Gordon Institute of Business Science
University of Pretoria

The effects of constraints on the performance of actively-managed funds in relation to their benchmark indices

Linda Minette Eiselen

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Abstract

Actively-managed funds have recently come under fire as it has been determined that they consistently underperform passive funds. Benchmarking, and the constraints placed on actively-managed funds, are standard practices within the industry, but research suggests that these constraints negatively affect fund performance.

This research paper explores the effectiveness of actively-managed funds in relation to their benchmark indices, in terms of tracking errors and weighting constraints. This is done by qualifying the effect of these constraints on the performance of hypothetically constructed portfolios in relation to the FTSE / JSE Top 40 Index. The results are presented graphically and show that tracking error limits did, as expected, limit the possible upside returns of these funds. It was found however, that the tracking error constraints had a much greater effect on limiting downside risk than they had on limiting upside effects. Weighting limitations did not have a single universal effect on the simulated portfolios' performance but affect performance in conjunction with tracking error limits.

It was concluded that for the hypothetically constructed portfolios for the period studied, constraints did not affect the possible upside return to such a magnitude that the constraints themselves could account for the underperformance of actively managed funds and they had an overall positive effect on performance.

Keywords

Actively-managed funds, Tracking Errors, Weights, Constraints, Benchmark Indices

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1 Introduction to Research Problem

Actively managed funds have been in the firing line in the recent press as it has been determined that after active managers' fees have been deducted, they consistently underperform passive funds (Guastaroba, Mansini, Ogryczak, & Speranza, 2016). This fact is understandably disconcerting due to the size of the industry. The value of stocks traded on the New York Stock Exchange has grown from three million to one and a half billion US Dollars in the last 50 years (Ellis, 2017). According to the Association for Savings and Investment South Africa (ASISA) (2017) the Collective Investment Schemes (CIS) industry showed a total net inflow of R160 billion at year end of 2017, which was the highest amount in the last four years. This illustrates the importance of research into the field of active portfolio management.

It is also important to recognise the importance of both types of funds: active and passive, as each has its place. The theory of an efficient market relies on an active-manager's behaviour to set the price (Currie, 2017). The problem that will occur if no active funds participate is the dislocations of the market (Currie, 2017). According to Du Preez (2016), the more sophisticated fund managers become, the more they have moved away from the debate over active versus passive, and are now blending active with passive investments. The purpose of this research will be to analyse an aspect of actively managed funds in order to determine what their maximum performance could have been if the constraints placed on them were removed.

There are numerous problems caused by the practice of benchmarking and implicitly, the constraints place on actively managed funds in relation to their benchmark indices. From the viewpoint of investors, a problem arises regarding the practice of benchmarking (Ward & Muller, personal correspondence, 2017). Fund managers are hired on the basis of outperforming benchmark indices. This forces asset managers to trade in specific styles to match the performance of the measurement index, sometimes resulting in purchasing over-priced stocks in order to "satisfy the tracking constraint" (Vayanos & Woolley, 2016, p. 6; Drenovak, Urošević, & Jelic, 2014). Investors also bid-up assets with high risks resulting in lower than expected performance (Frazzini & Pedersen, 2014). Market capitalisation benchmarks and the rational models of asset mispricing cause an inverse relationship between risk and return: highly volatility offers lower returns (Vayanos & Woolley, 2016).Thus benchmarking results in lower returns (Vayanos & Woolley, 2016; Drenovak, Urošević, & Jelic, 2014; Frazzini & Pedersen, 2014).

Within the context of South Africa and the Johannesburg Stock Exchange, most actively managed funds were unable to beat their indices recently, in 2017 (Erasmus, 2017; Stein, 2017). This was largely due to the fact that one stock, namely Naspers, performed so much better than all other stocks and because of its size constituted 20.5% of the FTSE / JSE All Share and 24.5% of the Top 40, whereas most actively managed funds are restricted by how much of one stock they can hold (Cairns, 2017). On the other hand, Naspers is also priced for perfection so true index trackers are at a disadvantage when they are forced to buy more of this giant (Ryan, 2016). The FTSE / JSE Swix Top 40 is one of the world's most concentrated indices, with a Herfindahl-Hirschman Index of almost 900 versus 100 for the S&P 500 and has very high turnover (Lambridis, 2017).

It is also important to note that within the context of South Africa, there is a lesser margin of underperformance of active funds than there is globally because passive funds in South Africa do not have the same tax exemptions as for example, the United States (Lambridis, 2017). The high concentration and turnover levels of the JSE indices also make an argument for active management.

1. 1 Research problem

This research will aim to explore opportunities for actively managed funds' tracking benchmarks to beat the market. This will be done by exploring the maximum and minimum opportunities which would be available to active fund managers if the tracking error and weighting within portfolios were adjusted from that of their benchmarks. This relationship will be explored by quantifying the relationship between portfolio returns and their weight allowances and tracking errors (the difference between the portfolio returns and performance of the benchmark or index). Their relationship will be explored by calculating the possible best and worst returns for a portfolio when adjusting for different levels of tracking errors and by changing the weightings of each share. The research will explore this relationship and attempt to determine the maximum possible returns that retrospectively could have been achieved (or were available to the fund managers) by actively managed funds that employ technical or fundamental analysis to drive investment decisions. Alternatively, the question as stated by Jiang, Verbeek and Wang (2014) is "[c]ould individual fund managers have performed better by being more active?" (p. 2039). Therefore the impact on returns will be shown when portfolios are allowed to deviate by different levels of tracking errors. The study will, in addition to tracking error adjustments, show how the alteration of constituent weighting will affect returns over different periods of time.

The research will refer to the long standing debate on whether active or passive investment strategies are preferable. Even though active funds have been found in recent press to underperform passive funds, this is not to say that all actively managed funds will forever underperform. There will always be an opportunity to take advantage of inefficiencies in the market that can only be realised by actively managed funds. The results of the study will illustrate whether actively managed funds (and enhanced index funds) that deviate from indices weightings could have offered better returns than passive funds which exactly track their indices. It must be noted however that large funds will be limited by their size when it comes to adjusting weightings as there may not be sufficient stocks to fulfil the weight adjustment. When the weighting is adjusted, larger funds will be restricted by the limit of available stocks of a specific company.

The research topic evidently falls within the financial field of study, as well as accounting and management science studies. Therefore the topic is relevant specifically to the financial industry and the business of active fund management.

1. 2 Purpose statement

The research aims to uncover the effectiveness of actively managed funds in relation to their benchmark indices if they were to be freed from their limitations and regulations of tracking error levels or weighting allowances. This will be done by quantifying the risk – return spectrum and determining what could have been the best or worst performance at different levels of constraints; particularly different levels of tracking error and weighting allowed in a fund. The purpose of this research is to analyse actively managed funds in order to determine what their maximum performance could have been if the limitations placed on them where removed. The findings will add information to the debate of active versus passive investment by qualifying the impacts of the limitations on actively managed benchmark trackers.

The study is conducted by simulating and then analysing the performance of hypothetically constructed portfolios with differing constraint conditions. For the purpose of this study the FTSE / JSE Top 40 Index was used as the basis for the research. The yearly total returns for the FTSE / JSE Top 40 Index has been an average of 11% for the last ten years (Morningstar, 2018). The research will show what the best and worst performance could have been in relation to the index for different tracking errors and weight allowances and will thereby quantify the effects of these constraints. This will illustrate what the effects of tracking errors and regulations on actively managed benchmarked funds are. The research aims to investigate the distortion of index benchmark constraints in an attempt, not so much to try and predict the future in order to make abnormal returns, but rather to analyse the past behaviour of the stock market and the practice of actively managed funds in order to better understand the nature of the industry, particularly in an emerging market. This study thus relates to the "hot" topic of the debate of active or passive, by attempting to better understand the nature of active funds, through the lens of academic research. Although the study does not specifically compare the results of active and passive funds, as this has been done numerous times with conflicting results (Guastaroba et al., 2016; Vayanos & Woolley, 2016), this study aims to add a layer of information to the wealth of research done on active fund performance in order to better understand how these funds operate and why they operate in the manner they do.

The practical implementation of the process conducted in this study is only relevant to funds which track indices. The study excludes the possibilities available to funds like unit trusts because unit trusts, for example, are restricted from holding more than five percent of any one share. However, the study could be of interest to managers and owners of unit trusts because it explains and qualifies the impact that the regulations have on returns in a negative and a positive way. The research is therefore explorative and descriptive in nature and will aim to describe the characteristics of active management in terms of its constraints. The study is different from many financial studies because it does not specifically try to formulate a winning strategy to beat the market. Instead, it investigates a portion of the industry with the hope of understanding it better.

The study found that tracking error constraints and weighting allowances affected the performance of funds differently. It was found that, for the hypothetical portfolios constructed in relation to the FTSE / JSE Top 40 Index, tracking error limits did, as expected, limit the possible upside returns of these funds. Interestingly however, it was found that the tracking error constraints had a much greater effect on limiting downside risk than the constraints had on limiting upside effects. It was therefore concluded that, for the hypothetically constructed portfolios for the time period studied, tracking error constraints had an overall positive effect on the performance outcomes of the benchmarked funds. This result is in contrast to some academic literature that found tracking errors to have an overall negative effect on actively managed fund performance in relation to passive index tracking funds (Bajeux-Besnainou, Portait, & Tergny, 2013; Guasoni, Huberman, & Wang, 2011; Vayanos & Woolley, 2016). The reason that tracking error limits had an overall positive effect on the performance of the hypothetical funds is because as they were based on an index of 40 stocks, the limitation of tracking error deviation enforced diversification which protects funds against downside risk. The reason that tracking error constraints did not have a large effect on the upside returns is because of the limit of opportunities available in terms of the performance of the index constituents.

It was found that the constraints of minimum and maximum weighting allowance did not have a single universal effect on the simulated portfolios' performance. For the majority of the portfolio scenarios, the permittance of short selling improved overall performance, but not consistently, due to increased downside risk. It was found that the greater the restriction of the amount that can be held of one particular stock, the less the possible downside risk, but at the same time, the upside returns were also restricted. This is expected due to the increased diversification of the portfolio with, for example, a maximum weight allowance of five percent per stock.

This study contributes to existing literature by quantifying the effect of constraints, namely tracking errors and weighting allowance, and thereby offering a better understanding of these effects on the performance of actively managed funds. For the portfolios examined in the study, it was concluded that the constraints placed on them did not affect the possible upside return to such a magnitude that the constraints themselves could account for the underperformance of actively managed funds compared to their benchmark indices and passive funds.

2 Theory and Literature Review

2. 1 Introduction

In order to formulate an argument to substantiate the research topic: *The effects of constraints on the performance of actively-managed funds in relation to their benchmark indices,* a literature review was initially conducted. Two main topics were addressed within the literature review in order to shed light on the topic and show the need for the research. These two main topics are: the nature of actively managed funds and then specifically, the constraints placed on them.

Within the topic of actively managed funds, the principles of known performance maximising strategies will be briefly explored. The nature of actively managed funds will also be reviewed in relation to the alternative, which is passively managed funds. Then the topic of the nature of actively managed funds will be distilled to the topic of constraints placed on them.

2. 2 Actively managed funds

The well known and well researched strategies for maximising fund performance within the financial field have been reviewed and the different results and conclusions are compared. From this comparison of known strategies and theories, a number of topics that form part of limited research become apparent. Within these limitedly researched subjects is an aspect of the topic of this paper. This aspect is that market indices have become the standard as the measure of performance for portfolio managers in contemporary financial stock exchanges and the effects of this need to be explored and quantified (Guastaroba et al., 2016). The need to quantify the effect is increasing as the prevalence of index based funds, for both passive and active management, has increased vastly across numerous countries in recent times (Guastaroba et al., 2016).

2. 2. 1 Types of benchmarked funds

The literature on different types of funds that are involved in the practice of index benchmarking was briefly reviewed. In practice, the total returns of constructed indices are used to benchmark or measure the performance of fund managers (Houweling & van Zundert, 2017). Exposure to different factors within the market is the reason for indices. Although contemporary performance measures are built on classical ideals, they differ from traditional measurements because they “asses the performance against a benchmark” (Guastaroba et al., 2016, p. 938) which then takes asymmetrical returns into account.

There is the major distinguishing characteristic between funds, namely whether they are active or passive. Petajisto (2013) states that not only are there different types of funds, for example active and passive, but that active funds differ due to the level of activity and the type of activity. Actively managed funds over- or under- weight specific securities compared to the benchmark based on the manger’s strategy in order to “exploit possible market inefficiencies” (Guastaroba et al., 2016, p. 939). It was found that more active funds, which have a greater deviation from their index, outperform “closet indexers” (Petajisto, 2013, p. 73) or funds that very closely follow their benchmark. This is simply because actively managed funds must outperform their benchmarks by a high degree in order to compensate for their fees (Petajisto, 2013).

The academic literature and industry news has offered conflicting views on whether active funds are able to outperform their passively managed benchmarks. In academic literature, numerous studies found active funds do outperform (Chen, Chu, & Leung, 2012; Guercio & Reuter, 2014; Jiang, Verbeek, & Wang, 2014) but in contrast, many found that on average, they do not (Guastaroba et al., 2016; Vayanos & Woolley, 2016, Frazzini & Pedersen, 2014). Industry news has reported the value of active funds (Plender, 2017) and of passive funds (Stein, 2017). In the context of an emerging market, like South Africa, industry news has also been contradictory with arguments for active (Lambridis, 2017; Currie, 2017; Ryan, 2016) and some for passive (Cairns, 2018; Erasmus, 2017). This study aims to examine a limited aspect of the industry, namely the impact of limitations, specifically tracking errors and weight allowances, on the performance of actively managed funds. It is hoped that the findings will add an additional layer to the debate of active versus passive performance.

Jiang et al. (2014) adjusted for market, size, value and momentum factors and concluded that active funds can in fact select better stocks than passive funds, which “stands in stark contrast to the disheartening message from performance literature that actively managed mutual funds, on average fail to outperform passive benchmarks” (p. 2038).

A debate exists as to whether Enhanced Index funds fall into the category of active or passive management. The fact that these funds track indices and are only allowed to deviate slightly (which in turn results in the management fees for these funds being much lower) means that they resemble passive funds. Alternative views are that because enhanced funds attempt to beat the performance of the market indices they do at least consist of a small portion of active management. Therefore Enhanced Index funds can be classified as actively managed funds that track a benchmark but attempt to beat the market with various adjustments which form the base of this research paper. Chen et al. (2012) applied the four-factor models of performance and used boot-strapping to study the effectiveness of Enhanced Index funds. The time period of their research was from 1997 to 2007. Despite the recent news that questions actively managed funds, this study did conclude that, after controlling for luck and sampling variability, Enhanced Index funds achieved superior returns. Guercio and Reuter (2014) also did not find evidence that index funds outperformed actively managed funds. Their study also concluded that retail investors preferred the risk-adjusted returns and so there is more investment in active funds.

2. 2. 2 Known performance maximising strategies for actively managed funds

The topic of strategies that maximise performance, effectiveness or alpha, has been widely studied within the field of finance for many years. The results of these studies have delivered numerous findings. These findings however, do not consistently reach the same conclusions (Angelidis & Tessaromatis, 2017; Ekholm, 2012; Houweling & van Zundert, 2017). This creates a challenge for the industry itself as well as for academic research. The aim of this research is to consolidate this information, build on it and add to the wealth of knowledge, specifically in the context of an emerging market.

The three main umbrella theories encompassing most of stock market theory is fundamental, technical and behavioural finance (Mitroi & Oproiu, 2014). These theories stem from the seminal work of Jensen (1968) "*The performance of mutual funds*"; Black and Scholes' (1972, 1973) asset pricing model; (Merton, 1973) option pricing formula and Fama's (1965, 1970) random walk theory and efficient market hypothesis.

In the seminal work "*The performance of mutual funds*", Jensen (1968) states that there is a great need for an "absolute standard" (p. 390) to measure the efficiency of a portfolio and in doing so, the performance of a fund manager in relation to performance and risk. The conclusion of the study found that although, on average, the funds did not outperform a policy of buying the market and holding one's position, the study did not address diversification in relation to risk. Therefore it could not be concluded that mutual funds do not provide a service to investors (Jensen, 1968).

The random walk theory proposed by Fama (1965) is further explored, by the analysis of the fluctuations of share prices in relation to the statistical theory of mean reversion or regression to the mean which was reviewed by Poterba and Summers (1988). The random walk theory concluded that historical patterns bear no significance on future returns, which is in direct contradiction with technical analysis theory which will be reviewed in this chapter.

The authors credited with first proposing a "quantitative approach to determine the optimal trade-off" (Bernard & Vanduffel, 2014, p. 469) between return and risk or mean-variance are Roy (1952) and Markowitz (1952). Cochrane (2014) stated that Mean Variance portfolio theory and equilibrium analysis is the study of long term portfolio issues. The author discussed the three aspects of Mean Variance theory. The first is the final payoff, second is the concept that a discounted amount is given and finally, long-run assessments are discussed (Cochrane, 2014). Another theory is the asset pricing models which assume that all parties have symmetrical information. The idea of freely available symmetrical information is based on the seminal work of Fama (1970) and the efficient market hypothesis. In a 2016 paper, the authors Johannes, Lochstoer, and Mou (2016) linked the capital asset pricing model to consumption dynamics theory. The third-degree stochastic dominance method of constructing portfolios was found to outperform portfolios based on second-degree stochastic dominance and mean-variance dominance approaches (Post & Kopa, 2017).

The seminal work by Grinold and later Grinold and Kahn (2000) on the fundamental law of active management described the relationship between the information coefficient and the expected performance of a fund in order to determine the value of the active management (Clarke, de Silva, & Thorley, 2002). The information coefficient refers to a manger's ability to accurately forecast returns or the manager's skill. The original law stated that the information ratio is equal to the product of the information coefficient or skill multiplied by the square root of the "breadth" or number of independent gambles made within an active portfolio. The expected performance was expressed as a measure of "the portfolio's expected active return divided by active risk" (Clarke et al., 2002, p. 50) defined as the information ratio. This described a broad way in which to identify trade-offs when constructing a performance-maximising strategy, but did not specifically quantify the effects of constraints (Clarke et al., 2002).

Modern Portfolio Theory can also be referred to as mean variance analysis, which consists of two main aspects: expected return and variance. Variance refers to the spread of the data points and the variability of the returns over time (Chabi-Yo, Leisen, & Renault, 2014). Further studies have suggested the addition of skewness to form a three fund separation theorem (Chabi-Yo et al., 2014). This study will review performance in terms of portfolio returns and variance expressed as standard deviation.

Recent studies have also given rise to and built on the concepts of the Sharpe, Sortino and Omega Ratio, to name a few (Bernard & Vanduffel, 2014; Canakgoz & Beasley, 2009; Guastaroba et al., 2016). The well known Sharpe ratio will be employed in this study to rank risk adjusted portfolio performance (Sharpe, 1964). A modified Sharpe ratio will be used when downside performance becomes negative as the traditional ratio does not offer consistent results under these conditions (Israelsen, 2005). There will be no elaboration of the Sortino and Omega ratios in this study.

An issue with the Sharpe ratio is that is penalizes the possible upside volatility to the same degree as it rates downside volatility (Schwager, 2017, p. 343). This equivalent scaling of up and downside validity is inconsistent to the manner in which risk is viewed by most investors (Schwager, 2017, p. 343).

Fundamental analysis consists of the study of companies in order to determine their intrinsic values and in so doing, maximise returns (Mitroi & Oproiu, 2014). Although this method is very important to the field of active fund management, this topic falls outside the scope of this research paper and will not be discussed further.

Behavioural finance incorporates financial and psychological theory in an attempt to explain irrational behaviour within markets and the maximisation of returns (Mitroi & Oproiu, 2014). Again, although behavioural theory is significant to the understanding of stock market behaviour, the theory is less relevant when practising technical analysis which forms part of the foundation of this paper and therefore, behavioural finance will not be examined further. Technical analysis forms the basis of this study because it attempts to explain the characteristics of the market as a whole through the exploration of portfolio performance under varying constraints. This study does not look at the characteristics of specific companies and therefore does not address fundamental analysis. This study does also not directly address the human element of the market and therefore does not specifically involve behavioural finance.

Technical analysis is the method of evaluating securities in an attempt to forecast future movements and maximise returns. This technical evaluation is done by analysing activities like volumes and price movements over time (Smith, Wang, Wang, & Zychowicz, 2016). Smith et al. (2016) found that technical analysis has been widely adopted and that the use of these techniques offered superior performance in times of high-sentiment.

Within the field of maximising fund performance, studies have shown that there is not one factor that should be used in active management of funds to maximise performance. Rather, it is the combination of multiple factors that lead to effective fund management. Returns are increased by security selection or picking stocks correctly (Ekholm, 2012). Funds based on multi-factor portfolio construction also reduce cyclicality when “correlation between the factors are imperfect” (Angelidis & Tessaromatis, 2017, p. 56). Four of these factors, namely: momentum, value, low-risk and size, were found not only to work in the equity market but also in the corporate bond market (Houweling & van Zundert, 2017).

According to Guasoni et al. (2011) the performance-maximising strategy for portfolio managers is a modification of the buy-write strategy, which incorporates writing call options on recently purchased stocks, with “options” being the right, not the obligation to buy or sell at a specified price. Managers can “generate a positive alpha relative to a benchmark” (Guasoni et al., 2011, p. 574) if they invest in options.

Guasoni et al. (2011) list four dimensions in which actively managed portfolios can benefit over their benchmarks. These dimensions are: predicting the returns of the benchmark and adjusting the weighting, trading securities which are outside the space of the benchmark, trading derivative assets of the benchmark and simply trading assets more frequently (Guasoni et al., 2011; Petajisto, 2013).
Massa, Yanbo and Hong (2016) concluded that the performance of international mutual fund benchmarks are negatively affected by currency risk and that currency concentration does not align with the optimal equity allocation strategy.

It has been found that frequent trading delivered better returns but at a much greater risk (Guasoni et al., 2011). Petajisto (2013) found that the stock pickers that were the most active could in fact outperform their benchmarks. However, in contrast, it was concluded that if the volatility of the options were higher than that of the benchmark, holding options were preferable (Guasoni et al., 2011). Petajisto (2013) found that active management was lower during periods of high volatility. The conclusion of Ekholm's 2012 study was that portfolio managers should actively select securities but must not attempt to time the market.

The concept of information content is also applicable to actively managed benchmarked funds, as research has shown that active funds, after adjustments, outperform passive funds up until the consensus view of the active managers becomes common knowledge (Jiang et al., 2014). This view is also evident in the fact that when portfolio managers rely less heavily on public information their performance tends to be better (Ekholm, 2012).

2. 3 Tracking error

The principal of tracking error, within the topic of benchmarked active funds, forms a major part of this research and thus will be discussed in more detail. Tracking error is the difference in returns between a constructed portfolio and its benchmark index. Tracking errors are used as performance measures to evaluate funds and fund managers (Petajisto, 2013). It is a means of quantifying risk. A definition of a tracking error, according to Ekholm (2012), is the "second moment of the equation residual from a standard portfolio performance evaluation model" (p. 350) or more simply, the standard deviation of the excess returns of a portfolio (not the performance itself) (Bajeux-Besnainou et al., 2013). Alpha is the excess return of a fund in relation to its benchmark index. The uncertainty of alpha is measured by tracking error (Guasoni et al., 2011). The "tracking problem" is said to be the issue of constructing a portfolio of stocks that can beat the benchmark index but also "bearing a limited additional risk" (Guastaroba et al., 2016, p. 939).

$$Tracking\ error = stdev\ (R_{fund} - R_{index})$$ (Petajisto, 2013)

There are different ways to measure tracking errors. Drenovak et al. in a 2014 study, set out four different models of tracking errors for exchange traded funds. The first of these models was simply the difference in returns between the fund and the index after different periods of time or active returns. The second model was the standard definition of tracking error, namely the standard deviation of active returns. It is noted that the standard deviation method does not distinguish between negative and positive active returns and is therefore proposed to be more suitable as a performance measure for passive funds rather than for active ones (Drenovak et al., 2014). The *ordinary least squares approach* was used as the third model which calculates the regression of the fund on index returns. The last model used a co-integration approach of fund and index values (Drenovak et al., 2014). Although it is important to take note of the different ways to measure and calculate tracking errors, all these methods go beyond the reach of this study and thus the standard deviation method will be used.

An alternative to tracking error, the measure of time-series standard deviation of returns, is Active Share (Petajisto, 2013). Active Share is simply the percentage of a fund that holds a, active position in relation to the total fund size (Petajisto, 2013). While tracking error represents systematic factor risk, Active Share characterises stock selection (Petajisto, 2013).

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N}\left|w_{fund,1} - w_{index,i}\right|$$

$w_{fund,1}$: weight of stock in portfolio

$w_{index,i}$: weight of stock in index (Petajisto, 2013).

This paper will include the Active Share calculations for comparison with tracking error as an example in emerging market. Active share will however not be set as a constraint, which could form part of future research.

Actively managed portfolios with the goal of outperforming the market, must deviate from their given benchmark index. However, according to Bajeux-Besnainou et al., (2013), the deviation options available are often constrained – be it explicitly or implicitly – by the tracking error volatility.

As mentioned, the major problem with benchmarking is that it limits opportunities or strategies that an asset manager can employ (Vayanos & Woolley, 2016). As Bajeux-Besnainou et al., (2013) state, this negative impact of the return to tracking error trade-off is comparable to the concept of Mean Variance Optimisation which refers to the trade-off between risk and return. This study will attempt to quantify this negative effect of limitations on performance.

A number of other problems have been identified with the principle of tracking errors with regard to evaluating asset managers' performance (Bajeux-Besnainou et al., 2013). However, as benchmarking with the use of tracking errors is the standard when measuring the performance of funds, these additional issues will not be addressed and this study will focus on qualifying the effects of tracking error constraints on fund performance.

Ekholm (2012) states that although the outcomes of portfolio managers' activities are important, another important dimension to consider is the level of activity in which the asset manager in fact engages. Tracking error often becomes a proxy for managers' activity levels because the tracking error number will "only deviate from zero due to (excess) portfolio manager activity" (Ekholm, 2012, p. 350). Jiang et al. (2014) determined that the degree or level of deviation of a fund from its benchmark could be used to predict future surprises in earnings. This means that active managers should be able to predict fundamental performances. The proposed research intends to add additional layers to the study conducted by Jiang, et al. (2014).

Substantial research has been done on minimising tracking errors for index tracking funds and enhanced index funds. The standard quadratic programming approach is used to optimise the weights of stock while limiting continuous and discrete data, namely the tracking error and the number of stocks (Canakgoz & Beasley, 2009). Other examples of older studies on minimising tracking errors include: meta-heuristic based simulated annealing derived from macro- economic variables to calculate optimisation; constraint aggregation, hierarchical clustering using Euclidean distances of stock prices and two-stage stochastic program with the number of shares, difference between tracking fund and index value and the value of deviation (Canakgoz & Beasley, 2009). For fund managers constrained by tracking errors it was found that global four factor portfolio construction, including; momentum, size, risk and value, creates a low tracking error risk portfolio of less than 2% tracking error (Angelidis & Tessaromatis, 2017).

Seminal academic research dealing with the concept of tracking errors specifically with enhanced indexation optimisation dates back to the 1990s (Canakgoz & Beasley, 2009). These older studies include: cointegration based strategies, historical stock price clustering, "mean absolute deviation objective" (Canakgoz & Beasley, 2009, p. 386) over different time periods, goal programming namely returns and tracking errors and Sortino ratio.

Lastly, in relation to tracking errors there is a contrasting finding to the efficient market hypothesis within the study of indices. The price increase of stocks directly after the addition of indices, due to forced buying by passive index funds and benchmarked active investors, results in a downward sloping demand curve. This is in contrast to the efficient market hypothesis which states that because of many substitutes, the demand curve of stocks should be flat (Chang, Hong, & Liskovich, 2015).

The university paper published by the Swiss Institute of Banking Finance and Universität St. Gallen, states that tracking error measures how actively managed a fund is, but that tracking error variance is open to sampling error (Ammann & Tobler, 2000). Although tracking error assess the achievement of the "replicating portfolio strategy" (p. 5) the main use is to indicate the benchmark risk or "how much risk relative to the benchmark has to be taken to achieve the outperformance" (Ammann & Tobler, 2000, p. 5).

The paper from the University of California Irvine, found that tracking errors increased the risk profiles of actively managed funds in relation to their benchmark and due to fees, as well as the increased volatility, could not outperform their benchmarks, except in the case of derivatives-based funds (Jorion, 2002).

Wang, Huang, & Chen (2015) found that negative past performance did not increase the tracking error or risk of mutual funds. The study did however find that funds with higher fees increase performance in the last half of the year to make up for poor performance in the first half by increasing tracking error.

Roll (1992), found that the strategy of maximising future excess returns with tracking error restrictions, would cause fund managers to completely ignore their benchmark index, which is not in the best interest of the investor (Jorion, 2003). Is was found that fund managers who benchmarked against, for example, the Russel 2000 or the S&P 500, would take the same action.

Another aspect to benchmarking and tracking errors is compensation in the terms of performance rewards for asset managers. Makarov and Plantin (2015) discovered that some managers would hide tail risk due to short term remuneration goals. The simple solution is rewards based on cumulative performance. Performance based fees however, incentivise managers to take additional risk. There is an attempt to mitigate the additional risk through tracking error volatility constraints. However, this causes mangers to “optimize in only excess-return spaces while totally ignoring the investor’s overall portfolio risk” (Jorion, 2003, p. 70). Excess-return optimization results in “systematically higher risk than the benchmark” (Jorion, 2003, p. 70) and thus the agency problem (Roll, 1992) . This is due to the focus on excess as opposed to total returns. Roll’s (1992) suggestion to mitigate this risk is to simply diversify through selecting multiple managers (Jorion, 2003).

It was also found that within the Russell 1000 and 2000 indices, that stocks that fell out of the indices’ decrease in price and those included had price increases (Chang et al., 2015). The additional affect can be as significant as three to seven percent in a month after the announcement of addition and is mostly permanent (Chang et al., 2015). This effect is often due to forced buying. Sparse tracking portfolios try and alleviate the “so-called index tracking problem” (Giuzio, Ferrari, & Paterlini, 2016, p. 257) of transactional costs to rebalance funds. Spares funds monitor costs and limit transactions through a regression equation (Giuzio et al., 2016).

Guasoni et al. (2011) stated that research on the topic of the measure of alpha in relation to tracking errors has been ad hoc resulting in no clear “magnitude of alpha that can be achieved” (p. 576) with multiple types of strategies. This research paper aims to quantify the magnitude of return for at least a few constraint dimensions adjusted at different levels.

2. 4 Weighting, Diversification and Risk

It was been found that creating portfolios from non-market capitalisation weighting methods and focusing on factor exposure increases diversification and factor tilting (Amenc, Goltz, Lodh, & Martellini, 2014; Angelidis & Tessaromatis, 2017). Angelidis and Tessaromatis (2017) found that there were insignificant changes to performance if momentum, size, value, and risk factors globally were combined using weighting schemes. However it was found that selecting the correct factor exposure caused greater improvements to performance than the weighting schemes (Angelidis & Tessaromatis, 2017). Asset managers must also decide whether changing the weightings, as the conclusion date approaches, would be beneficial (Bajeux-Besnainou et al., 2013).

Diversification is noticeably a method to reduce risk and thereby maximise performance. The diversification of a portfolio is affected by not only the number of different positions taken but also by the concentration of weights, the volatility of assets and their correlation. (Sénéchal, 2010). Angelidis and Tessaromatis (2017) found diversification across different countries' index funds and exchange traded funds to also be an effective way to achieve diversification. Specifically, it was found that the addition of emerging market into funds consisting of developed markets only, led to significant improvements due to the diversification of factor construction (Angelidis & Tessaromatis, 2017).

There are two main types of risk which are relevant to this study, namely: systematic and non-systematic risk. Systematic risk is the market or un-diversifiable risk, which is the inherent uncertainty of the whole market. Non-systematic risk is the specific diversifiable risk or the uncertainly associated with a particular industry or company in which ones invests. Therefore although market risk is ubiquitous, this study is particularly concerned with non-systematic risk.

There are five main statistical measurements of technical risk ratios used in modern portfolio theory namely; alpha, beta, R-squared, Sharpe ratio and standard deviation (Peterson, 2011). Alpha is the risk-adjusted excess returns of a fund in relation to its benchmark. Beta is the volatility of a fund or stock in relation to the market. R-squared (or coefficient of determination) measures the correlation of a fund and its benchmark on a scale of 0 to 1 (Peterson, 2011). Sharpe is the ratio of the average excess returns earned above the risk-free rate in relation to risk or volatility (Grable & Chatterjee, 2014; Israelsen, 2005). By subtracting the risk-free rate from the return it is possible to determine what the performance of the risk-taking activity was. Standard deviation measures how much an individual stock's or portfolio of stocks' returns differs from its mean return and is an indication of volatility (Jorion, 2003). The concept is that through diversification, one can attain a higher performance per unit of risk. If the stocks in a portfolio are not perfectly correlated, the total variance or risk can be reduced for a given level of expected return through the combination of stocks in varying weights. Due to the fact that the standard deviation of different stocks can be meaningfully represented graphically, together with portfolio returns, this method was used to analyse the risk of the simulated portfolios.

The risk associated with short selling is important; as long-only positions only have downside exposure to the amount invested, but short selling losses are theoretically unlimited. Research has however shown that allowing short selling in traditionally long-only restricted funds did not increase exposure to downside risk (Xu, 2007).

2. 5 Constraints

When discussing performance-maximising fund allocation strategies, it is important to take into consideration all the constraints that exist. There are implicit and explicit constraints placed on benchmarked funds. The management of active funds is generally "conducted within constraints that do not allow managers to fully exploit their ability to forecast returns" (Clarke et al., 2002, p. 48). Other research suggests that constraints cause inefficient portfolios because they effect optimal allocation (Scherer & Xu, 2007). The main question of this research is to explore the effects of the constraints placed on actively managed funds that track benchmark indices. It is important to note that there are two different types of constraints: limitations that are placed on the activity of fund managers and limitations that occur due to the nature of the industry. One limitation that occurs within the industry, for example, is the quantity of available stocks, particularly affecting the actions of managers of large funds, which are then implicitly restricted from purchasing smaller stocks because of availability. This study however, deals with the explicit limitation of tracking error and weight allowance placed on the activity of fund managers.

Other limitations include capacity constraints, illiquidity and transaction costs (Angelidis & Tessaromatis, 2017; Canakgoz & Beasley, 2009; Pillay, Muller, & Ward, 2010). There are also numerous disadvantages to full replication over and above transaction costs to rebalance portfolios when the index is revised. The attempt to fully replicate the index could also lead to holding excessively small quantities of some stocks (Canakgoz & Beasley, 2009). Angelidis and Tessaromatis (2017) state that academic research on the topic of portfolio structuring is challenging because this research often ignores constraints like stock liquidity, risk constraints, turnover and transaction costs. The researchers go on to state that "[i]mplementation constraints are likely to cause significant performance differences between pure academic factor portfolios and real-life investable stock-based factor portfolios offered by commercial indexes" (Angelidis & Tessaromatis, 2017, p. 56). Another constraint mentioned in an older 2008 study is the time it takes to process the most optimum portfolio compilation, although presently this issue seems to be less of a problem (Canakgoz & Beasley, 2009).

Boudt, Cornelissen and Croux (2013) review the effect of sustainability constraints on the "mean-tracking error efficient frontier" (p. 256). The study found a linear relation between the returns of a portfolio and the portfolio's sustainability for mean tracking error efficient portfolios. However the relationship was found to be "almost never statistically significantly different from zero" (Boudt et al., 2013, p. 259) and therefore the returns of conventional and sustainable funds were comparable. Although the concept of sustainability and socially responsible funds will not be review in this research the methodology of Boudt et al. (2013) is relevant and was reviewed.

From the review of academic literature on the topic of explicit constraints for actively managed funds, a debate arises around the effect of these constraints. Naturally, constraints offer advantages and disadvantages in light of performance-maximising strategies. It is generally accepted that although these constraints limit the upside opportunities, they do also protect the downside losses.This is generally accepted as the practice of applying constraints to active funds is an industry standard. The debate that arises is then the degree of the advantages and disadvantages of the constraints on active fund performance. Within academic literature there are conflicting findings on the severity of the positives and negatives of these constraints and herein lies the need for this particular study which aims to quantify these effects.

The constraints associated with benchmarking limits opportunities available to fund managers (Bajeux-Besnainou et al., 2013; Vayanos & Woolley, 2016). Additionally the maximum alpha that can "be achieved in practice is limited by institutional constraints" (Guasoni et al., 2011, p. 579) which will be quantified in this study. However an argument for constraints is that it has been shown that unconstrained strategies are "long with the market index and perform poorly in poor economic situations" (Bernard & Vanduffel, 2014, p. 469). It is also important to keep in mind the fundamental issue of benchmarked funds: because tracking error rules are transparent, outside fund managers can take advantage of known portfolio movements by pre-emptively short selling shares that will be dropped, lowering their price or buying shares to be included, thereby increasing their price (Drenovak et al., 2014).

Clarke et al., (2002) uses Grinold theory as a base for their study on the relationship between performance in terms of return-prediction processes and "the noise associated with portfolio constraints" (p. 58). The study used the transfer coefficient or modified "breadth" to calculate the "extent to which constraints reduce the expected value of the investor's forecasting ability" (Clarke et al., 2002, p. 61). The study concluded that if zero constraints equates to a transfer coefficient of 1, most portfolios range between 0.3 and 0.8 due to constraints. Therefore, it was found that constraints reduced performance by 20 to 70 percent. From the three types of constraints namely long-only, factor-neutrality (style based like value-growth and market capitalisation) and turnover constraints, they found that long-only constraints had the largest effect on the transfer coefficient and subsequently on returns. Clarke et al., (2002) also note that the long-only constraints are so ubiquitous that they are sometimes not even acknowledged as restrictions. Scherer and Xu, (2007) found that when long-only constraints are removed the most favourable relative weights within a constructed portfolio no longer depend on tracking error requirements. The reason that short selling restrictions have been so prevalent in the past is because of associated expenses and transaction costs, however these are substantially less than in the past (Xu, 2007).

Stucchi's (2015) research was based on the work of: Roll (1992) and Jorion (2003) who developed a tracking error variance frontier and showed that increased beta constraints may improve returns, and examined value at risk constraints. Value at risk is the future “measure of risk” or “forward-looking measure” (Jorion, 2003, p. 70) of tracking error volatility. Stucchi examined conditional value at risk but found that the outcomes were the same as the beta constrained optimal allocation strategy that may improve returns, suggested by Roll (1992).

Due to all of these conflicting findings, this study aims to quantify the effects of explicit constraints (particularly tracking error and weighting allowance) on the performance of benchmarked funds and to determine if these effects are positive, negative or neutral overall.

3 Research Questions

The study aims to examine the effectiveness of actively managed funds in relation to their benchmark indices. This will be explored in terms of quantifying the effects of different levels of tracking error and weighting allowed in a fund.

3. 1 Question One

Question one will examine the effectiveness of actively managed funds in relation to their benchmark indices in terms of tracking error constraints and will quantify the effect of tracking error constraints on the performance of these funds. By answering this question it will also be determined whether tracking error constraints have positive, negative or neutral effects on actively managed fund performance in relation to their benchmark.

Is there an association between increased tracking error limits and the expected performance of actively managed funds? Will actively managed funds outperform the market and beat their benchmark index if freed from tracking error limitations over various time periods? Are the effects of tracking error limitations positive, negative or neutral?

3. 2 Question Two

The effectiveness of actively managed funds in relation to their benchmark indices in terms of stock weighting constraints will be explored through question two. It will also be determined whether stock weighting limitations have positive, negative or neutral effects on actively managed fund performance in relation to their benchmark. The study aims to quantify the effects of stock weighting limitations on the performance of funds.

Is there an association between stock weighting constraints and the expected performance of actively managed funds? Will actively managed funds outperform the market and beat their benchmark index if freed from stock weighting limitations over various time periods? Are the effects of stock weighting constraints positive, negative or neutral?

The study will look at the individual effect of both tracking error and weighting constraints, as well as the combined effect of these limitations, on the performance of hypothetically constructed portfolios in relation to the FTSE / JSE Top 40 index.

4 Research Methodology and Design

The research methodology and design has ultimately been informed by the review of similar research that has been conducted and published in highly accredited peer reviewed journals. This research sought to explore the effectiveness of actively managed funds in relation to their benchmark indices. The scope of the research was confined to examining the association between limitation, namely tracking error and weight allowances and the expected performance of actively managed funds. The study was therefore conducted in an explorative and descriptive manner to examine the relationships between the expected performance of actively managed funds and the limitations placed on them. The study aimed to explore these relationships by quantifying the opportunities that were retrospectively available to active fund managers. This research explored the topic through constructing "hypothetical portfolios of varying" (Pillay et al., 2010, p. 1) constituent weights and tracking errors in relation to their benchmark index. For the purpose of this study the FTSE / JSE Top 40, J200 was selected. Historical data was used for nine years from December 2006 to December 2015. Data was analysed through simulation (Guasoni, Huberman & Wang, 2011). The analysis on the effects of constraints on portfolio performance was done with actual data and without the need to forecast or project any scenarios.

The process followed in this study to analyse the data was descriptive research, which included the "collection of measurable, quantifiable data" (Saunders & Lewis, 2011, p. 85) through the reanalysis of secondary data. This descriptive study aims to provide an accurate representation of the effects of constraints on actively managed funds. As the study is descriptive in nature, it could be considered a means to an end, which could be the forerunner to explanatory research, and not an end in itself.

4. 1 Research Design

The manner in which the data was selected, collected and analysed will be described below. The justification for decisions will be discussed under each subheading to follow. The study was conducted in the context of South Africa with performance data for the Johannesburg Stock Exchange (JSE). The context is therefore an example of an emerging market.

The research philosophy that was adopted to examine the relationship between actively managed benchmarked fund performance and different variables, namely tracking error and weighting allowances, was the philosophy of positivism due to the quantitative nature of the research. Positivism theory was implementable, as opposed to Interpretivism, as hypotheses, such as modern portfolio theory, have been generated by existing theories and could be used as a base for the study (Saunders, Lewis & Thornhill, 2009).

The approach used to determine the relationship between benchmarked fund performance and limitations, and thus answer the research questions, was deductive because the research builds on existing theory (Saunders & Lewis, 2011). The variables were observed through the collections of historical data which were then measured and analysed (Saunders & Lewis, 2011). The strategy of the study was explanatory with the purpose of explaining the relationship between performance and various limitations placed on actively managed funds (Saunders & Lewis, 2011). The strategy followed to collect the data was archival research, as the principle source of data was historical records of fund performance that were analysed (Saunders & Lewis, 2011).

The method chosen was mono method for the purpose of the proposed study as mixed or multi-methods falls outside the scope of the research (Saunders & Lewis, 2011). A "single data collection technique" (Saunders, Lewis & Thornhill, 2009, p. 151) was used and therefore the mono method is applicable.

The time horizon of the study is a historical longitudinal design since the study tracks events over time, namely the monthly total returns data for each constituent share in the selected index for the last nine years (Saunders & Lewis, 2011). A longitudinal study has the advantage of offering insights into changes occurring over the period of time (Saunders & Lewis, 2011). A disadvantage is that the data is secondary. This is a disadvantage because it was not designed specifically for this research project but is still pertinent (Zikmund, Babin, Carr & Griffin, 2010). The advantage of secondary data, which is also public, is that the research is unlikely to incur any ethical issues. The technique employed to analyse the numerical ratio data of the historical performance of funds from the JSE is thus quantitative.

The reliability of the study was ensured as the research philosophy adopted is based on a positivistic approach. Therefore the appropriate measurement and analysis methods were adopted in order to eliminate subjectivity as far as possible and to ensure that the study will be reliable so that any subsequent studies conducted in the same manner will reach the same conclusions (Saunders, Lewis & Thornhill, 2009). The validity of the research was insured due to the unbiased selection of the subjects, the collection of data and the measured performance (Saunders & Lewis, 2011).

4. 1. 2 Universe

The complete set or population of the study is the numerous index funds of the JSE. The investment universe is the JSE, as an example of a stock market in an emerging market, and the FTSE / JSE Top 40 was selected as the benchmark index for this study. Then different hypothetical portfolios were constructed by changing both the tracking error limitation and the maximum or minimum weight allowance deviation from the index for each constituent. Subsequently, simulation was used to “explore the boundaries of possible returns” (Pillay et al., 2010, p. 1) for each synthetic portfolio with adjusted weights.

Drawing from the numerous JSE indices, the research will be conducted by using performance data from the FTSE / JSE Top 40 (J200) as an example, for various reasons. Firstly, seminal research has shown that to create a fund that is well diversified, the portfolio must consist of 30 to 40 stocks (Statman, 1987). According to Personal Finance, 2006, the “anecdotal evidence from the South African fund management industry indicates that the number of shares held in equity portfolios varies between 40 and 65” (Pillay et al., 2010, p. 4). For these reasons the FTSE / JSE Top 40 Index has been selected for this study as it consists of around 40 constituents. Secondly, the FTSE / JSE Top 40 Index is constructed in the same way as most index funds: the returns of the indices are calculated each month “as the market value – weighted average excess return overall index constituents in that month” (Houweling & van Zundert, 2017, p. 102). Thirdly, the classification criteria from stocks to form part of the Top 40 were changed in 2016 from the largest companies to the most investable, or in other words, the constituents are selected according to nett market capitalisation adjusted for free float as opposed to the previous method of gross market capitalisation (JSE, 2016). Finally, research within the FTSE / JSE Top 40 is also significant because large funds are restricted to trading with these large cap stocks due to availability and because it is a good representative of the JSE because it represents 80% of the market (SA Share, 2018). Only one out of the numerous indices will be reviewed in order to limit the scope of the research to be feasible in the time available. This leaves the opportunity open for future studies to analyse further indices and to compare the findings.

4. 1. 3 Sampling

The extent of the data sampled refers to the number of years that are reviewed. The extent of the time period that could technically be studied, in the context of the JSE is 131 years, from 1887, when the JSE was founded to present day 2018. The time period for this study was selected after careful consideration of two factors. Firstly, the time periods selected for similar research that has been conducted and published in highly accredited peer reviewed journals was reviewed. Secondly, macroeconomic factors were considered, for example the 2008 financial crisis. By considering these two factors the time period of nine years was selected from 31 December 2006 until 31 December 2015. This period was chosen as it is in line with the length of time chosen for previous studies and because it includes performance before and after the global financial crisis. While a longer period of time would offer more insights, the scope of the study has been limited in order to make the research feasible in the time available. This leaves the opportunity open for futures studies to extend the time period and compare results.

As the entire population of index funds from the JSE can be gathered, probability sampling can be conducted (Wegner, 2015). However, because the size of the sample data will be determined by the period of time selected, it was not be feasible to use probability sampling as the number of funds in relation to nine years of monthly returns will fall outside of the scope of limitations of the study. This highlights potential future research possibilities.

4. 1. 4 Data gathering process

The secondary historical performance data for the JSE could be accessed through numerous databases for example; Iress (INet BFA) or Osiris, however the JSE Bulletin Excel Add-in provided the constituents of the JSE indices, their market capitalisation and total returns, in the most efficient manner. The actual equity fund data was collected from Thomson Reuters Datastream. The total Index returns for the FTSE / JSE Top 40 was collected from both databases so that the information could be checked for accuracy. The data was captured manually using Microsoft Excel and through a direct link to the JSE Bulletin. A portion of the data was then checked against the Google Finance Excel Add-in for accuracy and it was found that the data from the two sources is very similar and therefore is assumed to be accurate.

4. 1. 5 Unit of Analysis

The data used was the total monthly returns for each constituent forming part of the FTSE / JSE Top 40. The total returns include the dividends paid out which is important because they form a significant part of the received returns (Ekholm, 2012). The performance of benchmark index funds was expressed in a percentage.

The unit for analysis of tracking errors is calculated as the standard deviation of the excess returns of a portfolio (not the performance itself) (Bajeux-Besnainou et al., 2013):

$$= 1/(N-1)\sum(X_1 - Y_1)^2$$

Where: N = number of periods (monthly returns)

X_1 = fund's return for each given period

Y_1 = benchmark return for each period

The monthly benchmark and fund total return data was analysed in accordance with similar academic studies (Ekholm, 2012).

4. 1. 6 Measurement instrument

The measurement instrument is the performance of the benchmark indices over time. This data will be secondary archival data (Saunders & Lewis, 2011). Monthly returns, as opposed to daily returns, were collected, as monthly returns are sufficient for the type of analysis done and it limits the scope of the research in order to make it feasible in the time available (Ekholm, 2012) .

4. 2 Limitations

The ultimate limitation of this study, and many like it, is the measure of performance. In this study performance is measured in only one dimension in terms of financial return listed on the JSE.

Further limitations include the limitations of the scope. The study will only investigate the relationships of a few variables, namely actively managed benchmark trackers in relation to tracking error and weighting controls. The scope of the time period is also a limitation and can always be extended.

Lastly as a quantitative study, the research will only attempt to discover the relationships between the variables but will not explore the reasons for the specific relationships. The question of why, will not specifically be answered. To explore the reasons behind the findings and to answer the question of why, a qualitative study could be conducted in the future to add richness to the data.

This study did not take transaction cost into account. Transaction costs can be highly significant, as illustrated by the literature on sparse portfolios (Giuzio et al., 2016). Other research has ignored transaction costs for re-balancing when comparing different types of hypothetical portfolios because the costs will be "approximately the same between portfolios and immaterial" (Muller & Ward, 2013, p. 3). However this is not specifically important for this study as the constituents of the hypothetical portfolios are held constant for the five year time periods.

Survivorship bias is a concern within this study, however in a different manner than typical stock market research because the study is concerned with benchmark indices (Deaves, 2004). If a particular stock is delisted it falls out of an index and is replaced and therefore it does not affect the results of the research. The problem arises with the covariance matrix that is needed to determine the standard deviation or volatility of the portfolio. A consistent set of constituents are needed to construct the covariance matrix over a reasonable period of time, in this case five year sets. Therefore, the results are a snap shot, as the method used takes the 40 largest stocks in the JSE All Share and determines their total returns and covariance for the time period, irrespective of whether they had fallen out of the Top 40 in that time period.

A persistent problem in the research of the stock market, portfolio and company performance is look-ahead-bias which is including the financial statements' information from the year end data and not taking into account that these statements were only released months later. This bias is however not applicable to this research because only the market capitalisation and total prior returns including dividends paid were taken into consideration, which is information available daily that is not dependant on financial statements.

4. 3 Analysis Approach

The method of analysis was done as follows: the chosen index, namely the FTSE / JSE Top 40 (J200) was adopted as the benchmark. With the use of Microsoft Excel Solver, the data was explored in order to determine the best and worst possible performances within the constructed portfolio. Different variables were changed repeatedly and the outcomes recorded in order to compare the results (personal communication: Prof Ward). It is also important to note the effects on performance due to large macroeconomic events for example the 2008 financial crisis. The variables that were adjusted are:

- Level of tracking error around the benchmark, for three percent tracking error and then for fifteen percent which is essentially ignoring the tracking error limit as a constraint.
- Limit of under- or overweighting for each share, repeated for various percentages, namely: a maximum weight allowance of five, ten and fifteen percent and a minimum weight allowance of zero, minus five percent, minus ten percent and minus fifteen percent.

The databases used could provide the names of the Top 40 constituents for each quarter after review for the time period studied. However, after review of the list of constituents, it was found that longest period of consistent constituents was one year or four quarterly reviews. This short time frame does not provide enough information for analysis. It is also vital for the research to have continuous returns. Therefore the standard theoretical method when analysing portfolios was employed. This standard method involves constructing a hypothetical portfolio based on the selected index. In this case the FTSE / JSE Top 40 Index formed the base of the hypothetical index. Then the composition of the index was approximate as was the case in previous studies (Pillay et al., 2010). The hypothetical portfolio was “constructed by sorting” (Houweling & van Zundert, 2017, p. 100), the largest 40 companies according to market capitalisation from the JSE All Share for each of the five time periods.

Data integrity checks were conducted. First, the hypothetical portfolio weight adjustment was set to zero percent and therefore matched the index weighting exactly for a particular month. The total return of the portfolio was then compared to the actual quarterly return of the FTSE / JSE Top 40 Index and was found to match exactly. Due to the fact that these measures were taken, it was considered that the “data was sufficiently reliable” (Pillay et al., 2010, p. 5). The data was also checked for errors by excluding in favour of zero “any daily returns on shares which are less than -40% or greater than +40%” (Muller & Ward, 2013, p. 3).

4. 4 Best and worst possible index performance per weight adjustment

Firstly, the minimum and maximum performance for the hypothetical fund was determined on a quarterly basis for a slightly extended time period, December 2005 to September 2016. Visual Basic (VBA) coding was used to run multiple iterations of Solver for different weighting allowances and start dates. See Appendix 1 for the code.

The constituent list of 40 companies was constructed. Then each company’s market capitalisation was pulled into Excel using the JSE Bulletin Add-in. Then each company’s index weighting was calculated as a percentage of their market capitalisation to the total market size of the index. Then each company’s total quarterly return was pulled into Excel with the Add-in.

The natural logarithm of each total quarterly return was calculated. The natural logarithm is used to determine the percentage return change over a period because it mitigates the problem with standard arithmetic percentage changes. The problem with continuous compounding arithmetic percentage returns is that they are not symmetrical. In other words, if an amount appreciated by a specific percentage and then increases by the same percentage, the result is not the same as the original amount.

The first weighting allowance iteration used was zero percent to check the performance against the actual index for accuracy, which was found to be true. Then 11 weighting allowance iterations were done, in increments of half a percent from zero to five. In other words, the constraint placed on the hypothetical portfolio was the index weighting calculated by market capitalisation, adjusted in increments of half a percent up or down. Then Excel Solver was used to determine the best possible portfolio return and then the worst possible portfolio return for each quarter at each incremental weighting adjustment. The best and worst performance of 11 different weighting allowance constraint scenarios were calculated for 44 quarters, therefore 968 possible portfolio returns. Then the natural logarithmic percentage increases where cumulated over the period with a standardised starting point of one. Conventional research often uses "average monthly or quarterly portfolio returns" and then performance t-tests to check for significant differences (Muller & Ward, 2013, p. 4). However, analysing average monthly or quarterly returns is not as informative as cumulative returns, because averages "reveal relatively little" (Muller & Ward, 2013, p. 4). Therefore this study plots the cumulative portfolio returns over the time period and then compares the results visually (Muller & Ward, 2013). These results however only illustrate possible performance but do not clearly indicate volatility of the portfolio.

4. 5 Best possible performance in relation to risk

The next step was to determine the optimal performance of the portfolio, but in relation to the inherent risk levels. This was done over five time periods. First the natural logarithm of the monthly total returns for each of the previously determined portfolio constituents were calculated, again using the Excel JSE Bulletin Add-in, for the nine year period. The returns of the market capitalisation weighted index and the SWIX shareholder weighted index were also calculated for comparison. This equates to percentage returns for 60 months for 40 companies and 2 indices or 2 520 monthly returns for the five periods.

The data was then analysed for a period of five consecutive time periods. Each consecutive period analysed consisted of a five year span in order to compare the results. Five successive time periods, consisting of five years each, equates to nine years. The time period of data used spanned from December 2006 to December 2015, which equates to ten year ends. The five-year time period spans used were from 31 December to the same day five years (60 months) in the future for the following years: 2006 to 2011; 2007 to 2012; 2008 to 2013; 2009 to 2014; and 2010 to 2015 (see Appendix 3). The time periods spanned from 31 December to 31 December five years in the future in order (in other words five years and 1 month) so that the percentage change of returns could be calculated for 60 months or a five year period.

The average return was calculated at each month end for a period of five years. The monthly returns were calculated as the natural logarithm of the change in share price of the previous month to the current month presented as a percentage. From the 60 months of natural logarithm, with returns for each of the 40 constituents (2 400 return data points) the covariance matrix was calculated.

Then the median of the 60 returns for each constituent was calculated. The median of the historical results was used to represent the returns over the five year period. The median is used for the returns as opposed to the mean because it offers a more accurate presentation in the case of outliers. The standard deviation of the returns for each constituent was calculated as an expression of the volatility or risk of the companies' returns. Then the covariance of each constituent in relation to all the other constituents was calculated.

Next, the risk and return was analysed with the use of a Markowitz model and adapted efficient frontiers (Fabozzi, Gupta, & Markowitz, 2002). The riskiness of the portfolio is measured as the standard deviation of each individual stock's historical returns, specifically in this study, the five year periods of returns were used.

The model, and thus various performance opportunities, were constructed with differing constraint scenarios, namely maximum tracking error limits, maximum stock weights and minimum stock weight. Similar studies have attempted to define optimal portfolio constructions by reviewing the effects of beta, size and long-only constraints on weighting allocations (Scherer & Xu, 2007). In this study twenty-four different scenarios were modelled. Table 1 illustrates the description of the 24 different scenarios. The maximum tracking error of 3% is a representation of the norm, whereas the maximum tracking error of 15% essentially represents no tracking error. The maximum weighting of 5% then represents the restrictions placed on unit trusts which cannot hold more than 5% of any share and is then increased to 10% and 15%. The minimum weighting of zero is a restriction of no short selling. Then short selling is allowed to a limit of negative 5%, negative 10% and -15%.

Table 1: 24 Hypothetical Portfolios with varying constraints

	3% Tracking error limit					15% tracking error limit			
Scenario	A. 1.1	A 1.2	A. 1.3	A 1.4		B. 1.1	B. 1.2	B. 1.3	B. 1.4
MaxTrackingError	3%	3%	3%	3%		15%	15%	15%	15%
Max Weight	5%	5%	5%	5%		5%	5%	5%	5%
Min Weight	0%	-5%	-10%	-15%		0%	-5%	-10%	-15%
Scenario	A. 2.1	A. 2.2	A. 2.3	A. 2.4		B. 2.1	B. 2.2	B. 2.3	B. 2.4
MaxTrackingError	3%	3%	3 %	3%		15%	15%	15%	15%
Max Weight	10%	10%	10%	10%		10%	10%	10%	10%
Min Weight	0%	-5%	-10%	-15%		0%	-5%	-10%	-15%
Scenario	A. 3.1	A. 3.2	A. 3.3	A. 3.4		B. 3.1	B. 3.2	B. 3.3	B. 3.4
MaxTrackingError	3%	3%	3%	3%		15%	15%	15%	15%
Max Weight	15%	15%	15%	15%		15%	15%	15%	15%
Min Weight	0%	-5%	-10%	-15%		0%	-5%	-10%	-15%

The maximum and then minimum standard deviation or volatility risk was calculated for incremental portfolio returns for each of the 24 differently constrained portfolios. Increasing and decreasing returns in increments of 0.5% were tested for a possible solution given the limitations. The series of possible incremental returns ranged from negative five to positive seven and a half percent. Similar studies that have tested varying aspects used ranges between negative and positive two percent (Xu, 2007). The maximum and minimum standard deviations at different levels of returns were calculated using Solver by changing the weights of constituents within the simulated portfolio, in accordance with the specific scenario's constraints. For portfolio allocation problems, the standard deviation target can be set to minimisation (Jorion, 2003). This equates to 26 iterations of possible portfolio returns for both minimising and maximising the standard deviation which translates to 52 iterations. This was done for all 24 scenarios, which equates to 1 248 portfolio performance calculations. This was done for all five time periods which equates to 6 240 calculations.

The processing time, for manually running each iteration was between 20 minutes and 45 minutes. An average of 32.5 minutes per 24 scenarios is a total of 13 hours for a single time period. The processing time varied because the maximum possible increments of performance were 26 for the scenarios with the least constraints placed on them and as the constraints increased, the range of possible performance increments decreased. A Visual Basic code was then used to automate the processes for all five of the time periods (See Appendix 2). The automated processing time was considerably faster and it took about five hours to complete a time period.

The following variables were calculated and captured for each iteration of possible portfolio returns:

- Portfolio Standard Deviation
- SWIX Tracking error
- Active Share
- Sharpe Ratio
- Constituent Weights

The Sharpe Ratio was calculated in the standard way: portfolio return minus risk free rate divided by the portfolio's standard deviation and therefore, the higher the Sharpe Ratio the better (Grable & Chatterjee, 2014; Israelsen, 2005). The risk free rate was taken as eight percent per year, divided by 12 months to get a monthly rate of 0.67%.

$$\text{Sharpe Ratio} = \frac{\text{Portfolio Return} - \text{Risk Free Rate}}{\text{Portfolio Risk}}$$

Due to the explorative nature of the research, these results, of the relationships between funds and their benchmarks, in relation to varying constraints, were then captured on risk- return scatter plots and analysed graphically.

Table 2: Outline of methodology steps taken

Step	Process
1	Composition of the FTSE / JSE Top 40 Index was approximated, for five consecutive time periods of five years each, December 2006 to December 2015
2	Data Checked
3	Natural logarithm monthly returns calculated
4	Covariance matrix constructed
5	Monthly median and standard deviation calculated
6	VBA code used to calculate possible performance at varying levels of constraints
7	Set up : Constituent weights adjusted to achieve - Range of possible returns in increments of 0.5% between -5% and +7% At different levels of: maximum tracking error, maximum weighting and minimum weighting
8	Maximum possible standard deviation and then minimum possible standard deviation calculated and captured
9	Results plotted on risk-return graphs

5 Results

5. 1 Overview

Figure 1: Actual Index constituents graphic December 2005 and March 2016

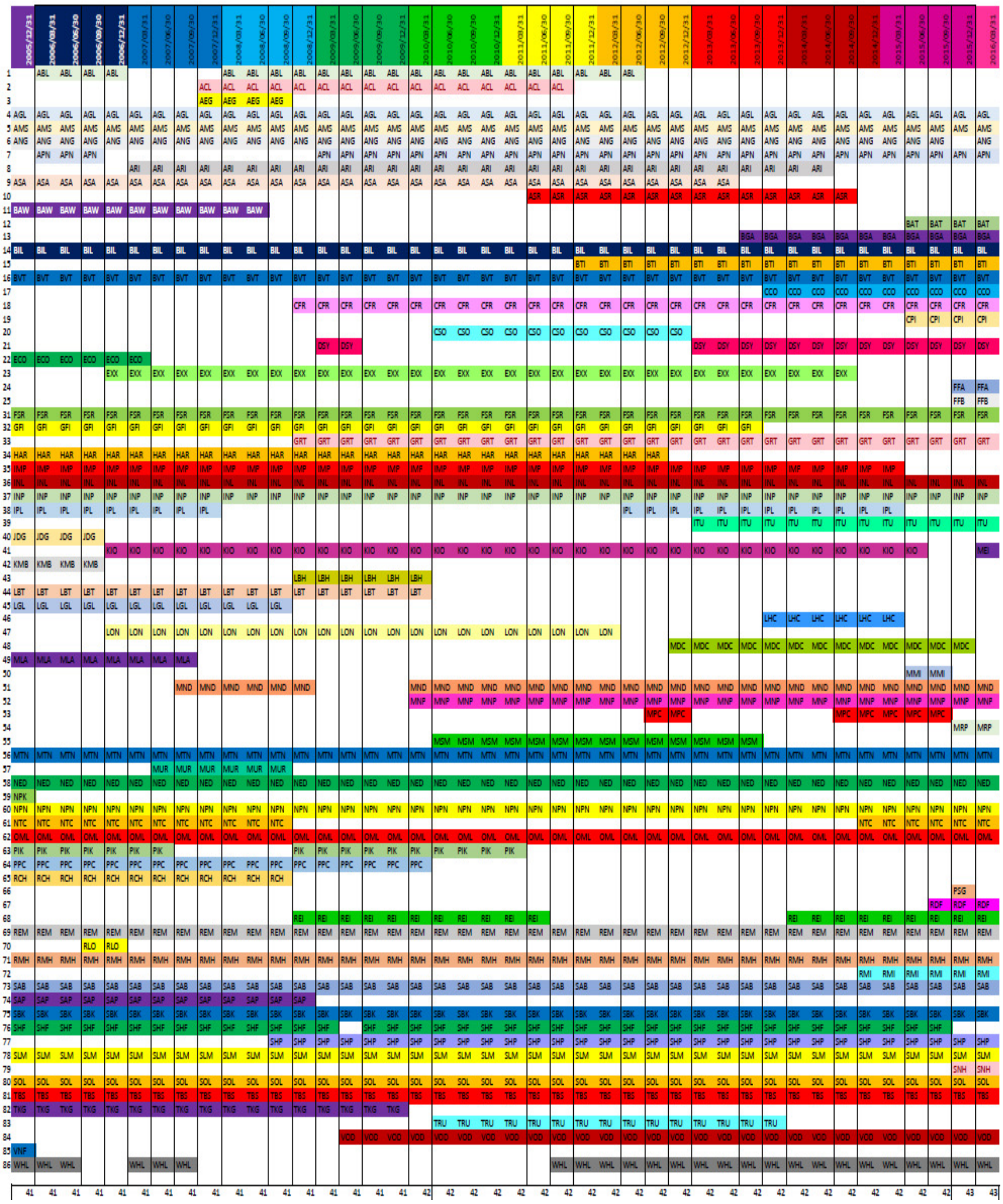


Figure 1 shows the consecutive period that constituents remained in the Top 40 index.

Figure 2: Annualised quarterly returns of the replicated index versus the FTSE / JSE Top 40

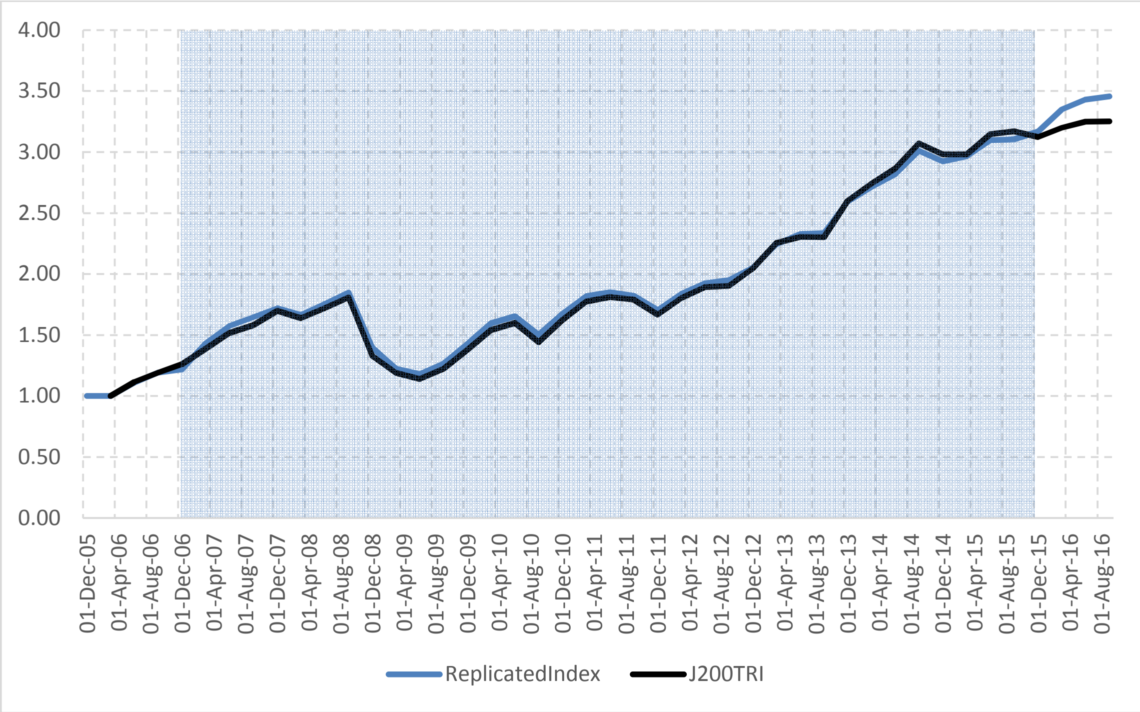
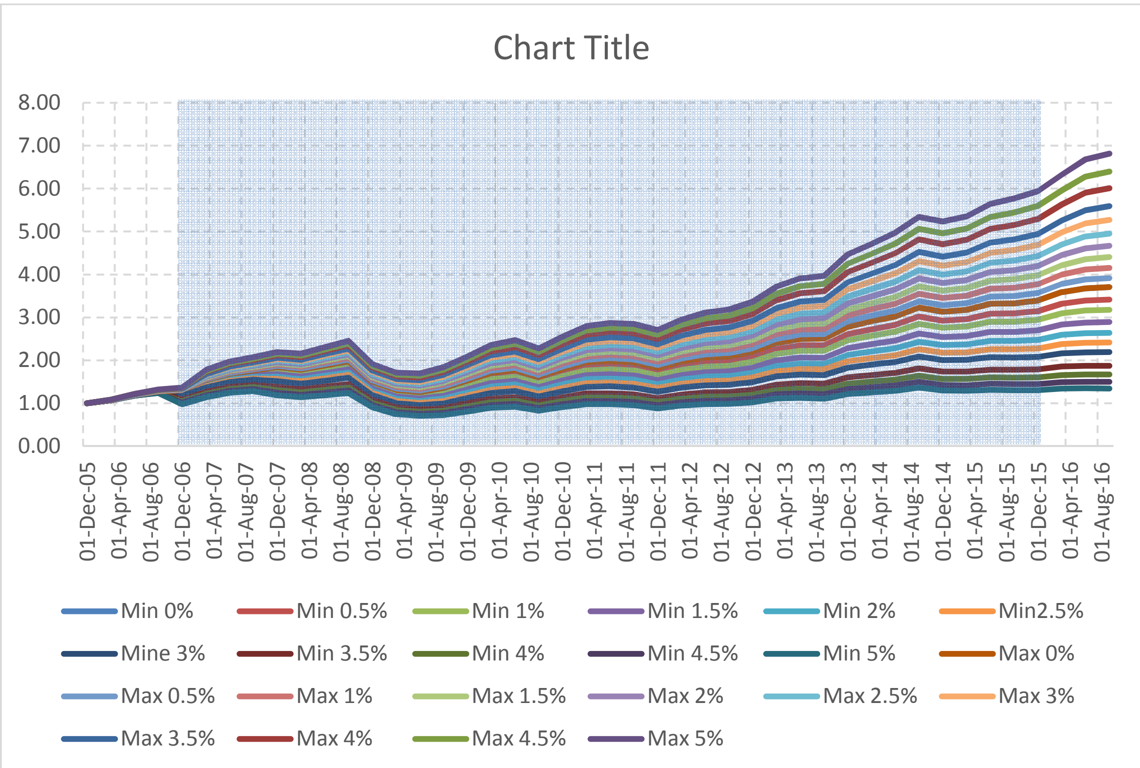


Figure 3: Best and worst possible quarterly index performance per weight adjustment



*Shaded area illustrate the period modelled in the “playing field” graphs

Table 3: Best and worst possible quarterly index performance per weight adjustment and the performance of equity fund

Maximum and minimum possible **quarterly** returns for the simulated Top40 tracker fund with different weight adjustments from 0.5% to 5% added or subtracted, Top40 & 15 equity funds from Dec 2005-Dec2016				
Portfolio	Ave Rtrn	MedianRtn	Stdev	Sharpe
Min 5%	0.99%	2.41%	8.42%	20.75%
Min 4.5%	1.22%	2.69%	8.24%	24.62%
Min 4%	1.46%	2.96%	8.06%	28.44%
Min 3.5%	1.72%	3.14%	7.88%	31.38%
Min 3%	2.06%	3.22%	7.60%	33.68%
NEDGROUP Entrep. *	3.88%	3.66%	8.70%	34.41%
Min 2.5%	2.28%	3.34%	7.50%	35.71%
Min 2%	2.48%	3.46%	7.42%	37.67%
MOMENTUM2 TOP40**	2.79%	3.93%	8.42%	38.79%
Min 1.5%	2.69%	3.66%	7.35%	40.69%
MOMENTUM1 TOP40	2.74%	4.11%	8.33%	41.35%
NEDGROUP A	3.19%	4.74%	9.62%	42.30%
Min 1%	2.91%	3.77%	7.29%	42.51%
OLD MUTUAL TOP40A	2.98%	4.25%	8.22%	43.63%
OLD MUTUALTOP40B	3.14%	4.33%	8.24%	44.42%
RMB TOP 40	3.02%	4.50%	8.29%	46.23%
STANLIB ALSI 40	3.11%	4.48%	8.07%	47.24%
Min 0.5%	3.08%	4.14%	7.26%	47.83%
KAGISO TOP 40	2.92%	4.58%	8.01%	48.84%
Max 0%	3.26%	4.44%	7.22%	52.21%
Min 0%	3.26%	4.44%	7.22%	52.21%
OLD MUTUAL R	3.22%	4.68%	7.67%	52.31%
Top 40 (J200)	3.06%	4.55%	7.40%	52.49%
Max 0.5%	3.40%	4.53%	7.24%	53.35%
ALLAN GRAY A	3.36%	4.27%	6.69%	53.80%
Max 1%	3.54%	4.62%	7.26%	54.52%
Max 1.5%	3.69%	4.72%	7.28%	55.64%
Max 2%	3.83%	4.80%	7.31%	56.56%
Max 2.5%	3.97%	4.90%	7.34%	57.72%
SANLAM GENERAL	3.36%	4.92%	7.36%	57.78%
CORONATION IND.	4.53%	5.02%	7.44%	58.51%
Max 3%	4.13%	5.00%	7.37%	58.72%
SIM GENERAL R	3.43%	5.00%	7.36%	58.93%
Max 3.5%	4.27%	5.09%	7.41%	59.71%
Max 4%	4.46%	5.22%	7.55%	60.27%
Max 4.5%	4.61%	5.36%	7.59%	61.81%
Max 5%	4.77%	5.55%	7.67%	63.59%
SIM INDUSTRIAL FUND R	4.47%	6.01%	7.43%	71.88%

* 8 of the largest equity funds

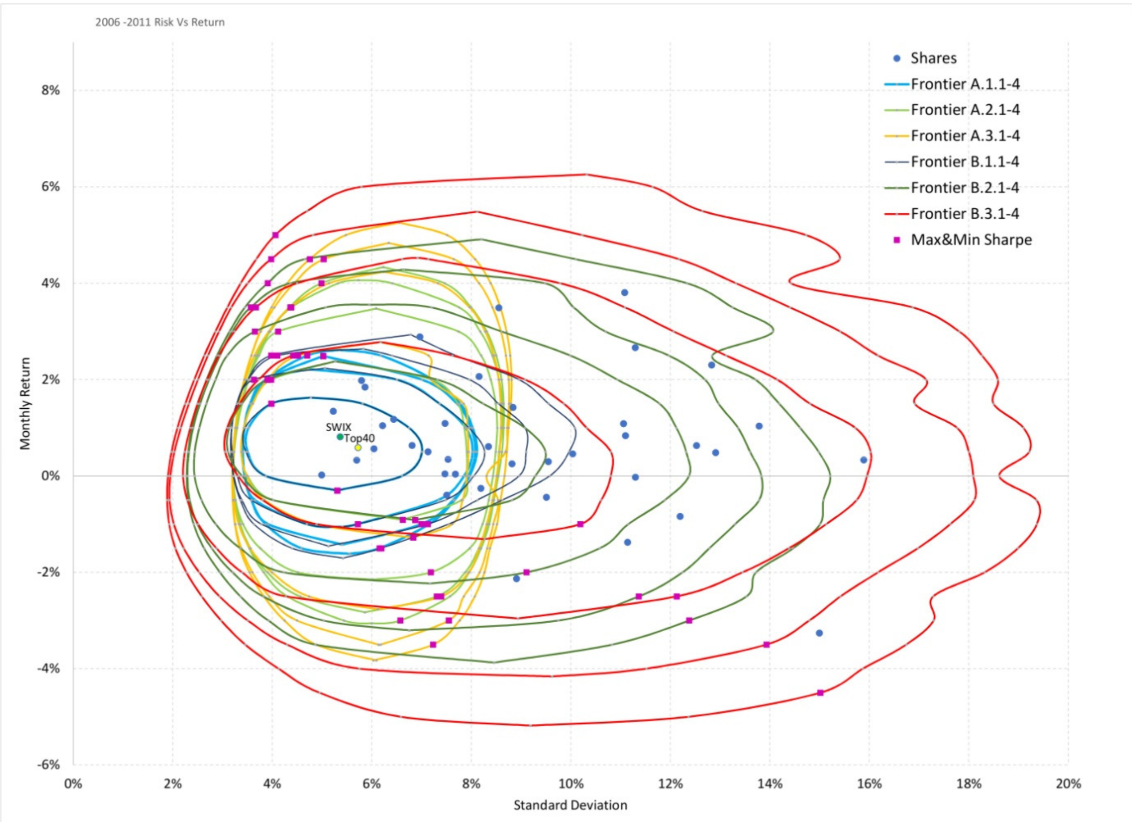
**7 Top 40 Index benchmarked funds

5. 2 Results of five time periods

The results are presented in Figure 3 as a Markowitz efficient frontier graph (Fabozzi et al., 2002). This can also be described as a mean-variance frontier (Jorion, 2003). The risk of the individual stocks, and then of the portfolio, are presented along the x-axis in terms of standard deviation. The standard deviation represents the volatility risk of the stocks or portfolios. The total monthly returns, in terms of the median over the five year period, are indicated as percentages along the y-axis.

The process was run for 5 consecutive years for two reasons. Firstly, the multiple time periods were modelled in order to verify that the results are consistent over time, and that one particular time period is perhaps not an outlier. The second reason was in order to be able to compare the results from different periods with each other, analyse how the results moved over time and to gain further insights. The results obtained for the five consecutive years are illustrated graphically in Figure 4, 5, 6, 7 and 8. Appendix 4 shows all five figures on a full page for clarity.

Figure 4: 24 constraint scenarios illustrating possible playing field for 2006-2011



*See Appendix 4 for full page versions of Figure 4 – 8

**Figures 4 – 8 calculated with monthly return data

Figure 5: 24 constraint scenarios illustrating possible playing field for 2007-2012

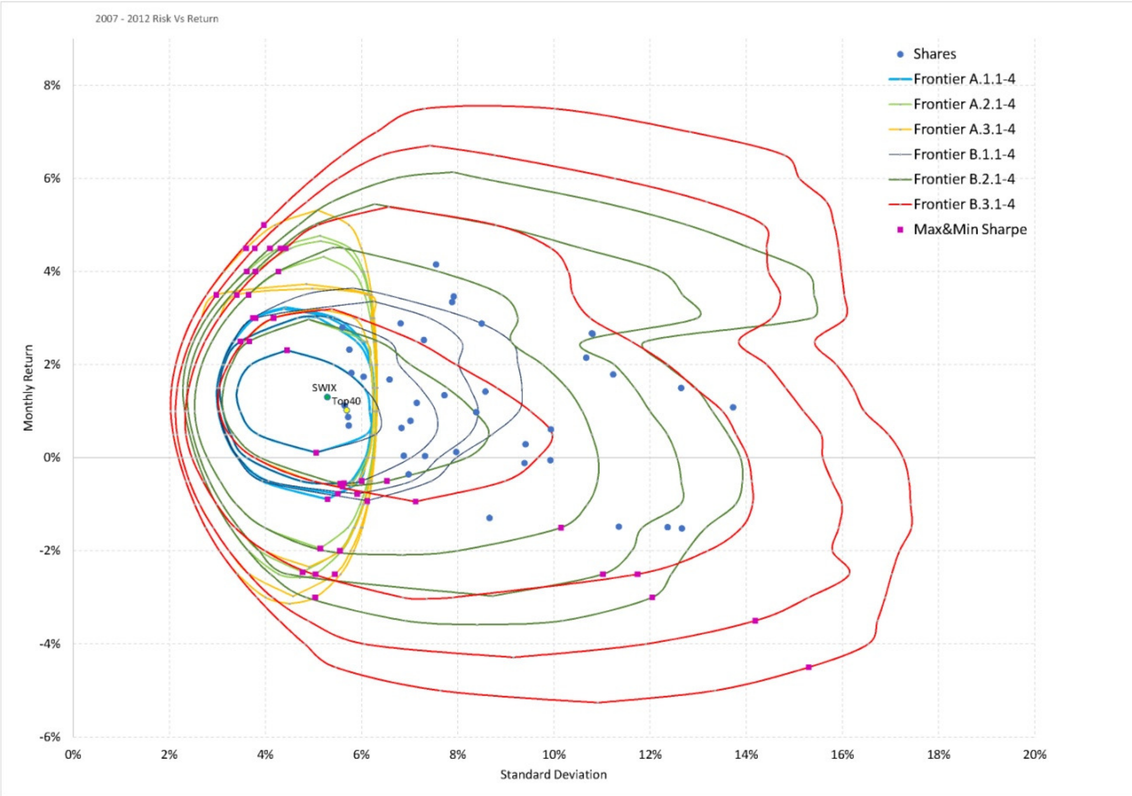


Figure 6: 24 constraint scenarios illustrating possible playing field for 2008-2013

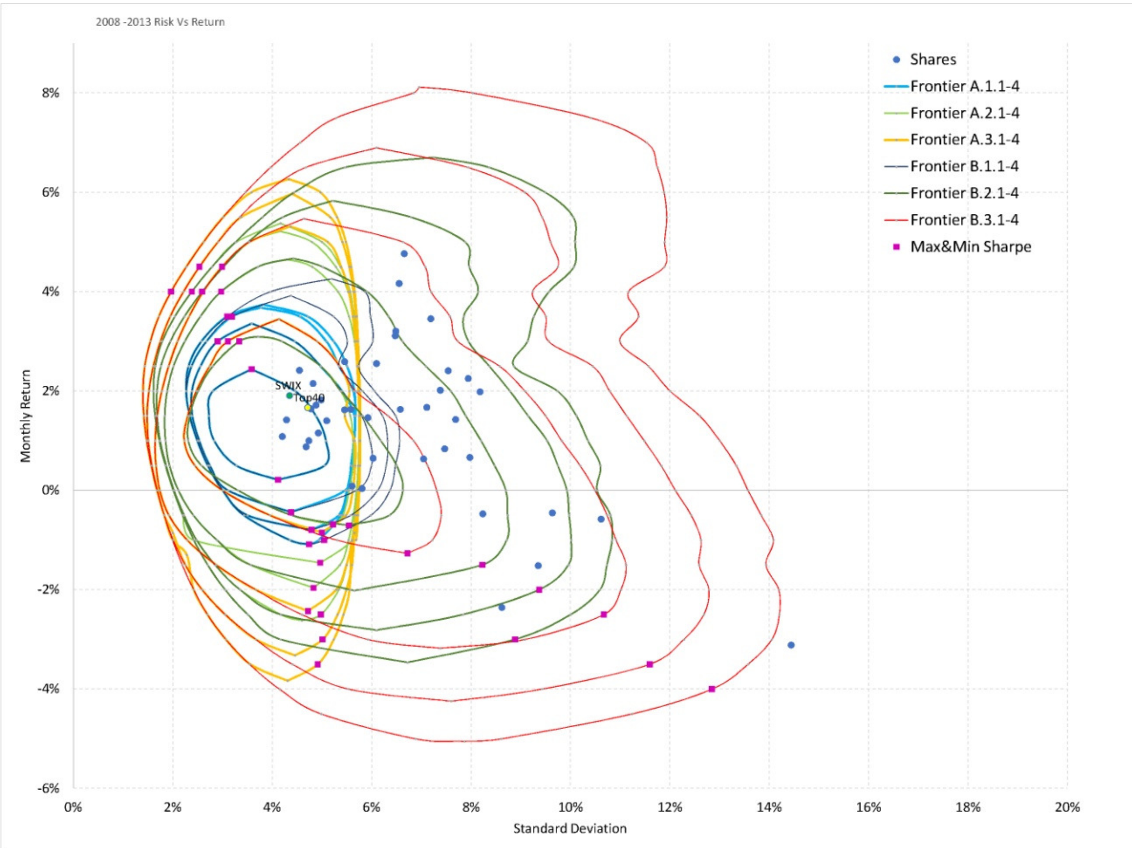


Figure 7: 24 constraint scenarios illustrating possible playing field for 2009-2014

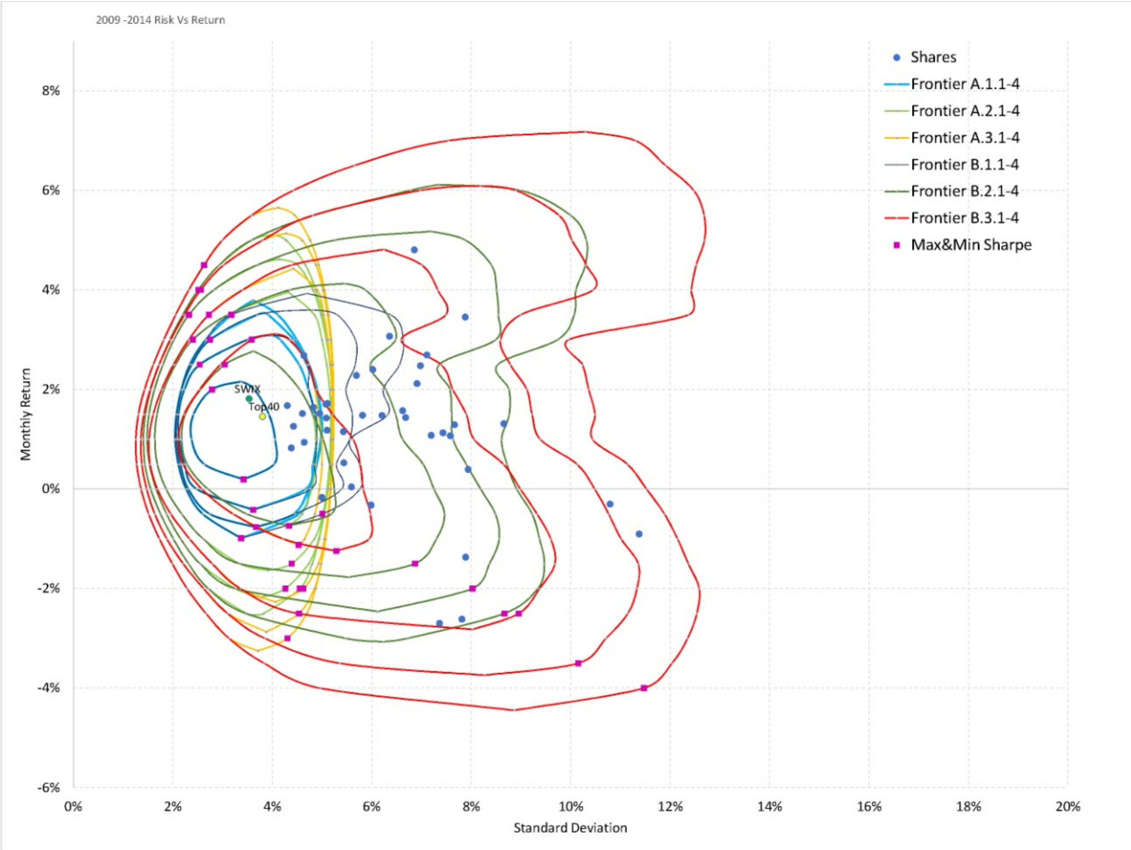


Figure 8: 24 constraint scenarios illustrating possible playing field for 2010-2015

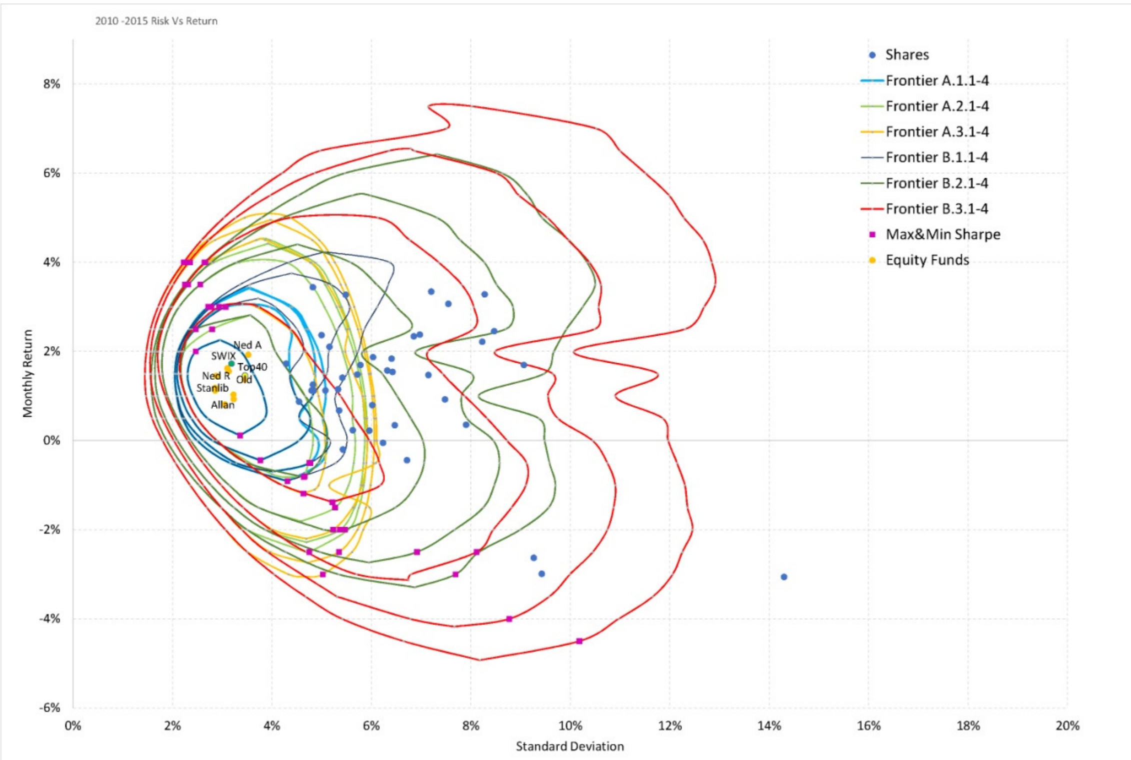


Table 4 : Minimum, maximum and median modified Sharpe ratios for each time period

2006 - 2011				2007 - 2012				2008 - 2013			
	PFRtn	PFStdev	Mod Sharpe		PFRtn	PFStdev	Mod Sharpe		PFRtn	PFStdev	Mod Sharpe
B. 3.4	-4.5%	15.0%	-0.8%	B. 3.4	-4.5%	15.3%	-0.8%	B. 3.4	-4.0%	12.8%	-0.6%
A. 1.1	-0.3%	5.3%	-0.1%	A. 1.1	0.1%	5.1%	0.0%	A. 1.1	0.2%	4.1%	0.0%
A. 1.1	1.5%	4.0%	20.9%	A. 1.1	2.3%	4.4%	37.0%	A. 1.1	2.4%	3.6%	49.6%
B. 3.4	5.0%	4.1%	106.7%	B. 3.4	5.0%	4.0%	109.3%	B. 3.4	4.0%	2.0%	169.7%

2009 - 2014				2010 - 2015			
	PFRtn	PFStdev	Mod Sharpe		PFRtn	PFStdev	Mod Sharpe
B. 3.4	-4.0%	11.5%	-0.5%	B. 3.4	-4.5%	10.2%	-0.5%
A. 1.1	0.2%	3.4%	0.0%	A. 1.1	0.1%	3.4%	0.0%
A. 1.1	2.0%	2.8%	47.9%	A. 1.1	2.0%	2.5%	54.1%
A. 3.4	4.5%	2.6%	146.1%	B. 3.4	4.0%	2.2%	149.9%

Table 5 : Relative performance of FTSE / JSE Top 40 and SWIX Shareholder Weighted Top 40 Index

	2006-2011		2007-2012		2008-2013		2009-2014		2010-2015		
	Top40	SWIX	Top40	SWIX	Top40	SWIX	Top40	SWIX	Top40	SWIX	
Return	0.59%	0.81%	1.02%	1.30%	1.67%	1.91%	1.46%	1.81%	1.46%	1.73%	
Std Dev	5.73%	5.36%	5.69%	5.28%	4.71%	4.35%	3.80%	3.53%	3.46%	3.18%	
	Difference: SWIX - Top 40										Avg
Return	0.22%		0.28%		0.24%		0.35%		0.27%		0.27%
Std Dev	-0.36%		-0.40%		-0.36%		-0.27%		-0.27%		-0.3%

5. 3 Grouped Results

The total results, of the 24 different scenarios that were simulated will be presented in six different groupings for comparison. The six different groups are presented as follows:

The 24 scenarios were grouped into four sets of 6 scenarios each, in order of the most restrictive constraints to the least restrictive, specifically scenario A.1.1 with a maximum of 3% tracking error, maximum 5% weighting of any stock and no short selling; to the scenario of least restrictions, specifically B.3.4, with a maximum tracking error or 15% (essentially ignoring tracking error), a maximum weight of 15% and a minimum weight of negative 15% (or short selling of 15%).

Table 1 under research methodology defines each group. The different hypothetical portfolios are labelled by a letter and then two numbers. The letter “A” or “B” describes whether the portfolio had a tracking error limit of 3% for “A” and 15% for “B”. The second character or first number defines the maximum weight allowance of the portfolio, “1” for 5%, “2” for 10% and “3” for a maximum weight allowance of 15%. The third and last character or second number, defines the minimum weight allowances; “1” for zero short selling, “2” for 5% short selling, “3” for negative 10% minimum weighting and “4” for negative 15% minimum weight allowance.

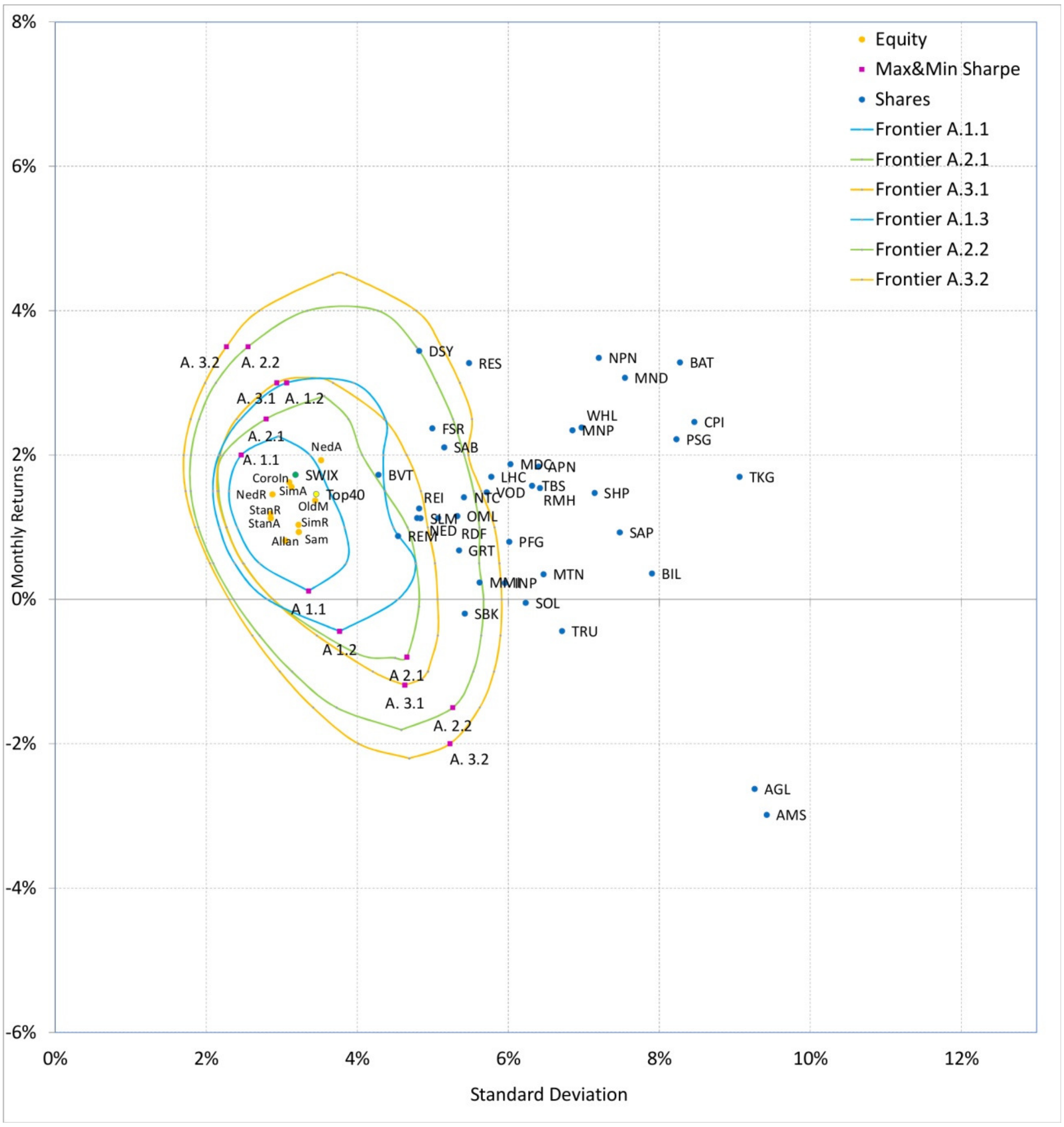
Group 1

The graph below shows the “playing fields” or range of outcomes that were available for a portfolio constructed by the Top 40 constituents on a particular date, for 3% tracking errors, five, 10 and 15% maximum weighting and zero or negative 5% minimum weighting.

Table 6 : Scenario for six portfolios with the tightest constraints

Scenario	A. 1.1	A 1.2
MaxTrackingError	3.00%	3.00%
MaxWeight	5%	5%
MinWeight	0%	-5%
Scenario	A. 2.1	A. 2.2
MaxTrackingError	3.00%	3.00%
MaxWeight	10%	10%
MinWeight	0%	-5%
Scenario	A. 3.1	A. 3.2
MaxTrackingError	3.00%	3.00%
MaxWeight	15%	15%
MinWeight	0%	-5%

Figure 9: Performance of six portfolios with the tightest constraints



The playing fields become concentrically larger as the constraints or limitations of the portfolio are relaxed, specifically in this scenario from five to 15% maximum weighting and zero to negative five minimum weighting. Scenario A. 1.1 with 3% tracking error, 5% maximum weighting and no short selling, is the only portfolio that gives a possibility of a negative return, but has the lowest possible upside. However, this lower upside still drastically outperforms the Top 40 market weighted index and the shareholder weighted index.

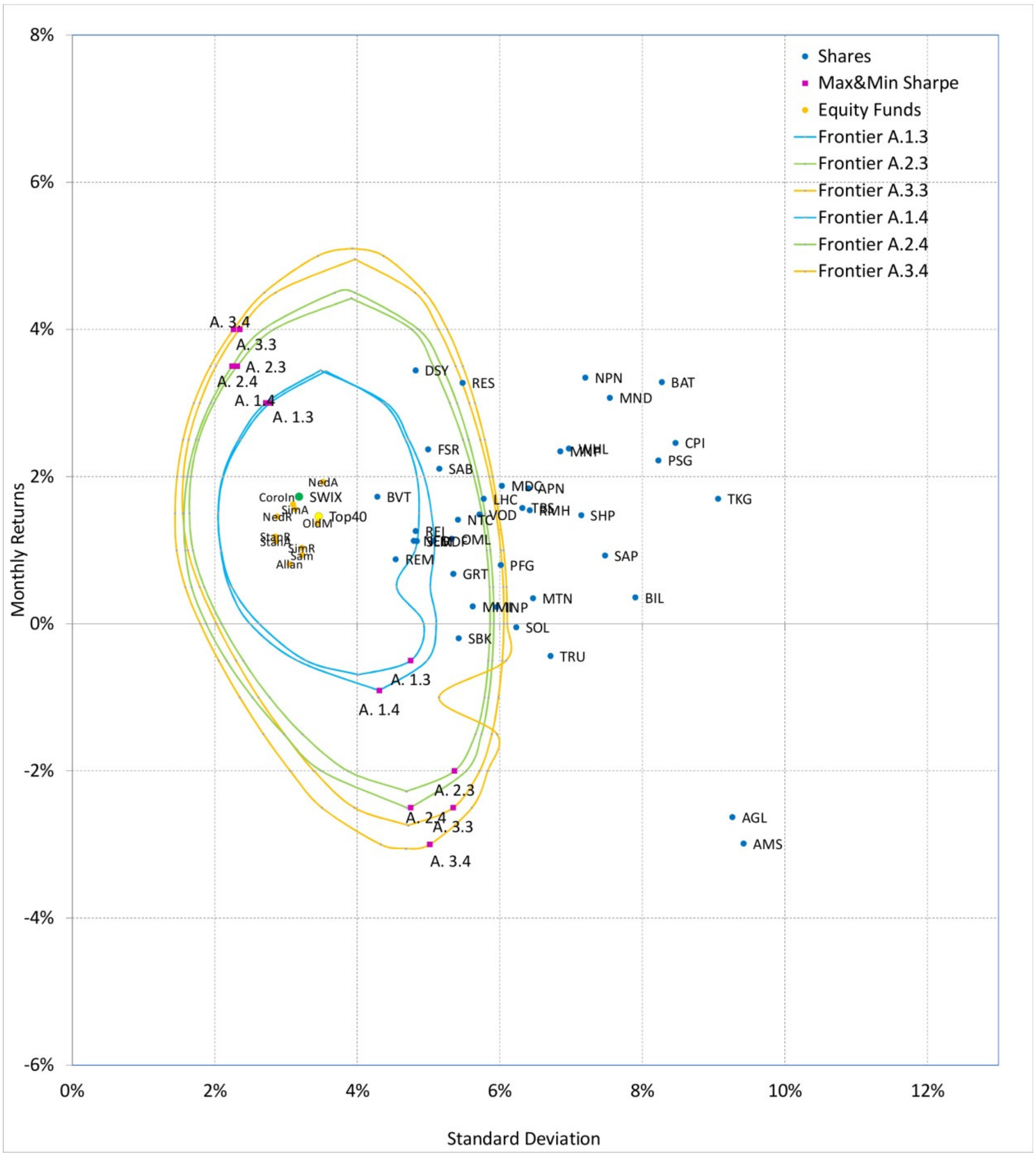
The next three scenarios have very similar upside returns but increasing downsides, these are scenarios A. 1.2 (short selling), A. 2.1 and A. 3.1. The next two scenarios; A. 2.2 and A. 3.2, have similar best and worst possibilities.

Group 2

Table 7: Scenario for six portfolios with the second tightest constraints

Scenario	A. 1.3	A 1.4
MaxTrackingError	3.00%	3.00%
MaxWeight	5%	5%
MinWeight	-10%	-15%
Scenario	A. 2.3	A. 2.4
MaxTrackingError	3.00%	3.00%
MaxWeight	10%	10%
MinWeight	-10%	-15%
Scenario	A. 3.3	A. 3.4
MaxTrackingError	3.00%	3.00%
MaxWeight	15%	15%
MinWeight	-10%	-15%

Figure 10: Performance of six portfolios with the second tightest constraints

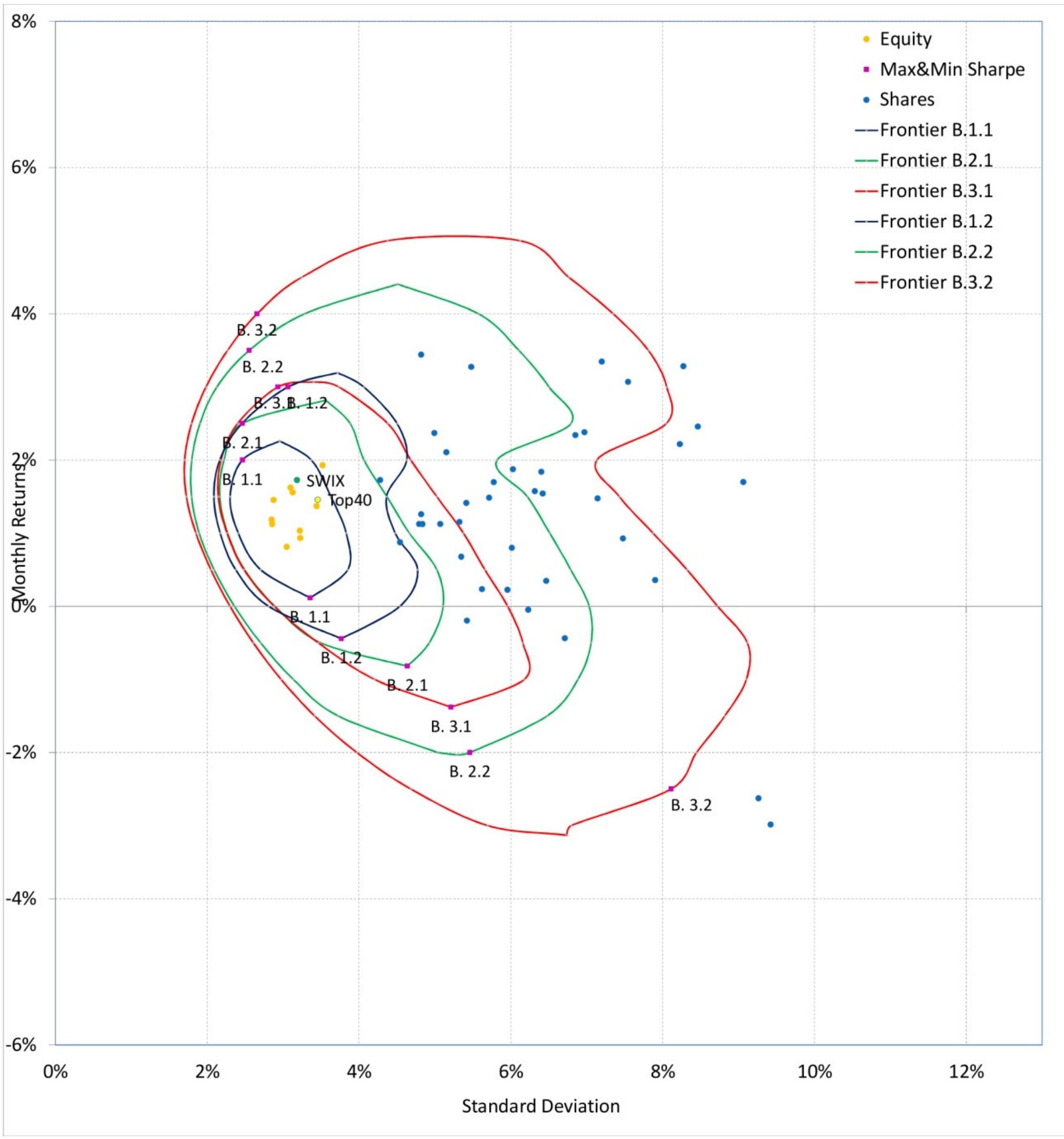


Group 3

Table 8: Scenario for six portfolios with the second most relaxed constraints

Scenario	B. 1.1	B. 1.2
MaxTrackingError	15.00	15.00
MaxWeight	5%	5%
MinWeight	0%	-5%
Scenario	B. 2.1	B. 2.2
MaxTrackingError	15.00	15.00
MaxWeight	10%	10%
MinWeight	0%	-5%
Scenario	B. 3.1	B. 3.2
MaxTrackingError	15.00	15.00
MaxWeight	15%	15%
MinWeight	0%	-5%

Figure 11: Performance of six portfolios with the second most relaxed constraints

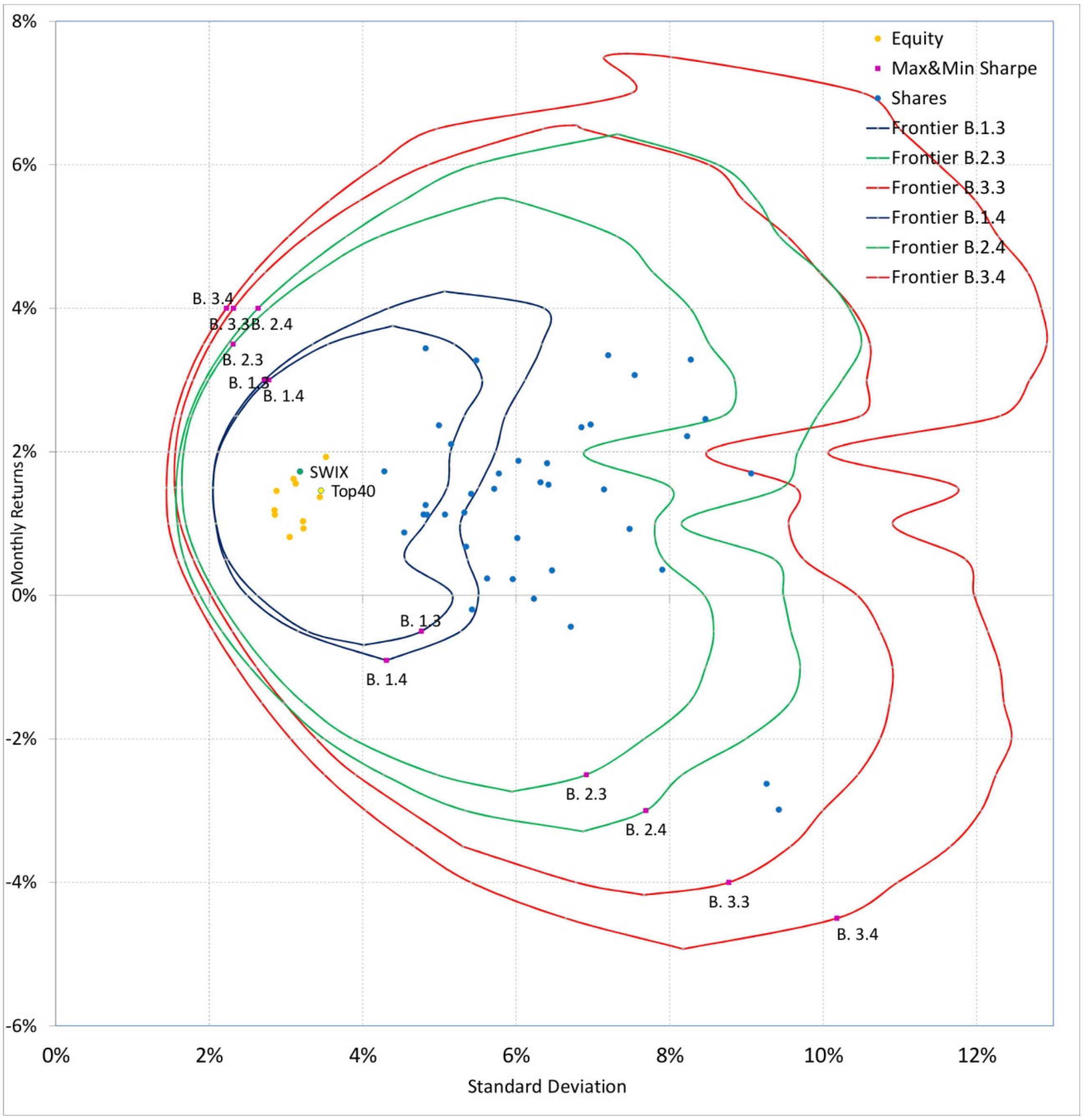


Group 4

Table 9: Scenario for six portfolios with the most relaxed constraints

Scenario	B. 1.3	B. 1.4
MaxTrackingError	15.00	15.00
MaxWeight	5%	5%
MinWeight	-10%	-15%
Scenario	B. 2.3	B. 2.4
MaxTrackingError	15.00	15.00
MaxWeight	10%	10%
MinWeight	-10%	-15%
Scenario	B. 3.3	B. 3.4
MaxTrackingError	15.00	15.00
MaxWeight	15%	15%
MinWeight	-10%	-15%

Figure 12: Performance of six portfolios with the most relaxed constraints



Group 5

Table 10: Scenario for 12 portfolios with the least and most constraints at three and 15% tracking error

Scenario	A. 1.1	B. 1.1	A 1.4	B. 1.4
MaxTrackingError	3.00%	15.00%	3.00%	15.00%
MaxWeight	5%	5%	5%	5%
MinWeight	0%	0%	-15%	-15%
Scenario	A. 2.1	B. 2.1	A. 2.4	B. 2.4
MaxTrackingError	3.00%	15.00%	3.00%	15.00%
MaxWeight	10%	10%	10%	10%
MinWeight	0%	0%	-15%	-15%
Scenario	A. 3.1	B. 3.1	A. 3.4	B. 3.4
MaxTrackingError	3.00%	15.00%	3.00%	15.00%
MaxWeight	15%	15%	15%	15%
MinWeight	0%	0%	-15%	-15%

Figure 13: Performance of 12 portfolios with the least and most constraints

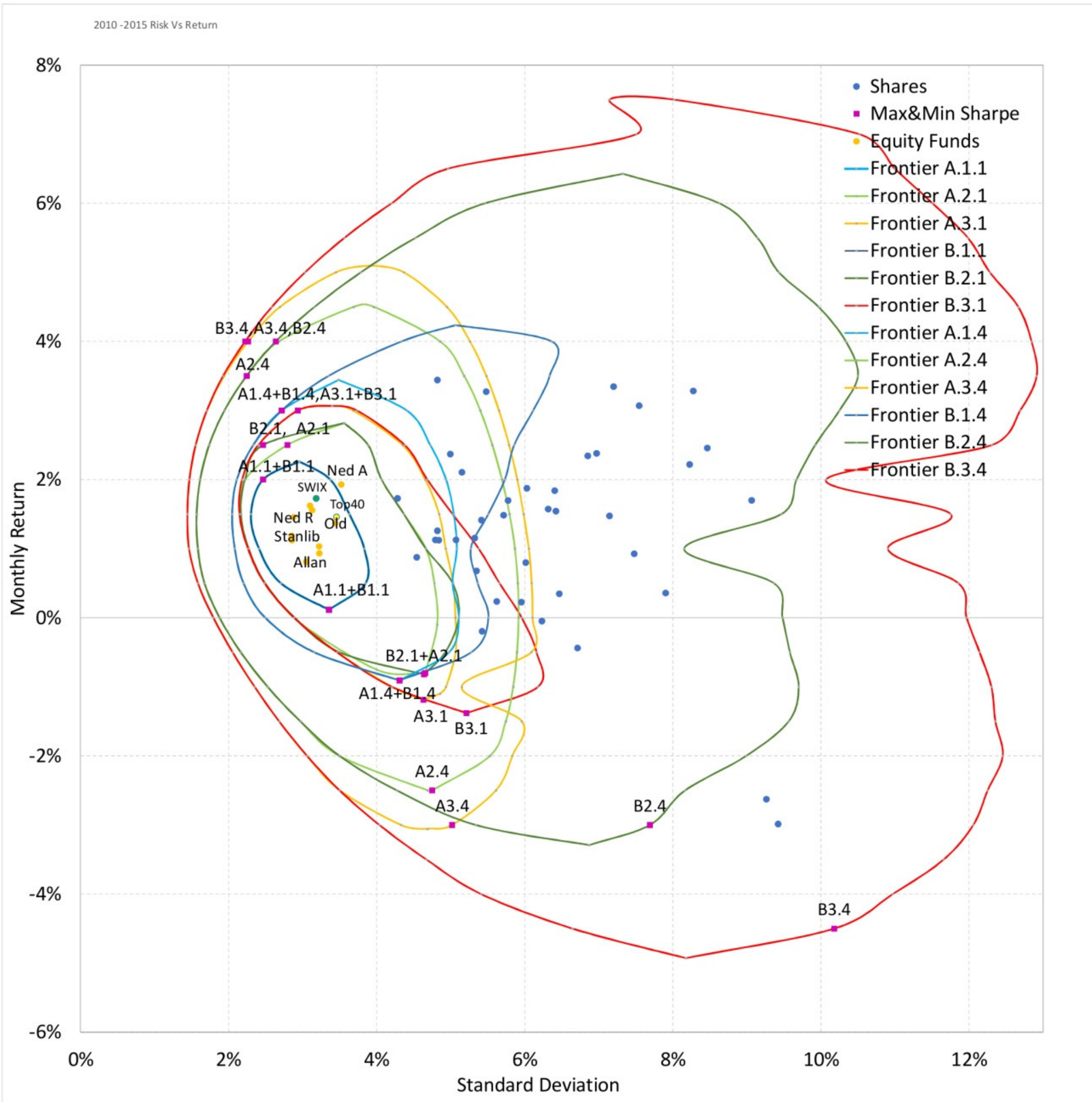


Figure 13 compared the 6 portfolios that allowed no short selling to the 6 portfolios that allowed up to 15%. The results are relatively consistent playing fields, except for B 2.4 and 3.4 due to a combination of increased tracking error, short sell of -15% and a maximum weight allowance of 10% or 15%.

Group 6

Table 11: Scenario for eight portfolios with the least and most maximum weighting constraints

Scenario	A. 1.1	A 1.2	A. 1.3	A 1.4
MaxTrackingError	3.00%	3.00%	3.00%	3.00%
MaxWeight	5%	5%	5%	5%
MinWeight	0%	-5%	-10%	-15%
Scenario	B. 3.1	B. 3.2	B. 3.3	B. 3.4
MaxTrackingError	15.00%	15.00%	15.00%	15.00%
MaxWeight	15%	15%	15%	15%
MinWeight	0%	-5%	-10%	-15%

Figure 14: Performance of eight portfolios with the least and most maximum weighting constraints

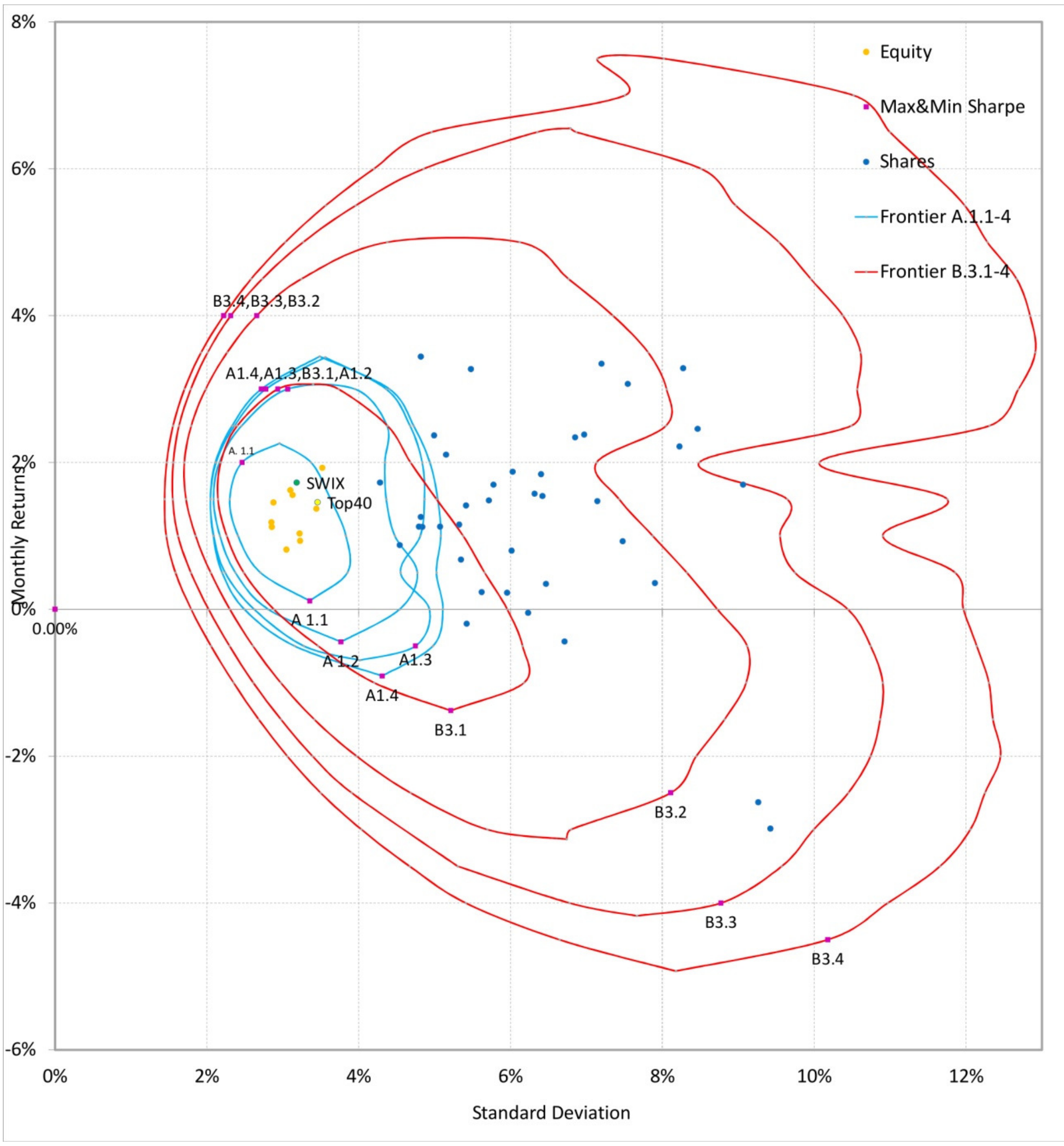


Figure 14 compares 4 portfolios with a tracking error of 3% and a maximum weight allowance of 5% with 4 portfolios with a 15% tracking error and a maximum weight allowance of 15% at different minimum weightings.

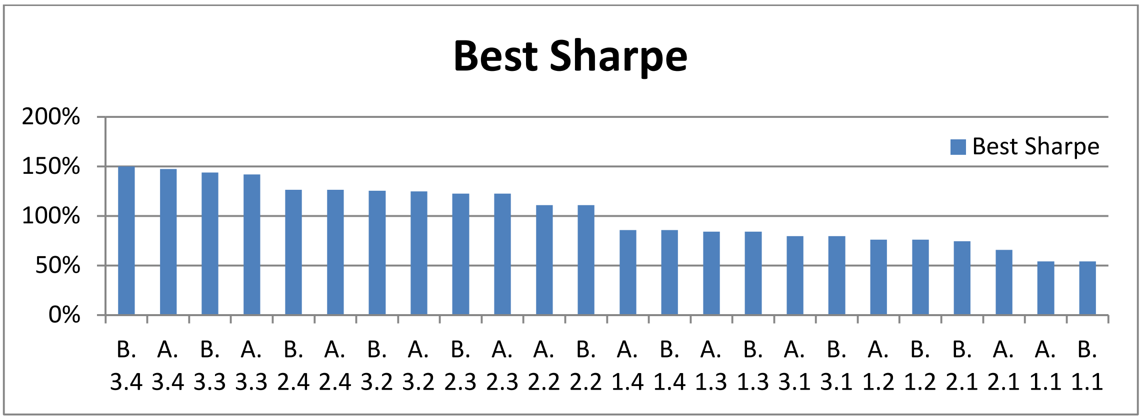
Table 12: Best and worst modified Sharpe ratios for each constructed portfolio in ascending order

Portfolio	PFRtn	PFStdev	Sharpe	SWIXTE	MaxTE	MaxWt	MinWt	ActiveSh	Modified Sharpe Ratio
B. 3.4	-4.50%	10.18%	-50.76%	9.22%	15.00%	15.00%	-15.00%	112.00	-0.526%
B. 3.3	-4.00%	8.77%	-53.19%	7.63%	15.00%	15.00%	-10.00%	95.77	-0.409%
B. 2.4	-3.00%	7.69%	-47.68%	6.53%	15.00%	10.00%	-15.00%	81.11	-0.282%
B. 3.2	-2.50%	8.11%	-39.04%	6.77%	15.00%	15.00%	-5.00%	73.68	-0.257%
B. 2.3	-2.50%	6.91%	-45.80%	5.84%	15.00%	10.00%	-10.00%	73.85	-0.219%
A. 3.4	-3.00%	5.02%	-73.06%	3.00%	3.00%	15.00%	-15.00%	88.70	-0.184%
A. 3.3	-2.50%	5.35%	-59.23%	3.00%	3.00%	15.00%	-10.00%	78.13	-0.169%
A. 2.4	-2.50%	4.75%	-66.67%	3.00%	3.00%	10.00%	-15.00%	67.71	-0.150%
B. 2.2	-2.00%	5.46%	-48.82%	4.19%	15.00%	10.00%	-5.00%	58.24	-0.146%
A. 2.3	-2.00%	5.37%	-49.70%	3.00%	3.00%	10.00%	-10.00%	66.94	-0.143%
A. 3.2	-2.00%	5.23%	-51.00%	3.00%	3.00%	15.00%	-5.00%	61.43	-0.139%
A. 2.2	-1.50%	5.27%	-41.14%	3.00%	3.00%	10.00%	-5.00%	53.03	-0.114%
B. 3.1	-1.38%	5.21%	-39.26%	3.81%	15.00%	15.00%	0.00%	33.00	-0.107%
A. 3.1	-1.19%	4.63%	-40.05%	3.00%	3.00%	15.00%	0.00%	32.00	-0.086%
B. 2.1	-0.82%	4.64%	-32.02%	3.00%	15.00%	10.00%	0.00%	30.00	-0.069%
A. 2.1	-0.80%	4.66%	-31.50%	3.00%	3.00%	10.00%	0.00%	29.22	-0.068%
A 1.4	-0.91%	4.31%	-36.54%	2.53%	3.00%	5.00%	-15.00%	35.00	-0.068%
B. 1.4	-0.91%	4.31%	-36.54%	2.53%	15.00%	5.00%	-15.00%	35.00	-0.068%
B. 1.3	-0.50%	4.77%	-24.48%	3.04%	15.00%	5.00%	-10.00%	33.00	-0.056%
A. 1.3	-0.50%	4.75%	-24.56%	3.00%	3.00%	5.00%	-10.00%	33.00	-0.055%
A. 1.2	-0.44%	3.77%	-29.46%	2.36%	3.00%	5.00%	-5.00%	30.00	-0.042%
B. 1.2	-0.44%	3.77%	-29.46%	2.36%	15.00%	5.00%	-5.00%	30.00	-0.042%
A. 1.1	0.11%	3.36%	-16.43%	1.42%	3.00%	5.00%	0.00%	20.00	-0.019%
B. 1.1	0.11%	3.36%	-16.43%	1.42%	15.00%	5.00%	0.00%	20.00	-0.019%
A. 1.1	2.00%	2.47%	54.09%	1.66%	3.00%	5.00%	0.00%	17.98	54.093%
B. 1.1	2.00%	2.47%	54.09%	1.66%	15.00%	5.00%	0.00%	17.98	54.093%
A. 2.1	2.50%	2.79%	65.63%	1.80%	3.00%	10.00%	0.00%	21.08	65.633%
B. 2.1	2.50%	2.46%	74.40%	2.00%	15.00%	10.00%	0.00%	26.86	74.400%
B. 1.2	3.00%	3.07%	76.09%	2.54%	15.00%	5.00%	-5.00%	27.75	76.092%
A. 1.2	3.00%	3.07%	76.09%	2.54%	3.00%	5.00%	-5.00%	27.72	76.092%
A. 3.1	3.00%	2.93%	79.53%	2.56%	3.00%	15.00%	0.00%	31.86	79.534%
B. 3.1	3.00%	2.93%	79.53%	2.56%	15.00%	15.00%	0.00%	31.86	79.534%
B. 1.3	3.00%	2.78%	83.96%	2.62%	15.00%	5.00%	-10.00%	29.82	83.962%
A. 1.3	3.00%	2.78%	83.96%	2.62%	3.00%	5.00%	-10.00%	29.82	83.962%
B. 1.4	3.00%	2.72%	85.86%	2.66%	15.00%	5.00%	-15.00%	31.14	85.859%
A 1.4	3.00%	2.72%	85.86%	2.66%	3.00%	5.00%	-15.00%	31.13	85.859%
B. 2.2	3.50%	2.55%	110.92%	2.95%	15.00%	10.00%	-5.00%	48.35	110.919%
A. 2.2	3.50%	2.55%	110.92%	2.95%	3.00%	10.00%	-5.00%	48.36	110.919%
A. 2.3	3.50%	2.31%	122.44%	3.00%	3.00%	10.00%	-10.00%	54.45	122.439%
B. 2.3	3.50%	2.31%	122.53%	3.07%	15.00%	10.00%	-10.00%	54.82	122.534%
A. 3.2	3.50%	2.27%	124.89%	3.00%	3.00%	15.00%	-5.00%	57.18	124.891%
B. 3.2	4.00%	2.66%	125.45%	3.30%	15.00%	15.00%	-5.00%	61.28	125.447%
A. 2.4	3.50%	2.24%	126.24%	3.00%	3.00%	10.00%	-15.00%	53.51	126.236%
B. 2.4	4.00%	2.64%	126.42%	3.30%	15.00%	10.00%	-15.00%	60.00	126.422%
A. 3.3	4.00%	2.35%	141.86%	3.00%	3.00%	15.00%	-10.00%	70.35	141.864%
B. 3.3	4.00%	2.32%	143.92%	3.28%	15.00%	15.00%	-10.00%	71.20	143.917%
A. 3.4	4.00%	2.26%	147.18%	3.00%	3.00%	15.00%	-15.00%	69.04	147.182%
B. 3.4	4.00%	2.22%	149.95%	3.33%	15.00%	15.00%	-15.00%	70.65	149.945%

Table 13: Consolidated Sharpe Ratio calculated from the sum of best and worst possible performance of the hypothetically constructed portfolio in ascending order.

Hypothetical Portfolio	PFRtn	PFStdev	Sharpe	SWIXTE	MaxTE	MaxWt	MinWt	ActiveSh	Modified Sharpe Ratio	SUM PFRtn	SUM PFStdev	SUM Mod Sharpe
B. 3.4	-4.50%	10.18%	-50.76%	9.22%	15.00%	15.00%	-15.00%	112.00	-0.526%	-0.50%	12.40%	-0.145%
	4.00%	2.22%	149.95%	3.33%				70.65	149.945%			-0.145%
B. 3.3	-4.00%	8.77%	-53.19%	7.63%	15.00%	15.00%	-10.00%	95.77	-0.409%	0.00%	11.09%	-0.074%
	4.00%	2.32%	143.92%	3.28%				71.20	143.917%			-0.074%
B. 2.4	-3.00%	7.69%	-47.68%	6.53%	15.00%	10.00%	-15.00%	81.11	-0.282%	1.00%	10.33%	3.227%
	4.00%	2.64%	126.42%	3.30%				60.00	126.422%			3.227%
B. 2.3	-2.50%	6.91%	-45.80%	5.84%	15.00%	10.00%	-10.00%	73.85	-0.219%	1.00%	9.23%	3.614%
	3.50%	2.31%	122.53%	3.07%				54.82	122.534%			3.614%
A. 3.4	-3.00%	5.0%	-73.1%	3.0%	3.00%	15.00%	-15.00%	88.70	-0.184%	1.00%	7.28%	4.577%
	4.00%	2.3%	147.2%	3.0%				69.04	147.182%			4.577%
A. 2.4	-2.50%	4.7%	-66.7%	3.0%	3.00%	10.00%	-15.00%	67.71	-0.150%	1.00%	6.99%	4.766%
	3.50%	2.2%	126.2%	3.0%				53.51	126.236%			4.766%
B. 3.2	-2.50%	8.11%	-39.04%	6.77%	15.00%	15.00%	-5.00%	73.68	-0.257%	1.50%	10.77%	7.738%
	4.00%	2.66%	125.45%	3.30%				61.28	125.447%			7.738%
B. 2.2	-2.00%	5.46%	-48.82%	4.19%	15.00%	10.00%	-5.00%	58.24	-0.146%	1.50%	8.02%	10.393%
	3.50%	2.55%	110.92%	2.95%				48.35	110.919%			10.393%
A. 3.3	-2.5%	5.3%	-59.2%	3.0%	3.00%	15.00%	-10.00%	78.13	-0.169%	1.50%	7.70%	10.828%
	4.00%	2.35%	141.86%	3.00%				70.35	141.864%			10.828%
A. 2.3	-2.0%	5.4%	-49.7%	3.0%	3.00%	10.00%	-10.00%	66.94	-0.143%	1.50%	7.68%	10.851%
	3.50%	2.31%	122.44%	3.00%				54.45	122.439%			10.851%
A. 3.2	-2.00%	5.2%	-51.0%	3.0%	3.00%	15.00%	-5.00%	61.43	-0.139%	1.50%	7.50%	11.115%
	3.50%	2.27%	124.89%	3.00%				57.18	124.891%			11.115%
B. 3.1	-1.38%	5.21%	-39.26%	3.81%	15.00%	15.00%	0.00%	33.00	-0.107%	1.62%	8.15%	11.700%
	3.00%	2.93%	79.53%	2.56%				31.86	79.534%			11.700%
A. 2.1	-0.80%	4.66%	-31.50%	3.00%	3.00%	10.00%	0.00%	29.22	-0.068%	1.70%	7.45%	13.871%
	2.50%	2.79%	65.63%	1.80%				21.08	65.633%			13.871%
B. 2.1	-0.82%	4.64%	-32.02%	3.00%	15.00%	10.00%	0.00%	30.00	-0.069%	1.68%	7.10%	14.291%
	2.50%	2.46%	74.40%	2.00%				26.86	74.400%			14.291%
A. 3.1	-1.19%	4.63%	-40.05%	3.00%	3.00%	15.00%	0.00%	32.00	-0.086%	1.81%	7.56%	15.136%
	3.00%	2.93%	79.53%	2.56%				31.86	79.534%			15.136%
A. 2.2	-1.50%	5.27%	-41.14%	3.00%	3.00%	10.00%	-5.00%	53.03	-0.114%	2.00%	7.82%	17.049%
	3.50%	2.55%	110.92%	2.95%				48.36	110.919%			17.049%
B. 1.4	-0.91%	4.31%	-36.54%	2.53%	15.00%	5.00%	-15.00%	35.00	-0.068%	2.09%	7.03%	20.285%
	3.00%	2.72%	85.86%	2.66%				31.14	85.859%			20.285%
A. 1.4	-0.91%	4.31%	-36.54%	2.53%	3.00%	5.00%	-15.00%	35.00	-0.068%	2.09%	7.03%	20.285%
	3.00%	2.72%	85.86%	2.66%				31.13	85.859%			20.285%
B. 1.3	-0.50%	4.77%	-24.48%	3.04%	15.00%	5.00%	-10.00%	33.00	-0.056%	2.50%	7.55%	24.297%
	3.00%	2.78%	83.96%	2.62%				29.82	83.962%			24.297%
A. 1.3	-0.50%	4.75%	-24.56%	3.00%	3.00%	5.00%	-10.00%	33.00	-0.055%	2.50%	7.53%	24.352%
	3.00%	2.78%	83.96%	2.62%				29.82	83.962%			24.352%
A. 1.1	0.11%	3.36%	-16.43%	1.42%	3.00%	5.00%	0.00%	20.00	-0.019%	2.12%	5.82%	24.878%
	2.00%	2.47%	54.09%	1.66%				17.98	54.093%			24.878%
B. 1.1	0.11%	3.36%	-16.43%	1.42%	15.00%	5.00%	0.00%	20.00	-0.019%	2.12%	5.82%	24.878%
	2.00%	2.47%	54.09%	1.66%				17.98	54.093%			24.878%
B. 1.2	-0.44%	3.77%	-29.46%	2.36%	15.00%	5.00%	-5.00%	30.00	-0.042%	2.56%	6.83%	27.662%
	3.00%	3.07%	76.09%	2.54%				27.75	76.092%			27.662%
A. 1.2	-0.44%	3.77%	-29.46%	2.36%	3.00%	5.00%	-5.00%	30.00	-0.042%	2.56%	6.83%	27.662%
	3.00%	3.07%	76.09%	2.54%				27.72	76.092%			27.662%

Figure 15.1: Bar graph of best and worst possible Sharpe ratios for each hypothetical portfolio with varying constraints in descending order



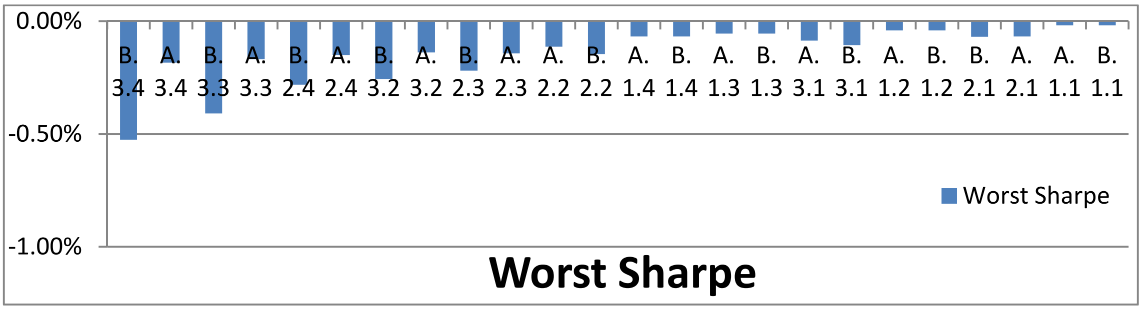


Figure 15.2: Sum of best and worst Sharpe ratio in order of Figure 15.1

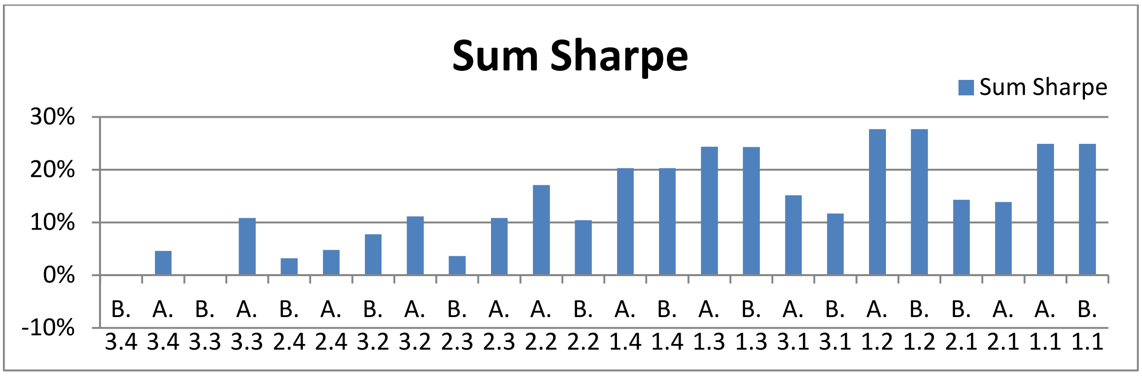
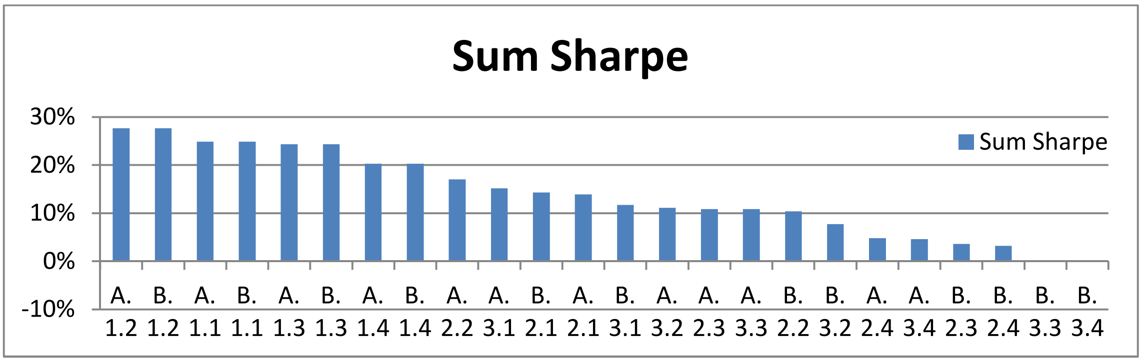


Figure 15.3: Sum of best and worst Sharpe ratio in descending order



The table below shows the ordered results for one scenario, namely A. 2.1, with the constraints of tracking error 3%, maximum weighting 10% and minimum weighting 0%. The results are ordered in four different ways for comparison. The first shows the order in which the model was run, which was from -5% to +7% first with minimising the standard deviation and then maximising the standard deviation. The results that could not be found, because there was no possible solution (i.e. the portfolio could not reach the specified returns with the specific constraints) are not displayed. The second group places the portfolio returns in descending order. The third group places the standard deviation in ascending order and the final group illustrates the practicality of the Sharpe Ratio which combines the portfolio returns and standard deviation so that the comparison can be made as to which combination provides the optimum risk adjusted return.

Table 14: Performance ranking

A. 2.1								
Ascending/ Descending PFRtn, min then max Stdev		Highest PFRtn		Lowest Stdev		Highest Sharpe ratio		
PFRtn	PFStdev	PFRtn	PFStdev	PFRtn	PFStdev	PFRtn	PFStdev	Sharpe
-	4.50%	2.82%	3.56%	1.50%	2.17%	2.50%	2.79%	65.63%
-	4.00%	2.82%	3.56%	2.00%	2.22%	2.82%	3.56%	60.42%
-	3.00%	2.50%	3.88%	1.00%	2.27%	2.82%	3.56%	60.42%
0.49%	2.50%	2.50%	2.79%	0.49%	2.50%	2.00%	2.22%	60.02%
1.00%	2.27%	2.00%	2.22%	2.50%	2.79%	2.50%	3.88%	47.20%
1.50%	2.17%	2.00%	4.07%	-	3.00%	1.50%	2.17%	38.47%
2.00%	2.22%	1.50%	4.37%	2.82%	3.56%	2.00%	4.07%	32.79%
2.50%	2.79%	1.50%	2.17%	2.82%	3.56%	1.50%	4.37%	19.08%
2.82%	3.56%	1.00%	4.66%	2.50%	3.88%	1.00%	2.27%	14.68%
2.82%	3.56%	1.00%	2.27%	-	4.00%	1.00%	4.66%	7.15%
2.50%	3.88%	0.50%	4.78%	2.00%	4.07%	0.50%	4.78%	-3.49%
2.00%	4.07%	0.49%	2.50%	1.50%	4.37%	0.49%	2.50%	-7.14%
1.50%	4.37%	-	4.82%	-	4.50%	-	4.82%	-15.92%
1.00%	4.66%	-	3.00%	-	4.66%	-	3.00%	-25.63%
0.50%	4.78%	-	4.00%	1.00%	4.66%	-	4.66%	-31.50%
-	4.82%	-	4.66%	0.50%	4.78%	-	4.50%	-32.83%
-	4.66%	-	4.50%	-	4.82%	-	4.00%	-35.47%

Through further review of the results, it was discovered that the conventional Sharpe ratio did not provide the correct ranking of portfolios when the expected downside became negative. Therefore the modified Sharpe ratio was used (Grable & Chatterjee, 2014; Israelsen, 2005)

Table 15: Relative performance position of largest ten equity funds, the FTSE / JSE Top 40 Index and the SWIX Shareholder weighted Top 40 Index.

Fund	PFRtn	PFStdev	Mod Sharpe
A. 1.1	0.11%	3.36%	-0.019%
B. 1.1	0.11%	3.36%	-0.019%
ALLAN GRAY EQ.FUND A CL.	0.8%	3.0%	4.797%
SANLAM GENERAL EQUITY FUND A CLASS	0.9%	3.2%	8.242%
SIM GENERAL EQUITY FUND R CLASS	1.0%	3.2%	11.386%
STANLIB WEALTHBUILDER FUND A CLASS	1.1%	2.9%	15.991%
STANLIB WEALTHBUILDER FUND R CLASS	1.2%	2.9%	18.208%
OLD MUTUAL INVESTORS FD. R CLASS	1.4%	3.4%	20.451%
Top40	1.46%	3.46%	22.890%
NEDGROUP INVESTMENTS ENTREPRENEUR FD.R CLASS	1.5%	2.9%	27.419%
SIM INDUSTRIAL FUND R CLASS	1.6%	3.1%	28.498%
CORONATION INDUSTRIAL FUND	1.6%	3.1%	30.850%
SWIX	1.73%	3.18%	33.273%
NEDGROUP INVESTMENTS FINANCIALS A	1.9%	3.5%	35.833%
A. 1.1	2.00%	2.47%	54.093%
B. 1.1	2.00%	2.47%	54.093%

Figure 16: Bar graph of weights

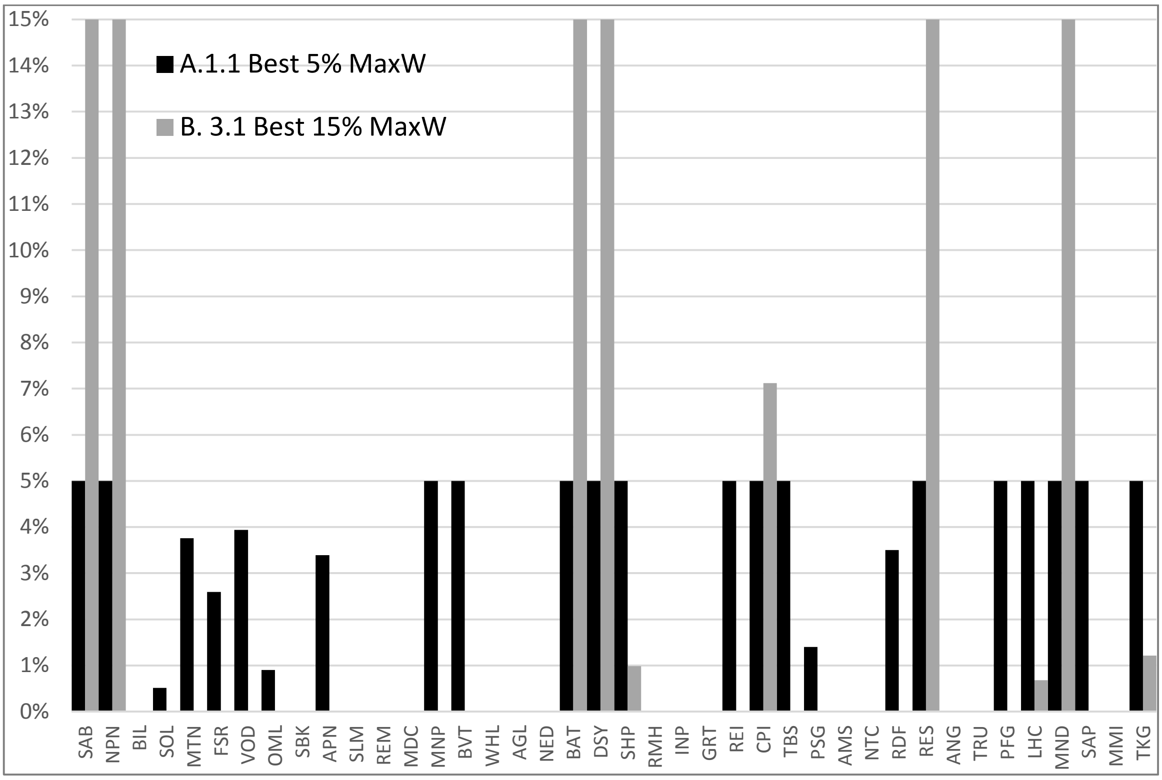
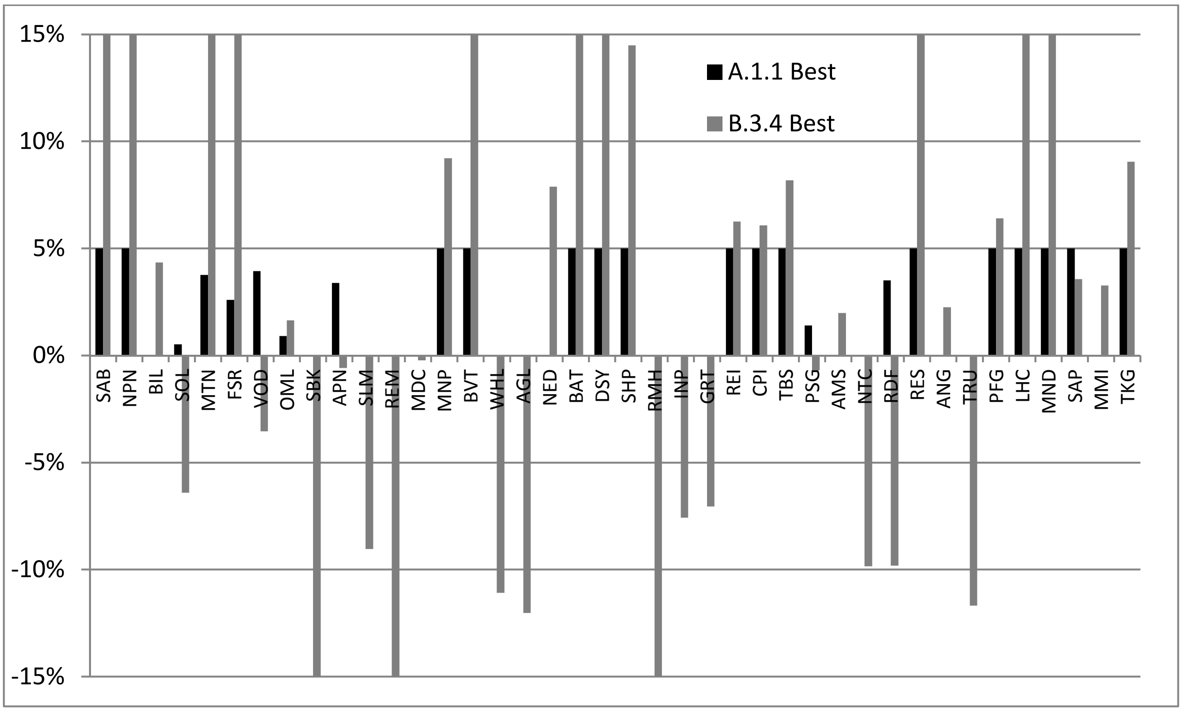


Figure 17: Constituent weights of portfolio A.1.1 (with the most constraints) versus B.3.4 (with the least constraints)



Portfolio A.1.1 with the most constraints holds 24 stocks, whereas B.3.4 with the least constraints holds 24 stocks and shorts 16 stocks (therefore has an exposure to all 40 constituents).

Figure 18: Constituent weights of the best and worst performance of portfolio B.3.4 (with the least constraints)

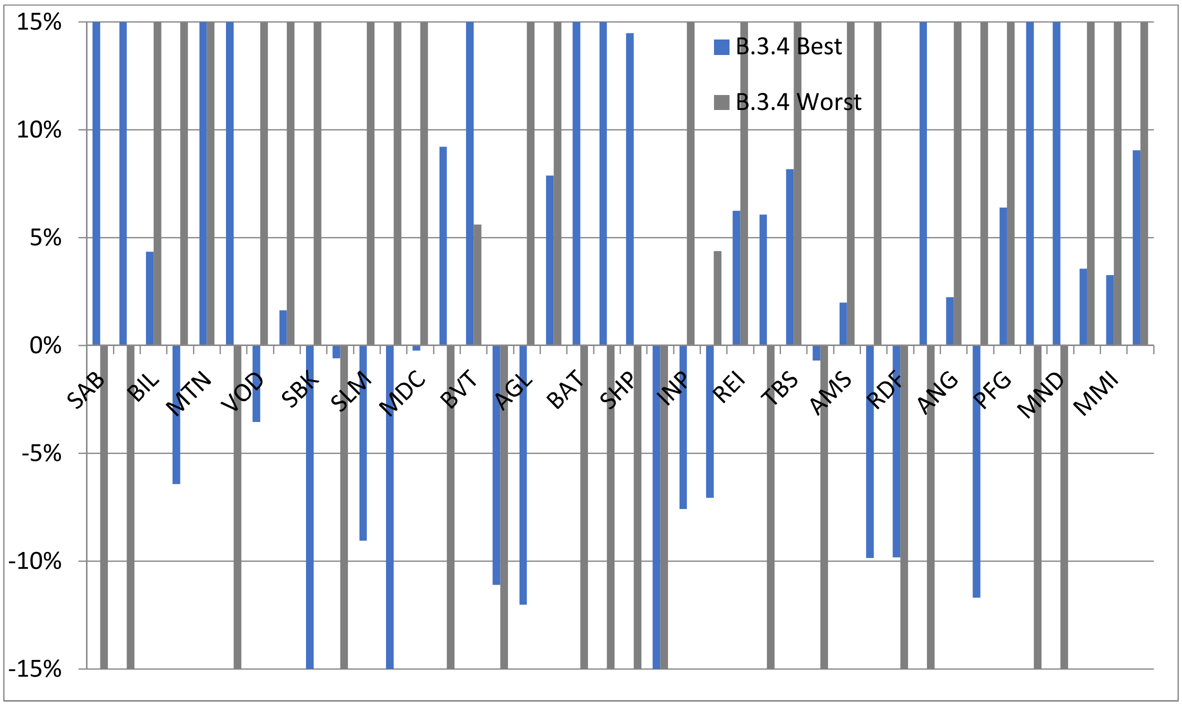
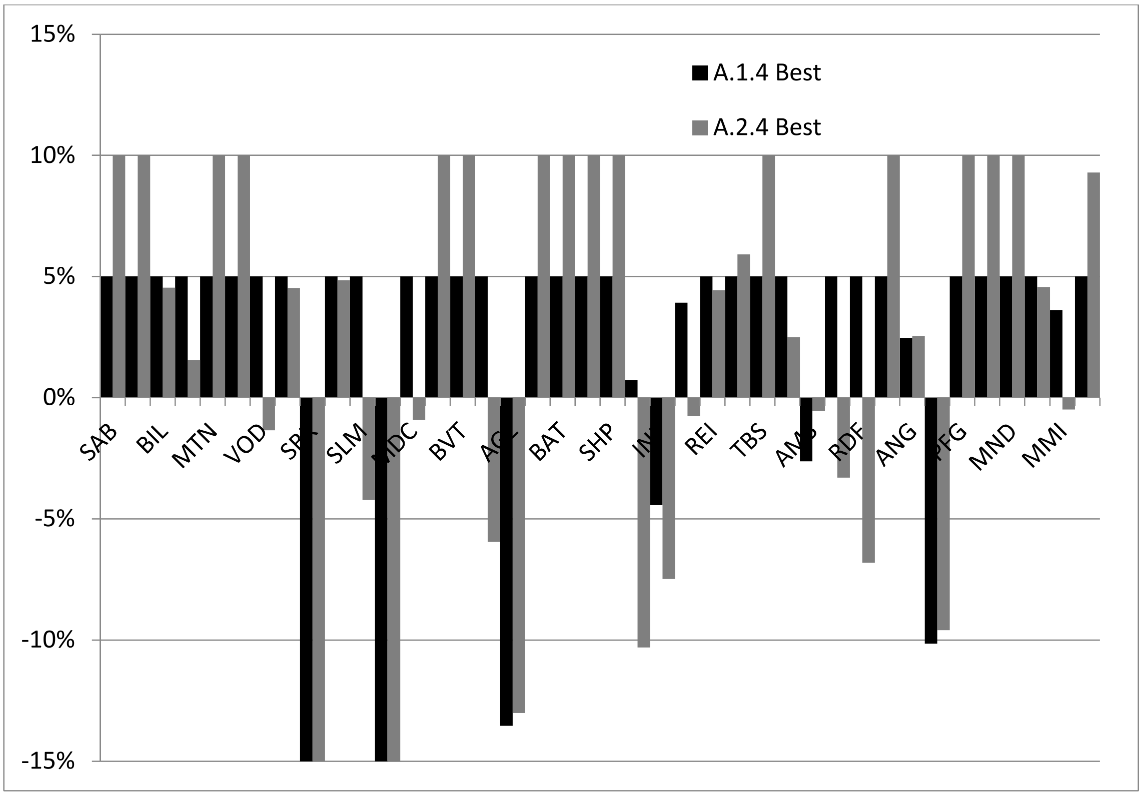


Figure 18 illustrates that the difference in weighting for the best and worst possible outcomes are not necessarily exact opposite portfolios, however are close.

Figure 19: Decrease in diversification with increased maximum weighting



6 Discussion of Results

The discussion of results begins with an overview by comparing the different periods with each other and then a more detailed discussion is conducted by focusing in on the performance of the different hypothetical portfolios in the last time period. When examining the effects of constraints on portfolio performance, it is important to take cognisance of other factors that would affect the performance. One of these factors relevant to the time period studied is the 2008 global financial crisis. Another factor specific to the JSE is that the market was relatively flat from 2014 to mid-2017.

6. 1 Overview

Figure 1, of the actual index constituents from December 2005 and March 2016, illustrates the maximum length of time with continuous constituents. The maximum length of continuous constituents was four quarters between June 2010 and March 2011 or one year. This illustrates why the index constituents had to be approximated and kept static, so that the past five years' of returns, and then the covariance could be calculated, without any missing information. The approximated constituents were rebalanced for each of the five time periods analysed, but then kept constant in order to calculate the covariance.

Figure 2 illustrates the annualised cumulative returns starting from a base of 1 for the hypothetically constructed replicated index and the FTSE / JSE Top 40. This graph validates the data and method of analysis as illustrated by the similar performance.

The results for the best and worst possible index portfolio performance returns per incremental weight adjustment illustrated in **Figure 3** were as expected: for every incremental weight adjustment allowance, the performance of the portfolio would incrementally improve or worsen. The question that then arises is: what is the risk involved in the departure for the index weights? This risk was then plotted in terms of standard deviation.

Table 3 shows the average quarterly return, medium return, standard deviation and Sharpe ratio of: the FTSE / JSE Top 40 Index; 15 actual equity funds; and the maximum and minimum possible quarterly returns for the hypothetically simulated FTSE / JSE Top 40 tracker funds with different weight adjustments from 0.5% to 5%

added or subtracted from the index weights, from December 2005 to December 2016. This table shows that of the 15 equity funds shown only five outperformed the FTSE / JSE Top 40 Index. This is in line with findings of the S&P Indices Versus Active (SPIVA) 2016 results that showed only 14% of active funds outperformed the index over a five year period (S&P Global, 2016).

6. 1. 1 Overview of playing fields

Figures 4 to **8** (as well as Appendix 4) illustrate the movement or change of the results over time. The first observation that can be made is that the results are not widely different. This moderate similarity confirms that no one time period is an outlier or fluke and therefore, the results of one period can be generalised for all the time periods if not tentatively for periods that fall outside of the sample. A larger time period than from 2006 to 2015 should be analysed in possible future studies in order to confidently generalise these results to out of sample periods.

The second set of observations that can be made are by comparing the results of the different time periods with each other. The first time period, 2006 – 2011, (**Figure 4**) shows most of the hypothetical portfolios with a horizontal ellipse-shaped playing field. This horizontal ellipse is indicative of increased amounts of risk for relatively less returns and thus an indication of the 2008 financial crisis. This high risk to lower return is also evident in the review of this period’s Sharpe ratios.

Through the comparison of each period, it is evident that the relative risk to returns decreases, or in other words the playing field becomes tighter and moves up and to the left, as the periods move away from the financial crisis. This can be seen through the movements of the playing fields from the first period, **Figure 4** which has horizontal ellipses, with gradual progression to the last period, **Figure 8** where the majority of the playing fields form vertical ellipses. These vertical ellipses of Figure 7 also moved upwards and towards the left of graph illustrating better possible returns for considerably less risk.

When looking at the overall shape of the graphs produced, and considering the risk and return in isolation, the following observations can be made: when considering only the possible returns over the five periods, for the first period, 2006 – 2011, the highest return is just above 6% and the lowest around -5%. The maximum return increases to about 8% and fluctuates around this point for the following four periods. The downside return, interestingly enough, seems to stay at more or less the same level of about 5% for all five periods. In conclusion the up- and downside return possibilities stay more or less constant over the five consecutive time periods. This is due to the relative depression of the market in the more recent years.

When looking at the standard deviation, in the first period, the maximum risk (the right side of the playing fields) of the 24 portfolios have a wide range, as the constraints loosen, from about 7% to 20% standard deviation. The range on the minimum risk side, on the left of the playing field, has a minimum possible risk of 2% (however with an approximate return of neatly zero) to just under 4%. Over the five year period the lowest risk reduces from a minimum of 2% to 1.5% standard deviation, while the maximum risk drops dramatically from just under 20% to just under 13%. This overall decrease in volatility over the time periods is again an indication of the decreased risk as the periods move away from the global financial crisis.

For a more accurate understanding of the effects of constraints on the performance of portfolios, the possible risk and returns must be viewed in conjunction with each other. This is most effectively done by reviewing the maximum and minimum modified Sharpe ratios as shown in **Table 4** (Grable & Chatterjee, 2014 and Israelsen, 2005). These results once again confirm that the 5 periods are relatively similar and that no one year is an outlier. These results reiterate the effects of the global financial crisis as the modified Sharpe ratios move from a maximum of 107% to 150% and a minimum of -0.8% to -0.5% from the first to last time period.

A further observation from the comparison of the different time periods is the jagged edge that the playing fields form towards the last period (2010-2015). For the majority of different levels of risk, the portfolios showed an upper or lower level of return. For example in **Figure 8**, at the maximum standard deviation of just under 13%, the returns ranged from 4% or -2%, however at the a standard deviation of 10% the returns ranged from 7% to -5% but also include 2%. This could possibly be due to the over-weighting of a few large stocks, however further research must be done to determine why this occurs.

The performances of the various portfolios over time are also compared to the performance of the SWIX Shareholder Weighted Top 40 and the FTSE / JSE Top 40 Index. It is noted, that the relative performance of the SWIX and Top 40 stay relatively constant over the five periods, **Table 5**. The SWIX consistently slightly outperforms the

Top 40 by an average of 0.27% more return and 0.33% less standard deviation. As expected, the two indices performances fall within the tightest constrained playing field for all five years. In the first period the two indices fall approximately in the centre of the first playing field. These playing fields then move towards the left of the indices' relative position in subsequent years, indicating that the constructed portfolios were able to achieve superior returns on the upside but at far less risk than their benchmark indices.

6. 2 Focused view

Now that an overall picture has been formed by the observations, the specific research questions can be addressed and the specific effects of the varying constraints on the simulated portfolios can be examined. The analysis will focus in on the last period (2010 – 2015) as shown in **Figure 9** to **14**.

The results illustrate moderately uniform concentric ellipse playing fields (Jorion, 2003). To start with they are circled around the Top 40 and SWIX 40. The playing fields become progressively larger as the constraints lessen, which is expected. The playing fields do however edge closely together, for the most part, on the minimum standard deviation side and also cluster together on the upside returns. In contrast to this, the playing fields increase dramatically to the side of increased standard deviation or volatility as the limitations lessen without the same increase in returns. This result is in confirmation of research that found that constraints limit upside but also protect against downside (Scherer & Xu, 2007). It is noteworthy that the limit to upside is not as significant when compared to the protection of downside risk that is created. The relatively uniform ellipses which change into circles, also start to distort widely with increased freedom.

The possible best returns cluster together between a small range of 2% to 4% (in other words a 2% range) while the worst case scenarios increase exponentially with every increased freedom from 0.11% to -4.5% (a 4.61% range, which is more than double the upside range). This means that the constraints did not affect the upside returns nearly as much as they limited the risk exposure. This is in contrast to the findings by Clarke et al., (2002) who found that constraints reduced performance up to 70 percent. These results are also contradictory to other recent research that found that constraints greatly limit upside returns (Jorion, 2003; Roll, 1992).

The returns for these hypothetically constructed portfolios are based on the actual returns for the period. It can be argued that a competent portfolio manager is very likely to at least do better than the worst possible outcomes when employing strategies like momentum trading, which has been shown to be affective within the JSE .Therefore the relevance of these results, as usual, are dependent on the risk appetite of the investor.

From **Table 12** of best and worst modified Sharpe ratios, the following results are obtained: of the 24 hypothetical portfolios, three sets produce identical best and worst possible returns. These sets were A 1.1 and B 1.1., A 1.2 and B 1.2 and A 1.4 and B 1.4. These results are expected because although the B portfolios have an increased tracking error (basically a negligible constraint) the limitations of maximum 5% weighting and minimum 0%, -5% and -15% respectively, did not provide the possibility of increasing the tracking errors dramatically. Surprisingly A 1.3 and B 1.3, both with a maximum weight allowance of 5% and a minimum of 0%, gave the same upside return, but B 1.3 had a slightly worse downside due to the increased tracking error limit.

Portfolio A 3.1 and B 3.1 (maximum weight of 15% and no short selling) also gave the same upside, but the B portfolio once again gave a worse downside due to the increased tracking error limit. A 1.4 (maximum weight of 5%) and A 2.1 (maximum weight of 10%) gave the same downside but A 1.4 provided a far superior upside return because of the short selling allowance of -15% compared to portfolio A 2.1 where short selling was completely restricted. These results are summarised in the table below.

Table 16: Pairs of portfolios that produced similar performance

Portfolio	MaxTE	MaxWt	MinWt	Upside PFRtn	Upside PFStdev	Upside Sharpe	Upside Mod. Sharpe Ratio	Downside PFRtn	Downside PFStdev	Downside Sharpe	Downside Mod. Sharpe Ratio
A. 1.1	3.00%	5.00%	0.00%	2.00%	2.47%	54.09%	54.09%	0.11%	3.36%	-16.43%	-0.019%
B. 1.1	15.00%	5.00%	0.00%								
A. 1.2	3.00%	5.00%	-5.00%	3.00%	3.07%	76.09%	76.09%	-0.44%	3.77%	-29.46%	-0.042%
B. 1.2	15.00%	5.00%	-5.00%								
B. 1.3	15.00%	5.00%	-10.00%	3.00%	2.78%	83.96%	83.96%	-0.50%	4.77%	-24.48%	-0.056%
A. 1.3	3.00%	5.00%	-10.00%					-0.50%	4.75%	-24.56%	-0.055%
B. 1.4	15.00%	5.00%	-15.00%	3.00%	2.72%	85.86%	85.86%	-0.91%	4.31%	-36.54%	-0.068%
A. 1.4	3.00%	5.00%	-15.00%								
A. 2.1	3.00%	10.00%	0.00%	2.50%	2.79%	65.63%	65.63%	-0.80%	4.66%	-31.50%	
A. 2.2	3.00%	10.00%	-5.00%	3.50%	2.55%	110.92%	110.92%	-1.50%	5.27%	-41.14%	-0.114%
B. 2.2	15.00%	10.00%	-5.00%					-2.00%	5.46%	-48.82%	-0.146%
A. 2.3	3.00%	10.00%	-10.00%	3.50%	2.31%	122.44%	122.44%	-2.00%	5.37%	-49.70%	-0.143%
B. 2.3	15.00%	10.00%	-10.00%					-2.50%	6.91%	-45.80%	-0.219%
A. 2.4	3.00%	10.00%	-15.00%	3.50%	2.24%	126.24%	126.24%	-2.50%	4.75%	-66.67%	-0.150%
B. 2.4	15.00%	10.00%	-15.00%					-3.00%	7.69%	-47.68%	-0.282%
A. 3.1	3.00%	15.00%	0.00%	3.00%	2.93%	79.53%	79.53%	-1.19%	4.63%	-40.05%	-0.086%
B. 3.1	15.00%	15.00%	0.00%					-1.38%	5.21%	-39.26%	-0.107%

The results are in contrast to the findings of Clarke et al., (2002) who found that "constraints reduce the expected value of the investor's forecasting ability" (p. 14) by a measure or 0.3 to 0.8 in a scale of 0 to 1. The results are in alignment with other studies that found that the increase in constraints improves the performance of actively managed funds (Jorion, 2003). The results of this study do however contradict a portion of Jorion's findings. Jorion (2003) found that tracking error constraints, as the only constraint, increased the risk of a portfolio. However, the results of this research found that tightening the tracking error restriction from 15% to 3%, with a very unrestrictive weighting allowance, had very a limited effect on the upside risk or return but definitely limited the downside risk.

Table 13 illustrates the consolidated Shapre Ratios calculated from the sum of the best and worst possible returns and standard deviations of the hypothetically constructed portfolio in acending order. The results in this table clearly show that when considering the best and worst possible outcomes together, the portfolios with the constraint that specifies a maxium weight limit of 5% per stock consistantly outperform all other scenarios, despire tracking error limits or shortselling constraints. This is due to the decreased downside risk because of increased diversification. Through the implementation of proven performance maximising strategies however, a skilled fund manager should succeed in avoiding the worst possible outcomes. These results do however quantify the effects of constraints on the various levels of risk that an investor can select.

Figure 13 compared the 6 portfolios that allowed no short selling to the 6 portfolios that allowed up to 15%. Expectedly, the zero short selling portfolios has the most restricted playing fields, even though the tracking error limits differed from 3% to 15% and the maximum weight allowance included 5%, 10% and 15%. Clarke et al., (2002) noted that the long-only constraints are so ubiquitous that they are not even acknowledged as restrictions at times, even though this constraint has a large effect on possible returns as shown by the data. There is a larger change in the size and shape of the playing fields between the maximum weight allowance of 5% to 10% than from the 10% to 15%.

Portfolio A. 1.4, with the least tracking error and maximum weight allowance restrictions, but with a short selling allowance of 15%, surprisingly tracks a very similar shape to portfolios A 3.1 and B. 3.1 This is surprising because the 3.1 portfolios allow a maximum weighting of 15% but no short selling. The performance for these three portfolios is a maximum risk adjusted return of 3%. Portfolio A and B 3.1 can achieve this return with 2.93% standard deviation volatility and portfolio A 1.4 with slightly less volatility of 2.72%. This slight difference in volatility at the same level of return does have an increased effect on the Sharpe ratio which drops from 85.9% for A 1.4 (and B 1.4) to 79.5% for A and B 3.1. This shows that more short selling does not necessarily increase risk. This is consistent with other research that found that allowing short selling in traditionally long-only restricted funds did not increase exposure to downside risk (Xu, 2007).

A change in playing field shape occurs with the constraint differences between A 1.4 and B 1.4 (both with a maximum weight allowance of 15% and a minimum of -15%), but A with 3% tacking error and B with 15%. The playing field of B 1.4 stretches further up and to the right, varying from the previous ellipse shapes to form a kidney shape, reaching a return of 4% at a risk of 6.4%. This just shows more opportunities available with the larger tracking error.

Portfolio A and B 2.1 and B 3.1 (allowing no short selling and 10% and 15% maximum weighting respectively) offer less upside return and more downside risk than portfolios A and B 1.4 (with 5% maximum but up to -15% minimum). This again illustrates that allowing short selling does not necessarily increase downside risk.

In **Figure 13** portfolios A and B 1.1, 2.1, 3.1 and 1.4 clustered together, for the most part, on the left of the frontier and in terms of maximum and minimum possible Sharpe ratios. Then there is a large jump in playing field size between these eight portfolios and the next four portfolios. The reason for this jump is the increase in short selling allowance from 0% to -15% combined with a maximum weight allowance of at least 10% and 15%. This relaxation on limitations increases the potential for returns from a maximum of 3% to a maximum of 4% and reduced volatility from 2.72% to 2.22% (or a Sharpe of 85.9% to 149.9%). However the downside risk increases exponentially from -1.38% with a volatility of 5.21% to a maximum of -4.5% return and 10.18% standard deviation volatility (or a modified Sharpe of -0.107% to -0.526%, standard Sharpe of -39.3% to -50.8%).

In summary therefore, for a possible 1% increase in upside return and 0.5% reduction of standard deviation volatility, the portfolio must increase the downside exposure by a possible -3.59% return and increase standard deviation of 5.87%, by increasing the maximum weight allowance by 10% from 5% to 15%. This in turn, is due to the increase in risk, due to the decrease in diversification. **Figure 16** and **19** illustrates the change in weighting allowance and the decreased diversification.

Figure 19 illustrates that with by increasing the maximum weighting allowances from 5% to 10% (keeping tracking error and short selling constant at 3% and -15%), the diversification of the portfolio decreases thereby increasing the downside risk. The diversification of a portfolio is affected by not only the number of different positions, but also the concentration of weights (Sénéchal, 2010). Although both portfolios A 1.4 and A 2.4, in **Figure 19**, have exposure to all 40 constituents, the degree of this exposure varies. Portfolio A 1.4, with 5% maximum weight, has about equivalent long exposure to 32 stocks, whereas A 2.4, with 10% maximum weight, only has equivalent long exposure to 16 stocks. This equates to exactly 50% less diversification as both portfolios are about equivalently short on only three stocks. Equally weighted portfolios are more diversified (Sénéchal, 2010). This causes a drastic jump in the downside risk, illustrated by the playing field in **Figure 13**. The two portfolios only have a 0.5% difference in upside return between 3% and 3.5%, with a small change in standard deviation from 2.72% to 2.24% but a 1.6% change in downside risk from -0.9% to -2.5% and a change of standard deviation of 4.31% to 4.75%.

The calculated active share of each portfolio intuitively increases with the increased maximum weight allowance and increased short selling allowance, but not in a consistently linear manner. The results did not consistently show that an increase in active share leads to an increase in performance and thia is reversed in most cases if comparing the combined best and worst returns of each portfolio. The result is more consistent when reviewing only upside returns. This is consistent with research that found equity funds with lower active share out-performed about 80% of general funds (Muller & Ward, 2011).

Portfolio A 2.4 and A 3.4, presented in **Figure 13**, with a change of 10% to 15% maximum weight have relatively the same uniform ellipse shape. Portfolio A 3.4 does however have the jagged indent on the right side of the ellipse which is repeated in all the subsequent less restricted portfolios. The jagged indent illustrates a sharp reduction in volatility (on the maximum edge of volatility or right side) at a particular level of return. The greatest jump in playing field size then occurs between Portfolio A 2.4 and A 3.4; and B 2.4 and B 3.4. This indicates that for relatively the same level of upside return, the risk in terms of standard deviation volatility on the downside increases dramatically when the constraint of tracking error is increased from 3% to 15%.

Figure 14 compares 4 portfolios with a tracking error of 3% and a maximum weight allowance of 5% with 4 portfolios with a 15% tracking error and a maximum weight allowance of 15% at different minimum weightings. The results are as expected with an increased upside and downside with every increase of freedom. This stays constant for all the portfolios except B 3.1 (which allows no short selling). This portfolio offers consistent downside results but offers less upside returns than A 1.3 and A 1.4 which have tighter constrains and less downside risk. This relatively negative upside performance of B 1.3 is due to the zero short selling constraint which does not restrict the downside exposure to the same degree. This illustrates that limiting short selling does not necessarily always limit downside risk to the same degree. The jump in upside performance from 3% to 4% returns, of B 3.2, 3.3 and 3.4 from the rest of the group, is due to the increased tracking error allowance as well as the increased maximum weighting allowance at different degrees of short selling. As previously concluded, the increase in tracking error alone did not have an effect on results. Increased tracking error as well as weighting allowance increases upside return but not proportionately to downside risk.

Figures 9 to **14** also indicate the relative positions of actual equity funds. The 10 largest equity funds are indicated for the period between 2010 and 2015. As expected the majority of the funds fall within the first and most constrained portfolio, with a tracking error of 3%, maximum weight allowance of 5% and no short selling. The only fund to fall outside of the first playing field is the Nedgroup Investments Entrepreneur R Class Fund. The reason that this fund does not fit to the constraints is because, although it is a large fund, it is benchmarked to small and medium capitalisation sector shares and therefore does not attempt to track the performance of the FTSE / JSE Top 40 largest market capitalisation index. All the funds including the FTSE / JSE Top 40 and SWIX Indices have performances less than the hypothetical portfolios' best upside, but more than all the possible worst downsides in terms of their Sharpe ratios, as indicated in **Table 15**. The best performing equity fund in the group for the time period was Coronation Industrial fund but benchmarks against the FTSE / JSE Industrial Index. The worst was Allan Gray A Class equity Fund. It is noteworthy that the median return and standard deviation performance of the equity funds is considerably better when quarterly data is used as opposed to the monthly data illustrating the volatility of the performance.

6. 3 Research question one

The association between increased <u>tracking error</u> limits and the expected performance of actively managed funds.

In summary, when the constraints on minimum and maximum weighting allowances are so that they do not restrict the oppositions of the portfolio, then the results show that an increased tracking error of 15% from 3% drastically increases the downside risk while hardly increasing the upside return. This is evident in the comparison of Portfolios A 2.4 and 3.4 and Portfolios B 2.4 and 3.4 (where the only constraint difference is the increased tracking error allowance). Therefore, the conclusion that can be made from the interpretation of these results is that the tracking error limitations have an overall positive effect on the outcomes of a performance of actively managed funds in relation to their benchmark indices.

6. 4 Research question two

Proposition: association between increased adjusted weighting limits and the expected performance of actively managed funds

Overall, the portfolios that are allowed some degree of short selling outperform long only portfolios. This was consistent except for portfolios A 1.2 and B 1.2 with short selling of -5%, which underperformed portfolios A 2.1 and B 1.2, which were long only. The more maximum weighting is allowed, the better the portfolios upside, but at the same time, the worse its possible downside, with the 5% maximum weighting portfolios being the less risky with less up- and downside. Higher diversification, through a maximum weighting of 5%, created the least amount of downside risk, progressively from 0% to -15% short selling. No other clear patterns emerge as the very unrestricted constraints of 15% tracking error, maximum weight of 10% or 15% and short selling between -5% and -15% are interchangeable.

7 Conclusion

7. 1 Principal findings

The objective of this research was to examine the effectiveness of actively managed funds in relation to their benchmark indices, in terms of the constraints placed on them, by quantifying the effect of tracking error and weight allowance constraints. The study aimed to add insight to the debate of active versus passive funds by examining an aspect of the nature of actively managed funds, namely constraints. The study also aimed to quantify the effect of these constraints on actively managed fund performance and determine whether these constraints have positive, negative or neutral effects of risk adjusted fund performance.

The research was done by constructing hypothetical portfolios based on the FTSE / JSE Top 40 Index as an example and analysing the effect of constraints on the funds' possible performance. The playing field of possible returns, in relation to volatility, were simulated at different constraint scenarios. The results were then presented graphically on an adjusted Markowitz efficient frontier graph and the effects of the constraints on the possible returns and level of risks available at these various levels of restrictions were quantified.

The study found that tracking error constraints and weighting allowances affected the performance of funds differently. It was found that, for the hypothetical portfolios constructed in relation to the FTSE / JSE Top 40 Index, tracking error limits did, as expected, limit the possible upside returns of these funds. Interestingly however, it was found that the tracking error constraints had a much greater effect on limiting downside risk than the constraints had on limiting upside effects. In terms of the research questions it was found that there is an association between increased tracking error limits and the expected performance of actively managed funds. However this association caused a far larger reduction to downside risk than on possible upside return. It was therefore concluded that, for the hypothetically constructed portfolios for the time period studied, tracking error constraints had an overall positive effect on the performance outcomes of the benchmarked funds (Stucchi, 2015; Bernard & Vanduffel, 2014). This result is in contrast to some academic literature that found tracking errors to have an overall negative effect on actively managed fund performance in relation to passive index tracking funds (Vayanos & Woolley, 2016; Bajeux-Besnainou et al., 2013; Guasoni et al., 2011; Clarke et al., 2002).

It was found that the constraints of minimum and maximum weighting allowance did not have a single universal effect on the simulated portfolios' performance. For the majority of the portfolio scenarios the allowing of short selling improved overall performance, but not consistently, due to increased downside risk. It was found that the greater the restriction of the amount that can be held of one particular stock, the less the possible downside risk, but at the same time the upside returns were also restricted. This is expected due to the increased diversification of the portfolio with, for example, a maximum weight allowance of 5% per stock. Although weighting allowance did not seem to have a single universal effect on the simulated portfolios' performance, it did in conjunction with tracking error constraints, limit risk exposure by increasing diversification.

The results showed that by drastically increasing freedom, the upside increased relatively little while the downside increased exponentially. It was found that, although the limitations placed on actively managed funds do expectedly decrease the upside returns, this limitation is less significant in comparison to the limitation on negative returns. The results of the study show that freeing actively managed funds from the constraints placed on them will not result in consistent outperformance of their benchmark due to the increased exposure to downside risk. It was found that the limitations of constraints on upside returns are less than the protection they offer on downside losses and therefore the study concludes that the constraints have an overall positive effect on actively managed fund performance in relation to their benchmark.

The study found that for the simulated portfolios, constraints do not drastically limit the upside performance of actively managed funds but do limit the downside. Therefore, actively managed funds that do underperform passive funds and their specific benchmarks do so for reasons other than the limitations placed on them, according to the results of this study.

7. 2 Limitations of the research and Suggestions for future research

Although the descriptive nature of this study offers information on and quantifies the effect of constraints on actively managed funds in relation to their benchmarks, it does not specifically reveal all the reasons why the constraints affect the results in this manner. For this reason the study gives rise to the possible future explanatory studies (Saunders & Lewis, 2011).

Only one out of the numerous indices was reviewed in order to limit the scope of the research to be feasible in the time available. This leaves the opportunity open for future studies to analyse further indices and to compare the findings.

The time frame from December 2006 to December 2015 could offer some degree of comparison and illustrate changes over time; however a longer period of time would offer more insights. This leaves the opportunity open for futures studies to extend the time period studied.

7. 3 Implications for the industry

The implications of the research are in support of the industry standard of benchmarking actively managed funds and placing constraints of tracking errors and weight allowances on them. It is determined that these constraints do not substantially reduce the possible upside returns that active funds can achieve relative to the reduction of downside risk, and therefore, are not specifically a cause of why active funds underperform their benchmarks or passive funds.

Recommendations to stakeholders, specifically fund managers and investors, based directly on the findings, are to continue to implement the industry standards of constraints. They should however, taking this research into account, understand the quantified effect that constraints have on possible upside returns and downside risks.

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Appendices

Appendix 1

```
Sub DoTableTwoD()
    Dim r                    As Long
    Dim c                    As Long
    Dim ws                   As Worksheet
    Static TableName         As String
    Dim TableTopLeft         As Range
    Dim RowDestination       As Range
    Dim ColDestination       As Range
    Dim CalculationStatus    As Variant

    TableName = InputBox("Table name:", "Table name", TableName)
    If TableName = "" Then Exit Sub

    CalculationStatus = Application.Calculation
    Application.Calculation = xlCalculationManual

    Set ws = Range(TableName).Parent

    Set TableTopLeft = Range(TableName)

    Set RowDestination = Range(TableTopLeft.Offset(0, 1).Comment.Text)
    Set ColDestination = Range(TableTopLeft.Offset(1, 0).Comment.Text)

    r = TableTopLeft.Row + 1
    Do While ws.Cells(r, TableTopLeft.Column) <> ""
        DoEvents
            'Copy index weights as values for startup

        Application.DisplayAlerts = False
        Range("IndexWeights").Copy
        Range("PortfolioWeights").PasteSpecial     Paste:=xlPasteValues,     Operation:=xlNone,
SkipBlanks _
        :=False, Transpose:=False
        Application.DisplayAlerts = True
            'Clear Clipboard
        Application.CutCopyMode = False
        Application.Calculate
        c = TableTopLeft.Column + 1
```

```
        Do While ws.Cells(TableTopLeft.Row, c) <> ""
            RowDestination.Value = ws.Cells(TableTopLeft.Row, c)
            ColDestination.Value = ws.Cells(r, TableTopLeft.Column)

            'Call Solver
        SolverOk SetCell:="$O$3", MaxMinVal:=1, ValueOf:=0, ByChange:="$H$3:$H$44", _
        Engine:=1, EngineDesc:="GRG Nonlinear"
            SolverOk SetCell:="$O$3", MaxMinVal:=2, ValueOf:=0, ByChange:="$H$3:$H$44", _
            Engine:=1, EngineDesc:="GRG Nonlinear"
        SolverSolve userFinish:=True

            If ws.Cells(r, c) = "" Then
                Calculate
                ws.Cells(r, c) = TableTopLeft.Value
            End If

            c = c + 1
        Loop

        Application.Calculate
        r = r + 1
    Loop

    Application.Calculation = CalculationStatus

    Beep

End Sub
```

Appendix 2

```
Sub mnet()

Dim a, b, c, d, m, x, y, z As Integer
Dim mar As Boolean
Dim dim1, dim2, center As Variant
Dim lower, upper As Variant
b = 0
kat = 0

  For x = 1 To 2
    If x = 1 Then MaxTrackError = 0.03
    If x = 2 Then MaxTrackError = 0.15
    For y = 1 To 3
      MaxWeight = 0.05 * y
      For z = 0 To 3
        MinWeight = -0.05 * z
        Worksheets("model").Cells(15, 2) = MaxTrackError
        Worksheets("model").Cells(16, 2) = MaxWeight
        Worksheets("model").Cells(17, 2) = MinWeight

        For m = 1 To 2 'max/min

          center = 0
          lower = Worksheets("model").Cells(4, 3)
          upper = Worksheets("model").Cells(4, 4)
          dim1 = lower / 100

          For t = 1 To 2

            If t = 1 Then
              Worksheets("model").Cells(5, 2) = 0
              center = 0
            Else
              Worksheets("model").Cells(5, 2) = -0.005
              center = -0.005
            End If

          Do Until (center > (upper / 100) And t = 1) Or (center < (lower / 100) And t = 2) Or
kat = 1
```

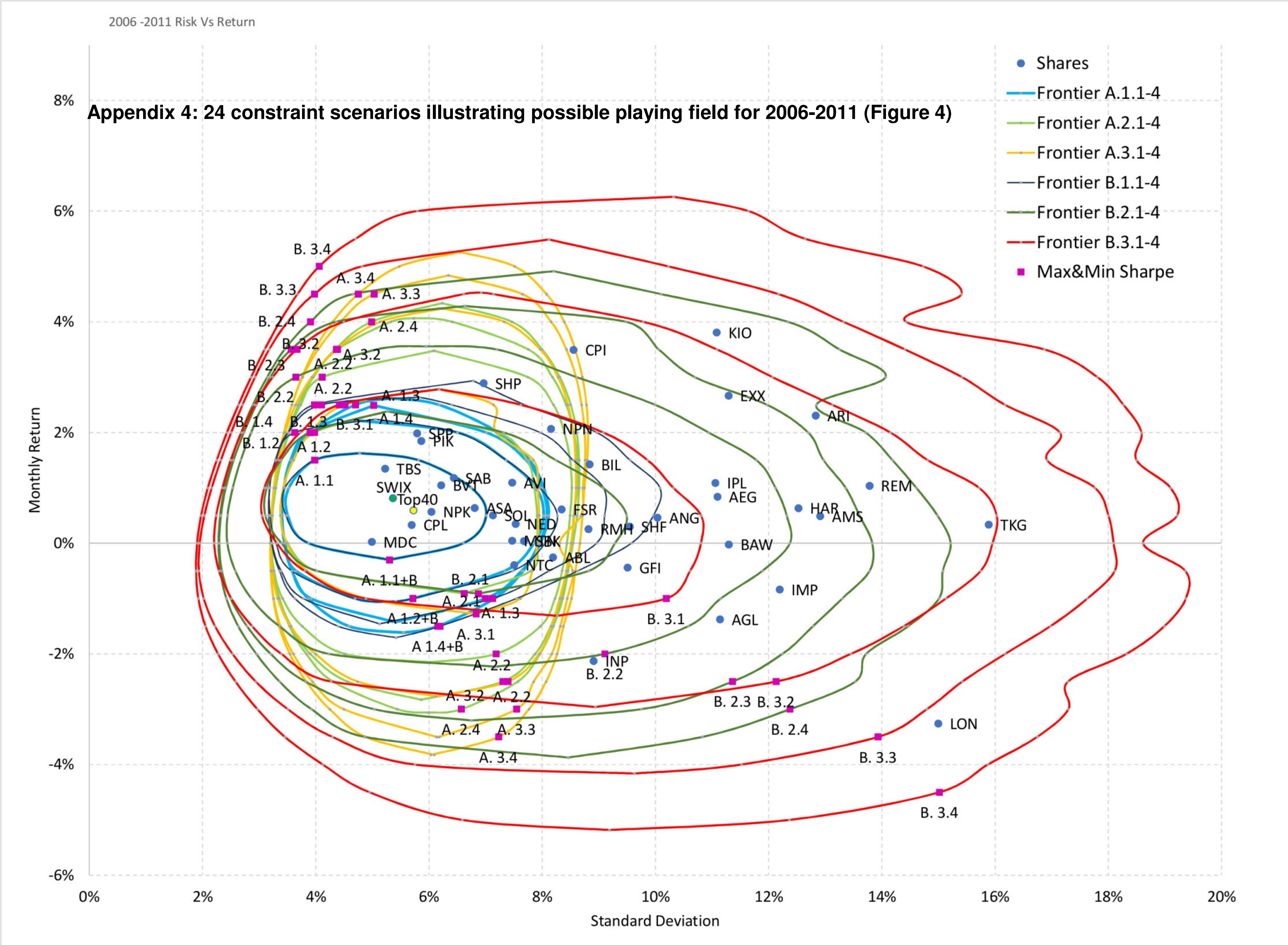
```
' reset values
  For a = 0 To 39
    Worksheets("model").Cells(2, 2 + a) = 0.023
  Next a
'end reset
'runsoler
  SolverOk SetCell:="$B$7", MaxMinVal:=m, ValueOf:="3",
ByChange:="$B$2:$AO$2"
  If SolverSolve(Userfinish:=True) > 2 Then kat = 1 Else kat = 0
'end solver
'form row
 Worksheets("model").Cells(6 + b, 4) = Worksheets("model").Cells(5, 2)
  Worksheets("model").Cells(6 + b, 5) = Worksheets("model").Cells(6, 2)
  Worksheets("model").Cells(6 + b, 6) = Worksheets("model").Cells(7, 2)
  Worksheets("model").Cells(6 + b, 7) = Worksheets("model").Cells(11, 2)
  Worksheets("model").Cells(6 + b, 8) = Worksheets("model").Cells(13, 2)
  Worksheets("model").Cells(6 + b, 9) = Worksheets("model").Cells(15, 2)
  Worksheets("model").Cells(6 + b, 10) = Worksheets("model").Cells(16, 2)
  Worksheets("model").Cells(6 + b, 11) = Worksheets("model").Cells(17, 2)
  Worksheets("model").Cells(6 + b, 12) = Worksheets("model").Cells(19, 2)
  If m = 1 Then Worksheets("model").Cells(6 + b, 13) = "max"
  If m = 2 Then Worksheets("model").Cells(6 + b, 13) = "min"
'end row
'step PST
  If t = 1 Then center = center + 0.005 Else center = center - 0.005
  Worksheets("model").Cells(5, 2) = center
'End Step PST
b = b + 1
Loop
kat = 0
Next t

Next m
b = b + 1
Next z
Next y
Next x
End Sub
```

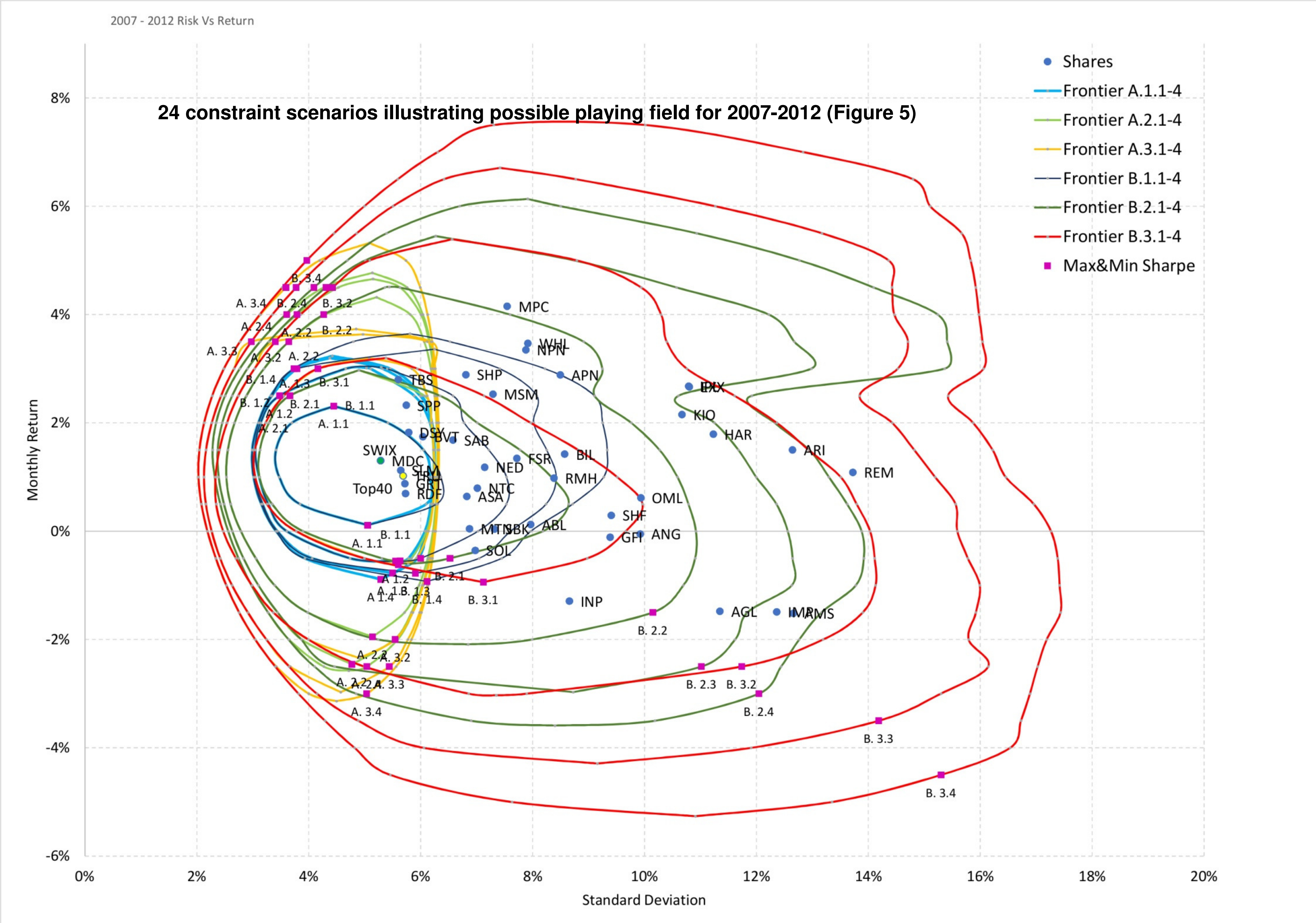
Appendix 3

Table 17: Five consecutive time periods of five years each

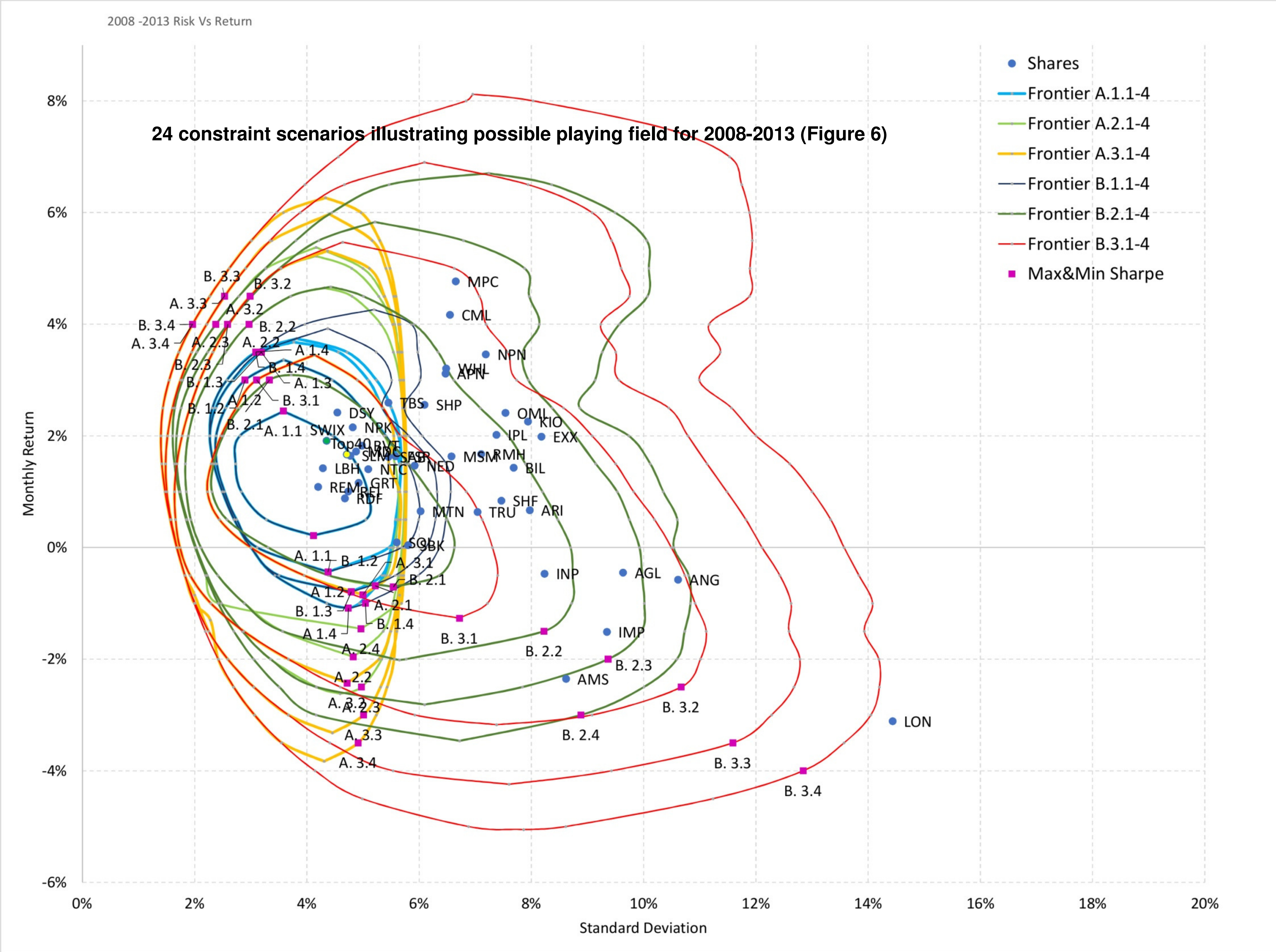
	#year ends:	1	2	3	4	5	6	7	8	9	10
	years:	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	#of years:		1	2	3	4	5	6	7	8	9
	Periods										
1	**2006-2011**		1	2	3	4	5				
2	**2007-2012**			1	2	3	4	5			
3	**2008-2013**				1	2	3	4	5		
4	**2009-2014**					1	2	3	4	5	
5	**2010-2015**						1	2	3	4	5



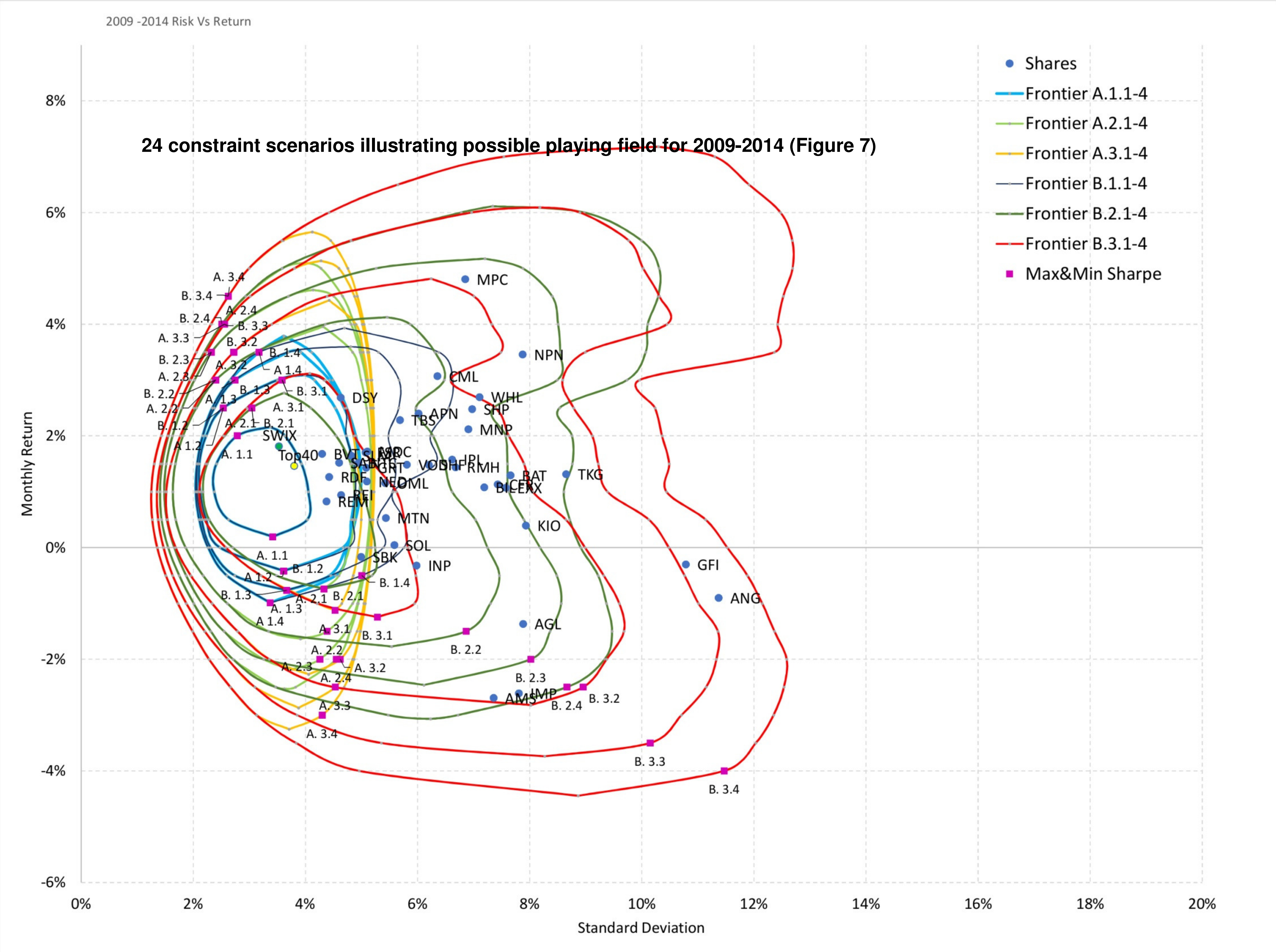
2006 -2011 Risk Vs Return
Appendix 4: 24 constraint scenarios illustrating possible playing field for 2006-2011 (Figure 4)
Shares
Frontier A.1.1-4
Frontier A.2.1-4
Frontier A.3.1-4
Frontier B.1.1-4
Frontier B.2.1-4
Frontier B.3.1-4
Max&Min Sharpe
Monthly Return
Standard Deviation
8%
6%
4%
2%
0%
-2%
-4%
-6%
0%
2%
4%
6%
8%
10%
12%
14%
16%
18%
20%
KIO
CPI
SHP
EXX
ARI
NPN
BIL
SPP
PIK
TBS
SAB
BVT
AVI
IPL
AEG
REM
HAR
AMS
TKG
SWIX
Top40
NPK
ASA
SOL
NED
FSR
CPL
RMH
SHF
ANG
MDC
BAW
ABL
NTC
GFI
IMP
AGL
INP
LON



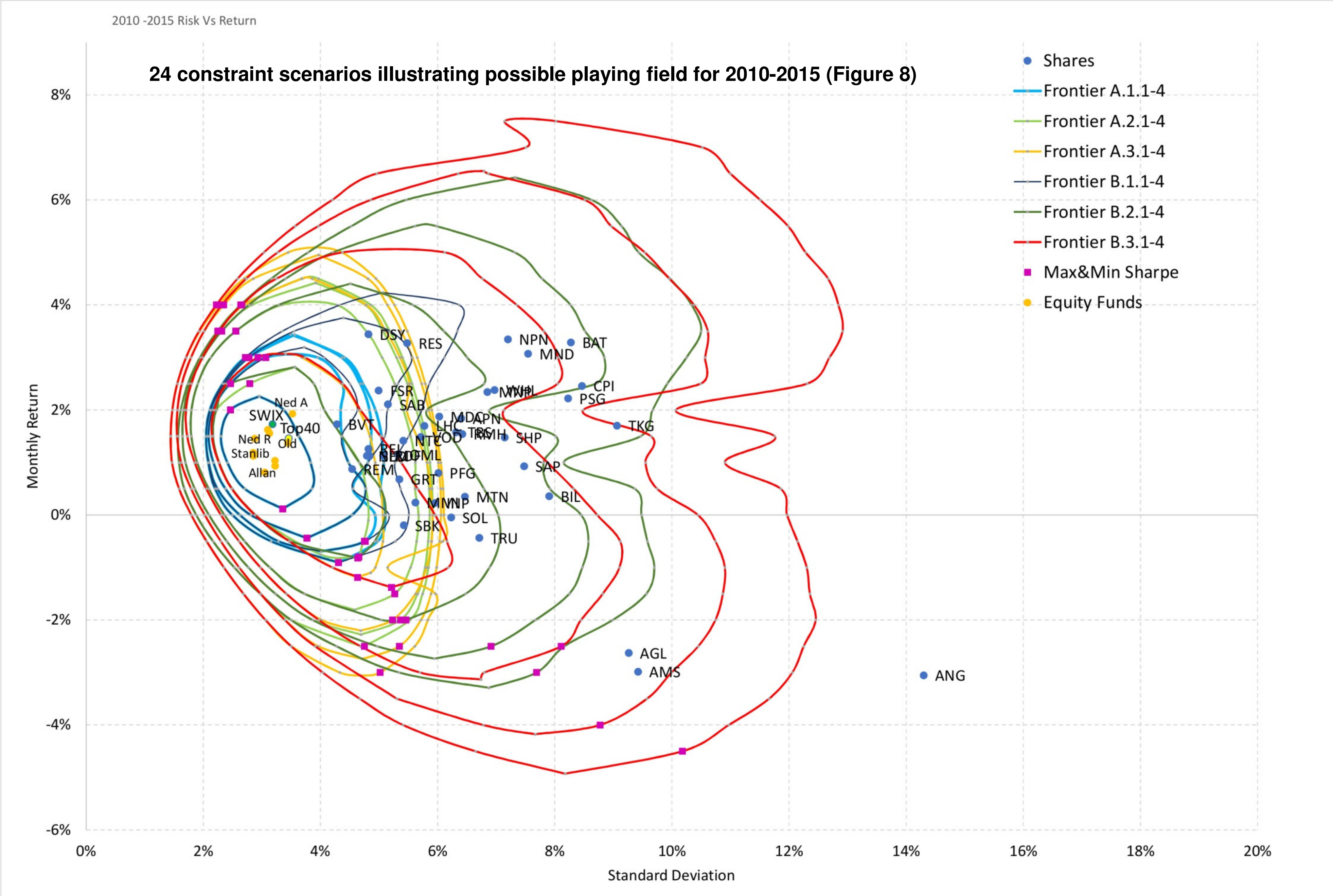
2007 - 2012 Risk Vs Return
24 constraint scenarios illustrating possible playing field for 2007-2012 (Figure 5)
Shares
Frontier A.1.1-4
Frontier A.2.1-4
Frontier A.3.1-4
Frontier B.1.1-4
Frontier B.2.1-4
Frontier B.3.1-4
Max&Min Sharpe
Monthly Return
Standard Deviation
8%
6%
4%
2%
0%
-2%
-4%
-6%
0%
2%
4%
6%
8%
10%
12%
14%
16%
18%
20%
MPC
WHL
NPN
APN
SHP
MSM
TBS
SPP
KIO
HAR
ARI
REM
SAB
FSR
BIL
NED
RMH
SWIX
MDC
Top40
RDF
NTC
ASA
OML
SHF
ANG
GFI
MTN
ABL
SOL
INP
AGL
AMS



2008 -2013 Risk Vs Return
24 constraint scenarios illustrating possible playing field for 2008-2013 (Figure 6)
Shares
Frontier A.1.1-4
Frontier A.2.1-4
Frontier A.3.1-4
Frontier B.1.1-4
Frontier B.2.1-4
Frontier B.3.1-4
Max&Min Sharpe
Monthly Return
Standard Deviation
8%
6%
4%
2%
0%
-2%
-4%
-6%
0%
2%
4%
6%
8%
10%
12%
14%
16%
18%
20%
MPC
CML
NPN
WHL
APN
TBS
SHP
DSY
OML
KIO
NPK
IPL
EXX
SWIX
Top40
MSM
RMH
LBH
NTC
NED
BIL
GRT
REM
RDF
SHF
MTN
TRU
ARI
SOL
SBK
INP
AGL
ANG
IMP
AMS
LON
B. 3.3
B. 3.2
A. 3.3
A. 3.2
B. 3.4
B. 2.2
A. 3.4
A. 2.3
A. 2.2
B. 2.3
A 1.4
B. 1.4
B. 1.3
A. 1.3
B. 3.1
B. 1.2
A 1.2
B. 2.1
A. 1.1
A. 1.1
B. 1.2
A. 3.1
B. 2.1
A 1.2
A. 2.1
B. 1.3
B. 1.4
A 1.4
B. 3.1
A. 2.4
B. 2.2
B. 2.3
A. 2.2
A. 3.2
A. 2.3
B. 3.2
B. 2.4
A. 3.3
B. 3.3
A. 3.4
B. 3.4



2009 -2014 Risk Vs Return
24 constraint scenarios illustrating possible playing field for 2009-2014 (Figure 7)
Shares
Frontier A.1.1-4
Frontier A.2.1-4
Frontier A.3.1-4
Frontier B.1.1-4
Frontier B.2.1-4
Frontier B.3.1-4
Max&Min Sharpe
Monthly Return
Standard Deviation
8%
6%
4%
2%
0%
-2%
-4%
-6%
0%
2%
4%
6%
8%
10%
12%
14%
16%
18%
20%
MPC
NPN
CML
WHL
SHP
MNP
APN
TBS
DSY
SWIX
Top40
BVT
SAP
GRT
RDF
NED
DML
REI
REM
MTN
SOL
SBK
INP
VOD
HPL
RMH
BAT
TKG
KIO
GFI
ANG
AGL
AMS
IMP


2010 -2015 Risk Vs Return
24 constraint scenarios illustrating possible playing field for 2010-2015 (Figure 8)
Shares
Frontier A.1.1-4
Frontier A.2.1-4
Frontier A.3.1-4
Frontier B.1.1-4
Frontier B.2.1-4
Frontier B.3.1-4
Max&Min Sharpe
Equity Funds
Monthly Return
Standard Deviation
8%
6%
4%
2%
0%
-2%
-4%
-6%
0%
2%
4%
6%
8%
10%
12%
14%
16%
18%
20%
DSY
RES
NPN
BAT
MND
CPI
PSG
TKG
FSR
SAB
SAP
BIL
MTN
SOL
TRU
SBK
PFG
GRT
REM
BVT
SHP
AGL
AMS
ANG
Ned A
SWIX
Top40
Ned R
Old
Stanlib
Allan

Appendix 5:

Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

25 October 2017

Eiselen Minette

Dear Minette

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

Gordon Institute of Business Science
Reg. No. 99/19816/08

26 Melville Road, Illovo, Johannesburg
PO Box 787602, Sandton, 2146, South Africa

telephone **(+27) 11 771 4000**
fax **(+27) 11 771 4177**

website **gibs.co.za**
University of Pretoria