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Prediction of Hedge Funds Strategies Returns using Tree regression model and Combination of forecasts method.

By

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ΣΧΟΛΗ ΕΠΙΣΤΗΜΩΝ & ΤΕΧΝΟΛΟΓΙΑΣ ΤΗΣ ΠΛΗΡΟΦΟΡΙΑΣ

ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ

ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ

Πρόβλεψη απόδοσης στρατηγικών για κεφάλαια αντιστάθμισης κινδύνου με tree regression μοντέλο και combination of forecasts μέθοδο.

Ελευθερία – Δάφνη Ιωάννου Ταμπίζηβα

ΔΙΑΤΡΙΒΗ

Που υποβλήθηκε στο Τμήμα Στατιστικής

του Οικονομικού Πανεπιστημίου Αθηνών

ως μέρος των απαιτήσεων για την απόκτηση

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ABSTRACT

The purpose of this thesis is to make out-of-sample predictions for hedge funds strategies returns, for 24 months after the 1st of February in 2006. For making these predictions we use two different methods. The first one is the combination of forecast method and the second one is the tree regression model. In both methods we create two complementary subsets from the initial dataset, the in-sample and out-of-sample datasets, with out-of-sample sub-dataset containing the last 24 observations of the data.

Combination of forecasts is a method where practically we combine the forecast of 14 individual predictive models each one built by one of the 14 explanatory indices in our dataset. For each of the 14 models we generate out-of-sample forecasts by using an expanding window which is continuously updated by adding one observation to the estimation sample at each step and then repeating the process until no more observations have left. Finally, we combine the forecasts we get by calculating the mean of the forecasted values to get the final forecast of the return of the hedge funds strategies.

By tree regression model we build the tree predictive model by using the in-sample dataset and then we use the model to make the predictions with the values in the out-of-sample dataset.

Finally, after obtaining the 24 forecasted returns from both methods we use the MSE performance measure in order to compare the results from the two methods and discuss whether one of them is more suitable, for predicting the returns of the hedge funds, than the other.

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Περίληψη

Σκοπός αυτής της εργασίας είναι να κάνει προβλέψεις για τις αποδόσεις των κεφαλαίων αντιστάθμισης κινδύνου, για 24 μήνες μετά την 1η Φεβρουαρίου του 2006. Για την πραγματοποίηση αυτών των προβλέψεων χρησιμοποιούμε δύο διαφορετικές μεθόδους. Πρώτη είναι η μέθοδος combination of forecasts και η δεύτερη είναι τα δέντρα-tree regression models-. Και στις δύο μεθόδους δημιουργούμε δύο συμπληρωματικά υποσύνολα από το αρχικό σύνολο δεδομένων, τα in-sampleκαι out-of-sampleδείγματα, με το out-of-sampleδείγμα να περιέχει τις τελευταίες, σε χρονολογική σειρά, 24 παρατηρήσεις των δεδομένων.

Το combination forecasts είναι μια μέθοδος στην οποία συνδυάζουμε στην πράξη την πρόβλεψη 14 μεμονωμένων προγνωστικών μοντέλων, κάθε ένα εκ των οποίων έχει κατασκευαστεί από έναν από τους 14 επεξηγηματικούς δείκτες που υπάρχουν στα δεδομένα μας. Για κάθε ένα από τα 14 μοντέλα παράγουμε προβλέψεις χρησιμοποιώντας ένα αναπτυσσόμενο παράθυρο το οποίο ενημερώνεται συνεχώς προσθέτοντας μία παρατήρηση στο δείγμα εκτίμησης σε κάθε βήμα και στη συνέχεια επαναλαμβάνεται η ίδια διαδικασία για όλες τις out-of-sample παρατηρήσεις. Τέλος, συνδυάζουμε τις προβλέψεις, υπολογίζοντας τον μέσο όρο των προβλεπόμενων τιμών της παραπάνω διαδικασίας, για να πάρουμε την τελική πρόβλεψη της απόδοσης των κεφαλαίων αντιστάθμισης κινδύνου.

Με το tree regression μοντέλο χτίζουμε ουσιαστικά ένα μοντέλο παλινδρόμησης στη μορφή δέντρου. Το δέντρο αναπτύσσεται βασιζόμενο στο in-sampleδείγμα δεδομένων και στη συνέχεια, αφού χτιστεί το δέντρο, τοεφαρμόζουμε στο out-of-sampleδείγμαπου περιέχει τόσες παρατηρήσεις όσες και οι προβλέψεις που θέλουμε να κάνουμε για τις αποδόσεις.

Τέλος, αφού λάβουμε τις 24 προβλέψεις των αποδόσεων και από τις δύο μεθόδους, χρησιμοποιούμε το μέτρο MSE για να συγκρίνουμε τα αποτελέσματα από τις δύο μεθόδους και να συζητήσουμε κατά πόσο και ποια από τις δύο μεθόδους είναι καταλληλότερη για την πρόβλεψη των αποδόσεων των κεφαλαίων αντιστάθμισης κινδύνου.

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Chapter 1: Introduction

When the first hedge fund was constructed by Alfred W. Jones in 1949by short sales in order to protect his portfolio against the decreasing share prices and by using leverage for increasing the performance of the portfolio, people couldn't have thought that these kind of funds would have been a matter of discussion in the decades to come. While someone considering hedge funds nowadays, either thinks of their huge growth in administrated capital or their incredible excess returns as well as their financial power and their influence to companies (Kuhn and Muske, 2007).

In practice, hedge funds are privately-owned companies that take money from investors and reinvest them into other financial products. Their main purpose is to outperform the market, by a lot. The investors have to be smart enough in order to create high returns no matter how the market does. They have to be able to afford the high minimum pay-ins, the higher-than-average compensations of fund managers and have to bear additional contract rules. Those additional rules usually force investors to keep their capital in the fund until a specified time in the future, before they get the allowance to terminate their investment in the fund. Therefore, mainly big institutional as well as wealthy private investors are privileged to access HFs and to profit from their performance (Kuhn and Muske, 2007).

In our data we have hedge funds strategies for which we want to forecast returns in order to examine their performance for 24 months after the 1st of February 2006. The highest the return is for the strategy the better its performance. In order to make these predictions we used two different methods, combination of forecasts and tree regression, and then we measured their predictive performance in order to compare the results of the two methods and see whether the one of them outperforms the other and with which one we get better results.

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Chapter 2: Literature Review for Hedge Funds Strategies

2.1. Hedge funds and how they work

2.1.1 Hedge Funds

With a number of 6000 funds managing about $400 billion in capital, hedge funds have yield great attention in the last years in both financial and academic world (Capocci 2007). These hedge funds that exist for about 50 years may not have been legally defined, but they do have some common characteristics that describe them. These are that all hedge funds use a broad range of instruments like short selling, derivatives, leverage or arbitrage in different markets (Capocci 2007). As mentioned in (https://www.thestreet.com/personal-finance/education/what-is-a-hedge-fund) a hedge fund is in practice an investment pool consisted by a small number of partners (investors) and operated by a professional manager having as primary goal to maximize returns and minimize risk. Because of their nature, hedge funds are open not only in institution or companies but also in individual investors with connections to the manager, with sometimes even managers themselves are the investors. The structure of the investment is created typically in two ways: One as a limited partnership and two as a limited liability company. The first one is a structure wherein the only liability the partners have is for the amount of money they personally invest, while the second is a corporate structure where investors do not have individual responsibility for the company's liabilities.

In spite of the structure, the hedge fund is operated by a manager who, in order to achieve the fund's goals, invests the money into different assets. For different types of hedge funds, we have different goals. For instance, if a fund invests in "long only" equities then it only buys common stock and not selling short. But all hedge funds have a common goal which is to make money regardless of how the market goes. Considering all the aforementioned we can say that managers is something like traders and that hedge funds have many different kinds of structures with different assets and securities.

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2.1.2 How do they work

The basic structure of a hedge fund is an investment or partnership pool where a fund manager invests in different securities and equities in such a way that can match with the fund's goals. Hedge fund managers recommend a strategy to investors, and those who buy in expect the manager to stick to said strategy. This strategy can either be a hedge fund that is only long or short on all their stocks, or a hedge fund that specializes in a specific kind of investment that can range from common stock to patents.

However, a peculiarity of hedge funds is that in the majority of times are available only to “accredited investors” or investors with large financial resources. As Anne Sraders mentions, (https://www.thestreet.com/personal-finance/education/what-is-a-hedge-fund-14662109) an investor is considered as "accredited," he or she must have one of the following qualifications: A very high personal annual income ($200,000or more for example in USA), a very big net (over $1 million), a higher-up (executive, director, etc.) involved in the hedge fund, or an employee benefit plan or trust fund at least $5 million (made before investing).

2.2. Hedge Funds Strategies

Investors of Hedge Funds have as primary purpose to maximize returns from their investments as we mentioned before. In order to achieve that, they need to understand how funds operate and the amount of risk investors take when they buy in to these financial products. There are several strategies that investors can follow in order to achieve their financial goals. Below we present a table with the basic and most common strategies/types of Hedge Funds.

Table 2.2.1:Hedge Funds Strategies

Long/Short Equity	Convertible Arbitrage	Fixed-Income Arbitrage
Market Neutral	Event Driven	Global Macro
Merger Arbitrage	Credit	Short Only

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2.2.1 Definitions of Hedge Fund Strategies

Below we present the definitions of Hedge funds Strategies that they also consist the target variables in our dataset to which we will refer to in next chapters. The definitions below were derived from (HFR Hedge Fund Strategy Classification System).

Equity Hedge: Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. Equity Hedge managers would typically maintain at least 50% exposure to, and may in some cases be entirely invested in, equities - both long and short. Equity Hedge is further subdivided into 7 sub-strategies.

Equity Market Neutral: Equity Market Neutral strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and leverage is frequently employed to enhance the return profile of the positions identified. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Equity Market Neutral Strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

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Quantitative Directional: Quantitative Directional strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. Statistical Arbitrage/Trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies which may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Quantitative Directional Strategies typically maintain varying levels of net long or short equity market exposure over various market cycles.

Short Bias: Short-Biased strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. Short Biased strategies may vary the investment level or the level of short exposure over market cycles, but the primary distinguishing characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets. Investment theses may be fundamental or technical and nature and manager has a particular focus, above that of a market generalist, on identification of overvalued companies and would expect to maintain a net short equity position over various market cycles.

Event Driven: Investment Managers who maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including but not limited to mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. Event Driven exposure includes a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the

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realization of the thesis predicated on a specific development exogenous to the existing capital structure.

Credit Arbitrage: Credit Arbitrage Strategies employ an investment process designed to isolate attractive opportunities in corporate fixed income securities; these include both senior and subordinated claims as well as bank debt and other outstanding obligations, structuring positions with little or no broad credit market exposure. These may also contain a limited exposure to government, sovereign, equity, convertible or other obligations but the focus of the strategy is primarily on fixed corporate obligations and other securities are held as component of positions within these structures. Managers typically employ fundamental credit analysis to evaluate the likelihood of an improvement in the issuer's creditworthiness, in most cases securities trade in liquid markets and managers are only infrequently or indirectly involved with company management.Fixed Income Corporate strategies differ from Event Driven Credit Arbitrage in that the former more typically involve more general market hedges which may vary in the degree to which they limit fixed income market exposure, while the latter typically involve arbitrage positions with little or no net credit market exposure, but are predicated on specific, anticipated idiosyncratic developments.

Distressed Restructuring: Distressed Restructuring Strategies which employ an investment process focused on corporate fixed income instruments, primarily on corporate credit instruments of companies trading at significant discounts to their value at issuance or obliged (par value) at maturity as a result of either formal bankruptcy proceeding or financial market perception of near term proceedings. Managers are typically actively involved with the management of these companies, frequently involved on creditors' committees in negotiating the exchange of securities for alternative obligations, either swaps of debt, equity or hybrid securities. Managers employ fundamental credit processes focused on valuation and asset coverage of securities of distressed firms; in most cases portfolio exposures are concentrated in instruments which are publicly traded, in some cases actively and in others under reduced liquidity but in general for which a reasonable public market exists. In contrast to Special Situations, Distressed Strategies employ primarily debt (greater than 60%) but also may maintain related equity exposure.

Merger Arbitrage: Merger Arbitrage strategies which employ an investment process primarily focused on opportunities in equity and equity related instruments of

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companies which are currently engaged in a corporate transaction. Merger Arbitrage involves primarily announced transactions, typically with limited or no exposure to situations which pre-, post-date or situations in which no formal announcement is expected to occur. Opportunities are frequently presented in cross border, collared and international transactions which incorporate multiple geographic regulatory institutions, with typically involve minimal exposure to corporate credits. Merger Arbitrage strategies typically have over 75% of positions in announced transactions over a given market cycle.

Private Issue/Regulation: Private Issue/Regulation D strategies which employ an investment process primarily focused on opportunities in equity and equity related instruments of companies which are primarily private and illiquid in nature. These most frequently involve realizing an investment premium for holding private obligations or securities for which a reasonably liquid market does not readily exist until such time as a catalyst such as new security issuance or emergence from bankruptcy proceedings occurs. Managers employ fundamental valuation processes focused on asset coverage of securities of issuer firms, and would expect over a given market cycle to maintain greater than 50% of the portfolio in private securities, including Reg D or PIPE transactions.

Multi-Strategy: Multi-Strategy Investment Managers who maintain positions in companies currently or prospectively involved in corporate transactions of a wide variety including but not limited to mergers, restructurings, financial distress, tender offers, shareholder buybacks, debt exchanges, security issuance or other capital structure adjustments. Security types can range from most senior in the capital structure to most junior or subordinated, and frequently involve additional derivative securities. Event Driven exposure includes a combination of sensitivities to equity markets, credit markets and idiosyncratic, company specific developments. Investment theses are typically predicated on fundamental characteristics (as opposed to quantitative), with the realization of the thesis predicated on a specific development exogenous to the existing capital structure. ED Multi-Strategy managers do not maintain more than 50% exposure in any one Event Driven sub-strategy.

Macro: Macro Investment Managers which trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic

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analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short-term holding periods. Although some strategies employ Relative Value (RV) techniques, Macro strategies are distinct from RV strategies in that the primary investment thesis is predicated on predicted or future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposed to EH, in which the fundamental characteristics of the company are the most significant and integral to investment thesis.

Relative Value: Investment Managers who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Managers employ a variety of fundamental and quantitative techniques to establish investment theses, and security types range broadly across equity, fixed income, derivative or other security types. Fixed income strategies are typically quantitatively driven to measure the existing relationship between instruments and, in some cases, identify attractive positions in which the risk adjusted spread between these instruments represents an attractive opportunity for the investment manager. RV position may be involved in corporate transactions also, but as opposed to ED exposures, the investment thesis is predicated on realization of a pricing discrepancy between related securities, as opposed to the outcome of the corporate transaction.

Fixed Income - Asset Backed: Fixed Income - Asset Backed includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a fixed income instrument backed physical collateral or other financial obligations (loans, credit cards) other than those of a specific corporation. Strategies employ an investment process designed to isolate attractive opportunities between a variety of fixed income instruments specifically securitized by collateral commitments which frequently include loans, pools and portfolios of loans, receivables, real estate, machinery or other tangible financial commitments. Investment thesis may be predicated on an attractive spread given the nature and quality of the collateral, the liquidity characteristics of the underlying instruments and on issuance and trends in collateralized fixed income instruments, broadly speaking. In many cases, investment

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managers hedge, limit or offset interest rate exposure in the interest of isolating the risk of the position to strictly the yield disparity of the instrument relative to the lower risk instruments.

Fixed Income - Convertible Arbitrage: Fixed Income - Convertible Arbitrage includes strategies in which the investment thesis is predicated on realization of a spread between related instruments in which one or multiple components of the spread is a convertible fixed income instrument. Strategies employ an investment process designed to isolate attractive opportunities between the price of a convertible security and the price of a non-convertible security, typically of the same issuer. Convertible arbitrage positions maintain characteristic sensitivities to credit quality the issuer, implied and realized volatility of the underlying instruments, levels of interest rates and the valuation of the issuer's equity, among other more general market and idiosyncratic sensitivities.

FOFs classified as "Strategic" exhibit one or more of the following characteristics: seeks superior returns by primarily investing in funds that generally engage in more opportunistic strategies such as Emerging Markets, Sector specific, and Equity Hedge; exhibits a greater dispersion of returns and higher volatility compared to the HFRI Fund of Funds Composite Index. A fund in the HFRI FOF Strategic Index tends to outperform the HFRI Fund of Fund Composite Index in up markets and underperform the index in down markets.

Hedge funds strategies are not standard. Each manager of a hedge fund has his or her own style of investment, but due to the high risk they take on, investors should investigate carefully a potential investment before putting their money in any hedge fund. The goal for investors is to determine the strategy they will follow and for that they need to decide ahead of the investment how aggressive and risky they want to be based on the capital they have. Some of the biggest hedge funds include Bridgewater Associates LP, JPMorgan Asset Management, Vanguard Russell 1000 Gro I, and Fidelity Sel Defense.

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2.3. Hedge Funds Performance

Although hedge funds have drawn a lot of attention because of their recent development, there have been few performance studies for them comparing to other investment tools like mutual funds. An explanation may be their private characteristics and the difficulties someone can face in order to have access to individual funds data. (Capocci 2007).

2.3.1. Hedge funds performance measures

In general, the higher the returns of a hedge fund are the better performance the fund has. There are several ways to measure the performance of hedge funds and these are called performance measures. In the eighties, the performance measures commonly used for hedge funds were based on the Capital Asset Pricing Model (CAPM), like Jensen's alpha and other of their extensions. But nowadays there is a particular interest in multi-factor models, as far as performance measurement is concerned, which comes from the literature on the cross-sectional variations in stock return. There have been several studies supporting measuring performance either with CAPM measures or with multi factor models but there exists no unanimously one and only accepted model.

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Chapter 3: Multiple Regression for predictive analysis

Predictive analytics is the use of statistical modeling, algorithms and other techniques in order to predict future outcomes from data we collected. The type of data we have determines the classification of predictive analytics that we are going to use. Cluster analysis for example and regression models are statistical methods used for predictive analysis and regression models are the key to predicting future outcomes.

3.1. Explanatory vs. Predictive modeling

As mentioned in (Shmueli 2010) the philosophy of science, it has long been debated whether explaining and predicting are one or distinct. The conflation of explanation and prediction has its roots in philosophy of science literature, particularly the influential hypothetico-deductive model (Hempel and Oppenheim, 1948), which explicitly equated prediction and explanation. However, as later became clear, the type of uncertainty associated with explanation is of a different nature than that associated with prediction (Helmer and Rescher, 1959). There is a range of perceptions as it concerns the relationship between causal explanation and empirical prediction. As far as the prediction is concerned, any form of predictive modeling focuses on generating as much predictive power as possible and on predicting unobserved data with a model used in an applied situation. On the other hand the main purpose for the explanatory modeling is to determine the relationship between the dependent and the independent variables and to explain the effect of the explanatory-independent variables on the response-dependent variable.

The above methods of analysis are also may require different models. Explanatory analysis requires simpler, more interpretable models usually in the form of a choice from the generalized linear models family as these models facilitate a more clear relationship between the output of the model and the response variable.The use of such models for statistical inference allows for investigating not only the relationship between two variables but also the confounding effects. This means that these models can identify, whether two or more of the explanatory variables having the same effect on the response or are identically distributed. If any of the hypotheses of the explanatory analysis is violated then the model will lose power. All the above require a large amount of manual input and diagnostics to determine the model which best

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explains the data with the result in many cases be that the model explains only a part of the response variable and that there may be other underlying factors that haven't been accounted for.

On the other hand, predictive analysis can use non-linear relationships and is not about how the model is formed but whether it fits well on unseen data in order to make future predictions as also mentioned above.

3.2. Predictive Analysis

Predictive modeling is defined as the process of applying a statistical model or data mining algorithm to data for the purpose of predicting new or future observations. In particular, I focus on prediction where the goal is to predict the output value (Y) for new observations given their input values (X). This definition also includes temporal forecasting, where observations until time t (the input) are used to forecast future values at time t + k, k > 0 (the output). Predictions include point or interval predictions, prediction regions, predictive distributions, or rankings of new observations. Predictive model is any method that produces predictions, regardless of its underlying approach: Bayesian or frequentist, parametric or nonparametric, data mining algorithm or statistical model, etc. (Shmueli 2010).

We can use many different models when doing predictive modeling based on the type of classification of predictive analytics and the type of the variables we have to work with and compare these models to find the one that is the best. We can use the traditional regression, but also decision trees and neural network analysis. Another way is to combine different models in order to make predictions. But whatever method of predictive modeling we are going to use it is important to focus on accuracy of the prediction instead of just identifying risk factors.

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3.3. Multiple Regression for predictive modeling

As predictive analytics is a tool of machine learning and big data, regression analysis is a primary tool for predictive analytics. Regression analysis for prediction doesn't mean necessarily that we are predicting the future but that we predict the mean of the response variable based on specific values of the independent variables where these values have been measured at the same point in time. Our primary goal when we use regression in order to make predictions is to produce predicted values that are precise and unbiased. That means that our predictions have to be not far from the real values and also close to the average of the distribution of the response values.

Regression analysis has a large number of applications and especially in finance and econometrics, some of them are the examples we set below:

- Supervised machine learning uses algorithms to fit a smoothing function in order to target data points and during fit a decision boundary between target data points.
- In finance regression helps traders to know what they need to buy or sell to replace high exposure stocks.
- Hedge funds, as we are going to examine later analytically, use regression analysis to trace the impact of changes in interest rates on the bonds prices.

There is linear and non-linear regression analysis and we are going to describe both methods below.

3.3.1. Multiple Linear Regression models for prediction

Linear Regression equation:

$$Y_i = a_0 + \sum_{i=1}^{k} a_i * X_{i,t-1} + \varepsilon_t \ , i = 1, \dots k \ and \ t = 1, \dots . T$$

Where:

α_0: intercept/constant term.

α_i: coefficients for each predicting/independent variable $X_{i,t-1}$.

ε_t: residuals, meaning the model's error term.

Four major **assumptions** of Linear Regression are the following:

- The dependent variable is linearly related with the independent variables

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- The independent variables are not too highly correlated with each other
- Y_i observations are a random sample of the population
- Residuals should be uncorrelated and normally distributed with mean zero and variance σ.

When the purpose of regression is to make prediction about future values of response variable (Y) then with the mathematical equation described above for multiple linear regression, or as called just multiple regression, we create a relationship between the response (dependent) variable with the independent variables. The coefficients from the explanatory (independent) variables are determined and then the values of predictors X are plugged in, in order to predict the corresponding value of Y. Two of the methods we have to estimate the regression coefficients are the ordinary least squares method and the maximum likelihood estimation.

Least Squares Estimators:

More analytically, in order to be able to predict the values of Y we need to estimate the coefficients of the predictors by least squared method. That means that our goal is to minimize the sum of squared residuals.

Let $Y = [Y_2 Y_3 \dots . Y_t]'$, $X = \begin{bmatrix} 1 & X_{1,1} \dots & X_{k,1} \\ \vdots & \vdots & \vdots \\ 1 & X_{1,t-1} \dots & X_{k,t-1} \end{bmatrix}$

$\alpha = [\alpha_0 \alpha_1 \dots . \alpha_k]'$,$\varepsilon = [\varepsilon_2 \varepsilon_3 \dots . \varepsilon_t]'$

Then the model can be written in a form using the above matrices:

$$Y = X * \alpha + \varepsilon$$

The least squares parameters α are those who minimize the below equation

$$\sum_{t=2}^{t} \varepsilon_t = \varepsilon\varepsilon'(y - X\alpha)'(y - X\alpha)$$

Our purpose is to find the "best" a in order to minimize the sum of squared residuals. The smallest values that the sum of squared residuals could be is zero. To calculate the estimated α coefficients we have to solve the normal equation:

$$\hat{\alpha} = (X'X)^{-1}X'Y$$

For the predicted values of Y, we perform the following calculation:

$$\hat{Y} = X * \hat{\alpha} \; or \; \widehat{Y_{t+1}} = \widehat{\alpha_0} + \widehat{\alpha_1} X_{1,t} + \dots + \widehat{\alpha_k} X_{k,t} \qquad (5)$$

Maximum Likelihood Estimation:

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The maximum likelihood estimation is almost identical method with this of the least squares estimation that we mentioned above. The purpose of this method is to estimate the αcoefficients by maximizing the likelihood function which is actually the joint probability distribution of the sample. The residuals here are also normally distributed with σ^2variance.

Thus,

$\hat{\alpha} = (X'X)^{-1}X'Y$ and $\widehat{\sigma^2} = \frac{(Y-X\alpha)'(Y-X\alpha)}{T}$

3.3.2. Non-Linear Regression models for prediction

It is known that not all the data can be presented by a linear model as we described above. Non-linear regression analysis is the one in which the observed data are modeled by a function which is a non-linear combination of the parameters and depends on one or more independent variables. A more accurate prediction could be produced with non-linear regression if we spot the variations in the data and their dependencies. Non-linear models use an iterative algorithm to estimate parameters rather than the linear approach of solving them directly with matrix equations. Some nonlinear regression problems can be moved to a linear domain by a suitable transformation of the model formulation. There are also regression models that are able to catch non-linearity between the data. Such an example is tree regression models and we will refer to them analytically in a next chapter. Below we present two types of non-linear regression models in order to set examples.

Polynomial regression:

Polynomial regression is very similar to linear regression but additionally, it contains independent variables with polynomial degree values. It is a form of regression analysis where the relationship between the independent and depended variables is defined by the nth degree polynomial in X.

Decision Tree Regression:

Decision Tree Regression works by splitting a dimension into different sections containing a minimum number of data points and predicts the result for a new data item by calculating the mean value of all the datapoints in the section it belongs to.

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That is, it breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is developed incrementally. Decision tree builds regression or classification models (based) in the form of a tree structure. As mentioned before we will refer to decision trees analytically as it is also one of the 2 ways we chose to model our data for making prediction of the hedge funds strategies returns.

Assessment of the model fit:

When developing predictive models and algorithms it is important to quantify how well the model fits to future observations. The traditional statistical approach is to examine how close predictions are to the actual outcome, in other words to calculate the error between the predicted value and the actual value. One of these errors is for example the Mean Square Error. It's called the mean squared error as you're finding the average of a set of errors. The Mean Square error is calculated by the following type:

$$MSE = \frac{\sum_{p=1}^{P}(y_p - \widehat{y_p})\text{^}2}{P}$$

Which is the mean of the square of the difference between the actual and the predicted values. The smallest the MSE is the better fit has the model. Although, what value which we can consider as small or big depends from the data. But generally, if MSE is close to zero then we can say that the model fits the data well and therefor it has good predictability. MSE is also used to compare two or more models, used to model the same data, and it can show us which model is better to use for prediction.

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Chapter 4: Methodology for Combination Forecasts and Tree Regression

In this chapter we analyze the theoretically background of two different methods we used for conducting a prediction analysis. The combination of forecasts method and the tree regression analysis which are the methods used to our research also.

4.1. Combination of Forecasts

As mentioned in (Aiolfi, Capistran, Timmermann 2010),since the Bates and Granger's (1969), forecast combinations are considered as an effective and actually simple way to improve the performance of forecasting over that offered by individual models. In present, forecast combinations are in widespread use in central banks, in private sector forecasters and also in academic studies. However, challenges remain in order to understand for what types of forecasts the combination is more beneficial, and which one is more optimal for each given forecast situation. As stated by Bates and Granger (1969)in the seminal paper and also mentioned by Rapach, Strauss and Zhou (2009), combinations of individual forecasts outperform the individual forecasts themselves. Recently, forecast combinations have received a lot of attention in the macroeconomic forecasting literature; Stock and Watson (1999, 2003, 2004), for example whose attention was for real output growth and forecasting inflation. Although forecast combinations are becoming more and more popular in economics, the applications in the finance literature are relatively rare. A significant example is Mamaysky, Spiegel, and Zhang (2007), who find that the number of mutual funds, with predictable out-of-sample alphas, is increasing significantly if we combine predictions from an OLS model and the Kalman filter model of Mamaysky, Spiegel, and Zhang (2008). In contrast, Rapach's, Strauss and Zhou (2009) paper, elaborates how to use forecast combination in order to improve equity premium forecasts.

The combining methods sometimes differ in the determination of the combining weights, two different approaches are mentioned here: The first one calculates the combination forecasts by using simple averaging measures such as mean, median, and trimmed mean, which is also the method we use in order to conduct our analysis, while the second one is based on Stock and Watson (2004), where the calculation of the combining weights at time t concerns functions of the historical forecasting performance of the individual models over the out-of-sample period. There is also an

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approach where the combining weights are calculated using in sample model fit, but this could cause unstable weights over time especially if the model structure is unstable. The above opinion also agrees with the forecasting literature, which mentions that simple combining methods typically outperform more complicated methods (Timmermann, 2006). Below we present in more details the mean combination of forecasts.

As written in (Aiolfi, Capistran and Timmermann, 2010), suppose that we want to forecast values for a variable, y, that we are interested in, for the next multiple periods. Let $h \geq 1$ be the horizon of the forecast and t be the time of the forecast, so $y_{t+h}$is the prediction we want to make given the information known at time t. Finally, let $y_{j,t+h|t}$ be the jth forecast that could be either a time series model forecast, or a survey forecast. Then we use equal-weighted combinations for the combination forecasts we made.

Except from one (the mean combination of forecasts), all other combination forecasts can have their combining weights changed at each time t. However, typically it is desirable to have relatively stable combining weights over time. Below is described the mean combination of forecasts which is calculate as follows:

$$\widehat{ynew_{t+h|t}} = \frac{\sum_{j=1}^{N} \hat{y}_{j,t+h|t}}{N} \quad (1)$$

where N is the number of forecasts we combine.

In our analysis we prefer using equal-weighted combinations, and more precisely the mean combination of forecasts, because we have a small number of observations in our dataset and so if we estimate forecast combination weights is most likely not going to improve the forecasting performance (Smith and Wallis, 2009).

4.2. Classification and Regression Trees (CART models)

Classification and Regression trees (CART) methodology was introduced by Breiman, Friedman, Olshen and Stone in 1984 and is an “umbrella” for two categories of decision trees which are used to model and estimate a target variable, Classification and regression trees. Classification trees are decision trees where the target variable is categorical and are used to identify in which "class" the target variable would likely fall into, while Regression trees refer to a continuous target

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variable and they are used to predict its value. Classification and Regression trees have many similarities but also many differences, with one of them being the measures used for splitting procedure. By using explanatory variables, trees explain variation of a single target/response variable. These explanatory variables can be either categorical or numeric or both. The main characteristics of CART are:

- The criteria for determining the splitting of the data procedure
- The rules that determine when the tree stops growing and no further splits can be done
- And finally, the prediction of the target variable in each leaf/terminal node

4.2.1. Development of a decision tree

Based on what De'Ath and Fabricius (2000) have documented, the development of the tree is conducting by splitting the data repeatedly. The split of the data is defined by simple rules, which is based on a single explanatory variable. Each split portions the data into two distinguished groups, with each one of them being as homogeneous (instances with similar values) as possible. Then for each subgroup created the splitting procedure is applied separately. The primary goal is to partition the initial dataset of the response variable into homogeneous subgroups/sub datasets, while in the same time the tree has to be small. The splitting process is continued until no further split by explanatory variables can be done. Then an overlarge tree is grown and pruned back in order to have the desired size. Each subgroup of the dataset is characterized by the mean value of the target/response variable, the group size and the values of the explanatory variables who define the subgroup.

The type of the explanatory variables determines the split. For example, a two-level categorical variable, can make only one possible split, with each subgroup, created from the splitting, defined by each level of the categorical explanatory variable. For categorical variables with k levels, there are 2^{k-1}-1 possible number of splits. For numeric (continuous or discrete) explanatory variables, a split is defined by inequalities, with variables be less than or/and greater than, a chosen value. The selection of which split we should make, is based on which of these splits maximize the homogeneity of the subgroups generated by the split. The type of the target variable defines which criteria we can use to determine the split in order to have homogeneity.

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4.2.2. Splitting Criteria and "stopping" rules

There are many measures of splitting criteria, which enable us to analyze many types of response variables. According to De'Ath and Fabricius (2000) the most common of them are:

The spitting criteria for classification trees are:

- The Gini index
- The Twoing index
- The Entropy index

And for the regression trees the two measures used as splitting criteria are:

- Sum of mean squared errors which is equivalent to the least squares in linear models.
- Sum of median absolute deviations which gives a robust tree (Breiman et al. 1984)

Trees can take also the form of statistical models, like generalized linear and linear models and also generalized additive models (Clark and Pregibon, 1992). Splits, in this approach, are based on statistical models only and the deviance of these models operates as a dissimilarity measure.

When building a decision tree the final goal is for the tree not to be too large. For this purpose, there are stopping rules that determine when further splitting is not possible. Stopping rules typically concern when a specific minimum number of cases in a node is reached and also when a maximum number of terminal nodes in the tree is reached. The number of terminal nodes in a decision tree can not be more that 2^{N-1} where N is the number of observations in the dataset.

4.2.3. Regression Tree for Prediction

Regression tree can be represented as a graph, having a root node, which is at the top of the tree and represents the undivided data. Then it has the branches and finally the leaf or terminal nodes, with each one of the terminal nodes represents a cell of the partition in which a simple model is attached, and it applies only in that cell.

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Basic regression trees divide the data into smaller subgroups, as we mentioned before, and then fit a simple constant for each one of the observations in the subgroup. The constant to predict is based on the average response values of all observations falling in the subgroup. In the case when all data, the response and the predictors/explanatory variables are numeric then in regression trees, the model in each node is a linear estimate of a response variable Y. Let's suppose that observations (x_1,y_1), (x_2,y_2)…, (x_n,y_n) belong to the terminal node k, then the model for node k is simple a linear model that we fit to all the points in the terminal node in order to make a prediction for the response. This gives a piecewise-linear model. There are also piecewise-constant models where we fit the mean of the target variable in the node. There are several advantages to the use of the aforementioned models:

- The predictions we make are fast with no complicated calculations
- By only looking at the tree is easy to locate which variables are important for the prediction
- If we have missing data, we may not be able to reach the leaf (terminal node), but we can either way make a prediction by averaging all the leaves in the sub-tree that we can reach
- Reliable and fast algorithms exist in order to learn these trees

4.2.4. Pruning the tree

As it can be implied by the name, pruning means that we are cutting back the tree. After the tree is built, overfitting may occur. The partition of the dataset in smaller subgroups, as discussed above, may often has as a result that the terminal nodes (final subsets) may consist of very few data points or even of one data point. This could mean that a new data point that has slightly difference might not be predicted well. And that's why we prune the tree. Here we present two approaches of pruning a regression tree.

- **Minimum error:** The tree is pruned back to where the cross-validated error is minimum. Cross-validation is a way to build a tree where most of the data are used and with the remaining being used to test the accuracy of the tree.
- **Smallest tree:** The tree is pruned back slightly further than the minimum error. Technically the pruning creates a decision tree with cross-validation error within 1

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standard error of the minimum error. The smaller tree is more intelligible at the cost of a small increase in error.

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Chapter 5: Empirical analysis and results.

In this section we illustrate the proposed approaches to analyze hedge fund single strategy indices. The analysis we will conduct to analyze and forecast returns of hedge funds strategies is based on two methodologies which we described in detail in previous chapters. The first one is the combination of forecasts method and the second one is the tree regression analysis. We will first analyze our data in order to detect relationship between predictors but also the impact they may have on the response variables. Moreover, we will analyze the dependent variables in order to examine their statistical characteristics and the existence of patterns and the change they may have through time. Then we will choose the right sample in order to apply and then test the methods we chose to make the predictions in the values of returns of the hedge funds strategies, and finally we will present our results.

5.1. Data

Our data concern hedge fund strategy indices that are actually hedge fund data collected from Hedge Fund Research (HFR), which are more relevant to style allocation decisions (Amenc and Martellini, 2003). The hedge fund indices from HFR are equally weighted average returns of hedge funds and are computed on monthly basis. We consider different HFR single strategy indices in our empirical study of the detection of nonlinear risk exposures of hedge funds to different risk factors, but for reasons of space we present results for six hedge fund strategies: Equity Hedge, Macro, Relative Value Arbitrage, Event Driven, Merger Arbitrage and Equity Market Neutral. Our study of these hedge funds uses net-of-fee monthly excess returns (in excess of the three-month US Treasury Bill) from January 1987 to January 2006.

The Independent Variables/Predictors:

In order to model the hedge funds returns and to be able to predict future unobserved values we will use different risk factors such as those that were discussed in Agarwal and Naik(2004) and further used by Vrontos et al. (2008) and Meligkotsidou et al. (2008).These factors include returns on the Russel 3000 equity index (RUS), the Morgan Stanley Capital International (MSCI) world excluding the USA index (MXUS), the MSCI emerging markets index (MEM), the Salomon Brothers world government and corporate bond index (SBGC), the Salomon Brothers world

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government bond index(SBWG), the Lehman high yield index (LHY), the Goldman Sachs commodity index (GSCI), the FederalReserve Bank competitiveness weighted dollar-index (FRBI); Fama and French's (1993) 'size' (SMB) and'book-to-market' (HML) as well as Carhart's (1997) 'momentum' factors (MOM); the difference between the yield on the BAA-rated corporate bonds and the 10-year Treasury bonds (DEFSPR); and the change in equity implied volatility index VIX. This dataset with all the predictors described above refers also to the period January 1987 to January 2006.

5.2. Descriptive Analysis

Below we present some insights of the data set we have. Specifically, we present the statistics of the dependent variables and graphs that give us some insight in the behavior of the hedge funds. For space economy we present the analysis and results of the 6 hedge funds we mentioned in the beginning of the chapter.

First of all, we will observe the returns of hedge funds for the period refers to our dataset in order to have an idea of how these strategies performed in the observation period from 1987 to 2006.

A summary statistics table is presented below.

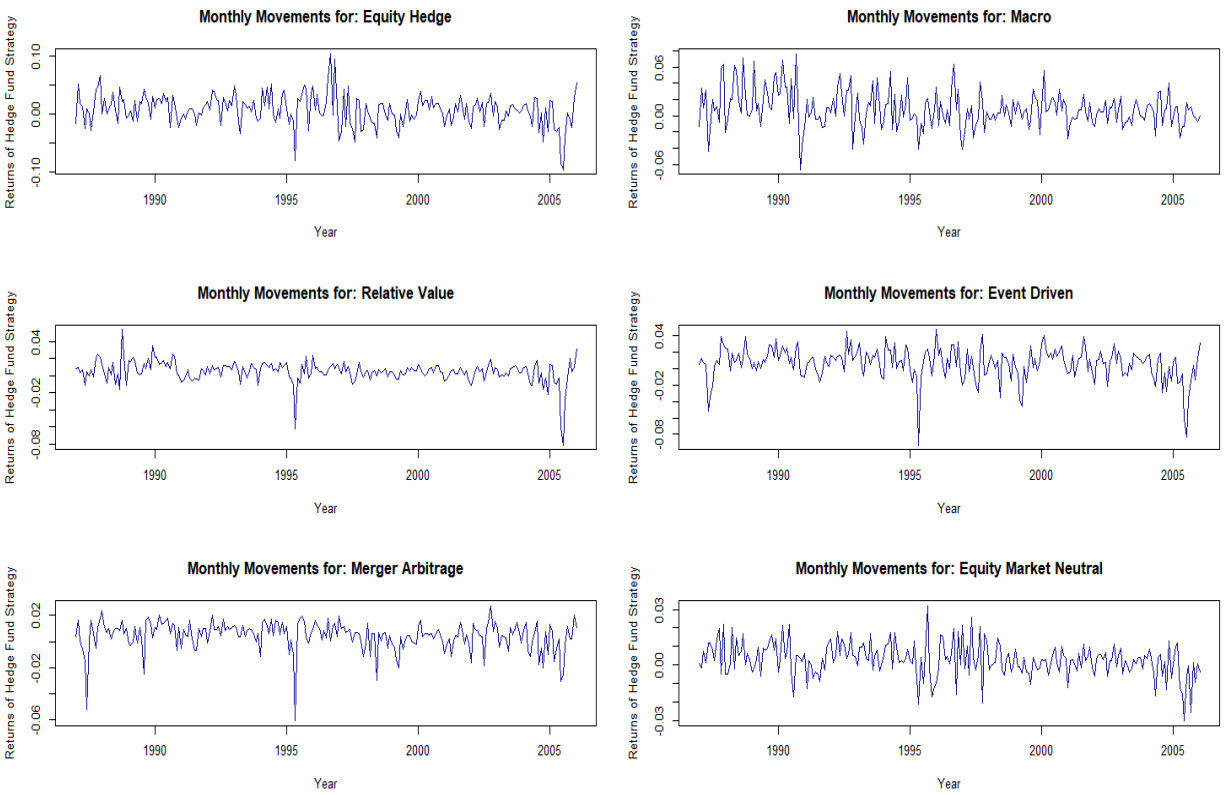
Table 5.2.1: Summary Statistics for hedge funds returns

Variables	Mean	St.Deviation	Median	Min	Max	Skew	Kyrtosis
Equity Hedge	0.01	0.03	0.01	-0.10	0.10	-0.25	1.96
Macro	0.01	0.02	0.01	-0.07	0.08	0.40	0.77
Relative Value	0.003	0.01	0.01	-0.08	0.05	-2.28	14.31
Event Driven	0.01	0.02	0.01	-0.09	0.05	-1.38	4.50
Merger Arbitrage	0.005	0.01	0.01	-0.06	0.03	-1.97	7.36
Wquity Market Neutral	0.003	0.01	0	-0.03	0.03	-0.20	1.14

In table 5.2.1 we observe that the Hedge Funds with the highest returns are the Equity Hedge, Macro and Event Driven something that we expected based on the performance measurement of the Hedge Funds strategies with the Sharpe Ratio, as presented above. On the other hand, we observe that the hedge fund strategies with the lowest returns are the Relative Value and Equity Market Neutral.

Below we present in graphs the monthly movements of the returns of the hedge funds from the beginning of the observation period through the end of it.

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The time plot shows some changing variation over time. As we can see from the time plots there is no trend observed as there are no patterns observed in the data. If no long-term increase or decrease is observed in the data, then we can say that there is no pattern in the time period the returns were observed.

Table 5.2.2: Correlation Matrix

	Equity Market Neutral	LHY	MOM	VIX	MSCI	SBGC	DEFSPR	Macro	SMB	Equity Hedge	Event Driven	MEM	RUS	MXUS	Relative Value	Merger Arbitrage	SBWG	HML	GSCI	FRBI
Equity Market Neutral	1																			
LHY	0.44	1																		
MOM	0.061	0.11	1																	
VIX	0.083	0.24	0.14	1																
MSCI	0.085	0.16	0.13	0.086	1															
SBGC	0.1	0.11	0.057	0.2	0.27	1														
DEFSPR	0.25	0.1	0.26	0.092	0.053	0.084	1													
Macro	0.3	0.18	0.031	0.17	0.094	0.24	0.13	1												
SMB	0.062	0.3	0.21	0.41	0.27	0.33	0.14	0.25	1											
Equity Hedge	0.43	0.0022	0.21	0.49	0.22	0.51	0.3	0.55	0.46	1										
Event Driven	0.34	0.16	0.19	0.52	0.37	0.5	0.22	0.51	0.57	0.81	1									
MEM	0.12	0.22	0.31	0.59	0.16	0.35	0.21	0.45	0.46	0.72	0.75	1								
RUS	0.2	0.29	0.24	0.69	0.11	0.22	0.12	0.34	0.5	0.75	0.73	0.73	1							
MXUS	0.19	0.18	0.39	0.56	0.14	0.21	0.2	0.37	0.44	0.67	0.65	0.73	0.76	1						
Relative Value	0.33	0.17	0.23	0.47	0.33	0.32	0.32	0.33	0.53	0.64	0.75	0.57	0.52	0.5	1					
Merger Arbitrage	0.3	0.13	0.09	0.46	0.27	0.33	0.11	0.31	0.41	0.56	0.74	0.59	0.56	0.52	0.57	1				
SBWG	0.24	0.65	0.048	0.0056	0.19	0.19	0.04	0.23	0.17	0.29	0.04	0.061	0.046	0.035	0.069	0.017	1			
HML	0.23	0.13	0.13	0.014	0.38	0.081	0.24	0.045	-8.1e-5	0.24	0.27	0.1	0.22	0.2	0.24	0.17	0.025	1		
GSCI	0.12	0.091	0.13	0.14	0.17	0.13	0.018	0.29	0.24	0.064	0.048	0.017	0.11	0.11	0.076	0.068	0.027	0.17	1	
FRBI	0.049	0.054	0.46	0.0055	0.18	0.093	0.088	0.13	0.074	0.011	0.052	0.026	0.052	0.27	0.053	0.012	0.0011	0.12	0.63	1

Table 5.2.2 shows the correlation between the risk factors we use as predictors and the hedge fund strategies whose returns we want to predict (target variables). Strong correlation around 0.7 is observed between the Morgan Stanley Capital International emerging markets index (MEM) and the Equity Hedge and Event driven strategies which indicates that if the MEM index increases or decreases then the aforementioned strategies will also increase or decrease in the same way as the index. The same strong correlation (approximately 0.7) exists between the MEM index and the Event Driven strategy. The above indicate that the MEM index could be a strong variable for predicting returns of the above strategies. Correlation (0.69) is also observed between the returns on the Russel 3000 equity index (RUS) and the change in equity implied volatility index (VIX) and 0.76 correlation between RUS and MXUS.

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5.3. Hedge funds strategies performance for the observation period 1987-2006

One more information we wanted to extract from the dataset was which strategies had the best performance for the observation period 1987-2006.Performance for hedge funds is about their returns as we mentioned in previous chapter. Here in order to measure the performance of the strategies included in our dataset we used the Sharpe ratio. Sharpe Ratio is used by investors in order to understand the return of their investment compared to the risk they have taken. Sharpe ratio is the average return earned in excess of the risk-free rate per unit of total risk.

$$Sharpe\ Ratio = \frac{R - R_f}{\sigma}$$

Where R: is the portfolio average return

R_f : is the free risk rate

σ: is the standard deviation of the portfolio

The higher a Sharpe ratio is, the better performance the fund has but this comparison stands for portfolios which are similar.

Based on the above, the strategy with the best performance in our dataset is the Merger Arbitrage strategy which was expected since it has the smallest standard deviation in terms of its mean return and that means that it has very small risk. The next strategy with the best performance is the Relative value strategy and then Macro and Equity market neutral strategy are next in line with the best performances. Below we present a table with the four strategies with the best performance in descending order and with each one's Sharpe Ratio value.

Table 5.2.3: Strategies Performance based on Sharpe Ratio

Hedge fund strategy	Sharpe ratio value
Merger Arbitrage	0.402850290
Relative value	0.381899797
Macro	0.357971877
Equity Market Neutral	0.336282801

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5.4. Combination of forecasts method for prediction

5.4.1. Methodology used

The purpose of this thesis is to predict future unobserved values of the returns of the different strategies, for the next 24 months after the last observation point in the dataset which is the 1st of January 2006. Here we present the method of forecast combinations we used in order to make these predictions. In order to make the predictions/forecasts we used 14 individual predictive regression models each one based on an economic factor (variable) of those 14 we have in our dataset and we mentioned previously in this chapter. Each predictive regression model is in the following form:

$$y_{t+1} = \widehat{\alpha_0} + \widehat{\alpha_1} * x_t + \varepsilon_{t+1}$$

Where $\widehat{\alpha_0}, \widehat{\alpha_1}$ are the coefficients of the regression model which we estimate using all the prior information we have from our data with matrices operations.

The methodology we used to make the predictions is similar to this from Goyal, Welch (2008), Rapach (2010) and later employed also by Meligotsidou, Panopoulou, Vrontos and Vrontos (2013). We make out-of-sample forecasts of the strategies returns using an expanding window. The actual process is that we separate the initial sample of let's say K observations into an in-sample portion of the first T observations and an out-of-sample portion of the last K-T observations which in this case are the last 24 observations, exactly the number of the forecasts we want to generate, we use for forecasting. We use the in-sample portion to estimate the coefficients and then use them along with the predictor's respectively value to generate the forecasted strategy return. The estimation window is updated, continuously, by following a recursive process which at each step we add one observation to the in-sample or else the estimation sample. And with the same process after each step of the recursion, the coefficients are re-estimated taking now into account the updated estimation sample (in-sample). Then we repeat the same process, as described above, until the end of the out-of-sample period, and this way we generated 24 out-of-sample forecasts for the returns of the hedge fund's strategy.

The above process is the same for all 14 different individual predictive regression models, each of them corresponds to each one of the 14 different economic indices we mention in the beginning of the chapter N. Then the final forecast, for the return of the

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hedge fund strategy, for the time period t with t in [1,...24], is made by combining all the 14 forecasts into one with the mean combination forecast method as describe analytically in chapter 4 by using the following formula:

$$\widehat{r_t} = \frac{\sum_{i=1}^{N} \widehat{r_{i,t}}}{N} \text{ , where } N\text{: number of individual models/predictors}$$

So, we have 24 combining forecasts for the hedge fund's strategy. The same process is followed for all the 15 hedge funds strategies we have in our dataset, but as mentioned before for purpose of space economy we will present bellow the results of the method for the 6 strategies we mentioned in the beginning of this chapter.

5.4.2. Results for Combination forecasts method

Below we present, for space economy, the 24 forecasted values of the returns of the 6 hedge funds strategies.

Table 5.4.1: Returns of the 6 hedge funds strategies with combination forecasts.

Forecast	Equity Hedge	Macro	Relative value	Event Driven	Merger Arbitrage	Equity Market Neutral
1	0,012	0,010	0,007	0,0100	0,0060	0,004
2	0,012	0,009	0,007	0,0103	0,0061	0,004
3	0,009	0,008	0,006	0,0076	0,0050	0,004
4	0,007	0,007	0,005	0,0050	0,0037	0,004
5	0,009	0,008	0,006	0,0073	0,0047	0,004
6	0,016	0,013	0,007	0,0120	0,0068	0,005
7	0,015	0,012	0,007	0,0110	0,0063	0,005
8	0,004	0,006	0,004	0,0036	0,0031	0,004
9	0,009	0,008	0,006	0,0071	0,0044	0,004
10	-0,004	0,003	0,004	0,0018	0,0023	0,003
11	0,010	0,010	0,006	0,0073	0,0044	0,004
12	0,008	0,008	0,005	0,0063	0,0041	0,004
13	0,014	0,011	0,007	0,0117	0,0065	0,004
14	0,013	0,010	0,007	0,0103	0,0059	0,004
15	0,004	0,005	0,004	0,0021	0,0022	0,004
16	0,005	0,006	0,005	0,0058	0,0039	0,003
17	0,007	0,007	0,006	0,0072	0,0046	0,003
18	-0,007	-0,002	0,002	-0,0036	-0,0002	0,002
19	-0,015	-0,007	-0,001	-0,0113	-0,0038	0,002
20	0,001	0,006	0,003	0,0001	0,0011	0,004
21	0,014	0,014	0,008	0,0125	0,0066	0,004
22	0,004	0,005	0,005	0,0045	0,0031	0,003
23	0,002	0,004	0,004	0,0017	0,0018	0,003
24	0,013	0,012	0,007	0,0113	0,0060	0,003

Below we present some conclusions about each strategy and their forecasted returns based on the above table:

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Equity Hedge: We observe that in 10, 18, 19 forecast the returns are negative and the maximum return is observed in the 6th forecast.

Macro: Negative returns, but slightly under zero, are observed in the 18, 19th forecasts and the maximum return is observed in the 21st forecast.

Relative Value: Only in 19th forecast, there is a negative return and the highest return of this strategy is observed in the 21st forecast. We can see that this strategy has rather small returns in all forecasted periods.

Event Driven: With this strategy we predict negative returns for the 18th and 19th month after the last observation point. The maximum return is observed for the 21st forecast.

Merger Arbitrage: The lowest value of return is observed in the 19th forecast where the return is also negative, and the highest return is observed in the 6th forecast.

Equity Market Neutral: With Equity market neutral we observe that there are no negative returns exist, but the returns are generally very low with the highest return be 0,005 which means 0,5% return, a rather low percent.

5.4.3. Performance of Combination of forecasts

The measure we used in order to assess the combination of forecasts method and how well predicts our data is the MSE measure. The table below shows the MSE, from the mean combination of forecasts method, of the forecasted values which are the returns we predicted and represented above in this chapter.

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Table 5.4.2: MSE for Combination of forecasts method

MSE for Mean Combination Forecasts	
Equity Hedge	0,00174
Macro	0,00016
Relative value	0,00056
Event Driven	0,00042
Merger Arbitrage	0,00002
Equity Market Neutral	0,00005

We observe that for all hedge funds strategies the MSE is quite small and very close to zero. It is expected for MSE to be close to zero since the values of the returns are also very close to zero themselves.

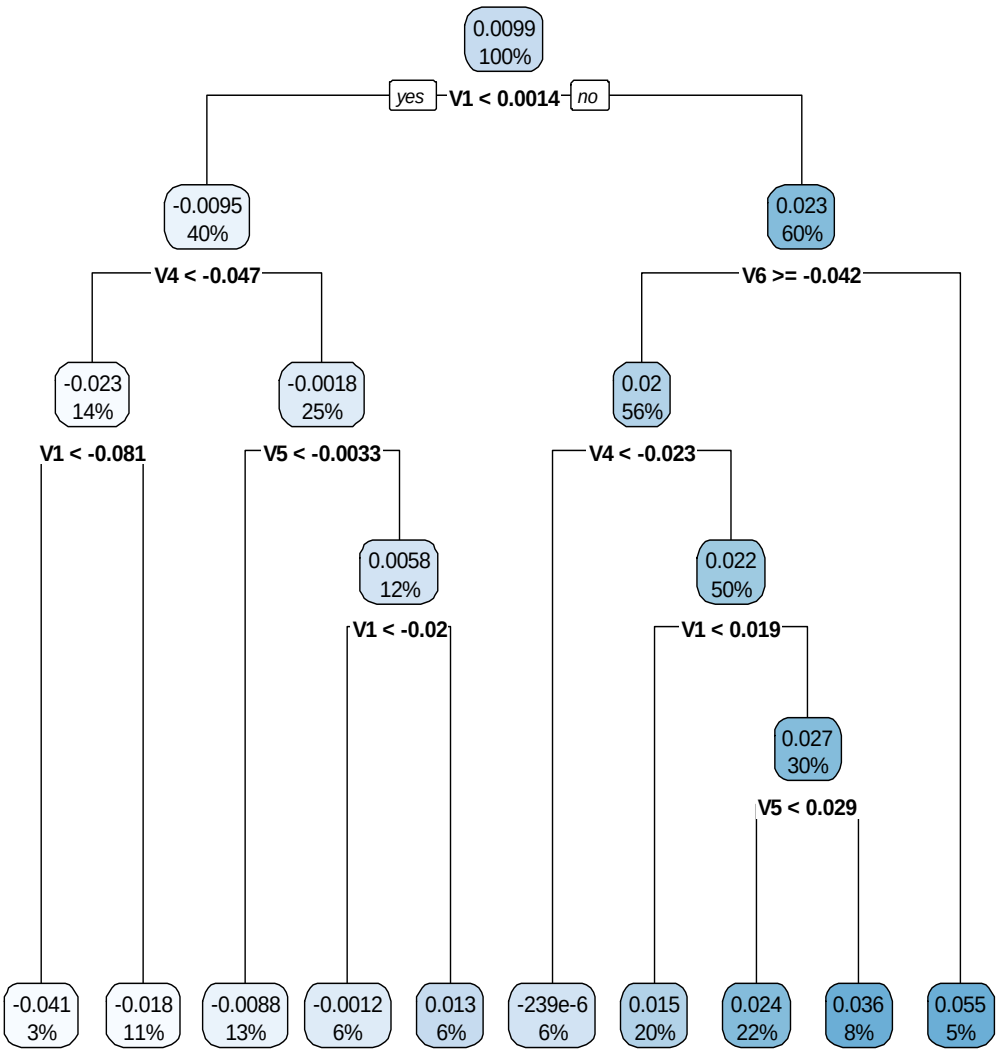
5.5. Tree regression method for prediction.

As a second method in order to predict the values of returns of the hedge funds strategies, we use the tree regression method in which we referred to analytically in chapter 4.First of all we split our initial dataset into 2 complementary sub datasets, the train and test dataset. The test dataset contains the last 24 observations of the initial dataset as the data we have are time-series data and we want to predict the next 24 returns from the last observation point. The tree regression model is build on the train dataset and then we use the test dataset to make out of sample prediction. We predict as many values as the number of observations in the test dataset. In order to build the tree on our train data set, we use the rpart routine in r and then we can visualize the tree using the rpart.plot command in r. Then we use the MSE in order to evaluate the predictions we made. As we have 15 strategies for which we want to predict their returns, in practice we build 15 different tree models. For space economy reasons we will analyze and present the graph of tree regression of one of the strategies (target variables).

The graph presented below is the one which visualizes the tree model for the first strategy in the data. We can see that the first node (on the top of the tree) contains all the observations and has a mean value of 0.0099 which is the mean return of the strategy in this node. The most informative variable where the first split is made, is V1 (RUS) as we can see from the graph. If the RUS index is lower than 0.0014 then 40% of all observations belong to the left “child” node with mean return -0.0095, else if RUS is greater than or equal to 0.0014 then the remaining 60% of 209 observations

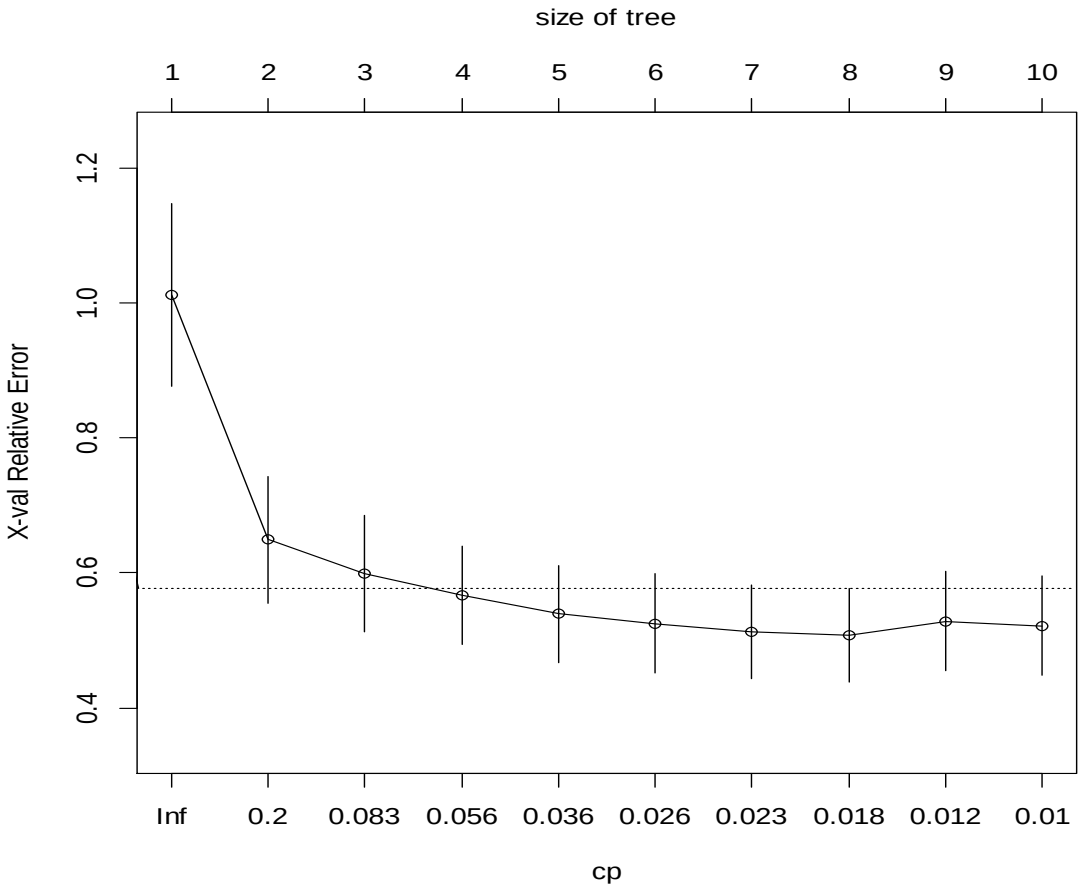
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from the training data set are going to the right “child ” node with mean return 0.023. And in the same way is build the rest of the tree. Finally, we have 10 terminal nodes with each one containing the predicted mean return for the observations belonging in the node.



Below we present a graph where y-axis is cross validation error (a behind the scene process for rpart in order to choose splits), lower x-axis is cost complexity value, upper x-axis is the number of terminal nodes. It is a graph showing the “best” size of the tree, where size is actually the number of terminal nodes.

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From this graph we can also see that the optimal number of terminal nodes for strategy Equity Hedge is 10.

5.5.1. Predicted returns from tree regression model

The predicted values we calculate when applying the tree model on the test dataset are presented in the table below and concern the 24 predicted returns for the first 6 strategies for which we presented their forecasted returns with the combination forecasts above in the chapter.

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Table 5.5.1: Returns of Hedge funds Strategies with Tree Regression

Forecast	Equity Hedge	Macro	Relative value	Event Driven	Merger Arbitrage	Equity Market Neutral
1	0,0236	0,0290	0,0101	0,0213	0,0145	0,0002
2	-0,0012	0,0061	0,0044	0,0029	0,0015	0,0015
3	-0,0088	0,0061	0,0044	-0,0108	0,0015	-0,0006
4	-0,0002	-0,0043	0,0094	0,0014	0,0060	0,0050
5	0,0236	0,0210	0,0101	0,0213	0,0071	0,0038
6	0,0553	0,0210	0,0094	0,0126	0,0091	0,0038
7	-0,0178	-0,0043	-0,0034	-0,0108	0,0015	-0,0067
8	0,0134	0,0070	-0,0017	0,0014	0,0060	-0,0006
9	-0,0178	-0,0197	-0,0034	0,0029	-0,0254	-0,0007
10	-0,0012	-0,0103	-0,0017	0,0029	0,0015	-0,0006
11	-0,0178	0,0293	-0,0034	0,0163	0,0060	-0,0006
12	0,0236	-0,0103	0,0101	0,0034	0,0071	0,0050
13	0,0553	0,0125	0,0094	0,0163	0,0145	0,0038
14	-0,0407	-0,0043	-0,0034	-0,0396	0,0015	-0,0006
15	0,0134	-0,0197	-0,0136	0,0163	0,0060	-0,0007
16	-0,0002	-0,0046	-0,0136	0,0163	0,0060	-0,0051
17	-0,0407	-0,0303	-0,0136	-0,0396	-0,0254	-0,0067
18	-0,0407	-0,0303	-0,0136	-0,0396	-0,0254	-0,0006
19	-0,0407	0,0293	-0,0136	-0,0396	-0,0059	-0,0006
20	0,0146	0,0125	0,0225	0,0289	0,0071	-0,0007
21	-0,0407	-0,0303	0,0225	-0,0396	-0,0254	-0,0051
22	-0,0407	-0,0043	-0,0136	-0,0396	-0,0254	-0,0006
23	0,0236	0,0416	0,0162	0,0289	0,0071	-0,0088
24	0,0357	0,0416	0,0225	0,0289	0,0145	-0,0088

As we did with the combination forecasts method, we are going to present, here also, some conclusions about the six strategies in the table above and their forecasted returns:

Equity Hedge: We observe that the maximum forecasted return is 0,0553 and it is observed in the 6th forecast. The minimum forecasted return is -0,0407 and is repeated 5 times.

Macro: We can see that the Macro strategy has a lot of negative returns, the half of them to be exact, with the minimum return be -0,0303 which is also repeated several times. The maximum forecasted return is 0,0416.

Relative Value: The maximum return for relative value is 0,0225 and is repeated 3 times in the last 5 forecasts.

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Event Driven: Event driven has 0,0289 maximum return and minimum -0,0396.

Merger Arbitrage: The lowest value of return is -0,0254 which is 1 of the two negative values of return, and it is repeated 5 times in the forecasting period. The highest return is 0,0145.

Equity Market Neutral: We observe that equity market neutral strategy has the lowest values of returns compared to the other 5 strategies with the maximum value of return be 0,005.

5.5.2. Performance of the Tree Regression model

As we did in the combination forecasts method, we use the MSE in order to evaluate how well the model predicts the data and how close are the predicted values to the real ones. Below we present the table with the MSE of tree regression model for the 6 aforementioned strategies.

Table 5.5.2: MSE for Tree Regression model

MSE for Tree Regression model	
Equity Hedge	0,000345
Macro	0,001823
Relative value	0,000070
Event Driven	0,000008
Merger Arbitrage	0,000012
Equity Market Neutral	0,000024

5.6. Comparison of the 2 methods

The primary purpose of this thesis, as we mentioned in the beginning of it, is to make predictions for the returns of different hedge funds strategies, using two different methods and then compare this method in order to examine which one is “better” at predicting the data. The word “better” can take many different definitions when referring to model’s performance. Here we used the same measure of performance for both method in order to compare it and see which model performs better. This measure is the MSE.

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Table 5.6.1: MSE for the 6 Hedge funds strategies for both methods

MSE Comparison		
Strategy	**Tree Regression**	**Mean Combination Forecasts**
Equity Hedge	0,000345	0,00174
Macro	0,001823	0,00016
Relative value	0,000070	0,00056
Event Driven	0,000008	0,00042
Merger Arbitrage	0,000012	0,00002
Equity Market Neutral	0,000024	0,00005

The mean squared error (MSE) measures the variability in forecast errors, as we have mentioned previously on other chapters. Obviously, the variability in forecast errors must be small. We observe that, the values of MSE for both models are pretty small and since all the models we used in our analysis have results with the same units, a straightforward comparison can be done. Obviously, we cannot state that there is one of the two models that is more accurate for all different strategies since each hedge fund strategy has different relation with the explanatory indices we used to model them in order to predict their future values. As we can see from the table above for the Equity Hedge, Relative Value, Event Driven, Merger Arbitrage and Equity Market Neutral strategies, tree regression model has smaller MSE value and thus we can say that is more appropriate for predicting the returns of these hedge funds although the difference with the combination forecasts method is small. For the Macro variable the model that fits best the data and is more suitable for predicting the returns of the strategy is the combination forecast method.

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Chapter 6: Conclusions.

By summarizing the research, we conducted in order to predict future values of the returns of hedge funds strategies, for 24 months after the last observed return in 1st of February 2006, we have the following conclusions:

Firstly, we saw that for the observed values that we have been given in our data, the **Equity Hedge**, **Macro** and **Event Driven** strategies are among those with the highest mean returns in the period of 229 months from January of 1987 until February of 2006. This is something that makes sense considering that there are among the strategies with the best performance for this time period based on the Sharpe Ratio we used to evaluate their performances. The best performance, based on the Sharpe Ratio, among all 15 strategies, has the **Merger Arbitrage** strategy. We also observed that for all target variables (strategies) through time series plots for the observation period mentioned above, there is no trend or pattern among for the strategies.

Moreover, we saw through correlation plots that strong correlation is observed between Morgan Stanley Capital International emerging markets index (**MEM**), which is one of the 14 indices we used as predictors/explanatory variables, and Equity Hedge and Event Driven strategies. Also, strong correlation exists between Russel 3000 equity index (**RUS**) and the change equity implied volatility index (**VIX**).

By using first, combination of forecasts method we saw that the predictions we made about the next 24 months after February of 2006 showed that **equity's hedge fund** strategy maximum return is predicted to be 6 months after the last observation point which is in august of the same year with the value of the return be 0,016 or 1.6%. Foe Equity Market Neutral we observed that the predicted/forecasted values of the returns are pretty small (very close to zero) and of the smallest among the strategies but they don't contain any negative value. All its predictions of returns are positive values.

With tree regression model we saw that we had a lot of values of the returns repeated in the 24 months for almost all the strategies as for example **Merger Arbitrage** where its lowest return is predicted to be -0,0254 or -2.5% and the same value is observed 5 times during the 24 months.

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Finally, we used the MSE performance measure in order to evaluate our predictions and afterwards to compare the results given by the two different methods we used to model our data. We saw that both methods make pretty accurate predictions since the forecasted errors are small for both methods and for all the strategies, we made the predictions for. Among the 6 strategies presented analytically in the previous chapter, we can see that tree regression has smaller MSE for all of them except for the Macro strategy for which combination forecast seems to "work" better.

Of course, which model is better for prediction is may based on the comparison of MSE measure, but it is not so strict conclusion as data and the variables we use to make the predictions and the interaction between the target and the predictors play a major role. As we saw in combination forecasts, we use the mean of the predictions of all independent variables in the dataset, but in tree regression the model chooses the variables it uses to build the tree, based on a measure.

A further analysis that would be interesting is, from economics view, is to compare the predicted/forecasted values of hedge funds strategies with the index S&P 500, (Metzger and Shenai 2019), as many consider it to be one of the best representations of the U.S. stock market.

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