Louvain School of Management

The evolution of hedge fund performance using artificial intelligence in their processes over the past decade.

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Abstract

In a world where technology is supposed to bring us solutions and performance, hedge funds did not miss the opportunity of the arrival of artificial intelligence a decade ago to improve their processes and hopefully their performance. The literature on the subject is quite recent and only a few studies go into the subject in depth. This thesis objective is to answer the following question: "How has the performance and hedging ability of AI-based hedge funds evolved relative to the market over the past decade?"

The methodology developed to answer this question consists of running performance analyses (risk-adjusted ratios, maximum drawdown) and a DCC-GARCH process to assess the conditional correlation between the market and the hedge funds using artificial intelligence. The results show impressive risk-adjusted performances relative to the market before the COVID-19 crisis, but mixed results since then.

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Contents

List of Figures

List of Tables

1 Introduction

In an ever-changing world, technology has always managed to help us in a meaningful way by providing effective solutions. Whether in agriculture, medicine, mechanics, or finance, technology has always allowed us to go beyond the limits of performance and results. What almost always allows us to go beyond is what we call innovation. Innovation is defined by the Oxford Learner's Dictionaries as "the introduction of new things, ideas or ways of doing something".

Despite the creative and beneficial aspect it brings to our society, innovation also has a dark side. Regardless of the involved sector, it has been demonstrated and scientifically proven that innovation has a destructive side; time and time again, in different ways and with different consequences, innovation has caused harm to our society (Coad, Nightingale, Stilgoe & Vezzani, 2020).

The latest and most famous in the field of finance is undoubtedly securitisation[1], which played a key role in the 2008 Global Financial Crisis (Bailey et al, 2008; Eggert, 2009). Some studies attempt to clarify the position of shadow banking, and the direct impact of securitization operations before the 2008 financial crisis (Lysandrou & Nesvetailova, 2014; Farhi & Antonio Macedo Cintra, 2009). In a more general study, Leaven (2014) associates shadow banking with ”lethal” innovations in which less regulated financial institutions could, among other things, excessively increase leverage and contribute to systemic risk, and endanger the entire financial system by putting intermediaries at risk.

In the aftermath of the crisis, the global economy on the one hand, is beginning to rise from the ashes in search of growth, supported by governments. On the other hand, the hedge fund industry, which represents a significant part of the so-called "shadow banking", has been severely hit. Due to the lack of transparency in hedge funds, the discovery of the Madoff fraud, and the global financial crisis, investors have lost confidence in hedge funds. In addition, new regulations from governments and international financial institutions do not help either. For example, the Volker Rule prohibited U.S. banks from participating in hedge fund operations. Shadow banking lacks investment alternatives and desperately needs innovation (Fischer, 2020).

The struggle will continue until 2014 when signs of recovery begin to appear. That year, the number of funds climbed higher than before the crisis. That same year, 76 billion dollars in new capital flowed into hedge funds, the highest amount since 2007. Despite an air of renewed confidence in the sector, a thorn remained in the side of hedge funds:

[1] Securitisation refers to a method of packaging loans to make securities out of it and to sell them to investors. Before 2008, this method was believed to be foolproof. After the Global Financial Crisis, low regulations and the abuse of securitisation by financial institutions played a significant role in the GFC (European Commission).

performance. The newcomers in finance, exchange-traded funds (ETFs) and index funds are giving hedge funds a hard time. The latter posted modest returns of 3% on average, while the S&P500 returned 15% at the same time (Raghavan, 2015).

Recently, we have started to hear about artificial intelligence and its virtues in terms of performance for some hedge funds. Some studies show that funds using these new technologies perform very well; regardless of the strategy employed, the higher the level of automation within the hedge fund's branches, the better the results (Niang, 2021; Wu et al., 2020).

Although previous studies covering the analysis of the different existing strategies employed by hedge funds, the study of strategies including artificial intelligence is rather incomplete. Only a few articles cover the performance and volatility of these AI-based funds. This article helps to answer the following question: "How has the performance and hedging ability of AI-based hedge funds evolved relative to the market over the past decade?" We find it interesting to study this question because the activity of AI and machine learning-driven hedge funds is gaining importance and can be considered a strategy in its own right (Niang & Fabian, 2021).

In this article, we will study the performance of hedge funds using artificial intelligence over the last ten years. The performance analysis will gather the Sharpe ratio, the information ratio, the Sortino ratio, and maximum drawdown. In addition, we will study their hedging capacity via a volatility analysis by a DCC-GARCH process, we will use the S&P500 index as a reference. Next, we will try to better understand how the conditional correlation extracted from the DCC can be explained by macroeconomic variables. These variables are US GDP growth, crude oil price, industrial production index, default, and credit spread.

The first chapter will present a review of the literature on the different themes of the study. The second chapter will specify the data used for the analysis and their sources. The third chapter will develop the method used to conduct the analysis. The fourth chapter will gather the empirical results. Finally, the fifth chapter will present the conclusion and limitations of the study.

2 Literature Review

2.1 Theoretical Background

Ordinary Least Square

In statistics, ordinary least squares (OLS) is one of the most common techniques used for for estimating unknown parameters in multivariate analysis. The method OLS recognizes the possible occurrence of errors in the relationship between dependent and explanatory variables (Chumney and Simpson, 2005).

Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) describes the relationship between the systematic risk and the expected return of assets, particularly stocks. The CAPM is widely used in finance to value risky securities and generate expected asset returns based on the risk of those assets and the cost of capital (W. Kenton, 2022). The CAPM equation is as follows.

$$ER_i = R_f + \beta_i(ER_m - R_f) \tag{1}$$

Where:

- ER_i = expected return of the investment
- R_f = risk-free rate
- β_i = beta of the investment
- $(ER_m - R_f)$ = market risk premium

The CAPM introduces important elements that will be used throughout this thesis. To begin, the risk-free rate is the rate of return of a risk free investment. In general, we use the U.S. Treasury bill rate, from the same period as the one studied, to represent the risk-free rate. Next, the beta of an investment represents the volatility of returns relative to the market, we will extend this further. Finally, the expected return represents the profit or loss that can be anticipated on an investment.

Value at Risk (VaR)

Holton (2014) defined Value at Risk (VaR) as measures supposed to indicate an amount of money with a probability that the portfolio will not lose more than that amount of money over that period. Then, losses above VaR are committed only with a low probability of occurrence.

There are three main ways to calculate VaR: the first is the historical method, which looks at an individual's past returns and ranks them in descending order of losses and gains. The second is the variance-covariance method. Rather than assuming that the past informs the future, this method assumes that gains and losses are normally distributed. The third method is a Monte Carlo simulation. This technique uses computer models to simulate expected returns over hundreds or thousands of possible iterations.

2.2 About Hedge Funds

According to Heje Pedersen (2015), hedge funds are investment vehicles that apply a variety of complex trading strategies to make money. The word ”hedge” refers to the reduction of market risk by investing in both long and short positions, and the word ”fund” refers to a pool of money contributed by the manager and investors.

An important particularity of hedge funds is that they are less regulated than other investment companies such as mutual funds. They have a lot of freedom in their operations, but in return, they are limited in how they raise money. To be accepted as an investor in hedge funds, you must be an "accredited investor" which means that you have enough financial wealth, probably to be able to face important losses without major consequences...

Their low level of regulation is also the reason for the term "shadow banking", which is a term for all financial institutions that raise short-term funds via the money market to buy long-term assets. The reason for the term "shadow" is that, because they are not regulated like traditional banks, they cannot borrow money "in extremis" from central banks in an emergency, unlike their traditional counterparts (International Monetary Fund, 2013).

The first hedge fund is believed to have appeared in 1949, using long-short positions in the money market, and is known to gain a 670% return between 1955 and 1965 (R. Levy, 2016). Since, hedge funds have grown in number and size, having millions of dollars under management and, together, assembling 2 trillion dollars before the Global Financial Crisis in 2008.

2.3 Hedge Funds and Artificial Intelligence

Since their first appearance on the market, hedge funds have sought to create value. The advent of new technologies has brought about innovations in many fields and businesses. The English Oxford Living Dictionary defines artificial intelligence as "the theory and development of computer systems capable of performing tasks that normally require human intelligence, such as visual perception, speech recognition, decision making, and translation between languages." The birth of artificial intelligence in hedge funds occurred around 2015 and brought with it a new wave of innovation. Satarino and Kumar (2017) trace the early development of artificial intelligence in a hedge fund, Man Group Plc.

After the initial positive feedback, the executive members of the fund still couldn't explain (to their client) what their development team had created. No one understood the strategies employed by the AI, not even the developers; the tool was a complete black box. But the results were promising and in 2014, Dr. Nick Granger, a mathematical logic major, took it out to test it. In other words, the AI was coming out of the simulation to perform in real markets and trade real money. Results: "It withstood everything we threw at it," Granger told Satarino and Kumar. Before long, AI was responsible for half the profits of one of the largest human funds.

Soon, artificial intelligence was used to execute transactions, make bets, and analyze press releases and financial reports. Almost every human service is looking for opportunities to use AI, and customers have begun to appreciate it. Over time, consideration of AI has shifted from skepticism to enthusiasm and encouragement. Man Group will go so far as to partner with Oxford University to collaborate on the development of AI to match it with financial stakes, a deal worth 14 million dollars.

As a result, returns are high and, more importantly, investors are regaining confidence, especially in technology. According to the authors, "computer-driven quantitative funds were the only part of the hedge fund industry that made progress [in 2016]." At the time, many other funds were leveraging AI, such as Two Sigma, Bridgewater Associates, and Point72.

However, the outstanding results provided by AI are not easy to achieve. For AI to work properly, you will first need a large number of state-of-the-art servers stored in a protected, cooled location. Then you will need a group of talented programmers and mathematicians to design the AI. Then you'll need the support of experienced traders and managers. Finally, and perhaps most importantly, you will need data. The data will be the memory of the AI, which will use every event stored in the database as a learning source. To do this, you will need data analysts to sort, section, and organize the database so that the AI can look for patterns and apply them in real life. Today, hedge funds with the highest level of automation outperform those with more manual control. (Grobys et al, 2022; Niang, Fabian, 2021).

2.4 Performance Analysis of Hedge Funds

The analysis of trading performance begins with alpha and beta. The former represents excess return after accounting for performance due to market movements and the latter represents market exposure, or in other words, the tendency to follow the market. Many hedge funds claim to be market neutral, meaning that their returns are not correlated to market movements and that their beta would theoretically be zero. Alpha and beta can be found via a regression, as shown in the following equation.

$$R_i^e = \alpha + \beta R_t^{m,e} + \varepsilon_t \tag{2}$$

Where:

- R_i^e = excess return of the security or portfolio
- α = return of the security or portfolio adjuted for market-related volatility
- β = measure of the volatility of the security or portfolio relative to the market
- $R_t^{m,e}$ = expected excess return
- ε_t = idiosyncratic risk[2]

In this hypothesis, by considering only the alpha value, we cannot conclude whether the performance is relevant or not. Simply because it does not take into account the amount of risk taken. The risk-reward ratios answer this issue.

Sharpe Ratio

The first ratio that will be used in this study is the Sharpe ratio. Also known as the risk-adjusted ratio, the Sharpe ratio is a method of evaluating the performance of a portfolio in a mean-variance framework. Sharpe ratio is the expected excess return over the expected standard deviation.

$$SR = E(R - R^f)/\sigma(R - R^f) \tag{3}$$

Where:

- SR = Sharpe ratio
- R = return of the security or portfolio
- R^f = risk-free rate (usually mean return on U.S. Treasury bills)
- E(R-R^f) = expected excess return
- σ(R-R^f) = standard deviation of excess return

[2] Idiosyncratic risk is a risk specific to a particular investment, as opposed to systemic risk, which affects all investments in a given asset class (Corporate Finance Institute).

The use of the Sharpe ratio is justified by the assumption that the distribution of portfolio returns is stable over time so that historical returns have predictive value for future performance. Levy (1972) showed that the Sharpe ratio cannot be interpreted independently of the investment horizon. Which means that the practical application of the Sharpe ratio would only be valid if the expected investment horizon is equal to the holding period of the returns used to calculate the ratio. A Sharpe ratio calculated using short return intervals (monthly, quarterly, annual) to evaluate portfolios or make asset allocation decisions will be biased for long-term investors and may lead to suboptimal results[3].

Despite the shortcomings of the original version of the Sharpe ratio, it remains one of the most widely used performance tools for portfolio evaluation. There are a variety of adjusted and modified Sharpe ratios, but in this thesis, we will stick to the original version.

Information Ratio

To overcome the shortcomings of the Sharpe ratio and to provide this study with more evidence on the evolution of performance over time, we will use other ratios. The next is the information ratio. Pedersen (2015) states that this ratio focuses on alpha and adjusts for risk translated by the standard deviation of idiosyncratic risk. Both terms come from regressing the hedge fund's excess return against a benchmark (see equation 2).

$$IR = \alpha/\sigma(\varepsilon) \tag{4}$$

Where:

- IR = Information Ratio
- $\sigma(\varepsilon)$ = standard deviation of idiosyncratic risk

When compared to a benchmark, the information ratio can be calculated as follows:

$$IR = E(R - R^b)/\sigma(R - R^b) \tag{5}$$

Where:

- IR = Information Ratio
- R^b = return of the benchmark
- E(R-R^b) = expected abnormal return

[3] According to the work of Levy (1972), popularized in the work of C. W. Hodges et al. (1997).

- σ(R-R^b) = standard deviation of abnormal return

In this case, the information ratio measures the strategy's ability to beat the benchmark, by looking at the difference between the returns of the strategy and the benchmark. The fifth equation is the one we will use.

In his study, Goodwin (1998) argues that the information ratio is "the best single measure of the mean-variance characteristics of an active portfolio." According to the author, the challenge is to choose the right benchmark that matches the investor's strategy. In this case, since there is only one index in our portfolio, there is no risk of misallocation among the different assets in the portfolio.

Sortino Ratio

The third and final ratio used in this thesis is the Sortino ratio. Pedersen (2015) describes it as a modified risk-adjusted return on capital (RAROC):

$$RAROC = E(R - R^f)/K_e \tag{6}$$

Where:

- RAROC = risk-adjusted return on capital
- K_e = Economic capital

Economic capital, the amount of cash needed to meet the most severe losses, takes into account the risk of a crash. Economic capital can be estimated by the value at risk, for example. In Sortino's ratio, we use what we call the downside risk as the denominator. The downside risk is the portion of the standard deviation reduced to some minimum acceptable return (MAR). The MAR is often set at the risk-free rate or zero, so the downside risk is the standard deviation taken that is below the MAR.

$$S = E(R - R^f)/\sigma^{downside} \tag{7}$$

Where:

- S = Sortino ratio
- $\sigma^{downside}$ = standard deviation above the MAR

The Sortino ratio gives another way to measure the performance of a portfolio or asset. As discussed by Srivastava and Mazhar (2018), along with the Sharpe ratio, IR should be used to compare different assets with each other or asset(s) with a benchmark because we cannot give much credibility to the ratio alone. They also concluded that IR is a strong tool to compare the performance of assets.

Maximum Drawdown

The last part of the performance analysis is the maximum drawdown (MDD), which is an important risk measure for hedge fund strategies. The first step is to calculate the cumulative returns, simply by adding up the returns over time. The curve created will show the general trend of the asset or portfolio. The next step is to identify the high water marks (HWM). The HWM measures the highest cumulative return it achieved in the past. Finally, the drawdown can be calculated.

Pedersen (2015) calculates the drawdown as follows, where the maximum drawdown is the largest loss experienced during the period under consideration.

$$DD_t = (HWM_t - P_t)/HWM_t \tag{8}$$

Where:

- DD_t = Drawdown
- HWM_t = high water mark
- P_t = expected abnormal return
- σ(R-R^b) = standard deviation of abnormal return

2.5 Volatility-Based Analysis

The Economic Times defines volatility as the rate at which the price of a security rises or falls for a given set of returns. The measure of volatility is the standard deviation. In CAPM, beta is the measure of the volatility of a portfolio or asset relative to the overall market. A beta greater than one suggests that the asset has greater volatility than the market, either negatively or positively, and vice versa.

As mentioned earlier, hedge funds often claim to be market neutral, i.e., have a beta equal to 0. According to Pedersen (2015), in reality, this does not happen often. Hedge funds are correlated with the equity market and so is their volatility. Depending on the fund's strategies, the beta may vary over time. One way to assess this evolution is to look at the joint volatility between two assets. Therefore, we will use a DCC GARCH process. We want to see how the correlation between the volatility of the market (i.e. the S&P500) and the volatility of the hedge funds using AI evolves.

DCC-GARCH Process

The GARCH (Generalized Autoregressive Conditional heteroskedasticity) process was developed by Robert F. Engel in 1982. This process describes an approach for estimating volatility in financial markets. Today, there are many variants of this model.

This process is called heteroscedastic because it assumes that the variation of the error term is irregular, as opposed to ordinary least squares (OLS) which assumes that volatility is constant (homoscedastic). Therefore, with the GARCH process, the observations do not conform to a linear model as is the case for asset returns. Indeed, the volatility of asset returns seems to vary over certain periods and depends on the past variance, hence the interest in heteroscedastic models such as GARCH.

By depending on past observations and past variances to model the current variance, the GARCH process is said to be autoregressive. This model makes this process very interesting for financial predictions and analysis because of its effectiveness in modeling asset returns and inflation. Financial markets' volatility can fluctuate, becoming higher during times of financial crises or major international events and lower during times of comparatively stable and steady economic growth, that can be described into GARCH models.

In this paper, we will focus on one of the latest versions of GARCH model introduced by Engle (2002), the dynamic conditional correlation (DCC) GARCH process. The interest in the DCC class of models is given by the fact that it calculates the correlation between asset returns based on their past volatility and the correlations between them (Acatrinei et al, 2013). The model will be specified in detail in the next chapter.

Linear Regression

From the DCC GARCH process, we can extract the dynamic conditional correlation of two assets, or in this case, a benchmark and an index. Then, the idea is to test if macroeconomic variables can explain the correlation between these two and to do this, we will use multiple linear regression.

Multiple linear regression is frequently used in the literature to explain variation in the response variable that is related to variance in the explanatory variables. Therefore, linear regression can be used to express that there is no association at all or to measure the strength of the relationship between the explanatory variables and the dependent variable. The following equation presents the most common way to write a multiple linear regression with k explanatory variables.

$$y = B_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \tag{9}$$

Where:

- y = dependent variable
- B_0 = intercept
- β_i = independent variables
- x_i = coefficients to predict
- ε = error term

In this case, the explanatory variables will be macroeconomic factors, developed in the next section.

2.6 Macroeconomic Factors

This section will consist of a quick review of the existing literature on macroeconomic factors in relation to the stock market in the first case and to hedge funds in the second. This review will allow the selection of the factors to be analyzed in this study. Subsequently, the selected factors will be examined in more detail.

It is widely known, and numerous studies have proven that macroeconomic factors influence and are influenced by stock and bond markets. Although their importance and magnitude may vary from country to country and stock market to stock market, shocks in these factors can impact price movements, returns, and volatility (Flannery & Protopapadakis, 2002; Hardouvelis, 1987; Oseni & Nwosa, 2011).

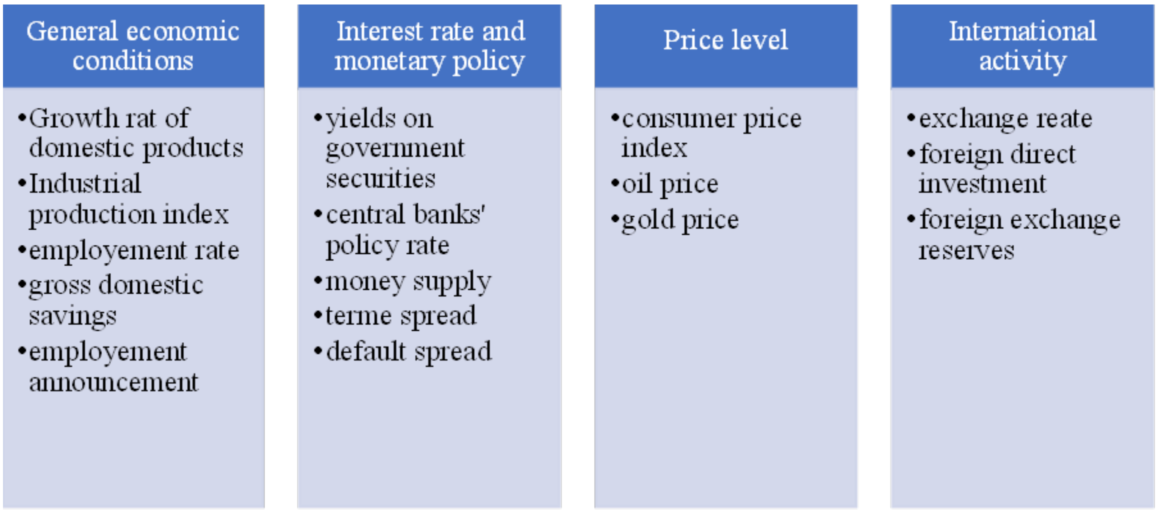

Figure 1: Categories of macroeconomic factors with examples.

Many macroeconomic variables have been studied in the literature. Tangjitprom (2012) reviewed the different macroeconomic factors used to perform the statistical tests. In figure 1, examples of the variable are identified, and grouped into four different categories, according to the author.

Hedge Funds and Macro Factors

Numerous published studies have shown that hedge fund performance is influenced by many types of risk factors, depending on the strategies on which the fund focuses. Macroeconomic factors are often studied to explain hedge fund performance or the volatility of hedge fund performance.

Turan G. Bali et al (2014) used as macroeconomic risk factors. inflation rate based on the U.S. consumer price index, excess return on the value-weighted NYSE/Amex/Nasdaq equity market index, relative T-bill rate defined as the difference between the 3-month and 12-month T-bill rate, the spread between 10-year and 3-month T-bill yields, and the monthly U.S. unemployment rate (Turan G. Bali et al, 2014, p.5).

Lambert and Platania (2020) identified four macroeconomic risk factors: the SP 500 monthly return index, the Small-minus-Big index calculated as the difference in monthly returns between the Russell 2000 and Russell 1000 indexes, the High-minus-Low index calculated as the difference in monthly returns between the Russell 1000 Value and Russell 1000 Growth indexes, and the yield on Moody's Baa corporate bonds relative to the yield on constant-maturity 10-year Treasury bonds.

The results of their studies reveals that macroeconomic factors play an important role in predicting hedge funds returns, despite variations of their impact in the simulation as a function of the length of the period studied.

2.6.1 Selected Factors

To avoid being too specific, the factors chosen will reflect different facets of the economy. The first factors included are the growth rates of the gross domestic product of the United States and the industrial production index, which will be used as indicators of general economic conditions. Second, the price of crude oil will be used as an indicator of the price level. Finally, the spread between default rates and interest rates will be used as an indicator of financial conditions. All of these factors represent three[4] of the four groups previously determined by Tangjitprom (2012).

[4] We did not choose to represent the fourth group, international activity, because we considered it was not relevant with the analyzed assets of the study.

U.S. GDP Growth

The first factor is gross domestic product growth. It is a famous macroeconomic factor among volatility and performance studies as independent and control variable. The results of M. H. Masoud (2013) suggest that there is a positive relationship between efficient markets and economic growth. Jareno and Negrut (2016) show a positive relationship between US GDP growth and the Dow Jones index that was used to represent the market. Karunanayake et al (2012) showed the existence of co-volatility between the U.S. GDP growth rate and its stock market, although the co-volatility is greater between stock markets than with GDP growth.

Crude Oil Price

Today, despite the desire for change due to environmental issues, oil remains an important fuel for our economy, this is why we will use crude oil price as the next factor. Although it varies by country and sector, its impact on the economy is certain. It is known to directly increase inflation and reduce economic growth (Federal Reserve Bank of San Francisco). Currently, the world is experiencing its impact due to the war in Ukraine. The punishment that Europe and Russia are facing, especially regarding the delivery and payment of fossil fuels from Russia, is putting upward pressure on inflation and downward pressure on global activity (Federal Reserve).

In addition, the literature on the link between speculators (including hedge funds) and oil prices is well supplied. Buyuksahin, H. Harris (2011) and Yue-Jun, Wu, and Yao-Bin (2019) suggest that hedge fund activity has a Granger relationship with oil price position. The latter study also suggests that hedge funds play an important role in the formation of oil bubbles, including the 2008 bubble.

Industrial Production Index

The industry is one of the three major sectors of an economy, along with agriculture and services. Thousands of people work in industry and manufacturing, providing a huge amount of employment and industrial output. An increase in industrial production, both domestic and export, is a sign of a strengthening economy. Central banks monitor industrial production and pay attention to inflation through supply flows (Yahoo Finance).

Whether industrial production has an impact on the stock market has been the subject of several studies, with different results. N. Subeniotis et al (2011) based on the work of Gultekin (1983), Fama (1981), Homa and Jaffee (1971), describe the study on this area as still an "open question" because the empirical results of the analyzed studies do not define a definitive and significant relationship.

Concerning Hedge Funds, Racicot & Théoret (2015) shows that an increase in industrial production growth rates leads to heterogeneous strategy returns; strategies react differently to the growing movement in industrial production. They state that "the impact of the conditional variance of industrial production on the cross-sectional dispersion of returns is far from negligible."

Default Spread

"The default spread as defined in this paper is a theoretical measure of the default component of the credit spread" (Delianedis Geske, 2001). The default spread is generally used to reflect the overall probability of default of firms. For example, during the COVID-19 pandemic, firms' earnings outlooks were downgraded increasing default spreads. Figure 2 shows the impact of the pandemic on default spreads in the U.S., U.K., and E.U..

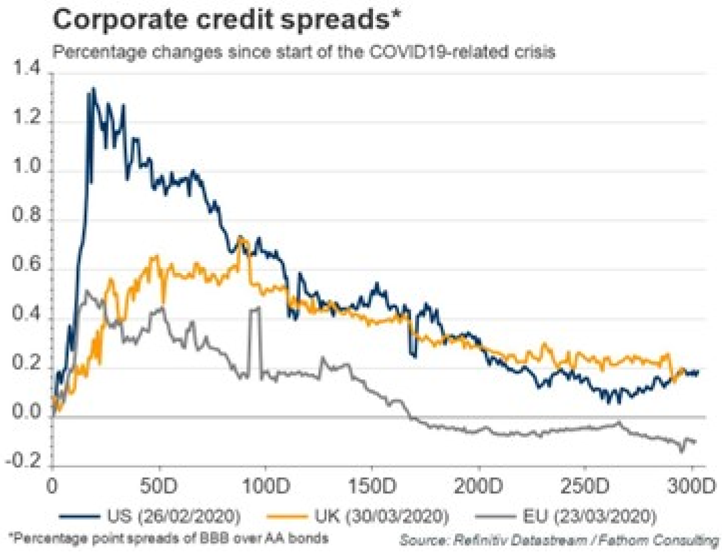

Figure 2: Impact of the pandemic on default spreads in the U.S., U.K. and EU..

More generally, the default spread is defined as the yield resulting from the difference between long-term BAA corporate bonds and long-term AAA bonds or U.S. Treasury bonds. Studies such as Fama and Schwert (1977), Campbell (1987), and Keim and Stambaugh (1986) suggest that the default spread as just defined can predict expected returns on stocks and bonds. Surprisingly, Elton et al (2001) show that the default spread is 85% explained by systematic risk, which is not related to default (Vassalou and Xing, 2002).

Depending on the position of the equity market, i.e. the S&P500 index, the dynamic risk exposure of hedge funds changes. Especially in bad economic times, it is common to use the credit spread as a risk factor. In times of uncertainty, rising BAA bond yields and increased demand for AAA bonds together lead to widening credit spreads. Coupled with funding liquidity risk shocks, an increase in the credit spread will lead to increased spreads, deleveraging, and margin calls. Ultimately, this generates losses and may even cause hedge funds to collapse (Billio et al., 2010).

Term Spread

The credit spread can be defined as the difference between the interest rates on short-term and long-term government securities (Federal Reserve Bank of New York). Along with the default spread, it is generally used as an indicator of business cycles. A negative value for the credit spread would mean that short-term bonds have higher interest rates than long-term bonds.

In addition, in the article by Dale L. Domian; William Reichenstein (1998), the authors examined that, in conjunction with other variables, the credit spread is known to predict long-term corporate bond and stock returns, several studies show. Amenc et al. (2003), Brealey and Kaplanis (2001), and Kat and Miffre (2002) suggest using the default spread and the credit spread to measure hedge fund market exposure.

3 Data Description

In this section, we will specify the data used to perform the performance analysis on the one hand, and the volatility analysis on the other. Each data set contains monthly data, starting in January 2010 and ending in March 2022, covering exactly eleven years and one quarter.

3.1 Performance Analysis

The first part of the analysis will require the returns of the Standard and Poor's 500 Index and the Eurekahedge AI Hedge Fund Index. Then, to make the analysis possible, we will need the risk-free rate to calculate the excess returns. For this purpose, we will use the 10-year Treasury bill rate as provided by the Federal Reserve Bank of St. Louis, USA.

- Eurekahedge AI Hedge Fund Index:
  - Unit: index starting in December 2009 at 100. Transformed to get the monthly return in percentage.
  - Source: Eurekahedge.
  - Link: `https://www.eurekahedge.com/Indices/IndexView/Eurekahedge/683/Eurekahedge-AI-Hedge-fund-Index`
- S&P500 index:
  - Unit: index data gathered from January 2010 to March 2022. The returns got from closing prices, in monthly percentages.
  - Source: Yahoo Finance.
  - Link: `https://finance.yahoo.com/quote/%5EGSPC/`
- Ten-year T-bill rate:
  - Unit: percentage, from January 2010 to March 2022.
  - Source: Federal Reserve Bank of St. Louis, USA.
  - Link: `https://fred.stlouisfed.org/series/DGS10/`

3.2 Volatility-Based Analysis

To run the Dynamic Conditional Correlation Generalized Auto-Regressive Heteroscedasticity (DCC-GARCH) model, we will use the returns of the Eurekahedge AI Hedge Fund index analyzed against the returns of the Standard and Poor 500 index as described above. Then, the macroeconomic variables used in the linear regression are described as follows.

- U.S. GDP growth rate:
  - Unit: Index transformed to have monthly growth for the ten past years.[5]
  - Source: Federal Reserve Bank of St. Louis.
  - Link: https://fred.stlouisfed.org/series/USALORSGPTDSTSAM
- Crude Oil Price:
  - Unit: index's financial information transformed to have monthly returns[5].
  - Source: Yahoo Finance.
  - Link: https://finance.yahoo.com/quote/CL%3DF/history?period1=1247443200&period2=1657670400&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true
- Industrial Production Index:
  - Unit: index where 2017 is the reference year (=100), transformed to get monthly returns[5].
  - Source: Federal Reserve Bank of St. Louis.
  - Link: https://fred.stlouisfed.org/series/INDPRO
- Default Spread:
  - Unit: Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity in monthly percentage.
  - Source: Federal Reserve Bank of St. Louis, USA.
  - Link: https://fred.stlouisfed.org/series/BAA10Y
- Term Spread:
  - Unit: 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity in monthly percentage.
  - Source: Federal Reserve Bank of St. Louis, USA.
  - Link: https://fred.stlouisfed.org/series/T10Y2YM

As control variables, we will add the CBOE Volatility Index (VIX) and the US Consumer Price Index.

- VIX:

[5] Returns/growth rate computed the following way: $(x_t - x_{t-1})/x_{t-1}$

  - Unit: index monthly value over the period of January 2010 to March 2022[5].
  - Source: Yahoo finance.
  - Link: https://finance.yahoo.com/quote/%5EVIX/
- U.S. Consumer Price Index:
  - Unit: monthly percentage over the period of January 2010 to March 2022.
  - Source: U.S. Bureau of Labor Statistics.
  - Link: https://www.rateinflation.com/consumer-price-index/usa-historical-cpi/

4 Methodology

In this chapter, we will establish which models will be used to analyze the data and why we chose them. The methodology is separated into two sections, the performance analysis which focuses on returns, and the volatility analysis which focuses on correlated volatility using a DCC-GARCH model, extended later.

First, regarding performance, we will base our analysis on the work of Lasse Heje Pedersen, a prominent academic but also an asset manager, who wrote a book named "Efficiently Inefficient" in 2015. The analysis performed during this study will bring together the ratios and techniques described in Chapter Two: "Evaluating Trading Strategies: Performance Measures". The ratios used here will be the Sharpe ratio, the Sortino ratio, and the Information ratio. These ratios will cover a two-year interval, i.e. from 2010/2011 to 2020/2021, to be able to observe the evolution of hedge fund performance over time. Two other techniques will also be used: cumulative returns and maximum drawdown.

Second, concerning volatility, we will use a DCC-GARCH model to analyze the conditional correlation between our benchmark, the SP500, and the hedge funds using artificial intelligence using the Eurekahedge index described in the previous chapter. After, we will run a linear regression on the conditional correlation with the macro variables to see if we can find a relevant relationship that would explain the correlation.

4.1 Unit Root Test

Stationarity appears in econometrics in what is called a stochastic process. Commonly called a random process, a stochastic process refers to the property of being well described by a random probability distribution (Adler Taylor, 2009). In this process, stationarity means that the statistical properties of a time series do not change over time. In other words, the mean and variance of the series do not vary over time; the values change but not the way they change. Several different notions of stationarity have been proposed in the econometric literature, but we will not go into detail here.

This concept is all the more important because, in financial analysis, market time series tend to be non-stationary, many studies tackle the issue (Mikosch and Starica, 2004; Granger, Starica 2004). The problem caused by the non-stationarity of time series is that the analyses we would make of them would be spurious, hence the name spurious regression or spuriousness. We can try to convert a non-stationary stochastic process into a stationary one by manipulating the time series or the portfolio.

To solve this problem, we will run an augmented Dicker-Fuller test (ADF) that tests the null hypothesis of the presence of a unit root (non-stationarity) in an autoregressive time series, where the term "augmented" refers to an extension that removes autocorrelation from the series. The original test was developed by Dickey and Fuller in 1979. We will run the test on all our variables.

Augmented Dickey-Fuller Test Results			
Data	**Dickey-Fuller value**	**Lag order**	**P-value**
U.S. GDP growth rate	-6,529300	5	<0,01
Industrial Production Index	-5,440300	5	<0,01
Crude Oil Price	-5,251100	5	<0,01
Term Spread	-4,003100	5	0,01105
Default Spread	-2,993100	5	0,1628
Consumer Price Index	-4.296700	5	<0,01
CBOE Volatility Index (VIX)	-6,960100	5	<0,01

Table 1: Augmented Dickey-Fuller Test Results.

The results shown in table 1 suggest that we can reject the null hypothesis that a unit root is present in all but two of our variables, the default and term spread. To correct the series, we will use the differentiation method. This method consists of subtracting from each observation the value of the previous period. We will switch to a second-order differentiation to reject the null hypothesis of the ADF test, as table 2 shows.

Augmented Dickey-Fuller Test Results			
Data	**Dickey-Fuller value**	**Lag order**	**P-value**
Term Spread*	-6.942100	5	<0.01
Default Spread*	-8.631700	5	<0.01

* Second-order differencing applied

Table 2: Augmented Dickey-Fuller Test Results After Differencing.

Now that we are guaranteed that our time series does not have a unit root, we can safely proceed with the method. The last step is to define which input corresponds to which data series.

- The risk-free rate (Rf) is represented by the ten-year U.S. T-bill rate.
- The return of the index (R), returns obtained via the Eurekahedge AI Hedge Fund Index.
- The return of the benchmark (Rb), returns obtained via the S&P500 index.

4.2 Performance Analysis

To evaluate the performance of hedge funds using artificial intelligence, we will first compare their returns with a benchmark. In this case, we would like to analyze their returns with those offered by the market, the S&P500. We would like to know if investing in this type of hedge fund would have been a reliable and valid alternative from 2010 to 2022, in terms of performance. To answer this question, we conducted four analyses directly from Pedersen's book and the existing literature.

Sharpe Ratio

The Sharpe ratio used in this study is formulated and computed as in the following equation.

$$SR = E(R - R^f)/\sigma(R - R^f) \tag{10}$$

Where:

- R = the returns of the index
- R^f = the risk-free rate
- E(R-R^f) = the expected excess returns
- σ(R-R^f) = the standard deviation of excess returns

Information Ratio

The Information ratio used in this study is formulated and computed as in the following equation.

$$IR = E(R - R^b)/\sigma(R - R^b) \tag{11}$$

Where:

- IR = Information Ratio
- R^b = return of the benchmark
- E(R-R^b) = expected abnormal return
- σ(R-R^b) = standard deviation of abnormal return

Sortino Ratio

The Sortino ratio used in this study is formulated and computed as in the following equation. The minimum acceptable return is set at 0%.

$$S = E(R - R^f)/\sigma^{downside} \tag{12}$$

Where:

- S = Sortino ratio
- E(R-R^f) = the expected excess returns
- $\sigma^{downside}$ = standard deviation above the MAR

Maximum Drawdown

As discussed in the literature review, the first step is to calculate the cumulative returns. For this purpose, we will use the excess returns of the Eurekahedge AI Hedge Fund Index and the S&P500 Index. Then, using RStudio, we calculate the maximum drawdown as a single value for both the index and the market, but we will also generate a table tracing the evolution of the drawdown for the whole period.

4.3 Volatility-Based Analysis

DCC-GARCH Process

In volatility analysis, it is common to use GARCH models. GARCH stands for generalized autoregressive conditional heteroskedasticity. The GARCH process was developed by economist Robert F. Engle in 1982 to analyze volatility in financial markets. As explained in section 2, we will perform a DCC GARCH that we will extend here[6].

The estimation of Engle's DCC-GARCH model consists of two steps. The first is the estimation of the univariate GARCH model and the second is the estimation of time-varying conditional correlations. As follows, the multivariate DCC-GARCH model.

$$X_t = \mu_t + H_t^{1/2}\varepsilon_t \tag{13}$$

$$\begin{cases} H_t = D_t R_t D_t \\ R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \\ D_t = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, ..., \sqrt{h_{NN,t}} \end{cases} \tag{14}$$

Where,

- $X_t = (X_{1t}, X_{2t}, ..., X_{nt})$ is the vector of the past observations
- H_t, the multivariate conditional variance
- $\mu_t = (\mu_{1t}, \mu_{2t}, ..., \mu_{Nt})$, the vectore of conditional returns

[6] Via Talbi & Halima (2019) and A. P. Thomaidou (2018).

- $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt})$, the vector of the standardized residuals
- R_t, a NxN symmetric dynamix correlations matrix
- D_t, a diagonal matrix of conditional standard deviations for return series. It is obtained from estimating a univariate GARCH process with $\sqrt{h_{hii,t}}$ on the ith diagonal, $i = 1, 2, ..., N$

Then, the DCC specification is defined as follows.

$$Q_t = (1 - \psi - \zeta)\bar{Q} + \zeta Q_{t-1} + \zeta \delta_{i,t-1}\delta_{j,t-1} \tag{15}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{16}$$

Where,

- $(Q_t) = [q_{ij,t}]$ is (NxN), time varying covariance matrix of standardized residuals $(\delta_i t = \varepsilon_{it}/\sqrt{h_{it}})$
- $\bar{Q}$, the unconditional correlations of $\delta_{i,t}\delta_{j,t}$
- ψ and ζ, non-negative scalar parameters that satisfies $\psi + \zeta\langle 1. Q_t^* = [q_i^* i, t] = [\sqrt{q_{ii,t}}]$
- $[\sqrt{q_{ii,t}}]$, a diagonal matrix with the square root of the i^{th} diagonal element of Qt on its i^{th} diagonal position,

Thus, for a pair of markets i and j, their conditional correlation at time t can be defined as follows:

$$\rho_{ij,t} = \frac{(1 - \psi - \zeta)\bar{q}_{ij} + \psi \delta_{i,t-1}\delta_{j,t-1} + \zeta q_{ij,t-1}}{[(1 - \psi - \zeta)\bar{q}_{ii} + \psi \delta_{i,t-1}^2 + \zeta q_{ii,t-1}]^{1/2}[(1 - \psi - \zeta)\bar{q}_{jj} + \psi \delta_{j,t-1}^2 + \zeta q_{jj,t-1}]^{1/2}} \tag{17}$$

Where,

- q_{ij} is the element on the i^{th} line and j^{th} column of the matrix Q_t

Bollerslev et al. (1992) introduced the quasi-maximum likelyhood method (QMLE) that will be used to estimate the parameters. Eventually, assuming estimators are noramlly distributed, the log-likelihood of the estimators is computed as follows.

$$L(\nu) = -\frac{1}{2}\Sigma_{t=1}^{T}[(nlog(2\pi) + log|D_t|^2 + \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t) + (log|R_t| + \delta_t' R_t^{-1} \delta_t - \delta_t' \delta_t] \quad (18)$$

Where,

- n, the number of equations
- T, the number of observations
- ν, the vector of parameters to be estimated

The analysis will concern the hedge funds using artificial intelligence and the S&P500. We will run this process in Rstudio thanks to the packages "rugarch" which allows us to get the conditional correlations to finally perform the regression.

Linear Regression

In studies involving statistical tests, linear regression is amongst the most common tools for establishing a potential correlation between a dependent variable and independent variables; control variables are often used to improve the robustness of results. The variables used in this model are the following.

$$Y = B + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon \quad (19)$$

Where, the dependent variable:

- Y = conditional correlation extracted from the DCC-GARCH process

The explanatory variables:

- X_1 = U.S. GDP growth rate
- X_2 = Industrial Production Index
- X_3 = Crude Oil Price
- X_4 = Term spread (after the second order differencing)
- X_5 = Default spread (after the second order differencing)

The control variables:

- X_6 = Consumer Price Index
- X_7 = CBOE Volatility Index (VIX)

5 Empirical Results

This section will provide the empirical result in direct analysis of the results obtained after running the extended tests in the methodology. We will start with the three ratios and the maximum drawdown and end with the GARCH process and the regression.

5.1 Performance Analysis

Sharpe Ratio

The Sharpe ratio measures the amount of return per unit of risk. This performance measure alone is not reliable enough as the interpretation of the value may differ depending on the risk aversion profile of the manager or the type of strategy it is supposed to measure. This is why we used it to compare risk-return ratio of hedge funds using the AI relative to the market, i.e. the SP500. Therefore, we will not only look at the value itself but also at its evolution over time.

As we can see in table 3, on the one hand, from 2010 to 2015, hedge funds had a clear advantage over the SP500 in terms of risk-adjusted returns. During the periods 2010 to 2011 and 2014 to 2015, hedge funds outperformed the market by more than ten times. This is an early indicator of the impressive returns that AI-driven hedge funds could deliver.

In contrast, over the last three periods, the trend reverses. From 2016 through the end of 2021, the market appears to be performing better than the funds in terms of risk-adjusted returns. Especially during the 2018 to 2019 period, when the global economy collapsed, we see that hedge funds are now four times worse than the market when the market is already at almost minus one. In the aftermath of the crisis, hedge funds are still below the market, but the sector has come a long way compared to the S&P500.

Period	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021
SR (p=95%)						
HF using AI	3.8642	1.9577	4.3257	0.5608	-4.1040	0.6465
S&P500	0.3004	2.1182	0.4276	0.9401	-0.9075	0.9144

Table 3: Comparison of results of Sharpe ratios (SR) for each 2-years period from 2010 to 2021 for hedge funds using AI and the S&P500.

Information Ratio

The information ratio measures how well a portfolio or strategy beats the benchmark per unit of tracking error risk. The tracking error is the difference between the returns of the portfolio or strategy and those of the benchmark, and the risk is its standard deviation.

Looking at table 4, the evolution is in favor of the market. Indeed, although the first period from 2010 to 2011 looks good for hedge funds, it seems to change rapidly over time. The ratio starts to decline substantially in 2016-2017 and continues to decline until 2020-2021. Interestingly, unlike the Sharpe ratio which seems to show a recovery for hedge funds using AI between 2019 and 2021, the Information ratio does not and continues to drag it down.

Period	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021
Tracking Error	0.0579	0.0265	0.0291	0.0271	0.0338	0.0447
Annualised T.E.	0.2005	0.0919	0.1006	0.094	0.1172	0.1548
IR	1.379	-1.444	0.8934	-0.5128	-0.6187	-0.9049

Table 4: Results of the Information ratios for each 2-years period from 2010 to 2021 for hedge funds using AI relative to the S&P500.

Sortino Ratio

Finally, the last ratio used in this study is the Sortino ratio, which also takes excess return in its numerator but, instead of the classical standard deviation like the Sharpe ratio, the denominator only takes into account the downside risk, beyond a certain minimum accepted return (MAR). In this case, we set the MAR at 0%.

The idea behind this ratio is that investors are mostly concerned with downside risk. As we can see in table 5, the results are not the same as those of the Sharpe ratio. Indeed, the periods of bad and good performance of hedge funds coincide, but in this case, hedge funds seem to perform even better. In the first and third periods, 2010-2011 and 2014-2015, hedge funds performed more than 40 and 50 times better than the market, respectively.

Subsequently, in the last three periods, the performance of hedge funds using AI is much lower than the previous periods but not that much different than the market performance, compared to the Sharpe ratio. The last period showing that the two performances are almost identical despite a larger difference is the period from 2018 to 2019.

Period	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021
Sortino (0%)						
HF using AI	8.0201	1.0683	9.9807	0.3073	-0.8038	0.3240
S&P500	0.1754	1.0299	0.2314	0.4939	-0.2824	0.4347

Table 5: Comparison of results of Sortino ratios at MAR = 0% for each 2-years period from 2010 to 2021 for hedge funds using AI and the S&P500.

Despite slight differences in the interpretation of the results of the three ratios, we can distinguish three main periods for hedge funds using AI performance. The first one takes place before the financial crisis, from 2010-2010 to 2014-2015, when returns are high and the risk is low. The second starts in 2016-2017 and ends in 2018-2019. This period is marked by poor performance for both hedge funds and the market, with the COVID-19 crisis certainly being most of the cause. The third period is the post-crisis period, where the resurgence of risk-adjusted performance is nuanced from one ratio to another.

Maximum Drawdown

The drawdown is the amount lost since the last peak in returns. Looking at the drawdown is interesting in that it gives an idea of recent losses and overall growth in returns. The maximum drawdown is the largest loss during the period under study.

When we look at the maximum drawdown faced by hedge funds using AI and the market, we see that the loss, as a percentage of cumulative returns, is huge. Amounts fall 43.77% for hedge funds versus 44.61% for the S&P500 from mid-2017 to early 2020. Hedge funds, in the words of Pedersen (2015) often face large losses when a crisis is due to systemic risk. In this case, the loss is indeed large, but not much larger than the market.

Two interesting insights emerge from the charts in appendix 3. The first is that hedge funds using AI outperformed the market almost literally twice as much through 2017. This is consistent with recent findings that hedge funds using AI in their processes are performing very well. Another remarkable feature that stands out in this chart is the slide to a loss of 43.77% in two and a half years.

The second idea concerns recovery. The ratio analysis showed us nuanced results on the performance that occurs after the COVID-19 crisis. In these charts, we can see where this is coming from. The market has almost reached its last best post-crisis cumulative performance at the end of 2021. On the contrary, hedge funds are struggling to regain their previous position, which was almost 100% higher.

The average growth of hedge funds coupled with the rapid growth of the market in terms of cumulative returns explains the results we obtained from the ratios in the last identified period (2020-2021). The Sharpe ratio, taking into account all standard deviations, shows a positive value for hedge funds but is effectively lower than the market as we can see in Table 3. The information ratio, comparing the two evolutions, will naturally show values in favor of the market given their growth in terms of cumulative return. Finally, the Sortino ratio shows two almost identical values because, even if the market rises faster and higher, the curve is more volatile than the one for hedge funds, hence the decrease of the difference.

5.2 Volatility-Based Analysis

DCC-GARCH Process

As we have seen before, a DCC GARCH process is often used to analyze the joint volatility of two assets, an asset and a benchmark, etc. The idea is to test how hedge funds using AI and the S&P500 are correlated and how it evolve over time. The results of the DCC-GARCH process are shown in appendix .1.

We can see that not all constants are significant, which could imply that our sample is not sufficiently large. Anyway, to be able to validate the results, we look at the alpha and beta ("joint dcca1" and "joint dccb" respectively) and see if their joint value is equal to one. The alpha being equal to 0.041 and beta equal to 0.942, we can consider the correlation robust. The former is statistically significant at the 95% confidence interval and the latter at 99%.

In general, to be able to validate the results, we look at the alpha and beta ("joint dcca1" and "joint dccb" respectively) and see if their joint value is equal to one. The alpha being equal to 0.041 and beta equal to 0.942, we can consider the correlation robust.

Once the results are obtained, we can extract the conditional correlation, shown in figure 3 next page. In the previous section, via ratios and maximum drawdown analysis, we identified three main periods of activity.

During the first main period, from 2010 to 2015, the conditional correlation increases until 40%. An interesting observation would be that during the same period, although both the market and hedge funds using AI experienced increasing returns, the correlation only reaches 40% maximum, and only between 2012 and 2016. This suggests that the correlation between the two assets increases when returns are high.

During the second major period identified through the ratio analyses, from 2016 to 2019, the correlation is very low, at only 20% from 2016 to 2018. Looking at the cumulative returns shown previously, we see that both slopes are stagnating as they begin to decline over the next few years, but the S&P500 slope appears to be much more volatile, which would explain the low correlation during this short period.

Then, from 2018 to 2019, the conditional correlation begins to rise, peaking in 2020 at about 60% correlation. The shark's teeth observed in the slope of the correlation between 2018 and 2020 can be explained by the downward resistance that the S&P500 curve seems to exhibit when looking at the maximum drawdown chart, resulting in significantly uncorrelated short phases.

Finally, during the recovery phase identified earlier, from 2020 to 2021, the conditional correlation remains at around 60% and does not appear to show a significant downward turn. Ratio analyses can help to understand this behavior. The combination of high volatility in hedge funds and market returns, coupled with their different growth patterns, may be behind this high correlation.

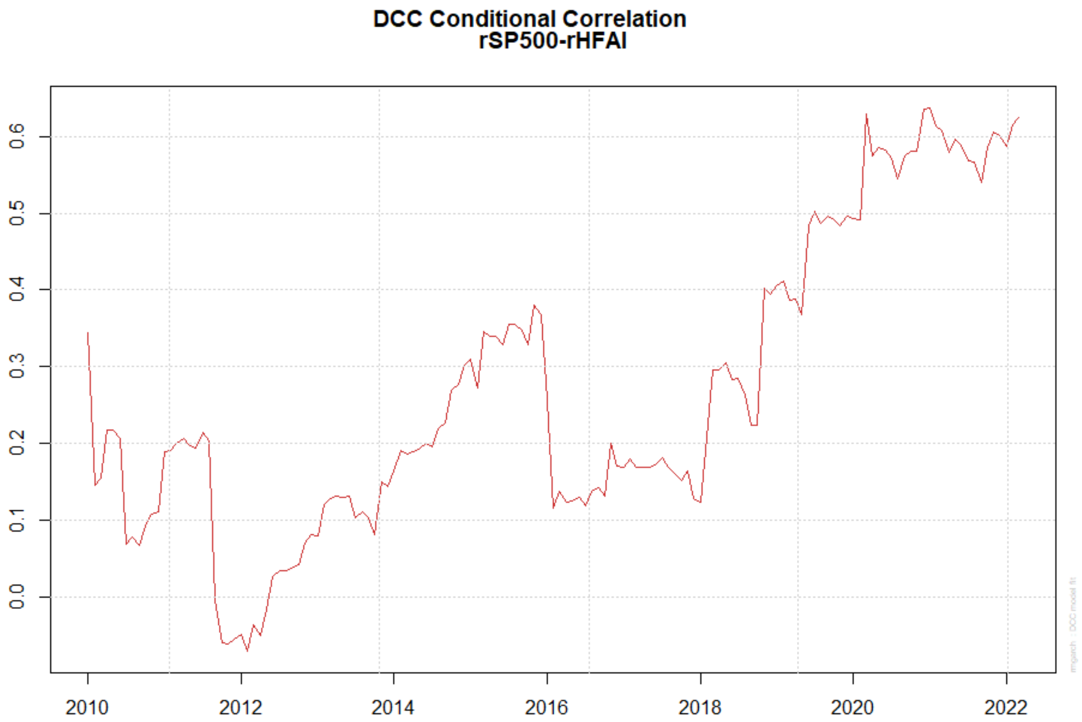

Figure 3: Conditional correlation between the returns of hedge funs using AI and the S&P500 from 2010 to 2022.

In general, the conditional correlation remains quite low, with a maximum of 60% after the COVID-19 crisis. However, it is interesting to observe how the correlation changes between 2018 and early 2022. The high correlation cannot be explained by the high returns of hedge funds, as we could interpret between 2012 and 2016. On the contrary, hedge funds using AI seem to struggle to regain their growth, especially if we look at the maximum drawdown curve which remains very low compared to the market, even though their cumulative return is not that different (around 0.8 for hedge funds and 1 for the market).

Linear Regression

In this last section, we test whether macroeconomic variables can explain the conditional correlation curve. It has been shown in many studies that macroeconomic factors have an impact on hedge fund returns as seen in section 2.6. While the topic is not yet well documented for hedge funds using AI, through this short analysis, we seek to gain additional insight into the behavior of the conditional correlation curve [7].

As a reminder, the independent variables are the US GDP growth rate, the industrial production index, the crude oil price, the credit spread and the default spread (antipenultimate and latter after second order differentiation). Then, the control variables are the consumer price index and the CBOE volatility index (VIX).

Looking at the overall statistics of the regression results in appendix .2, it appears that the model is quite weak, significant at the 95% confidence interval (P-value = 0.02484) and a fairly low F-statistic (2.383). Moreover, the model does not seem to explain much of the dependent variable, if we consider the adjusted R-squared value, which is only 6.26%.

Subsequently, the macroeconomic factors are virtually all irrelevant. The only factors that seem to have a relationship with the curve are the default spread and the term spread. The former with a 99% confidence interval and the latter with a 90% confidence interval. In both cases, an increase in the value of the factor would imply an increase in the conditional correlation.

Thus, an increase in the default spread, meaning that the overall default risk of firms is increasing, as in a crisis, tends to increase the conditional correlation studied here. intuitively, if companies start to have difficulties, the market and those who invest in these companies will feel the impact.

Finally, the relationship between the term spread and the conditional correlation could mean that good economic times would increase the conditional correlation between hedge fund returns and the market. This is consistent with what we have analyzed via the ratios and the maximum drawdown, especially during the 2012-2015 period.

[7] We performed an Augmented Dickey-Fuller test to the conditional correlation vector that came out from DCC GARCH and we could not reject the null hypothesis stating there was a unit root. We solved the issue with differencing, second order. See the results appendix 8.

6 Conclusion

The objective of this study was to evaluate the performance of hedge funds using artificial intelligence relative to the market, over the past ten years. This study is particularly interesting because of the artificial intelligence emergence in our daily and professional lives. The literature has already begun to address the issue by analyzing the performance of hedge funds using AI when this thesis was written[8].

This study contributes to a better understanding of the performance of hedge funds using AI over the last ten years. We used three risk-adjusted performance ratios (Sharpe, Information, and Sortino ratios), maximum drawdown, a DCC-GARCH process, and the linear regression correlation analysis. All these methods have given us the necessary tools to answer our research question.

From the extraordinary results of 2010 to 2016 to the mixed recovery after the COVID-19 crisis, managers working in hedge funds branches using AI must have had a hectic life over the past decade. From the results, we can say that in good times, hedge funds using AI have historically performed almost twice as well as the market, accumulating almost twice the market's returns in 2016 and having better ratings from 2010 to 2016.

Then things changed with the advent of the COVID-19 crisis, which seems to have wiped out half of the pre-trained returns in previous years. More than that, the current global economic and political situation that has persisted since the end of the COVID-19 crisis seems to continue to impact hedge funds returns, which are struggling to reconcile with their post-crisis performance. So much so that at the beginning of 2022 and for the first time on record for hedge funds using artificial intelligence, their cumulative excess returns were lower than the market.

Finally, despite their young age in the business sphere, hedge funds using artificial intelligence are performing impressively. Unfortunately, the COVID-19 crisis put an end to this, and then political tensions replaced it with uncertainty. Nevertheless, cumulative returns of the last months have shown positive growth. Hopefully, the current political and military tensions will fade away and hedge funds will catch up with their impressive performance.

Let's not forget the major crisis that is climate change. People are starting to change their consumption habits, governments are taking steps to reduce carbon emissions, investors are starting to look for "green" performance, etc. All this will most certainly change markets behaviors in ways never seen before. This could be one of the biggest challenges that artificial intelligence could face since no historical data could prepare them for it.

[8] See the paper of Grobys et al. (2022), "Man versus machine: on artificial intelligence and hedge funds performance", published in April of this year.

Limitations

Although we have used many different methods to conduct our analysis, and no matter how carefully we have developed our method and conclusions, we must be aware that our analysis will always have limits.

The first one is what we call ”backfill bias". This bias reflects the fact that poorly performing hedge funds are less likely to share their performance information, which may never appear in the database we used to conduct our research. Another common problem is that there is no comprehensive database for hedge funds. Companies can share the data they like and keep the data they don’t like. For instance, to conduct this study, we entirely relied on the database of Eurekahedge and trust them with their databases and index.

The second limitation is the content of the Eurekahedge database. We claim to analyze hedge funds using artificial intelligence in their processes, but the database does not only provide the branches of the firms that use only AI. Therefore, there is included in the database a part of the companies that do not use artificial intelligence to achieve their results. The level of automation is not specified either in the database, which may alter the returns, as we have seen in the literature.

The third limitation is that we compared the performance of hedge funds to the market. Few strategies aim at beating the market directly. Some will focus on certain types of securities and comparing them to the market would not make sense. We still perform the analysis because the use of artificial intelligence does not seem to be used in a single type of strategy, but internal processes specific to companies, or branches of companies. Their results are therefore not to be attributed to a single type of strategy, except that of using such technology in their process.

The last limitation concerns the available literature on the subject, only a few articles exist and even less are available to the public.

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Appendices

.1 DCC GARCH Results

DCC GARCH Fit

Distribution	mvnorm
Model	DCC(1,1)
No.Parameters	13
[VARGARCHDCCUncQ]	[0+10+2+1]
No.Series	2
No.Obs.	147
Log-Likelihood	6942011
Av.Log-Likelihood	4.72

Optimal Parameters

Coeficient	Estimate	Std. Error	t value	Pr(>t)
[HFAI].mu	0.008329	0.001230	6.77136	0.000000
[HFAI].ar1	0.120029	0.109917	1.09200	0.274834
[HFAI].omega	0.000009	0.000017	0.51366	0.607493
[HFAI].alpha1	0.130861	0.114192	1.14598	0.251805
[HFAI].beta1	0.830552	0.032218	25.77892	0.000000
[SP500].mu	0.010442	0.002898	3.60371	0.000314
[SP500].ar1	-0.177369	0.085465	-2.07535	0.037954
[SP500].omega	0.000446	0.000383	1.16550	0.243816
[SP500].alpha1	0.306992	0.134387	2.28439	0.022349
[SP500].beta1	0.412347	0.304816	1.35277	0.176128
[Joint]dcca1	0.041277	0.019952	2.06887	0.038558
[Joint]dccb1	0.942180	0.028895	32.60649	0.000000

Information Criteria

Akaike	-9.2680
Bayes	-9.0036
Shibata	-9.2821
Hannan-Quinn	-9.1606

Table 6: DCC-GARCH process results between hedge funds using AI (HFAI) and S&P500 (SP500).

.2 Multiple linear regression results

	Model 1
(Intercept)	0.00
	(0.01)
U.S. GDP Growth	−0.02
	(0.08)
Industrial Production Index	0.40
	(0.38)
Crude Oil	−0.01
	(0.05)
Term Spread	0.06
	(0.03)
Default Spread	0.07^{**}
	(0.03)
CBOE VIX Index	−0.03
	(0.02)
Consumer Price Index	0.76
	(1.60)
R^2	0.11
Adj. R^2	0.06
Num. obs.	146

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $p < 0.10$

$F - statistic : 2.383$ on 7 and 138 DF; $p - value : 0.02484$

Table 7: Multiple linear regression results of macroeconomic variables on the conditional correlation.

.3 Comparison of cumulative returns and of drawdown of hedge funds using AI index and S&P500

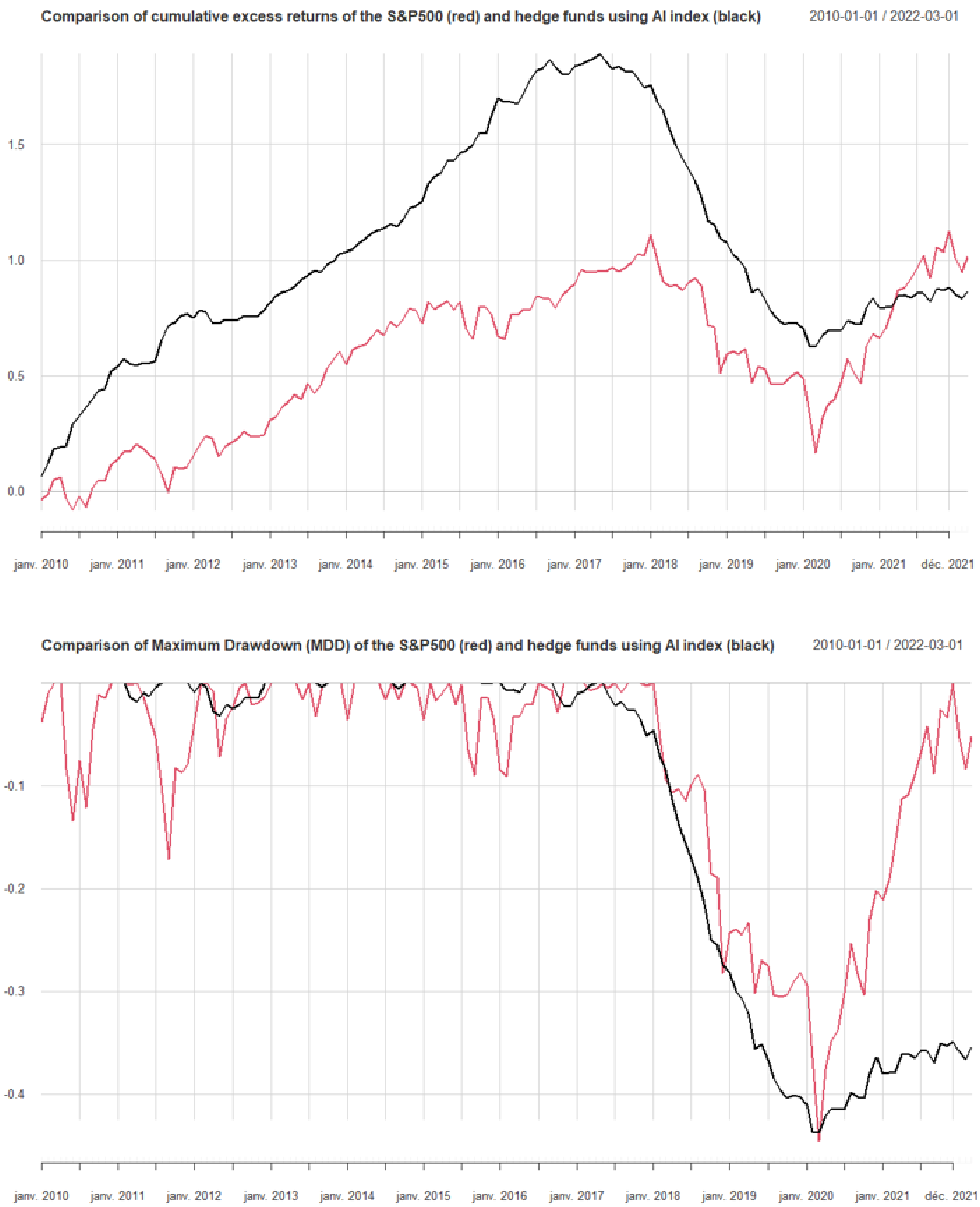

Figure 4: Comparison of cumulative returns (above) and of drawdown (below) of hedge funds using AI index and S&P500.

.4 Results of the Augmented Dickey-Fuller test on the conditional correlation obtained from the DCC GARCH process.

Augmented Dickey-Fuller Test Results			
Data	**Dickey-Fuller value**	**Lag order**	**P-value**
Conditional Corr	-2.7617	5	0,2592
Conditional Corr*	-9.2907	5	$<$0,01

* Second-order differencing applied

Table 8: Augmented Dickey-Fuller Test Results on conditional correlation.