An Empirical Analysis of the Performance of a VIX Futures Trading Strategy versus a Long Straddle Strategy

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Abstract

This paper examines the performance of two derivative trading strategies related to volatility. The Volatility Index (VIX) has become a popular investment since the inception of its derivatives in 2004 due to its negative correlation to the S&P 500. Current literature comparing the performance of two volatility-mitigating trading strategies is scarce. The aim of this paper is to perform a backtest in order to compare the risk and returns of a long straddle strategy on the S&P 500 against a VIX futures strategy. The study is based on time series data comprising of monthly S&P 500 options and VIX futures, totalling 132 observations between 1st January 2010 to 31st December 2020. The findings of this empirical analysis reveal the option strategy outperformed the VIX futures trading strategy over the period. The accuracy of the VIX in forecasting realized volatility is also investigated within this paper. This study provides investors and researchers with insights into the performance of two strategies commonly used to mitigate against volatility risk.

Keywords: Volatility Index, VIX, Derivate Trading Strategy, Backtesting.

Declaration

Submission of Thesis and Dissertation

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Chapter One: Introduction

The concept of risk is arguably one of the most important topics in modern finance and has been the centre of extensive research since at least the 1900s. Volatility has been used as a risk proxy since Markowitz (1952) and can be defined as the spread of all likely outcomes of an uncertain variable. Measuring and forecasting market volatility has been a pursuit for academics and practitioners for many years because of the advantage it gives investors to be better informed about the current and future market, enabling them to optimise their investments and decision-making. In more recent years, volatility has become the subject of substantial amounts of study investigating its potential as an asset class for investors.

While volatility has been witnessed for as long as markets have existed, for an investor it has not always been accessible as an investable product. However, in 2004 this changed as the introduction of VIX futures contracts enabled investors to trade volatility. VIX futures are a derivative product which are based on the value of the CBOE Volatility Index (VIX). While the VIX has since become well-known for its diversification benefits after being subject to comprehensive research, it is also viewed as a predictor for future volatility. Because the VIX is calculated using options on the S&P 500 Index it has become the benchmark for expected volatility, also known as implied volatility.

1.1 Research Question & Objective

This paper examines two areas of study surrounding the VIX. The main aim of this dissertation is to conduct an empirical investigation into the performance of a volatility-related investment strategy involving VIX futures. The VIX strategy is compared with a straddle strategy, a popular trading strategy that does not involve VIX products but is essentially designed to profit from volatility. A backtest is performed and the historical performance of both strategies is examined and compared from both a risk and return perspective in order to highlight the optimal performing strategy over the previous ten years. A hypothesis test is conducted to examine whether any observed differences between the returns are statistically significant.

A subtopic also investigated within the paper considers the predictability power of the VIX. While extensive literature argues both for and against the use and accuracy of the VIX as an indicator of implied volatility, this paper aims to further the research of Kownatzki (2016) in examining the accuracy of the VIX in predicting future volatility. The findings of this paper are in line with previous research; the VIX overestimates volatility during ‘normal’ market conditions and underestimates volatility during market turmoil.

1.2 Relevance of the Study

This research is original for several reasons. Studies into the comparison of trading strategies versus a VIX trading strategy are scarce, therefore making this paper very relevant. Various academics have researched the benefits of investing in VIX, but few have compared trading strategies surrounding volatility investing. Seminal papers by Szado (2009) and Moran and Dash (2007) delve into the benefits of volatility exposure while the works of Gao et al. (2018) and Goltz and Lai (2009) investigate the historical returns of straddle strategies. However, a gap in the literature exists in comparing the performance of two strategies surrounding volatility over an up-to-date time horizon. This study aims to fill this gap. The investigation into the historical performance of the VIX will also highlight return statistics that are important for an investor considering using the VIX as an asset class.

This paper can also be considered an extension of Kownatzki (2016) as the subtopic investigates the volatility forecasting accuracy of the VIX. Because the VIX is considered the benchmark indicator of volatility in modern finance, and widely used by investors for future volatility predictions, it is important to research whether the measure is accurate and if the findings of previous literature still hold.

1.3 Organization of the Study

The remainder of the paper is structured as follows: Chapter 2 provides an introduction into and an in-depth description of the VIX and details its relationship with the S&P 500 index. It is important to explain the properties of the VIX and how it relates to the S&P 500 prior to investigating the performance of trading strategies involving its derivative. Chapter 3 reviews relevant literature surrounding investing in VIX and its predictability power. The chapter also discusses the straddle strategy and examines previous literature encompassing its historical performance. Chapter 4 is dedicated to the subtopic in question of this paper, investigating the accuracy of VIX implied volatility. Chapter 5 summarises the data that is used for the main research question and outlines the methodology used to carry out the research. Chapter

6 presents and discusses the ex-post findings of the study and Chapter 7 concludes the paper and highlights the limitations of the study and areas of potential future research.

Chapter Two: Relationship between VIX and S&P 500 Index

2.1 Background

The CBOE Volatility Index is an indicator of 30-day implied volatility. It is important to understand the relationship between the two indices before investigating trading strategies relating to volatility. By understanding the causation behind the movement in the VIX, an investor can better utilise the information to optimise trading decisions. It is also important to understand the relationship between the VIX and its derivatives, such as VIX futures, to better understand the research within this paper.

An index is a measure, or an indicator of something. The S&P 500 Index (SPX) tracks the performance of the top 500 companies in the United States. It has become the benchmark performance indicator of the United States. Similarly, a Volatility Index is an indicator or measure of uncertainty in the market.

The VIX, officially termed the CBOE Volatility Index, was introduced by Robert Whaley in 1993 (Whaley, 1993). The main purpose of the VIX was to provide investors with an indication of expected short-term volatility. When it was first introduced it measured the 30-day implied volatility based on at-the-money options on the S&P100 Index. However, in 2003 this calculation changed and the VIX is now derived from options on the S&P 500 Index. This measurement of markets expected 30-day volatility is found to be more robust as it includes all options traded within the first two contract months and makes it less sensitive to any single option price, and therefore less capable of manipulating (Black, 2006). Since the calculation of the VIX is based on options on the S&P 500 it gives a reasonable indication of how investors expect the market to move over a short-term period. It could be said that it is a 'crowd-sourced' estimate about the uncertainty in the market in the short-term.

The exact calculation of the VIX is quite complex (Appendix 1). The calculation is based on the S&P 500 Index call and put options. In general, call options give the holder the right to buy the asset or security at a specified price sometime in the future. Put options are similar however they give the holder the right to sell the asset at a specified price. The calculation involves the midpoint between the Bid/Ask spread of the options and the contracts are rolled over each month which makes the VIX a 30-day expectation of future volatility.

The movements in the VIX, as well as the inverse relationship between it and the SPX, can be explained as follows; When investors are uncertain about the movement in the S&P 500, or fear that the market will dip, they will look to protect their investments. There are several ways in which they can protect themselves, one popular method of protection is found by buying options on the SPX to hedge against the downside risk. The increase in demand for options, particularly put options, drives the prices of the options up. Since the calculation of the VIX is based on these options, this drives the price of the VIX up, thus increasing the level of implied volatility. This implied volatility is often used as an indicator of future movement in the underlying asset because it is forward-looking as it is based on the options for the next 30 days. This also explains why the VIX was termed the "investor fear gauge" by its creator Robert Whaley (2000). The index spikes when investors are looking to protect their investments because they are forecasting uncertainty in the market. As more investors purchase put options and drive the VIX price up, other investors will see the rise in the VIX as an indicator for increased market uncertainty and will also look to protect their investment. This cycle results in the VIX often overestimating the realized volatility and has been referred to as a "premium" in VIX.

Figure 2.1: Historic Relationship S&P500 versus VIX 2010-2020

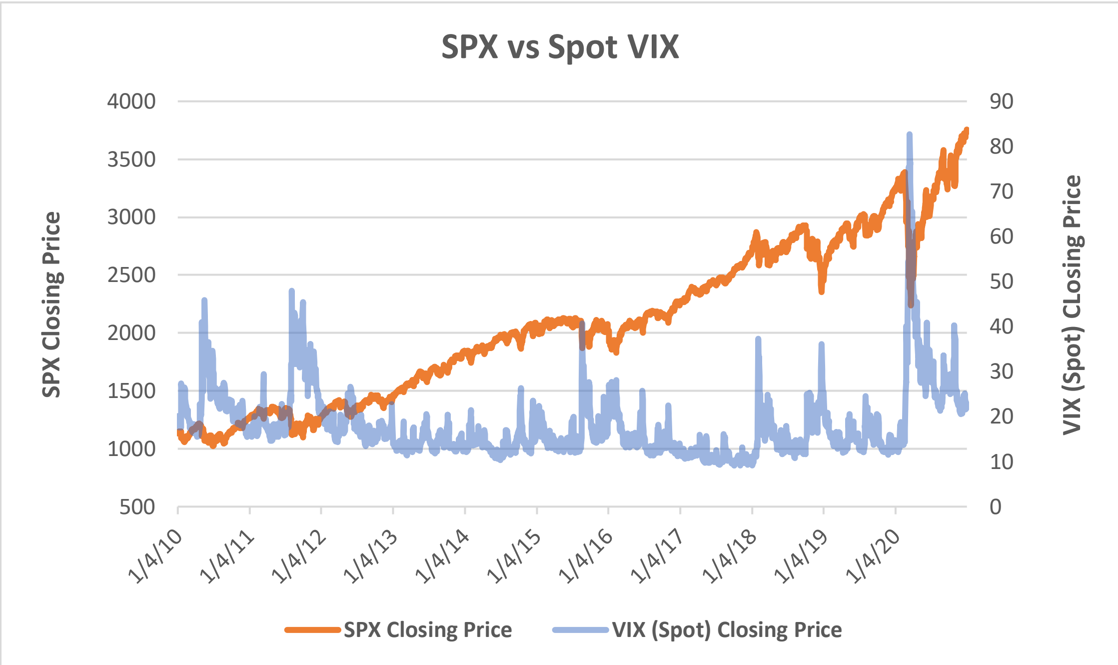


Figure 2.1 shows the relationship between the daily closing prices of the SPX and VIX between the study period of January 2010 through December 2020. The graphic depicts how the S&P 500 has increased over the previous 10 years while the VIX remains relatively

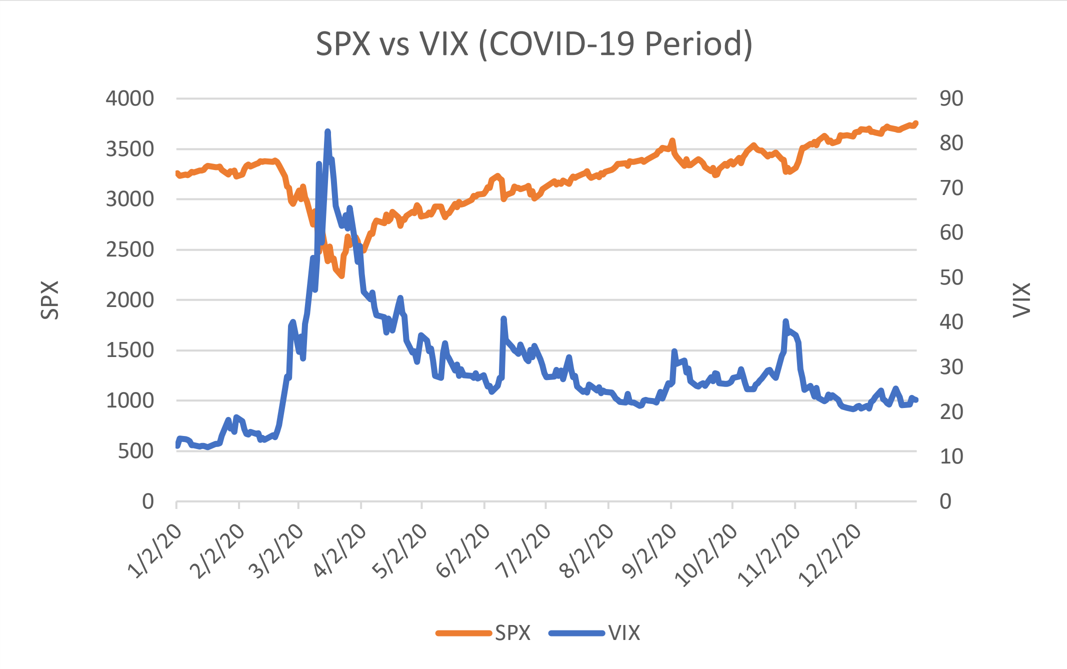
unchanged over the period besides its obvious spikes. As shown by the graph, the VIX has a strong mean reversion tendency. This claim is backed by Hafner (2003), Fouque et al. (2008) and Wong and Lo (2008), who all find mean reversion tendencies in the VIX in their studies. Mean reversion refers to an assets price returning to its average over time and is the reason the VIX graphic is flat relative to the S&P 500. From Figure 2.1 we can clearly see how the VIX returns to its 'normal' state after a spike. From the graph we can infer that a spike in the VIX seems to always correlate to a dip or large movement in the S&P 500. To a certain degree the above graphic depicts the negative correlation between the two indices; as a dip in the S&P 500 occurs, volatility rises and therefore the VIX spikes.

2.2 Spikes in VIX

A 'flash crash' caused by high-frequency traders caused the VIX to spike in 2010. Political disputes in the U.S. resulted in a spike in the VIX in 2011. Protests and threats about defaulting on U.S. debt by the Tea Party caused investors to panic. Alongside this, the credit quality of the U.S. was downgraded by Standard & Poors which resulted in volatility increasing. Concerns over emerging markets and slowing global manufacturing demand hurt stock markets causing the S&P 500 to fall approximately 11% in 2015. This drop caused investors to panic and protect against downside risk by buying options and therefore the VIX increased. The colossal spike in early 2020 is due to the market crash caused by COVID-19. It is worth noting that the uncertainty and volatility for the period that followed the crash has remained relatively higher than average depicting the prolonged effect of the pandemic on the market.

As seen in Figure 2.2, sometimes the inverse relationship is not exhibited. At times the VIX and SPX move in the same direction. Between September and November 2020 there was a slight increase in both indices. During this period the market was rising, however with investors displaying increasing uncertainty about the markets next movement due to the pandemic, volatility implied by the VIX was increasing also.

Figure 2.2: COVID-19 Market Crash



The inverse relationship between the SPX and VIX appears to be significantly stronger for large downward movements in the S&P 500. From this it would be reasonable to assume that the relationship is conditional and time-varying; the indices reflect an inverse relationship however this may not always be the case.

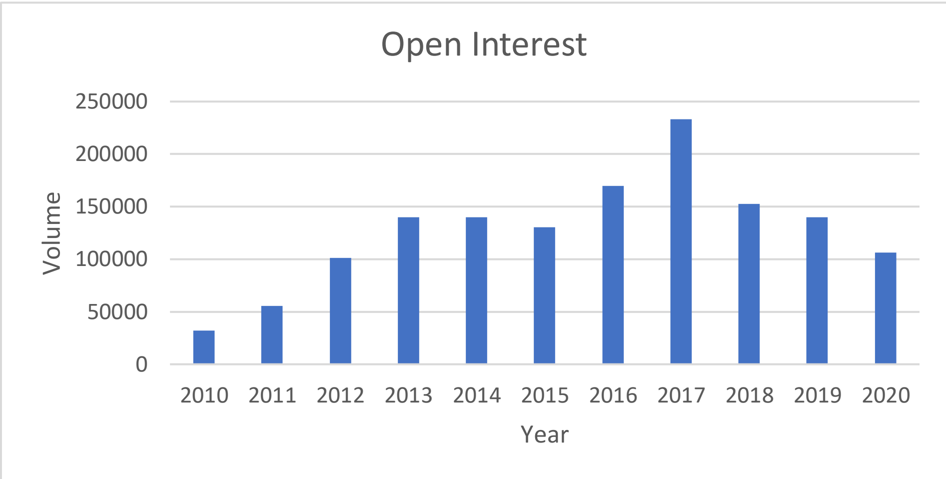
2.3 VIX & VIX Futures

Since the spot VIX is not a tradable product, previous research investigating its potential hedging benefits are merely hypothetical (see Daigler and Rossi (2006) for example). However, the introduction of VIX Futures in 2004 by the CBOE made it possible for investors to trade a product that was directly related to the VIX, subsequently making it possible for investors to utilise the diversification benefits of volatility.

A futures contract is an agreement to buy or sell a particular asset or commodity at a predetermined price at some specified future date. For example, on 1st September, the November futures price of the VIX may be $28. This is the price that an investor agrees to buy or sell the VIX for delivery in November. VIX one-month futures expire on the third Wednesday of the contract's month, for instance a November contract will expire on the third Wednesday in November.

The value of a VIX futures contract represents the expected VIX price as of the expiration date of the contract. For example, in Figure 2.4 we can see that the market expects the VIX to trade around $22 in September. An investor will profit from a VIX future contract if the price at maturity is above the price they paid for the contract. In our earlier example, the investor would profit if the VIX finished above $28. While not regularly traded following their initial launch, VIX futures have experienced a tremendous increase in popularity since post financial crisis as volatility is now viewed as its own an asset class. Open interest refers to the number of contracts that are still outstanding, or in other words, have not yet been settled or reached expiry. A large open interest reflects a large amount of trading activity in the contract. As seen in Figure 2.3, trading volume on VIX futures has increased dramatically since 2010.

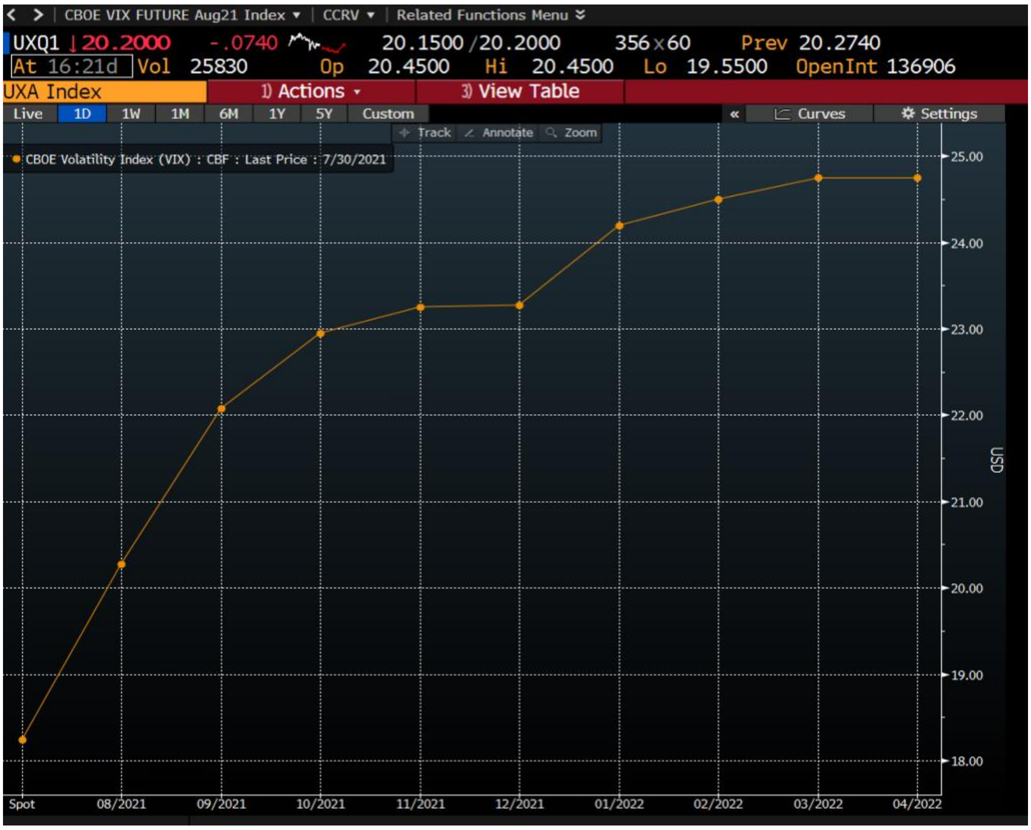
Figure 2.3: VIX Futures Open Interest



Source: Bloomberg

Figure 2.4 displays the pricing of VIX futures contracts for August onwards as an example. The graph perfectly illustrates a contango effect that is persistently exhibited in VIX Futures pricing. 'Contango' refers to the futures contract prices being greater than the spot price. This tends to occur when the VIX is currently trading below its long-term mean. Since the VIX futures pricing generally exhibits a contango effect, it can be expensive to hold a permanent long position in them. The opposite usually occurs when the VIX is trading below its long-term mean, the futures contract prices will tend to trade at a discount compared to the index. This is referred to as backwardation. From Figure 2.4 we can see how uncertainty is reflected in the price of the futures contract. Since there is more uncertainty in longer dated contracts, they are priced higher, and this is known as the 'risk premium'.

Figure 2.4: VIX Futures Pricing



Source: Bloomberg

Chapter Three: Literature Review

3.1 Introduction

This section is split into three parts. Both seminal and peripheral contributions to the area of study are reviewed and analysed. The section begins by explaining the rise in popularity surrounding the VIX, outlining its uses as well as the potential benefits it provides for an investor. A brief description on the unfavourable changing relationship between asset classes is set out, followed by the recommendation to consider VIX as an asset class. Empirical studies are reviewed outlining its benefits and are included as evidence supporting this recommendation. Next, an alternative, but similar trading strategy to the VIX is presented and explained along with a review of previous studies on the performance of the strategy. Lastly, Section 3.5 presents the accuracy of the VIX in forecasting future volatility and also stock market returns. Previous research both supporting and opposing the claim is reviewed. Section 3.5 is important as it closely relates to the subtopic in question within this paper, and ultimately is a review of literature that motivated me to pursue an investigation into the topic.

3.2 Investing in VIX

Thanks to Markowitz's revolutionary paper, every investor will be well informed of the diversification benefits of holding various asset classes with low correlations within a portfolio in order to reduce overall risk (Markowitz, 1952). A high correlation between two asset classes signifies a large common risk factor between them. It is a measure of how two variables move together. For example, if there is a strong positive correlation between two stocks and one falls in price, the other will also fall in price. Markowitz (1952) found that selecting a portfolio of assets that have weak correlations with each other lowers the overall risk of the portfolio. The reasoning behind this is that if the price of one asset falls, it won't have much effect on the other assets in the portfolio. This process is referred to as diversification.

Previous research into financial crashes explain how they have a disastrous effect for the average investor's portfolio. Markwat (2012) found that during market downturns almost all diversification opportunities disappear for an investor. With correlation being a significant input into portfolio construction and the risk-return relationship of investments, extensive research has been carried out on the subject. Chow et al. (1999) conducted their study on correlations between different asset classes during market downturns. Not only did they find that the volatility of returns for all the asset classes increased, but also that the correlations between the classes all strengthened during periods of large market turbulence. Butler and Joaquin (2002) support this finding as they observed non-normal behaviour in correlations over a 30-year period between 1970 and 2000. Their research also concluded that correlations were significantly stronger during bear markets in comparison to bull markets. This is reasonable because in market downturns, such as financial crises, it is expected that all asset classes will dip together, thus resulting in their correlations increasing.

A perfect example of where this was witnessed was during the Global Recession of 2008 and the years that followed. Portfolios that would have been considered strongly diversified based on historical data and theory, were found not to be. This was largely due to the fact that prior to the crisis, correlations between asset classes were relatively weak. However, similar to the findings of Chow et al. (1999) and Markwat (2012), Szado (2009) found that in 2007 and 2008 during the financial crisis the correlations between asset classes increased significantly, thus reducing the typical diversification benefits of a portfolio that were normally observed in years previous.

Commodities, in particular gold, are often considered a perfect hedge or diversifier for periods of market downturns thanks to their low correlation to the market. For this reason, Chow et al. (1999) recommended to consider commodities to effectively diversify a portfolio, however even commodities correlations have risen of late. As per Daskalaki & Skiadopoulos (2011) and Lombardi and Ravazzolo (2013), commodities have not been able to offer the same benefit in diversification since 2008.

Alongside commodities, bonds are usually looked upon as a 'safe' investment and commonly utilised in diversifying a portfolio due to their low-risk characteristics. However, Alexander and Korovilas (2012) also observed an increase in correlation between international bonds. They also observed the equity-bond correlation to have increased. Prior to this study, Kearney and Lucey (2004) surveyed existing literature on international equity markets and contribute findings that diversification benefits from equities are shrinking.

With correlations increasing between asset classes, investors have had to look elsewhere in order to gain effective diversification within their portfolios, with volatility being a popular candidate as of recent. Engle and Ng (1993) state that negative returns are generally associated with an increase in conditional volatility. This mechanism is known as 'asymmetric volatility', and this is more present during a market downturn. As returns fall, volatility increases. This negative correlation between volatility and the market makes volatility an ideal tool for diversification for hedging downside risk. In 2008-2009 when the markets dropped by approximately 50%, the VIX increased by around 125% (Heslinga, 2013).

Both Munenzon (2010) and Alexander and Korovilas (2012) claim volatility should be considered as a natural diversifier. When the market falls it causes volatility to rise, thus making it reasonable to assume negative returns are generally associated with increases in volatility. This supports the claim that the inverse relationship makes volatility a contender for an excellent hedging tool, because it is most effective when it is needed most. Grant et al. (2007) provide further evidence that in 'hostile markets' volatility provides effective diversification. By adding volatility to their asset allocation, they found the Sharpe ratio increased from 0.46 to 1.82 and the investor achieved higher average returns for any given level of portfolio risk. Brière et al. (2010) investigate mean-variance optimisation and potential diversification benefits of different asset classes for long equity holders. They review the period from 1990 until 2008 and discover that by including a pure volatility investment, an investor can significantly reduce the risk profile of a portfolio.

The VIX, officially known as the CBOE Volatility Index, was introduced by Professor Robert Whaley in 1993 (Whaley, 1993). After the calculation of the VIX changed in 2003, methods were introduced in 2004 which allowed investors to take positions in the VIX using VIX options and exchange-traded products (ETPs). The introduction of tradable products based on the VIX led to extensive research into the use of these products to investigate the effectiveness of including them in a portfolio. Since the introduction of VIX options, it has been found that holding positions in the VIX offers a variety of advantages, in particular for hedging a portfolio against downside risk (Knight and Satchell, 2007).

Daigler and Rossi (2006) found daily correlation between the SPX and VIX to be between -0.45 and -0.82, thus implying significant benefits to adding volatility to a portfolio of stocks. They found that risk-return benefits can be achieved by including the VIX as an asset in an S&P500 portfolio. Their findings suggested that the inclusion of volatility in the portfolio significantly reduced risk without having too much effect on the return. However, their research is limited in scope as it focuses on spot VIX data which is not an investible product and therefore is hypothetical.

The use of tradable VIX products was researched by Szado (2009). Their research investigated the benefits of a long volatility exposure between the period of 2006 and 2008. Tests were carried out to examine if the inclusion of a 2.5% or 10% long volatility position had diversification benefits on three common types of portfolio. Performing a test on a pure equity portfolio, an equity-bond portfolio and a 'typical well-diversified institutional investment portfolio', it was discovered that the addition of VIX futures would have provided effective diversification during the 2008 financial crisis. The exposure to volatility for the three portfolios both increased returns and reduced the standard deviation.

Szado’s finding was supported in a report published by Merrill Lynch, by Bowler et al. (2003) who state that by including a 10% VIX holding in an S&P500 portfolio (SPX/VIX 90%/10%) reduced the risk by approximately 25% and had a positive effect on returns also. Specifically, returns were enhanced by 5% since 1986. Moran and Dash (2007) conducted a similar study focusing on the period between 1990 through 2007. Findings supported and extended that of Bowler at al. (2003), focusing on a 5% VIX holding rather than 10%. The 5% VIX inclusion reduced overall portfolio volatility by 92 basis points and increased the Sharpe ratio while only reducing the return by 6 basis points. The importance of the results of the abovementioned research is invaluable. Such findings have provided the investor with an alternative method of diversifying their portfolio, which, as we have seen, has become increasingly difficult since 2008.

However, Alexander et al. (2016) argue that exchange-traded volatility only proved to be an effective diversifier during the period of the financial crisis. This study identified that outside of this period, long equity portfolios (and bond portfolios) encompassing volatility as a means of diversifying did not perform as well as the portfolios excluding it. This could be explained by the negative returns commonly exhibited by holding a constant position in the VIX. Alexander et al.’s (2016) noteworthy findings form part of the motivation for this paper. I aim to investigate the profitability of a VIX Futures position to identify if it is a viable investment strategy for an investor.

As previously mentioned, gold has always been considered a safe haven for investors looking to hedge against downside risk when uncertainty rises in markets. The performance of gold versus the VIX as a portfolio hedge was investigated by Hood and Malik (2013). They conclude that the VIX not only outperformed in hedging the portfolio and offered to be more of a 'safe-haven' for a pure U.S. equity investment, but in extreme high or low volatility periods it maintained a negative correlation to the stock market, something which gold did not.

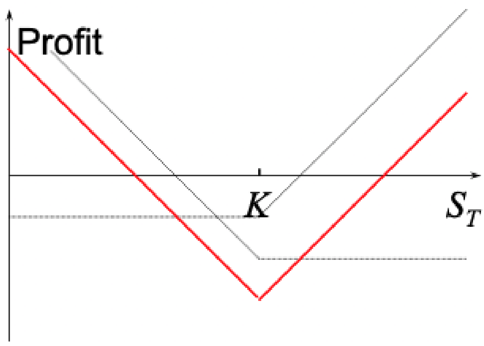
An advantage of trading VIX futures is that they do not require active management the way a straddle strategy, or majority of option strategies would. McMillan (2007) explains how for a straddle, the investor is often required to rebalance the portfolio so to maintain a 'delta-neutral' position in order to ensure directional neutrality. For a strategy involving VIX futures, a more passive approach to management can be taken. The investor can let one contract 'roll' into the next relatively cheaply and without active management as the position does not require rebalancing via the delta-hedging process. McMillan (2007) also further supports the finding of Bowler et al. (2003) in claiming that a low allocation (approximately 10%) can sufficiently hedge an equity portfolio.

As outlined and discussed in this section, there is extensive literature proclaiming the effectiveness of the VIX in hedging downside risk. The section also gives an abundance of evidence as to why the VIX has become such a popular investment product. However, there is a gap in the current literature with regards to comparisons between a pure VIX trading strategy and an option strategy of similar nature. I aim to fill this void in the literature by identifying the optimal strategy between a VIX futures strategy with that of a straddle strategy. A strategy of holding only VIX futures and a straddle strategy are essentially both 'bets' on volatility as they profit from changes in volatility. The purpose of this research paper is to identify the better performing strategy over the last 10 years for an investor.

3.3 Option Trading Strategy - A Straddle

There are many different types of option strategies available to an investor that enable them to hedge or take advantage of certain scenarios in the market. These trading strategies combine calls and puts in various ways depending on the investors aim. For example, a straddle is an option strategy consisting of a combination of a long position in an at-the-money call option and a long position in an at-the-money put option, on the same underlying asset, with the same expiry and strike price (Hull, 2015). The sum invested in both the put and the call option can be selected so as to obtain an overall beta of zero, this is referred to as 'beta neutral'. A 'beta neutral' strategy is one that is employed to seek to profit from both an upward and downward movement in the market. Because the strategy is both long and short the same underlying with the same strike and expiry, it can generate a profit without being exposed to market risk. Conversely, a strategy that is said to be 'delta hedged' is one that is protected against large movements in the underlying asset's price.

Figure 3.1: Straddle Strategy Payoff



(Hull, 2015)

Buying an option straddle is quite similar to investing in volatility because the straddle option price will depend on the volatility of the underlying and therefore the payoff is dependent of the underlying's price volatility. Events that cause large volatility, or large movements in the stock price, can lead to a profitable straddle strategy. A significant payoff occurs from a straddle when the underlying price exhibits a significantly large increase or decrease, i.e. when volatility is high. This strategy is usually selected when the investor is confident the underlying price will move, but is not sure in which direction, hence why it is referred to as a 'bet' on volatility. The maximum potential loss from a straddle is the premium paid and is only incurred if the price at maturity equals the strike price.

Although the research and investigation into option trading and strategies is abundant, relatively few focus solely on a straddle strategy as a primary research topic and particularly comparing it with a similar investment strategy. The profitability of the straddle strategy, however, has been researched by a number of academics. Since buying an option straddle is similar to investing in volatility, some researchers have tried to use straddles to attempt to profit from volatility forecasts (Noh at al., 1994). The returns of at-the-money straddle positions were investigated by Coval and Shumway (2001). Findings suggest that the strategy typically exhibits negative returns. Their strategy of buying zero-beta straddles averaged a negative 3% return per week. It should be noted that this study is somewhat dated as it was carried out using the S&P100 data between 1986 and 1995. There is a notable gap in the current literature to update this research. Goltz and Lai (2009) found similar returns for a straddle strategy. Their research used data from the German stock exchange (DAX) from 1999 through 2005. They also used beta-neutral straddle strategies and conclude that on average the strategy exhibits "significantly" negative returns. A valuable extension on this research could be made by including the years following this time period, accounting for the financial crisis from 2008 onwards, and examine if such findings were maintained. A paper encompassing the financial crisis period may yield differing results due to the extreme volatility exhibited during the crash.

Buying a straddle involves an investor going long in a put and call on the same underlying asset, with the same strike and maturity, however an investor can also sell or 'short' a straddle. Selling a straddle occurs when an investor takes a short position rather than a long position in an identical call and put option on the same underlying. Negative returns are also observed in a short straddle strategy (Nandi and Waggoner, 2001). A short straddle is profitable if volatility is low and the underlying price remains relatively unchanged. Nandi and Waggoner (2001) studied the period between 1990 and 1995. An interesting finding in this research was that when the market dropped, the value of the straddle dropped considerably more compared to a loss from a long position in the market. The probability of significant negative returns by holding a short straddle far exceed the probability of positive returns. Again, the selected time period for the study will affect the results due to different volatility levels being observed. Hence, employing a wider time horizon, or including a period which exhibited large spikes of volatility may be beneficial in providing a more accurate representation.

The relationship between the slope of the implied volatility term structure and straddle returns is described as being positive (Vasquez, 2017). As the volatility term structure increases, the one-week future straddle return also increases. The volatility term structure curve represents the difference between the implied volatilities of options with the same exercise price but differing maturities. Portfolios with higher volatility term structure slopes outperformed those with lower slopes. Since the volatility term structure is essentially the markets expectation of future volatility, an upward sloping curve (meaning volatility is expected to rise) would result in greater payoffs for long straddle strategies.

Straddle trading strategies have also been studied using individual stocks and the findings are in line with the findings aforementioned. Straddles constructed using puts and calls on individual stocks were also found to yield negative returns on average (Gao et al., 2018). However, their study found a positive relationship between earnings announcements and at-the-money straddle returns. Between the day before an earnings announcement and the day of the announcement the straddle on average returned approximately 2.3%.

The relationship between implied volatility, realized volatility and the returns on a straddle strategy was studied by Goyal and Saretto (2009). This research demonstrated that the difference between implied volatility and realized volatility had predictive power on the returns of the straddle. When implied volatility was less than the historical volatility, the straddle tended to return positive returns and when the implied volatility was lower than historical realized volatility, the straddle's returns tended to be negative. This finding was the driving factor to include a study on realized volatility versus VIX implied volatility within this paper, as future research could benefit from extending on this literature, and further examining this relationship.

Based on previous research, a straddle strategy either long or short, appears on average to be negatively returning. This characteristic is somewhat similar to the VIX. Since the VIX is often a negative returning asset class, this study will use the previous 10 years in order to identify which strategy is optimal for an investor. The findings of this paper will also aim to fill a gap in the current literature by updating the observed return data for a long straddle strategy while providing a performance and profitability evaluation of the strategy. With the majority of previous research uncovering the negative returns of a straddle position, this papers finding will either further bolster previous literature or add alternative findings to the research area.

3.4 Predictive Power of the VIX

The VIX has become one of the most frequently used measures for predicting future short-term market volatility (Sarwar, 2012). Due to its derivation being based on an average of out-of-the-money puts and calls on the SPX, it can be used to give an estimate future volatility. Whaley (2008) conducted a test to investigate the predictability of future volatility using VIX data and inferred that the volatility index "works reasonably well as a predictor of the expected stock index movements". He estimated that the VIX closed within the range of 12 - 29 approximately 75% of the time and made his prediction of the movement of the S&P500 from this. This research is relevant to this study as I aim to examine the accuracy of the forecasts by the VIX by comparing it with 21-day realized volatility.

Corrado and Miller (2005) opine that the predictability power of the VIX for the S&P500 has increased since 1995. They investigate the forecast quality of implied volatility using the VIX and posit that it outperforms historical volatility (GARCH (1,1) Model) in forecasting future realized volatility. More recently this was also backed by Zhu (2018) who claims that in most situations, volatility indexes provide a more accurate forecast compared to GARCH (1,1) models for indexes such as the S&P500. Blair et al. (2001) also compared the forecasting power of the VIX implied volatility versus historical volatility and found implied volatility to give a more accurate result, concluding that the VIX contains predictive power for future volatility.

Despite the extensive research and evidence in relation to the VIX being used as a predictor of future volatility, some previous literature has revealed arguments against such findings. One of the earlier papers to oppose the superiority of the VIX in forecasting volatility was by Lamoureux and Lastrapes (1993). Their research found that implied volatility did not provide more accurate predictions of volatility when compared with GARCH models. It should be noted that their research sample was on 10 individual stocks rather than a market index. This can cause an issue in the fair pricing of the options due to some of the options having a low liquidity. Another issue with their sample selection also is that there was a maturity mismatch with the options which results in inaccurate calculations of the implied volatility. Similarly, Day and Lewis (1992) conducted a study comparing the implied volatility from options on the S&P100 index with GARCH-type models and also found that the options could not provide a more accurate forecast.

The primary argument opposing the VIX's prediction properties is that 'implied' volatility differs to 'realized' volatility. The VIX is argued not to be an accurate estimate for actual volatility by Traub et al. (2000). In their study of the period between 1985 and 1999, the VIX appeared to overestimate actual volatility. From their investigation, the average realized volatility of the S&P500 was 14.7% but the implied volatility over the period was 19.8%. Chow et al. (2014) find in their empirical study between 2005 and 2014 that volatility was underestimated. In particular, as market volatility further increased, the underestimation of volatility enlarged significantly.

The discrepancies between the two aforementioned papers can be explained by Kownatzki (2016). His study reveals that the VIX consistently overestimates actual volatility in 'normal' market conditions but underestimates it in times of market crashes. This finding is crucial for investors to be aware of and raises questions about the suitability of the VIX for many risk management applications. The finding can be used to explain why Chow et al. (2014) found volatility to be underestimated because their research was focused on the time of the financial crisis and why Traub et al. (2000) found volatility to be overestimated because they studied a period of low volatility. Within Chapter Four, I aim to extend on the research of Kownatzki (2016) to determine if his findings hold true within a more recent time horizon. It is also important to discover the accuracy of the implied volatility in order for investors to make investment decisions and is why it is worthy of research to fill the current gap in the literature.

Not only has research delved into the predictive power of the VIX for volatility, but some authors have tested whether it could help predict future stock returns. Both studies by Christensen and Prabhala (1998) and Chernov (2007), state that because the VIX contains information about future stock market volatility, it can be utilised to predict the future movement of the S&P500. A widespread belief among investors is that changes in implied volatility can give indications on the future direction of the market. Bollerslev et al. (2009) provide empirical evidence that VIX data can be used to predict stock market returns. Their study focuses on the difference between implied and realized volatility, focusing on weekly, monthly, and quarterly time horizons. The paper concludes that the degree of predictability from the VIX data is largest at quarterly time horizons. Motivation behind my subtopic of research of implied volatility versus realized volatility stemmed from this paper. Giot (2005) found that there was a positive relationship between the VIX and stock market returns. Their finding was that future returns are almost always positive when VIX levels are highly spiked. This is an interesting and impactful finding as it could highlight a buy signal for investors. Their study is based on the S&P100 rather than the S&P500 and therefore not totally applicable to the CBOE VIX, however, it still shows the predictive power element of a volatility index.

Heslinga (2013) also identified that in certain circumstances the VIX has the ability to be a stock market indicator. The author claims that a strategy can be constructed using the VIX in order to identify future potential crises. An earlier research paper by Copeland and Copeland (1999) also explored whether the VIX can be used as a stock market indicator. Their study focused on whether changes in the level of the VIX had any predictive power for large capitalization stocks' daily returns. It was discovered that positive daily returns for large-cap stocks could be expected when the VIX had increased from its previous close price.

Cipollini and Manzini (2007) also observe predictive power in the VIX. However, the prediction or the signal from their model was only “loud and clear” when the VIX was high. When the VIX levels are low their model is not as effective in predicting future movements of the market. This claim is in line with previous literature in terms of the 'fear gauge' property of the VIX. At times when investors are worried about the market the VIX increases, so a movement in the market would be expected as traders are viewed as the 'best-informed' in terms of market information.

3.5 Conclusion

Outlined in this chapter are both seminal and peripheral research papers surrounding the topic of investigation within this paper. Extensive research has been conducted on volatility in the past because of its importance in finance. The ability to be able to accurately predict future volatility for an investor is invaluable. It allows for them to make optimal decisions surrounding their investments by giving them an indication of future stock market movements. More recently, volatility as an asset class has been subject to immense research because of its natural diversification characteristics for a portfolio. The findings of these papers provide investors with valuable information in relation to the potential uses of the VIX within a portfolio.

Chapter Four: VIX Implied Volatility vs Realized Volatility

4.1 Introduction

As mentioned in Chapter 1, there has been abundant research within the area of volatility and on how accurately the VIX estimates future realized volatility, see Chow et al. (2014); Traub et al. (2000); Whaley (2008) for reference. Volatility forecasting is an important part for any practitioner making investment decisions. It aids not only in asset allocation, but particularly for volatility targeting strategies, such as the ones under investigation in this paper. For this reason, it is important for an investor to be able to accurately forecast future realized volatility. As previously mentioned, the VIX is now one of the commonly used metrics in predicting future realized volatility. This section is somewhat of an extension on current literature by Kownatzki (2016) in identifying the accuracy of the prediction of realized volatility (RV) by VIX Implied Volatility (IV).

Volatility is the most common risk measure used in the financial field. Commonly measured by the variance or standard deviation of an asset's returns, it is a measure of how much the returns fluctuate around the mean. RV is a backward-looking measurement; it is calculated using historical return data of an asset for a particular period of time. IV is a forward-looking measurement. As described earlier, the VIX is a consistent measure of volatility that is expected to be witnessed in the following 30 calendar days, or 21 trading days. It is for this reason investors use it as an indicator for what direction volatility is expected to follow. Because of its popularity, academics continue to test the accuracy of its predictive power.

Kownatzki's (2016) study is carried out for the period between 1990 through to 2014. He found support for the argument set out by Traub et al. (2000) that the VIX overestimates actual volatility. He furthered their study by concluding that it overestimates volatility in non-crisis periods, and underestimates volatility in times of financial crises. I aim to extend this research by updating the time period under review. This section of the paper investigates the accuracy of IV by the VIX versus 21-day RV for the period between 2014 and 2021. The motivation behind this study was to update the research topic with a more current financial crash in order to discover if previous literature findings still hold. This period of study incorporates the global stock market crash in 2020 due to the COVID-19 pandemic. This specific topic is important to research, with significant practical implications. Because the VIX is considered the benchmark measure for volatility, it is vital to know how accurate it is.

4.2 Data

The conclusion of this section was drawn from two different time series. Firstly, VIX daily price data already extracted from Bloomberg to conduct the main research question of this paper was used. The sample period was narrowed down to only include the study period of the 2nd January 2014 (first trading day) through to 30th June 2021. Daily data was important as it would be difficult to calculate the 21-day realized volatility if we had weekly or monthly data. The second time series used in the study was of daily prices of the S&P 500 index (SPX) for the same period. 21-Day realized volatility was chosen for consistency between this and the study of Kownatzki (2016), to increase the comparability of results.

4.3 Methodology

For the analysis in this section, I assumed 252 working days as this is considered the average amount of working days per year. To calculate the realized volatility the daily returns were required from the price data. The log daily returns were calculated and once the returns were found, the 21-Day realized volatility could be computed. Realized volatility is computed by the following formula:

$$Realized\ Volatility\ (RV)\ =\ \sqrt{}Variance\_of\_Returns\ *\ \sqrt{}working\_days$$

Using the above formula and plugging in the variance of the returns and working days values, the 21-Day RV was calculated. The RV was then compared with VIX in order to draw conclusions on the two measures.

4.4 Findings and Analysis

Without too much inspection, we can suggest from the statistics in Figure 4.1, that it is likely the VIX overestimates RV. Taking the mean for the six-year period, we can see the VIX was significantly larger. The standard deviation value is larger for the RV which could be due to the mean reversion characteristic of the VIX, resulting in the VIX value being less likely to deviate from its mean.

Figure 4.1: IV vs RV Descriptive Statistics

Descriptive Statistics		
	21-Day Realized Vol	*VIX*
Mean	13.69%	17.28%
Standard Deviation	10.68%	7.69%
Kurtosis	26.24099322	15.4256313
Skewness	4.367650132	3.10519922
Minimum	3.39%	9.14%
Maximum	95.20%	82.69%

Take special notice of the maximum and minimum values also. On the day RV was lowest, the VIX had overestimated it by approximately 6%, yet while RV peaked at 95.2%, the VIX only reached 82.69%. This is quite a large difference (12.51%) between the two maximum prices and would be reasonable to suggest that it backs the findings of Chow et al. (2014) as discussed in Chapter 3.3, that the underestimation by the VIX appears to get significantly larger the more volatility increases. Similar differences in maximum and minimum values are found in previous literature by Carr and Wu (2006) and later by Adameic and Rhoads (2018) who study periods from 1990 to 2005 and 2008 to 2016.

A potential explanation for the difference between realized and implied volatility is the risk premium involved in trading options. The risk premium is payable to the seller of the option to compensate them for the short position they effectively take in the market. Because of the premium increasing the price of most options, options generally are priced with an elevated volatility assumption which in turn affects IV.

Kurtosis is a measure of how 'fat' the tails of a distribution are. Because of the stochastic nature of volatility, the distribution may not follow that of a normal distribution. This results in the tails of the distribution being 'fatter'. A kurtosis of 3 is considered normal; due to the statistical properties of volatility, the kurtosis for the overall period is considerably large and will be larger than if we were to identify the kurtosis values for each individual year. The kurtosis value is a measure of how extreme outliers or values in our sample affect the overall variance value. A reason for the VIX to have a lower kurtosis than the 21-day RV could be because of the mean reverting tendency of the VIX.

Figure 4.2: IV vs RV 2014-2021

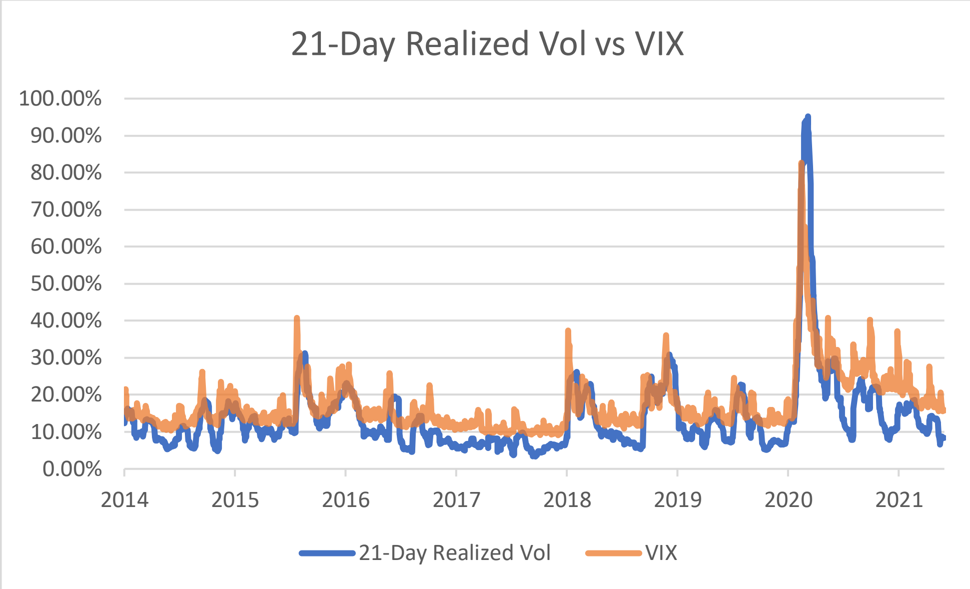
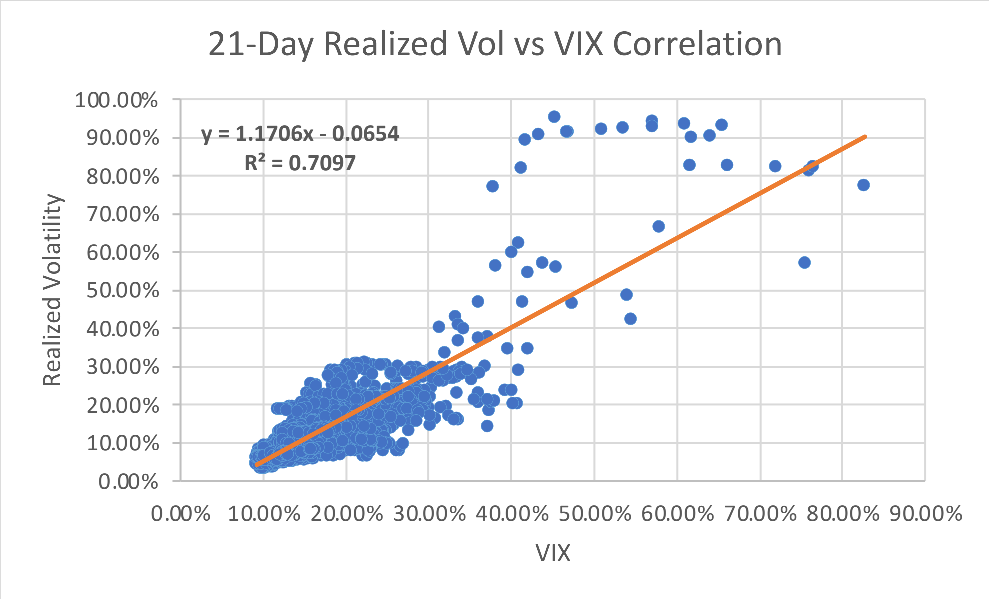


Figure 4.2 displays what we are trying to prove in this section. Over the period we notice how the VIX is constantly above the realized volatility value until the large spike in 2020 due to the COVID-19 pandemic. The graph also excellently portrays the mean reversion tendency of the VIX. We can see most spikes in the VIX are short-lived before the VIX returns to its regular levels. The lasting effects of the pandemic on investor uncertainty can be seen on the graph however. After the large spike in volatility from the market crash in February 2020, the VIX returned to a higher-than-average level in the months that followed, clearly depicting the uncertainty that remained due to the pandemic. From Figure 4.3 below, we can see an R^2 value of 0.7097, this indicates quite a strong relationship between realized volatility and the VIX. The value suggests that in a simple linear model, approximately 71% of the variation in RV is explained or attributable by the VIX. Interestingly, the slope of the trendline is greater than 1, meaning the RV is positively related to the VIX IV. This means that on average, the RV is higher than the VIX, which opposes the argument that the VIX overestimates volatility during 'normal' market conditions.

Figure 4.3: IV vs RV Correlation



4.5 Conclusion

The findings of this section are in line with previous studies, see Carr and Wu (2006); Adameic and Rhoads (2018), but most importantly with Kownatzki (2016), as the motivation for this research topic stemmed from his paper. This section identifies the overestimation by the VIX of implied volatility when compared with 21-day realized volatility for 'normal' periods and an underestimation during crisis periods.

The importance of this section was three-fold. Firstly, due to the ever-growing popularity of the VIX as the benchmark for implied future volatility, it is important to keep research up to date on its accuracy in order for investors to make optimal investment and risk decisions. Secondly, as discovered by Goyal and Sorretto (2009), straddle returns can be somewhat predicted by the difference between IV and RV. Therefore, it is important to know the accuracy of the VIX in forecasting implied volatility as it can aid in the investment strategy choice for an investor. Lastly, and possibly most importantly as it reverts back to the main research question of this dissertation, is that the investigation into the movements and statistics behind the VIX and realized volatility can help explain, to an extent, why the VIX futures and straddle strategy performed how they did. For instance, the identification of severe outliers in this section has explanatory powers in the profitability of both strategies for my main research question. Having identified the above, we can undergo a more informed and accurate study on the performances of both strategies.

There are several potential questions for future research left here. Implied volatility using the VIX is examined in this study, an alternative measure of IV could be used to compare if it has greater accuracy in forecasting future volatility. A recent paper by Tchorbajian (2019) questions the use of the VIX as a volatility benchmark and therefore an investigation into alternative measures could be pursued. Alternatively, different length periods of realized volatilities other than 21-day could be examined in order to see if the accuracy of the VIX implied volatility increases as the realized volatility period changes. Previous literature has investigated this however updating the period under study could be a potential focal point.

Chapter Five: Methodology

5.1 Introduction

In line with previous research, such as Szado (2009), Heslinga (2013), a quantitative approach is taken for this dissertation study. This approach is taken as I am using data to calculate returns and compare the profitability of investment strategies. Therefore, a qualitative approach would not be suited. This approach allows for results to be easily compared within the paper while also accommodating a comparison of final findings with previous literature. A quantitative approach is also preferred as it allows for the data to be precise and easily presentable for the reader making it less challenging to understand. It should be noted that a quantitative approach to research can sometimes lead to a structural bias or a false representation of data. Taking this into account, I have used data from Bloomberg and kept the time series consistent throughout to attempt to ensure the representation and comparison of both strategies is fair. This is further discussed later in the section.

5.2 Data

The aim of this paper is to investigate the performance of investment strategies related to volatility. I consider two trading strategies: a VIX futures strategy and a long straddle strategy. The data for the VIX futures strategy is represented by the CBOE Volatility Index (VIX) and VIX futures price data which were accessed via Bloomberg. S&P 500 daily price data was required for the construction of the straddle strategy. From this data, option prices could be calculated. The sample data for the S&P 500 index (SPX) was extracted from Bloomberg. In order to price the put and call options, data for the volatility and the interest rate at each corresponding date was also required and this too was taken from Bloomberg. The volatility level is represented by the SPX 1M 100 VOL BVOL Index. The study comprises of 132 monthly observations.

5.3 Motivation

The selected period of study for this dissertation dates from 1st January 2010 through to 31st December 2020. The motivation behind why this period of study was selected is detailed below. Firstly, a large number of academics have investigated volatility as an asset class or as an investible product primarily encompassing the period around the financial crisis. This paper aims to extend current seminal and peripheral literature (see Traub et al., 2000; Szado 2009; Whaley 2008), by extending the study period under review. By focusing on an up-to-date time period, this paper has potential to bolster previous findings, resulting in making them more robust and reliable. Conversely, the paper will add conflicting or alternative arguments to seminal findings that may open up potential future research areas. While a lot of existing literature published after the financial crisis focuses on the same study period, their findings may be somewhat biased and therefore the motivation for my study period was to investigate if seminal findings around the VIX still hold for recent years. Since VIX futures have only been available to investors since 2004, majority of research is conducted between the period of 2004 to 2013. This paper will extend findings in this research area to a more up-to-date period.

Secondly, the period of the previous ten years was selected due to the varying levels of volatility exhibited during this time. This period displayed both lulls and spikes in volatility, as set out in Figure 2.1, which increases the effectiveness of the study. By selecting a period with varying levels of volatility data, it increases the robustness of the findings and also decreases the possibility of any potential bias in the findings. Contrary to previous studies focusing on periods of predominantly high volatility, (see Chow et al., 2014), this study aims to answer whether the VIX has been a viable investment over the past 10 years, particularly when compared with a similar volatility strategy such as a straddle by selecting a period that exhibited both high and low levels of volatility.

5.4 Methodology

Backtesting is a method to investigate the performance a strategy ex-post. To compare the two trading strategies, this research paper performs a backtest on each strategy in order to assess how well they would have performed over the selected period. Backtesting also helps to identify the potential future accuracy or performance of a strategy. For trading strategies with short holding periods, usually 2 to 3 years of data is considered sufficient. This paper tests both strategies over the previous 10 years to achieve robust findings that will help investors select the best strategy in the future. The results from the backtest will then be compared to identify which strategy better performed over the time horizon. Identifying this will help investors decide an optimal strategy for future bets on volatility and is why the research is important.

5.4.1 Constructing a VIX Futures Strategy

In order to backtest the strategy involving VIX futures, the sample data for the study period was extracted from Bloomberg. Spot VIX and VIX futures daily prices were taken for the period between the 1st January 2010 through 31st December 2020. 'Spot' VIX is simply the VIX Index's price on a given day, however it is not a tradable product. The strategy I am testing is a buy-and-hold strategy for one-month futures contracts - the investor will buy a futures contract with expiry one month from that date. Both spot and futures price data was required because the settlement price at maturity of the futures contract is the Spot VIX price on the expiration date. For example, if an investor enters into a one-month futures contract for November delivery for $25, they will profit if the Spot VIX price on the expiration day is above $25.

All VIX futures contracts expire on a Wednesday. VIX monthly contracts expire on the third Wednesday of the month. The trading strategy therefore begins from the third Wednesday in January 2010 where an investor buys a one-month VIX futures contract and holds until expiry on the third Wednesday in February and so on.

Once each futures contract price and the corresponding settlement price were identified, a profit or loss could be calculated at expiration of each contract. It is important to note the mechanics of a VIX futures contract. The VIX is a measure of implied volatility as mentioned already, therefore the tradable products based on the VIX are profitable as a result of an upward movement in volatility. For that reason, the option 'vega' is an important part of a VIX futures contract. The option Greek 'vega' refers to an option or security's sensitivity to a one percentage point change in implied volatility. VIX futures contracts have a fixed vega of $1,000 meaning if VIX increases by one point, the investor gains $1,000. This is important to note especially for the construction of the straddle strategy which is further explained later.

5.4.2 Constructing a Long Straddle Strategy

As mentioned previously, a straddle strategy is a combination of a put and call option on the same underlying asset with the same strike price and maturity. It must be noted that investors that take a position in a straddle strategy often ensure their strategy is 'delta-hedged'. The delta of an option refers to the option value's sensitivity to a movement in the underlying asset, for example in our straddle strategy, this would be referring to a movement in the S&P 500. Due to a straddle being constructed using a put and a call option on the same underlying asset, a straddle is considered delta-hedged when it is first set up thanks to the delta of the call option essentially offsetting the delta of the put option, making it delta-neutral. A move in the underlying asset in a certain direction causes the delta of both options to move in opposite directions, for example an upward movement in the S&P 500 will increase the delta of the call option while decreasing the delta of the put option by a lesser amount, thus wiping the delta neutral position of the straddle. Delta-hedging involves rebalancing the delta of the straddle so that it remains delta-neutral. An assumption in this paper is that the straddle is not delta-hedged. I do not rebalance the deltas of the puts and call options, instead the contract is entered into and let run until maturity and the next straddle begins. This approach was taken for an ease of calculations and running of the experiment. Although most straddles would be rebalanced and it should be noted that the process within my study is not very common in real-world investing, it will still provide a good indication of the straddle performance.

In line with previous literature, I apply the Black-Scholes (1973) option pricing model to the SPX data. However, in my study I assumed a dividend yield of 1.5% and therefore a modification of the Black-Scholes model is preferred since the Black-Scholes model is used for pricing options that do not pay a dividend. The modified model is known as the Garman-Kohlhagen model and allows for the inclusion of a dividend yield (Garman and Kohlhagen, 1983):

$$C = S.e^{-q.t}.N(d_1) - K.e^{-r.t}.N(d_2)$$

$$P = Ke^{-r.t}.N(-d_2) - S.N(-d_1)$$

where:

C = Call Option Price

P = Put Option Price

S = Spot Price

q = Dividend Yield

t = Time to Maturity

r = Interest Rate

N () = Cumulative normal distribution

$$d_1 = \frac{ln\left(\frac{S}{K}\right)+\left(r+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

I input this formula as code using VBA to create a function (see Appendix 2) and calculated the option prices for both puts and calls with a 1-month maturity. A maturity of 1-month for the options was preferred for the study for several reasons. Firstly, the paper aims to test returns over the short term. One-month options are more likely to react to short term volatility. With the VIX being an indicator of implied volatility over the next 30 days, testing a one-month option strategy offers greater comparability against the investment in the VIX. Secondly, the sample size affects the precision of the study and is important in determining the validity of the findings (Faber and Fonseca, 2014; Nayak, 2010). Michaelides (2020) explains the importance of significance in a sample size. Examining various sample sizes across 180 publications in finance journals, the paper highlights the importance of the significance of the sample rather than the use of an excessively large sample.

Taking the above-mentioned paper's findings into account, I chose to use one-month options for this study. Using yearly maturities would result in only 10 outcomes (1 for each year) which would result in a small sample size for the study and affect the robustness of the findings. One-month options provide twelve independent outcomes per year and therefore provides more data and a larger sample size to perform the research on, thus making any findings more robust, while also not being too large, as would have been the case if weekly maturities were used. A total of 132 outcomes are observed.

With both option prices now calculated over the 10 years, a straddle can then be constructed. An arbitrary straddle strategy was first constructed using a notional investment amount of $5,000,000. This was done to calculate the premium involved in buying both the call and put for each date, the payoff from both options and the overall profit or loss on each date. The payoff from a straddle comes from either the put or the call because they are bets on opposite movements of the underlying asset, and therefore only one can ever expire in-the-money. For example, if the underlying asset *increases* in price, the put expires worthless and the call expires in the money, and vice versa if the underlying *decreases* in value. Once the payoffs were recorded for each option at each date, the overall profit from the strategy was recorded by subtracting the premium from the payoffs.

Although the straddle was constructed, the results were not comparable to the VIX futures strategy. In order to make the strategies comparable, the vega of the straddle was then calculated. The VIX futures strategy has a fixed vega; the investor will gain $1,000 for every one-point increase in the VIX, which corresponds to an average implied volatility. To make the option strategy comparable with the VIX, the option notional amounts were chosen so as to achieve an initial vega sensitivity of $1,000. Since the VIX futures were already set up in terms of vega, the vega value of the straddle needed to equal $1,000 also so to make both portfolios comparable. To do this, first the vega of the call and put options were calculated using the Black Scholes (1973) option vega formula:

$$Vega = 0.01 \times (S.e^{-q.t}.n(d_1))$$

where:

S = Spot Price

q = Dividend Yield

t = Time to Maturity

n() = The Standard Normal Probability Density Function.

$d_1 = \frac{ln\left(\frac{S}{K}\right)+\left(r+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$

It should be noted that the vega of a put and a call are always equal due to an implication of Put-Call Parity. Introduced by Hans R. Stoll (1969), Put-Call Parity explains how a call option and a put option on the same underlying asset with identical strike prices and times to maturity should equal the price of a forward contract on the asset. Put-Call Parity states:

$$C - P = Se^{-q.t} - Ke^{-r.t}$$

where:

C = Call Option Price

P = Put Option Price

K = Strike Price

S = Underlying Price

r = Interest Rate

t = Time to Maturity

When we differentiate both sides of the Put-Call Parity equation with respect to volatility we arrive at:

(Where ν = Vega)

$$Left\ Hand\ Side: \quad \frac{\partial}{\partial\sigma}(C - P) = \nu_C - \nu_P$$

$$Right\ Hand\ Side: \quad \frac{\partial}{\partial\sigma}(Se^{-q.t} - Ke^{-rt}) = 0$$

$$\nu_C - \nu_P = 0$$

$$\therefore \quad \nu_C = \nu_P$$

Using VBA, I input the vega formula to create the function to calculate the vega, see Appendix 3. The vega for both the put and call option were calculated and added together to get a total vega in percentage terms for the straddle strategy. From this, the notional amount could be found which would result in an option vega for the straddle equal to $1,000 to match the VIX futures contract. It was important to do this as the strategies are now similar in a way that allows us and an investor to compare the results. Prior to working out a notional amount to be invested, using $5,000,0000 as the notional for example, meant both strategies were completely different, you could not compare a strategy of $5,000,000 invested in calls and puts versus a strategy consisting of one VIX futures contract.

Alternatively, the vega of the straddle strategy could have been calculated assuming a nominal amount of $1,000,000 for example, invested in call options and in put options and then from that calculate the amount of VIX futures contracts required to match that vega. However, since this study is primarily focused on the VIX and a VIX futures strategy I opted to calculate the straddle to match the futures strategy.

Having identified the nominal amount required to be invested in calls and in puts to achieve a vega of $1,000, the payoff at each date for the straddle was calculated and the profit or loss was then computed as the payoff minus the premium paid. I now had weekly data for the straddle strategy but to compare the strategy with the VIX futures strategy, I had to extract the data corresponding to the third Wednesday of each month over the 10-year period so to match the monthly futures contracts. By doing this I can now directly compare both strategies, one involving entering a one-month VIX futures contract on the third Wednesday of the month and the other entering long positions in a put and a call option on the S&P 500 Index. Since both contracts run for identical periods of time it increases the effectiveness of the comparison.

5.4.3 Performance Evaluation

Having identified the profit or loss of each contract within the two strategies, their overall performances now had to be compared. There are many ways of evaluating a trading strategy or portfolio. For my research I chose to evaluate the strategies' performances in line with previous literature using the following:

Mean Return & Standard Deviation

The return of a portfolio is arguably the most important part of an investment; the first value an investor will look at is the potential return and then the risk attached is considered. Mean return is an important measure as it also gives an indication of future expected returns. The mean return of both strategies was calculated by averaging the returns over the ten-year period and then compared. Before determining which strategy had a greater mean return a hypothesis test was implemented to investigate if there was a statistical difference between the means.

The standard deviation of both strategies was then calculated and compared. Standard deviation measures the riskiness of an investment by determining how volatile its returns are. The higher the standard deviation, the more volatile its returns and therefore the riskier it is. The standard deviation of the strategies was calculated and compared.

Value at Risk (VaR) & Expected Shortfall (ES)

VaR is a risk measure commonly used by investors to quantify, usually to a 95% or 99% confidence level, the maximum loss that could happen over a certain period. Due to the nature of the data in question, I implement a Historical VaR at both 95% and 99% probability levels. VaR is calculated by ranking each return from smallest to largest and then finding the 95th and 99th percentile worst return.

Expected Shortfall (ES) answers the question that VaR cannot. ES is a measure similar to VaR however it indicates what the average expected loss over a selected period given that the returns are already below the VaR value. Where VaR poses the question "what value of the portfolio is at risk?", ES asks "if things do get bad, what could the expected loss be?" (Hull, 2017). ES is also calculated using confidence levels. To calculate the 95% and 99% ES, I averaged the returns of the worst 5% and 1% of contracts, the findings of which are discussed in the next section.

Sharpe Ratio

The Sharpe ratio is a popular performance measure in portfolio management. It indicates how well a strategy or portfolio performs when compared to the return on a risk-free investment, such as government bonds.

$$Sharpe\ Ratio\ = \frac{R_p\ -\ R_f}{\sigma_p}$$

where:

R_p = *Portfolio Return*

R_f = *Risk-free Rate*

σ_p = *Standard Deviation of Portfolio's Excesss Returns*

Calculating the Sharpe Ratio for a derivatives strategy such as the VIX futures strategy in this paper can be difficult due to uncertainty surrounding the nominal amount invested. The interest rate used for the risk-free rate is one-month US Libor, which acts as a proxy for the one-month Treasury yields and has a maturity consistent with the investment horizon, namely one month. In order to calculate a comparable Sharpe Ratio for the strategies, the annualized Sharpe Ratio was first calculated for straddle strategy assuming a nominal amount of $900,000. The nominal amount was selected as the average nominal amount of the put and call options was $453,125 per leg, as there are two option legs per strategy, this value was rounded to $900,000. The same nominal amount was applied to the VIX futures strategy, since the VIX futures strategy has the same vega risk characteristics as the S&P 500 straddle strategy. Therefore, both strategies now have the same initial investment amount, and their ratio can be compared consistently – similar to the methodology behind the vega workings earlier in the paper. Assuming the same nominal investment of $900,000 for the VIX futures strategy, the Sharpe Ratio was calculated, and the findings are discussed in the next chapter.

Chapter Six: Findings & Analysis

6.1 Introduction

The strategies under review in this study were compared using a number of different performance measures. The mean returns are compared first to determine which strategy produced a greater expected return. To bolster the findings and allow us to make a more informed conclusion about the means, a statistical test was imposed to examine the hypothesis that the mean returns of both strategies were the same.

In addition to examining the mean returns, measures of risk for each strategy were considered; the standard deviation of monthly returns, the historical Value at Risk (VaR) and Expected Shortfall measures and the Sharpe Ratio for both strategies were computed in order to compare the risk and return characteristics of each strategy.

6.2 Mean Return and Standard Deviation

The mean return for the VIX futures strategy is in line with previous literature in that it yielded a loss. The mean return for the VIX futures strategy totalled -$619.96 over the study period. The finding for the straddle however goes against previous research discussed in Chapter 3. The straddle strategy in this study yielded an average return of $743.93 over the ten-year period. Over the ten years, 64.4% of the observations within the VIX futures strategy yielded negative returns, compared to only 53.8% for the straddle. It is important to consider the make-up of both strategies when interpreting this finding. The S&P 500 straddle strategy is constructed using options that are designed to profit from a market movement in either direction and therefore has a greater probability of achieving a positive return. The call option will be in the money from an upward movement in the market, while the put option will profit if the market makes a downward move. However, for the VIX futures strategy, positive returns are only achieved from an upward move in volatility.

From the study, the performance of the VIX Futures strategy leaves much to be desired for an investor aiming to make a positive return. A reason for the negative performance could be due to the persistent contango effect witnessed in VIX futures pricing. As discussed previously, 'contango' refers to the event where the futures price of the asset is higher than its spot price and this results in an upward sloping term structure. Long positions in futures contracts are only profitable when the spot price is greater than the pre-agreed futures price. If they are persistently priced persistently higher than the spot price, it decreases the possibility of positive returns for the contracts and an overall strategy.

The observed mean monthly return of the straddle strategy was greater than the mean monthly return of the VIX strategy. A Student t-test was applied to the data to test the hypothesis that there is a statistical difference between the observed mean values. A hypothesis test is a means of testing the plausibility of a hypothesis or statement made about a population which is supported by the sample data. It is important as it identifies whether the findings are 'statistically significant' or not. In other words, it informs us whether the outcome of the study occurred due to chance.

6.2.1 Hypothesis Test

As mentioned in the introduction chapter, I am testing the hypothesis that the mean return of the VIX futures strategy equals that of the one-month straddle strategy. The alternative hypothesis is that the means are not equal. The test is proposed as follows:

$$H_0: \quad \mu_{VIX} = \mu_{STRADDLE}$$

$$H_A: \quad \mu_{VIX} \neq \mu_{STRADDLE}$$

A two-sample t-test for equal means is used to test the above hypothesis which was introduced by Snedecor and Cochran (1989). From this test we will be able to identify if there is a statistical difference between the mean returns of the strategies. There are two types of t-tests, one assuming equal variances between the sets of data and one assuming unequal variances.

In order to determine which t-test to use, an F-test is required to identify if the variance between the two samples is equal. The F-test is set up as follows:

$$H_0: \quad \sigma^2_{VIX} = \sigma^2_{STRADDLE}$$

$$H_A: \quad \sigma^2_{VIX} \neq \sigma^2_{STRADDLE}$$

F-Test Two-Sample for Variances		
	Straddle P/L	*VIX Futures P/L*
Mean	743.93	-619.96
Variance	257101326	56723718.5
Observations	132	132
df	131	131
F	4.53251889	
P(F<=f) one-tail	6.8224E-17	
F Critical one-t	1.33438286	

Based on the results of the F-test, we reject the null hypothesis in favour of the alternative hypothesis because the F-value is larger than the F-critical value. From this we can infer that the variances of the two samples are not equal, and we should use a t-test assuming unequal variances.

The results from applying a two-sample t-test for equal means assuming unequal variances are below.

t-Test: Two-Sample Assuming Unequal Variances		
	Straddle P/L	*VIX Futures P/L*
Mean	743.93	-619.96
Variance	257101326	56723718.51
Observations	132	132
Hypothesized M	0	
df	186	
t Stat	**0.8845527**	
P(T<=t) one-tail	0.1887700	
t Critical one-t	**1.6530871**	
P(T<=t) two-tai	0.3775399	
t Critical two-t	**1.9728001**	

From the results of the hypothesis test, we fail to reject the null as the t-statistic is smaller than the t-critical value. This suggests that there is no statistical difference between the mean returns of the two strategies. Although there appears to be a larger mean returns from the sample for the straddle strategy, the difference is not statistically significant. This means that the outcome may have occurred due to chance.

From data simple visual inspection of the sample data, one could infer that there is a clear difference between the means of the two strategies. This inference is contradicted by the hypothesis test, highlighting the importance of such a test, as it identifies the potential that a sample wrongly represents the population. Having performed the hypothesis test to a 95% confidence level, we can say that there is no significant difference between the means of the strategies. This outcome may seem unusual because of the clear difference apparent in the results of our study however this may have occurred for a number of reasons. Most likely, failure to reject the null hypothesis was due to the variability of the sample data. Because the sample period was highly volatile, especially for the straddle as outlined later in this section, the outcome may have been affected. The observed difference in average returns looks large however when taking the variability of the returns into consideration, it is less compelling. A larger sample size may have helped but only in a limited way - it would be dependent on how volatile the extended period was. Also as discussed, the sample may have been victim to sampling bias. The monthly contracts selected for the study gave rise to a positive mean return whereas the mean return of all contracts was -$710.99, thus falsely representing the population.

Standard deviation measures the dispersion of the sample data relative to its mean. In finance, it is a common measurement for risk as it outlines how spread out the numbers are from their average. The further, or the more dispersed the data, the higher the standard deviation and therefore the higher the risk. The standard deviation value for the VIX futures was $7,531.52, while the value for the straddle was far greater at $16,034.38, indicating the straddle strategy is over twice as volatile. The mean reversion characteristic of the VIX is a probable cause for the lower standard deviation for the VIX futures strategy. Since the price tends to revert quickly to its average, the volatility or uncertainty surrounding the price is reduced.

6.3 Value at Risk (VaR) & Expected Shortfall (ES)

To further investigate the market risk involved in both strategies, VaR and Expected Shortfall measurements were applied. Both measures are commonly used in industry and represent measures of portfolio risk; higher VaR and ES values are consistent with riskier portfolios. Both VaR and ES were measured at 95% and 99% confidence levels. The results are summarised below:

Value at Risk		
Confidence Level	95%	99%
VIX Futures	-$8,548.50	-$13,497.00
Straddle	-$13,413.95	-$24,716.57

Expected Shortfall		
Confidence Level	95%	99%
VIX Futures	-$13,237.14	-$21,720.00
Straddle	-$21,257.01	-$29,228.56

All four risk measures rank the straddle strategy as being riskier than the VIX futures strategy as the respective risk measures (VaR and ES) are higher in all cases. From this we can infer that the straddle strategy has greater downside risk or possesses a greater potential for large losses, which is in line with it being the riskier portfolio. The 95% VaR of the VIX futures strategy was $8,548. This indicates that in a given month, an investor can be 95% certain that they would lose no more than this amount. The equivalent VaR for the straddle strategy was $13,413, indicating that this is a riskier strategy. Furthermore, the 95% ES for the VIX futures strategy was $13,237, which indicates over a one-month time horizon, the expected loss in the 5% tail of the profit and loss was this amount. In other words, in the event losses exceed the VaR figure, the expected loss would be $13,237 for the VIX strategy. The equivalent ES value for the straddle strategy was $21,257, which again indicates that this is a riskier strategy than the VIX strategy.

6.4 Sharpe Ratio

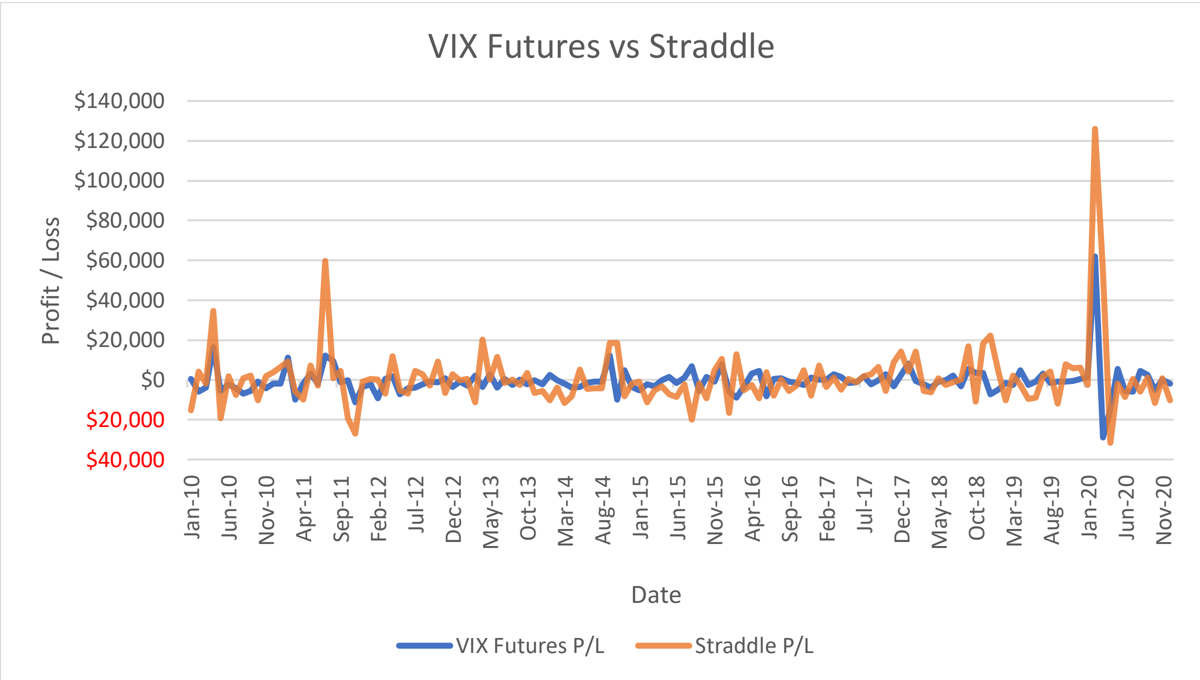
Both risk and return have been identified and compared thus far. The Sharpe ratio was implemented to further compare the strategies' performance by investigating the risk-adjusted return performance. The Sharpe ratio informs an investor of the best performing strategy by combining both risk and return, allowing for investors to make better-informed decisions. An investment with a higher Sharpe ratio value is considered superior.

The Sharpe ratio results are in line with what would be expected based on both mean returns of the strategies. Based on the Sharpe ratio, the straddle strategy is not a very profitable investment with an average annual Sharpe ratio of 0.05. This value implies the strategy gave a net return of almost zero in excess of the risk-free rate and once divided by the volatility of returns. However, based on the data under review, it is still considered a better investment compared to the VIX futures strategy. A negative Sharpe ratio of -0.53 was observed for the VIX futures strategy, which is expected due to the negative returns over the period. When compared with the risk-free rate, neither investment is deemed a considerable investment for an investor as the Sharpe ratio is either negative or almost zero.

6.5 Further Analysis & Recommendation

It is important to note that the data sample used in the study resulted in a degree of sampling bias within the research. After a closer inspection of the straddle strategy, it appears the one-month option contracts that were used give an unfair representation of its actual performance. Because we had to match the straddle strategy contract's expiry with the expiration of the VIX Futures (third Wednesday expiration), it has given rise to sampling bias. As mentioned, the mean returns of the straddle for our period were found to be $743.93 however there are significant outliers somewhat distorting the result, as seen in Figure 6.1 where the straddle had two large spikes over the sample period. When analysing the full sample's mean return i.e. all weekly contracts rather than just the third Wednesday, the mean return is found to be -$710.99. This is a more reasonable and expected value, as it is in line with previous literature surrounding negative straddle returns.

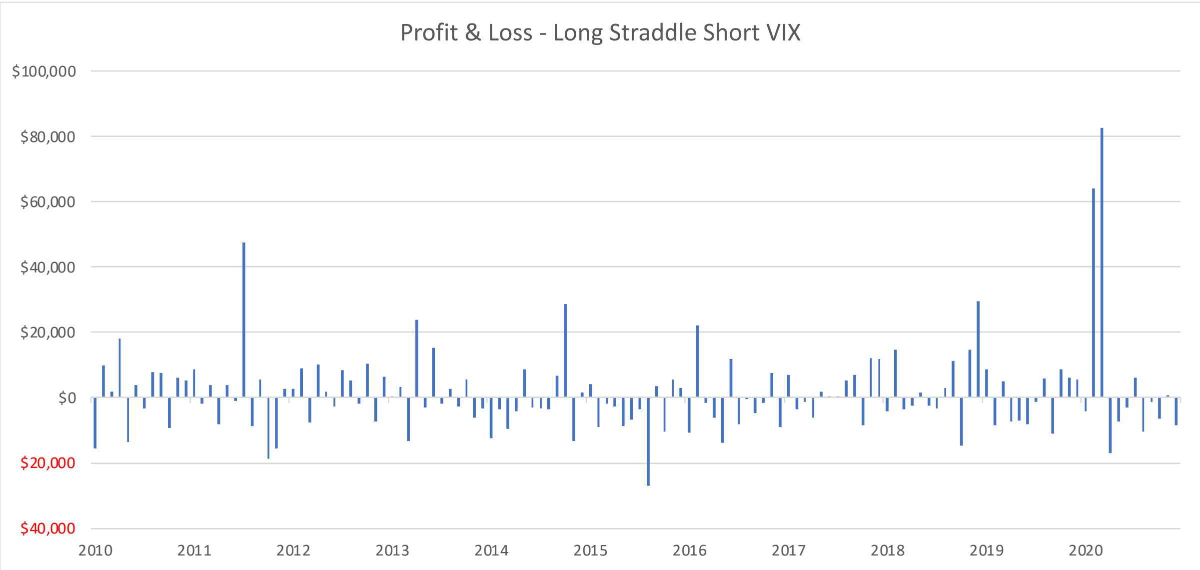
Figure 6.1: VIX Futures vs Straddle Profit & Loss



The negative return profile of the VIX futures strategy suggests that there is potential for it to be profitable if an investor was to short the strategy. Also worth noting is that VIX futures are a 'bet' on vega only, whereas the straddle strategy represents a bet on vega and gamma. Gamma explains how a 1-point move in the price of the underlying asset affects the option's delta. The VIX Futures strategy is ultimately a bet on the vega because it depends on the movement of the underlying asset which is the VIX. The VIX futures strategy only profits from upwards movements in the VIX.

Having identified the profitability of both strategies, a combination of the two were then investigated to test how the mean return could be enhanced. The profit or loss was investigated of a strategy consisting of a long straddle strategy and short position in the VIX future strategy.

Figure 6.2: Long Straddle Short VIX Profit & Loss



Portfolio Statistics	
Mean Return	$1,364
Std Deviation	$11,365
% Observations are Losses	52.20%

Portfolio Risk		
Confidence Level	95%	99%
VaR	-$13,710	-$18,266
Expected Shortfall	-$17,478.03	-$22,844.70

As can be seen from the statistics above, a combination of the strategies improves the return for an investor. The losses from the straddle strategy are reduced due to the profitability from being short the VIX futures strategy, thus greatly increasing the mean return. The risk level of the investment remains somewhat in between the two individual strategies. In comparison to the straddle strategy alone, the risk-return profile is massively increased; the mean return is larger while reducing the overall risk.

Chapter Seven: Conclusion

7.1 Conclusion

Since their inception, the open interest growth in VIX futures highlights the growing popularity of volatility investing in modern finance. Due to their negative correlation to the market, they are viewed as a natural diversifier for an equity portfolio. Previous literature into comparisons between option trading strategies and VIX trading strategies is scarce. This paper attempts to fill this gap by employing an empirical study to examine the performance of two derivative trading strategies: a VIX futures strategy and a straddle strategy. The purpose of the study was to investigate the risk and return characteristics of two strategies that are designed to mitigate volatility risk and determine which one was the optimal investment.

The findings indicate that the straddle strategy outperformed the VIX futures strategy in terms of mean return over the period. When investigated further, the difference between the mean returns of the strategies was not statistically significant and therefore we cannot conclusively determine that the straddle strategy is better than the VIX futures strategy. The data set ranges from 1st January 2010 to 31st December 2020 and the sample data used was affected by heavy outliers which may have caused the initial findings for the option strategy to misrepresent the population data. The Sharpe ratio was calculated for both strategies to measure risk-adjusted return and highlights how the option strategy barely outperforms the VIX futures strategy or the risk-free rate. From this research, from a standalone investment viewpoint, neither strategy are worthy investments for an investor aiming to earn a considerable return. Overall, this paper provides useful information on volatility-mitigating trading strategy performance and has applications to the investment industry as fund managers commonly overlay derivative strategies on cash portfolios.

7.2 Limitations & Future Research

The results of this dissertation paper make way for many potential future research questions and areas of study within volatility investing. This paper compared two derivative strategies that were designed to mitigate volatility risk. I investigated the performance of both as individual investments on a risk and return basis. A future research study could overlay both strategies upon a cash portfolio of stocks in order to test and compare the performance in alleviating volatility risk for an investor. Furthermore, an examination into the hedging benefits of shorting both strategies could be valuable to an investor.

An assumption made in the study was that the straddle strategy was not rebalanced. For straddle investors, weekly or monthly rebalancing of the portfolio is a common practice in order to maintain a delta-neutral position. This assumption somewhat distorts the performance results of the straddle strategy within this study. Future research could explore this further by applying a weekly or monthly rebalance of the hedge, thus identifying a more practical representation.

Furthermore, only a straddle strategy was investigated here versus the VIX. Comparisons between alternative trading strategies, such as a strangle, could be made to identify if they have a greater return over the same time period when compared with a VIX futures strategy. Alternatively, options with longer maturities could be examined. This paper only investigated one-month options and futures contracts. Future research could explore longer time horizons such as three-month maturities.

Lastly, as previously mentioned, the findings of this paper were subject to a level of sampling bias. The selected option contracts for the study were chosen in order to make the findings comparable with the VIX futures contracts. As a result, the sample gave rise to an unfair representation of the straddle strategy. To reduce the sampling bias, a larger sample size could be considered. However, there is limited scope for this as the data set examined in this paper starts in 2010 and the VIX futures contract only started trading in 2004.

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Appendix

Appendix 1: VIX Calculation (Source: CBOE, 2019)

Stock indexes, such as the S&P 500, are calculated using the prices of their component stocks. Each index employs rules that govern the selection of component securities and a formula to calculate index values. VIX is a volatility index comprised of options rather than stocks, with the price of each option reflecting the market's expectation of future volatility. Like conventional indexes, VIX employs rules for selecting component options and a formula to calculate index values. The generalized formula used in the VIX calculation from the CBOE website is:

$$\sigma^2 = \frac{2}{T}\sum_i \left[\frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i)\right] - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2, where$$

- σ = VIX/100
- T = Time to expiration
- F = Forward index level derived from index option prices
- K_0 = First strike below the forward index level, F
- K_i = Strike price of the i^{th} out-of-the-money option; a call if $K_i > K_0$, a put if $K_i < K_0$, and both a call and a put if $K_i = K_0$
- $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2} = The\ interval\ between\ strike\ prices\ on\ either\ side\ of\ K_i$
- $\mathrm{R = Risk - free\ interest\ rate\ to\ expiration}$
- $Q(K_i)$ = The midpoint of the bid-ask spread for each option with strike K_i

VIX measures 30-day expected volatility of the S&P 500 Index. The components of VIX are near- and next-term put and call options, usually in the first and second SPX contract months. "Near-term" options must have at least one week to expiration; a requirement intended to minimize pricing anomalies that might occur close to expiration. When the near-term options have less than a week to expiration, VIX "rolls" to the second and third SPX contract months. For example, on the second Friday in June, VIX would be calculated using SPX options expiring in June and July. On the following Monday, July would replace June as the "near-term" and August would replace July as the "next-term."

The VIX calculation measures time to expiration, T, in calendar days and divides each day into minutes in order to replicate the precision that is commonly used by professional option and volatility traders. For the purpose of calculating time to expiration, SPX options are deemed to "expire" at the open of trading on SPX settlement day (8:30 AM on the third Friday of the month). The time to expiration is given by the following expression:

$$T = \frac{M_{Current\ day} + M_{Settlement\ Day} + M_{Other\ days}}{Minutes\ in\ a\ year}, where$$

- $M_{\text{Current day}}$ = minutes remaining until midnight of the current day
- $M_{\text{Settlement day}}$ = minutes from midnight until 8:30 am on SPX settlement day = 510 minutes
- $M_{\text{Other days}}$ = Total minutes in the days between the current day and settlement day = 1,440 minutes times the number of days in between the current day and settlement day.
- Minutes in a year = 525,600 minutes

The risk-free interest rate, R, is the bond-equivalent yield of the U.S. T-bill maturing closest to the expiration dates of relevant SPX options. As such, the VIX calculation may use different risk-free interest rates for near- and next-term options.

STEP 1 Select the options to be used in the VIX calculation

The selected options are out-of-the-money SPX calls and out-of-the-money SPX puts centered around an at-the-money strike price, K0. Only SPX options quoted with non-zero bid prices are used in the VIX calculation. One important note: as volatility rises and falls, the strike price range of options with nonzero bids tends to expand and contract. As a result, the number of options used in the VIX calculation may vary from month-to-month, day-to-day and possibly, even minute-to-minute.

For each contract month:

- Determine the forward SPX level, F, by identifying the strike price at which the absolute difference between the call and put prices is smallest.

$$F = Strike\ Price + e^{RT} * (Call\ Price - Put\ Price)$$

- Determine $K_{0,t}$ – the strike price immediately below the forward index level F_t (F_1 for the near-term and F_2 for the next-term).
- Select out-of-the-money put options with strike prices < K0. Start with the put strike immediately lower than K0 and move to successively lower strike prices. Exclude any put option that has a bid price equal to zero (i.e., no bid).
- Next, select out-of-the-money call options with strike prices > K0. Start with the call strike immediately higher than K0 and move to successively higher strike prices, excluding call options that have a bid price of zero. As with the puts, once

two consecutive call options are found to have zero bid prices, no calls with higher strikes are considered.

- Finally, select both the put and call with strike price K0. Notice that two options are selected at K0, while a single option, either a put or a call, is used for every other strike price.

STEP 2 Calculate volatility for both near-term and next-term options

Applying the VIX formula (1) to the near-term and next-term options with time to expiration of T1 and T2, respectively, yields:

$$\sigma_1^2 = \frac{2}{T}\sum_i \left[\frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i)\right] - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

$$\sigma_2^2 = \frac{2}{T}\sum_i \left[\frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i)\right] - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

STEP 3 Calculate the 30-day weighted average of σ_1^2 and σ_2^2. Then take the square root of that value and multiply by 100 to get VIX.

$$VIX = 100 * \sqrt{\left(T_1\sigma_1^2\left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}}\right] + T_2\sigma_2^2\left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}}\right] + \frac{N_{365}}{N_{30}}\right)\ ,where}$$

- N_{T1} = number of minutes to settlement of the near-term options
- N_{T2} = number of minutes to settlement of the next-term options
- N_{30} = number of minutes in 30 days = 30 * 1,440 = 43,200
- N_{365} = number of minutes in a year = 525,600

Appendix 2: VBA Code for Black-Scholes Option Pricing Model Function

```
Option Explicit
Function optionPrice(S, K, r, q, tMat, vol, callPut)
'Implementation of the Black Scholes Option Pricing model
Dim d1, d2


d1 = (Log(S / K) + (r - q + 0.5 * vol * vol) * tMat) / (vol * Sqr(tMat))
d2 = d1 - vol * Sqr(tMat)

If callPut = "C" Then
   optionPrice = S * Exp(-q * tMat) * Application.NormSDist(d1) - K * Exp(-r * tMat) * Application.NormSDist(d2)
ElseIf callPut = "P" Then
   optionPrice = K * Exp(-r * tMat) * Application.NormSDist(-d2) - S * Exp(-q * tMat) * Application.NormSDist(-d1)
Else
End If

End Function
Function optionDelta(S, K, r, q, tMat, vol, callPut)
Dim d1, d2
d1 = (Log(S / K) + (r - q + 0.5 * vol * vol) * tMat) / (vol * Sqr(tMat))
d2 = d1 - vol * Sqr(tMat)

If callPut = "C" Then
   optionDelta = Exp(-q * tMat) * Application.NormSDist(d1)
ElseIf callPut = "P" Then
   optionDelta = -Exp(-q * tMat) * Application.NormSDist(-d1)
Else
End If

End Function
```

Appendix 3: VBA Code for Vega Function

```
Function optionVega(S, K, r, q, tMat, vol, callPut)
Dim d1 As Double

d1 = (Log(S / K) + (r - q + 0.5 * vol ^ 2) * tMat) / (vol * Sqr(tMat))

optionVega = S * Exp(-q * tMat) * Application.NormDist(d1, 0, 1, False) * Sqr(tMat)
optionVega = optionVega * 0.01


End Function
```