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THE FEASIBILITY OF ALTERNATIVE INDEXES IN PASSIVE INVESTING ON THE EXAMPLE OF FINNISH STOCK MARKET

Master's Thesis

Supervisor: Lector Kalle Ahi

Tallinn 2015

I declare I have written the master's thesis independently.

All works and major viewpoints of the other authors, data from other sources of literature and elsewhere used for writing this paper have been referenced.

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ABSTRACT

This thesis studies the feasibility of alternative weighting approaches in indexing and their feasibility for investors to receive better risk adjusted return. More traditional weighting methods (price and especially market capitalization) in index construction have been proven to suffer from flaws and alternative weighting approaches (also known as smart betas) have been proposed to substitute the traditional weighting approaches. The research seeks to answer the following: Do alternative indices outperform market capitalization weighted indices? And can alternative indices be used by passive investors (and or managers) to reach better risk adjusted return? The Objective of this thesis is to study alternative approaches' (models) weightings and their risk adjusted return performance to other more traditional market capitalization based indices. Using data of Finnish equities from the period 1988 – 2014, a backtesting was performed on the weighting strategies discussed in this thesis. Previously conducted empirical and theoretical studies were also utilized to study the feasibility of alternative indices for passive investors. The backtest results indicate that while some of the alternative indices strongly outperform the traditional market capitalization and price weighting approaches, there are significant differences between the indices' performances. The optimization based weighting in general outperformed most of the heuristic methods, with maximum diversification being the leading method in terms of risk and return. It was concluded that alternative indices can be of use for passive investors and active investors who'd want to take a more passive stance in investing.

Keywords: smart beta, alternative indexes, backtesting, Finnish equities, mutual funds, risk and return, active and passive investing

INTRODUCTION

This master's thesis covers the topic of alternative indexes, also known as smart beta (or as advanced beta, alternative beta, or strategy beta) and its feasibility to passive investing and passive asset management. It also covers how passive approach differs from active investing and active management. Alternative indexing is a more recent way of building indexes in equities in order to capture better risk adjusted return than traditional market capitalization weighted indexes such as FTSE 100, Nasdaq-100, and OMX Helsinki 25. There is no exact time when alternative indexes were conceptualized, but their underlying idea of providing better risk adjusted return is a promising concept among risk concerned investors (especially when one considers the impact of 2008's financial crisis had on investors). Alternative indexes differ from traditional market capitalization weighted indexes as these traditional indexes have been criticized for being influenced too much by a few very large companies which can account for a major share of the index. Also, stock price changes that occur in the short term can reflect investors' emotions which will lead to the index allocating higher weight to overpriced companies, and subsequently underweight undervalued companies.

Alterative indices strategies try to achieve better risk/return than traditional market cap weighted index approach by using alternative weighting schemes that are based on metrics such as volatility and/or dividends. Essentially smart beta indexes try to resolve (some) of the shortcomings that actively managed market capitalization weighted stock mutual fund portfolios have.

The research question for this thesis is to find out whether alternative indexes perform better (in terms of risk and return) than traditional market capitalization weighted indexes, and could usage of alternative indexes be a feasible choice for both passive and active investors. The research conducted in this thesis uses Finnish stocks for the index modeling. The research that has been already conducted on alternative indexes on US stock indexes would indicate that certain specific alternative index strategies do perform better (in terms of risk/return) than traditional market capitalization weighted indexes in certain conditions and time periods with

significant differences between different alternative index strategies risk/return. There is however little research done on whether different alternative index approaches would also show good performance when used only on the stocks of a smaller country (essentially having not as many global stocks). Therefore research on alternative indexes in their possible risk/return difference for other market capitalization weighted indexes is deemed both interesting and useful.

The research objective is to study active and passive investing and see whether alternative weighting models can be of use for both passive and active investors.

Research tasks set are the following:

1) review literature on active and passive investing,

2) cover previous empirical studies on alternative indices,

3) conduct a backtest using the different alternative weighting models.

The following hypothesis:

1) Risk/return performance of alternative indices makes them feasible choice for passive investors.

Main method of research is a quantitative backtest of alternative models, using Finnish stock data from the period 1988-2014, the main tool used for this is Excel (and its in-built Solver and Data Analysis tools). The connection between passive and active to alternative indexes is more qualitative and relies on previous academic studies that have been published in established scientific journals (in the field of business, economics, and finance), but also taking into account studies on alternative indices that have been conducted by individual institutions which are not academic, but more practical market oriented.

This thesis is divided into 4 chapters. First chapter covers basic principles of market indexes, passive and active management, and their differences. It also includes all the different types of weighting models and the mathematical theory that is crucial for understanding the differences between the models and how they are later applied in the empirical section. Chapter two includes the literature review of active and passive investing, and the studies previously conducted on alternative indices. Chapter three covers the more precise methodology of the alternative indices and how the models were constructed, and the tools used. In chapter four all the results are presented and discussed. Chapter four is followed by a conclusion, references, and appendix.

1. FUNDAMENTALS OF INDEXES AND PASSIVE INVESTING

The first sub-chapter covers the fundamental history and the importance of using indices as investor's tools, and explain the advantages for investors to choose passive portfolio management rather than use more active based investing strategies. Second sub-chapter covers the concept of risk and return, a crucial component in index constructing and understanding the underlying risk related reason behind alternative indexes. Third sub-chapter gives short review on several different portfolio performance measurements. Sub-chapters four and five concentrate on both traditional indices and alternative indices, including the mathematical formulas.

1.1 Importance of indices as investors' tools and their role in passive investing

Stock index is an aggregated value derived from combining stocks or other investment instruments like bonds together and then expressing their total value against a value from an earlier date. Indexes that cover a large quantity of different stocks are intended to represent the whole stock market (usually for a specific market) and its changes over time. Well known indexes such as S&P 500, and Nasdaq-100, Nikkei 225, and FTSE 100 are regularly used by investors as benchmark indexes who then compare the return (and risk) of their own portfolios to these benchmarks. Movement changes in different indexes also work to serve as indicators of the current health of the market and as a forward looking indicators.

The history of indexes started in 1896 when Charles H. Dow unveiled the first stock index, Dow Jones Industrial Average which was an average of top 12 stocks in the New York Stock Exchange at the time. This index was a price-weighted and the average was a simple calculation of adding all the stock prices together and then dividing them by the amount of

stocks. Though simple, it enabled Dow to follow the market and identify whether the market was bearish or bullish. In the following century when indexes gained more notion, various different indexes emerged such as the well-known market capitalization based S&P 500. S&P 500 has its roots in 1860 when the first financial history of Railroad and Canal digging companies was published, intended to provide information for investors who were outside banking district (S&P Dow Jones Indices, McGraw Hill Financials). Though it was first known as S&P 90 due to the limits at the time related to calculating indexes that had more than 90 companies.

Indexes helped to bring better understanding and transparency to the underlying forces behind stock markets. They have helped and proved invaluable to traders, contrarians (investing style where the investor buys poorly performing stocks and sells them when they perform well), momentum investors (investing style where the investors tries to capitalize on the continuing trends in the market), and of course for index funds and passive investors. For funds and passive investors, having an efficient and reliable indexes is important and to whom from the previously mentioned investors, they would also be most interested in developing a better passive index models (for better risk adjusted return and avoid unwanted events like bubble crash of late 90's that wasn't avoided by the market capitalization based indexes). Most importantly though indexes act as benchmarks for which different investors and investment managers can measure their own performances (see whether their portfolios are performing better or worse than the current market) and enable people with little to none financial skills to manage their own portfolios and gain moderate return for their investments just by following the indexes.

Passive investing has its roots in the foundations of modern portfolio theory, one of the earliest being the work of a Nobel prize winner Harry Markowitz who in he's work "Portfolio Selection" (1952), showed that trough estimating individuals stocks risk and return, it's possible to define risk and return for a whole portfolio. This enabled investors to compare different portfolios' risk and return. Markowitz further demonstrated that diversification can lead to decrease in risk and increase in return, with each portfolios optimal balance of risk and return can be found on efficient frontier trough portfolio optimization (Markowitz 1952). Advancement in modern portfolio theory was later done by William Sharpe in 1964 with the capital asset pricing model (CAPM) (Sharpe 1964). According to CAPM, investors can only increase the expected return of their portfolio by taking more risk exposure (Beta). The risk

has to be specific and diversified, as increasing expected return by investing in an undiversified and fluctuating asset doesn't work. CAPM theory indicates that given the values of expected return, correlation coefficients, standard deviation, and investors' personal tolerance for risk, an optimal portfolio could then be calculated. CAPM has contributed to the rise in the use of market-indexing, as it gives a rationale for the strategy used in market-indexing.

Major underlying concept in passive investing is that instead of trying to systematically beat the market, investor tries to match it. This approach relies on the security markets to be efficient and there have been criticism on market efficiency and the random walk hypothesis, claiming and that stock prices are predictable to some degree based on previous historical patterns. While evidence has been found concerning short term persistence and momentum in stock prices (please refer to chapter two for literature review), the markets are still concerned to be efficient and passive investing would still prove to be the winning choice even if markets were somewhat inefficient (Malkiel 2003a, 2) (Malkiel 2003b, 60). Similar results regarding markets still being efficient was previously concluded by Eugene F. Fama in 1997, who showed that inconsistencies and abnormalities are fragile and occur without any regard to stock prices. It has also been proposed that the market inefficiency that occurs is due to investor behaviorism, Shiller (2003, 101-102) criticized Fama's (1997) take on the inconsistencies and abnormalities disappearing to be a proof of market efficiency or a sign of markets acting rationally to stock price changes. A common example frequently used in describing investors behavior and effect on stock prices are boom periods where speculation overrules rational expectations. The author of this thesis would conclude that while markets might show inefficiencies, it doesn't seem that markets show significant inefficiencies that might affect negatively the reasoning behind using passive investing.

In passive index investing approach (called indexing) the portfolio is structured to follow the return of a benchmark index by allocation weights to same stocks (or stocks that are similar to those of the benchmark) so that the portfolio is very similar to the benchmark. No active approach is taken so the passive index approach portfolios have generally a good stock diversification and low trading activity. This passive approach has cost advantage (over actively managed portfolios) that comes from transaction costs (mainly brokerage fees) since these are lower because there is less trading activity, this in turn of course reduces the cost of investing (Fredman, 1999, 7-9). Average cost of fees in terms of percentage of assets might

look low if they are little under or over 1% (different rates for individuals and institutions), but when calculated as percentage of returns, the fees are significantly higher at rates between 6% and 12%. A fee from index funds that are available now at such low rates as 0.05% - 0.2% further shows the significance of the differences in fees between active and passive investing (Ellis, 2012, 4-6). In contrast to active portfolio investing, passive portfolio investing work under the general assumption that markets are efficient and it's very difficult to outperform other investors (yet alone for every investor to outperform the market). Therefore it's argued that in order to capture the overall market return, low cost index investing should be used. Indexing should be taken as a long term investing approach and not a short term solution since indexing gains its advantages over longer time period through the broad diversification and buildup of the cost advantages that accumulate over the years. Proponents of active approaches might argue that by using right timing, active portfolio management can take advantage of the inefficient markets and trough this gain extra return that would offset the additional costs that come with more active trading (and therefore outperform the market). Moreover, while there certainly are active portfolio managers who do manage to gain exceptional return over the market, the majority of active portfolio managers do not perform better than the market (Barras et al. 2010, 214-215). Evidence on the underperformance of an average active fund managers was found by Russ Wermers (2003, 15-17) who showed that majority of the actively run funds (data of U.S domestic equity funds) underperformed the S&P 500 benchmark. Similar results to Wemers were also found by Rompotis (2009, 8-10), who expanded the study of passive versus active by using ETFs listed in U.S and concluded that active ETFs underperform both their passive counterparts and the benchmark. Rompotis noted however that the underperformance of active ETFs can be contributed to the managers' lack of skill or possible to U.S market being efficient enough which leaves little opportunities for excess return. The role of market efficiency might indeed play a significant role and a Thesis by Kremnitzer (2012, 31-33) tested the performance of active mutual funds that invest in emerging markets and found results that indicate the active funds to outperform their passive counterparts. Lower market efficiency gives more opportunities for arbitrage and therefore it should not be as surprising to see differences in the performance of active and passive investing styles when the market in question changes. Based on this, it can be theorized that passive investing shows better performance in more efficient markets, while active investing has advantage in markets that are less efficient. Also, results from the resent

(midyear 2014) SPIVA U.S (Standard & Poor's Indices Versus Active) scorecard show that majority of U.S domestic active funds failed to provide returns above their benchmark. However, the same SPIVA results also show that majority of the active funds investing in emerging markets also underperformed their benchmarks. This thesis doesn't concentrate on emerging markets and the author of this thesis would note that the evidence for alternative indices and their feasibility for passive investing found here, might change in a scenario where their feasibility is tested in an emerging market.

The differences between active and passive investing styles are summed up in table 1. What comes clear is that the vast majority of both individual investors and in bond fund assets are using active investing, though there is a growing interest towards passive investing (Ernest and Young 2014, 8, 16). This growing interest is linked to this thesis's topic of alternative indices which, as previously already mentioned, are passively managed. The returns between the two styles show that in annualized (effectively meaning long term returns) passive fund portfolios are outperforming active portfolios that hold only actively managed funds (Ferri, Benke 2013, 9-21). From the proponent's perspective, the ones who advocate the active investing style are those who gain most from this, essentially meaning all brokers and all financial service providers. These parties derive at least portion of their revenue from the expenses of their clients (therefore the reader shouldn't be surprised to find studies that would indicate actively managed funds to outperform their passive counterparts). For an individual investor, choosing passive over active investing style would serve better their own long term interests, but for a financial service provider, offering passive investment choices would not be as beneficial for the company. Other benefit of passive investing can be a more psychological, a more relaxed state of the mind that comes with having to cope with less stress, not having to actively spent time on following and rebalancing portfolios. Even more so if one considers the possible emotional effect that investor can be exposed to when they realize repeated short term losses. Such argument is not without solid ground, research on investor behaviorism shows that individual investors who undergo such scenarios are emotionally effected, with even severe scenarios of distress and panic. With such negative emotional magnitude also increasing in instances such as the dot com bubble in 2000 and the financial crisis of 2008 (Elan and Goodrich 2010, 11). Barber and Odean (2011, 36-37) conclude in their research that in practice investors tend to participate in active trading

(ignoring low cost, diversification, and hold-wait advices), and often so cause harm to themselves.

Table 1.1 Active Investing versus Passive Investing

Subject	Active Investing	Passive Investing
Return Objective	beat a market	match a market
Style Definition	53 % drift from classification (SPIVA 2013)	pure and consistent classification
Average Equity Individual Investor Returns Over 30 years	3,69% per year according to Dalbar for 30-year period ending 2013	S&P 500 = 11,1% Annualized Return Global equity IFA Index Portfolio 100 = 12,33% Annualized Return for 30-year period ending 2013
Approach	stock picking, time picking, manager picking, or style drifting	buy, hold and rebalance a globally diversified portfolio of index funds
Taxes	high Taxes (about 20-40% of return over 10 years)	low Taxes (about 10% of the return over 10 years)
Portfolio Turnover	a weighted average of fund categories in index portfolio 100 had a turnover of 64,6% in 2013	turnover of 11,2% in 2013 (IFA Index Portfolio 100)
Net Performance	expected to lag the index return by the level of expenses. higher taxes may results from more frequent realizing of capital gains	the index return minus low fees, low taxes
Individual Investors	around 74% of equity funds (2013)	around 26% and growing (2013)
Bond Fund Assets	around 86% of bond funds (2013)	around 14% and growing (2013)
Proponents	brokerage firms and brokerage training programs, active mutual fund companies, market timing services	several Nobel price recipients, dimensional fund advisors, Warren Buffet, and Charles Schwab & Company
Analytical Techniques	can be both qualitative and quantitative, forecasting and predicting the future, can show signs of betting and speculation	quantitative, risk management and statistical analysis, accurate performance measurements.
State of mind	more stressed	more relaxed

Source: https://www.ifa.com/12steps/step1/active_versus_passive_investing/

It should be noted that the elements in Table 1 might hold some bias, for example active analytical techniques can also be based on fundamental analysis and some of the proponents of passive investing may also utilize active investing methods and not purely passive. "Indexing (passive investing)" is associated with mutual and exchange traded funds (ETF), and since this thesis's main concept of alternative indices is linked to funds (the one form of investing that has most to do with alternative indices), next step is to understand the workings of funds and just how meaningful are alternative indices (and indices in general) to funds. Note that ETFs can be both passively managed and actively managed, this comes from the very basic differences between mutual funds and ETFs, and though for the most part indexing tends to be more associated with mutual funds than with ETFs. There are different types of funds, but for this thesis only mutual funds are considered since it's the type of fund that's closest to the topic of this thesis. Note that while index funds are in general considered to be passively managed, this doesn't mean that necessarily all passively managed funds are index funds.

1.2 Concept of Risk and Return

Since risk efficient expected return is the underlying reason why alternative indexes should be consider to be used as portfolio benchmarks over market capitalization indexes, this chapter will briefly cover certain risks that affect both index model approaches and of which the reader or investor for that matter, should be aware of before considering using either index types as portfolio benchmark.

The central difference between standard indices and alternative indices is the concept that alternative indices give larger emphasis on risk management and not just maximization of return. Modern portfolio theory is based on the idea that investors can reach certain level of return given a certain amount of risk exposure, and build portfolios to emphasize risk-averseness or profit maximization. It should be then possible to construct an efficient frontier of portfolios that would yield the highest possible expected return for certain given risk level. This is of course achieved by diversification process in order to get rid of all possible diversifiable risk, leaving only non-diversifiable market risk remaining. The previously covered standard indexes have been built on the modern portfolio theory and on the notion

that higher return means taking more risk, and that market capitalization weighted indexes would lie at the point in efficiency frontier where Sharpe ratio is maximized. Previous studies have however showed that market capitalization weighted indices are inefficient when it comes to risk and return (Amenc et al. 2010, 21-34). And while market capitalization weighted indexes do provide good representation of the market, they are not necessary as good to be used as benchmarks for investor portfolios.

Alternative index model approaches that were covered in previous chapter were created with the mindset that it is possible to achieve better risk adjusted return than the standard form indexes. However they are not without their own risks and the risks depend quite a lot on the methodological background of the different index construction models that lead to certain risk factor exposure. For example indices that use companies' economic size as indicators can end up suffering from style biases like value or small cap, and model that uses low volatility approach can lead to overexposure in certain sectors and different exposure to volatility factor. As many of the alternative index models give higher exposure to smaller stocks than in the market capitalization weighted indexes, this can lead to overexposure to less liquid stocks. The alternative models therefore covered in this thesis require the investors using the said alternative index models to receive exposure to certain systematic risks that cannot be solved by diversification. As with all new type of indexes that differ from a more traditional market capitalization weighted indexes, there is a lack of well-established track record and relying only on past performance data (constructed trough simulated back testing) is not as reliable as tack record that has been established over long term live performance (of which alternative indices are not capable of duo to their fairly recent emergency). This weakens the statistical reliability of the alternative indices for those investors who are primary concerned of the robustness of the past performance.

This thesis is not centered on managing the risks of the alternative index models, but when inspecting the results these underlying risks in the models must be kept in mind in order to have better understanding of the feasibility of the alternative index models.

The basic idea behind standard indices is that they are constructed using market capitalization (Such as S&P 500, and Nasdaq), but the problem with this approach is that when dealing with equities the model tends to overweight overpriced stocks (example: IT Stocks in 2000, illustrated in figure 1), and with bonds the overweight is on more indebted issuers (example: Japanese bonds, illustrated in appendix 1). This will lead to market cap

using investors to buying too much stocks and bonds that might not be necessary good for them. This had led to investors to consider other type of indices in order to take beta exposure.
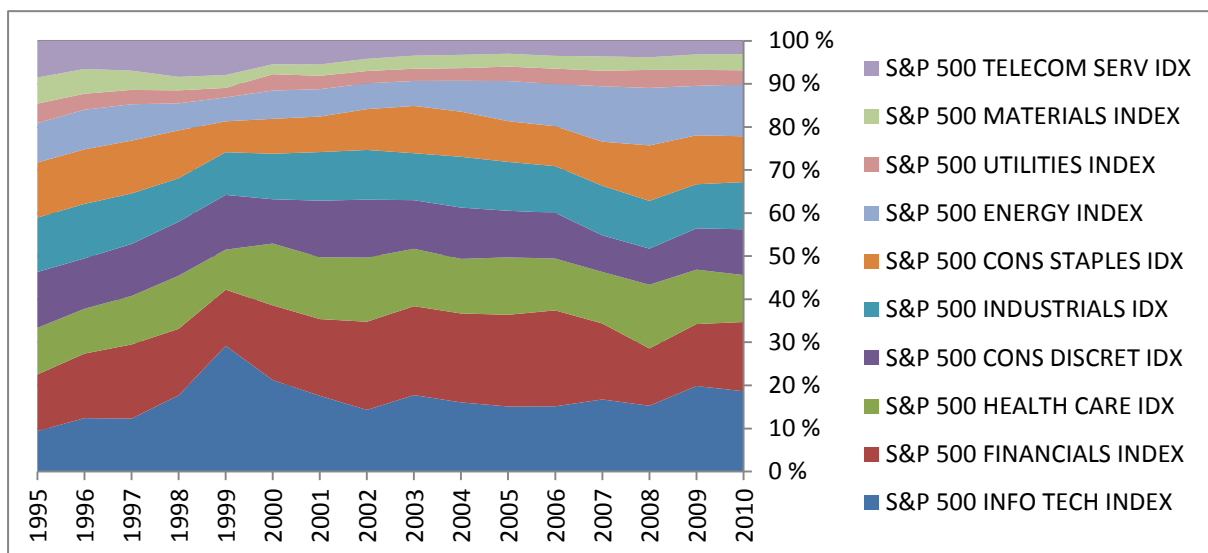

Figure 1. Weights in S&P 500 for 1995- 2010

Source: Author's calculation

The overweight period in Info Technology during the end of 90's is clearly visible with followed drop in the weighting right after the bubble crash. Using capitalization weighting can lead to a higher profits during the boor period, but this will then of course lead to significant losses when the stock prices come down and companies lose much of their market value. It can be argued that the returns gained during the boom period are enough to offset the losses of later periods, but such volatility from investors' point of view in general is not desirable as this will lead to a non-efficient risk return. Alternative indices which are built with the underlying idea that by using different weighting schemes such overweighting risks can be avoided and the risk adjusted return of the indices would be higher.

Most of today's broadly used indexes are market capitalization weighted, and large price moves in the largest components can lead to significant changes on the value of the index. In actively managed portfolios where market capitalization weighted indexes are followed, a fall in a specific company stock will lead to smaller market capitalization and henceforth the portfolios will also own less of that company. In long term such changes happen gradually, but in short term price can be affected by many different factors such as

emotion which can lead to certain stocks (IT in 2000) to become overpriced and the portfolios will then buy more of those type of stocks (and not on underpriced stocks).

Nowadays there are many different indexes that cover different sectors, industries, and nations. For an investor, choosing the correct index as benchmark can have large impact on the expected risk and return. While passive investing would seem to have certain advantages over active investing, there are large differences between different index approaches and understanding why an investor should prefer one over another will be covered next.

1.3 Measuring portfolio performance

Even if a portfolio might carry a higher returns than other portfolios, it does not necessary mean that this portfolio is the best portfolio. Since higher return earning portfolios can also carry significantly larger risk than other portfolios, what becomes important is to measure the portfolios overall risk and return. Objective of portfolio performance measuring is to measure the risk and return of portfolios in order to compare and rank them. While there are many methods to do this, the ones reviewed in this thesis are perhaps few of the more well-known models. The first one is Sharpe ratio which was devised by William F. Sharpe in 1966 and it is a ratio that compares the return of a portfolio to the amount of risk taken by dividing the risk premium (Total portfolio return minus risk free rate) by the standard deviation. The output then indicates the portfolios degree to yield excess return of the risk free rate (per unit of risk). The better the performance of the portfolio, the higher is the Sharpe ratio. Sharpe ratio itself is quite simple, but still important and widely used. A formula of Sharpe ratio is as follows:

$$Sharpe\ ratio = \frac{Re - Rf}{\sigma} \tag{1}$$

Where
Re – expected return
Rf – risk free rate used
σ - standard deviation

Sharpe ratio however doesn't distinguish downside deviation from upside deviation, and a variation of Sharpe ratio called Sortino ratio was devised by Frank A. Sortino in 1983. Sortino ratio differentiates from Sharpe ratio by using only downside deviation as a

denominator, this way only the negative volatility is penalized. Although both methods measure the risk adjusted return, the process in which this is done is quite different and leads to different results and conclusion on the performance of the portfolios. The exact way in Sortino ratio is calculated is depicted below.

$$SortinoRatio = \frac{Re - Rf}{\sigma_d}$$

(1.1)

Where
Re- expected return
Rf- risk free rate used
σd – standard deviation of negative returns

Unlike Sharpe and Sortino ratios, Treynor's ratio (by Jack L. Treynor 1966) uses the portfolio's beta as a denominator to calculate the portfolios performance. The ratio is otherwise identical to Sharpe's ratio, with only this change. The underlying theory behind the ratio is that since systematic risk (represented by beta) cannot be diversified away, it should be penalized. The drawback of this is that since only systematic risk is taken into account, and since diversifiable risk is not taken into account, this leads to less diversified portfolios having the same ratio value as more diversified portfolios. Other well-known portfolio performance measurements includes Jensen's Alpha, devised by Michael Jensen in 1968 and is directly related to CAPM. Jensen's Alpha is essentially a measurement of the portfolios excess return to the expected return given by CAPM, based on the notion that investors are interested in positive alphas since this indicates abnormal returns. It can be argued that markets are efficiency enough, so that earning high Alphas in consecutive years should be quite unlikely. Jensen's ratio is still quite viable and should be used together with other performance measurements.

This thesis doesn't concentrate on costs related to portfolios, their implementation, management or effect on portfolio performance, yet the cost advantages related to transactions are a factor that the reader should keep in their mind.

1.4 Standard indices

In order to understand the main differences between alternative indexes and the more known standard indexes, a short overview of the standard indexes and their workings will be covered next. Standard indices are constructed by using different weighting methods, with the most common ones being price-weighted index, and market value weighted (capitalization weighted) index.

1.4.1 Price-weighted approach

In price-weighted index the stock weights are based on their price per share, with the value of the index generated by adding the stock prices together and dividing the total by the number of total stocks. Higher priced stocks have greater weight and therefore influence the performance of the index more than low priced stocks. Arguably, one of the most well-known price-weighted index is Dow Jones Industrial Average (DJIA) which includes the stocks of the 30 largest companies in U.S, with a large change in this index corresponding to a change in the whole market. This index has the advantage of being easy to compute and the data for the large companies is readily available (ease of back testing), but it also has the disadvantage that the companies with large weights in the index receive these weights for no fundamental reasons. The return of the index is given by the following formula:

$$R = \frac{V_1}{V_0} - 1 \qquad (2)$$

where
R - return for the one period
V0 - price weighted value at the beginning of the period
V1 - price weighted value at the end of the period.
The price weighted values are given by the following formulas:

$$V_0 = \frac{(S_1 + S_2 + S_3 + S_4)}{S_i} \qquad (2.1)$$

$$V_1 = \frac{(S_{11} + S_{21} + S_{31} + S_{41})}{S_{i1}} \qquad (2.2)$$

where
S - represents different stock prices, four stock prices used here as illustration
Si - the total number of different stocks.

As can be seen, the price weighted index is essentially just a simple arithmetic average of price of all the stocks used in the index. The reason why price-weighted index is not used by most stock indices can be described by the bias that the stocks that nominally have larger stock price carry more weight. The problem here is of course that a large share price companies can't necessarily be considered significantly more important for the economy and for the stock market (for more extreme example consider google with share price of 568 and Citigroup with share price of 52).

1.4.2 Market capitalization weighting method

Market value weighted (also referred as capitalization weighted) indexes give larger weights to companies with largest market capitalizations. Of the standard indexes, market value weighted indexes, as many broad market indexes such as S&P 500, Nasdaq, Wilshire, Hang-Sheng, and EAFE are market value indexes. Main advantage of this indexing type is that unlike price-weighted indexes, it automatically adjusts to corporate decisions and share price changes, and mirrors the overall changes in the stock market better. Disadvantage of this type of indexing (as already stated) is that it overweight's overvalued stocks and ignores undervalued stocks. Total market indices like Wilshire 5000 are essentially capitalization weighted indices that are just broader than other market capitalization weighted indices. The reason for the wide use of market capitalization based indices is mainly the result of capital asset pricing model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966) that builds on Markowitz's (1952) theory of portfolio selection (Oderda 2013, 3). A market capitalization weighted index is the number of shares outstanding time the share price, mathematic formula for this is as follows:

$$Index = \frac{\Sigma_i P_{i1} Q_{i0}}{\Sigma_i P_{i0} Q_{i0}} \tag{3}$$

where
P i, 1 - the price of each stock at time 1 in the index.
Q I, 0 – is the number of shares used in the index calculation.

The denominator is the price of each stock at time 0 (the base), multiplied by the number of shares used (McGraw Hill, Index mathematics 2015, 6). It's a simple way of seeing the percentage change that the underlying stocks on average have gained or lost.

A small change in the stock price of a stock that has large market capitalization can lead to quite significant change in the weights. Subsequently a change in the price of small cap stock would have little effect on the weights. It's not uncommon for large market capitalization indexes to be dominated by few stocks with large market capitalizations.

There is also a free float approach in which the market capitalization is calculated, that differs from the standard market capitalization weighted index calculation method. In free float the market capitalization is calculated by multiplying the stock price by the number of shares that are available for investors. This method essentially excludes stocks that are held by entities such as governments and promoters. The market capitalization that is derived from the float approach is smaller than that derived from the standard market capitalization. The formula of free float is as follows:

$$FFM = P(Qa - Qna)$$
(3.1)

where
Qa – shares outstanding
Qna – shares not available

Another method is modified capitalization weighted index where the weights of the constituents are determined by the user, some stocks having certain maximum weight constraints. When the prices of the stocks change, the modified capitalization weighted indices have to be rebalanced from time to time, leading to higher transaction costs.

1.5 Different alternative index models

Alternative indices come in different base models and can be constructed by two weighting methods; heuristic and optimized. Heuristic models are simple and easy to understand and construct. The heuristic models that will be covered in this thesis are: equal weighted, risk-cluster equal weighting, diversity weighting, equal risk contribution weighting, and inverse volatility weighting. Optimized weighting strategies are more complex and more subjective to errors in covariance and return estimations. Optimized strategies covered in this thesis are: minimum variance weighting, maximum diversification weighting (maximum Sharpe ratio), and risk efficient weighting.

1.5.1 Heuristic Models

Equal weighted index give the same weight to all stocks, though it's easy to construct and similar to the method in which many individual investors distribute their holdings. This ensures that the portfolio avoids the concentration risk of market capitalization weighted indexes. This is also one of its drawbacks as unlike large stocks, the small stocks also have the same weight, but are also less liquid which is a risk itself. This model is also highly sensitive to the number of included stocks. Price changes in the underlying stocks can however require frequent rebalancing (and the more frequent, the more higher the transaction costs will be) and smaller companies would also have relatively higher weight than larger companies. Although equal weighting is not a new approach as it has been used for quite some time now, it is still an alternative approach to the more standard forms of index weighting models (Chow et al. 2011, 38-39). The weight formula for each stock is the simplest of all the alternative models, defines as:

$$w_i = 1/N \tag{4}$$

where
wi - the weight assigned for each individual stock
N - represent the total number of stocks

Each individual stock then has its weight multiplied by the return of that stock. The return from all the stocks that are part of the index is then:

$$R = \sum_{i=1}^{N} w_i r_i \tag{4.1}$$

where
R = index return
ri = return from individual stock

Risk cluster weighting method improves on the equal weighting model by instead of equally weighting different stocks; it assigns weights based on risk and correlation to the stocks as groups (sectors, countries). Identifying risk clusters usually relies on more complex statistical procedures, but a simplified method is to divide stocks based on their sectors and then give each sectors equal weight, but have the individual stocks in these clusters be market capitalization weighted (Clare et al. 2013, 6).

Diversity weighting still uses market capitalization as a starting point, but uses weight caps on individual stocks so that any quota over the stocks cap gets redistributed to other stocks. Concerns with equal-weighting approach is the relatively high tracking error (compared to market capitalization weighted) and excess portfolio turnover. The solution is simple to combine features both from market capitalization weighting (subject to maximum constraints for individual stocks) and the equal weighting method to reduce the levels of turnover and tracking error. The question that arises with this model is that at how high the weight constrain level should be set since the higher the level the closer the index will be to a pure market capitalization weighting while very low level brings it closer to equal weighting method. Stock market diversity, Dp, will be defined as according to the approach first proposed by Fernholz (Clare et al. 2013, 4-5):

$$Dp\left(xMarket\right) = \left[\sum_{i=1}^{N}\left(xMarket, i\right)^{p}\right]^{1/p} {}_{,p\varepsilon(0,1)}$$

(5)

where
(xMarket) - is the weight of the i: th stock in market capitalization weighted portfolio, and the portfolio weightings are defines as:

$$xDiversity, i = \frac{\left(xMarket, i\right)^{p}}{\left[Dp\left(xMarket\right)\right]^{p}} i = 1....,N, p\varepsilon\left(0,1\right)$$

(5.1)

where
P - the targeted level of portfolio tracking error measured against capitalization weighted index.

The intuition behind diversity weighting is that it can be viewed as a method to combine both capitalization weighting and equal weighting. This process redistributes weights from larger companies in the capitalization weighting portfolio to smaller companies as p moves from 1 to 0. At P=0 the portfolio is equal to equal weighted portfolio and when P=1, the weightings are as in market capitalization portfolio. For a balanced back testing, portfolios with different levels of p should be used (Chow et al. 2011, 42-43).

Fundamentally weighted indexes differ from market capitalization weighted indexes in a way in which the companies and the portfolio weights are selected. Fundamental indices base their selection on more fundamental metrics like dividends, revenue, book value, earnings, or basically any economic factors that one would use when evaluating companies. The basic concept behind this is that these metrics provide more aggregate measurement of the market (because of the overweight and underweight problem in market capitalization indexes). Interesting fact about fundamental indices is that the line between active and passive management may not always be that clear, depending on the exact management style of the funds, but still it's more of a passive index than an active index, and will be considered a passive index in this thesis. Chow et al. used the same principal methodology for weighting in which the companies' account sizes are measured by reported variables such as book value and sales. Using accounting based measured for size weighting should improve the fundamental model to that of equal weighting approach by reducing the relative tracking error and turnover (to capitalization weighted index) while simultaneously providing better liquidity and capacity for the portfolio over to equal weighting. In principal the accounting metrics used can be anything, such as average cash flows, total dividends paid, average sales, book. For each fundamentally weighted portfolio, the stocks were taken from the largest N = 1000 companies, sorted by descending account size. The portfolio weight of each stock (ith) is defined as:

$$x\,AccountingSize, i = \frac{AccountingSize_i}{\sum_{i=1}^{N} AccountingSize_i}$$

(6)

The fundamental portfolio index itself is constructed by averaging the dividends, sales, book values, and cash flows of the market capitalization weighted portfolios. All the accounting data used represent annual financial company performance and should also be lagged by two years in order to prevent look-ahead bias (Chow et al. 2011, 43-44).

Equal risk contribution weighting model is an approach of equal weighting all stocks in the index based on their volatility. Based on this all the individual stocks in the index would have percentage weight, but stocks with high levels of volatility will contribute more to the overall volatility of the index than those stocks with low levels of volatility. Due to the correlations that stocks may have with each other, an alternative method of building the equal risk contribution model would be to measure each stocks historical volatility and correlation

with other stocks and then assign weights so that each stock's total volatility will contribute the same amount in the whole index. Based on this notion of stock correlations and risk modeling, the following helps to understand the methodology behind the model:

Letting the risk of the portfolio x be expressed as:

$$\sigma(x) = \sqrt{x^T \sum x}$$

(7)

where

$\sum$ - denotes the covariance between different stocks

And through the Euler decomposition we get:

$$\sigma(x) = \sum_{i=1}^{n} \sigma_i(x) = \sum_{i=1}^{n} x_i * \frac{\partial \sigma(x)}{\partial x_i}$$

(7.1)

where

$\partial xi \; \sigma(x)$ - the marginal risk contribution

$\sigma i(x) = xi \times \partial xi \; \sigma(x)$ - expresses the risk contribution of the i: th stock.

The idea of equal risk contribution approach is to find a balanced risk portfolio so that each stock has the same risk contribution (Maillard et al. 2008, 4-6):

$$\sigma_i(x) = \sigma_j(x)$$

(7.2)

Table1.2 visualizes the equal risk contributions of different stocks in a portfolio

Table 1.2 Visualization of equal risk contribution

$\sigma(x) = 9.5\%$	xi	$\partial xi \; \sigma(x)$	$xi \times \partial xi \; \sigma(x)$	ci (x)
1	19,2%	0,099	0,019	20%
2	23,0%	0,082	0,019	20%
3	20,8%	0,091	0,019	20%
4	17,7%	0,101	0,019	20%
5	19,2%	0,099	0,019	20%

Source: Maillard et al. (2008)

In the table, xi is each stocks weight in the portfolio, $\partial xi \; \sigma(x)$ is the risk associated with each individual stock, $xi \times \partial xi \; \sigma(x)$ is the individual stock's risk after its adjusted to the

market capitalization weights in the portfolio, and ci (x) represents the relative contribution of the stock i's risk to the portfolios' risk, being calculated with the following formula:

$$c_i\left(x\right) = \frac{x_i * \partial_{xi}\sigma\left(x\right)}{\sigma\left(x\right)}$$

(7.3)

Equal risk weight approach is in a sense, somewhere between and equal weight strategy and minimum variance strategy. Note that the model takes the assumption that there is no short selling, partly due to the reasoning that many investors can't take short position and that the equal risk contribution weighting is more comparable to the other portfolio index models. The correlations between each stocks are not as straightforward to explain, but suffice to say, the correlation is factored into each stocks weight as follows:

$$x_i = \frac{\beta_i^{-1}}{\sum_{j=1}^{n} \beta_j^{-1}} = \frac{\beta_i^{-1}}{n}$$

(7.4)

The weight that is allocated for each stock i is inversely proportional to its beta, meaning that stocks with either high volatility or correlation with other stocks will be penalized, higher beta leading to a lower weight, n = average of the volatilities. There is more behind the methodology of equal risk contribution weighting, further information on the model is provided by Maillard et al. in their work: On the properties of equally-weighted risk contributions portfolios (2008, 2009).

Inverse volatility weighting is based on low volatility investing where stocks with lower volatilities tend to yield higher returns than high volatility stocks, as demonstrated by Haugen and Heins in 1970s. This type of index in constructed by estimating the standard deviations of the return of every stock for any given time period. Then the inverse value of the deviation is calculated so that lowest volatility stocks will have the highest inverted volatility value. The total sum of the inverted volatilities is then calculated and the weight of each stocks will be assigned by dividing each individual stocks inverse standard deviation by the total inverted standard deviation. Therefore stocks with the lowest inverted volatilities will be assigned the highest weight, and stocks with highest inverted volatilities will have the lowest weights (Haugen and Heins 1975). The individual weight of each stock can be formulated as:

$$w_i = \frac{(1/\sigma_i)}{\left(\sum_{i=1}^n 1/\sigma_i\right)} \tag{8}$$

where
$1/\sigma i$ - the inverse value of individual stocks standard deviation.
Wi - the weight assigned to the stock in the portfolio.

1.5.2 Optimization Models

Due to difficulty in forecasting returns and the high chance for errors, it was suggested by Chopra and Ziemba (1993, 10) that the portfolios' risk and return could be improved by assuming that all the stocks will have the same expected returns. This would give the notion that minimum variance portfolios are optimal, and as demonstrated by Haugen and Baker (1991, 38-40) and Clarke et al. (2006, 19-21) that this type of portfolios do indeed perform better than capitalization weighted portfolios by having better returns with lower risk (Chow et al. 2011, 40) . There are two approaches to estimating the weights: traditional, and OLS approach. The weightings of minimum variance are based on mean variance optimization where the point with the lowest possible standard deviation is selected from the efficient frontier. This can lead to a stock concentration problem which would undermine the idea behind alternative indices and therefore weight constraints should be set for the stocks (the exact magnitude of the restriction should depend on the number of different stocks being used). The weights can be expressed as a solution for the optimization problem:

$$min_x(x'\hat{\Sigma}x) subject, to \begin{cases} \Sigma_{i=1}^N x_i = 1_{\forall i} \\ l \le x_i \le u \end{cases} \tag{9}$$

where
X – vector of portfolio weights.
$\sum{}^\wedge$ - estimated covariance matrix.
L – minimum stock weight
U – maximum stock weight

Given the theoretical unlikeness of the assumptions behind minimum variance that all stocks have the same expected return, maximum diversification weighting is based on the heuristic assumption that expected return is proportional to risk and all stocks have their return directly linked to their volatility. So that the more volatile the stocks return is the

higher will be its total return on average. The model covered in this thesis is that of Choueifaty and Coignard (2008) where optimization technique is used to generate the highest sharpe ratio by identifying the weights of different stocks (Chow et al. 2011, 40). The optimal stock weights are found by maximizing the "Diversification ratio" which takes the form of Sharpe ratio (subject to the same constraints as minimum variance):

$$E\left(R_i\right) - R_f = \gamma\sigma_i \tag{10}$$

$$D(w) = \frac{w'\sigma}{\sqrt{w'\sum w}} \tag{10.1}$$

where
w – vector of stock weights.
$\sum$ - estimated covariance matrix.
σ - vector of the estimated stock return volatilities

Working under the previously stated heuristic assumption that expected returns are proportional to risk, then:

$$E(R) = w'\sigma \tag{10.2}$$

And maximizing D(w) means maximizing:

$$\frac{E(R)}{\sqrt{w'\sum w}} \tag{10.3}$$

Which is the Sharpe ratio of the portfolio

Risk efficient weighting is based on Amenc's et al. (2010) developed approach based on the heuristic assumption which assumes that unlike maximum diversification approach, the stocks return is proportional to the stocks downward deviation (They argued that investors are not as interested with gains as they are concerned with losses). The downside return is calculated similarly to the standard deviation, but by using only negative stock returns (Chow et al. 2011, 40-41).

To show how this type of strategy approach is constructed, we start by the definition of the downside semi-volatility as:

$$\partial_i = DownsideSemi-Volatility_i = \sqrt{E\left[min(R_{i,t}, 0)^2\right]} \quad \text{(11)}$$

where
Ri,t - the return for a specific stock I at time t.
     With this assumption, the mean variance optimal (MVO) problem can be expressed as:

$$max_x \frac{x'\hat{\partial}}{\sqrt{x'\hat{\sum}x}} subject, to \left[\begin{matrix} \sum_{t=i}^{N} x_i = 1 \forall i \\ l \leq x_i \leq u \end{matrix} \right. \quad \text{(11.1)}$$

where
X - the portfolio weights vector.
Σ - the estimate covariance matrix.
$\hat{\partial}$ - the estimated downside semi-volatilities' vector.

Estimating the semi-volatilities for the stock is done by using a heuristic two-stage method in which empirical semi-volatilities are computed and the stocks are sorted by these estimates, into deciles. Stocks in the same deciles are then set the same semi-volatility that is equal to the median value of the semi-volatilities in the decile. This approach also sets strong individual weight restriction for each stock, a lower restriction of $l=1/(\lambda N)$, and upper restriction of $u=\lambda/N$. Impact λ's restriction to the portfolio should be tested by back testing portfolios with different λ. Chow et al. used values $\lambda=2$ and $\lambda=50$, so that the portfolio weight would lie somewhere between 0,002 % and 5%. They also implemented another restriction for the back testing by having a turnover restriction which prevents the rebalancing on reconstruction if there has not been significant deviation between the old weights and new model weights.

2. REVIEW OF PREVIOUS RESEARCH ON ALTERNATIVE INDEXES

This chapter covers previously conducted research that has been done in the field of alternative indexes, and also contains literature review on academic research that has been conducted on fund performances. Even though alternative indexes are quite new phenomenon, there has been quite extensive research conducted on them by different institutes, the ones considered here are some of the more prominent. The first sub-chapter covers the previously conducted researches on alternative indices, and the second sub-chapter covers literature review on the fund performances.

2.1 Previous empirical research on alternative indices

The following previously conducted research and literature on alternative indexes will be covered next: A survey of alternative equity index strategies (Chow et al. 2011), an evaluation on alternative equity indices (Cass Institute, 2013), a review of alternative approaches to equity indexing (Vanguard, 2011, smart beta 2.0 (EDHEC-RISK institution, 2013). The previously mentioned studies are chosen to provide a broad picture of the previously conducted research and what has been the outcome and the general consensus towards alternative weighting strategies and their feasibility.

In their research: A survey of alternative equity index strategies; Chow et al. (2011) conducted a back testing by constructing a U.S and a developed global portfolios. They used 1000 largest stocks, and using data from 1964 through 2009 for the US portfolios, and data from 1987 through 2009 for the global portfolios. The data for the U.S was taken from merged CRSP/Compustat database, and for the adjusted global a merged Worldscope/Datastream database. All the alternative index portfolios used were backtested by using annual and quarterly rebalancing frequencies, this was done in order to observe model robustness to varying rebalancing frequencies. Market price at the last market closing date

were used both in the case of annual portfolios, and quarterly portfolios. They base their research on the same notion that recently passive indexes have gained popularity and even though such strategies such as equal-weighting and minimum variance have been known for a long time already, they have only recently gained interest. They aimed to provide comparison of the alternative indexes in controlled back testing environment and examine the performance (risk adjusted return) of the models. Fees and other expenses related to asset management that differ across different commercial products were not analyzed.

They found in their back testing that all the alternative indexes outperformed the market capitalization benchmark index, noting that the outperformance is entirely due to positive exposure to size and value factors (they have no Fama-French alpha). This is what makes alternative indexes valuable as conventional small capitalization and value indexes have negative Fama-French alphas as was documented by Hsu et al. (2010, 16). Alternative indexes that have lower implementation costs and higher portfolio liquidity were deemed useful alternatives for investors who are looking better performing indexes over the capitalization weighted indexes. Alternative indexes can also be combined to mimic each other's, enabling desired value, market, and size tilting levels to be targeted in investors' portfolios.

The study conducted by Clare et al. at the Cass institute (An evaluation of alternative equity indices, 2013), builds on a previously conducted discussion paper by Sengupta et al. (2012), entitled: Alternative indexing of equities: An improvement on the Market-capitalization approach? The key aspects underlying the discussion paper were: the broad amount of different alternative index models for the market capitalization approach that have emerged recently, and explaining them in detail to give a good summary for investor. They note that choosing index weights is of particular importance for those investors who track indices passively. In the conducted study, Clare, Motson, and Thomasby used 1000 largest US stocks from 1968 to 2011 in constructing their alternative index models. The alternative indexes were categorized in two groups: heuristics (as described by Chow et al 2011) and those that are based on optimization techniques.

The technique used was backtesting, with the key goal to construct measurement of the performance of the stock indexes, and the return the investors would have received had they adopted the usage of such indexes for this data period. Advantage of using the same large data set for all the alternative indexes is that it enables a very definitive comparison of the

models and their differences. The results that they found would indicate that by using the alternative strategies, investors could gain better risk adjusted return, rather than by just having a passive exposure to the market capitalization index (the market capitalization index was also constructed by using the same data as for the alternative models). Though they note that the really important finding was that after the late 90's, the market capitalization weighted index has performed quite poorly in comparison to the alternative indexes.

Christopher B.Phillips, Francis M.Kinniry Jr, David J.Walker, and Charles J.Thomas conducted their research on alternative indices for Vanguard (2011), and for them the reason to undertake this kind of study was the criticism towards standard index construction strategy; market capitalization with its disadvantage of overweighting large overvalued stocks. The analysis that hey conducted supports capitalization weighted indexes over alternative models, both from theoretical basis and practicality. Their results show that the alternative indexes have not produced any positive excess return, and actually produce systematic risk towards small cap and value stocks. They conclude that an investors who chooses to have a more exposure towards small cap stocks, should instead use market capitalization indexes that are focused on small cap value stocks, as such indexes would give the investors a more cost effective, transparent, and statistically equivalent strategy to the alternative equity models. Their paper discusses only equal-weighted, divided-weighted, and fundamentally weighted indexes. However, they point out that low volatility strategies show similar factor tilts (as shown by Clarke et al. 2006, 17-18) as the alternative models that they examined.

Vanguard's research would indicate the exact opposite regarding alternative indices feasibility than has been concluded by the other studies covered so far. However, the findings by EDHEC concerning conflicts of interest of the researchers may prove useful in explaining the different stances that proponents of different weighting methods might have.

Amenc et al. (2013) at the EDHEC-Risk institute examine a new approach to alternative indices, called smart beta 2.0 approach. Their approach is to conduct an analysis of the risk and performance of alternative weighting strategies, and not so much rely on demonstration of how the alternative indices outperform traditional index weighting models. Their paper concentrates on discussing different risks associated with each index benchmark models, in particular the risk associated with exposure to systematic risk factors, strategy specific risk and risk association with relative performance to traditional market capitalization weighted benchmarks. The paper discussed previous finding by EDHEC in the increased

interest in passive investing in both North America and Europe. They conducted surveys in 2011 with results showing that around 90% of the survey correspondents use indices as part of their equity investing. And more than 40% are already using alternative weighting strategies, and over 50 % view the capital weighted indices they are using as problematic. They identified the main problem of market capitalization indexes to be in their role as inefficient benchmarks (though they work well to represent market movements). The authors conclude that proponents of each different alternative model tend to pollute the research in alternative indices by adding their own conflicts of interest, and then distinguishing scientific evidence from the authors' personal interests of promoting certain weighting methods. The authors continue to state that many (most) of the articles that are supposed to deliver an objective comparison of different weighting models, are in fact written by assets managers with the main intention to sell one or few particular weighting strategies.

The author of this thesis agrees with the authors of the above papers when it comes to the amount of weighting strategies being promoted by certain asset management providing companies. Although one fact that has to be pointed out is that managers who concentrate on just few weighting strategies also tend to do this due to wanting to specialize into few weighting schemes in order to become better at said models. It's not surprising if the same managers then publish works that tend to concentrate only on few weighting strategies and then have their own interests on stake in order to prove the feasibility of the models from which they derive their income.

2.2 Review of studies on fund performances

Another part of this academic literature review concentrates on the performance and differences between actively and passively managed funds. Concentration is on investing in actively managed funds and especially mutual funds and the focus of the academic literate is on the performance of actively managed funds. It's acknowledged that empirical literature on equity fund performance is very broad and therefore only some selected ones were chosen (mostly based on the number of times the literature has been quoted (how well they are known), where it was published, and what new insight they provided). The works reviewed are presented in chronological order and while the topics of the studies change and sometimes reflect on the studies conducted by other researches. It's important to keep this chronological

order so the reader understands the clear development that has occurred regarding the research done on mutual funds performances. First work chosen is that done by Grinblatt and Titman (1989, 410-415) which concludes that some funds (funds as a group) do outperform benchmark indices (before deduction of costs) and that the outperformance is mainly due to aggressive growth funds and funds that have low amount of assets under management. However, it's noted that the outperforming funds do usually have high costs, and after these costs are deducted from the return it's found the fund managers' differentiation ability doesn't benefit the investor. Malkiel (1995, 570-571) came to similar conclusion, showing that as a group, funds underperform benchmark portfolios even before transaction costs were deducted, it was also shown that survivorship bias of funds is much larger than Grinblatt and Titman assumed. The conclusion was that an investor could profit more by buying index funds that have low costs, rather than rely on skilled active fund managers. A more recent study by Fama and French (2010, 1941-1942) reinforced the conclusions from previous studies, stating that after taking into account the deduction of costs, equity funds do underperform. Their conclusion is in line with the fact that investing is zero sum game. Costs of mutual funds would mean that the average group performance of funds is negative. These three studies conclude together that group performance of actively managed equity funds do not outperform benchmark indices.

Of course even though as a group actively managed equity funds might be underperforming, but individual funds might not. By studying the persistence of returns and by assuming that a fund manager with the ability of diversification can achieve multiple periods of positive returns in a row, the performance of individual funds returns on multiple periods can be studied. First person to investigate the persistence of mutual funds' performance (in relation to other funds) was Sharpe (1966, 134-138) who by using Sharpe ratio to rank funds for the period 1944-1963 found a non-significant (but positive) correlation between two periods that both had positive outcome. It was also found that mutual funds as a group do not outperform their price-weighted benchmark. He came to the conclusion that both as a group and after taking into account the deduction of costs, mutual funds do not outperform their benchmark indices. A similar research was conducted by Jensen (1968, 396-415), but who instead of using Sharpe ratio used Jensen's Alpha who came to similar weak but positive correlation outcome as Sharpe. The reason for this correlation was mainly due to persistence of negative results. He's conclusion on the possibility of funds outperforming

benchmark price-weighted indices was the same as Sharpe's. A decade and so later, fund managers abilities to both buy and sell at the right time (by expecting future movements) was investigate by Henriksson (1984, 80-93) for the period 1960-1980. He's research came to the same conclusion as both Sharpe (1966) and Jensen (1968), stating that after taking into account the costs of transactions, mutual funds don't outperform. Furthermore, the empirical results showed that fund managers are not able to use strategies that would prove successful predictions at the right time. It's important to use the right measurement of performance, as was stated by Lehman and Modest (1987, 263-264) who showed significant negative persistence during 1968-1982. This persistence is however highly dependent on the measure of performance used with differences between using CAPM rankings or APT. It was shown that both Jensen's and Treynor-Black appraisal measurements of individual funds are very sensitive to the ATP construction method. The effect of survivorship bias on the persistence of returns for multiple periods is also important, and this was researched by Brown et al. (1992, 575-576). When they used dataset not adjusted for survivorship bias, they identified positive correlation and persistence in returns. They came to the conclusion that the lack of adjustments for survivorship bias can give false interpretation of the persistence of returns and therefore previous studies that had identified persistence in returns could therefore be in fact false. Survivorship bias can be significant enough to give false estimate of results that would indicate significant persistence. A bit different conclusion on the persistence of returns was concluded by Grinblatt and Titman (1992, 1983) who studied the persistence by constructing their own benchmark using their own equity picking style they devised in their previous work in 1989. Their results would indicate that on the basis of their own benchmark, fund returns during 1974-1984 are actually persistent. And according to them, this persistence is also in line with the fund managers' abilities to reach outperformance. Based on these results, it was concluded that past positive returns contain useful information when it comes to make investing decision. Similar results to those of Lehman and Modest (1987) were reached by Elton et al. (1993, 4-21) who used CAPM and Fama-French three factor model to study the persistence of returns during 1965-1984 for 143 funds. Their results showed that measurement does have significant impact on the results. In addition, their results indicate significant correlation for two successive periods (this was however concentrated among the poor performing funds, making it difficult to draw any generalizing conclusions). Persistence in the short run was studied by Hendricks et al. (1993, 122) who found that in the short run

mainly growth oriented funds show persistence in the short run (especially for periods of no more than 1 year). A strategy where the best performing mutual funds are chosen each quarter gives significantly better return than a typical average mutual fund. This strategy however still doesn't really outperform any better than some benchmark indices. Other things that was noted is that funds with poor performance show stronger persistence in negative returns than well performing funds show in good performance. It should be noted that survivorship bias and other measurement errors that the authors were aware off cannot be counted as the reason for the results. Similar results regarding persistence in the poor performing funds by Elton et al. (1993) were reached by Brown and Getzmann (1995, 697-698) for the period 1976-1988 by using benchmarks in their study. The data was adjusted for survivorship bias and shows persistence among the returns of mutual funds (mainly in poor performing funds). Brown and Getzmann (1995) suggest that the behavior seen in persistence for poor performing funds could be related to issues in the market not reacting to poorly performing funds. There has also been research on the behavior of mutual fund managers and the extent to which they buy and sell stocks based on their past returns. A study by Grinblatt et al. (1995, 1093-1104) found that 77% of the mutual fund managers were momentum investors, though they did not sell past losers. They came to the conclusion that on average, momentum investors realized significantly better performance. Also weak evidence was found that funds have a tendency at the same time to both buy and sell same stock. A high correlation was estimated between buying historically outperforming stocks, herding behavior, and performance of individual funds. Similar to the results found by Hendricks et al. (1993) regarding the persistence of returns in short term, Elton et al. (1996, 156) also found that in the short term past returns can predict future returns. They conclude from their study that the past carries information about the future so funds that performed well in the past tend to continue the positive performance in the future. They also compared passive and active funds and found that active funds with the same amount of risk as the passive funds tend to perform better than the passive funds even after costs are taken into account. The previously reviewed findings on the persistence of fund returns that took into account survivorship bias had until this point had been accepted as strong evidence on the persistence. Momentum factor was then added to the Fama-French model by Carhart (1997, 79-81). He's study explained that the persistence in mutual funds is completely explained by common factors of sensitivity to the model and transaction cost differences. He rejected the notion that persistence would reflect the diversification abilities of

the fund managers, basing the outperformance of funds on momentum effect. He concluded that there was no support for the argument for the existence of skillful investors, and that there is a strong negative correlation between returns and costs with a unit increase in costs seemingly reducing returns by more than 1 unit. For a rational investors who try to maximize returns, he would suggest to: avoid funds that have shown persistence in poor performance, significantly higher return providing funds for one year won't provide the same return for the next consecutive years, and that all costs and fees have directly negative impact on the funds' performances. The last review on persistence is by Bollen and Busse (2005, 594-595) who studied persistence and giving emphasis on short term findings. Unlike Carhart (1997), their result showed significant returns in the funds they ranked at the top decile in their model. It should be noted that the differences in the results for them and those of Carhart (1997) could be explained by the different way persistence was calculated. And though their result showed strong statistical significance, they question the economic significance of the performance persistence (abnormal returns) in mutual funds. They state that even in the case that short term returns are predictable, an investor could just as well follow a simple buy and hold approach in order to generate superior returns, since costs erode the benefits of using active approach.

The previously covered literature on the persistence in returns shows different results for different time periods and studies, with the overall direction towards the conclusion that active mutual fund managers (stressed as on average) can't gain abnormal returns and fund performance by skill of differentiation and that the active approach tends to underperform (or at least not outperform) passive approach. The persistence that was found only applied in short term and even if investors could predict the returns in short term, they would still be better off by using passive approach rather than actively managed funds. The impact of costs on the return seemed to be the main shortcoming of active approach. Also, even if investor would successfully separate the skilled and well performing active fund managers from the average ones, the returns that the active managers have gained is not fool proof guarantee that in the future their performance would stay at the same level.

There have been several studies since Bollen and Busse (2005) that have concentrated on studying whether return is more due to luck or skill rather than on persistence of returns. As an example, study conducted by Cuthbertson et al. (2008, 632) on UK equity funds concentrated on determining whether the return is due to luck or the fund manager's differentiation abilities. Using data for the period 1975-2002 and using cross section bootstrap

method, they found that 5% to 10% of the best performing mutual funds have their return more attributable to skills in stock selection rather than luck. Their results would also indicate that the majority of the poorly performing UK equity funds have their results attributed to bad skills on the managers' behalf, rather than bad luck. Finally, for the majority of the funds that have positive abnormal returns, the results were attributable to luck rather than manager's skills. It would be difficult for an average investor to identify funds that show genuine skill of the manager, rather than luck. Also to note that it's not possible to point out winning funds in advance, but it is possible to point losing funds which show persistence in their poor performance.

If most active funds then do not show outperformance, why would an investor still invest in them? Active funds are still greatly used and there have to be investors who then continue using them. A study by Gruber (1996, 806-808) states that the investors' behavior to use actively managed funds is partly due to the predictability of future performance, based on past performance. The well informed and sophisticated investors direct their wealth to funds based on the funds' performances, while less sophisticated investors base their decision making on external influences such as marketing, or are under other restricting factors such as pensions plans and capital gain taxation reasons can make it inefficient to move money away from these funds for some investors. On the other hand, investors who are not under restrictions and are well informed, do indeed switch funds if they are dissatisfied with the performance. The author of this thesis would also like point out that while assuming that every average investor is rational and tries to maximize return, there are also other type of investors who might not care as much of the best possible return possible, and are comfortable with having a certain level of return for their investments, even though the return may not be the best one available.

3. METHODOLOGY AND DATA

This chapter discusses the methodology and the data used for the backtesting analysis of this thesis. All the data was taken from DataStream and consists of different end of the day prices of Finnish stocks, and accounting data that was used for the fundamental weighting model. All the modelling was done using excel versions 2010 and 2013. Different versions were used due to author working with different computers that had significant differences in computing power. More computing power was required to perform the optimization techniques which could take hours to perform. After the output from the empirical backtesting were received, the possible connection and feasibility of alternative indices to passive investing and portfolio management was studied and the final results for the research objectives of this thesis were derived.

3.1 Description of the data

The data used contained 197 companies from the Helsinki stock exchange from the period 1988 – 2014, the data was taken from datastream (database provided by Thomson Reuters). Datastream's database includes a maximum number of 525 companies for Helsinki stock exchange and the first 300 were taken as initial sample (the first 300 had more data available). From this sample, 103 companies had to be removed due to inconsistencies in the availability of different forms of data that was available (for example: some companies might have data for revenues for a certain time period, while lacking data for book value, and such company could not then be compared to other companies that had both types of data). And finally a maximum number of 100 companies were used (market capitalization was used to choose the companies) for the index weights and returns at a single given year, this was due to limitations in Excel solver function which puts restrictions on the maximum number of variables and constraints. Initially a longer time period was considered (1975 – 2014), but due to lack of data, a shorter time frame was taken. It should be noted that the earlier years, from

1988 to 1998 didn't have as many company data available as the more recent years and therefore the number of companies used for these years was a bit lower, but only during 1988 – 1993 was the number of companies used lower than 50. The author firmly believes that increasing the initial sample from 300 to include the remaining 225 companies for which some data was available would not at least significantly increase the final sample pool as those remaining companies were categorized as low quality companies (in terms of some data being available for them) and therefore would have been very likely omitted from the final sample pool. There is also the case where for certain companies (including some more well-known large companies like Nordea) surprisingly no data could be extracted. The author acknowledges that in order to fulfill these gaps in the data, another data acquisition tool and method could have been used, but those of which the author was aware of, are not available for the author to use due to cost limitations. There was also the choice of searching the data for the companies using second hand sources, but this method is usually best done when the amount of companies for which the data is being searched is small. The omitted 103 companies had delisted, merged, or ceased all operating activities many years ago and finding the missing data for them proved to be impractical.

The choice of using excel instead of other software is based on the author's familiarity and experience with excel. It is possible that by using different software (not available to the author due to cost limitations) excels limitations could have been avoided, but the author believes that excel is enough to provide reliable and usable results for the purpose of this thesis. There is also the advantage of using excel in the backtesting process that every part of the models could be inspected individually (due to the user-friendly interface of excel) to see any abnormal behavior in the models. Also replacing one year's data with another year's data to quickly solve for new output essentially cut significantly the time that was required to conduct the backtesting (easy to replace data used in the models).

All the data obtained from datastream consisted of the following: Stock prices, number of shares (ordinary, no preferred shares was used), cashflow to revenues, total revenues, and book value per share. Market value of the company was calculated by the author using stock prices and number of shares, book value was calculated with number of shares and book value per share. Initially the previously mentioned metrics were intended to be gathered from datastream, but they were not available so the author decided to use other values from which

then the previously mentioned metrics could then be calculated. Since the author doesn't have personal access to datastream, the access was provided by the authors' university.

3.2 Description of the methodology and models used

The empirical testing is conducted by performing a backtest on the different weighting strategies. This approach is chosen primary due to it being a good way to find out whether the alternative strategies would have performed well in the past, in contrast to the capitalization weighted method. Since alternative indices have not set a strong historical record on their performances, performing a back test on the historical data allows a suitable solution. This also enables the researcher to identify similarities in the indices performances and how they perform in certain market conditions (example of stock boom period of late 90's). There is of course limitations to backtesting, namely that historical performance is not a guarantee of future performance and can therefore give false interpretation of the models reliability. Actual results an investor could receive from live trading by using alternative indices as a benchmark can therefore deviate from what historical testing would indicate.

Many of the models used follow the basic principal outlines as they were defined in chapter 1, but the exact method in which they were constructed may differ.

First the monthly returns were calculated from the stock price changes for the whole time period and then used separately for each of the heuristic models. Annualized returns were used as the alternative index weight approaches are passive in nature and investors are not supposed to calculate the new weights on monthly bases, but on annual bases. In order to make the capitalization weighted index comparable to the alternative models, capitalization weighted approach was conducted in annual terms even though market capitalization indices can be rebalanced at different time intervals (weekly, monthly quarterly).

After this process, the stock weights were calculated for each strategy. The approach for heuristic models was to have multiple excel sheets consisting of the cleaned data and estimated stock weights, then calculate the return each weighting scenario would have for a specific year. Heuristic models used the same mathematical methodology as was described for them in chapter 1. However, equal-risk contribution (pages. 24-26) strategy was done using the same optimization approach as was done for the optimization strategies. This was due to difficulties arising in estimating covariance and how it affects each stock's weight in the

portfolio (difficult when dealing with a large stock pool). Since the assumption (and as was proven by the model) was that not all 100 stocks would end up having the same risk contribution due to differences in how stocks correlate with each other's, the solver model was given the restriction that individual stocks could have a minimum of 0% weight in the portfolio. Even this however was not enough for some years and a well differentiated solutions could not be found starting from year 1998. Therefore it's regrettable that equal-risk contribution approaches results cannot be compared for the other strategies in this thesis. The author would like to state that the solver model used, contained no errors and besides this one case, the model worked as intended for the rest of the weighting optimizations. What follows next is an individual description of each weight scheme and how they were done.

Market capitalization weights were calculated by first estimating the average annual total market capitalization of the stocks in the portfolio for a specific year, and then each individual stocks weight was calculated from this total market capitalization. The stocks' weights for each year were then multiplied by the annualized return each stock had for a given year. Market price method was very similar to market capitalization, just instead of using market capitalization, pure historical stock prices were used. Equal weight model used the total amount of different stocks that were used for a specific year and assigned the weights on each stock according to this (after 1997 the weights were always equal to $1/100 = 1\%$, formula on pg. 22). Risk clustering method is quite dependent on the amount of different clusters that are used for each year. In this thesis the stocks were clustered in a simplified method in which the companies' main operating sectors were used. The problem with this model is that the amount of stocks included in each sector cluster could differ quite significantly. As an example a cluster for companies operating in chemicals (the sectors were taken as they were assigned in datastream, for companies that had no sector assigned for them, the sector was assigned by the author relying on info that was provided by the companies themselves) contained only one company (Kemira), while the forestry and paper sector (a much more significant sector for Finland) contained 12 companies. While at first this might sound a very significant, the author would like to point out that the sectors that had a significant amount of companies included in them never had all the companies counted towards the sector weight (in a single year), therefore the market capitalization weights (on which the companies inside the clusters were assigned weights) were not that low for each companies. Also, clusters that had lower amount of companies in them, were not counted

towards the total cluster weights for every year because the companies inside the clusters were not operating, therefore the total amount of clusters was lower. The total number of clusters was 35, with 33 being the largest number that was used for assigning the cluster weights at one single year. The author would like to point out that while such clustering does affect the weightings and therefore the overall performance of a portfolio, this kind of results are to be expected when dealing with data for a country like Finland that may not have equal number of companies working for each sectors. In larger countries it's more likely that the number of companies inside each cluster is more even for each year, leading to a better diversification.

Diversity index (page 23) was conducted using two different values of P: 0.5 and 0.1, the index ended up working as expected, balancing between capitalization weights and equal weights. Inverse volatility index was conducted according to the method described in chapter one, the standard stock return deviations for each year were calculated, these deviations were then summed up and used to assign individual weights for each stock. For the fundamentally weighted model (page 24), three different data sets were used and they were chosen based on how they differ from each other and from market capitalization. First data set was cashflow, and as mentioned previously no direct data for total cash flow was available, so the closest one that was cashflow to sales (a ratio) was chosen instead. Second data set used was total sales (revenues), as sales reflect the company's operational performance and therefore can reflect better on how the company is performing. Third data set used was total book value of the companies, this was chosen since the book value of the company's assets can differ significantly from the market value of the company (overpriced companies can have significantly higher market value than their book value, as was the case for example in many of the companies during the dot.com bubble). The weighting calculation for the fundamental strategies followed the formula (6) on pg. 24.

The last weighting models are the three optimization approaches: Minimum variance, maximum diversification, and risk efficient weighting. For these methods, a separate excel solver model was built from scratch, the model firstly estimates the correlations between the stocks, then the covariance. Note that the matrixes were built so that they would be updated automatically when a bit of the input data was changed, in other worlds they were constructed by hand and not by using excels own inbuilt matrix calculator. This was done mostly due to the fact that when using as many as 100 stocks, the time it takes for excel to construct the

matrixes using its own system can be up to couple of hours (depending on the speed of the computer and the data), therefore the manual approach was chosen. After the covariance matrix, a final matrix was constructed that takes into account how the relations between the stocks change when the weights given for each individual stocks change, and from this matrix the portfolios total variance was calculated. After this excel solver was used to find the optimum weights. In minimum variance's case, solver was assigned to maximize expected return while trying to hold standard deviation of the portfolio as close as it could to 0.5. For some years excel managed to keep it at 0.5, but for some years the deviation ended being a bit higher. In order to avoid solver assigning too high weights for individual stocks (which would go against the diversification principle of alternative indices) a maximum weight restriction of 5% was used for most of the years. For the years in which there were lower stock pools (namely the years before 1998) the restriction was between 6% and 10% since otherwise there was no solutions where a 100% total distribution among all the stocks could have been possible. Maximum diversification used the same base model as minimum variance, but was assigned to maximize the estimated Sharpe ratio for the portfolio, but still implementing the same weight restrictions for stocks as was used in minimum variance. Risk efficient approach estimated first separately the downside deviations of each stock, the stocks where then grouped by deciles then the median downside deviation of each decile was used to assign the proxy estimated returns for the stocks. Using these proxy returns, solver was then used to maximize Sharpe ratio, and after this the annualized stock returns were used to see how the weightings would have performed. Note that a hypothetical risk free rate of 1% was used, this is purely just to estimate the Sharpe ratio and see how the weighting schemes compare to each other's. Acknowledging the limitations of Sharpe ratio (pg. 17) Sortino ratio is also calculated due to it being better suited to calculate high volatility portfolios which may just be the case with some of the weighting strategies.

4. EMPIRICAL RESULTS

The first sub-chapter covers the results from the backtest and also compares the results to those that have been found by other studies. Second sub-chapter focuses on determining the feasibility of alternative indices to passive investing by utilizing the backtest results and the findings from the literature review. To help visualize the development of Finnish stock market (and how the graphed results from backtest compare to it), figure 4.1 depicts OMX Helsinki which contains all the available stocks, weighted by their market capitalization. Note that when comparing the magnitude of upside and downside developments in figure 4.1 to the graphs on alternative indices performances, it should be remembered that OMX Helsinki contains different amount of companies (more) then was used in the backtest. As can be seen in the figure 4.1, the stock boom in late 90's and financial crisis in 2008 are quite visible.
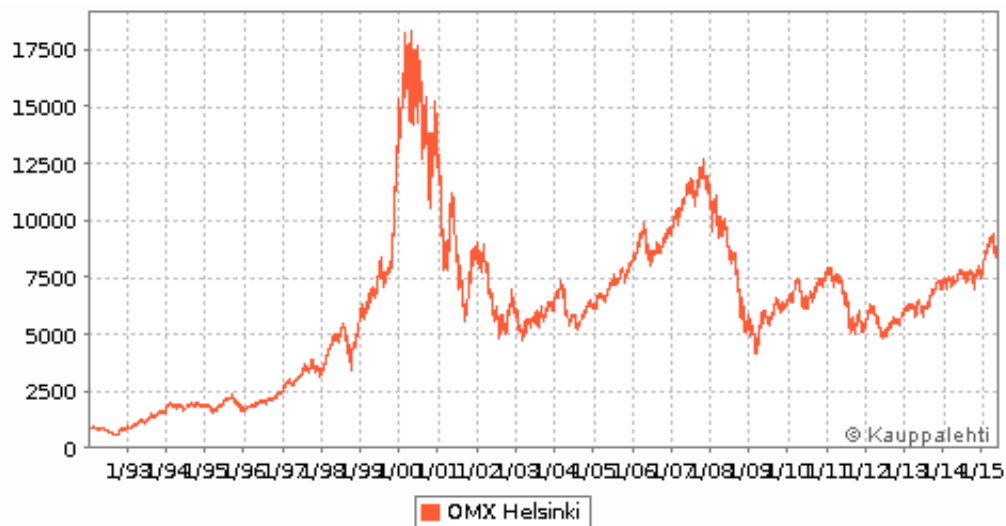

Figure 4.1 OMX Helsinki 1992 - 2015

Source:Kauppalehti.fi : http://www.kauppalehti.fi/5/i/porssi/porssikurssit/indeksi.jsp?
indid=OMXHCAPGI&days=max&x=7&y=8

4.1 Results from backtesting

While the results from the backtesting seem to support the initial assumption that alternative indices perform better in terms of risk and return, there are differences in the performances of the indices. Figure 4.2 depicts the performance of the alternative indices using rebase of 1000 (to compare with the OMX Helsinki).
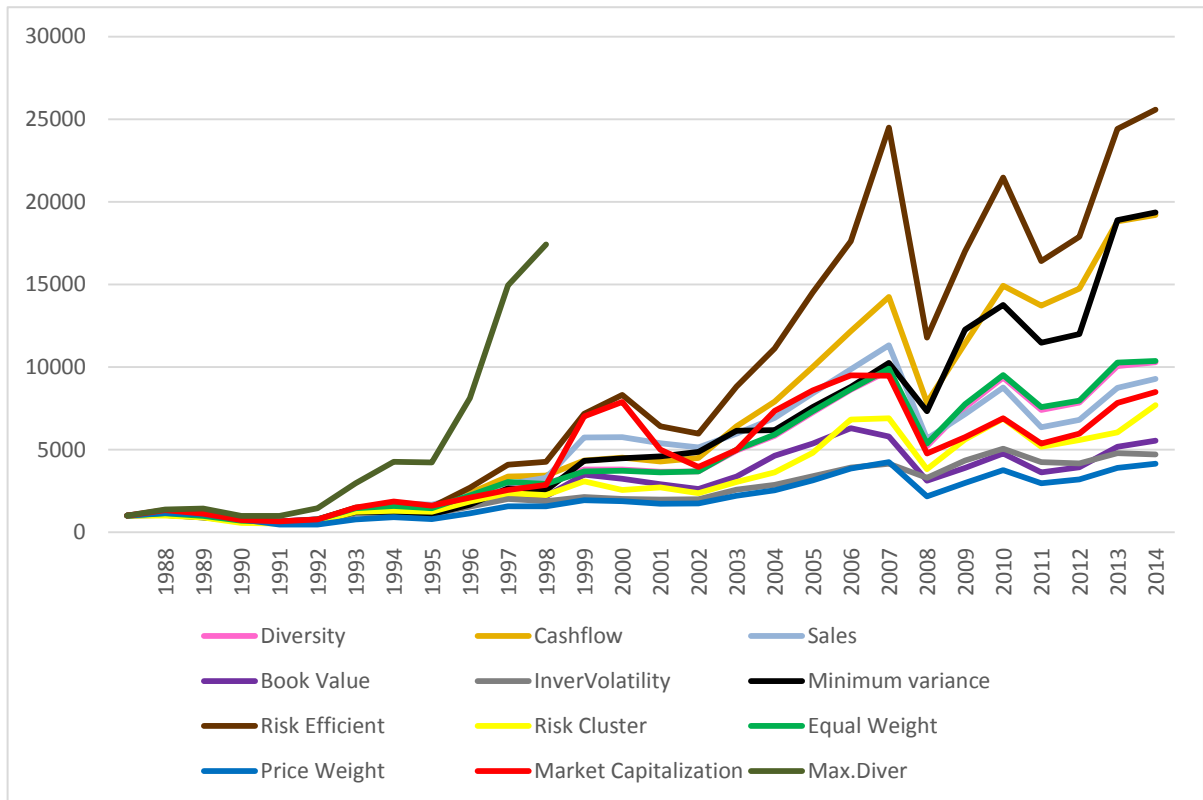

Figure 4.2 Graph on the performance (return) of weighting strategies for 1988 – 2014

As can be seen from the graph, all the indices follow the same up and down patterns, but while weighting approaches such as cashflow and minimum variance end up having similar final value in 2014, they differ in terms of magnitude of their volatility. Cashflow performed better before 2007 when the financial crisis hit and it came down to the same level as minimum variance which saw much smaller decrease during this period. This is even more reflected in risk efficient method which shows significantly more drastic ups and downs but in the ends up having only slightly better Sharpe ratio than cashflow and minimum variance. From this can be concluded the importance of choosing the weighting strategy that best serves the investors risk tolerance and personal preferences when it comes to comparing different

strategies. Note that maximum diversification is not shown here completely due to this model increasing to such high values that the other indices become incomparable to it in the graph. Also the indices that had more or less the same graph are not so disguisable from each other in figure 4.2 Therefore separate graphs for the maximum diversification and the other indices can be found in the appendixes. Table 4.1 covers more descriptive statistics of the indices performances.

Table 4.1 Returns, standard deviations, Sharpe and Sortino ratios

	Annual Return (mean)	St.Dev	Sharpe ratio	Sortino ratio
Market Capitalization	13.2%	39.5%	0.31	0.86
Price Weight	8.4%	25.9%	0.28	0.46
Equal weight	12.2%	27.6%	0.41	0.81
Risk Cluster	12.1%	30.4%	0.37	0.82
Diversity p=0.5	11.9%	29.4%	0.37	0.79
Diversity p=0.1	12.1%	27.6%	0.40	0.79
Inverse Volatility	7.7%	21.6%	0.31	0.95
Cashflow	14.7%	27.6%	0.49	1.00
Sales	12.1%	28.3%	0.39	0.72
Bookvalue	9.3%	28.4%	0.29	0.69
Minimum Variance	15.5%	30.8%	0.47	2.07
Maximum Diversification	36.8%	42.5%	0.84	2.10
Risk Efficient	18.0%	34.7%	0.49	1.07

Source: Author's calculations

As can be seen, the standard weighting methods of market capitalization and price weighting indices were outperformed (in terms of Sharpe) by the vast majority of the alternative weighting strategies. As was initially suspected, optimization strategies performed significantly better due to the models trying to maximize either expected return (while trying to retain low level of risk) or Sharpe ratio, only one heuristic fundamental weighting method seemed to perform as good as minimum variance and risk efficient weighting strategy. The obvious over performer of the methods seems to be maximum diversification which over performed significantly the other indices in return and Sharpe ratio, it did of course boast much higher standard deviation between the annual returns. Judging from the weighting model and the excel solver approach chosen for the optimization indices, it's quite clear that

optimization models performed much better due to the model seeking out maximizations instead of just assigning weights at to the stocks based on some heuristic assumptions. Although as cashflow method proves, they are not however the only way to gain significantly better results and the heuristic reasoning's behind the models seem the play a big part as well.

Price weighting method has the lowest Sharpe ratio, as was initially assumed. This weighting method was expected to underperform every other index although the difference from market capitalization is not much. Equal weighting performed significantly better than market capitalization or price weighted, going through the periodic data it's clear that the better performance is attributed to lower amount of exposure to more risky stocks, though when using 100 stocks each stocks weight becomes 1% and therefore the method doesn't take advantage of stocks that are performing better than other stocks. Risk cluster had the same underlying principles as the equal weighting method, but since better performing stocks that were in the same sector cluster had their weights reduced significantly more in those years when a large amount of clusters were operating and contained many companies who then had their weights set by the market capitalization of the cluster. And while the return stayed almost exactly the same, this method showed more risk than the equal weight strategy. Diversity weighting showed the combination of both equal weighting and market capitalization strategies, though for investors who are mainly concerned only with the risk efficient return, using diversity weighting seems unnecessary since equal weighting seems to always provide better Sharpe ratio regardless of what value of P is used. On the other hand those who wish to combine the two approaches to gain a bit larger return while being indifferent to extra risk might find this approach of some use. Though only p=0.1 and p=0.5 values where used, the expected return is expected to rise when values higher than 0.5 are used.

Though the underlying theory behind low volatility weighting was to gain higher returns than capitalization weighting, it seems the method is strongly risk averse, the expected return of this model is the lowest of all the weighting strategies but so is also the standard deviation. Despite not really performing any better than market capitalization in terms of Sharpe ratio, risk averse investors might still find it of some use if they are willing to accept lower expected returns. The three fundamental weighting approaches all performed differently with cashflow obtaining the highest Sharpe ratio and better expected returns than sales or book value approaches. The simple heuristic assumption taken in cashflow was that

companies that generate stronger cashflows tend to perform better which is then reflected in their stock price. This seems to work well since from all the heuristic approaches cashflow had the strongest performance and managed to obtain even the same level of Sharpe as two optimization strategies. Considering such a good performance from cashflow, it is evident that the underlying theory behind the methodology of the weighting strategy is important and can make large difference in the performance of the model. Also considering that although the optimization strategies can be described a more "scientific" or at least more technically advanced, a simpler heuristic approach may still outperform them. While minimum variance maximized expected return while keeping standard deviation as low as possible in order to gain the highest level of expected return for least amount of risk, maximum diversification and risk efficient methods solved for the weights that maximize the Sharpe ratio with risk efficient approach just using downside deviations as proxies. Of all the methods tested, maximum diversification had the largest Sharpe ratio, and though such outcome was not expected (not at least so drastic difference of Sharpe ratio) it does show that when building the optimization weighting models and solving for some different factors' maximization or mineralization (return, standard deviation, Sharpe) has significant importance in the expected performance of the model. And while it's possible to generate various different optimization models just based on the notion of maximization or minimizing of certain specific factors, the importance is to have the models based on some underlying theory of how a better risk return performance can be achieved.

The performance differences as they are depicted in table 4.1 follow to certain extend similar value trends as in previously conducted researches. In the backtest performed by Chow et al. (2011, 42) the optimization weightings performed better (in terms of Sharpe, return, and volatility) than the heuristic or market capitalization weighting methods when U.S stocks were used. When using global stocks however the results are not so one sided, with risk cluster and fundamental weightings performing significantly better (in terms of Sharpe and return) than maximum diversification and risk efficient methods. It's worthwhile to note that minimum variance performed best from the optimization methods with maximum diversification not expressing such huge performance difference as was found in this thesis's backtesting. Minimum variance was also found to outperform (in terms of Sharpe, Sortino, and st.deviation) all the other weighting schemes in the backtest conducted by Clare et al. (2013, 9) on U.S stocks. Maximum diversification was found to perform poorest from the

optimization models, though the only weighting approach that came to the results of market capitalization (which performed the poorest) was risk clustering (nearly the same Sharpe and return). Note that the study by Chow et al. used time period of 1987 – 2009 and Clare et al. used 1969 – 2011. Clarke et al. (2013, 43) who used U.S stocks from 1968 to 2012 also found minimum variance to perform better than the other 4 weighting schemes that were tested. Interestingly in their case maximum diversification underperformed market weighted approach, this was due to maximum diversification having higher standard deviation (the authors' state this can be due to indications of higher portfolio concentration). In general market capitalization was shown to underperform all the other weighting schemes, and optimization models in general performed better than heuristic models. The data sets used in this thesis and the ones used by the other authors are however quite different.

In table 4.1 the value differences between the Sharpe and Sortino ratios quite significant, but one most remember that the use of either Sharpe or Sortino depends on whether investors wants to concentrate on standard deviation or downside deviations. Sortino ratio is more effective measurement when dealing with high volatility portfolios, and Sharpe ratio is better for low volatility portfolios. To further elaborate the differences between different weighting models' performances, and the differences between Sharpe and Sortino ratios, table 4.2 depicts the differences in the amounts of positive and negative years each weighting model had and the minimum and maximum returns that occurred.

Table 4.2 Positive and negative years, maximum and minimum values

	Positive years	Negative years	Minimum	Maximum
Market Capitalization	18	9	-49.6%	144.2%
Price Weight	18	9	-48.9%	64.7%
Equal weight	19	8	-45.8%	86.9%
Risk Cluster	18	9	-44.6%	96.7%
Diversity p=0.5	18	9	-49.3%	85.9%
Diversity p=0.1	19	8	-46.8%	86.2%
Inverse Volatility	16	11	-20.7%	73.5%
Cashflow	20	7	-44.8%	84.3%
Sales	19	8	-49.9%	83.3%
Bookvalue	16	11	-46.1%	83.2%
Minimum Variance	20	7	-28.5%	79.5%
Maximum Diversification	21	6	-47.7%	102.9%
Risk Efficient	19	8	-51.9%	94.9%

Source: Author's calculations

While most of the indices had either 18 or 19 positive years, few indices had above or below these values as one can expect by looking at the expected return, standard deviations and Sharpe ratio from table 4.1. Minimum and maximum values are also quite even for majority of the models, with some exceptions. Namely the worst performing model (in terms of Sharpe ratio) was price weighted and as the table shows, this strategy had the lowest maximum value while in contrast the market capitalization model had the highest value. But as the underlying reason behind market capitalization tells us, this weighting strategy has high standard deviation which makes it less attractive choice for investors who are concerned with having risk efficient returns. The only model that had 21 positive years was also as expected, maximum diversification which also had second highest maximum value and lowest amount of negative years. The strategy that had the lowest standard deviation was inverse volatility and it was also one of the two alternative weighting models that had only 16 positive years and 11 negative years. Even so though, the lowest value for any given year was only -20,7% which is more than half of the average minimum values across the other indices with only minimum variance managing also to have minimum downside less than -30%. What should be noted from many of the alternative methods is that while some of the boast higher amount of maximum upside values and some lower minimum downside values, the still retain around the same Sharpe ratios. A good example is cashflow and minimum variance strategies since both have the same amount of positive and negative years and the same Sharpe ratio value of 0.49, their maximum and minimum values are more reversed with cashflow having higher maximum value and minimum variance having lower minimum value. This shows that even when dealing with alternative weighting models that might show equal performance, any investor who would consider using such alternative weighting methods should also concern him or herself on which aspect to give higher importance and what aspect is more important: having either a larger return during the best periods, or having smaller loss during the worst year. The investor's personal preferences are therefore still important even in the cases where some weighting strategies would indicate equal importance in terms of risk efficiency.

Since Sortino ratio is calculated by using the downside deviation of negative returns, it's not as reliable performance measurement when the amount of negative years is low, with some of the indices providing good example. Namely minimum variance and maximum diversification who both have nearly the same Sortino ratio even though they have vastly different Sharpe ratios. With almost equal amount of negative years, minimum variance ends

up having the same Sortino ratio as maximum diversification due to the lower minimum downside value (and in contrast maximum diversification has higher maximum upside value). In the case of models that have more negative years such as inverse volatility and bookvalue (both which had Sharpe ratio similar to market capitalization), inverse volatility due to its low minimum value has higher Sortino ratio than market capitalization, while bookvalue has the second lowest Sortino ratio. This is expected of course since weighting strategies that have low minimum value have lower change of experiencing high losses. Figure 4.3 illustrates how the alternative indices performed differently each year in comparison to market capitalization. Value above 0% indicate that the alternative index showed higher returns than market capitalization, and values below 0% indicate that market capitalization instead showed higher returns.

Figure 4.3 The differences of the indices' annual returns compared to market capitalization

As can be seen, while some of the indices showed similar return rates like market capitalization during the early 90's, in the later years the differences start to be more

significant. Maximum diversification namely has quite different return rates from the rest of the weighting strategies and during the late 90's when all the other indices showed drastically worse performance, maximum diversification was not that much far behind the market capitalization. In general there seems to be only few distinct years when market capitalization showed significantly higher returns: late 90's, and 2004. While the overweight in I.T companies during the dot com bubble can explain the large returns in market capitalization during late 90's, 2004 seems to be more in line of "lucky guess" since the performance of market capitalization in this particular year was due to one specific and large company performing significantly better. In general sense however, nearly all the alternative indices show higher returns during all the other years, and even in those years when they do not show significantly better returns, they don't show significantly lower rates of return.

To explain more of the distribution of the weighting strategies, table 4.3 shows the kurtosis and skewness of each weighting model.

Table 4.3 Kurtosis and skewness

	Kurtosis	Skewness
Market Capitalization	4.229	1.515
Price Weight	0.263	-0.245
Equal weight	1.205	0.412
Risk Cluster	1.159	0.527
Diversity p=0.5	0.860	0.378
Diversity p=0.1	1.140	0.356
Inverse Volatility	2.039	1.158
Cashflow	0.779	0.290
Sales	1.562	0.405
Bookvalue	0.807	0.484
Minimum Variance	-0.474	0.744
Maximum Diversification	-0.923	-0.081
Risk Efficient	-0.015	0.145

Source: Author's calculations

Market capitalization shows significantly higher kurtosis (leptokurtic) value as this weighting strategy has high maximum upside value and also large standard deviation. Combined with large positive skewness, the underlying faults of market capitalization's stock concentration becomes more evident as the strategy tends to have large extreme gains during stock boom periods, but otherwise underperforms in terms of risk efficient return and most the returns tend to concentrate to the left from the mean. The second weighting model that

shows high values of both kurtosis and skewness (after market capitalization) is inverse volatility weighting. Though it has significantly lower Kurtosis than market capitalization, its skewness is not that far from market capitalization. For these two models, the high level of kurtosis would imply that small changes happen less frequently, but there is a higher chance of experiencing either a large loss or gain. Of the remaining weighting models only three have negative kurtosis, and these are the optimization models. The negative values indicate that these three models have lighter distribution tails and flatter peak. A risk-averse investor would prefer to have portfolio that has low kurtosis so that the returns are much closer to the mean, and negative skewness (rather than positive skewness) so that there are rather frequent small gains and fewer instances of large losses as opposed to having frequent small losses and few large gains. Therefore, judging from table 4.3, the model most in line with this preference would be maximum diversification. Other models that would also seem to be quite attractive for risk averse investors would be risk efficient, and to some extend also price weighting.

4.2 Feasibility of alternative indices to passive investing

The results from the backtesting indicate different levels of performance between the alternative weighting strategies and market capitalization and price weighting approaches. While in general it can be stated that most of the alternative weighting models do provide better risk adjusted return compared to the traditional models. There are significant differences in the performances, with some models showing lower maximum losses, higher maximum gains, and some showing lower standard deviations, but end up having similar Sharpe and Sortino ratios. From this the author would suggest that when dealing with alternative weighting strategies, an investor should consider different factors that would suit the traits they themselves are looking for. And while method such as maximum diversification lead to significantly better results (in terms of Sharpe ratio), it is possible that the same method might not prove to be as good when used in for different data sets. Other alternative models might show improvement (or decrease in performance) when some parts of the data that is being tested changes (such as the number or type of clusters used, or total amount of companies used changes). The impact of taxation on passive investing was not studied as this was out of scope fir this thesis, but the effect it would have on the indices return would be dependent on country specific jurisdictions regarding tax rates for both active and passive

investing. The author would therefore advice anyone interested in practical appliance of alternative weighting strategies, to carefully consider their own position, the type of equities being used, and how they might affect some of the models.

Combining the results from the backtest and the output from the literature review, it cannot be concluded with outmost certainty that passive investing is better choice than active investing in all aspects, or that all actively run funds always underperform passive indexing approaches. There is however sufficient evidence to state that passive investing is better choice to an average mutual fund (especially for an average investor with limited capabilities on choosing the funds and run them with skill) and therefore attempts to improve passive investing could lead to even better performance. Constructing a benchmark index (that is based on one of the alternative modeling approaches as was presented in this thesis) for an investor to follow could then lead to a higher, more risk efficient return. And for average investors who would still prefer an active approach, the author would recommend using some of the heuristic models, as these models are intuitively more understandable and not as heavy on more complex math and formulas which might deter away less mathematically oriented investors. And from a more practical point of view where an average investor may not be concerned in achieving the best possible results, or is due to other factors not as interested in constructing his or her own benchmark portfolios to follow. The author would recommend to compare the past performances of different types of mutual fund portfolios available to the investor and then choose those that show a certain level of persistence in positive return for consecutive years and then from these funds, identify those funds that have their stock pickings based on in economically understandable methodology that is consistent with results. The investor should also always take into account the fees and costs related to actively managed funds and think carefully whether the true realized return for the investment is truly worth their money, and time.

CONCLUSION

This research on alternative indices and passive investing covered an empirical backtest of alternative index models using Finnish stock data from the period 1988-2014, and a literature review on passive and active investing and performance of mutual funds. The objective was to conduct a research on alternative weighting models and see how they perform in terms of risk and return to market capitalization and price weighting approaches. In addition to this, using empirical results and literature, feasibility of alternative weighting models for investors was also studied. Results from the backtest indicate that some alternative weighting strategies do indeed provide a better risk return performance than standard indexes. There are however significant differences between the models, with some models performing significantly better than others. Optimization based weighting schemes were found in general to perform better than heuristic models, specifically maximum diversification showed significantly higher average annual rate of returns and standard deviation than any other weighting method. The findings for maximum diversification is not supported by previously conducted empirical backtests, and it's quite possible that the performance of maximum diversification is more related to the data sets used. Therefore, investors interested in using alternative weighting strategies should consider their own situation (the type of stocks they have in their portfolio) and preferences when choosing which alternative model would best help to serve their interests and needs. Review of literature on passive and active investing and the performance of actively managed mutual funds indicates that actively managed funds in general tend to underperform their benchmarks and investors could gain better results just by following benchmark indices and using simple buy and hold strategies. Note that while there are also well performing funds whose managers show skill in their abilities, funds' performance as group is dragged down by the average and poorly performing funds, making it difficult for an average investor to separate the good from the bad.

The output of this thesis would support the hypothesis that alternative indices are indeed shown to be feasible for investors, the author would however stress that while different types of investors can find some weighting methods more usable than others, and alternative

indices in general do seem to prove valuable for both passive and active investors to consider using. It cannot be however stated that passive investing is superior to active since there are differences between certain active funds performances, leaving it to be stated that passive investing would in general be superior to an average actively run mutual fund, but certain individual actively managed funds do outperform passive investing.

The author would suggest more future studies to be conducted on regional equities where a larger portion of the regions total equity population could be used. This is to see how some of the alternative weighting strategies would behave under different data sets, since the results for some weighting strategies shown in this thesis do differ to certain extent from those covered by others studies on U.S stocks. The problem with using only stocks from Helsinki stock exchange is that it cannot be generalized to state that the weighting methods results would show exactly similar performance when different countries' company stocks are used. One way to overcome this is of course to use equities from global stock pool, but this on the other hand might not be as intuitively attractive to all investors who might be reluctant to invest in stocks of a company that operates in an industry and region unfamiliar to the investor. Other problem that the author wishes to acknowledge here is the limitation imposed by the limitations of software used. It would be more preferable that the possible future backtests are conducted by using a software than can work with ease and efficiency on a larger data sample, and not be constrained to only 100 stocks.

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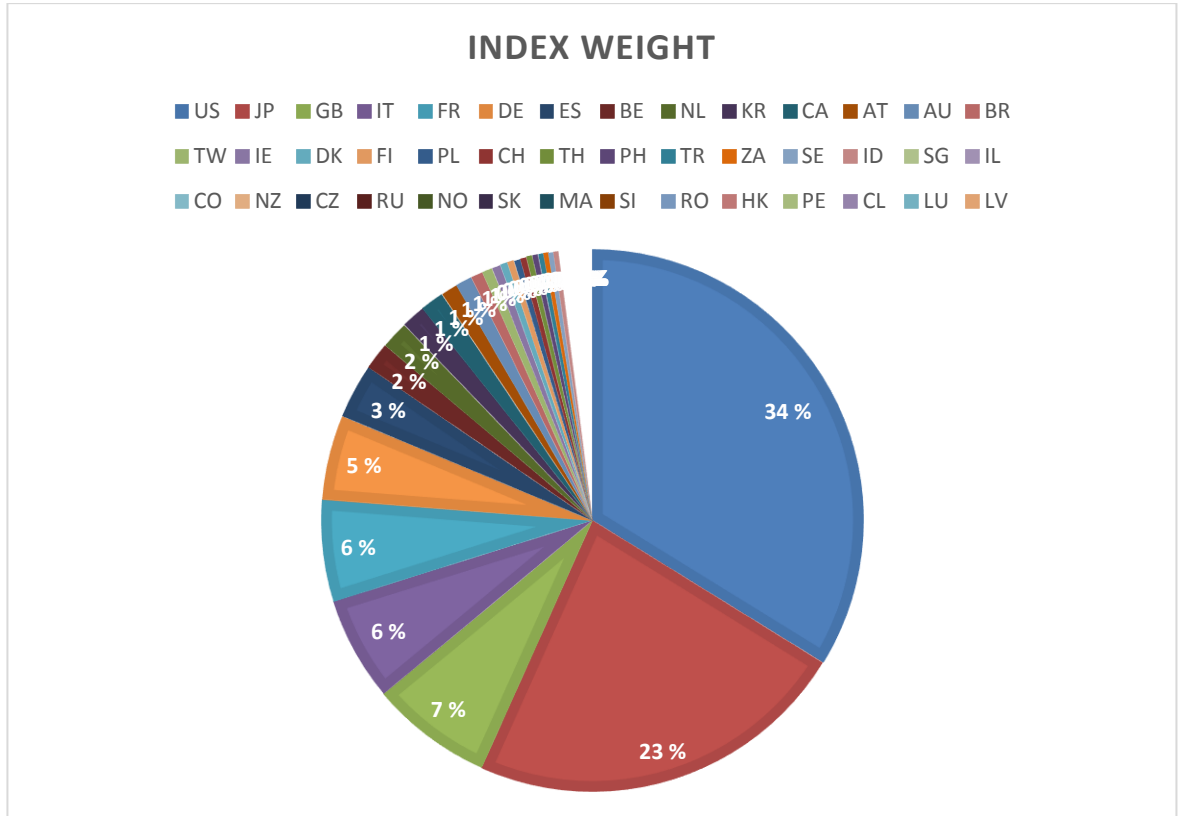# APPENDICES

Appendix 1. Index bond weight example

Figure 2. ML Global Broad market sovereign plus index allocation in December 2014.

Source: Author's calculations

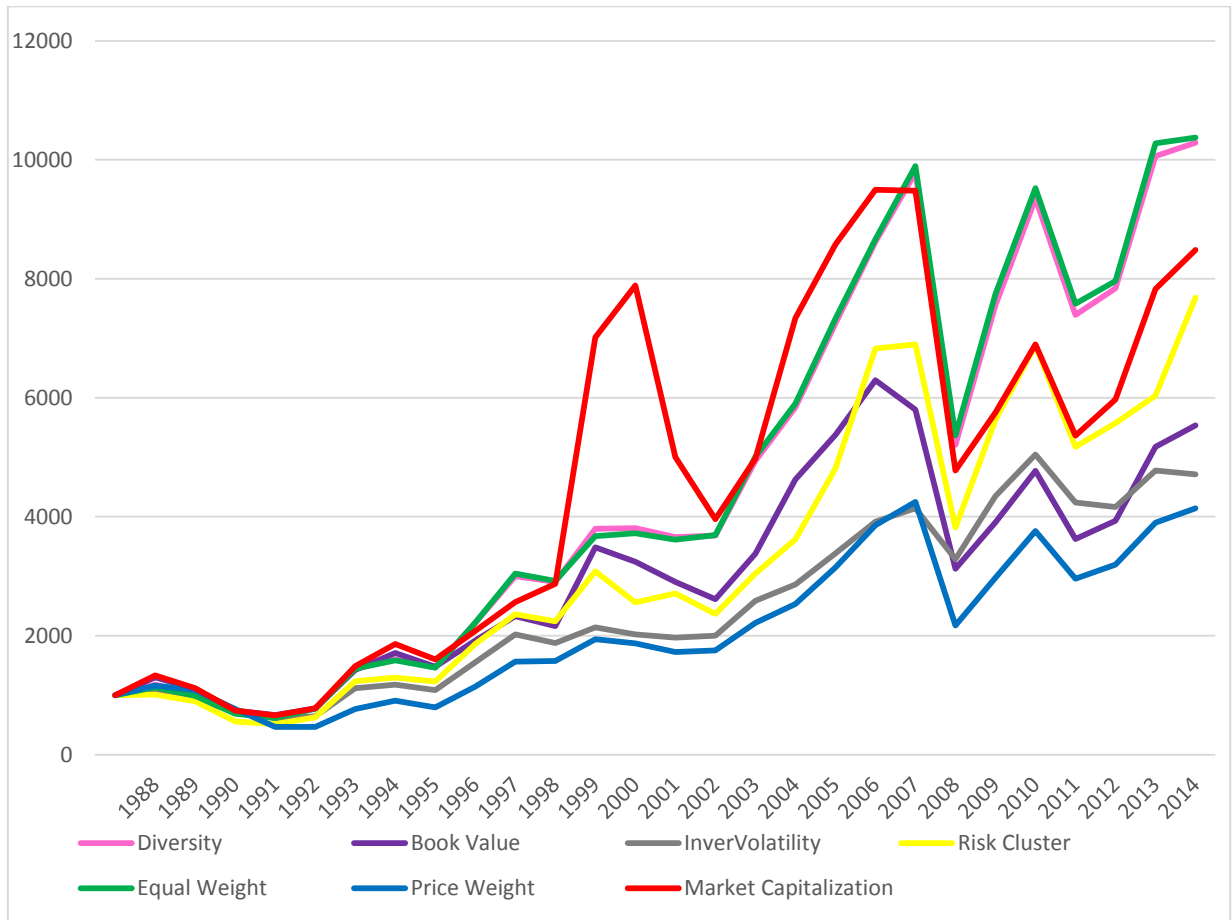**Appendix 2. Alternative indexes graph**

Figure 5. Alternative graph including only smaller portion of the alternative weighting strategies

Source: Author's calculations
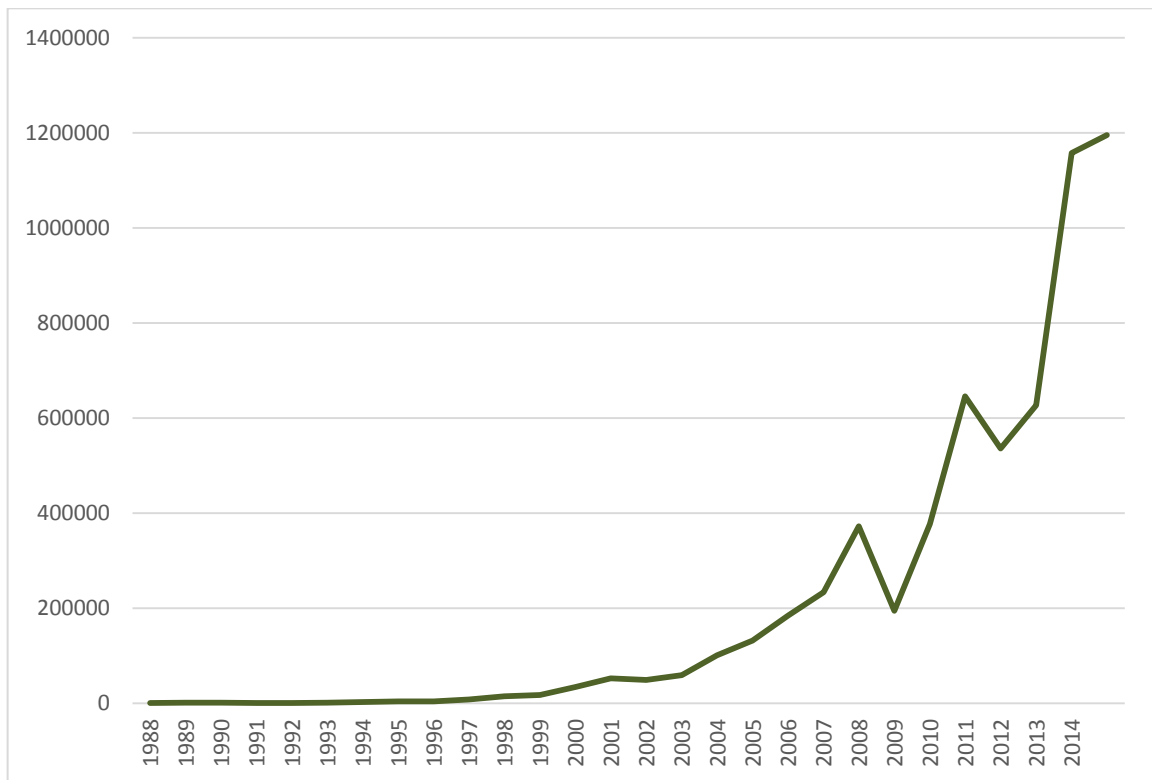
Appendix 3. Maximum diversification index

Figure 6. Graph depicting the maximum diversification approach

Source: Author's calculations