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THE IMPACT OF EQUITY AND OIL MARKET UNCERTAINTY ON HEDGE FUND RETURNS

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ABBREVIATIONS

BSM	Black-Scholes option pricing model
CTA	Commodity Trading Advisors
CBOE	The Chicago Board Options Exchange
ETP	Exchange Traded Products
FED	Federal Reserve System
LTCM	Long Term Capital Management fund
NASDAQ100	NASDAQ’s 100 Index
NYSE	New York Stock Exchange
OVX	CBOE Crude oil ETF implied volatility index
S&P500	Standard and Poor’s 500 Index
S&P100	Standard and Poor’s 100 Index
SEC	Securities and Exchange Commission
VaR	Value-at-Risk
VIX	CBOE Implied volatility index
VVIX	CBOE Volatility of implied volatility index

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ABSTRACT

This thesis examines the impact of equity and oil market uncertainty on hedge fund returns in different market conditions. VIX and OVX are used as proxies for equity and oil market uncertainty, respectively. Study covers period from October 2007 to January 2020 and to study the effects of crisis period separately, crisis period is specified to span from October 2007 to November 2011. Data contains monthly observations of VIX, OVX, five hedge fund indices based on implemented strategy and Total hedge fund index to reflect the hedge fund industry as a whole.

Results obtained from applied multivariate regressions show that both equity and oil market uncertainty have a statistically significant negative contemporaneous impact on hedge fund returns. The negative impact is substantially stronger during the crisis period, and compared to returns of S&P 500, the impact tend to be weaker, but otherwise very similar, suggesting that hedge funds does not provide significant cross-asset diversification benefits against increasing equity or oil market uncertainty, especially during crisis periods, when the need for diversifications is most needed. Furthermore, the negative impact does not consistently persist to the following month, suggesting the efficient information-processing and portfolio adjusting of hedge fund managers.

In contrast to evidence from equity markets, the impact of uncertainty is not asymmetric in case of hedge funds returns. Weak asymmetry is observed for some hedge fun strategies, but results obtained from Wald test reject statistically significant effect. Moreover, when impact of VIX and OVX is examined simultaneously, results suggest possible signaling effect, where uncertainty flows from U.S. equity markets to global oil markets.

KEY WORDS: Hedge funds, uncertainty, VIX, OVX, volatility index

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TIIVISTELMÄ

Tämän tutkielman tarkoituksena on tarkastella osake- ja öljymarkkinoilla vallitsevan epävarmuuden vaikutusta hedge-rahastojen tuottoihin eri markkinaolosuhteissa, hyödyntäen VIX- sekä OVX-indeksejä epävarmuuden mittaamiseen. Tutkielmassa käytetty aineisto kattaa yhteensä 148 kuukausittaista havaintoa, lokakuun 2007 ja tammikuun 2020 välillä. Jotta hedge-rahastojen tuottoja voidaan tarkastella eri markkinaolosuhteissa, kriisiajanjaksoksi on määritelty lokakuun 2007 ja marraskuun 2011 välinen ajanjakso. Aineisto sisältää kuukausittaisia havaintoja VIX- ja OVX-indekseistä, viidestä hedge-rahastoindeksistä, perustuen hyödynnettyyn strategiaan, sekä yhdestä koko hedge-rahastotoimialan kehitystä kuvaavasta Total hedge fund -indeksistä.

Tutkielman tulosten perusteella sekä osake- että öljymarkkinoiden epävarmuudella on tilastollisesti merkitsevä negatiivinen ja samanaikainen vaikutus hedge-rahastojen tuottoihin. Negatiivinen vaikutus on merkittävästi voimakkaampi kriisiajanjaksolla, ja verrattuna S&P 500 -indeksiin, vaikutus on heikompi, mutta muilta osin hyvin samankaltainen. Tulokset viittaavat siihen, että epävarmuuden lisääntyessä osake- ja öljymarkkinoilla, hedge-rahastot eivät tarjoa merkittävää hajautushyötyä eri omaisuusluokkien välillä, etenkään kriisiajanjaksoilla. Lisäksi, negatiivinen vaikutus ei kestä johdonmukaisesti seuraavaan kuukauteen, mikä viittaa siihen, että hedge-rahastoiden hoitajat kykenevät tehokkaaseen tiedonkäsittelyyn sekä portfolion sopeuttamiseen vallitsevan markkinatilanteen mukaan.

Toisin kuin osakemarkkinoilta saatujen tutkimustulosten perusteella, epävarmuuden vaikutus hedge-rahastojen tuottoihin ei ole epäsymmetrinen. Joidenkin hedge-rahastostrategioiden tuottojen osalta vaikutuksen havaitaan olevan epäsymmetrinen, mutta Wald-testin perusteella epäsymmetria ei ole tilastollisesti merkitsevä. Lisäksi, kun VIX- sekä OVX-indeksien vaikutusta tutkitaan samanaikaisesti, tulokset viittaavat mahdolliseen signaalivaikutukseen, jossa epävarmuus virtaa Yhdysvaltojen osakemarkkinoilta globaaleille öljymarkkinoille.

AVAINSANAT: Hedge-rahastot, epävarmuus, VIX, OVX, volatiliteetti-indeksi

1. INTRODUCTION

Extreme events in the stock markets are the most disconcerting periods for majority of the market participants, leading to increased uncertainty across the financial world. Last years have been bumpy in the financial markets; events such as conflict in Ukraine, United Kingdom's process to leave the European Union, U.S. presidential elections, trade war between U.S. and China and most recently COVID-19 pandemic have systematically increased the instability through the markets and exposed majority of different investment classes to rising uncertainty. During times of high uncertainty, market participants actively seek tools for portfolio protection, affecting explicitly on investment decisions and increases the demand of hedging instruments. During the last couple of decades, financial markets have exhibited severe crises, which have substantially increased the interest towards instruments that have ability to efficiently hedge investments and therefore reduce the downside risk. One way to protect the portfolio from downside movements is through volatility. Traditionally volatility has been one of the most used risk indicators, but nowadays there are also other applications for volatility in the financial markets, which has led to that volatility itself has started to be considered as an asset class of its own.

Volatility-based trading has recently become more popular among both institutional and non-institutional investors, and opportunities offered by the volatility has led to a creation of various exchange traded volatility products. The primary reference for stock market uncertainty and expected future market volatility is the VIX Index, which is widely known and followed through the financial world. VIX is often referred as the investors' fear indicator, representing the market participants' expectations of future volatility of the stock market and hence capturing the overall sentiment of the market. Success of VIX has led to creation of various other implied volatility based indices., such as OVX, which tracks the implied volatility of crude oil prices.

According to Alexander and Korovilas (2011), after global financial crisis, integration has increased in the financial markets and asset classes have become more correlated with each other. This expose individual markets to global shocks, leaving investors to seek alternative ways for portfolio diversification. Therefore, like volatility, also other alternative investments, such as hedge funds, have gained popularity in the eyes of investors. Hedge funds are known for using various exotic and complex trading instruments, including volatility-based products. Over the last decades, both academics and investors have taken an increasingly active interest in hedge funds and other alternative investment classes. As a result of massive growth of the hedge fund industry, it is a major player in today's financial markets, having over $3 trillion assets under management. In consequence of dramatic stock market declines of the 2000s and increasing assets of large pension funds, both individual and institutional investors have started to seek alternative investment possibilities to achieve higher returns or for portfolio protection, which is reflected into the growth of the whole industry.

Hedge fund risks and returns differs from the more traditional investment classes, such as mutual funds, and because of unique risk and return characteristics, hedge funds have become an attractive option for wealthy individual investors and institutions. They aim for absolute returns, regardless of the overall market environment, by using flexibly leverage, derivatives and short positions without any restrictions. Due to lack of any formal supervision by public authorities, hedge funds are able to exploit numerous complex and dynamic trading strategies, where market swings are often offset through long and short positions in various securities. These simultaneous long and short positions lead to low correlation with more traditional assets classes, which makes hedge funds an attractive option for portfolio diversification purposes. (Chan, Getmansky, Haas & Lo 2005; Fung & Hsieh 2002). Hedge funds do not have any legal requirements to report about their performance, so providing information to external parties is completely voluntary. Therefore collected data may have several biases and irregularities, that have to take into consideration when studying hedge funds. (Jagannathan, Malakhov & Novikov 2010.)

According to Fung and Hsieh (1997) dynamic trading strategies employed by hedge funds are showed to have option-like return characteristics while maintaining low or zero correlation with various other asset benchmarks. This observation indicates that, like option prices, also hedge fund returns are related to changes in volatility, which exposes hedge funds to volatility risk. The link between hedge fund returns and uncertainty is quite unexplored, and this thesis aims to supplement the existing research around the topic.

1.1. Purpose of the study and hypotheses

Purpose of this study is to examine the cross-market impact of stock and oil market uncertainty on hedge fund returns across different strategies during different market periods. VIX and OVX, benchmarks of implied volatility measuring the market's expectation future volatility, are used as a proxy for stock and oil market uncertainty, respectively. Especially VIX is often referred as market's fear indicator, capturing the overall sentiment of the market participants. Overall, implied volatility is interpreted as market participants' expectations of future volatility and therefore it provides observable measure for market uncertainty.

The contemporaneous negative relationship of VIX and equity markets is well documented by many academics. Fleming, Ostdiek and Whaley (1995), Giot (2005), Whaley (2009), and many others find strong negative relationship between implied volatility indices and underlying stock indices, such as S&P100, S&P500 and NASDAQ100. As for oil market uncertainty, Xiao, Zhou, Wen and Wen (2018), suggest that oil price uncertainty, through OVX, has an similar negative impact on equity market returns than VIX. Krause (2019) shows that hedge funds that have stronger exposure to uncertainty measured by VVIX Index, which tracks the volatility of volatility, outperform the funds with low uncertainty sensitivity. Therefore, motivated by previous studies about the impact of the equity and oil markets uncertainty proxied by VIX, OVX, VVIX on equity market and hedge fund returns, the first hypothesis is set in the following form:

H_1: Equity and oil market uncertainty has a negative effect on hedge fund returns.

Measured by volatility indices, uncertainty has historically been at relatively high levels during crisis periods. According to Sarwar (2014), the negative relation between changes in VIX and European equity market returns were twice as strong during European debt crisis in beginning of 2010s than before the crisis period. Alexander et al. (2011) arrive at similar results, since they find that the negative correlation coefficient between the daily returns of S&P 500 index and the VIX strengthened during the financial crisis. If the first hypothesis is supported, indicating that stock and oil market uncertainty have negative contemporaneous impact on hedge fund returns it is meaningful to investigate more deeply whether the relation varies during different market conditions. The second hypothesis is thus stated as following:

H_2: The impact of equity and oil market uncertainty on hedge fund returns is significantly stronger during crisis periods.

Dutta (2018) shows that there is a long-term association between VIX and OVX, indicating linkage between uncertainty of U.S. stock market and global oil market, and according to Liu, Ji and Fan (2013), VIX acts as driving force for crude oil volatility index, since the changes of OVX are affected by the changes of VIX, suggesting that oil market uncertainty is sensitive to shocks from U.S. stock market. Based on previous studies, it is expected that VIX and OVX are able to explain together substantially proportion of variation of hedge fund returns Therefore, the third hypothesis is set in the following form:

H_3: Equity and oil market uncertainty have a simultaneous impact on hedge fund returns.

1.2. Contribution and motivation

This thesis aims to contribute to existing literature in several ways. The equity market uncertainty, measured by implied volatility of equity-index options, is widely studied by academics, and previous studies have for example found strong evidence about the negative contemporaneous relation of implied volatility indices and equity markets. However, the combination of equity market uncertainty and alternative investment classes, such as hedge funds, have not got similar attention.

In addition, one major contribution to existing literature is to examine whether oil market uncertainty affect hedge fund returns. Dutta, Nikkinen and Rothovius (2017) show that oil price uncertainty, through OVX, has an impact on the realized equity market volatility, especially in oil-depending countries. Oil has a major impact in economies across the world, and according to Jo (2014) oil price uncertainty has a substantially effect on economic activity globally. Therefore, global oil markets are important part of the overall financial markets, and therefore it is relevant to study the impact of oil market uncertainty on the hedge fund returns. Previous literature about oil market uncertainty and hedge fund returns are extremely scarce, and therefore this thesis aims to offer new information related to the topic and fill the gap in this particular field.

Generally, previous results suggest the diversification benefits of including hedge funds into investment portfolio. This thesis aims to provide new information about the opportunities offered by both equity market and oil market uncertainty in the hedge fund industry. Data used in thesis is divided into two periods, crisis period and after crisis period. Crisis period spans from October 2007 to November 2011, covering significant economic events during global financial crisis in and European debt crisis, causing several radical spikes to both VIX and OVX. During this period, implied volatility levels from different markets rose sharply well above from their historical average levels. Therefore one objective is to examine the effects of these extreme market conditions, and analyze whether the impact of uncertainty of different markets varies between different periods.

As stated, two types of economic uncertainty, stock market and oil market, are included in order to examine more deeply the effects of uncertainty on hedge funds returns. Also, this thesis utilizes several hedge fund indices, in order to examine if the effects of uncertainty varies across different strategies implemented by hedge funds. The results of this study have potential to provide previously unexplored information about the relationship between uncertainty and hedge funds during different market conditions. This is crucial especially in times of high market uncertainty, when asset allocation decisions are emphasized. Deeper understanding about the subject have important implications for portfolio optimization in hedge fund industry, cross-market diversification and hedging purposes, and it also provides insights about utilizing volatility as an investment tool.

1.3. Structure of the thesis

The structure of the thesis is following. Second chapter covers the literature review, introducing previous studies around the subject. Third and fourth chapters cover the theoretical framework of the thesis, introducing the definitions, main properties and characteristics of hedge funds, uncertainty and volatility indices. Fifth chapter introduces the data and methodologies used in this thesis. Empirical results are presented and analyzed in the chapter 6. Finally, chapter 7 concludes the thesis, providing also ideas for future research.

2. LITERATURE REVIEW

The interest towards hedge funds, stock market uncertainty and implied volatility has resulted increasing amount of researches over the last decades. Previous studies relevant to this thesis' subject are briefly introduced and discussed in this chapter.

2.1. Hedge fund performance characteristics

Many previous studies have documented that due to their complexity and dynamic features hedge fund returns and risk levels differ greatly from other, more traditional asset classes. Fung et al. (1997) examine the characteristics of hedge fund strategies and according to their findings, trading strategies implemented by hedge funds are often highly dynamic. Having minimal exposure to systematic market risk, these dynamic strategies are showed to have nonlinear return profiles, having low or negative correlation to other asset class returns. Therefore traditional linear-factor models, which are more appropriate for buy-and-hold strategies, are not suitable for capturing hedge fund returns.

Fung et al. (1997) also show that mixing dynamic trading strategies to a traditional buy-and-hold portfolio provides diversification benefits and can enhance portfolio's returns without adding additional risk. Performance of traditional portfolio with only bond and equity investments can be improved by allocating 50 percent of funds to dynamic strategies with equal weights, leading to higher annualized mean returns with lower annualized standard deviations. Dynamic strategies have also option-like return profile, which can provide protection during downside markets. During observation period, maximum monthly loss of portfolio containing only bond and equity investments was 5.93 percent. Again, allocating half of the funds to dynamic strategies with equal weights, the maximum monthly loss is reduced to 2.87 percent.

Brooks and Kat (2002) study the correlations between returns of hedge fund indices and those of the stock and bond market indices. Based on their results, majority of different hedge fund indices have very low or negative correlation with the bond markets and somewhat higher correlation with stock market, varying from 0.08 to 0.70. Researchers suggest that surprisingly high correlations with stock markets is explained by the sample period, since data is collected between 1995 and 2001, when many hedge fund invested heavily in technology stocks. Although individual hedge fund returns are showed to be uncorrelated with current market conditions, it seems that at least hedge fund indices carry relatively high systematic equity market risk.

Fung and Hsieh (1999) examine performance differences between different hedge fund strategies, S&P500 and mutual funds. They find that annualized returns of equally weighted hedge fund portfolios are only 1.1% lower than returns of S&P500, but they are achieved with lower volatility. When compared to mutual funds, which are strongly correlated with only U.S. stock and bond markets, hedge fund portfolios are more widely exposed to other asset markets as well, including non-U.S. stocks, emerging market stocks, commodities and foreign currencies. In addition, part of this exposure is negative, indicating short positions.

Portfolios managed by hedge funds contains often complex and nonlinear assets, and therefore their risk characteristics differ dramatically from more traditional investments. Gupta and Liang (2005) study the risks and capital sufficiency of hedge fund industry using Value-at-Risk (VaR) approach by examining nearly 1500 hedge funds. Since hedge fund returns are showed to be strongly non-normal, they find that VaR approach is more suitable to estimate hedge fund risks, because traditional measures of risk including normality-based standard deviation and leverage ratios, are not able to properly capture the risks of dynamic hedge fund returns. Results also show that based on VaR estimations, vast majority (97.3 percent) of live funds are adequately capitalized but in case of dead funds, the proportion of undercapitalized funds is significantly higher (nearly 11 percent), which indicates that undercapitalization is one of the reasons for closing down the fund.

Low or even negative correlation of alternative investments and other more traditional asset classes have shown to protect investors from equity tail risk especially during equity crisis periods. In their studies, Fung and Hsieh (2001) and Lundström and Peltomäki (2016), investigate the performance of commodity trading advisors (CTAs) or the managed futures hedge funds, during market crisis periods. CTAs focuses mainly on trend following strategies, aiming to capture the recurring price patterns and therefore profit from prevailing price trends. Empirical results show that trend following strategies are long-volatility investments, achieving positive returns during market turmoil periods and therefore they can provide significant diversification benefits during market crisis periods. If VIX is used as a proxy for market risk, during high levels of VIX, which are characterized by unanticipated risk shocks, especially short-term CTAs show superior performance, gaining profits from crisis alpha opportunities. Correspondingly during low levels of VIX, they are able to avoid the negative exposure to risk shocks. Therefore exposure of CTA returns to risk shocks increases during high-volatility periods, providing hedging possibilities for equity tail risk.

2.2. Uncertainty and volatility indices

The concept of uncertainty have been popular topic among academics studying the financial markets. Baltussen, van Bekkum and van der Grient (2018) examine effects of uncertainty on stock returns by measuring volatility of expected volatility (vol-of-vol). They find negative relation between uncertainty and stock returns; higher volatility of volatility predicts lower future stock returns compared to similar stocks with lower volatility of volatility characteristics. Possible explanations for this are that investors prefers high uncertainty and are willing to pay premium to bet for extremely uncertain events or that investors have simply heterogenous expectations and uncertainty preferences.

As stated in the previous sections, there is clear and strong negative relation between the implied volatility and equity markets. The negative correlation between S&P 500 Index and VIX have been particularly strong during periods when the S&P 500 exhibits substantial downside movements, like at the end of 2008 during financial crisis. The dynamic and time varying relation indicates that during times of market turmoil, long positions in VIX may provide efficient diversification benefits, at least to equity portfolios. (Szado, 2009.)

Amount of researches focusing on oil price uncertainty and OVX has also grown during the last years. As discussed earlier, Dutta et al. (2017) show that oil price uncertainty, through OVX, has an impact on the realized equity market volatility, especially in oil-depending countries. Xiao et al. (2018) studies the impact of OVX on Chinese equity markets and findings suggests that the negative and asymmetric relation exists also between oil market volatility and equity markets, and especially shocks rising the oil price have a significant impact on equity market returns. Jo (2014) shows that oil price uncertainty has a substantially effect on economic activity globally, and high uncertainty in the oil markets can explain alone the decrease in industrial production growth.

DeLisle, Doran & Krieger (2010), test the hedging properties of VIX during declining markets hypothetically by adding pure VIX exposure to the portfolio. They found that slight proportion of VIX added decreases risk levels of the portfolio and protects it from downside market movements. But since VIX is only hypothetically investable, the exposure on volatility must be taken either through VIX futures, options or other VIX-based products. This has an effect on results, because VIX-related derivatives do not capture the same characteristics as the index itself. Despite the differing properties, VIX-based exchange traded products (ETPs) are able to neutralize the portfolio from downside market movements while remaining the potential upside in market expansion.

However, there are contrary results regarding the suitability of the volatility products for portfolio hedging. Alexander et al. (2011) examines whether it is optimal to add long VIX futures into a long-only equity portfolio in order to gain diversification benefits. According to results, only onset of market crises are optimal periods for portfolio diversification, due to negative carry and roll yield of volatility, which effectively reduce the returns. Also due to steep rises and rapid mean reversion properties, it is usually too late to hedge portfolio by adding volatility exposure after the crisis have broken out. Szado (2009) ends up to similar conclusion that long positions on volatility provides an efficient protection when the markets are in turmoil, but during stable periods it may lead to lower returns, which makes it an inefficient diversification tool for the long-term.

However, implied volatility is not directly investable, making it more complicated to use it for hedging purposes or achieve the diversification benefits. Therefore desired positions and levels of exposure must be taken implicitly through volatility-based derivatives, such as options and futures. Several papers study the hedging possibilities of volatility-based products. Warren (2012), examines the effects of volatility exposure by constructing portfolio similar to the typical U.S. pension fund. He evaluates the volatility exposure by simulating return series of a portfolio that does not contain volatility products, and compares it to a portfolio, where volatility products, such as VIX-futures and forward volatility swaps, are added. Results indicates that short positions in volatility offer opportunities for return enhancement through volatility risk premium, while long positions reduces the total risk of the portfolio at a minimal cost.

Fahling, Steurer, Schädler and Volz (2018) analyze the long-term performance of volatility options as risk management tool by examining VIX options' ability to hedge a long position of S&P 500 Index with protective put strategy. The long position is fully protected by the corresponding at-the-money VIX put options, and returns of combined portfolio is compared to returns of S&P 500 Index from 1990 to 2018. Findings suggest that VIX options are not efficient long-term hedging tool, since roughly 80 percent of the returns of S&P 500 Index are wiped out by the negative cash balance caused by options. During the sample period, the annualized returns of combined portfolio are 4.6 percent points lower compared to unhedged stock portfolio. Interestingly, lower annualized returns are connected to higher levels of annual volatility, meaning that unhedged stock portfolio significantly outperforms the combined portfolio over 20 year period. On the other hand, during shorter periods, especially during times of high volatility, combined portfolio manages to outperform the pure buy-and-hold stock portfolio. This indicates that volatility-based options might offer shorter term hedging benefits, especially during times of market stress. To conclude, previous studies show that in the equity markets, VIX might be a useful hedging and diversification tool, at least in short-term. But since VIX itself is not investable, hedging must be done through VIX-related products, which are shown to be less efficient option for long-term portfolio insurance.

Dondoni, Montagna and Maggi (2018) examine the profitability to short implied volatility, by using short positions on VIX futures. Authors construct different trading strategies based on short positions and according to their results, since the creation of first VIX futures, shorting the VIX has been profitable strategy in eight out of 11 years, generating total return of 198 percent between 2004 and 2015. Only in 2008, during financial crisis, and in 2014-2015, when VIX rose due to short-term falls of the equity markets, the strategy generated negative profits. Profitability is explained by risk premium created by the differences between implied and realized volatility; implied volatility, and thus the VIX, is typically higher than realized volatility, and therefore short positions on the VIX futures enables to capture the risk premium of implied volatility. Still, it is noteworthy that the practical implementation of the strategy is complex, since when implied volatility spikes steeply, like during financial crisis, strategy is highly volatile and possibilities for huge losses are very likely.

According to Dondoni et al. (2018), during neutral market periods, the term structure curve of VIX futures is contango; implied volatility increases with the time to maturity. But during periods of markets turbulence, when VIX is high, the term structure may be in backwardation, meaning that implied volatility decreases as maturity of futures increases, since investors are expecting that in the future volatility will decrease. However, backwardation is not sustainable state, and term structure will revert back to contango within weeks, or even days. This is because high uncertainty over long-term leads to higher premium demands than high short-term uncertainty. VIX Index itself has a strong and positive relationship with its term structure, but the correlation decreases as maturity increases. For example, VIX and futures with one month to maturity have correlation of 0.98, but futures that will expire in three months has notably lower correlation coefficient with VIX; 0.87.

During the last couple of years, there has been serious concerns about the manipulation of the VIX. Based on their research, Griffin and Shams (2017) state that it is feasible to manipulate the settlement prices of the VIX futures by trading the far out-of-the-money options that are used to calculate the VIX. They show that during VIX settlement periods, these less liquid options have notable spikes in trading volume, which are not similar to other index options, and they do not occur outside the settlement periods. Such unusual pricing and volume patterns expose the VIX to market manipulations. However, Saha, Malkiel and Rinaudo (2019) conduct similar test using both daily closing values of VIX and settlement prices of VIX futures, and their findings do not support the manipulation hypothesis. They argue that VIX values on futures expiration days is explained by market fundamentals, not by manipulation. In 2003, Chicago Board Options Exchange (CBOE) began to recalculate the VIX by using option prices of S&P 500 Index instead of S&P 100 Index. They also included out-of-the-money options, which contain valuable information about the demand for portfolio insurance. These changes were made to make VIX less sensitive to any single option price and thus less susceptible to manipulation. (Whaley 2009.)

2.3. Hedge funds and implied volatility

In his research, Krause (2019) utilize the concept of volatility of volatility, and investigates how uncertainty affects hedge fund returns. By using VVIX Index as a proxy for uncertainty, author discovers that hedge funds that have stronger exposure to uncertainty outperform the funds with low uncertainty sensitivity. On average, funds in the highest quintile of VVIX Index exposure outperform the lowest quintile almost by 6 percent annually, indicating that higher exposure to uncertainty is compensated with higher returns.

Bali, Brown and Caglayan (2014) end up to similar findings. They study how exposure to economic uncertainty factors affect hedge fund returns and whether these factors' are able to capture differences in hedge fund returns. Macroeconomic risk measures, for example default and term spreads, inflation rate and short-term interest rate changes, are used as a proxy for economic uncertainty, to generate estimates for uncertainty betas. Performance of uncertainty betas are examined to determine the ability to predict cross-sectional variation in hedge fund returns. Cross-sectional regressions show the positive relationship between uncertainty beta and risk-adjusted returns; funds with higher uncertainty beta achieve higher average annualized returns compared to funds with lower uncertainty beta. Findings also indicates that compared to mutual funds, hedge funds are able to adjust their positions and exposure to macroeconomic risk factors depending on current macroeconomic conditions; the predicting power of uncertainty betas is partly explained by this ability to time macroeconomic changes. In general, empirical results agree that hedge fund are able to capture uncertainty premiums and uncertainty betas have predicting power over future hedge fund returns.

Peltomäki (2007) examines whether the volatility risk have an impact on returns of various hedge fund strategies during different market states. By comparing the hedge fund returns to contemporary changes in VIX, findings show that volatility risk affects hedge fund returns in a non-linear way, since mean returns differs significantly depending on the current levels of VIX and market state.

3. HEGDE FUNDS

Chapter introduces the theoretical framework of hedge funds. Hegde funds differ substantially from more traditional investment classes, due to their unique characteristics, performance and highly dynamic trading strategies.

3.1. Characteristics of hedge funds

Hedge funds are alternative investment vehicles aiming for absolute returns, regardless the general market development and although they represent they own asset class, there is no exact and unambiguous definition for hedge funds. Compared to more traditional mutual funds, operating outside of the supervision by the authorities allows hedge funds to utilize wide variety of complex and flexible investment strategies. Other typical characteristics of hedge funds are abundant use of leverage, short positions and derivative contracts, and the limited number of shareholders. (Ackermann, McEnally & Ravenscraft 1999).

Even though the funds managed by hedge funds represent only a small fraction of the total wealth moving through financial world, they have a significant impact on the overall functioning and efficiency of present-day financial markets. According to Malkiel and Saha (2005), trades made by the hedge funds on the New York Stock Exchange (NYSE) represents more than half of the total number of the trades made on daily basis. This is the result of explosive growth of assets under management during the 2000s; Figure 1 shows that in 1997 hedge funds managed assets worth around $100 billion, but during this decade the total amount of assets under management has increased to almost $3.2 trillion. As a result of the global financial crisis that began in 2008, the volume of assets under management temporarily declined, but with exception of years 2007-2008, funds managed by hedge funds has grown steadily for the last 20 years.

Interest towards hedge funds has grown tremendously over the last decades, mainly because of their unique characteristics and ability to generate positive alphas despite the prevailing market condition. Numerous studies show that hedge funds do not follow strongly market trends and they have relatively low correlation with other asset classes, thus offering an useful tool for portfolio optimization. Due to the high minimum investments, which typically ranges from $250 000 to $1 million, main investors of the funds are typically institutions, other funds and wealthy individual investors. (Lo 2010; Yin 2016.)

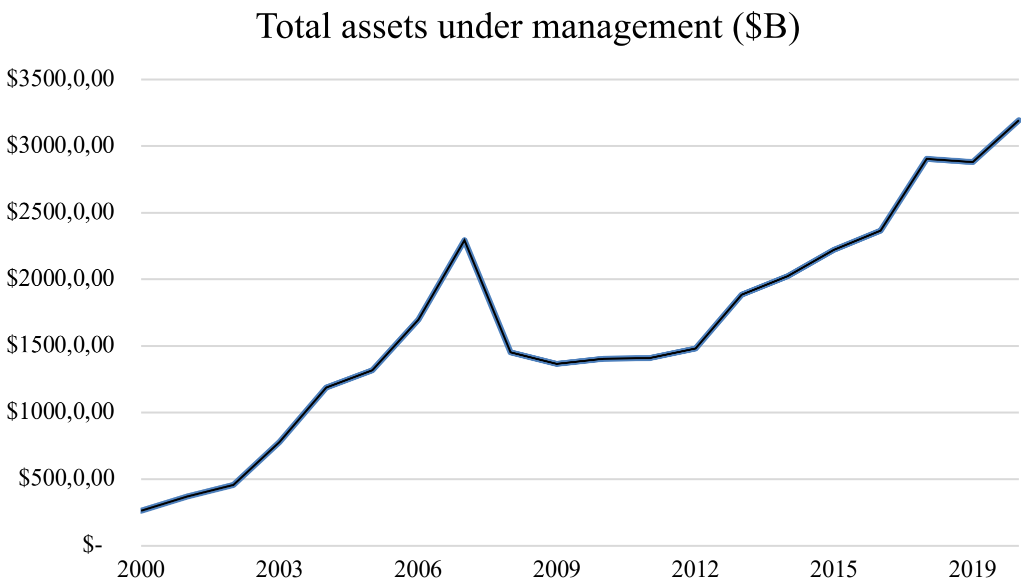

Figure 1. Total assets under management of hedge fund industry from 2000 to 2019, in $ billions. (BarclayHedge, 2020).

3.2. History of hedge funds

Hedge funds are not a new phenomenon in the financial markets, as they have existed for 70 years. In 1949, American Alfred W. Jones founded an investment fund that is considered to be the first fund to meet the definition of hedge fund. Many of the approaches he represented at the time have remained as the main features of modern hedge funds. Structure of the Jones’ fund was exceptional, since it did not need to comply with the requirements of the United States Securities and Exchange Commission (SEC), which allowed Jones to use leverage, short selling and concentration on its investments.

He introduced a new fee structure, in which the fee he received from managing the fund was based on fund's returns. Performance-based structure was uncommon, but nowadays widely used in the hedge fund industry. (Connor & Woo 2004.)

Core of the Jones fund's investment strategy was extensive use of leverage and short positions, which both had long been used in financial markets, but the fund combined them in unprecedented way. Jones was aiming to hedge the fund's returns against systematic market risk while maximizing the returns of individual stock picks. In order to protect the fund from general market movements and reduce its exposure to systematic risk, Jones utilized a market-neutral strategy by buying undervalued stocks and short-selling overvalued stocks. This long-short strategy reduced the overall exposure to market movements. In addition, he used the capital received from short-selling as an leverage to new investments (Brown & Goetzmann 2003; Connor et al. 2004.)

The Jones fund's annualized returns were significantly higher compared to more traditional mutual funds, which caught investors' attention. The emergence of new hedge funds was strong, until the oil crisis of the early 1970s and the consequential negative stock market development, which led to disappearance of numerous hedge funds. During the next ten years hedge fund industry experienced a fierce decline in popularity, since in 1984 there were only 68 active hedge funds, which was less than half of the late 1960 figures. The popularity of hedge funds began to grow again in the 1980s and 1990s, for instance Julian Robertson's Tiger Fund achieved 43 percent annual return during its first active year, while the S&P 500 index's return for the same period was 19 percent. Tiger Fund's strategy was based on global macroeconomic and political phenomena, utilizing leveraged positions in securities and currencies. The success of the Robertson's fund made the hedge fund industry an attractive option for investors again, and they increased their reputation as high-yield investment during the pound crisis in 1992. Macro-based Quantum Fund, managed by George Soros, made significant gains during the crisis by speculating on the devaluation of the pound. (Connor et al. 2004; Stefanini 2010.)

3.3. Long Term Capital Management

In 1998, the reputation of hedge funds suffered severely. Renowned Long Term Capital Management fund (LTCM), which had achieved exceptional returns for previous years and among others was managed by two Nobel laureates in Economics, experienced losses more than $ 4 billion. This exposed banks, financial institutions and brokers to danger of insolvency, which in the worst case would have caused a global financial crisis. The reason was wide use of leverage. LTCM mainly utilized market-neutral interest rate, currency and index future arbitrages to take advantage from the changes in interest rates and exchange rates. Because of the narrow spreads between rates, LTCM had to use extremely high leverage, up to 25 times its own equity. (Stefanini 2010.)

In the summer of 1998, the Russian debt crisis caused global anomalies in the interest rate markets, leading to an unexpected increase of interest rate spreads around the financial world. As a result of debt crisis and LTCM's extremely high leverage and derivative positions, the fund lost 90 percent of its value. However, the rapid reaction of the Federal Reserve System (FED) and the bankruptcy of the LTCM saved the financial markets from the serious global crisis. (Connor et al. 2004; Stefanini 2010.) According to Fung and Hsieh (2000), LTCM's returns were relatively low compared to other hedge fund and asset classes, and the volatility of the returns was equivalent to the S&P 500 index. Event demonstrated that while strategies exploited by hedge funds may minimize the exposure to market risk, there are lot of other risk factors to which funds are still exposed. The risk included in the hedge funds' operating activities can be extremely high, and if realized, cause global financial market disruption.

3.4. Hedge funds compared to mutual funds

Hedge funds have many unique characteristics compared to more traditional mutual funds. According to Fung et al. (1997), most of the mutual funds and fund managers have specific return targets and assets are typically invested in predetermined asset classes, such as equities and bonds. Mutual funds aim to achieve and exceed the average returns of these asset classes, within the regulated restrictions, and as a result returns typically correlated strongly with average returns of those asset classes. As for hedge funds, they do not set predetermined return targets, but aim for absolute returns regardless of the prevailing market situation, which leads to relative low correlation with other asset classes, including mutual funds.

Unlike mutual funds, hedge funds are not subject to supervision by the banking and securities regulators**.** US Investment Company Act of 1940 defines the exact maximum number of investors that fund may have in order to exclude from regulatory control. Most recent act limits the total number of investors to maximum of 499, requiring each investor to have at least wealth of $ 5 million and deep understanding of financial markets. (Brown, Goetzmann & Ibbotson 1997). Under the Securities Exchange Act of 1934, hedge funds with more than 499 investors are required to report about their activities on quarterly basis and the shares of the fund can be traded publicly. In general, hedge funds are not seeking public investors and they are reluctant to report on their activities, hence the number of investors in an individual hedge fund is typically less than 500. (Aragon, Liang & Park 2014.)

Compared to hedge funds, mutual funds are significantly more open about their activities, for instance, they conduct a daily valuation and they must report regularly to external stakeholders. In the case of hedge funds, the lack of reporting requirements leads them to conduct valuation less frequently, for example on a monthly basis. In addition, citing trade secrets, most hedge funds do not disclose their investment strategies and projects. (Aragon et al. 2014.) The privacy also has restrictive effects since hedge funds cannot publicly raise funds from investors, nor can they widely market themselves to the public audience. Marketing and fundraising must be aimed at a limited audience, which usually includes institutions and wealthy individual investors. (Anson 2003.)

Because of their absolute target of returns, many hedge funds focus their investment strategies on a specific industry or market. Compared to mutual funds, portfolios of hedge funds are notable more concentrated and due to lack of regulation and regulatory oversight, they are able to utilize more sophisticated strategies in their investment operations. Hedge funds employ widely derivative contracts and short selling, but they are restricted or completely prohibited from mutual funds. Mutual funds have either highly limited or fully banned access to debt, whereas hedge funds have typically extremely aggressive leverage, up to ten times of fund's net asset value. In 1990s, the leverage used was even higher, but since the collapse of Long Term Capital Management fund, the debt ratios have fallen significantly (Agarwal & Naik 2000; Connor et al. 2004).

Hedge funds have also different type of fee structure and the net fees are considerably higher compared to mutual funds. Mutual funds have usually a fixed fee structure or it is only partially based on exceeding a pre-determined return target or benchmark index, whereas hedge funds' fee structure can typically be divided into two parts; the fixed fee and the performance-based incentive fee. Based on several studies (Fung et al. 1999; Ackermann et al. 1999), the average annual fixed fee is 1-2 percentages of assets under management and the average performance-based incentive fee is between 15-20 percentages of the achieved returns. In addition, incentive fees are asymmetric, they reward the fund manager for positive performance, but do not correspondingly penalize for losses.

The role of performance-based fees is significant in the hedge fund industry; it motivates fund managers to aim for the absolute returns rather than a pre-determined and specific return target. Aiming for high absolute returns, fund managers must utilize strategies that have low correlation with general market movements and that generate positive returns regardless of the prevailing market situation. (Ackermann et al. 1999.) Generally, a performance-based incentive fee is only charged if the fund's returns exceed a certain pre-determined level. Funds employing the "high water mark" method do not charge the incentive fee until the returns have fully covered past losses. In certain situations, incentive fees and "high water mark" method may result additional and unnecessary risk being taken by the fund manager. However, fund managers often invest significant amounts of their own funds in the fund, which may reduce the unnecessary risk taking.

3.5. Biases in hedge fund databases

When conducting a study of hedge funds, it is essential to acknowledge that data gathered from databases may potentially contain several biases. As mentioned previously, hedge funds are not obligated to disclose their activities to external parties, which makes data gathering more complicated. Due to lack of regulatory control and reporting obligations, hedge fund databases may possibly contain various statistical biases and irregularities, which can alter the results obtained in the flawed and unrealistic direction. (Jagannathan et al. 2010.) Utilizing data collected from funds-of-hedge funds, the effects of biases on results can be reduced or even eliminated. The most common biases in hedge fund databases are selection bias, survivorship bias and backfilling bias

In general, selection bias can emerge when the data sample is not representing the whole population, potentially leading to biased conclusions. Since hedge funds are not required to disclose their activities and therefore reporting is voluntary-based, characteristics and performance of reporting funds may differ greatly from non-reporting funds. Often only funds that have performed well in the past are willing to disclose their activities to the public databases. As a result, funds that are represented in the database have higher average returns than average returns of the whole hedge fund universe. This can significantly distort the accuracy of the data obtained from the database, as the sample focuses only on successful funds. The effects of selection bias is weakened by the well-performed funds that are not interested to report their success, as they have already reached the target level of capital or the target number of investors. For instance, the Long Term Capital Management fund did not report its exceptional returns during its active years. (Fung et al. 2000.)

Databases typically contain data only from existing and active funds. A survivorship bias is a distortion caused by the funds that have once been included in the database, but have ceased to exist, due to bankruptcy, merger, renaming the fund or sudden cessation of reporting. Inactive funds have typically performed worse than still existing funds, and when they are removed from database, the historical performance of the funds included in the database is too high compared to the whole hedge funds universe, and thus positively distorted. (Fung et al. 2000.)

It is advantageous for hedge funds to report its performance if it is seeking new investors and the fund has achieved positive returns over the longer period. The backfilling bias arises, when fund does not report its performance immediately after starting its operations, but only when it has generated a decent return history. If the fund is able to achieve satisfactory and positive returns, it begins to report about its performance, including the past return history**.** This leads to positive distortions in databases, since return histories of the funds are often better than average returns of the whole hedge fund industry. (Malkiel et al. 2005.)

3.6. Classification of hedge funds

Investment strategies used by hedge funds are often classified into either two or three main categories, with each main group divided into a numerous subgroups. In dual classification, strategies are divided into market neutral and directional strategies. Market neutral strategies are characterized by very low correlation with general markets and thus they do not seek to benefit from market movements. Directional strategies have stronger correlation with the market, since they are focusing to predict the future market development more closely. (Agarwal et al. 2000.)

More generally strategies are categorized into three main categories; market neutral, event-driven and global macro strategies. Again, market neutral strategies have very low correlation with markets, whereas other two groups focus on predicting the future market events, leading to a stronger positive correlation. In addition, funds of funds, which invest in other hedge funds, can be considered as its own group. Minimum investment in individual hedge fund ranges from $ 250 000 to $ 1 million, therefore constructing a broadly diversified portfolio of individual hedge funds requires significant amount of free capital. However, funds of funds enables investors to construct widely diversified portfolio of hedge funds with considerably lower capital requirements. (Fung et al. 2000; Lo 2010.) Funds of hedge funds have become increasingly popular as an alternative investments to those investors who do not have a lot of experience from hedge funds or do not have required capital to create sufficiently diversified hedge fund portfolio by themselves. One notable disadvantage of funds of hedge funds is their aforementioned typically high fees. (Darolles & Vaissié 2012.)

4. IMPLIED VOLATILITY AND VOLATILITY INDICES

Chapter introduces the theoretical background of implied volatility and volatility indices. In modern financial theory, volatility (σ), is a measurement of uncertainty regarding the future returns of a security. The volatility is measured by the standard deviation of the return provided by the security in one year, and in case of stocks, annualized volatility is averagely between 15% and 60%. These historical volatilities are backward looking since they are based on realized price data, whereas volatility that market participants expect to see in the future is known as implied volatility. (Hull 2012: 318-319)

4.1. Implied volatility

Implied volatility can interpreted as market's assessment of future expected volatility of underlying asset, or investors' opinion about the future fluctuations of security's price. As its definition suggests, implied volatility is implied from a market price of an option. Option pricing formulas, such as the Black-Scholes model (BSM) or binomial models, utilize several parameters in order to determine the price of individual option, including the price of an underlying asset, risk-free interest rate, time to expiration, strike price of an option, dividend yield and the volatility of an asset. Other parameters, excluding the volatility, are relatively easy to estimate accurately, which leaves the price of the option dependent on the volatility of an underlying asset. Volatility parameter can be estimated by using the historical price data of an asset to derive the value of the option. Or, if the market price of the option is known, the option pricing formula can be inverted, and by equating the option price to model, it is possible to determine the unknown volatility parameter. The volatility parameter, implied from market price of an option, is implied volatility of the option. (Canina & Figlewski, 1993; Mayhew, 1995.)

Implied volatilities are essential part of today's market structure, but traders and other market participants operating with implied volatilities are exposed to a risk of using incorrect inputs or even erroneous models while. For instance, traditional option pricing formulas assume the volatility parameter to be constant, but academics have refuted this assumption. In practice, volatility of the option fluctuates over its lifespan, and fluctuations is observed to happen clusters, since both absolute and squared returns have shown to display significant autocorrelations. Due to this autocorrelation, clustering effect might indicate that current level of volatility is a good estimator for short-term future volatility. There are various different factors affecting the behavior of volatility, such as supply and demand, liquidity of options and markets' expectations of the future volatility. Still, regardless of the weaknesses, the majority of traders and other markets participants utilize theoretical pricing models in order to determine the implied volatility of an asset. (Fahling et al. 2018.) Among traders, implied volatility of an option is often more quoted than the option price itself, since it less volatile to fluctuations. In addition to stock options and stock index options, implied volatility can be calculated for example from the prices of currency, commodity and other more exotic options. (Hull 2012: 319; Mayhew 1995.)

If option markets are efficient, implied volatility should accurately estimate the expected future volatility. Several former studies have examined, whether the estimates should be based on historical volatilities, implied volatilities or combination of them, and the results are not completely consistent. Early studies focus on static cross-sectional tests, utilizing mainly basic Black-Scholes model and other variants, and they agreed, that implied volatility is better estimator for future realized volatility. More recent papers around the topic have somewhat mixed results since they are using more advanced and dynamic methods, and focusing on the information content provided by implied volatility. Although the results are not completely consistent, the general consensus is that implied volatility tends to be more accurate for predicting future realized volatility. (Canina et al. 1993; Mayhew 1995; Christensen & Prabhala 1998)

4.2. Volatility indices

Nowadays there are growing amount of volatility indices, measuring the market expectations of future volatility on numerous different markets and asset classes. The most famous and followed volatility index in the financial world is the VIX Index. Originally, the idea of volatility index was driven by the need for proper hedging tools against changes in volatility. In 1993, Chicago Board Options Exchange (CBOE) introduced new Market Volatility Index, the VIX, to provide a benchmark of expected future short-term volatility and to provide an index, that enables volatility-based futures and options contracts to be written. The original VIX was based on index option prices of S&P 100, but since S&P 500 Index became the most active option market structure measured by average daily trading volume, CBOE changed the VIX to be based on index option prices of S&P 500. In general, VIX is comparable to other indices in the financial markets, except it measures volatility, not asset prices. Nowadays there are various volatility-based indices across the financial world, but VIX have become the most followed volatility index and primary reference to determine the value of volatility as an asset class among both academics and practitioners. Although VIX was initially mainly used for hedging purposes against changes in volatility, it has grown its popularity also as a speculative instrument among investors. (Whaley 2009; Caloiero & Guidolin, 2017; Dondoni et al., 2018.)

Value of VIX is implied from current short term S&P 500 index option prices. Like implied volatility, VIX is also forward looking, interpreted as market participants' expectations of future volatility over 30 calendar days. It is computed during every trading day on real-time basis from numerous put and call options. Expected future volatility can be viewed as a signal of the level of nervousness in the markets, and nowadays VIX is important piece of market information for investors, and therefore financial actors have begun to pay increasingly more attention towards it. Index is often referred as investors' fear gauge, since high level of VIX often indicates turmoil in the financial markets. VIX is forward-looking, measuring volatility that the investors expect to see in the future and fundamentally like a yield to maturity of a bond; bond's yield is implied from its current price, illustrating the future return over the bond's remaining life. Similarly VIX is implied from option prices representing the expected future volatility in the market. It is noteworthy that VIX and volatility itself has a mean-reverting property, since after each spike and drop, VIX tends to return closer to its long-term mean (Whaley 2009.)

CBOE’s crude oil volatility index, OVX, reflects the uncertainty of the global oil markets. Applying similar methodology as VIX, OVX measures the market’s expectations of 30-day volatility of crude oil prices, by utilizing United State Oil Fund’s options with wide range of strike prices. United State Oil Fund is exchange-traded product designed to track the crude oil price fluctuations. Using short-term futures contracts and cash, the performance of the fund designed to follow spot price of West Texas Intermediate light, sweet crude oil as near as possible. Liu et al. (2013.)

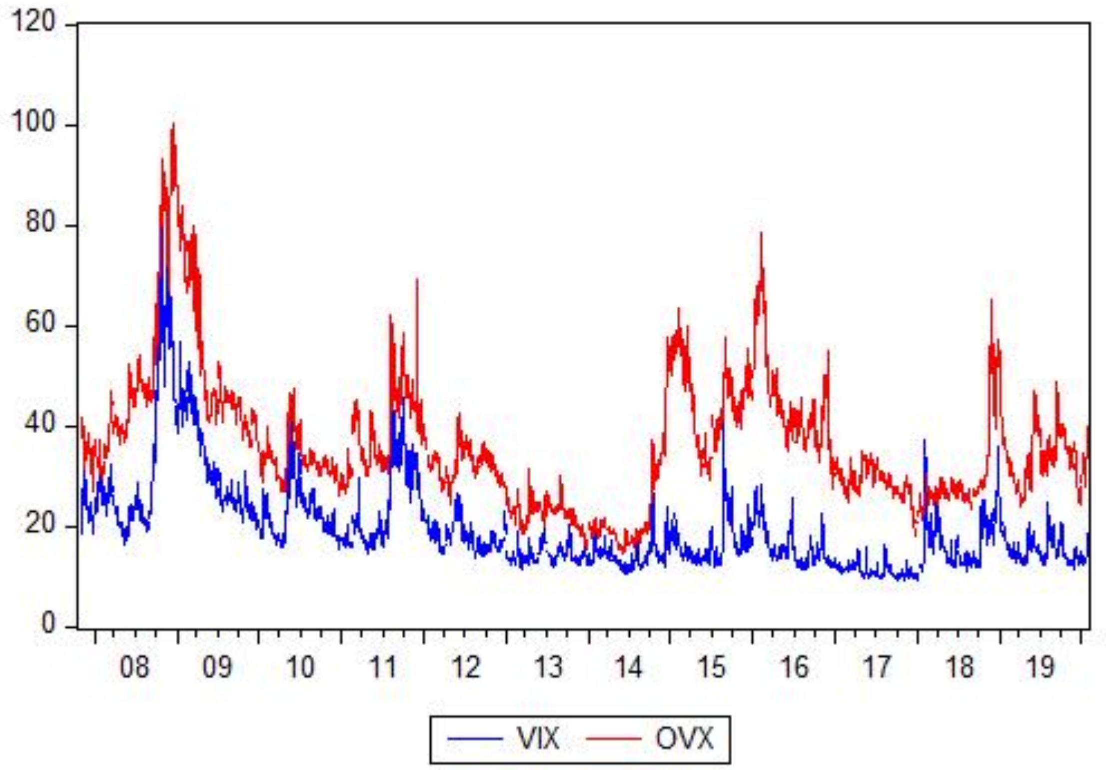

Figure 2. Closing values of VIX and OVX from 1/10/2007 to 31/1/2020.

Figure 2 shows the historical values of the VIX and OVX from 2007 to 2019. The most conspicuous phenomenon is the occasional spikes and jumps, which seems to be related to economic and political events; the sub-prime crisis and the followed by global financial crisis between 2007-2009, European debt crisis and Libyan war in 2011. According to Dutta (2018) the oil industry was in downturn during 2015-2016, caused possibly by oversupply or declining demand of crude oil, strong U.S. dollar or Iran nuclear war, causing the several spikes of OVX. However, behavior of both indices supports the argument that high levels of volatility are related to the events affecting the political and economic environment. As the turbulence in the financial markets increases, the nervousness and therefore the future volatility expectations among market participants increases as well.

4.3. Implied volatility and the stock market

The negative relationship between implied volatility, thereby also the VIX, and the stock markets is widely documented by numerous studies. Periods of financial turmoil are the most radical illustrations of this relationship; when VIX spikes, equity markets tend to plummet sharply, as in 1997 or 2008. For example Giot (2005), examines the correlation coefficients between 1-day returns of implied volatility indices, including VIX, and underlying stock indices. According to his findings, the rolling 60-day correlation for S&P 100 is approximately -0.8 and for NASDAQ100 around -0.7, indicating strong negative correlation.

Hafner and Wallmeier (2007), offer two separate theories of why higher volatility is associated with lower stock prices; the first theory is the "leverage effect", which states that higher market volatility is caused by increased leverage of corporations during declining market periods. However, this theory is disproved by empirical observations. They suggest the alternative theory, the "volatility feedback" theory, which argues that higher volatility is related to higher risk premium, leading to falling equity prices. Second theory is supported by modern financial theory; if expected future market volatility rises, investors demand higher rates of return on stocks, which leads to falling stock prices.

It seems that relation between rates of changes in the VIX and equity prices is highly dynamic and not symmetric; negative returns for stocks yield much larger relative changes in VIX than do positive returns. Explanation for this is the demand for portfolio hedging during times of stock market turmoil; demand to buy defensive put options of the underlying stock index increases, which drives up the prices of put options and implied volatilities. This causes a sharp increase in the VIX, whereas during bullish times, investors are not equally eager to use the leverage offered by buying the call options, in which case relative changes of VIX are weaker. This asymmetric relation indicates that VIX is more gauge of investors' fear of downside movements than gauge of excitement of markets upward movements. (Giot 2005; Whaley 2009.)

Figure 3 illustrates this asymmetry; the scatter plot of rolling 30-day returns of the VIX and S&P500 Index become steeper as the stock index fall and correspondingly flattens when index achieve positive returns. Figure shows that the rate of change of the VIX increases as the stock markets fall, indicating that VIX may provide an efficient protection to an equity portfolio during downside markets.

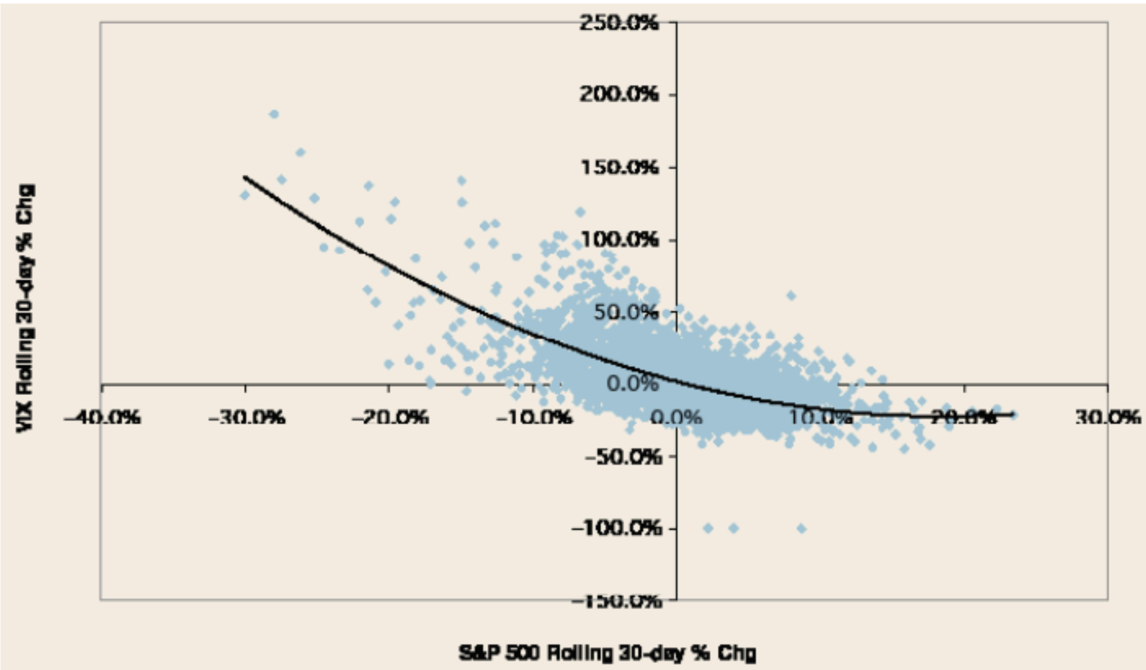

Figure 3. Rolling 30-day percentage changes in the S&P 500 Index and VIX Index between 1990 and 2010 (Stanton 2011).

4.4. Volatility as an asset class

Volatility has become widely accepted asset class, and portfolios utilizing volatility exposure have increased substantially across financial world during last decades. As stated previously, volatility is not constant over time, it tend to fluctuate in clusters and there is a strong negative relationship between equity markets and volatility movements. But volatility has also other characteristics affecting to its behavior. According to Fahling et al. (2018), trading volume is correlated with changes in volatility, but the causality is however complex to observe. The coefficient varies by the chosen time period, and therefore the impact of trading volume on volatility should be evaluated critically. Another characteristic of volatility is linked to its distribution, which is suggested approximately to be log-normal and strongly skewed to the right, since the periods of high-volatility are much more common than normal distribution would suggest.

Due to mentioned properties of volatility, it offers opportunities for risk diversification or return enhancement for investors. As modern portfolio theory states, higher level of risk or uncertainty increases the expected return and vice versa. And like any other asset classes, volatility can be traded to manage the risk and expected return. For instance, volatility can be used for speculative purposes to bet on the direction of short-term expected volatility, or for trading purposes based on the spread between realized volatility and current level of VIX. In case of near-term volatility spikes, it can be used as an risk management tool to hedge against tail-risks or as a diversification tool by buying volatility through VIX futures and options. Therefore opportunities offered by volatility varies in accordance with characteristics of an investor, such as risk preference, investment horizon, degree of sophistication and overall objects of investor. (Markowitz 1952; Whaley 2013.)

Volatility trading requires position that has pure exposure only to volatility, without being affected by fluctuations of the underlying asset. Methods traditionally used in volatility trading, such as at-the-money straddles, do not satisfy this requirement, and maintaining the position delta-neutral also requires frequent rebalancing, which leads to high transaction costs. Through VIX, investors are able to have pure exposure on volatility.

However, there is one major issue concerning the volatility trading through the VIX and other volatility-based indices, since they and also volatility itself are not directly investable. Since the exposure on volatility must be taken either through VIX futures, options or other VIX-based products, and VIX-related derivatives do not capture the same characteristics as the index itself, which may lead to biased and false results. (Hafner et al. 2007; DeLisle et al. 2010.)

According to Simon & Campasano (2014) and Caloiero et al. (2017), VIX or any other volatility index, can be replicated by using underlying basket of options, but trading large number of options and rebalancing the position on a continuous daily basis have some major issues; it is expensive due to high transaction costs and it is hard and time consuming to implement in practice. However, CBOE launched VIX futures contracts in March 2004 and VIX option contracts in February 2006, to facilitate the volatility trading among investors. This has led to a creation of various different exchange traded products (ETPs) that offer direct exposure to the VIX as an investment. Over the years, the market for VIX-related financial products has expanded sharply and they are widely used as an risk management tool, particularly for hedging purposes. Still, despite of wide range of new ETPs, VIX futures contracts have remained as a centerpiece for academics and investors. (Alexander et al. 2011).

5. DATA AND METHODOLOGY

5.1. Data

Data used in this thesis consist several different data series. For hedge fund returns, six individual hedge fund indices are included into dataset, offered by Credit Suisse. Following five individual hedge fund indices are included based on their implemented strategy; equity market neutral, event driven, long/short equity, managed futures and global macro. Also the Credit Suisse Hedge Fund Index, tracking approximately 9000 funds and covering broadly the whole industry, is included in order to examine the impact of uncertainty to the returns of the hedge fund industry as a whole. The Appendix 1 provides descriptions for all included strategies. For comparison purposes, also monthly return data of S&P 500 Index is included into dataset, as a proxy for market return.

Daily closing prices of the VIX is used as a proxy for stock market uncertainty and OVX is used as a proxy for oil market uncertainty. They are calculated on daily basis, which makes it complex to compare with hedge fund return data, which is available usually only on monthly basis. Therefore, to make the data series comparable, the daily observations of the VIX, and OVX are recalculated into average intra-month values. These intra-month averages are used to get the monthly logarithmic changes for each volatility indices. The data sample covers period from October 2007 to January 2020, containing 148 monthly observations.

To examine whether crisis period have an impact on the relationship between uncertainty and hedge fund returns, dataset is divided into two periods, referred as crisis period and after crisis period. Crisis period spans from October 2007 to November 2011 and after crisis period from December 2011 to January 2020. Crisis period covers events caused by both global financial crisis and European debt crisis.

5.2. Methodology

Previous findings have shown the mean reverting properties of VIX, and its strong negative contemporaneous relationship with equity markets. (Fleming et al. 1995; Giot 2005; Whaley 2009; Sarwar 2014). Motivated by these previous studies, purpose of this thesis is to study whether negative contemporaneous relation is found between stock market uncertainty and hedge fund industry as well, by using VIX and OVX as an proxy for stock and oil market uncertainty, respectively. Following Sarwar (2014), to study the impact of equity and oil market uncertainty on hedge fund returns, following multivariate regression is applied:

$$R_{h,t} = \alpha + \sum \beta_{V,i}\, \Delta V_{t+i} + \beta_{|V|}\, |\Delta V_t| + \varepsilon_t,\ i = -j, \ldots, j \qquad (1)$$

Where, $R_{h,t}$ is the hedge fund index return at time t, ΔVt is the change in volatility index at time t + 1, $|\Delta V_t|$ is the absolute change of volatility index at time t, $\beta_{V,i}$ is the regression coefficient of the relation between ΔV_{t+j} and $R_{h,t}$, $\beta_{|V|}$ is the regression coefficient for $|\Delta V_t|$, α is the regression intercept and ε_t is the error term.

Therefore, the regression coefficient $\beta_{V,0}$ is expected to have a negative sign, indicating negative relation of hedge fund returns and volatility indices. These expectations are in line with previous studies, since capital asset pricing models suggest that rise in expected volatility leads to declining equity prices, which is consistent with the prediction of negative value of coeffcient $\beta_{h,0}$. Furthermore, the discounted cash flow model supports the expectations, since increase in expected volatility increases simultaneously the discount rate for discounted cash flows. This will lead to fall in equity prices, assuming no changes in expected cash flows. (Sharpe, 1964; Sarwar 2014). The mean reverting properties of VIX indicate that negative contemporaneous relationship could be followed (preceded) by a positive lead (lag) coefficients. Equation 1 is expected to capture the possible mean reversion feature. Therefore, it is expected that lead and lagged coefficients $\beta_{V,i}$ to be positive. The Schwartz and Akaike information criteria is used to determine the number of lagged and lead variables included in regression.

According to Schwert (1990), Fleming et al. (1995) and Sarwar (2014) relation of equity market returns and implied volatility is not symmetric; the impact of positive changes of volatility index on hedge fund returns is stronger than the impact of similar negative changes of volatility index on hedge fund returns As it is expected that equity market returns and hedge fund return have similar exposure on volatility indices, impact of positive changes of volatility indices on hedge fund returns is expected to be larger than impact of similar negative changes. Therefore the magnitude of positive joint coefficient ($\beta_{V,0}$ + $\beta_{|V|}$), representing the effects of positive changes of volatility indices on hedge fund returns is expected to be larger than the negative joint coefficient ($\beta_{V,0}$ - $\beta_{|V|}$), representing the effects of negative changes of volatility indices on hedge fund returns.

Based on studies of Dutta et al. (2017) and Xiao et al. (2018), oil price uncertainty, through OVX, has an impact on the realized equity market volatility and it has an similar negative relationship with equity market returns than VIX. According to Dutta (2018), the U.S. economy is highly sensitive to oil volatility shocks, and uncertainty in global crude oil market has become an essential indicator for the U.S. economy. There is a strong long-term association between VIX and OVX, suggesting that changes in volatility in U.S. stock market may cause significant movements in international crude oil markets and vice versa. Therefore, it is expected that VIX and OVX have a similar negative contemporaneous relation with hedge fund returns.

According to Liu et al. (2013), VIX acts as driving force for crude oil volatility index, changes of OVX are affected by the changes of VIX, meaning that changes in U.S. stock market uncertainty flows to the crude oil market, suggesting that oil market uncertainty is sensitive to shocks from U.S. stock market. Based on previous studies, it is expected that VIX and OVX are able to explain together substantially proportion of variation of hedge fund returns. To examine the simultaneous effects of stock market and oil market uncertainty on hedge fund returns, and whether uncertainty from U.S. stock markets flows to global oil markets the following regression is applied:

(2) $$R_{h,t} = \alpha + \beta_1 \Delta VIX_t + \beta_2 \Delta OVX_t + \varepsilon_t,$$

Where $R_{h,t}$ is the hedge fund index return at time t, $\Delta VIXt$ is the change in VIX at time t, $\Delta OVXt$ is the change in OVX at time t, β_1 is the regression coefficient for ΔVIX_t, β_2 is the regression coefficient for ΔOVX_t, α is the regression intercept and ε_t is the error term.

6. EMPIRICAL RESULTS

Table 1 presents descriptive statistics of monthly returns of six different hedge fund indices, S&P 500 Index and logarithmic changes in the intra-month value of VIX and OVX. Total sample period is divided into two periods; 10/2007-11/2011, referred as crisis period and 12/2011-1/2020, referred as after crisis period. Mean hedge fund returns vary across strategies, but interestingly, only market neutral strategy exhibits negative mean return during crisis period, in addition to S&P500 Index, indicating that hedge funds are able to generate absolute returns even during extreme market conditions. Global macro and managed futures strategies are delivering higher mean returns during crisis period compared to after crisis period, supporting the view that proportion of hedge funds are not following market trends. As expected standard deviation levels are higher during crisis period for all strategies and S&P500, but it is noteworthy that during both periods, standard deviation levels of hedge funds are consistently lower compared to standard deviation of S&P 500 Index, implying that profits generated by hedge funds exhibit less fluctuations regardless the market prevailing market conditions, compared to average U.S. stock market returns.

Sharpe ratio is annualized by subtracting the annualized average 3-month U.S. treasury bill rate from annualized mean return, and this excess return is divided by annualized standard deviation. During crisis period, the annualized Sharpe ratio is lower only for market neutral strategy compared to S&P500 Index. In contrast, during times when the financial markets are in more stable state, all of five strategies and the total hedge fund index fail to deliver better risk-adjusted returns compared to S&P500 Index. This indicates that hedge funds in general are able to generate more stable risk-adjusted returns in all market conditions, compared to average equity markets, which are more dependent from the prevailing market state. However, based on Fung et al. (2000), this kind of linear statistical measures may not be optimal measurements for hedge funds, due to their highly dynamic strategies.

Table 1. Descriptive statistics of the hedge fund indices, S&P 500 and volatility indices.

	Mean	Max	Min	Std. Dev.	Kurtosis	Skewness	Annualized Sharpe ratio	Obs.
10/2007-11/2011								
Total hedge fund index	0,13	3,98	-6,78	2,27	1,63	-1,09	0,114	50
Market neutral	-0,82	3,59	-51,84	7,55	44,84	-6,54	-0,384	50
Event driven	0,07	4,13	-5,92	2,43	0,20	-0,77	0,031	50
Global macro	0,57	4,35	-6,86	2,06	3,25	-1,25	0,909	50
Long/short	0,01	5,10	-8,14	2,96	0,42	-0,68	-0,054	50
Managed futures	0,40	6,40	-5,20	3,24	-1,11	0,02	0,378	50
S&P 500	-0,40	10,23	-18,56	5,98	0,44	-0,59	-0,260	50
VIX	0,73	70,47	-24,35	20,79	3,48	1,80	-	50
OVX	0,85	39,55	-26,53	13,90	1,04	0,84	-	50
12/2011-1/2020								
Total hedge fund index	0,34	2,68	-2,61	0,99	0,42	-0,48	1,026	98
Market neutral	0,09	3,41	-4,39	1,25	1,42	-0,48	0,077	98
Event driven	0,32	2,77	-3,50	1,33	0,47	-0,72	0,700	98
Global macro	0,28	3,93	-2,67	1,12	1,08	0,00	0,714	98
Long/short	0,48	3,83	-4,63	1,54	1,34	-0,69	0,983	98
Managed futures	0,10	7,23	-7,79	2,92	-0,33	-0,12	0,056	98
S&P 500	0,97	7,97	-9,63	3,14	1,33	-0,77	1,070	98
VIX	-0,85	70,84	-37,29	17,17	2,39	0,81	-	98
OVX	-0,33	45,82	-35,60	14,25	1,12	0,48	-	98

Monthly observations, expressed as percentages.

The mean monthly logarithmic change is positive for both VIX and OVX during crisis period, whereas it turns to negative after crisis. The monthly change of VIX varies from a minimum of -24.35% to a maximum of 70.47% during crisis period and from a minimum of -37.29% to a maximum of 70.84% during after crisis period. The monthly OVX ranges from a minimum of -26.53% to a maximum of 39.55% during crisis period and from a minimum of -35.60% to a maximum of 45.82% during after crisis period. Interestingly, OVX exhibits higher standard deviation (volatility of volatility) during after crisis period. Monthly mean levels of hedge fund returns, VIX and OVX are varying between two examined periods, which possible indicates that the relationship between hedge fund returns and uncertainty, through volatility indices, are substantially different during different market conditions.

Tables 2 and 3 present the results for the equation 1. Based on Schwartz and Akaike information criteria, two lagged and lead variables are included in regression. Results on table 2 reveal a statistically significant contemporaneous and negative impact (β_0) of changes in VIX on hedge fund returns. During crisis period, the magnitude of contemporaneous significant coefficients varies from -0.036 (Global macro) to -0.131 (Market neutral). For instance, one percent change in VIX is associated with 0.097 percent inverse change in total hedge fund index returns. VIX does not seem to have any significant impact only on returns of managed futures strategy, which is excepted since strategy focuses mainly on trading futures. Very low value of coefficient of determination (Adj. R^2) supports the observation.

Table 1. Impact of VIX changes on S&P500 and hedge fund indices returns.

Period	Intercept	β_{-2}	β_{-1}	β_0	β_1	β_2	$\beta_{\|VIX\|}$	Adj. R^2
S&P500								
10/2007-11/2011	-0.005	0.012	-0.067	**-0.186**	-0.052	0.017	0.021	0.43
	(0.49)	(0.38)	(2.13)**	**(4.06)*****	(1.64)*	(0.51)	(0.35)	
12/2011-1/2020	0.009	-0.012	-0.004	**-0.116**	-0.008	0.025	-0.007	0.41
	(2.41)***	(0.80)	(0.28)	**(7.81)*****	(0.55)	(2.01)***	(0.34)	
TOTAL HEDGE FUND INDEX								
10/2007-11/2011	-0.001	-0.022	-0.035	**-0.097**	-0.008	-0.021	0.025	0.66
	(0.38)	(2.40)***	(3.78)***	**(7.15)*****	(0.85)	(2.20)***	(1.47)**	
12/2011-1/2020	0.004	-0.004	-0.008	**-0.031**	0.002	0.003	-0.011	0.35
	(3.58)***	(0.88)	(1.64)*	**(6.45)*****	(0.55)	(0.84)	(1.58)*	
MARKET NEUTRAL								
10/2007-11/2011	-0.027	-0.087	-0.174	**-0.131**	0.015	0.011	0.162	0.27
	(1.89)**	(1.90)**	(3.84)***	**(2.00)****	(0.31)	(0.23)	(1.91)**	
12/2011-1/2020	0.001	-0.000	-0.007	**-0.009**	0.001	0.004	-0.001	0.01
	(0.44)	(0.02)	(0.94)	**(1.19)**	(0.01)	(0.64)	(0.15)	
EVENT DRIVEN								
10/2007-11/2011	-0.001	-0.025	-0.039	**-0.104**	-0.003	-0.019	0.024	0.68
	(0.43)	(2.60)***	(4.10)***	**(7.50)*****	(0.35)	(1.96)**	(1.35)*	
12/2011-1/2020	0.004	-0.012	-0.016	**-0.045**	0.002	0.003	-0.014	0.41
	(2.69)***	(1.98)**	(2.57)***	**(7.17)*****	(0.27)	(0.75)	(1.53)*	
GLOBAL MACRO								
10/2007-11/2011	0.008	-0.002	-0.005	**-0.036**	-0.002	-0.027	-0.013	0.14
	(1.80)**	(0.15)	(0.39)	**(1.88)****	(0.19)	(1.93)**	(0.52)	
12/2011-1/2020	0.004	-0.002	-0.000	**-0.022**	0.003	0.004	-0.010	0.12
	(2.34)***	(0.37)	(0.12)	**(3.52)*****	(0.40)	(0.82)	(1.06)	
LONG/SHORT								
10/2007-11/2011	-0.004	-0.015	-0.030	**-0.130**	-0.021	-0.027	0.041	0.62
	(1.04)	(1.19)	(2.40)***	**(7.04)*****	(1.68)*	(2.05)**	(1.71)**	
12/2011-1/2020	0.0057	-0.005	-0.007	**-0.046**	0.005	0.002	-0.011	0.26
	(2.75)***	(0.68)	(0.94)	**(5.63)*****	(0.61)	(0.29)	(0.95)	
MANAGED FUTURES								
10/2007-11/2011	-0.000	-0.020	0.028	**-0.039**	0.037	-0.039	0.035	0.01
	(0.125)	(0.880)	(1.26)	**(1.19)**	(1.64)*	(1.63)*	(0.82)	
12/2011-1/2020	0.003	0.007	0.009	**-0.011**	0.001	0.016	-0.016	0.01
	(0.63)	(0.37)	(0.46)	**(0.62)**	(0.04)	(1.07)	(0.58)	

*,**,*** significant at 10%, 5% and 1% respectively. The absolute t-statistics reported in parentheses.

Fleming et al. (1995), Giot (2005), Whaley (2009), Sarwar (2014) and others show the existence of this relationship in both U.S. and European equity markets, and results show that similar relationship prevails also for hedge funds. This suggests that VIX acts as an fear indicator, not only in equity markets, but in the hedge fund industry as well, yet the magnitude of the negative relation is weaker for hedge funds. Overall the impact of VIX is substantially stronger on S&P500 Index compared to any individual hedge fund strategies, for instance, the average impact of VIX for total hedge fund index is approximately half of the magnitude compared to an impact on the S&P500 Index. One possible explanation for the similar impact for hedge fund and S&P500 returns is the relatively high correlation coefficients which does not vary substantially between periods. For instance, correlation between returns of total index and S&P 500 is 0.75 during crisis period and 0.74 after crisis period, implying that returns of hedge fund industry in general follows quite closely the returns of U.S. stock markets. Correlation matrices are provided for both periods in Appendix 2. However, since negative impact of uncertainty flows simultaneously also into hedge funds but the impact is weaker, asset allocation between U.S. equity markets and hedge fund industry may provide some diversification benefits, but achieved benefits from risk diversification are weak, since increasing stock market uncertainty affects negatively for both hedge funds and U.S. stock markets. Results suggests that portfolio including either hedge funds or U.S. stocks (or both), may be hedged from increasing stock market volatility simply by taking a long position in VIX based options or futures.

For after crisis period, results show statistically significant negative contemporaneous relationship with VIX for total hedge fund index and event drive, global macro and long short strategies varying from -0.046 to -0.009. However, the magnitude of relation is substantially weaker compared to crisis period, for instance for total index, the contemporaneous coefficient drops from -0.097 to -0.031. Similar effect is observed for S&P 500, the coefficient drops from -0.186 to -0.116. Interestingly, the magnitude of change between periods is stronger compared to S&P500 returns. This is possible explained by the flight-to-quality phenomenon during periods of high turbulence, in which investors allocate assets to more traditional and possibly more safe asset classes, which leads to large withdrawals for hedge funds, forcing them to strongly liquidate assets, therefore boosting the losses.

Results are in line with evidence from equity markets, since findings suggest strongly that impact of VIX on hedge fund returns is substantially stronger during crisis period, and that hedge fund returns reacts substantially stronger to fluctuations in the stock market volatility. Therefore H_2, stating that the negative relation is stronger during crisis period, is supported. Sarwar (2014) and Nefelli and Resta (2018) show that the impact of VIX is substantially stronger on equity market returns in Europe and BRIC-countries during crisis period, and according to Cheung, Fung and Tsai (2010), cross-market contagion effects strengthens during crisis periods. Therefore, results jointly indicate that integration between different markets and asset classes, including hedge funds, strengthens substantially during turbulent market periods, leading to descending portfolio diversification benefits, at the times when need for diversification is most needed.

Due to mean reverting features of VIX, lead coefficients are expected to have positive sign, although Sarwar (2014) show that the negative effects of VIX persist to the following day in European stock markets. For hedge funds, same effect is not found in a monthly basis, since lead-one coefficient (β_1) is weakly significant for long/short and managed futures strategies at 10% level only during crisis period, implying that that negative impact of VIX does not persist consistently to the following month for hedge funds. One possible explanation for this is that information-process is efficient and hedge fund managers are able to adjust their portfolios in accordance with prevailing market situation within the following month.

The coefficient for contemporaneous absolute returns ($\beta_{|VIX|}$) is significant and positive during crisis period for total index and for market neutral, event driven and long/short strategies, which suggests that during crisis period there is a positive relation between VIX and the size of hedge fund returns, regardless of the direction of the movement. Interestingly, this relation is inverse during after crisis period, but statistically significant only for total index and event driven strategy, supporting the view that uncertainty-return relation varies between different market conditions. Coefficient of determination

(Adj. R^2) is consistently higher during crisis period, providing supporting evidence about strengthened impact of VIX on hedge fund returns during crisis period.

Table 3. Impact of OVX changes on S&P500 and hedge fund indices returns.

Period	Intercept	β_{-2}	β_{-1}	β_0	β_1	β_2	$\beta_{\|OVX\|}$	Adj. R^2
S&P500								
10/2007-11/2011	0.013	-0.003	-0.095	**-0.149**	-0.098	-0.028	-0.148	0.24
	(1.18)	(0.06)	(1.75)**	**(2.50)*****	(1.83)**	(0.52)	(1.68)*	
12/2011-1/2020	0.002	0.015	-0.022	**-0.063**	-0.060	0.030	0.063	0.18
	(0.45)	(0.69)	(1.04)	**(3.01)*****	(2.82)***	(1.81)**	(1.93)**	
TOTAL HEDGE FUND INDEX								
10/2007-11/2011	0.005	-0.008	-0.046	**-0.086**	-0.022	-0.027	-0.030	0.39
	(1.44)*	(0.46)	(2.47)***	**(4.25)*****	(1.24)	(1.47)*	(1.01)	
12/2011-1/2020	0.003	0.004	-0.009	**-0.023**	-0.009	0.003	0.007	0.13
	(1.70)	(0.59)	(1.36)	**(3.47)*****	(1.29)	(0.55)	(0.64)	
MARKET NEUTRAL								
10/2007-11/2011	-0.006	-0.009	-0.208	**-0.101**	-0.075	0.095	0.013	0.09
	(0.393)	(0.12)	(2.76)***	**(1.23)**	(1.01)	(1.26)	(0.11)	
12/2011-1/2020	0.002	0.009	-0.004	**-0.020**	-0.002	0.001	-0.006	0.02
	(0.76)	(1.01)	(0.51)	**(2.28)*****	(0.26)	(0.01)	(0.47)	
EVENT DRIVEN								
10/2007-11/2011	0.006	-0.005	-0.055	**-0.092**	-0.018	-0.016	-0.040	0.41
	(1.50)*	(0.298)	(2.85)***	**(4.34)*****	(0.97)	(0.82)	(1.26)	
12/2011-1/2020	0.002	-0.006	-0.023	**-0.033**	-0.019	0.001	0.004	0.24
	(1.28)	(0.71)	(2.59)***	**(3.91)*****	(2.20)***	(0.07)	(0.35)	
GLOBAL MACRO								
10/2007-11/2011	0.007	0.002	-0.006	**-0.046**	0.003	-0.046	-0.011	0.10
	(1.69)**	(0.11)	(0.33)	**(2.09)****	(0.18)	(2.25)***	(0.36)	
12/2011-1/2020	0.001	0.003	0.001	**-0.015**	-0.004	0.003	0.007	0.01
	(1.05)	(0.46)	(0.01)	**(1.83)****	(0.56)	(0.48)	(0.59)	
LONG/SHORT								
10/2007-11/2011	0.006	0.002	-0.039	**-0.096**	-0.036	-0.040	-0.049	0.29
	(1.15)	(0.07)	(1.50)*	**(3.39)*****	(1.42)*	(1.53)*	(1.17)	
12/2011-1/2020	0.002	0.005	-0.010	**-0.033**	-0.016	0.005	0.015	0.10
	(1.22)	(0.47)	(0.94)	**(3.04)*****	(1.49)*	(0.61)	(0.92)	
MANAGED FUTURES								
10/2007-11/2011	0.003	-0.012	0.011	**-0.010**	0.100	-0.022	-0.001	0.08
	(0.53)	(0.39)	(0.35)	**(0.30)**	(3.11)***	(0.69)	(0.01)	
12/2011-1/2020	-0.000	0.034	0.013	**-0.000**	0.024	0.021	0.018	0.01
	(0.20)	(1.54)*	(0.55)	**(0.04)**	(1.10)	(1.18)	(0.53)	

*,**,*** significant at 10%, 5% and 1% respectively. The absolute t-statistics reported in parentheses.

Table 3 presents the regression results for OVX, suggesting that also oil market uncertainty has a significant contemporaneous negative impact on hedge fund returns. Results are very similar compared to results obtained from the impact of VIX in table 2, since a statistically significant negative and contemporaneous relationship (β_0) can be observed during both periods for all individual strategies and total index, excluding market neutral strategy during crisis period. The magnitude of contemporaneous coefficient varies from -0.101 (market neutral during crisis) to -0.015 (global macro after crisis). Magnitude of impact is slightly weaker compared to VIX (for total index, -0.097 versus -0.086 during crisis and -0.031 versus -0.023 after crisis), but overall effects of oil market uncertainty behaves similarly compared to equity market uncertainty. Therefore, increasing uncertainty in global oil markets is associated with lower returns in hedge fund industry, implying that global oil markets are important factor explaining not only returns of equity markets but also returns those of hedge fund industry.

Similar to VIX, the magnitude of negative impact of OVX is substantially stronger during crisis period than after crisis period. For instance, the contemporaneous coefficient of total index drops from -0.086 to -0.023. Impact for S&P500 Index returns is stronger compared to any individual hedge fund strategy or total index, implying that also equity markets are in connection with uncertainty of the oil markets. Similar to VIX, results suggest that allocating assets between U.S. equity markets and hedge fund industry may provide hedge against oil markets, but the diversification benefits may remain insignificant. Lead-one coefficient (β_1) of OVX is significant and negative for event driven, long/short strategies and managed futures strategies, indicating that negative impact of OVX does persist to the following month, but results are not consistent for all hedge fund strategies. The coefficient for contemporaneous absolute returns ($\beta_{|OVX|}$) is insignificant for all strategies and total index, suggesting that there is not significant relation between changes in OVX and size of hedge fund returns, regardless of direction of the movement. The coefficient of determination (Adj. R^2) is higher during crisis period for all strategies and total index, supporting the results that the impact of OVX is stronger during crisis period.

Results of contemporaneous asymmetric impact of stock and oil market uncertainty on hedge fund returns are presented in tables 4 and 5 respectively. The coefficients for VIX, β_{VIX-} (β_{VIX+}), is calculated by subtracting (adding) $\beta_{|VIX|}$ from (into) $\beta_{VIX,0}$, , coefficients for OVX is calculated similarly. Coefficients captures the contemporaneous relation of absolute changes in VIX and OVX and hedge fund returns. The Wald test is performed to obtain additional evidence about the asymmetric relationship, statistically significant Wald Test values reject the null hypothesis $\beta_{VIX-} = \beta_{VIX+}$ ($\beta_{OVX-} = \beta_{OVX+}$), suggesting statistically significant asymmetry.

Table 4. Relationship of VIX changes with positive and negative changes in S&P500 and hedge fund indices returns.

		VIX			
Period	β_{VIX+}	β_{VIX-}	Wald Test	$\beta_{VIX,0}$	$\beta_{\lvert VIX \rvert}$
S&P500					
10/2007-11/2011	-0.165	-0.207	0.354	-0.186	0.021
12/2011-1/2020	-0.123	-0.109	0.346	–0.116	–0.007
TOTAL HEDGE FUND INDEX					
10/2007-11/2011	-0.072	-0.122	1.474	-0.097	0.025
12/2011-1/2020	-0.042	-0.020	1.587	-0.031	-0.011
MARKET NEUTRAL					
10/2007-11/2011	0.031	-0.293	1.916	-0.131	0.162
12/2011-1/2020	-0.010	-0.008	0.154	-0.009	-0.001
EVENT DRIVEN					
10/2007-11/2011	-0.080	-0.128	1.349	-0.104	0.024
12/2011-1/2020	-0.059	-0.031	1.538	-0.045	-0.014
GLOBAL MACRO					
10/2007-11/2011	-0.049	-0.023	0.523	-0.036	-0.013
12/2011-1/2020	-0.032	-0.012	1.06	-0.022	-0.01
LONG/SHORT					
10/2007-11/2011	-0.089	-0.171	1.72	-0.130	0.041
12/2011-1/2020	-0.057	-0.035	0.951	-0.046	-0.011
MANAGED FUTURES					
10/2007-11/2011	-0.004	-0.074	0.828	-0.039	0.035
12/2011-1/2020	-0.027	0.005	0.589	-0.011	-0.016

Wald test reported in t-statistics.

According to results presented in table 4, after crisis period, one percent increase in VIX is associated by 0.042 percent drop in total hedge fund index, whereas one percent drop in VIX is related with 0.020 percent increase in index, meaning that negative change coefficient is approximately half of the positive change coefficient, indicating contemporaneous asymmetric relationship. However, Wald test does not support the existence of asymmetric impact of VIX on hedge fund returns, since null hypothesis, $\beta_{VIX+} = \beta_{VIX-}$, is not rejected for any individual hedge fund strategy nor the total index. Results are similar for OVX, table 5 shows that null hypothesis, $\beta_{OVX+} = \beta_{OVX-}$, is not rejected in any case based on values of Wald test. Therefore, statistically significant asymmetric impact of stock or oil market uncertainty is not observed, though weak asymmetric relation is observed for some strategies, suggesting that characteristics of hedge fund returns differs from equity market returns. Findings are in contrast to studies focusing on equity markets, since Schwert (1990), Fleming et al. (1995) and Sarwar (2014), all find asymmetric impact of VIX on equity market returns. This inconsistency between equity markets and hedge funds might be explained by the hedge funds' highly dynamic trading strategies.

Finally, based on equation 2, table 6 reports the results of simultaneous effects of VIX and OVX on hedge fund returns. Coefficients for changes in VIX, ΔVIX, remains highly significant and negative for total hedge fund index, event driven, global macro and long/short strategies during both periods, and for managed futures strategy for after crisis period. Contemporaneous negative impact of VIX remains approximately at the same level compared to results in table 2. For total hedge fund index, contemporaneous coefficient of VIX is -0.097, whereas after including OVX, the coefficient is -0.074. Consistent with the results from table 3, the impact of VIX is statistically significant and substantially stronger during crisis period. However, after including both VIX and OVX in the same regression, and examining effects of stock and oil market uncertainty together, impact OVX remains negative but it is statistically significant for returns of total index, market neutral and event driven strategies and only during after crisis period, indicating possible uncertainty transmission from stock markets to oil markets in these cases. However, stock and oil market uncertainty does not have consistent simultaneous impact on hedge fund returns across all studied strategies, since equity market uncertainty is the leading factor explaining the negative impact on hedge fund returns, suggesting that uncertainty from equity markets might flow into global oil markets.

Table 5. Relationship of OVX changes with positive and negative changes in S&P500 and hedge fund indices returns.

		OVX			
Period	β_{OVX+}	β_{OVX-}	Wald Test	$\beta_{OVX,0}$	$\beta_{\|OVX\|}$
S&P500					
10/2007-11/2011	-0.297	-0.001	-1.683	−0.149	−0.148
12/2011-1/2020	0,000	-0.126	1.939	−0.063	0.063
TOTAL HEDGE FUND INDEX					
10/2007-11/2011	-0.116	-0.056	-1.011	−0.086	−0.030
12/2011-1/2020	-0.016	-0.030	0.640	−0.023	0.007
MARKET NEUTRAL					
10/2007-11/2011	-0.088	-0.114	0.110	-0.101	0.013
12/2011-1/2020	-0.026	-0.014	-0.476	-0.020	-0.006
EVENT DRIVEN					
10/2007-11/2011	-0.132	-0.052	-1.268	-0.092	-0.040
12/2011-1/2020	-0.029	-0.037	0.359	-0.033	0.004
GLOBAL MACRO					
10/2007-11/2011	-0.057	-0.035	-0.361	-0.046	-0.011
12/2011-1/2020	-0.008	-0.022	0.595	-0.015	0.007
LONG/SHORT					
10/2007-11/2011	-0.145	-0.047	-1.177	-0.096	-0.049
12/2011-1/2020	-0.018	-0.048	0.927	-0.033	0.015
MANAGED FUTURES					
10/2007-11/2011	-0.009	-0.011	-0.014	-0.010	0.001
12/2011-1/2020	0.017	-0.019	0.538	-0.001	0.018

Wald test reported in t-statistics.

Table 6. Simultaneous impact of VIX and OVX on S&P500 and hedge fund returns

Period	Intercept	ΔVIX	ΔOVX	Obs	Adj. R^2
S&P500					
10/2007-11/2011	-0.002	-0.220	0.063	50	0.41
	(0.45)	(4.53)***	(0.87)		
12/2011-1/2020	0.008	-0.116	-0.001	98	0.40
	(3.52)***	(7.16)***	(0.01)		
TOTAL HEDGE FUND INDEX					
10/2007-11/2011	0.002	-0.074	-0.007	50	0.49
	(0.80)	(4.30)***	(0.28)		
12/2011-1/2020	0.003	-0.028	-0.009	98	0.32
	(3.83)***	(5.27)***	(1.41)*		
MARKET NEUTRAL					
10/2007-11/2011	-0.007	0.021	-0.124	50	0.01
	(0.68)	(0.26)	(1.03)		
12/2011-1/2020	0.001	-0.001	-0.021	98	0.05
	(0.63)	(0.06)	(2.23)***		
EVENT DRIVEN					
10/2007-11/2011	0.001	-0.080	-0.010	50	0.52
	(0.59)	(4.48)***	(0.38)		
12/2011-1/2020	0.002	-0.037	-0.019	98	0.35
	(2.61)***	(5.18)***	(2.23)***		
GLOBAL MACRO					
10/2007-11/2011	0.006	-0.034	-0.007	50	0.12
	(2.21)***	(1.69)**	(0.24)		
12/2011-1/2020	0.002	-0.023	-0.001	98	0.12
	(2.48)***	(3.43)***	(0.13)		
LONG/SHORT					
10/2007-11/2011	0.001	-0.120	0.029	50	0.54
	(0.24)	(5.61)***	(0.91)		
12/2011-1/2020	0.004	-0.042	-0.011	98	0.27
	(3.31)***	(4.82)***	(1.03)		
MANAGED FUTURES					
10/2007-11/2011	0.004	-0.006	-0.000	50	0.01
	(0.85)	(0.19)	(0.01)		
12/2011-1/2020	0.001	-0.026	0.024	98	0.01
	(0.30)	(1.36)*	(1.12)		

*,**,*** significant at 10%, 5% and 1% respectively. Absolute T-statistics reported in paranthesis.

Findings suggest that stock market uncertainty, through VIX, is the driving force for oil market uncertainty. This is partly consistent with Liu et al. (2013), since according to their study, stock markets are driving force for uncertainty, whose changes are transmitted into crude oil market. However, uncertainty transmission between VIX and OVX is very short-term, since positive impact lasts for initial day, but then disappears, which might explain the insignificance of the OVX when examined simultaneously with VIX, since research is based on monthly observations.

Overall, presented findings suggest that stock and oil market uncertainty have significant and negative contemporaneous on hedge fund return, when examined individually. The magnitude of negative impact varies across different strategies and as expected, while impact strengthens during crisis periods. Comparing the uncertainty-return relation between hedge fund returns and S&P500 Index returns, the contemporaneous negative impact is substantially weaker for hedge fund returns. For instance, impact of VIX on total hedge fund index is approximately half of the magnitude compared to impact on the S&P500 Index returns. When examined individually, effects are approximately at the same level for both VIX and OVX. For some hedge fund strategies, negative impact of VIX appear to persist to the following month, but effect is to consistent during both examined periods and across all examined hedge fund strategies. Result for asymmetric impact are in contrast with the findings from equity markets, since statistically significant asymmetric impact is not observed, indicating that decrease in hedge fund returns from positive changes in stock or oil market uncertainty does not differ compared to increase in returns from negative changes. When effects of stock and oil market uncertainty are examined together, the impact remains negative for both VIX and OVX, but results for OVX are insignificant for most of the hedge fund strategies during both periods, indicating that equity market uncertainty is the driving force for oil market uncertainty.

7. CONCLUSIONS

This thesis aims to study the impact of equity and oil market uncertainty on hedge fund returns and provide further analysis about the relationship between them. Using monthly data from October 2011 to January 2020, five individual hedge fund strategy indices and Credit Suisse Hedge Fund Index, covering broadly the whole industry, is examined. For comparison purposes, also S&P500 Index returns are included into dataset, used as an proxy for market return. To study effects during different market conditions, dataset is divided into two periods, crisis period and after crisis period. Crisis period ranges from October 2007 to November 2011 and after crisis period from December 2011 to January 2020.

Empirical results of this thesis provide evidence about the negative contemporaneous cross-market impact of equity market uncertainty on hedge fund returns across all examined strategies, excluding managed futures strategy, during both studied periods. When examined individually, results are very similar for oil market uncertainty, although magnitude of negative impact is slightly weaker, suggesting that also uncertainty arising from global oil markets are affecting on hedge fund returns. Results contradicts with fundamental intention of hedge funds to be able to provide absolute returns regardless the prevailing market conditions. One possible explanation, as stated by Alexander et al. (2011) and Liu et al. (2013), is that after global financial crisis, different asset classes have become more correlated with each other and cross-market contagion effects have strengthened, which would indicate that also hedge funds are behaving more similarly compared to more traditional asset classes. This is supported by Fung et al. (2000), since during extreme market returns of hedge funds tend to follow returns of equity markets more closely. However, impact of both equity and oil markets uncertainty is approximately only half in magnitude compared to impact on S&P500 Index, but still it is evident that effects of uncertainty from both stock and oil markets spread into hedge fund industry, indicating that both VIX and OVX can both be viewed as an fear indicator in hedge fund industry as well. Presented results support the hypothesis about the negative contemporaneous impact of uncertainty on hedge fund results. Impact is quite similar for both hedge funds and S&P500, hedge funds seem to be weak protection against high uncertainty, since negative impact of uncertainty flows simultaneously also into hedge funds industry, asset allocation between U.S. equity markets and hedge fund does not offer any significant risk diversification benefits.

One major finding is that impact of uncertainty varies between periods, and it is significantly stronger during crisis period, therefore the hypothesis regardin the varying magnitude of the impact during different market conditions is supported. The magnitude of change between periods is stronger compared to S&P500 returns, which might be explained by the flight-to-quality phenomenon during crisis periods. Although hedge funds are aiming to generate absolute returns regardless the current market state, they are still considered to be high-risk investment compared to more traditionally asset classes, making them vulnerable of large withdrawals especially during times of high market uncertainty. Results show that the negative effect of VIX or OVX does not significantly persist to the following month, suggesting the efficient information-processing and ability for portfolio adjusting of hedge fund managers. Also, the uncertainty-return relationship is reported to be asymmetric for equity markets, but the effect is not observed in case of hedge funds, possible explained by the highly dynamic trading strategies of hedge funds. Weak asymmetric relation is observed for some strategies, but Wald test does not support the existence of statistically significant asymmetric relationship.

Finally, stock market uncertainty is the driving force in respect of hedge fund returns. When examined separately, both VIX and OVX have statistically significant negative impact, but when examined simultaneously, only VIX is exhibiting statistically significant results, and impact of OVX becomes insignificant, therefore hypothesis regarding the simultaneous impact of equity and oil market uncertainty is not supported. This might indicate possible signaling effect, where uncertainty flows from U.S. stock markets to global oil markets. U.S. is one of the leading economies in the globe, and effects from macroeconomic and financial events might spread uncertainty into other markets, through contagion effect. This is consistent with Liu et al. (2013), which show that uncertainty flows from U.S. stock markets to oil markets.

It is important to consider that all research related to hedge fund must be treated with sufficient cautious. Due to the limited reporting obligations of the hedge funds, the hedge funds databases may contain a number of biases that may distort the obtained research results, and thus substantially change the conclusions drawn from the results. The biases are explained in more detail in chapter 3. Changes in the investment strategy or investment style of individual hedge fund is typical, which may also cause potential inconsistencies and distortions in research results. Also, hedge fund data is usually available on the monthly basis, which limits the amount of observations dramatically and compared to daily observations may smooth the large variations in returns, caused by extreme market events. Conflicting research results may also be due to the dataset used in the particular research. The returns of individual hedge funds and hedge fund indices can vary widely in relation to each other, so the choice of research data has a significant impact on the research results particularly in a case of hedge funds.

Hedge funds offer an interesting option for asset allocation, yet the results show that their exposure to equity and oil market uncertainty tend to be very similar compared to U.S. equity markets. However, results of this thesis still help to understand more deeply the relationship between uncertainty and hedge funds, as well as the risk characteristics of hedge funds in different market conditions. Uncertainty of the financial markets has grown its popularity among academic research, and for future research, it would be relevant to study the features of uncertainty more closely. Amount of volatility based indices has grown over the past years, and for instance, the studies focusing on uncertainty of European equity market is quite scarce. Also, future research could focus to examine the effects of ongoing COVID-19 pandemic on cross-market uncertainty to gain better understanding from the effects of uncertainty surrounding the financial markets.

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APPENDICES

APPENDIX 1. Description for hedge fund strategies

Equity Market Neutral: Strategy aims to generate market-neutral returns, regardless of the prevailing market conditions, by taking simultaneous long/short positions in equity portfolios.

Event Driven: Strategy aims to exploit anticipated corporate events, such as merges, acquisitions, spin-offs, liquidations and bankruptcies.

Global Macro: Strategy aims to generate returns by exploiting political trends and global macroeconomic events.

Long/Short Equity: Strategy is based on taking simultaneous long and short positions, typically focusing on specific markets or sectors.

Managed Futures: Also known as commodity trading advisors, CTAs, strategy invest in financial and commodity futures.

(Source: Ackerman et al. 1999; Peltomäki 2007)

APPENDIX 2. Correlation matrices for VIX, OVX, hedge fund indices and S&P500

10/2007-11/2011	VIX	OVX	Total Index	Market Neutral	Event Driven	Global Macro	Long/Short	Managed Futures	S&P500
VIX	1.00								
OVX	0.76	1.00							
Total Index	-0.71	-0.56	1.00						
Market Neutral	-0.11	-0.18	0.40	1.00					
Event Driven	-0.73	-0.58	0.93	0.32	1.00				
Global Macro	-0.39	-0.31	0.67	0.02	0.49	1.00			
Long/Short	-0.73	-0.50	0.93	0.21	0.91	0.55	1.00		
Managed Futures	-0.04	-0.03	0.20	-0.07	0.12	0.51	0.14	1.00	
S&P500	-0.65	-0.43	0.75	0.31	0.75	0.29	0.82	-0.10	1.00

12/2011/01/2020	VIX	OVX	Total Index	Market Neutral	Event Driven	Global Macro	Long/Short	Managed Futures	S&P500
VIX	1.00								
OVX	0.4	1.00							
Total Index	-0.56	-0.36	1.00						
Market Neutral	-0.12	-0.25	0.35	1.00					
Event Driven	-0.57	-0.43	0.84	0.23	1.00				
Global Macro	-0.37	-0.18	0.77	0.09	0.52	1.00			
Long/Short	-0.52	-0.32	0.88	0.44	0.78	0.49	1.00		
Managed Futures	-0.09	0.05	0.45	0.03	0.01	0.54	0.19	1.00	
S&P500	-0.63	-0.30	0.74	0.18	0.72	0.47	0.81	0.13	1.00