserves can be used by central banks to support their domestic currency or to import foreign products. To be used as a reserve currency, a currency's domestic financial market must be sufficiently robust in terms of credit risk, liquidity risk, and volatility risk (2009, p. 20) discovered that since the introduction of the Euro as a common currency, the Euro's volume has increased and there is less concern about various risks due to the stability provided by a single currency. To account for FX risk, we would therefore use the US Dollar Currency Index and Euro Currency Index as approximations.

2.7 Yield Curve Risk

Yield curve risk is the risk associated with variations in the yield curve's shape, and it is measured by the spread between forward rates on bonds of varying maturities (Nicola Carcano, 2011, p. 2991). In this instance, yield curve risk is proxied by the difference between the 1-year forward rates of the 30-year and 10-year German government bonds (Coleman, 2011, p. 2). The structure of the yield curve is influenced by changes in borrowing rates determined by monetary policy and reflects the expectations of market participants for future inflation and economic growth. This change in interest rates has an impact on bond prices and the yield curve, which incorporates information and future expectations regarding the economy and price stability. The spread between forward rates of bonds of various maturities can be used to calculate the term premium, which is the additional financial reward investors require for holding debt with an extended maturity. The pricing of the spread on the market reflects the anticipated path of term premia.

2.8 Volatility Risk

The pricing of the spread on the market reflects the anticipated path of term premia. Volatility risk is measured by indices such as MOVE ("Merrill Lynch Option Volatility Expectations") and VIX ("CBOE Volatility Index"). The MOVE Index measures the change in bond market prices with a weighted maturity of 2, 5, 10, and 30 years, as implied by the derivatives market one month in advance.

Table 3: Descriptive Statistics of Factors

	Interest_Rate_ Risk_Factor	Credit_Risk_ Factor	Liquidity_Risk_ Factor	Inflation_Risk_ Factor	Event_Risk_ Factor	FX_Risk_Fa ctor_1	FX_Risk_ Factor_2	Yield_Risk_Curve_ Factor	Volatility_Risk_ Factor_1	Volatility_Risk_ Factor_2	Sovereign_Risk_ Factor
Mean	0,3037	85,7498	38,9841	0,1704	27,1345	89,6365	1,2209	46,8022	77,6365	19,6044	26,9366
Standard Error	0,0146	0,5880	0,2497	0,0164	0,1051	0,1488	0,0020	0,2839	0,4480	0,1368	0,3753
Median	-0,0760	74,6130	36,7992	-0,0466	27,2300	92,2260	1,1904	48,6500	71,2000	17,3300	18,5800
Mode	-0,2731	146,5000	37,9676	-1,3990	25,5400	82,0870	1,1151	64,9800	89,8000	13,7900	10,8000
Standard Deviation	0,8706	35,0502	14,8834	0,9794	6,2650	8,8672	0,1210	16,9233	26,7024	8,1529	22,3728
Sample Variance	0,7579	1228,5198	221,5157	0,9593	39,2507	78,6270	0,0146	286,3983	713,0155	66,4691	500,5432
Kurtosis	0,2719	0,9182	1,9205	-0,8122	-0,3531	-1,0083	-0,9666	1,1068	1,5414	6,0855	3,2161
Skewness	1,1331	1,1810	1,1964	0,3713	-0,0659	0,0173	0,3004	-1,0084	1,2733	1,9194	1,9177
Count	3553	3553	3553	3553	3553	3553	3553	3553	3553	3553	3553

Note: Proxy Indicator used as a factor indicator:1. Interest Rate Risk Factor- 1Y forward Eonia Rate , 2. Credit Risk Factor - European CDS Index, 3. Liquidity Risk Factor-EUR Swap Spread, 4. Inflation Risk Factor-Forward Inflation Index, 5. Event Risk Factor- Credit Suisse Fear Index, 6. FX Risk Factor 1- DXY Index, 7.FX Risk Factor 2- EUR Index, 8.Yield Curve Risk Factor- 10s30s German Government Bond, 9.Volatility Risk Factor 1- MOVE Index , 10.Volatility Risk Factor 2- VIX Index, 11.Sovereign Risk Factor- German Sovereign CDS Index

The VIX Index measures variations in the equity market based on options on the S&P 500 Index one month in advance. Investors utilize the option market to mitigate against market volatility or to modify their future price stability expectations. For instance, if market participants anticipate falling stock or bond prices, they can use VIX-based options to mitigate their risk.

The 10-year US Treasury bond market's term premium is influenced by the VIX and MOVE indices (2023, p. 4). The MOVE and VIX indices as indicators of volatility in the bond and stock markets but suggests that her built-in index is superior to the MOVE index (2018, p. 585). The relationship between volatility in the equity and debt markets is influenced by the volume of trading by investors during a crisis, which influences volatility in both markets (2017, p. 24). Bond market volatility can be used to predict stock market volatility and that the gap between the two indices widened due to the different market structures of the two assets, with reduced policy rates and greater market liquidity.

2.9 Sovereign Risk

A financial instrument known as a sovereign credit default swap (CDS) safeguards investors against the risk of a government defaulting on its debt. Bond spreads and CDS premiums for the same duration asset for the same entity are closely correlated (Anne-Laure Delatte, 2012, p. 482). The German Government 5Y CDS is used as a proxy for measuring sovereign risk. A rise in sovereign credit risk causes foreign investors to sell assets in a nation, influencing the cost and flow of currency value and economic growth. The CDS market contains more information than the bond market, making it a more accurate measure of sovereign risk. Following the banking crisis of the 2010s, the volume of credit default swaps (CDS) increased, although it remains smaller than the underlying sovereign debt (Francis A. Longstaff, 2011, p. 75). However, CDS considers the likelihood of sovereign debt default.

3. Target Variable

Table 4: Target Variables for Analysis (own processing)

Relevant Factors	Implications on Option Volatility Strategy		
Part 1:Regression	Part 2:Statistical Linkage	Part 3:Factors significance out of sample forecast	
		Factor based Short Condor Strategy	
Target Variable	Target Variable	Target Variable	
Implied Volaitility Index	Short Condor Strategy PnL	Short Condor Strategy PnL	
		Training Set (6yr)	Testing Set (2yr)

As shown in Table 4, the quantitative analysis will be divided into three sections. First, the target variable for PLS regression will be the daily data of the Implied Volatility Index. Next, the target variable for the statistical linkage test will be the ROI of a short condor strategy. The target variable for the out-of-sample test will be the performance of the short condor strategy, which will be partitioned into a training set and a testing set with 6 and 2 years of data, respectively.

3.1 Regression

In order to answer the query "which factors explain the current dynamics of the implied volatility of Bond futures," we would conduct a Partial Least Square regression analysis, henceforth referred to as PLS regression. This analysis would consider risk factors from the fixed income market that could influence the dynamics of implied volatility from January 2009 to November 2022. PLS regression is appropriate when there are a large number of predictors (fixed income risk factors), as it reduces the dimensionality of the predictors and identifies a reduced number of independent components that explain the most variance in the response variable. (implied volatility index). Thus, PLSR can aid in identifying the most influential factors on the implied volatility index.

Table 5: Structure of Quantitative Analysis (own processing)

Quantitative Analysis						
	Relevant Factors		Implications on Option Volatility Strategy			
	Part 1:Regression		Part 2:Statistical Linkage		Part 3:Factors significance out of sample forecast	
					Factor based Short Condor Strategy	
	Input	Output	Input	Output	Input	Output
Target Variables :	Implied Volaitility Index	Relevant Factors	Short Condor Strategy PnL	Statistical Linked/Unlinked Factors	Short Condor Strategy PnL	Factor based short condor strategy PnL
Feature Variables:	Fixed Income Risk Factors		Relevant Factors		Fixed Income Risk Factors	

Utilizing various regression methods may not yield the desired outcome, as some researchers seek to identify explanatory variables in theregression that provide a high degree of fit with the regression, the variables' explanatory factors are not always known (1980, p. 47). Numerous researchers consider only financialfactors for regression, but there is no appropriate method for evaluating variables' relevantfactors. As a solution, partial least square regression is used. PLSR makes it easy to evaluate prospective risks and assemble aportfolio of assets. (2011, p. 254). Furthermore, the study demonstrated that PLSR can be utilized toidentify and eradicate less significant financial market risk factors. This can contribute toincreased investment returns. PSL regression can be used to identify explanatory variables (2023, p. 5). PLS regression identifies explanatory factors based on the "cross-section of covariance" of the factors and choosesthe optimal factors that can define the dependent variable (Woodward, 1986).

As PLS regression is a three-step method, First Step, score step and equation is denoted by,

$$F^{m} = N^{km} * W \qquad where\ m = 1,2 \ldots.,5\,, \qquad k = 1 \ldots\ldots..,10 \qquad (1)$$

F is a latent factor m in the score model, N^{km} is the total number of factors considered, and W is the weightings for predictable factors. In this instance, the algorithm will identify the linear combinations of the predictor variables (N) that are weighted by the weighting matrix (W) such that the scores (F) are maximally correlated with the response factor. (Yt). The second phase of the PLS algorithm is to identify the linear combinations of predictors with the highest level of correlation with the latent variables. This phase is most referred to as the "loading step."

Second Step, the loading step equation is denoted as follows:

$$P^{km} = N^{(km)'} * F^{m} \ where\ m = 1,2 \ldots.,5\,, \qquad k = 1 \ldots\ldots..,10 \qquad (2)$$

P^{km} km is a loading factor of dimension (number of predictable factors) * (number of components), N(km) is the transpose of all number of factors of dimension (number of predictable factors)* (number of samples), and Fm is a latent factor of m of dimension(number of components)*)*. (Number of samples). In this phase, the algorithm identifies the linear combinations of the predictor factors (N) that have the highest correlation with the latent variables (F) identified in the score step. The loadings (P) are linear combinations of the predictor variables (N) that are maximally correlated with the latent variables (F), and they are computed by multiplying the transpose of the predictor variable matrix (N') by the latent variable matrix (F).

The third phase, observation, is expressed by:

$$\mathrm{Yt} = ß * \mathrm{F}^{\mathrm{m}} * \mathrm{B}^{\mathrm{t}} \qquad \mathrm{where\ t} = 1,2 \ldots\ldots,5 \qquad (3)$$

Y_t is a response variable (Implied Volatility Index) in the observation phase, ß represents beta, F is a latent factor m, and Bt denotes the regression coefficient.

The implied volatility is a linear relationship between the factors from the fixed income market, which include interest rate risk, credit risk, liquidity risk, inflation risk, event risk, FX risk, yield curve risk, volatility risk, and sovereign risk, as demonstrated by Equation 3. The objective of PLS regression is to reduce the number of factors required to define implied volatility, thereby optimizing results and investigating the impact of each factor on the strategy for option volatility. The Python code used to conduct the PLS analysis can be found in Appendix A. In conclusion, PLS regression is a technique that reduces the dimensions of a data set while retaining the majority of the original information by discovering latent variables, also known as PLS components, that describe the covariance between the features and response variable. These components are discovered using equation 2, which is denoted by F^m, and they produce a low-dimensional representation of the original data while maintaining its maximum variance.

3.2 Hypothesis Test

To examine the implications of explanatory factors on the option volatility strategy, we will first determine whether there is a statistically significant relationship between the explanatory factors from PLS regression and the performance of the option volatility strategy, such as the short condor strategy, between March 2014 and July 2023. The Granger Causality Test, a statistical method for testing hypotheses, is employed to determine if there is a statistically significant relationship between the explanatory variables from PLS regression and the PNL of the short condor strategy. A time series of explanatory factors is said to Granger-cause short condor performance if it can be demonstrated, typically through experiments on explanatory factor values, that the values of these explanatory factors move in tandem with short condor performance. This will answer the query, "Is there evidence of Granger causality between factors and the option volatility strategy?

The relationship between two variables consists of two distinct categories of time series correlation, each closely associated with one of the causes (1969, p. 424). Granger causality is based on the linear prediction of one time series to another. The study suggests that this form of causality is predicated on the notion that if one time series can help predict the other, then it can be said that it causes the other. It is comparable to the transmission of data from one time series to another. If the past value of one variable (the independent variable) can be used to predict the future value of another variable (the dependent variable), then there is a relationship between these two variables. This association is known as Granger causality (2020, p. 3).

The Granger causality test to be valid, the two examined time series must be stationary. This indicates that the values of both variables should increase with time at a similar rate. Even if the two variables are not explicitly related, if they both increase at the same rate over time, they may still exhibit a strong relationship. The ADF unit root test was utilized to verify for stationarity. This test enables us to determine whether the time series increase at a constant rate over time (Wayne A. Fuller, 1979).

Given below is the equation (4) for univariate Granger Causality.

$$A(t) = a + b1\,A(t-1) + \cdots + bpA(t-p) + c1X1(t-1) + \cdots + cqX1(t-q) + e(t) \tag{4}$$

Where A(t) is the dependent variable at time t, an is the constant term, b1,b2,...bp are the coefficients of lagged values for A, c1,c2. cq are the coefficients of lagged values for X (the dependent variable), and e(t) is the error term.

The univariate granger causality test examines each independent variable's causal relationship with the dependent variable by determining whether the coefficients of the lagged values of the independent variables are statistically significant. If the coefficients are significant, the independent variable may be producing a Granger effect on the dependent variable. It is determined by the precision of the predictions and the direction ofthe relationship between the two variables (Erdost Torun, 2020, p. 3). The Python code for conducting the analysis can be found in Appendix B. Theunivariate Granger causality test examines the statistical significance of the coefficients ofthe lagged values of the independent variables to determine the causal relationship betweeneach independent variable and the dependent variable. If the coefficients are statistically significant, this indicates that the independent variable has a Granger effect on the dependent variable.

3.3 Factors significance in out of sample forecast

To answer the question "Are factors significant in the out-of-sample forecasts of the option volatility strategy? ", we will construct a factor-based option volatility strategy todetermine if it outperforms the basic buy-and-hold bonds futures options short condor strategy. To ascertain whether factors have a significant effect on the out-of-sample forecasts of option volatility strategies, a factor-based option volatility strategy will beconstructed and compared to a simple buy-and-hold bonds futures options short condorstrategy.

The Light GBM machine learning method will be used to allocate scores to key factors in predicting the performance of the short condor strategy. These scores will demonstrate the sensitivity of each factor to the performance of the strategy. For the out-of-sample test, a fair value brief condor performance will be generated using the Light GBM model's training data. This will be used to evaluate the estimation error in the test with non-sampledata. Using the predicted values generated by the Light GBM model and a threshold value,a trading signal will be generated. The data will be classified into training and testing sets. Six years of data will be used to train the Light GBM model and assign scores to factors using the training set. Then, these factors will be incorporated into the fair value short condor performance factor-based option volatility strategy. The remaining two years of data will be used to evaluate the performance of both strategies: the factor-based short condor performance and the simple buy-and-hold strategy dubbed short condor performance. It will be determined whether the factor-based strategy outperforms the basic buy-and-hold strategy on out-of-sample data by comparing the results.

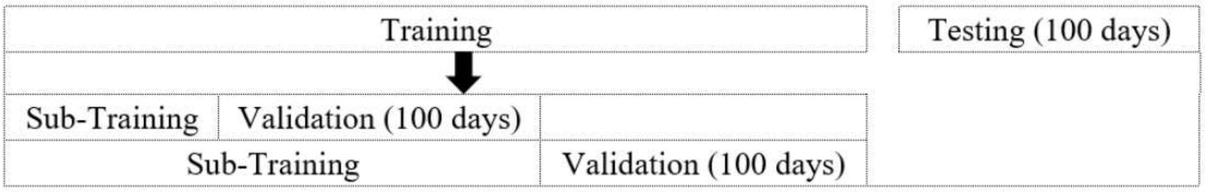


Figure 8: Splitting of Dataset as mentioned by Akhilesh Prasad et al. (2022, p. 10)

In a classification method, historical data can be used to predict the likelihood of future change. Light GBM is a new model that addresses the shortcomings of the traditional gradient model, such as poor performance when coping with many features. They accomplished this by introducing two new techniques known as "Gradient-Based One Side Sampling" (GOSS) and "Exclusive Feature Bondling" (EFB). During training, Light GBM employs "GOSS and EFB" to rank features. The GOSS and EFB algorithms are utilized to evaluate the features by selecting the most informative ones for each boosting process iteration (2020, p. 1).

GOSS divides data points and characteristics based on their gradients, whereas EFB creates a new feature space by combining the original characteristics. This contributes to effective feature selection and improved model performance.

Light GBM uses a technique called gradient boosting to rank features during training. Weak models, such as decision trees, are trained and their predictions are summed up. “The weights are learned by minimising a loss function, such as mean squared error or cross-entropy," and "the final prediction is a weighted sum of all the weak models' prediction” (Belle Fille Murorunkwere, 2023). A unique feature about the Light GBM is that it splits leaf node in downward direction compared to other models where it split the leaf in sideway direction (Sun Xiaolei, 2020, p. 3). Light GBM uses a method called leaf-wise to quickly and effectively find the best feature to split on by continuously looking for the “leaf node” with the largest benefit. However, this method can be slow in terms of computation. To speed up the calculation process, Light GBM limits the deepest possible level of “the decision tree”, which reduces “the number of calculations and prevents overfitting”.

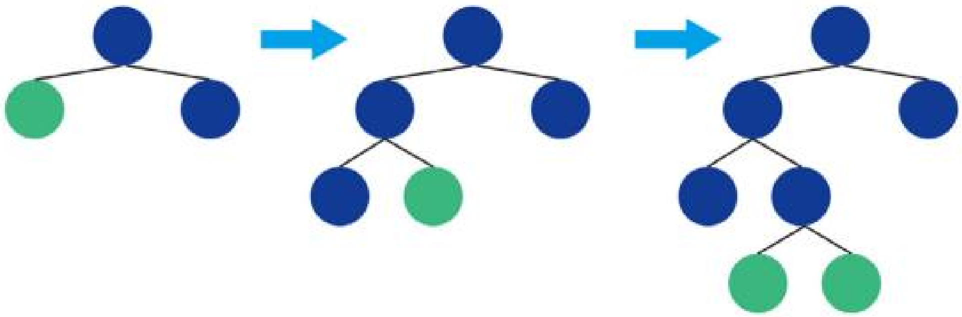


Figure 9:Horizontal Leaf-wise Tree Growth based on the work of Shangchen (2020, p. 3)

The general equation of the Light GBM model for ranking the features is:

$$G(x) = \Sigma\big(w_i * h_{i(x)}\big) \quad (5)$$

Where, G(x) is the final forecast made by the model for a given input x, w_i is the weight assigned to the i-th weak model, $h_i(x)$ is the estimate made by the i-th weak model for input x, Σ denotes the sum over all the weak models.

The value of each feature is used to make a prediction by each individual tree, and the algorithm learns how each feature is related to the target variable during training. The final prediction is the sum of the weights assigned to each individual tree, with higher weights indicating a greater influence on the final prediction. Each weak model or tree is trained to correct the errors of the predecessor trees. The error is the spread of the actual value and the predicted value of the previous tree.
The aim of the Light GBM is to reduce the loss function L which is given by:

$$L = L\big(y, G(x)\big) + \Sigma(w_i) \quad (6)$$

Where L(y, G(x)) is the objective function, y is the target variable and G(x) is the final prediction made by the model for a given input x.

Figure 10 shows, "num_leaves, learning_rate, max_depth, min_data, feature_fraction and bagging_fraction" are the main components of the Light GBM (Sun Xiaolei, 2020, p. 3). Shangchen (2020, p. 4) and Xiaolei et al. (2020, p. 3) mentions that the consideration of main parameters of the Light GBM are important for good results and overfitting issues. The more decision trees you build (num_leaves), the better the performance of the model, however it also increases the risk of overfitting. It is a hyperparameter that controls the number of trees to be built in the model. Learning_rate is a hyperparameter that controls the step size of the optimizer, it is used to prevent overfitting. Lower values of learning rate means slower convergence but more optimal solution, while high values of learning rate leads to faster convergence but may converge to suboptimal solution. The analysis will be conducted in Python, and the code can be found in Appendix C. The goal of the Light GBM model is to learn a function that can accurately predict ranking score based on the input features of the instance. The Light GBM model is an ensemble of decision trees, and each tree contributes a certain weight to the final prediction. The weights are learned during the training process, and the importance of each tree depends on its performance on the training data. Each decision tree makes a prediction based on the input features of the instance, and the final prediction is the sum of the predictions of all the trees weighted by their importance.

Parameters	Interpretation
num_leaves	This is the number of leaves per tree.
learning_rate	This controls the speed of iteration.
max_depth	This describes the maximum depth of the tree. It is capable of handling model overfitting.
min_data	This is the minimum number of the records a leaf may have. It is also used to deal with overfitting.
feature_fraction	This is the fraction of features selected randomly in each iteration for building trees.
bagging_fraction	This specifies the fraction of data to be used for each iteration and is generally used to speed up the training and avoid overfitting.

Figure 10:Parameters of Light GBM Model based on the work of Xiaolei et al.

4. FINDINGS AND THEIR IMPLICATION ON VOLATILITY STRATEGY.

4.1 Result from Regression.

As previously discussed in the PLSR model description outlined in equations 1, 2, and 3, the PLSR regression attempts to find the linear combination of latent and predictable factors through a weighting methodology, and then investigates the relationship between these latent factors and the target factor. (implied volatility index).

The PLSR model initially tests for linear combination between the factors, followed by the implied volatility index. In a similar manner, the correlation matrix investigates the relationship between these factors. It is plausible that factors with a high degree of correlation explain the implied volatility index. The primary objective of PLSR regression is to identify the factors of the implied volatility index that account for the greatest amount of data variation.

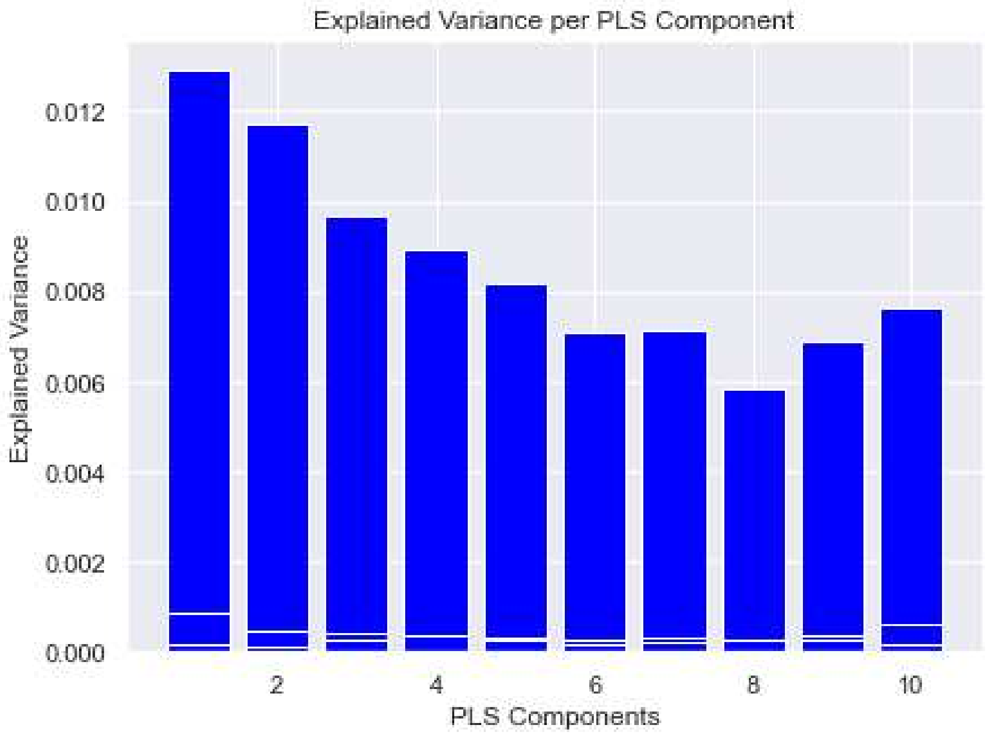


Figure 11: Variance Explained by Components as a Percentage in Fixed (own processing)

Figure 11 depicts the implied volatility index's correlation matrix with fixed income market factors from January 2009 to July 2023. High correlation coefficient of 0.7546 exists between the MOVE volatility risk factor and the implied volatility index. In contrast, the implied volatility index and yield curve risk factor are negatively correlated, with a correlation coefficient of -0.5631.

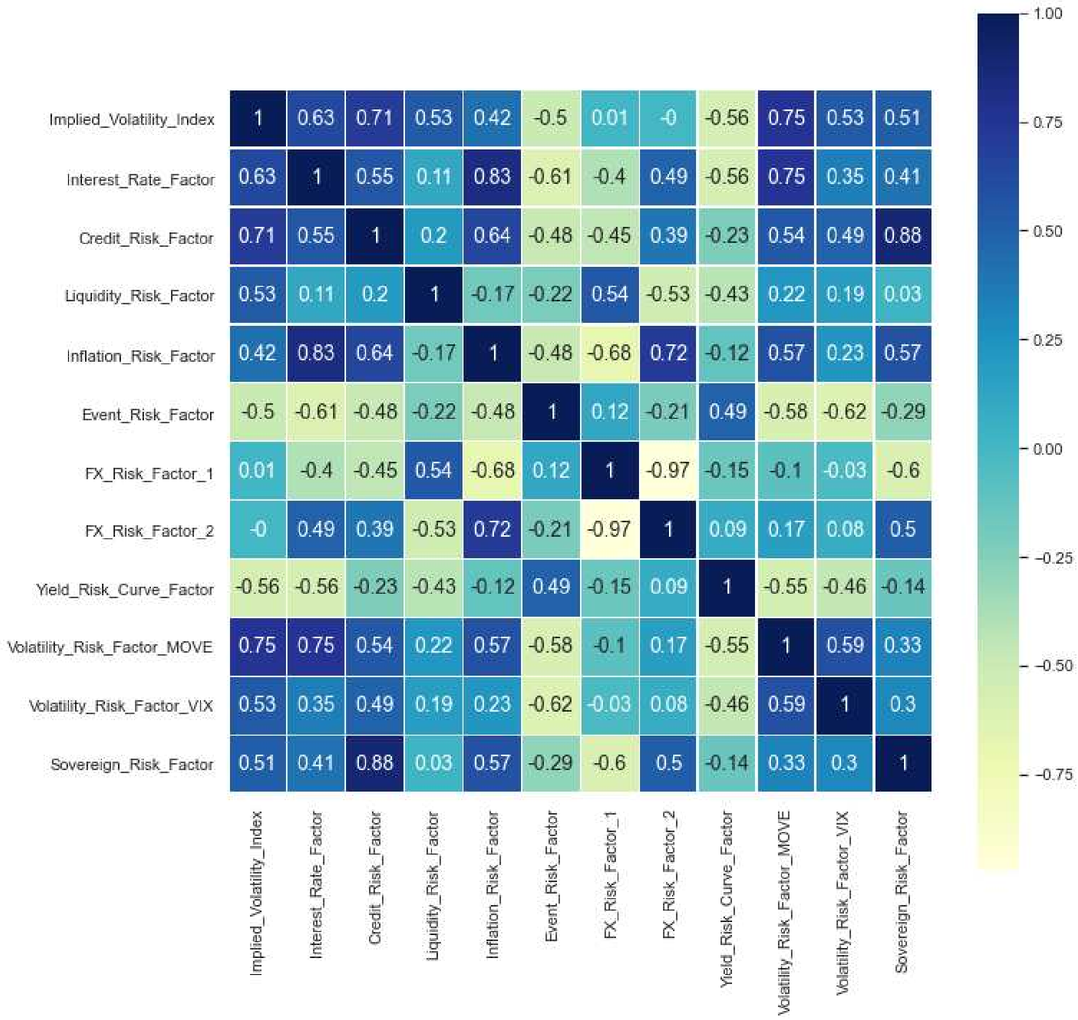


Figure 12: Correlation Matrix of Implied Volatility Index with respect to Factors (own processing)

Figure 12 depicts the variance accounted for by the PLS components utilizing the fixed income risk factors matrix, a key predictor of the dependent variable, the implied volatility index. PLS regression is employed to identify a subset of latent variables that reflect the most significant patterns in the fixed income risk factors, while simultaneously optimizing the covariance between the fixed income risk factors and the implied volatility index. The number of components used in PLS regression can be chosen based on the ratio of the model's explained variance. PLS1 accounts for just 12% of the total variation, PLS2 accounts for close to 12% of the total variation, and PLS3 accounts for close to 10% of the total variation, suggesting that these components may be especially valuable for predicting the implied volatility index.

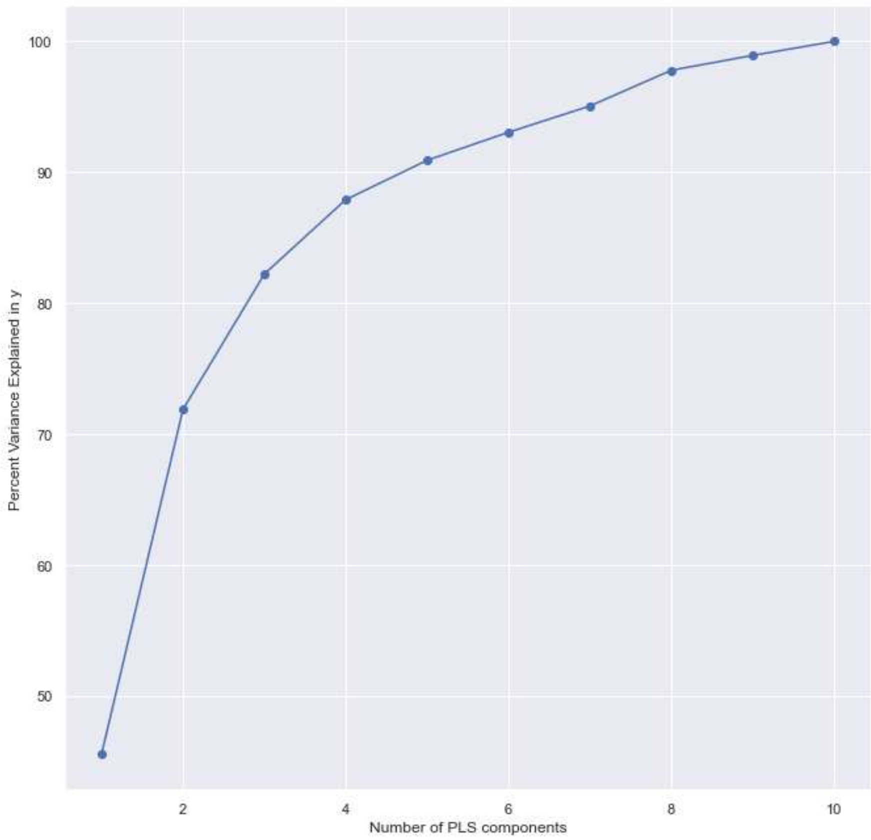


Figure 13:Variance Explained by Components as a Percentage (own processing)

Figure 13 depicts the variance accounted for by the various PLS components. In PLS regression, the objective is to identify a subset of latent variables that best explains the covariance between X and y, while also revealing the data's structure. These latent variables are known as "components of partial least squares." The number of components used in PLS regression can be chosen based on the ratio of the model's explained variance. The five components can explain over 90 percent of the variation in the predictor variables. These figures (13 and 14) provide valuable insights into the variance explained by the PLS components, highlighting the significance of selecting the optimal number of components to obtain the highest predictive power for the implied volatility index.

R2 (Coefficient of determination), a measure of how well the predictor variables can explain the disparity in the target variable, is then applied. (Implied Volatility Index). According to the results of the PLS regression, five factors (Volatility Risk Factor MOVE, Volatility Risk Factor VIX, Inflation Risk Factor MOVE, Event Risk Factor, and FX Risk Factor_2) have a significant relationship with the Implied Volatility Index (Rsquared value of 0.83925). The EUR/USD Index represents the FX Risk Factor_2. The results also indicate that the number of variables included in the PLS regression has an impact on the R-squared value, but the difference is not statistically significant. For instance, the R- squared value ranges from 0.8311 to 0.8397 when 3 or 6 factors are considered, and from 0.5694 to 0.5694 when only the Volatility Risk Factor MOVE is considered (Results shown in Appendix A).

Appendix A displays the scatter diagram between the explanatory factors and the implied volatility index. Figure a depicts the relationship between the implied volatility index and the volatility risk factor MOVE. As the values of both variables increase, the relationship between them becomes less dense. The interaction between the implied volatility index and the volatility risk factor VIX is depicted in Figure b. The relationship's distribution becomes more dispersed as both factors increase. Figure (c) illustrates a downward linear relationship between the event risk factor and the implied volatility index, with greater density when both factors are low. As both factors increase or decrease, figure (d) depicts a non-linear interaction between the implied volatility index and the inflation risk factor with a dispersed density. Figure e depicts a non-linear interaction between the implied volatility index and the FX Risk Factor_2, in which the density becomes more dispersed as FX Risk decreases. These graphs illustrate the unique relationship between each factor and the implied volatility index.

The results of the partial least squares regression analysis indicate that five factors are significant in determining the implied volatility of Bond futures: Volatility Risk Factor MOVE, Volatility Risk Factor VIX, Event Risk Factor, Inflation Risk Factor, and FX Risk

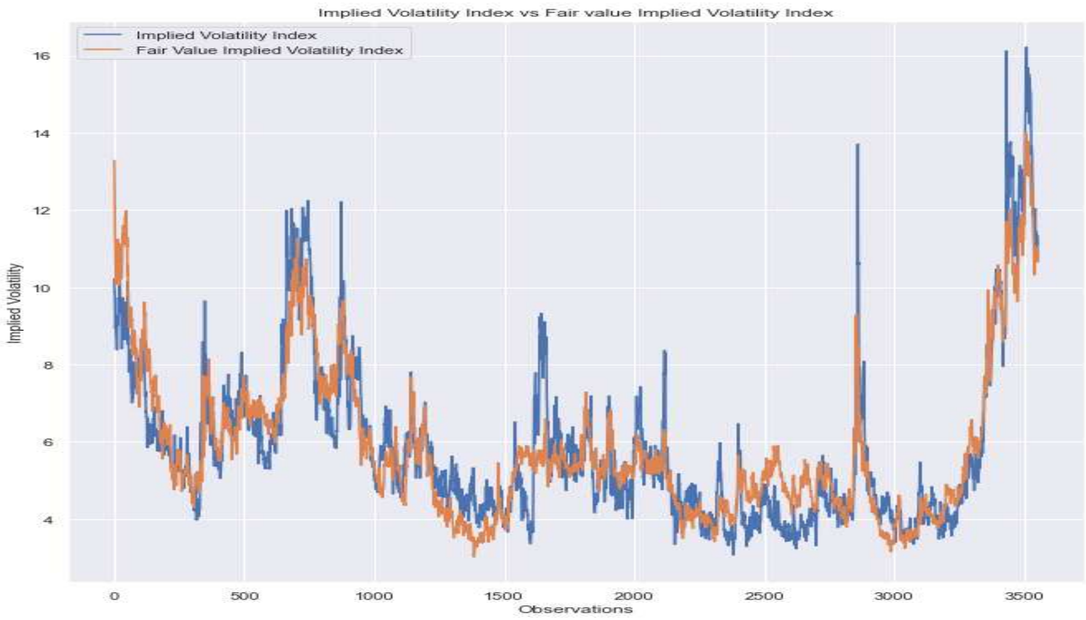
Factor_2. The high R-squared value of 0.83925 confirms the robustness of these five factors in explaining the implied volatility index variance.

Moreover, the significance of Volatility Risk Factor MOVE is highlighted by multiple studies (2017, p. 1), (2023, p. 4), (2018, p. 585). This demonstrates the importance of MOVE as a measure of uncertainty in the fixed-income market and its impact on the implied volatility of Bond futures. Furthermore (2023, p. 4), (2017, p. 24) demonstrate that there is a correlation "between bond market volatility and equity market volatility." The significance of MOVE as a gauge of uncertainty in the fixed income market is highlighted by this, as is the impact it has on the implied volatility of Bund futures. Moreover, Tompkins (2003) also supports this by finding a relationship between the European and US benchmark assets. Additionally Zhou (2014, p. 227), Kumar et al. (2023, p. 4), Pan (2018, p. 585), Budd (2017, p. 24) show that there is a relation “between the volatility in the bond market and equity markets”. As such, we have considered the VIX index as an additional volatility factor, which has been shown to be relevant in determining implied volatility. During times of crisis, uncertainty in the market's future expectations leads to increased demand for protection of investments, such as the use of derivatives based on the US Equity Index of top 500 companies weighted on market capitalization. The VIX index captures this risk.

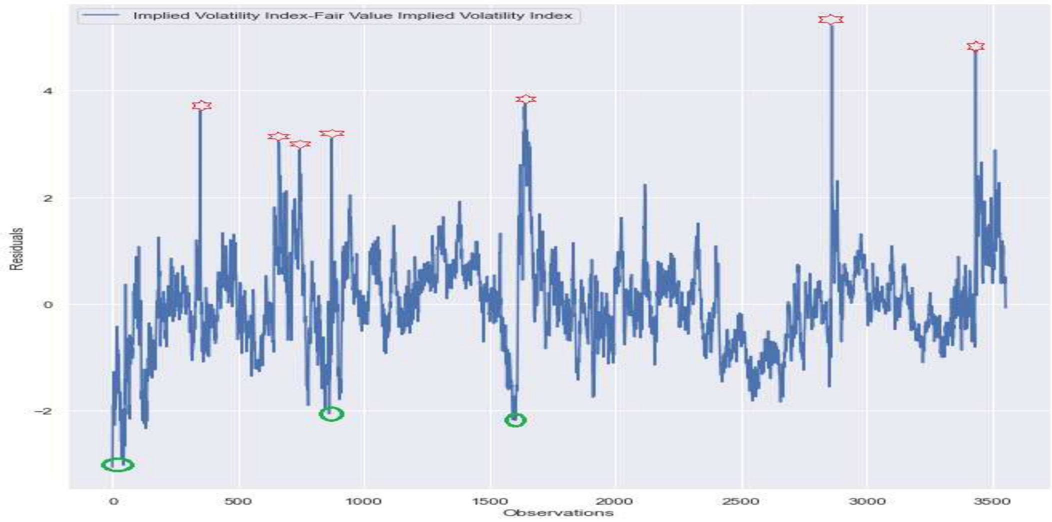
"The Credit Suisse Fear Barometer" (CSFB Index) used as proxies to measure event risk. The CSFB Index, based on the US Equity Index options, captures the mood of investors 3 months ahead, while the VIX Index, based on the offers and bids of 30-day options on the US Equity Index options, reflects market uncertainty in the present. Studies by authors such Kim et al. (2001), Mallick et al. (2017), Vähämaa S. W. et al. (2005) demonstrate that rising uncertainty in the market often occurs during the release of economic data or monetary policy decisions, which can be captured through the event risk factor. These findings are supported by our results obtained through PLS regression, which indicate that event risk and inflation risk factors are relevant in determining the implied volatility of Bund futures. The inflation risk factor represents a change in market expectations of inflation, which has an impact on bond prices. Our PLS regression results align with the literature, confirming the significance of event risk and inflation risk factors in explaining the implied volatility of Bund futures.

The introduction of the Euro as a common currency in the Euro area resulted in a decline in bond yields, which affected bond prices and bond futures. The euro currency reflects this reduction of ambiguity in individual country sovereign risk and liquidity risk, as well as increased bond trading (2015).

Furthermore, our findings indicate that the Euro plays a significant role in the implied volatility of bond futures.



(a)



(b)

Figure 14: Fair Value of Implied Volatility Index (own processing)

Note: (a) Fair Value of Implied Volatility Index based on 5 Factors. (b) Residuals (ErrorTerm simply y_pred minus y)

Figure 14 depicts the fair value of implied volatility index based on five factors andresiduals, which are error terms between predicted and original values. The PLS regression model can provide a comprehensive view of the underlying dynamics of implied volatility in the Bond futures market by incorporating all five of these variables. In addition, theresults illustrate the significance of contemplating multiple factors when attempting to comprehend the complexity of implied volatility in fixed-income markets. Figure 14 (b) illustrates the volatility's affordability or costliness relative to its fair value; it can be used as an indicator to purchase or sell volatility utilizing various option volatility strategies. (Red Star- High Volatility compared to Fair Value and Green Circle- Low Volatility compared to fair value). Traders can use short volatility strategies to profit during periods of high volatility by selling options (2018, p. 69). These strategies take advantage of the decline in volatility, allowing traders to profit from the decline. Traders can profit from using the fair value implied volatility indicator to accurately predict market direction during downturns and rallies. The primary objective of this study was to identify factors that explain implied volatility, but the results can also be used as an indicator for purchasing and selling volatility via various option strategies. By considering the five factors in this analysis, we can effectively address the research question of identifying the explanatory factors of implied volatility in the Bond futures market. PLS regression is used to reduce the dimensions of a data set while retaining the majority of the original information by identifying latent variables, also known as PLS components, that explain the covariance between the features and response variable.

4.2 Result of Factors Significance.

Next, a Granger causality test will be conducted to examine the relationship between the explanatory variables of the implied volatility index derived from the PLS regression and the short condor profit and loss. (PNL). The objective is to determine whether there is a causal connection between the explanatory factors and the short condor PNL, where the short condor strategy is a volatility-based strategy. It is necessary to determine whether the data is stationary prior to conducting a causality test. We utilized the ADF (1969, p. 424) test with a 1-day latency and a significance level of 5%. The outcomes are displayed in Appendix B. The Volatility Risk Factor MOVE, Inflation Risk Factor, Event Risk Factor, FX Risk Factor_2, and Volatility Risk Factor VIX datasets were determined to be stationary, implying that at a 5% significance level, the p-value is less than 0.05, refuting the null hypothesis. After confirming the ADF Test, we conducted the Granger Causality test for all five factors with a 1-day lag and a significance level of 5%.

Figure 13 illustrates the results of the Granger causality test between the Short Condor PNL and five risk factors (Volatility Risk Factor MOVE, Inflation Risk Factor, Event Risk Factor, FX Risk Factor_2, and Volatility Risk Factor VIX). (For Python results refer to Appendix B). The EUR/USD Index represents the FX Risk Factor_2. Inflation Risk Factor, Event Risk Factor, and Volatility Risk Factor VIX do not have a causal relationship with Short Condor PNL at a 1-day latency and 5% significance level. However, it is discovered that Volatility Risk Factor MOVE and FX Risk Factor_2 have a causal relationship with Short Condor PNL. This makes sense, given that a Short Condor strategy should perform well in a low-volatility market with stability and predictability, but unfavorably in a high- volatility market with uncertainty and surprises. The MOVE Index considers the volatility of the U.S. bond market across maturities. Exchange rate fluctuations can impact volatility and the performance of the Short Condor, so the FX Risk Factor_2 also has a causal relationship with Short Condor PNL. In conclusion, the Granger causality test is utilized to determine the causal relationship between independent variables and a dependent variable by analyzing the statistical significance of the coefficients of the lagged values of the independent variables. If the coefficients are statistically significant, this indicates that the independent variable has a Granger effect on the dependent variable. According to the results of the Granger causality test, it was determined that two factors have a Granger cause.

Table 6:Granger Causality Test Results (own processing)

Factor	Lag	est Statistic	p-value	Summary
Volatility RiskFactor MOVE	1	11,31027	**0,00077**	Null hypothesis of no causalityis **rejected** at 5% significance level
Inflation RiskFactor	1	0,92267	0,33678	Null hypothesis of no causalityis **accepted** at 5% significancelevel
Event RiskFactor	1	3,50623	0,06114	Null hypothesis of no causalityis **accepted** at 5% significancelevel
FX Risk Factor_2	1	8,24800	**0,00408**	Null hypothesis of no causalityis **rejected** at 5% significance level
Volatility RiskFactor VIX	1	1,66104	0,19746	Null hypothesis of no causalityis **accepted** at 5% significance level

4.3 Result of out of sample forecast

We conducted an out-of-sample test to evaluate the forecasting accuracy of factors from the fixed-income market on the option volatility strategy using data not included in the sample. The dataset was separated into training and testing sets, with the training set containing data from six years and the testing set containing data from two years. In our analysis, we considered parameters including "max depth = - 1, learning rate = 0.1, n estimators = 100, subsample for bin

= 200,000, objective ='regression,' class weight = None, min split gain = 0.0, min child weight = 0.001, and min child samples = 20." (2020, p. 4), (2020, p. 3).

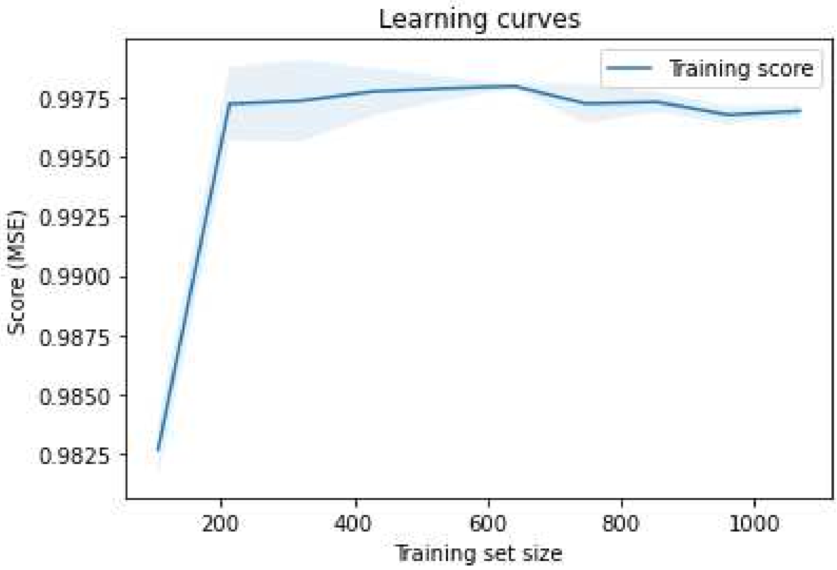


Figure 15:Model Performance as Size of Training Set (own processing)

To better fit the model, we set n estimators to 100 and the learning rate to 0.1. The fitting effect is influenced by both the n estimator parameter and the learning rate. A low value for n estimators can lead to underfitting. As an assessment parameter for evaluating the performance of the model, the mean squared error can be utilized. Figure 15 illustrates how the efficacy of the model changes as the size of the training set grows. The larger the dataset, the more data the model must learn from, allowing it to better fit the data to the objective variable. The learning rate parameter modifies the training process's step size. A slow learning rate can prevent the model from diverging and converging to extremes. However, if the learning rate is set too low, convergence can be sluggish and training durations can be extended. The value of 200000 for the subsample for bin indicates the number of samples used to construct the histogram and compute the splitting points on trees. The sample weights of leaf nodes are determined by the min child weight parameter, which we have set to 0.001. We can see from equation 5 that Light GBM makes predictions based on the performance of the model. In our model, we used mean squared error to evaluate the model and then assigned weights to the factors. The Light GBM model is configured as a regression model, and the objective is to evaluate the model's precision using the mean squared error.

Light GBM is an algorithm for machine learning that makes predictions using decision trees. Each decision tree generates a prediction based on the feature values for a specific instance. (e.g.

fixed income risk factors). During training, the algorithm discovers the optimal weights to allocate to each individual tree in order to minimize the loss function, which measures the accuracy with which the model predicts the target variable (e.g. short condor PnL). Based on the feature values, the algorithm divides the dataset into subsets and applies a decision tree to each subset. At the time of prediction, the algorithm combines the predictions of all individual trees to produce a final prediction for a given instance. It accomplishes this by calculating the prediction of each individual tree and combining them using the training-learned weights.

The weights designated to each tree are dependent on its performance on the training data and its contribution to the model's overall accuracy. During training, the algorithm determines which feature to divide on at each node of the tree based on how much each split improves the model's ability to predict the target variable. This means that various subsets of features and split points may be used by each decision tree in the ensemble to make predictions.

Even though the individual trees are not connected in the conventional sense, they are combined in a manner that enables them to work in tandem to make accurate predictions for the target variable. During the In sample forecast, Light GBM learns from the training set which factors help minimize the brief condor PnL loss function. Based on its efficacy on the training data, the algorithm assigns weights to each tree. For Out-of-Sample Prediction, we use the betas of the feature factors based on the training-assigned ranking weights of the Light GBM model. Due to the fact that the model was not trained on these data, its accuracy may differ from the In sample prediction.

4.3.1 In Sample Test

The training data spans six years, from 2014 to 2019, with the performance of the short- tailed condor serving as the target variable and all other factors serving as feature variables. The Light GBM model is utilized to manage numerous multiple factors, with all fixed income market factors considered feature variables. Only two factors (Volatility risk factor Move and FX risk factor_2) were found to have a Granger cause with the short condor performance based on the results of the Granger causality test. The results of the Light GBM Model with only these two parameters are presented in Appendix C, but the predicted values did not correspond well with the actual values. This indicates that using only these two variables to predict the performance of the short-term condor may be ineffective. In addition, it may indicate that the Granger causality model is not an accurate predictor, as the factors that Granger identifies as influencing the performance of the short condor have larger residuals. Therefore, all factors were deemed capable of achieving the objective of predicting the performance of the short condor strategy using fixed income market factors.

Light GBM is an algorithm for machine learning that is well-suited for large datasets and is renowned for its rapid training speed and high degree of accuracy. The algorithm constructs decision trees iteratively and employs gradient boosting to enhance the prediction accuracy of the model. The boosting algorithm treats each data sample equally by assigning the "class weight" hyperparameter to None. As specified in equation 5, it begins by feeding the data to the first machine learning model, also known as the base algorithm. The boosting algorithm then evaluates the model's predictions and increases the weight of samples that were incorrectly classified by a greater margin. Each model's weight is also based on its efficacy, which is measured using objective "regression" and mean squared error. If a model makes accurate predictions, it will have a significant effect on the performance of the short condor. As indicated by equation 6, wherein our objective function was set to minimize the mean square error for the factors and their weights were assigned based on the model's performance, a model that generates accurate predictions was developed.

The features are ranked ascendingly in Figure 16, where the factor importance of each factor determines the weight or score assigned by the Light GBM model, demonstrating that each factor contributes to minimizing the mean squared error. All fixed income market factors were regressed using the Light GBM Model, with short condor performance in the training set serving as the target variable. Figure 17 (b) illustrates the relationship between the difference between expected and actual values of the short condor's performance in the 6-year training set.

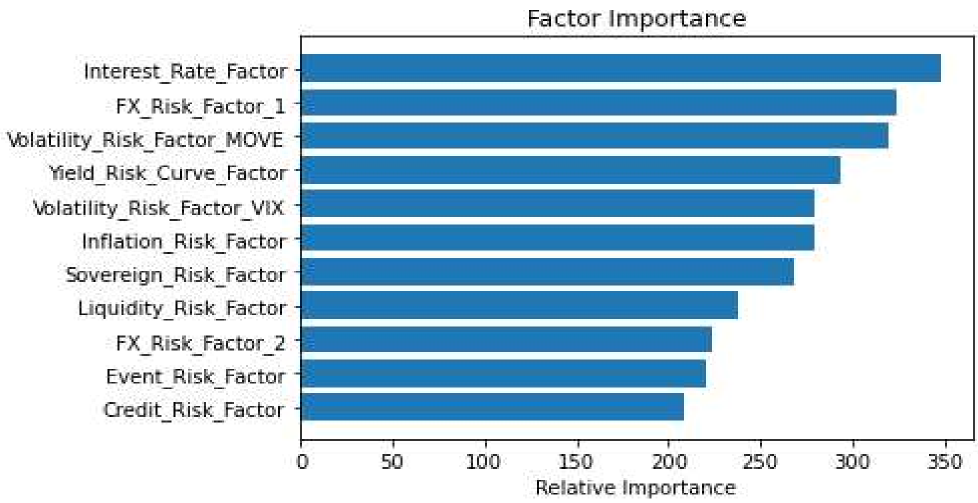
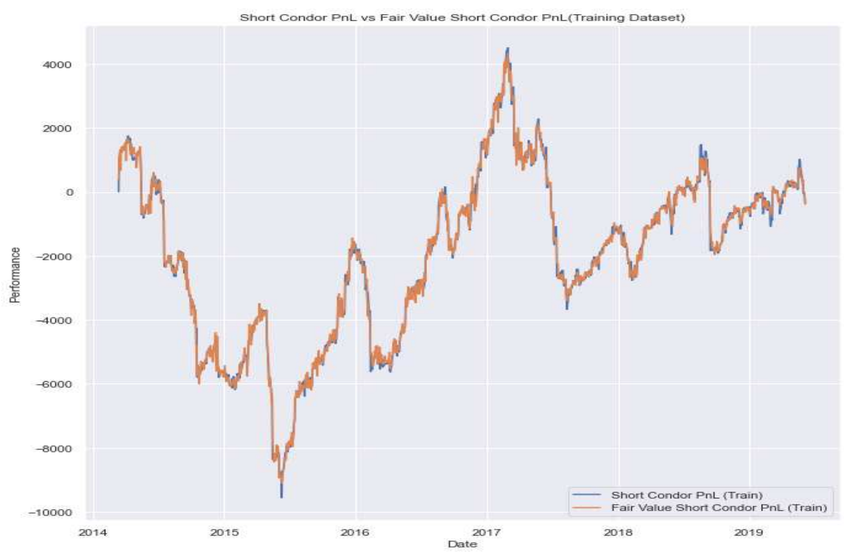


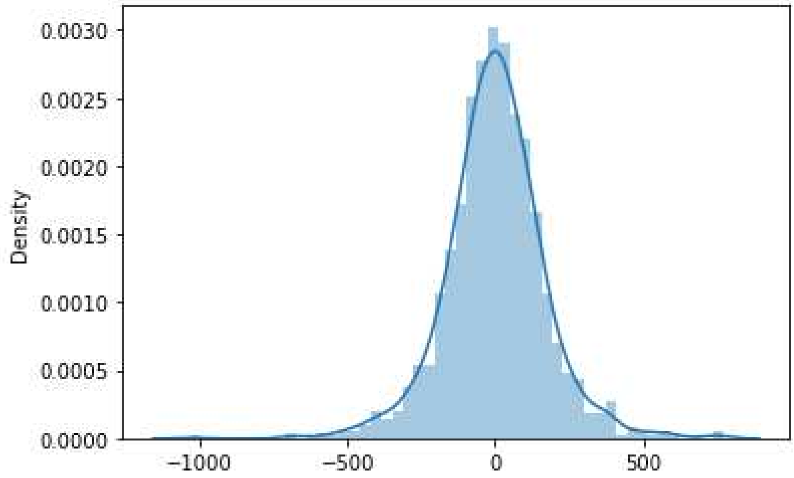
Figure 16: Factor Importance of Light GBM (own Processing)

Figure 17 (a) demonstrates that the predicted values, labeled fair value short condor PNL, and the actual values, labeled short condor PNL, are very similar. The difference between expected and actual values is greatest for the positive PNL, which is approximately 750 euros, and the negative PNL, which is approximately -1,000 euros. This indicates that the predicted values closely match the actual values and that the error term is minimal.

After achieving success on the training set, the model was evaluated using two years of data from an independent data set. The mean squared error was utilized as a performance accuracy metric. Figure 18 demonstrates that the mean squared error for the training set (represented by the blue bar) is modest, whereas the mean squared error for the test set, in which all factors from the fixed income market were considered as feature variables, is higher. For out-of-sample data, the disparity between the predicted values (fair value short condor performance [Test Data]) and the actual values (short condor performance) grows.



(a)

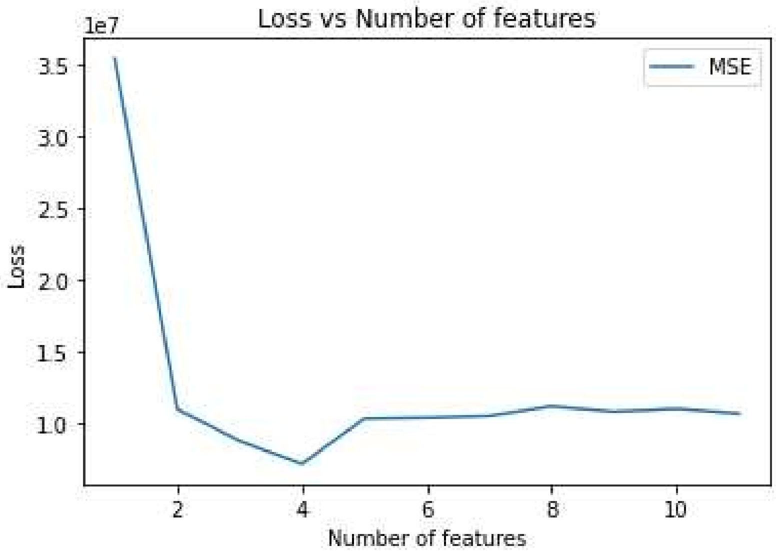


(b)

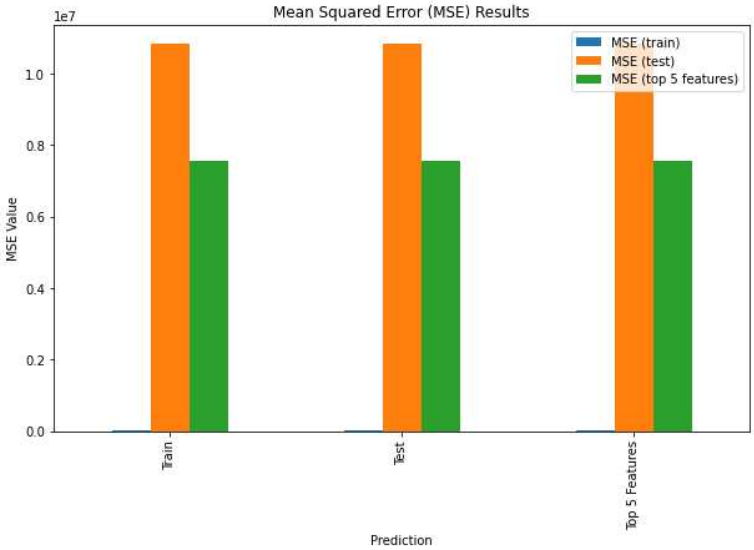
Figure 17:In-Sample Forecast (own processing)

Note: (a) In Sample Performance (Short Condor PNL vs Fair Value Short Condor PNL) (b) Residuals (Error Term= Short Condor PNL- Fair Value Short Condor PNL) plotted as Normal Distribution Curve.

In our case, we trained the model with all features and then selected the five most important features based on their significance in minimizing the MSE on the test data. This is known as feature selection, where you attempt to identify the most essential features that contribute to the efficacy of the model. Selecting only the top five features simplifies the model and prevents overfitting, which occurs when a model becomes overly complex and adapts to noise in the training data. Reducing the number of features can enhance the model's ability to generalize to new data. Figure 20a illustrates the loss function of a Light GBM model versus the number of features. The loss function quantifies the disparity between expected and actual values. By plotting the loss function against the number of features, one can determine how adding or removing features affects the model's performance. This plot is useful for determining how the number of features affects the efficacy of the model.



(a)



(b)

Figure 18:Mean Squared Error (own processing)

Note: (a) Loss Function of a Light GBM Model vs Number of Features [Training Data Set], (b) Mean Squared Error.

Note: Blue Bar: Training Data Set, Orange Bar: Testing Data Set with All Factors and Green Bar: Testing Data Set with 5 Factors.

Figure 18 (b) demonstrates that using the top five factors (represented by the green bar) from the training set for out-of-sample prediction on two years of data resulted in a decrease in mean squared error compared to using all factors from the fixed income market. The tops indicate that the top five factors have a higher predictive accuracy in the out-of-sample data set than all factors. This demonstrates that the Light GBM model can produce highly accurate predictions, particularly when the top five factors are considered. These results indicate that the model's predictions, particularly those based on the top five factors, have a substantial impact on the ultimate decision.

Interest Risk Factor, FX Risk Factor_1 (Dollar Index), Volatility Risk Factor Move, Yield Risk Curve Factor, and Volatility Risk Factor VIX are the top five factors influencing the performance of the short condor in the training set, which includes data from six years. The Light GBM model assigned each factor a score based on its influence on the final prediction. The objective of the model is to minimize the loss function and generate accurate predictions.

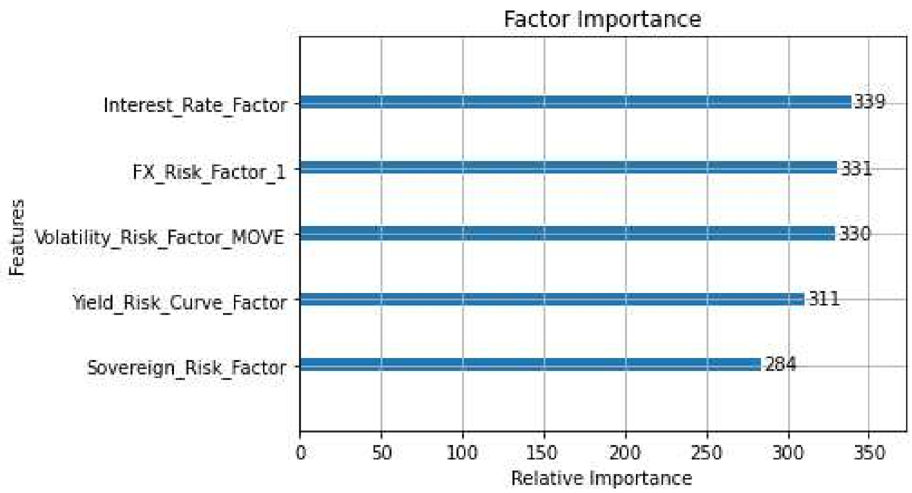
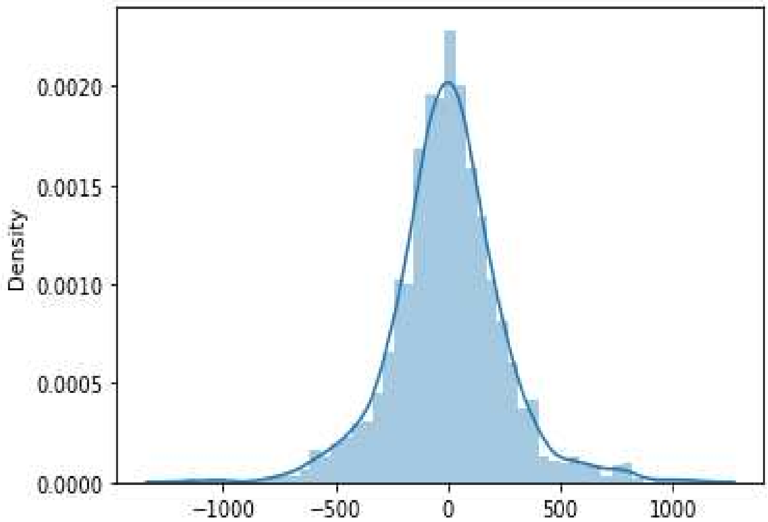


Figure 19:Top 5 Factor Importance of Light GBM (own processing)

Comparing the factors obtained for the Implied Volatility Index from the results of the PLS regression as shown in section 4.1 to the Short Condor Performance factors as depicted in Figure 19, it is evident that different factors have an effect on the Short Condor, but are not the primary factors of the Implied Volatility Index. This may be due to the various models used to obtain the results. The PLS regression method was used to identify the Implied Volatility Index's explanatory factors, while the Light GBM model was used to make accurate predictions. Nevertheless, the Volatility Risk factor MOVE and the Volatility Risk factor VIX influence both the Implied Volatility Index and Short Condor Performance. The VIX Index measures fear in the equity index and can be affected by macroeconomic factors such as the US currency, gold price, and crude oil price (2022, p. 2). A low MOVE Index value indicates market stability, whereas a large value indicates investor uncertainty or fear.

(a)



(b)

Figure 20:In-Sample Forecast with top 5 factors (own processing)

Note: (a) In Sample Performance (Short Condor PNL vs Fair Value Short Condor PNL [5 Factors]) (b) Residuals (Error Term= Short Condor PNL- Fair Value Short Condor PNL [5 Factors]) plotted as Normal Distribution Curve

Figure 20 depicts the correlation between predicted and actual results for the short condor's performance in the top five factors over a six-year period. The predicted values, known as the Fair Value Short Condor PNL, and the actual values, known as the Short Condor PNL, appear to be in close agreement. The largest difference between expected and actual values can be seen in the positive PNL, which is approximately 1000€, and the negative PNL, which is approximately -1000€. This indicates that the approximated values accurately reflect the actual values, with a small margin of error. Note: (a) In Sample Performance (Short Condor PNL vs Fair Value Short Condor PNL [5 Factors]) (b) Residuals (Error Term= Short Condor PNL- Fair Value Short Condor

PNL [5 Factors]) plotted as Normal Distribution Curve

To test the Light GBM model, we ranked all fixed income factors according to their relevance within the model. Then, we used these variables to predict the performance of the brief condor for the sampled data set. The outcomes were favorable due to the minor residuals between the predicted and actual values. Next, we conducted an accuracy test on the two-year test data set that was not part of the sample. We discovered that the mean squared error (MSE) for the out-of-sample test considering all factors was greater than the MSE for the top five factors. Then, we retrained the Light GBM model with the top five factors and predicted the brief condor PNL values. However, the prediction errors were smaller than all test data factors but still greater than all training data factors.

We divided the data set appropriately to improve the model's precision. We utilized six years of data for the training set and two years of data for the unseen, out-of-sample test set (2022, p. 9).

This helped prevent overfitting. We trained the model on the training set and then evaluated its performance on the test set, which the model had never seen (2019, p. 10).

4.3.2 Out of Sample Test

After training, the model's performance was evaluated on an out-of-sample (with 5 factors) test data set it had never seen before. Figure 21 depicts the relationship between the predicted and actual values of the brief condor performance in this test set. The test set contained data for two years. Figure 21 (a) illustrates the dispersion between the predicted (labeled "fair value short condor PNL") and actual values. (referred to as "short condor PNL"). The residuals, which are the differences between the predicted and actual values, are depicted as a normal distribution curve in Figure 21 (b). Nevertheless, the shape of the curve is not bell-shaped, as it does not have a mean of zero and a standard deviation of one. The curve is skewed to the left, and the y-axis represents density, which represents the probability per unit on the x-axis. The highest density is between 0 and -2000€, indicating that the predicted values for the short condor performance are the most distinct from the actual values, and the probability of occurrence is also the highest per unit of PNL. This indicates that the predicted values do not correspond to the actual values and that the error term is substantial, as demonstrated by the dispersion in Figure 21 (a).

4.3.3 Performance comparison using trading signals.

To evaluate the predictive capability of the Light GBM model, we propose a method for optimizing trading or investment strategies based on predicted values. This system employs a threshold value comprised of the error value from the training set to compare the predicted values with the actual values and improve the performance of our buy-and-hold short condor strategy. This will provide an answer to the third sub-question of our thesis, namely the importance of factors in the out-of-sample test. This will also help determine whether the factor-based options short condor strategy outperforms the buy-and-hold options short condor strategy. We can identify trading signals that outperform a basic buy- and-hold strategy by comparing the predicted value of short condor performance to its actual performance. This system simplifies complicated models, facilitates risk management and portfolio decisions, and capitalizes on the predictability of factor-based models. Additionally, it enhances the performance of option volatility trading.

As a trading signal, the trading module in our system employs the predicted values generated by the Light GBM model and a threshold value. The threshold is set to the utmost allowable difference between the predicted and actual values of the short condor performance, which is determined by the error value of the training set.

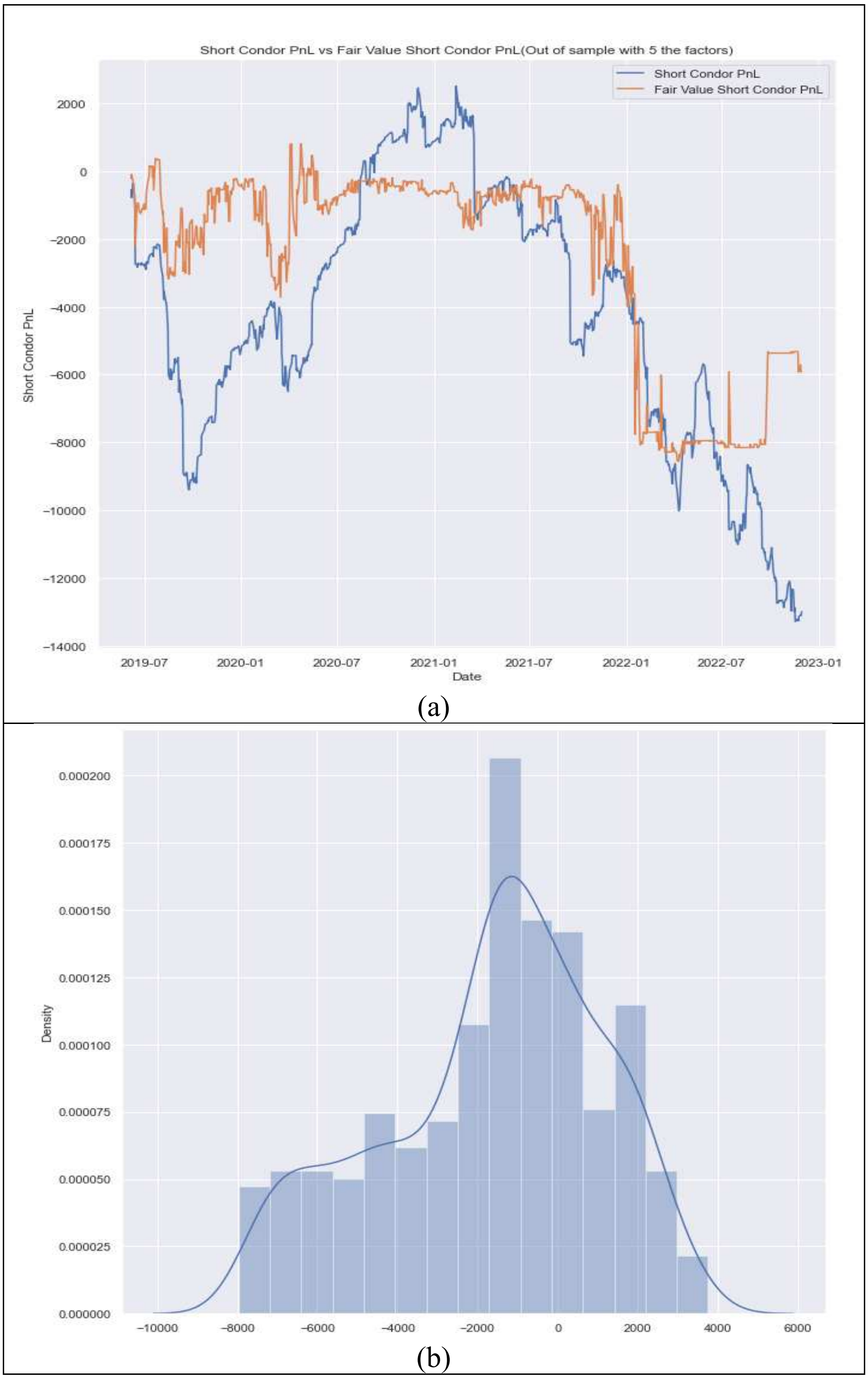


Figure 21:: Out of Sample Forecast with Five Factors (own processing)

Note: (a) Out of Sample Performance with five factors (Short Condor PNL vs Fair Value Short Condor PNL). (b) Residuals ((Short Condor PNL - Fair Value Short Condor PNL)) plotted as Normal Distribution Curve.

We have selected a trading signal threshold of -1000, which lies on the left side of the performance distribution for the short condor in the training set. This value was chosen based on the research finding (2020, p. 842) who demonstrated that the distribution of volatility rewards is biased to the left, where volatility rewards are the performance of the option volatility strategy. This indicates that the preponderance of rewards is at the higher end of the scale, with a few exceptions at the lower end. By setting our threshold to -1000, we can capture the relatively uncommon but crucial instances in which performance falls below the average for our trading strategy. The trading signal functions as a state machine containing Buy and Sell states. The following is how trades are executed based on the trading signal:

- If Actual Value - Predicted Values < Threshold, the Buy label is selected, indicating that the Short Condor Strategy is being employed. This action is represented by the position Buy in the test signal for the same day.
- If Actual Value - Predicted Values > Threshold, the label chosen is Sell, which indicates that we are selling the Short Condor Strategy, i.e. the Long Condor position is taken, which is explained in greater detail below. This action is indicated by the Sell in test signal position for the same day.

When the signal is "Buy," the Short Condor strategy is purchased, and when it is "Sell," the strategy is closed and the Long Condor strategy is entered for the out-of-sample test. As depicted in Figure 6, the Short Condor strategy consists of four option legs, including the purchase of one higher out-of- the-money call option and the sale of one out-of-the-money call option, as well as the purchase of one higher out-of-the-money put option and the sale of one out-of-the-money put option. When the signal is "Sell," the Short Condor strategy is closed by selling one higher out-of-the-money call option and purchasing one out-of-the-money call option, and entering the Long Condor strategy by selling one higher out-of-the-money put option and purchasing one out-of-the-money put option. The daily PNL for each "Buy" and "Sell" signal is calculated, and the cumulative PNL is obtained to yield the Factor-based Short Condor PNL for the test dataset.

Figure 22 compares the net profit margins of the Factor-based Short Condor Strategy and the Simple Buy and Hold Strategy. The graph demonstrates that the Factor- based Short Condor Strategy is superior to the Simple Buy and Hold Strategy. While the factor-based strategy outperforms the buy-and-hold method, the accuracy of the buy and sell signals is less than 50%, which means that the strategy may not always generate positive daily returns when the signals are activated.

The trading module's threshold affects the accuracy of the trading signal, and adjusting the threshold can also affect the daily returns. Various thresholds can be evaluated to improve accuracy and performance.

Our findings are consistent with previous research on trading strategies based on volatility. Buying volatility strategies can help reduce market uncertainty (2010, p. 3). Directional neutral option trading strategies are vulnerable to volatility risk. Purchasing implied volatility can increase portfolio diversification, whereas a negative risk premium may cause long-term investments in volatility strategies to underperform (2006, p. 814) (2009, p. 68).

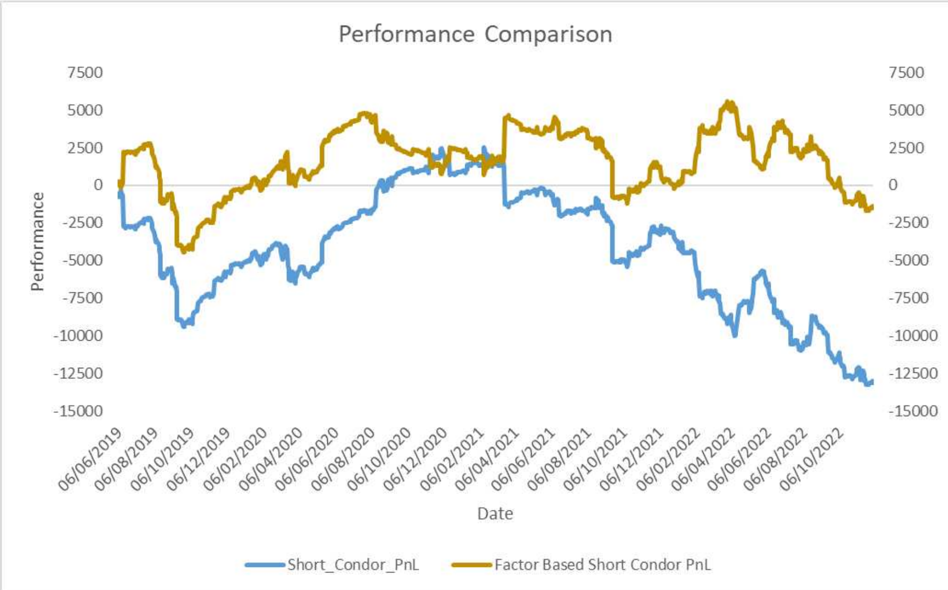


Figure 22: Performance Comparison (own processing)

On the other hand, it has been demonstrated that shorting volatility generates an excess risk premium. In our circumstance, however, we discovered that shorting volatility via a short condor strategy underperformed. In contrast, our Factor-based Short Condor Strategy outperformed simply shorting volatility by incorporating both long and short volatility signals. Our findings suggest that our strategy may be a more viable alternative for traders seeking to minimize risk and maximize returns.

The market as having two states – "high risk and low risk" (2014, p. 227) - and we discovered that incorporating both signals, via our Factor-based Short Condor Strategy, outperformed a straightforward Buy and Hold Short Condor Strategy. This is consistent with the findings (2001) (2018, p. 65) that options strategies can be utilized to capitalize on market volatility. Our Buy and Sell Signals correspond to periods of low and high volatility, respectively, and our analysis demonstrates that this results in superior performance. Consequently, our results indicate that our Factor-based Short Condor Strategy is a viable option for traders seeking to mitigate risk and maximize returns.

Several variables contribute to the effectiveness of the proposed trading model. Using various hyperparameters, the Light GBM model provides highly accurate predictions in the training set, thereby minimizing the overfitting problem. Secondly, the Leaf-wise analysis enables the identification of critical performance factors for the brief condor. This is crucial for decreasing the loss of function and obtaining superior results. By using a threshold from the training set and a prediction as a trading signal, the proposed factor-based short condor model outperformed the basic buy-and-hold short condor model. The Light GBM model incorporates performance-related information, which is why it performed better.

In addition, the selection of factors that explain the performance of the brief condor is also crucial. The Light GBM makes predictions using a gradient boosting algorithm that sequentially constructs decision trees and employs a leaf-wise structure. The gradient boosting algorithm corrects the errors made by earlier models and combines the predictions of all models to produce a final prediction. The algorithm computes the gradient of the loss function, which quantifies the disparity between the expected and observed values relative to the predicted values. A basic model, such as a decision tree, is then fitted to the negative gradient, which is then used to minimize the loss function.

CONCLUSION

In this thesis, traders, portfolio managers, and investors who use options to minimize risk, achieve nonlinear profits, or mitigate against the underlying market are introduced to a new approach. The method employs Light GBM models to develop a trading module that uses signals derived from Light GBM model predictions. Granger causality was used to determine whether there was a statistically significant relationship between these factors and the performance of the short condor option volatility strategy. Initially, the PLS regression was utilized to identify the explanatory factors that drive the implied volatility of Bond futures. However, only two variables were identified as Granger causes for brief condor PNL. Further analysis using the Light GBM model revealed that the training error term was larger than anticipated for only two factors with Granger cause, prompting us to include all factors from the fixed income market in the training dataset.

The findings confirm "that a significant risk premium exists for options on bond futures" on the German market. The study examined fixed income risk factors that outperformed the simple buy-and-hold strategy, indicating that these factors are influencing option prices that are priced by markets, which is consistent with (2003, p. 32) conclusion that some standardized and broad factors are the cause of the higher price of options. The paper discusses key findings for research queries including.

1. **Key Findings for R.1.1.**

Observations pertinent to the research subject R.1.1 "which factors explain the current dynamics of the implied volatility of Bond futures", for R.1.1 we used Partial Least Square Regression (PLSR) to determine the explanatory factors that influence the implied volatility of Bond futures. PLS regression reduces the dimensionality of the predictors and identifies a reduced number of uncorrelated components that account for the greatest variance in implied volatility. Five factors, including the Volatility Risk Factor MOVE, the Volatility Risk Factor VIX, the Event Risk Factor, the Inflation Risk Factor, and the FX Risk Factor_2, are significant in determining the implied volatility of Bond futures, according to the study. The high R-squared value of 0.83925 confirms the robustness of these five factors in explaining the implied volatility index variance. The predicted values derived from the PLS regression model can serve as an indicator for purchasing and selling volatility utilizing various option volatility strategies. The findings provide a comprehensive comprehension of the underlying dynamics of implied volatility on the Bond futures market and can be applied to make prudent trading decisions.

2. Principal Results for R.1.2

Using the Granger Causality Test, the research question R.1.2 investigated the relationship between the variables identified by the PLS regression and the option volatility strategy. Only two factors, Volatility Risk Factor MOVE and FX Risk Factor 2 (EURO Index), have a statistically significant relationship or granger cause with the short condor PNL, as determined by the test. The MOVE index measures the volatility of the US bond market across maturities, while exchange rate fluctuations can impact volatility and the performance of the Short Condor. These results are intriguing because they suggest that only two variables affect the short condor's expected profit and loss.

Also, the success of the proposed trading model can be attributed to the Light GBM model's accurate forecasts, the leaf-wise analysis, and the proper selection of factors to explain the short condor performance. The capacity of the gradient boosting algorithm to correct the errors of previous models and to combine the predictions of all models also contributed to the success of the model.

3. Key Observations for R.1.3

In order to answer the research question R.1.3, "Are factors significant in the option volatility strategy's out-of-sample forecasts?", we used the Light GBM Model, a gradient boosting algorithm that constructs decision trees to make predictions, to determine the answer. Each decision tree makes a prediction based on the feature values for a particular instance (e.g., fixed income risk factors). During training, the algorithm discovers the optimal weights to allocate to each individual tree in order to minimize the loss function, which measures the accuracy with which the model predicts the target variable (e.g. short condor PnL). At the time of prediction, the algorithm combines the predictions of all individual trees to produce a final prediction for a given instance. It accomplishes this by calculating the prediction of each individual tree and combining them using the training- learned weights. Using risk factors from the fixed income market, we evaluated the Short Condor Performance in the Bond Futures Options market using the model. Initially, we used only two factors that were discovered to have a Granger cause with the brief condor performance. However, we discovered that the model's predictions did not correspond well with the actual values in the training set. Subsequently, we utilized all the risk factors from the fixed income market, and the predicted values with small residuals matched the actual value precisely. Then, we selected only five factors that reduced the mean squared error and proposed a trading module called Factor-based Short Condor PNL to evaluate the model's predictive power. The outcomes demonstrated that the model outperformed the buy-and-hold strategy.

Both the Implied Volatility Index and Short Condor Performance were discovered to be affected by the Volatility Risk Factor MOVE and the Volatility Risk Factor VIX. However, it is essential to keep in mind that while distinct factors impact the Short Condor, they are not the primary determinants of the Implied Volatility Index. The success of the Factor-based Short Condor PNL can be attributed to the accurate predictions of the Light GBM model, the leaf-wise analysis, and the correct selection of factors to explain the short condor performance. The model was trained on six years of data and tested on two years of out-of-sample data, with promising results. Due to data availability constraints, however, this analysis only considered data from 2014 to 2023. There is a need for additional analysis using a larger data set to corroborate these promising results. Despite the limited dataset, the model's results are still promising, and incorporating factors into the investment strategy provides greater value than a standard buy-and-hold approach. It is also important to observe that neither the training nor testing sets included transaction costs.

4. Discussion

Our strategy outperformed the performance of a straightforward buy-and-hold short condor, indicating that fixed income market risk factors can serve as leading indicators of future developments in options volatility strategies. Our factor-based model can support risk management and portfolio decisions by offering a simplified version in comparison to complex models and enhancing the trading performance of option volatility. Consequently, the findings of this research may have substantial ramifications for market participants seeking to manage their portfolios more effectively and efficiently. Some future work concepts that can be explored. (2021, p. 4) suggest using the "ridgeless least square prediction" method, which considers more feature factors than the training data set. In contrast to our approach, which sought to minimize the feature in order to improve predictions in the out-of-sample test, this approach minimizes the feature. It would be intriguing to compare the outcomes of these two methods and investigate the "virtue of complexity (Abhishek Kumar, 2023)."

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INDEX OF ABBREVIATIONS

ATM	At the Money
OTM	Out of Money
ITM	In the Money
VIX	CBOE Volatility Index
FX	Foreign Exchange
OTC	Over the Counter
PLS	Partial Least Square
GBM	Gradient Boosting Machine
MOVE	ICE BofAML Bond Volatility Index
TIPS	Treasury Inflation Protected Securities
GDP	Gross Domestic Product
ECB	European Central Bank
S&P 500	Standard and Poor's 500 Stock Market Index
USD	US Dollar
M2 Supply	Money Supply
ATMF	At the Money Forward
EU	European Union
QT	Quantitative Tightening
CDS Index	Credit Default Swap Index
EUR	Euro Currency
CSFB	Credit Suisse Fear Barometer
COVID-19	Coronavirus
ADF	Augmented Dickey–Fuller
GOSS	Gradient Based One Side Sampling
EFB	Exclusive Feature Building
PNL	Profit and Loss
MSE	Mean Squared Error

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APPENDIX A

Python Code for Partial Least Square Regression

```
"""
Created on Wed Aug 2 10:01:38 2023
@author: Nirav Vyas
"""
import pandas as pd
```

```
from sklearn.cross_decomposition import PLSRegression import matplotlib.pyplot as plt from
sklearn.metrics import r2_score, explained_variance_score import numpy as np import seaborn as
sns
```

#Read data from excel

```
Data=pd.read_excel('C:\Nirav Vyas\Masters\Thesis\Analysis_1.xlsx'))
```

#Selecting Independent and Dependent variables

```
X=Data[['Interest_Rate_Factor', 'Credit_Risk_Factor','Liquidity_Risk_Factor',
'Inflation_Risk_Factor', 'Event_Risk_Factor', 'FX_Risk_Factor_1', 'FX_Risk_Factor_2',
'Yield_Risk_Curve_Factor','Volatility_Risk_Factor_MOVE','Volatility_Risk_Factor
_VIX', 'Sovereign_Risk_Factor']]
y=Data[['Implied_Volatility_Index']]
```

 # Compute the correlation matrix and round the values to 2 decimal places

```
corr = Data.corr().round(2)
```

 # Set the square size of the heatmap cells to uniform size

```
sns.set(font_scale=1.0)

sns.set(rc={'figure.figsize':(11, 11)})
```

 # Plot the heatmap

```
ax = sns.heatmap(corr, annot=True, cmap="YlGnBu", square=True, linewidths=.5,
annot_kws={"size": 14})
```

 # Save the heatmap as an image

```
plt.savefig("corr_heatmap.png", bbox_inches = "tight")
```

 # Define PLSR model with components

```
pls = PLSRegression(n_components=5)
```

 # Fit the model to the data

```
pls.fit(X, y)
```

#predicted values of the dependent variable y_pred based on this independent data. y_pred = pls.predict(X) Error=mean_squared_error(y, y_pred) print(mean_squared_error(y, y_pred), r2_score(y, y_pred))

 # predicted values of the dependent variable y_pred based on this independent data.

print("rsquared:",r2_score(y, y_pred))

plt.title ("Implied Volatility Index vs Factors Implied Volatility Index") plt.xlabel("Observations")

plt.ylabel("Implied Volatility")

plt.plot(y,label="Implied Volatility Index") plt.plot(y_pred,label="Factors Implied Volatility Index") plt.legend(loc="upper left")

 # ErrorTerm y_pred minus y (Compute the fitted response and display the residuals) plt.plot(y -y_pred,label="Implied Volatility Index-Factors Implied Volatility Index") plt.xlabel("Observations")

plt.ylabel("Residuals") plt.legend(loc="upper left")

#variance explained in X

#refers to the proportion of variation in the X matrix(Features variable matrix) that is explained by each PLS component

Define the number of PLS components n_components = 10

Create PLS regression object

pls = PLSRegression(n_components)

Fit the model to the data pls.fit(X, y)

 # Get the explained variance of each component in X x_explained_variance = pls.x_scores_ ** 2 / (X.shape[0] - 1) x_cumulative_variance = np.cumsum(x_explained_variance)

 # Plot the explained variance of each component in X

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,5))

 # plot explained variance of each component

for i in range(n_components):
ax1.bar(i+1, x_explained_variance[i], color='blue', linewidth=1)

ax1.set_xlabel('PLS Components') ax1.set_ylabel('Explained Variance') ax1.set_title('Explained Variance per PLS Component')

 # calculate explained variance ratio of scores scores_var = np.var(pls.x_scores_, axis=0) scores_var_ratio = scores_var / scores_var.sum() cum_scores_var_ratio = np.cumsum(scores_var_ratio)

 # plot explained variance ratio
plt.plot(range(1, 11), cum_scores_var_ratio * 100, '-bo')plt.xlabel('Number of PLS components') plt.ylabel('Percent Variance Explained in y')

plt.show()

 # Get the names of the components
components = X.columns unique_factors = set()

 # Iterate through the x_weights_ array and add the names of the factors to the set
for i in range(len(pls.x_weights_[0])):
factor_index = np.argmax(np.abs(pls.x_weights_[:, i]))
unique_factors.add(components[factor_index])

if len(unique_factors) == 5:
break
#print("Names of components:", components)
print("5 most important explanatory factors:", unique_factors)

 # Create a table to store the resultscomponents
unique_factors = list(unique_factors)
resultscomponents = pd.DataFrame(unique_factors, columns=['5 most important explanatory factors'])print(resultscomponents)

 # Calculate evaluation metrics

explained_variance = pls.score(X, y) r2 = pls.score(X, y)

 # Print evaluation metrics
print(f'Explained Variance: {explained_variance:.2f}')# Print R-squared value

print(f'R-squared: {r2:.2f}')

 # Create a table to store the results
results = pd.DataFrame({'Explained Variance': explained_variance,'R-squared':r2 },index=['PLSR Model'])

print(results)

from matplotlib.backends.backend_agg import FigureCanvasAgg as FigureCanvas from matplotlib.figure import Figure

fig = Figure(figsize=(5,5)) canvas = FigureCanvas(fig)

results.plot(ax=fig.gca()) canvas.print_figure('results.png', dpi=100)

#Scatter Plots
for factor in unique_factors:
plt.scatter(x=X[factor], y=y)plt.xlabel(factor)

plt.ylabel("Implied Volatility Index")plt.show()

#Defining R2 value for individual explanatory factors
unique_factors = ["Volatility_Risk_Factor_MOVE", "Inflation_Risk_Factor", "Event_Risk_Factor", "FX_Risk_Factor_2","Volatility_Risk_Factor_VIX"]

Initialize a dictionary to store the resultsresults_dict = {}

Loop through the number of componentsfor factor in unique_factors:

Define PLSR model with n componentspls = PLSRegression(n_components=1)

Fit the model to the data for the current factorpls.fit(X[factor].values.reshape(-1,1), y)

# Calculate evaluation metrics
explained_variance = pls.score(X[factor].values.reshape(-1,1), y)r2 = pls.score(X[factor].values.reshape(-1,1), y)

Add the results to the dictionary results_dict[f"{factor}_{unique_factors}"] = [explained_variance, r2]

 # Create a DataFrame from the dictionary
results_df = pd.DataFrame.from_dict(results_dict, orient='index',columns=['Explained Variance', 'R-squared'])

print(results_df)

 # Define a list to store the number of components
n_components = [3, 4, 5, 6, 7]

 # Initialize a dictionary to store the results
results_dict = {}

 # Get the names of the components
components = X.columns

 # Loop through the number of components
for n in n_components:

 # Define PLSR model with n components
pls = PLSRegression(n_components=n)

 # Fit the model to the data

pls.fit(X, y)

 # Get the names of the 5 most important explanatory factors

unique_factors = set() for i in range(n):

factor_index = np.argmax(np.abs(pls.x_weights_[:, i]))

unique_factors.add(components[factor_index])

 # Calculate evaluation metrics

explained_variance = pls.score(X, y) r2 = pls.score(X, y)

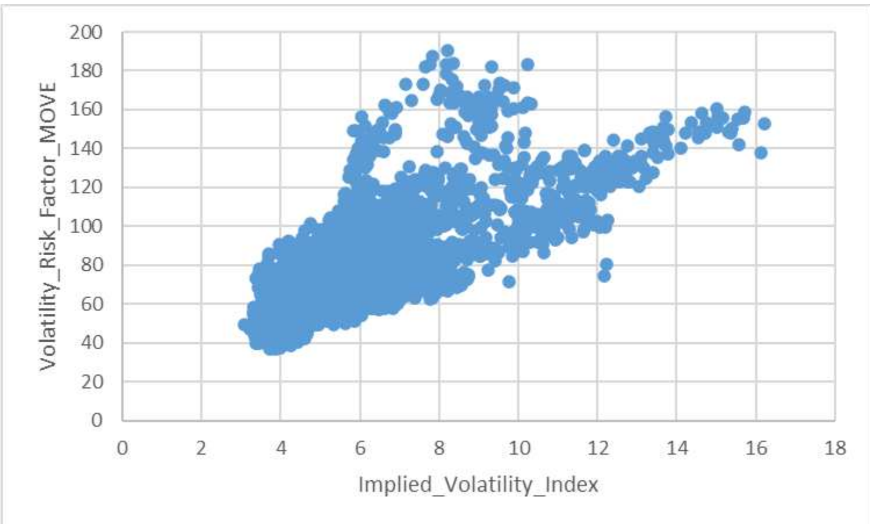
 # Add the results to the dictionary

results_dict[n] = [explained_variance, r2, unique_factors]

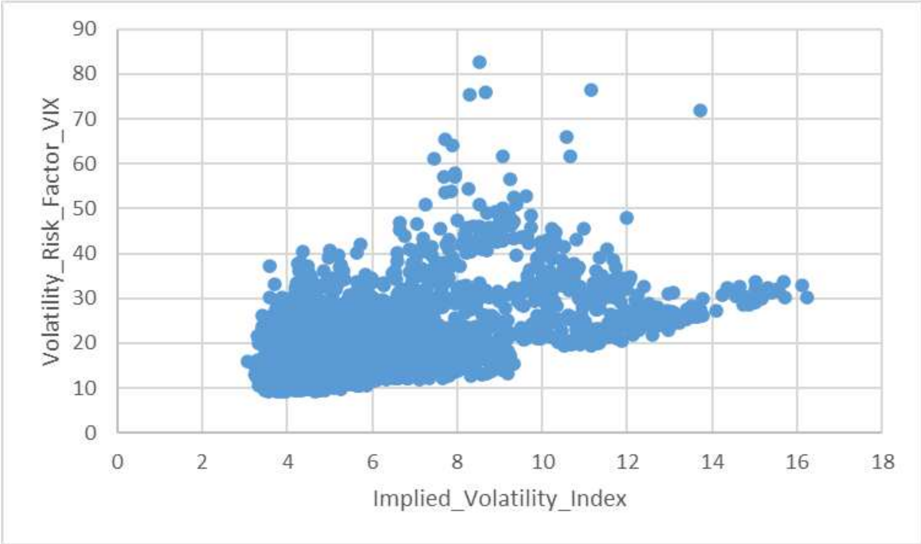
Create a DataFrame from the dictionary

results_df = pd.DataFrame.from_dict(results_dict, orient='index', columns=['Explained Variance', 'R-squared', '5 most important explanatory factors'])

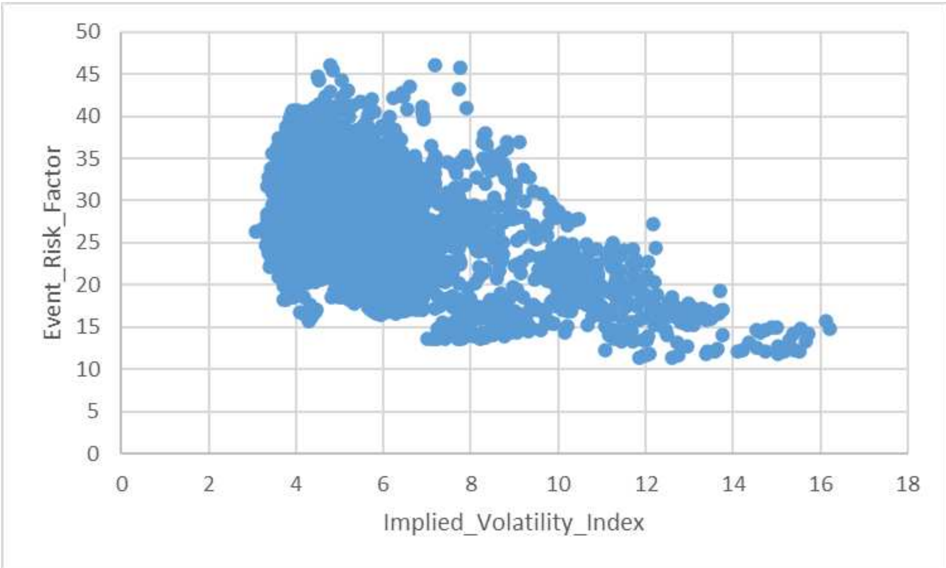
print(results_df)



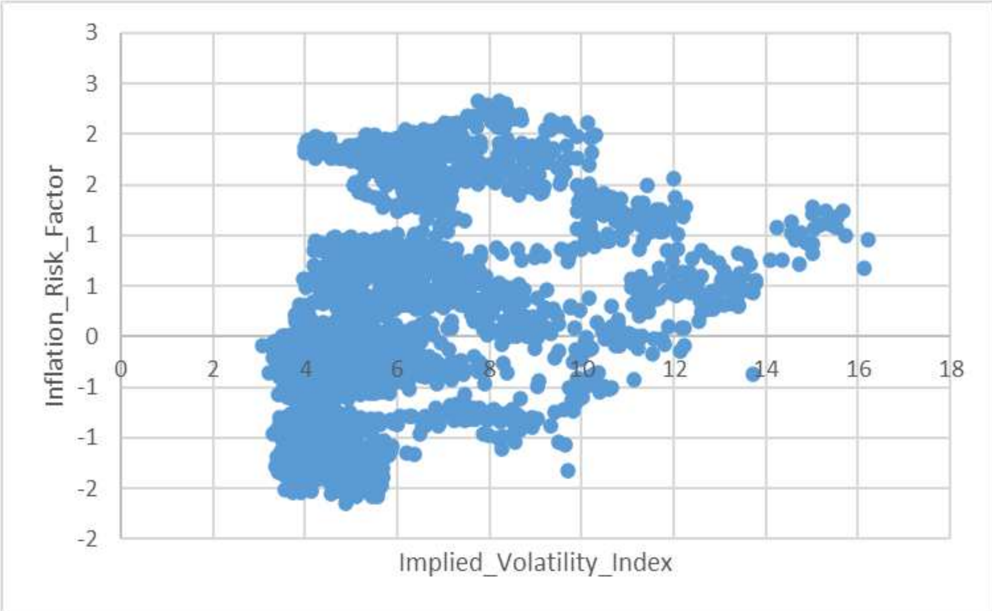
(a)


Volatility_Risk_Factor_VIX
Implied_Volatility_Index
0
10
20
30
40
50
60
70
80
90
0
2
4
6
8
10
12
14
16
18

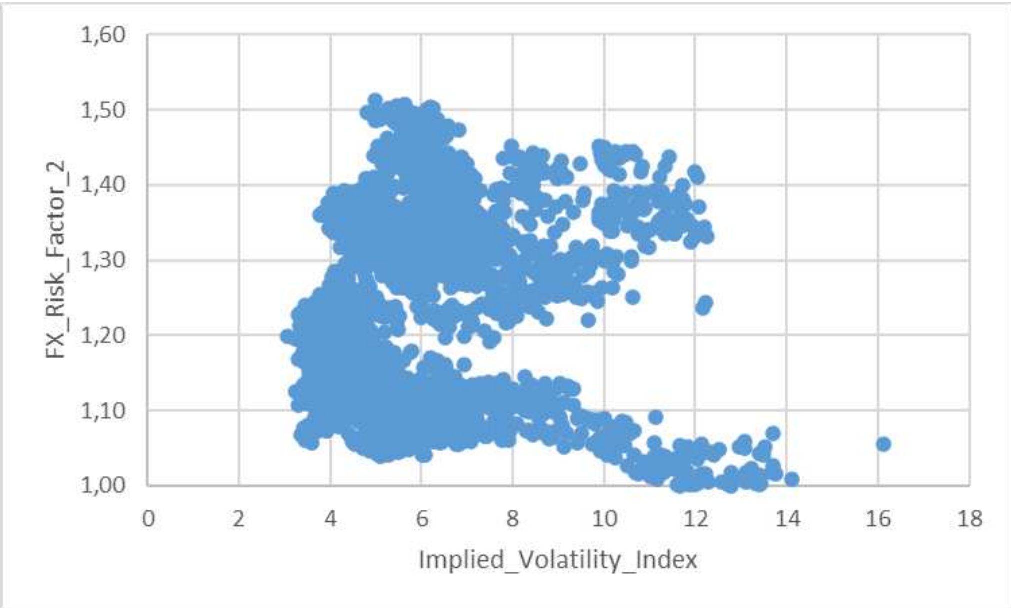
(b)


Event_Risk_Factor
Implied_Volatility_Index
0
5
10
15
20
25
30
35
40
45
50
0
2
4
6
8
10
12
14
16
18

(c)



(d)



(e)

Plot of Implied Volatility Index and Explanatory Factors.

Notes: (a) Scatter plot of Volatility Risk Factor MOVE vs Implied Volatility Index,

(b) Scatter plot of Volatility Risk Factor VIX vs Implied Volatility Index, (c) Scatter plot of Event Risk Factor MOVE vs Implied Volatility Index, (d) Scatter plot of Inflation Risk Factor vs Implied Volatility Index, (e) Scatter plot of FX Risk Factor_2 vs Implied Volatility Index.

Factors	R^2
Volatility_Risk_Factor_MOVE, FX_Risk_Factor_2, Event_Risk_Factor	0,831159
Volatility_Risk_Factor_MOVE, FX_Risk_Factor_2, Event_Risk_Factor, Inflation_Risk_Factor	0,834475
Volatility_Risk_Factor_MOVE, Volatility_Risk_Factor_VIX, FX_Risk_Factor_2, Event_Risk_Factor, Inflation_Risk_Factor	**0,839253**
Volatility_Risk_Factor_MOVE, Volatility_Risk_Factor_VIX, FX_Risk_Factor_2, Event_Risk_Factor, Inflation_Risk_Factor, Interest_Rate_Risk_Factor	0,839765
Volatility_Risk_Factor_MOVE	**0,569462**
Inflation_Risk_Factor	0,175198
Event_Risk_Factor	0,245678
FX_Risk_Factor_2	0,000003
Volatility_Risk_Factor_\	0,277035

Figure 22: Coefficient of Determination (R2) of Factors

APPENDIX B

Python Code for Augmented Dickey-Fuller Test(ADF) and Granger Causality Test

-*- coding: utf-8 -*-
"""
"""

#ADF unit root test (Stationary Test)
import pandas as pd
from statsmodels.tsa.stattools import adfuller, grangercausalitytests from
statsmodels.tsa.statespace.tools import diff

 # Define the time series data for the independent variables and dependent variable
Data=pd.read_excel('C:\Nirav Vyas\Masters\Thesis\Analysis\Analysis_2.xlsx'))
Data=Data.fillna(method='backfill') Data=Data.dropna()

x = Data[["Volatility_Risk_Factor_MOVE",
"Inflation_Risk_Factor", "Event_Risk_Factor",
"FX_Risk_Factor_2","Volatility_Risk_Factor_VIX"]] y =
Data[['Short_Condor_PNL']]

 # Perform lag transformation
x_diff = diff(x, k_diff=1) # k_diff is the number of lags used in the transformation

 # ADF test
summary = []
for factor in x_diff.columns:
result = adfuller(x_diff[factor])
print(f"ADF test results for {factor} after lag transformation:")
print(f"Test statistic: {result[0]}")
print(f"p-value: {result[1]}")
print(f"Critical values: {result[4]}") if result[1] < 0.05:
print(f"The null hypothesis of non-stationarity is rejected for {factor} at 5% significance level.")
else:
print(f"The null hypothesis of non-stationarity is accepted for {factor} at 5% significance level.")
print("\n")

result_df = pd.DataFrame(columns=['Factor','Test Statistic', 'p-value','Critical Values']) for factor in x_diff.columns:
result = adfuller(x_diff[factor])
temp_df = pd.DataFrame([[factor,result[0], result[1],result[4],summary]],columns=['Factor','Test Statistic', 'p-value','Critical Values','Summary'])
result_df = result_df.append(temp_df)

```
ADF test results for Volatility_Risk_Factor_MOVE after lag transformation:
Test statistic: -11.148370394823285
p-value: 2.9863447172709325e-20
Critical values: {'1%': -3.433327239607306, '5%': -2.8628552495229194, '10%':
-2.5674701716229276}
The null hypothesis of non-stationarity is rejected for Volatility_Risk_Factor_MOVE at 5%
significance level.


ADF test results for Inflation_Risk_Factor after lag transformation:
Test statistic: -15.23964900690298
p-value: 5.1841317055930455e-28
Critical values: {'1%': -3.433327239607306, '5%': -2.8628552495229194, '10%':
-2.5674701716229276}
The null hypothesis of non-stationarity is rejected for Inflation_Risk_Factor at 5%
significance level.


ADF test results for Event_Risk_Factor after lag transformation:
Test statistic: -19.978966804500935
p-value: 0.0
Critical values: {'1%': -3.4333003744032, '5%': -2.8628433872007037, '10%':
-2.5674638557393124}
The null hypothesis of non-stationarity is rejected for Event_Risk_Factor at 5% significance
level.


ADF test results for FX_Risk_Factor_2 after lag transformation:
Test statistic: -47.892800099954684
p-value: 0.0
Critical values: {'1%': -3.4332910857642114, '5%': -2.862839285780364, '10%':
-2.567461672014718}
The null hypothesis of non-stationarity is rejected for FX_Risk_Factor_2 at 5% significance
level.

ADF test results for Volatility_Risk_Factor_VIX after lag transformation:
Test statistic: -16.086594328357467
p-value: 5.308197685333278e-29
Critical values: {'1%': -3.4333030390861787, '5%': -2.8628445637953743, '10%':
-2.567464482195541}
The null hypothesis of non-stationarity is rejected for Volatility_Risk_Factor_VIX at 5%
significance level.
```

Figure 23: Result of ADF Test for Factors

#Granger Causality Test for multiple factors

from statsmodels.tsa.stattools import grangercausalitytests

import pandas as pd

 # Define the time series data for the two variables

#Read data from excel

Data=pd.read_excel('C:\Nirav Vyas\Masters\Thesis\ Analysis_2.xlsx'))

Data=Data.fillna(method='backfill') Data=Data.dropna()

#Changing Date to Datetime format

Data['Date'] = pd.to_datetime(Data['Date']) Data.set_index('Date', inplace=True)

 # List of factors to test for causality

```
factors =        ["Volatility_Risk_Factor_MOVE",    "Inflation_Risk_Factor",
          "Event_Risk_Factor", "FX_Risk_Factor_2","Volatility_Risk_Factor_VIX"]

result_df = pd.DataFrame(columns=['Factor','Lag','Test Statistic', 'p- value','Summary'])
factors =        ["Volatility_Risk_Factor_MOVE",    "Inflation_Risk_Factor",
          "Event_Risk_Factor", "FX_Risk_Factor_2", "Volatility_Risk_Factor_VIX"]
summary = []

for factor in factors:
x=pd.DataFrame(Data[[factor]])
y=pd.DataFrame(Data[['Short_Condor_PnL']])
result = grangercausalitytests(pd.concat([x,y], axis=1), maxlag=1)
 for lag, res in result.items():
print(f"Granger causality test results for lag {lag}:")
print(f"Test statistic: {res[0]['ssr_chi2test'][0]}")
print(f"p-value: {res[0]['ssr_chi2test'][1]}")
if res[0]['ssr_chi2test'][1] < 0.05:
print(f"The null hypothesis of no causality is rejected for {factor} at 5% significance level.")
else:
print(f"The null hypothesis of no causality is accepted for {factor} at 5% significance level.")

temp_df = pd.DataFrame([[factor,lag,res[0], res[1],summary]],columns=['Factor','Lag','Test
Statistic', 'p-value','Summary']) result_df= result_df.append(temp_df)

result_df.to_csv('granger_causality_results.csv'
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=11.2950 , p=0.0008  , df_denom=2224, df_num=1
ssr based chi2 test:   chi2=11.3103 , p=0.0008  , df=1
likelihood ratio test: chi2=11.2816 , p=0.0008  , df=1
parameter F test:         F=11.2950 , p=0.0008  , df_denom=2224, df_num=1
Granger causality test results for lag 1:
Test statistic: 11.310265925134823
p-value: 0.0007707973231051453
The null hypothesis of no causality is rejected for Volatility_Risk_Factor_MOVE at 5%
significance level.

Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.9214  , p=0.3372  , df_denom=2224, df_num=1
ssr based chi2 test:   chi2=0.9227  , p=0.3368  , df=1
likelihood ratio test: chi2=0.9225  , p=0.3368  , df=1
parameter F test:         F=0.9214  , p=0.3372  , df_denom=2224, df_num=1
Granger causality test results for lag 1:
Test statistic: 0.9226651838854182
p-value: 0.336776153736092
The null hypothesis of no causality is accepted for Inflation_Risk_Factor at 5% significance
level.

Granger Causality
number of lags (no zero) 1
ssr based F test:         F=3.5015  , p=0.0614  , df_denom=2224, df_num=1
ssr based chi2 test:   chi2=3.5062  , p=0.0611  , df=1
likelihood ratio test: chi2=3.5035  , p=0.0612  , df=1
parameter F test:         F=3.5015  , p=0.0614  , df_denom=2224, df_num=1
Granger causality test results for lag 1:
Test statistic: 3.506229760416534
p-value: 0.06113843957233236
The null hypothesis of no causality is accepted for Event_Risk_Factor at 5% significance
level.
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=8.2369  , p=0.0041  , df_denom=2224, df_num=1
ssr based chi2 test:   chi2=8.2480  , p=0.0041  , df=1
likelihood ratio test: chi2=8.2328  , p=0.0041  , df=1
parameter F test:         F=8.2369  , p=0.0041  , df_denom=2224, df_num=1
Granger causality test results for lag 1:
Test statistic: 8.24799598691653
p-value: 0.004079701649911387
The null hypothesis of no causality is rejected for FX_Risk_Factor_2 at 5% significance
level.

Granger Causality
number of lags (no zero) 1
ssr based F test:         F=1.6588  , p=0.1979  , df_denom=2224, df_num=1
ssr based chi2 test:   chi2=1.6610  , p=0.1975  , df=1
likelihood ratio test: chi2=1.6604  , p=0.1975  , df=1
parameter F test:         F=1.6588  , p=0.1979  , df_denom=2224, df_num=1
Granger causality test results for lag 1:
Test statistic: 1.6610400179723972
p-value: 0.19746296121783125
The null hypothesis of no causality is accepted for Volatility_Risk_Factor_VIX at 5%
significance level.
```

Results of Statistical Significance Test for Factors.

Notes: (a) Granger Causality Test of Volatility Risk Factor MOVE, Inflation Risk Factor, Event Risk Factor, FX Risk Factor_2, Volatility Risk Factor VIX and Short Condor PnL for 1 day lag.

APPENDIX C

Python Code for Light GBM Out of Sample Test.

.# -*- coding: utf-8 -*-"""

Created on Wed Aug 2 17:02:32 2023"""

import pandas as pd import numpy as np import lightgbm as lgb

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

import matplotlib.pyplot as plt

import scipy.stats as stats

import seaborn as sns

#Read data from excel
data=pd.read_excel("C:\Nirav vyas\Masters\Thesis\Analysis\Analysis_3.xlsx')
data=data.fillna(method='backfill')data=data.dropna()

 # Convert the date column to datetime format
data['Date'] = pd.to_datetime(data['Date'])

 # Sort the data by date
data = data.sort_values(by='Date')

 # Define your feature and target variables features=['Interest_Rate_Factor','Credit_Risk_Factor', 'Liquidity_Risk_Factor','Inflation_Risk_Factor','Event_Risk_Factor', 'FX_Risk_Factor_1','FX_Risk_Factor_2','Yield_Risk_Curve_Factor','Volatility_Risk _Factor_MOVE','Volatility_Risk_Factor_VIX','Sovereign_Risk_Factor'] target = ['Short_Condor_PnL']

 # Create date range
date_range = pd.date_range(start='2014-03-13', end='2022-11-30', freq='D')

 # Filter data to include only trading days within the date range

data = data[data['Date'].isin(date_range)]

 # Calculate the number of trading days

num_days = len(data)

 # Define train and test sizes train_size = int(num_days * 0.6) test_size = num_days - train_size

 # Split the data into train and test sets

train = data.iloc[:train_size, :]test = data.iloc[train_size:, :]

 # Extract the feature and target variables for each set

X_train = train[features]y_train = train[target] X_test = test[features] y_test = test[target]

 # Use the LightGBM model with hyperparameters

lgb_model = lgb.LGBMRegressor(boosting_type='gbdt',
max_depth=-1,
learning_rate=0.1,
n_estimators=100,
subsample_for_bin=200000,
objective='regression',
class_weight=None,
min_split_gain=0.0,
min_child_weight=0.001,
min_child_samples=20)

Train the model on the training data

lgb_model.fit(X_train, y_train)

factor_score = lgb_model.feature_importances_

 # Get the indices of the features, sorted by importance

sorted_indices = np.argsort(factor_score)

pos = np.arange(sorted_indices.shape[0]) + .5

 # Print the feature importances in ascending order

for i in sorted_indices:

print(f'Feature: {X_train.columns[i]}, Importance: {factor_score[i]}')

 # Plot feature importances

```
plt.barh(pos, factor_score[sorted_indices], align='center')
plt.yticks(pos, X_train.columns[sorted_indices])
plt.xlabel('Relative Importance')
plt.title('Factor Importance')plt.show()
```

#Predict the values of the dependent variable on the training data

```
y_pred_train = lgb_model.predict(X_train)
```

 # Create a dataframe to store the results

```
results_train = pd.DataFrame({'Date': train['Date'], 'Short Condor
    PnL':y_train.values.flatten(), 'Predicted Short Condor PnL': y_pred_train})
```

#Plot the actual Short Condor PnL values against the predicted values

```
sns.lineplot(x='Date', y='Short Condor PnL', data=results_train, label='Short CondorPnL (Train)')
sns.lineplot(x='Date', y='Predicted Short Condor PnL', data=results_train, label='Fair Value Short
Condor PnL (Train)')
plt.title ("Short Condor PnL vs Fair Value Short Condor PnL(Training Dataset)")
plt.xlabel("Date")
plt.ylabel("Performance")
plt.legend(loc="lower right")
plt.show()
```

#Calculate the mean squared error of the training predictions

```
train_mse = mean_squared_error(y_train, y_pred_train)

print("TrainMSE:", train_mse)
```

 # ErrorTerm y_pred minus y (Compute the fitted response and display the residuals)

#Plot the distribution of the prediction errors

```
y_pred_train = y_pred_train.flatten()
y_train = y_train.ravel()
error_train = y_train - y_pred_train
error_series = pd.Series(error_train.ravel())
sns.distplot(error_series)
plt.show()
```

 # Get the indices of the top five features, sorted by importance

```
top_five_features = sorted_indices[-5:]
```

 # Plot the feature importances

lgb.plot_importance(lgb_model, max_num_features=5)
plt.xlabel('Relative Importance')
plt.title('Factor Importance') plt.show()
# Get the feature data for the top five features
X_train_top_five = X_train.iloc[:, top_five_features]
X_test_top_five = X_test.iloc[:, top_five_features]

 # Train the model using only the top five features

lgb_model = lgb.LGBMRegressor(boosting_type='gbdt',
max_depth=-1,
learning_rate=0.1,
n_estimators=100, s
ubsample_for_bin=200000, objective='regression',
class_weight=None,
min_split_gain=0.0,
min_child_weight=0.001,
min_child_samples=20)
lgb_model.fit(X_train_top_five, y_train)

#Predict the values of the dependent variable on the training data

y_pred_train_top_five = lgb_model.predict(X_train_top_five)

 # Create a dataframe to store the results

results_train_top_five = pd.DataFrame({'Date': train['Date'], 'Short Condor PnL': y_train.flatten(), 'Predicted Short Condor PnL': y_pred_train_top_five})

#Plot the actual Short Condor PnL values against the predicted values
sns.lineplot(x='Date', y='Short Condor PnL', data=results_train_top_five, label='Short Condor PnL (Train)')
sns.lineplot(x='Date', y='Predicted Short Condor PnL', data=results_train_top_five, label='Fair Value Short Condor PnL (Train 5 Factors)')
plt.title ("Short Condor PnL vs Fair Value Short Condor PnL(Training Dataset 5 Factors)")
plt.xlabel("Date")
plt.ylabel("Performance")
plt.legend(loc="lower right")
plt.show()

#Calculate the mean squared error of the training predictions

train_mse = mean_squared_error(y_train, y_pred_train_top_five)

print("Train Top 5 MSE:", train_mse)

 # ErrorTerm y_pred minus y (Compute the fitted response and display the residuals)
#Plot the distribution of the prediction errors

```
y_pred_train = y_pred_train_top_five.flatten()
 y_train = y_train.flatten()
error_train_five = y_train-y_pred_train
error_series = pd.Series(error_train_five.ravel())
sns.distplot(error_series)
 plt.show()
```

 # Make predictions for the test data

```
y_pred_five = lgb_model.predict(X_test_top_five)
```

 # Create a dataframe to store the results

```
y_pred_five = y_pred_five.flatten()
y_test = y_test.values.ravel()
results = pd.DataFrame({'Date': test['Date'], 'Short Condor PnL': y_test, 'Fair Value
Short Condor PnL': y_pred_five})
```

 # Plot the results

```
sns.lineplot(x='Date', y='Short Condor PnL', data=results, label='Short Condor PnL')
sns.lineplot(x='Date', y='Fair Value Short Condor PnL', data=results, label='Fair Value Short Condor
PnL')
plt.xlabel('Date')
plt.ylabel('Short Condor PnL')
plt.title('Short Condor PnL vs Fair Value Short Condor PnL(Out of sample with 5 the factors)')
plt.legend()
plt.show()
```

#Plot the distribution of the prediction errors

```
y_pred_five = y_pred_five.reshape(-1, 1)
 y_test = y_test.reshape(-1, 1)
error = y_test - y_pred_five error_series = pd.Series(error.ravel())
 sns.distplot(error_series)
plt.show()
```

 # Calculate the mean squared error

```
mse_train = mean_squared_error(y_train, y_pred_train) mse_five = mean_squared_error(y_test,
y_pred_five)

index = ['Train', 'Test', 'Top 5 Features']
results_summary = pd.DataFrame({'MSE (train)': [mse_train], 'MSE (top 5 features)':
[mse_five],},index=[index])
```

 # Plot the MSE results

ax = results_summary[['MSE (train)','MSE (test)', 'MSE (top 5 features)']].plot(kind='bar', figsize=(10, 6))ax.set_title('Mean Squared Error (MSE) Results')
ax.set_xlabel('Prediction') ax.set_ylabel('MSE Value')
ax.set_xticklabels(['Train', 'Test', 'Top 5 Features'])

#Save the Results in the Dataframe for Training Data

results_training_signals = pd.DataFrame({'Date': X_train.index.ravel(),'Short Condor PnL': y_train.flatten(), 'Fair Value Short Condor PnL (top 5 features_train)': y_pred_train_top_five})

#Save the file as CSV

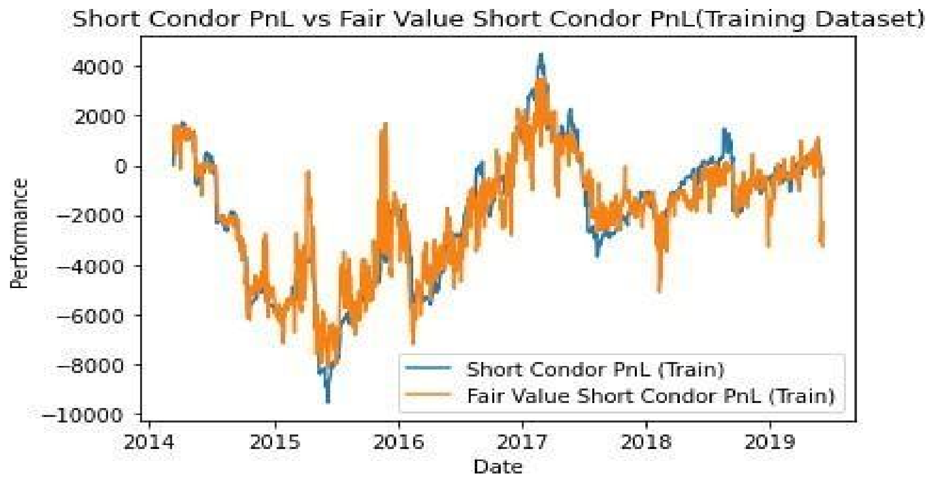
results_training_signals.to_csv("C:/Nirav Vyas/Masters/Thesis/Analysis/results_training_signals.csv ", index=False)

 # Create a dataframe to store the results for Test Data Set

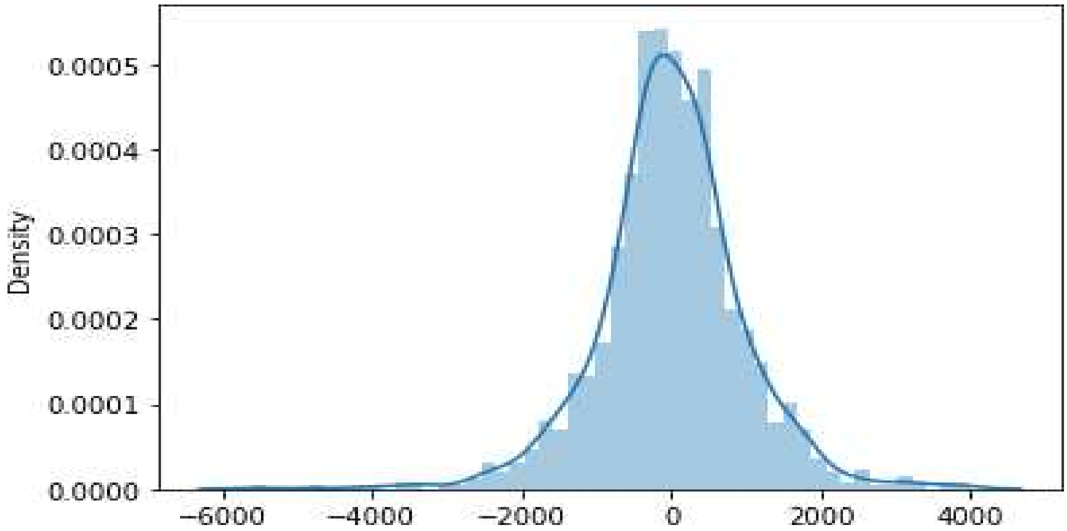
results_test_signals_Long = pd.DataFrame({'Date': X_test.index.ravel(), 'Short Condor PnL': y_test.ravel(),
'Fair Value Short Condor PnL': y_pred_five.ravel()})

#Save the file as CSV

results_test_signals_Long.to_csv("C:/Nirav Vyas/Masters/Thesis/Analysis/results_test_signals_Long.csv ", index=False)



(a)


Density
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
−6000
−4000
−2000
0
2000
4000

(b)