LUND UNIVERSITY
School of Economics and Management

Departments of Economics

NEKH01

Economics: Bachelor's Essay, 15 credits

HT2021

A Blindfolded Monkey as Portfolio Manager

An empirical study on the performance of actively managed Swedish funds and randomly assembled portfolios

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Abstract

This study aims to investigate whether chance can beat an actively managed equity fund during a ten year period on the Swedish stock market. Since the stock market consists of fierce competition among investors, the EMH would suggest that stock price movements should not be far from reflecting all available information. Due to the highly unexpected nature of new information, such as news, price fluctuations should follow a random walk. Therefore a highly competent investor, e.g. a fund manager, should not be able to consistently outperform an investor basing his investments on a blindfolded monkey throwing darts at a stock list. The result shows that, on average, randomly generated portfolios of stocks, annually rebalanced during a ten-year period, outperformed the mean fund in return as well as alpha. However, quite expectedly there's a larger spread of the returns, entailing a larger standard deviation, yet there is a fairly similar Sharpe ratio in comparison to the funds.

Keywords: The Efficient Market Hypothesis (EMH), random walk, intelligent investor, annual portfolio adjustment

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1. Introduction

1.1. Background

Investing in the stock market can be a good alternative to saving in a traditional bank account, especially with today's low rate where money is eaten up by inflation. However, for the ordinary retail investor deciding what to invest in the stock market can be gruelling. To be able to digest the myriad of information requires a lot of time, interest, and competence. It might therefore be more reassuring to entrust an institutional investor to manage your investment, because of their presumably better chances as a professional investor, to succeed in the stock market. In Sweden, 7 out of 10 retail investors allocate private investments into funds (Kantar Sifo, 2020).

On the other hand, The Efficient Market Hypothesis assumes that stock market price behavior could be approximated with a random walk (Fama, 1965; Malkiel, 2003). The theory suggests that stock prices only reflect new information as it arises, so when news is published, common stock prices incorporate it without delay. This questions tools used for analyzing the stock market, such as technical analysis, the study of past stock prices in an attempt to predict future prices, and fundamental analysis, which is the analysis of financial information such as company earnings, asset values to anticipate under- or overvalued stocks. The Efficient Market Hypothesis, therefore, implies that a professional investor should not be able to consistently achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks with comparable risk. The economist, and an advocate of EMH, Burton Malkiel therefore jokingly claimed that "a blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by experts." (2020).

1.2. Problem statement

Common equity funds should be a secure source of investment since fund managers are assumed specialists within financial markets. However, if the efficient market hypothesis holds, even the fund managers are not able to predict future prices. Retail investors pursue common equity funds since they do not wish to devote their own time researching and performing complex analysis of companies. If the financial markets truly are random, everyone should more or less have the same opportunity to generate returns regardless of the time spent on research and previous experience. This notion has previously been addressed by Swedish media when well established index providers released data on returns among actively managed funds and market indices (DI, 2018; S&P, 2018).

1.3. Objectives

The thesis aims to study how chance performs against Swedish actively managed funds. This will be conducted by simulating a large number of portfolios constructed by randomly selecting stocks, a strategy that could be easily applied by an average retail investor, meaning not requiring a continuous amount of time spent on analysis, as an alternative to investing in a fund. Financial metrics will be used to study the performances of the portfolios and funds during the same period, investing within similar market constraints and using an active strategy, thus acting as intelligent investors. Restricting the market enables a fair comparison with common equity funds that specialize in these markets. This also enables for analysis of performance measurements between different sized, market capitalization, companies, which will be a key contribution in this study. The findings will evaluate if there are incitements for the retail investor to pursue funds as a means of money management.

Research questions

1. Is an actively managed Swedish equity fund more profitable than a randomly selected portfolio?
2. Does an institutional investor add value in terms of financial metrics?

1.4. Findings

The results from the study show reason to question the value of an actively managed equity fund. Overall, the simulated portfolios outperform the funds in several financial metrics. The results suggest professional investors can not consistently outperform pure chance, which aligns with the random nature of stock's price movement that EMH implies. However, the study lacks some practical aspects of trading to fully claim that the random strategy is the more successful investment strategy in the real world.

1.5. Disposition

Literature review: Aims to give the reader an introduction to known theories that instigated this research and to present similar studies findings together with its methodology.

Method: This section will present the strategy behind the simulations, how the performance will be measured, detail the data sample and the hypothesis.

Empirical analysis: A presentation of the results from the simulation and funds, and analysis of how the performance metrics uphold.

Discussion: Discusses the methodology, data sample and sources of errors that might have affected the result.

Conclusion: We will summarize the findings and answer the research questions.

2. Literature review

2.1. Theoretical background

During the 1960s prominent economists were widely accepting the efficient market hypothesis, and evidence accumulated that price movement for common stocks could be approximated using a random walk (Fama, 1965; Malkiel, 2003). The Efficient Markets Hypothesis (EMH) is primarily made up of concepts from Eugene Fama's study “Efficient Capital Markets” (1970). EMH advances the belief that prices of financial assets reflect all the available information. Fama introduces three different levels of efficiency of pricing financial assets depending on the level of information. The three different forms are weak, semi-strong, and strong. For the weak form, EMH suggests that asset prices have discounted all historical data on stock prices. By only taking historical information into account technical analysis is obsolete to predict the market. However, in the weak form new information from financial reports can through fundamental analysis help to identify under- or overvalued assets in the market. For a semi-strong form, EMH suggests that all relevant public information is incorporated and quickly reflected in the prices of the financial assets. This includes financial reports which are quickly incorporated by the market participants so that a new equilibrium is created as a result of the new supply or demand forces. In the second form of efficiency, fundamental analysis can not help an investor predict the market consistently. However, information that is not readily available to the public, such as insider information, can give an investor an advantage. The strong form incorporates all existing information, public as well as private, in the current price of the financial assets. The EMH proposes that in the strong form a perfect market exists, where it is practically impossible for investors to beat the market (Fama, 1970). Fama (1965) means that since a stock exchange has a lot of rational profit maximizers actively competing, the price equilibriums that follow can be regarded as efficient and it is therefore believed that an investor can not consistently beat the market by anticipating prices of financial assets.

A random walk is a term loosely used in the financial economics literature to describe a series of independent price movements, where every change is a random departure (Malkiel, 2003). Therefore, past movement or trend of a stock price or market can not be used to consistently anticipate its future movement (Fama, 1965). The rationale behind the idea is that if the stock exchange is an example of an efficient market, as Fama (1965) suggests it might be, then tomorrow’s stock prices will only reflect tomorrow’s information from news, hence it is irrelevant to make a prediction out of the price changes of today. By definition, an investor is unable to anticipate news, resulting in price changes that must be unpredictable and random. Consequently, prices fully reflect all known information, and even uninformed investors buying a diversified portfolio will gain a return as generous as that achieved by the experts (Fama, 1965). Thus, advocates of the Random Walk theory advise investing in index funds rather than increasing risk by trading individual stock (Malkiel, 2003). The theory seriously questions the validity of many methods for describing and anticipating stock price behavior, methods that have considerable popularity outside of the academic world (Fama 1965). Considering the fees portfolio managers at funds charge further questions the value of investing in an actively managed fund.

By the start of the twenty-first century, the intellectual dominance of the efficient market hypothesis had become less universal. Many financial economists and statisticians began to believe that stock prices are at least partially predictable (Malkiel, 2003). Critics against the EMH and Random Walk theory suggest that anomalies occur for long-term returns. DeBondt and Thaler (1985) argue for a pattern where past stocks return winners tend to be future losers and vice versa when observing three- to five-year periods. The reason behind these reversals, according to Debondt and Thaler (1985), is due to investor overreaction. By forming expectations, investors put too much weight on the past performance of firms and too little on the fact that performance tends to mean-revert. Overreaction to past information is a general prediction of the behavioral decision theory of Kahneman et al (1982). Thus, one could take overreaction to be the prediction of a behavioral finance alternative to market efficiency. Fama (1998) claims that if apparent overreaction was the general result in studies of long-term returns, EMH would be dead, replaced by the behavioral alternative of DeBondt and Thaler (1985). Fama (1998) believes that the EMH answers the questions of the behavioral financial theories, suggesting over and underreaction, that it is solely by chance. The expected value of abnormal returns is zero, but due to chance anomalies occur which split randomly between over- and underreaction (Fama, 1998). Malkiel (2003) further argues that any repetitive pattern that can be discovered in the stock market, and can be arbitraged, will be exploited by investors, and eventually disappear.

2.2. Previous literature

Previous research has covered several aspects of the interest behind this thesis, the purpose of the section is to highlight the knowledge of previous research connected to the area of study. Biondo et al. (2013) conducted a comparative study on the performance between random trading strategies and technical trading strategies. The data is based on several indices and time periods between 15 and 20 years. The main results are that even though standard trading strategies, and their algorithms, are successful in small temporary windows of opportunity, a pure random trading strategy has a higher performance and is less volatile in the continuum. In this respect, for the individual trader, a purely random strategy represents a costless alternative to expensive professional financial consulting, being at the same time also much less risky, if compared to the other trading strategies. Further investigations (Arnott et al. 2013) in this area were made and the findings suggested that the reason for the high return is due to small cap and value bias, meaning that when choosing random equities, there is a larger chance of picking small cap equities which historically have a higher return than large and mid cap. Moreover, Arnott et al. (2013) found that Malkiel had underestimated the monkeys' performance. The results showed that, even with high volatility and beta, the Sharpe ratio was respectable and the information ratio proved skill in stock picking. The CAPM Alpha was surprisingly high and verging on statistical significance.

Fama (1998) discussed the distinction between value- and equal-weighted portfolios with the notion to investigate anomalies in the long-term. Value-weighted is when a portfolio is created using the reference of common stock value in comparison with total market value, meaning that a fair market portfolio can be created. On the other hand, equal-weighted is when a portfolio is equally divided between common stocks or markets, i.e. 50% of the portfolio is large cap and 50% is small cap. An equal-weighted portfolio is therefore biased towards small cap common stocks since they obtain higher influence than they should have. Moreover, concerning the portfolio allocation, DeMiguel et al. (2009) cover the theory of a naive portfolio allocation, also called the 1/N portfolio strategy, which is designed to diversify all assets equally in the portfolio. In the study, the 1/N portfolio strategy was compared with 14 portfolio diversification models. Different time periods and data samples were tested to conclude a significant result. The surprising results deduced that no other portfolio diversification model could outperform the 1/N strategy constantly, especially when comparing Sharpe ratios where the 1/N strategy was superior to all else. The minimum-variance frontier is a method for optimizing the weighting of a portfolio. The efficient frontier shows the relationship between risk and return by different portfolio constructions. Using the efficient frontier we are able to distinguish the minimum-variance frontier which will provide the lowest variance for any target return. The global minimum-variance portfolio is located at the point where the variance is at the lowest value for all of the options. Every portfolio located above the global minimum-variance portfolio is the best risk-return combination and is called the efficient frontier of risky assets. For every portfolio below the global minimum-variance portfolio, there is another portfolio that is risky and provides a higher expected return (Bodie, 2014). However, a critical moment of any investment strategy is portfolio management, with concerns within rebalancing and the timing of rebalancing.

Jennings (1971) investigated the impact of the portfolio's size on return by two investment strategies, "buy-and-hold" (BH) and "annual-portfolio-adjustment" (APA). The simulation was performed by an 1/N portfolio allocation and that each equity was as likely to be picked randomly. The results indicated that the

APA strategy was associated with a higher expected wealth relative when transaction costs were taken into account, and had in both scenarios a greater risk. Nersesian (2005), studied different methods of rebalancing and timing, finding that year-end periodic rebalancing was more effective than both monthly and semi-annually. Other research (Vashakmadze, 2012) suggests that annual rebalancing increases Sharpe ratio for portfolios. Arnott et al. (2013) investigated how common active investment strategies compared to that of the same strategies but inverted performed, in this study it was assumed to rebalance once every year on the last trading day in December. Haug and Hirschey (2006) studied the importance of the “January effect” as a behavioral finance phenomenon and how active the theory still is. The activity of the “January effect” used to be apparent, however, as of the tax reform act of 1986 the phenomenon has seen a steep decline when taking into account large cap equity. On the other hand, small cap equities still possess such a phenomenon and are proof of behavioral finance within trading, where a preferred selling/purchasing period is December/January.

3. Method

3.1. Strategy

To investigate whether chance can beat an actively managed fund this study will simulate 10,000 portfolios, for three different scenarios consisting of randomly selected stocks from historical data during a 10 year period (Appendix B). The strategy for the portfolios is to be considered non-intelligent, where a specific trading instruction has been implemented and no other information will be taken into account unlike a fund manager that will react to new information thus acting as an intelligent investor. The three scenarios will differ in the proportion of large and mid cap common stock. Financial economic metrics will be used to measure the performance of the randomly assembled common stock portfolios and compared to the performance of actively managed equity funds during the same period. The simulation of the portfolios is executed with the use of Python and thereafter the result is exported to Excel for calculation of performance metrics. The script used to execute the program is attached in Appendix D.

In a report from Euroclear (2021), information concerning the Swedish average retail investor's portfolio includes that the average Swedish investor has five companies in their portfolio. On the other hand, Avanza showcased data that their most profitable customers had at least 10 companies in their portfolio. Furthermore, the report from Euroclear (2021) claims almost 42% of all retail investors in Sweden have a single stock in their portfolio, forcing an aggressive decrease in the average amount of common stock held by Swedish retail investors. Since the study has a Swedish retail investor’s perspective the simulations will use eight assets per portfolio. According to previous research, the 1/N portfolio weight strategy is the most consistent compared with a number of optimal portfolio strategies (DeMiguel et al., 2009). The 1/N, or naive diversification, strategy divides all assets in the portfolio with equal weight, hence, the effect of a single asset will account for 12.5% of the portfolio in our case. Moreover, no short position will be taken into account in the simulation as not every retail investor has this ability.

The portfolios and funds performance will be studied during a 10 year period and observations are done on a yearly basis. With a longer time period comes less data, especially concerning the large cap list and the number of funds. 2010 is a reasonable starting year since the markets and funds have had the opportunity to recover from the financial crisis during 2007-2008. In order to investigate the performance of the investors operating the actively managed funds, an annual adjustment for the portfolio strategy will be implemented for the portfolios. The annual-portfolio-adjustment strategy means that at the beginning of the period a portfolio is created with randomly selected stocks and at the end of the first year, the original portfolio is sold and replaced with a new, randomly selected portfolio (Jennings, 1971; Vashakmadze, 2012). This process is repeated each year for the entire period. Previous studies discuss a January-effect on the stock market (Haug and Hirschey 2006). Since the study has a retail perspective on investments the purchase will occur in January.

To perform a fair comparison, the simulation will include three scenarios of different portfolio weights between mid and large cap stocks. On the Swedish large cap list, there are more than 100 companies and more than 150 on the mid cap list. This aims to showcase how the different market proportions affect the performance measurements and compare them to the benchmarks. The following scenarios will be included:

	Mid-cap, Large-cap (%)	**Mid-cap/Large-cap (#)**
Scenario 1	25, 75	2, 6
Scenario 2	50, 50	4, 4
Scenario 3	75, 25	6, 2

Table 1

3.2. Performance metrics

3.2.1. Return

The return is one of the most important and efficient indicators to be able to compare the performance of the simulations and the benchmarks. Return in contrast to stock prices is able to be negative and therefore showcases the true performance. The return of the simulations will be generated through the arithmetic mean of the individual portfolio returns, which will enable a simplified comparison with the benchmarks (Bodie 2014):

$$r_i = \frac{p_{sale} - p_{buy}}{p_{buy}}$$

where r_i is the individual return for a portfolio or a fund, P_{sale} is the price at which the portfolio is sold and P_{buy} is the purchase price.

3.2.2. Standard deviation

The standard deviation is a statistical measurement that showcases the deviation from the mean of the data. In financial performance measurements, it is used to portray the risk in the investment portfolio. The value of standard deviation indicates how much the portfolio has fluctuated over time. A larger value indicates higher risk with more price movements, meanwhile, a smaller value indicates a lower risk with fewer price movements. In the case of randomly assembled portfolios, the use of standard deviation as a performance measurement enables a concrete comparison between the subjects (Bodie 2014):

$$Variance\ = \sigma_i^2 = \frac{1}{1-n}\sum_{t=1}^{n}[\,r_i - \bar{r}\,]^2$$

$$Standard\ deviation\ = \sigma_i = \sqrt{\sigma_i^2}$$

where σ_i is the standard deviation for an individual portfolio, r_i is the return of a single portfolio and $\bar{r}$ is the mean return of the data, n is the number of observations.

3.2.3. Sharpe Ratio

The Sharpe ratio is a measurement of the expected return per unit of risk (Sharpe, 1994). In other words, the Sharpe ratio measures the excess return (return of portfolio - risk-free rate) in comparison with the risk (standard deviation). The ratio is well established and often used as a measure of how well a fund or portfolio performs when accounting for risk. Since the ratio is established and makes for a distinct comparison between subjects, it is a valid performance measure (Bodie 2014):

$$Sharpe\ Ratio\ = S_p = \frac{Excess\ Return}{Standard\ deviation\ of\ Excess\ return} = \frac{r_i - r_f}{\sigma_i}$$

where r_i is the return on the portfolio, r_f is the risk-free return and σ_i is the standard deviation of excess return.

3.2.4. Beta

Beta measures the covariance of the market portfolio and the subject portfolio in comparison with the variance of the market portfolio. This shows the portfolio's sensitivity towards the market, i.e. systematic risk. A value above one indicates a portfolio that moves more than the market, and a value below one indicates a portfolio that moves less than the market. The beta is a relevant measurement in this study in order to conclude how the random portfolio is affected by systematic risk and as a factor included in Treynor’s index (Bodie 2014):

$$\beta_i = \frac{\sigma_{i,M}}{\sigma_M^2}$$

$\sigma_{i,M}$ is the covariance between the study portfolio and the market portfolio, σ^2_M is the variance of the market portfolio.

3.2.5. Treynor's Index

Treynor’s Index was established in 1961 by James Treynor. The index measures the risk-adjusted performance when taking into account systematic risk. The measurement is a complement to the Sharpe ratio as they are calculated with the same formula except for which risk is taken into account (Bodie 2014):

$$Treynor's\ Index = T_i = \frac{r_i - r_f}{\beta_i}$$

r_i is the return on a portfolio, r_f is the risk free return and β_i is the beta of the portfolio.

3.4.6. Jensen’s Alpha

Alpha is a measurement that compares the market's return, adjusted with a beta, with the return on the portfolio. A positive alpha value shows that the portfolio performed better than the market and a negative value shows that the portfolio performed more poorly than the market. This measurement provides value to the results in the simulation since we want to find how effectively a randomized portfolio can perform (Bodie 2014):

$$\alpha_i = E[r_i - r_f] - \beta_i E[r_m - r_f]$$

Where α_i is the individual alpha for the portfolio, r_i is the return on the portfolio, r_f is the risk-free return, β_i is the beta of the portfolio.

3.3. Data

3.3.1. Common Stocks

The portfolios will be constructed using stocks listed on NASDAQ OMX Stockholm or Nordic Growth Market extracted from the Bloomberg Terminal. Bloomberg terminal is a globally established financial data provider and is therefore considered to be a suitable source of information on common stock. Moreover, the companies were filtered for a valuation range that meets the requirements for Swedish large or mid cap according to Nasdaq (2021). At the Nordic exchanges, companies with a market value exceeding EUR 1 billion are considered large cap, while companies with a market value between EUR 150 million and EUR 1 billion belong to the mid cap (Nasdaq, 2021). Small cap companies will be excluded since they are not as closely monitored as larger companies, which favors fund managers due to their knowledge. Furthermore, Arnott et al. (2013) found that a randomly selected portfolio has been affected by small cap and value bias, thus we will focus this study on the more recognizable large and mid cap. Find the full list of stocks for the sample in Appendix E.

3.3.2. Swedish equity funds

As stated earlier, the study has a retail investor perspective on the choice between managing your own portfolio or paying a fund manager to actively manage your investments. Therefore it is deemed suitable for the choice of funds used in this paper to be initially based on Avanza’s fund list. Avanza is considered to be reliable since it is a well-established Swedish stockbroker. Filters were applied for period, region, and equity funds. This narrowed the amount of the list to 82 funds in total. Thereafter funds that were index-based were removed since only actively managed funds were to be used. Funds that were labeled as focused on small cap, sustainability-focused were also removed. Finally, funds that had less than 70% exposure to Swedish equity were removed and the list ended up with 22 funds. Thereafter, the data for the funds performances were manually gathered from their Avanza profile. The sample includes actively managed funds that are mostly focused on large and mid cap equity in Sweden. Furthermore, they have to have existed at least from 2010-01-01 to 2020-01-30. The sample only includes funds that have labeled themselves as Swedish investors, meaning that their investments do not exceed 30% of foreign companies. The study aims to investigate the ability of actively managed equity funds to achieve returns, with the only constraint being large and mid cap markets. Since the sustainability funds neglect companies that do not comply with their investment criteria, i.e. further constraints, these are excluded. Below is the complete list of funds that will be examined in the study.

Actively managed Swedish equity funds existing 2010-01-01 until 2020-01-01	
Aktie-Ansvar Sverige A	Humle Sverigefond
AMF Aktiefond	Lannebo Sverige
Carnegie Sverigefond A	Lannebo Sverige Plus
C WorldWide Sweden 1A	Nordic Equities Sverige
Cliens Sverige A	Quesada Sverige
Didner & Gerge Aktiefond	SEB Sverigefond
Enter Select A	SEB Sweden Equity C (SEK)
Enter Select Pro	SEB Sverige Expanderad
Enter Sverige A	SEB Value Fund
Enter Sverige Pro	Spiltan Aktiefond Stabil
Handelsbanken Sverige Tema	Swedbank Robur Sverigefond A

Table 2

3.3.3 Risk-free rate

Risk-free rates are defined as safe investments. Therefore treasury bonds are suitable for estimating a rate of return. The study is done on Swedish equity and therefore Swedish treasury bonds will be used. The interest rate of 3-month treasury bonds during a 10 year period is collected from the Swedish Central Bank's website (Riksbanken, 2021). Thereafter an average during the 10 year period is calculated and assumed as the risk-free rate.

3.3.4 Market portfolio

The market portfolio is supposed to reflect the development of the Swedish economy to be usable for the calculation. *Affärsvärldens generalindex* is the oldest Swedish market index found and was established in 1937. It takes solely into account fluctuations from rising and falling equity prices and not IPOs, SEOs, or acquisitions (Nasdaq, 2021). The benchmark, therefore, provides a clear picture of the development of the market.

3.4. Hypothesis

Fama suggests that stock prices’ market behavior can be modelled by a random walk. Furthermore, EMH therefore implies that using fundamental value methods or technical analysis will not give an investor an advantage because it is derived from public information. Hence, one could argue that the average return of actively managed equity funds should not outperform the average of a portfolio constructed by randomly selected stocks. An individual stock’s price fluctuations will have a larger impact on the simulated portfolios, consisting of only eight stocks, than the equity funds, that is by law dictated to have at least 16 assets, with a maximum of 10% invested in one individual stock. Furthermore only four stocks are allowed to make up 10%, thereafter the rest of the assets can only make up 5% of the fund's total value (SFS, 2004:46). The random portfolios are therefore expected to have a wider spread than the funds. Due to the 1/N nature of the simulated portfolios, the standard deviation is expected to be greater than that of the equity funds. Since the market portfolio is value-weighted and the simulated portfolios are 1/N-weighted a low correlation is expected. Moreover, since the simulated portfolios annually sell and buy common stock implies that they will hold their position regardless of the fluctuations which the actively managed funds might try to avoid. The effect is believed to be amplified by the low amount of assets and the random nature of the strategy.

4. Empirical analysis

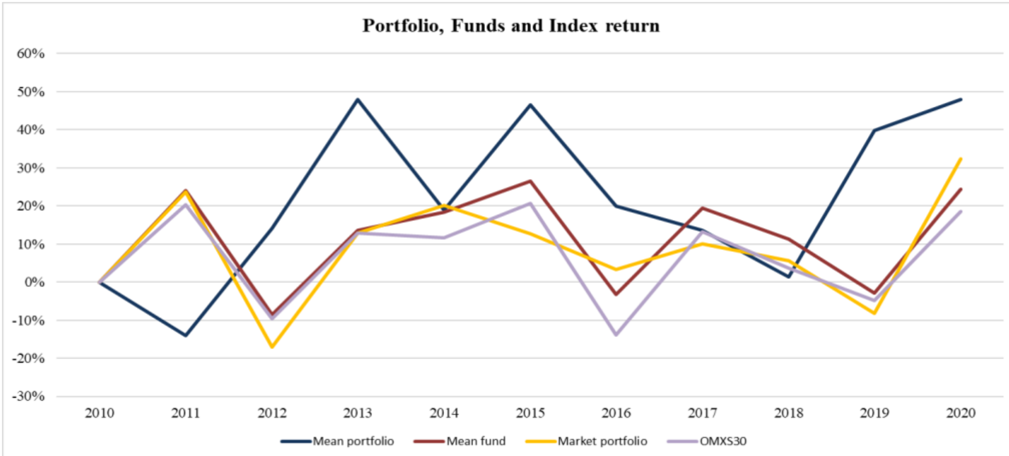

Figure 1

Correlation Matrix	***OMXS30***	***Funds***	***Market Portfolio***	***Scenario 1***	***Scenario 2***	***Scenario 3***
OMXS30	1					
Funds	0.970	1				
Market Portfolio	0.815	0.856	1			
Scenario 1	0.029	-0.009	-0.015	1		
Scenario 2	0.106	0.093	0.069	0.981	1	
Scenario 3	0,168	0,177	0,136	0,936	0,986	1

Table 3

Figure 1 shows the yearly return of the mean simulated portfolio and the benchmarks. The three scenarios have been joined to showcase a standardized simulation result in comparison to the result of the mean fund's return. The market portfolio and OMXS30 are included to be able to distinguish standard market movement. The benchmarks have the same trending results throughout the period, which can be a cause of macro-economical events, e.g. Greece debt crisis in 2011. Judging by the results, a randomly assembled portfolio, annually rebalanced, achieves a greater return than an actively managed equity fund during the 10 year period. The simulated results also exceed the standard market benchmarks, OMXS30, and the market portfolio. Table 3 shows the correlation between the different scenarios and benchmarks. The intention is to distinguish between market-moving portfolios and the simulated portfolios, as well as to show how the scenarios behave compared to each other. The three scenarios are highly correlated, between 0.93 and 0.99, which shows that there is no large effect on the return when diversifying the portfolio within large and mid cap stocks. Table 3 also showcases that the funds and market portfolio are highly correlated, 0.86. However, the benchmarks and the simulations are less correlated with each other, even negatively correlated, as between scenario 1 and both the benchmarks. Since the fund managers are assumed to be intelligent investors, who take active decisions in their stock picks, and due to the nature of the chosen funds, a return following the market is expected. The opposite can be said about the simulations, whereas the non-intelligent investor is acting, which explains the dissimilarity to the benchmarks.

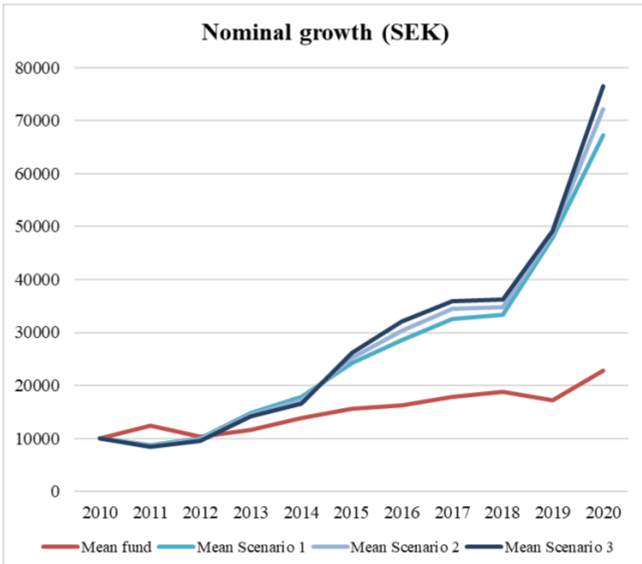

Figure 2

Yearly Return	Mean	Standard Deviation	Median	Min	Max	Spread
Scenario 1	22.40%	0.25	21.53%	6.01%	62.04%	56.03%
Scenario 2	23.60%	0.28	22.43%	3.87%	69.64%	65.77%
Scenario 3	24.70%	0.32	23.20%	1.29%	75.17%	73.88%
Funds	12.30%	0.13	0.30%	10.80%	15.10%	4.30%

Table 4

Return end of period	Mean	Median	Min	Max	Spread
Scenario 1	571.60%	483.38%	52.34%	5620.65%	5568.32%
Scenario 2	618.90%	508.07%	25.95%	5055.41%	5029.45%
Scenario 3	663.30%	519.88%	-2.76%	6060.84%	6063.60%
Funds	197.10%	195.82%	147.16%	291.97%	144.81%

Table 5

Figure 2 illustrates the nominal growth of the scenarios and benchmarks when the starting value is SEK 10,000. This shows how well a retail investor would have performed, excluding fees, during the period if SEK 10,000 had been invested in either of the scenarios or funds. Moreover, 82.5% of the random portfolios generated a higher return than the funds (Appendix A). The mean portfolio has the best performance during the period, however, this comes with increased volatility and risk. One explanation for the high growth among the portfolios can be due to the chosen period, where the Swedish stock market experienced high growth (Appendix C). Scenario 3 was the most favorable weighting of mid and large cap in regards to return, implying that mid cap grew the most during the period. But at the same time, this scenario generated some of the portfolios with the lowest return. The lower nominal growth of the equity funds can be caused by several factors such as the judicial system, market constraints, and their portfolio strategy. The Swedish judicial system constricts equity funds to a maximum position of 10% in a single asset. This has an impact on growth and diversification. Swedish equity funds are therefore forced to sell stocks that rise quickly to keep in the frame of the judicial system, which forces a constraint on growth (SFS, 2004:46). As stated earlier, the fund managers are assumed to be intelligent investors and by constraining these to markets, geography, and size of companies, the opportunities that might be found and acted upon will decrease. The mid- and large cap lists are set to a number of companies, which change each year and therefore limit the fund manager's choice of assets. Comparing the simulation strategy with the equity funds, there is an advantage in rebalancing the whole portfolio annually. This rebalancing means that the portfolio performance only will maintain decreasing assets for one year, however, the same holds for increasing assets.

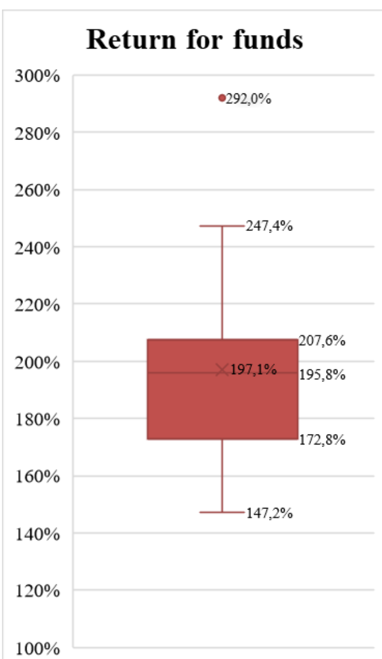

Figure 3

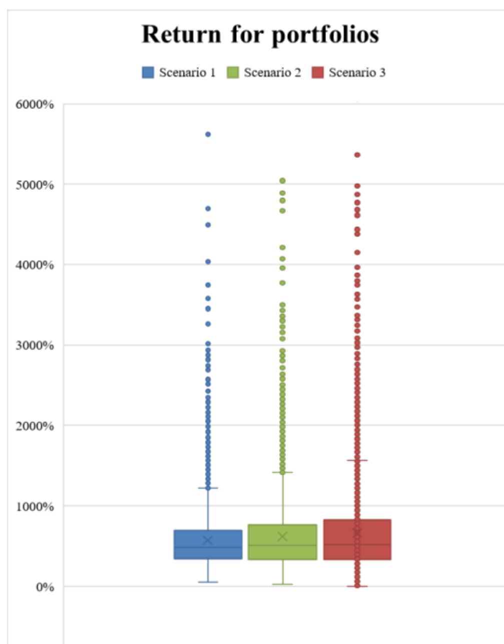

Figure 4

Figure 3 shows the return spread of the funds included, see table 4. This shows that the mean return for the funds was 197.1%, and the best-performing fund, Spiltan Aktiefond Stabil, had a return of 292.0%. Figure 4 shows the returns spread of all simulations in the three scenarios. Showing a mean return of 600% for all of the scenarios, as well as the highest performing portfolio with just above 6,000%. This figure showcases the large spread within each scenario. Furthermore, the worst possible scenario for the random portfolio is to lose 100% of its value which is highly unlikely. Rather the contrary happens in this study among the portfolios, with one portfolio (figure 4) gaining as much as 6,000% and 9, 15, and 22 portfolios gaining at least 3,000% for scenarios 1, 2, and 3 respectively. These outliers, therefore, affect the return from the mean portfolios, however, not too much as the mean-median difference is small. However large these outliers are then indicates that the results should be reliable and that a majority of simulations tested are similar to one another.

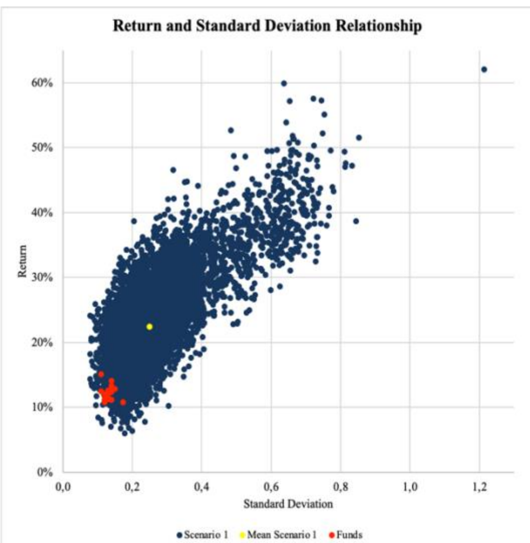

Figure 5

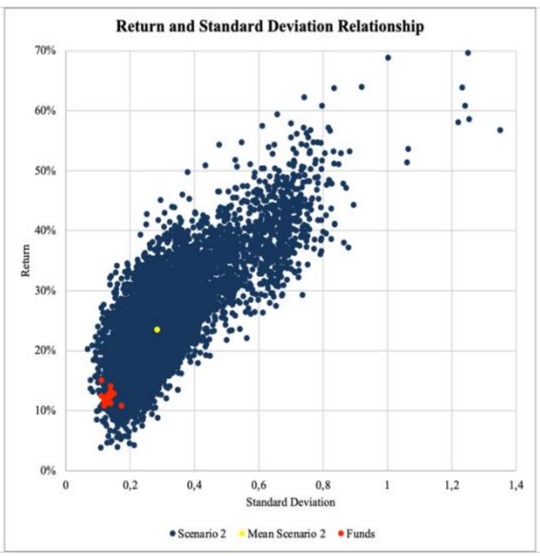

Figure 6

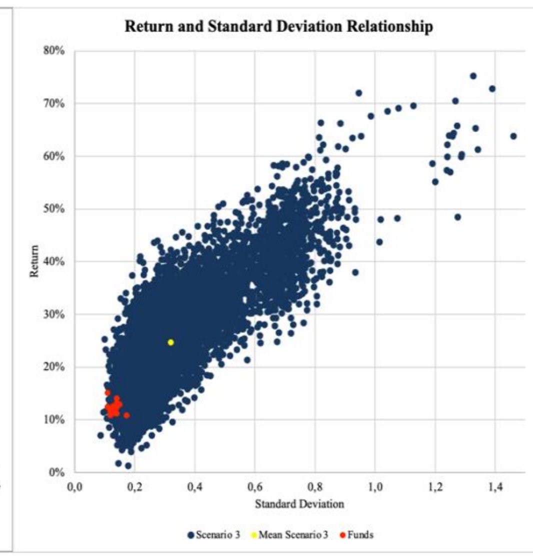

Figure 7

Standard Deviation	**Mean**	**Median**	**Min**	**Max**	**Spread**
Scenario 1	0.250	0.224	0.079	1.214	1.135
Scenario 2	0.283	0.247	0.069	1.350	1.281
Scenario 3	0.321	0.275	0.087	1.460	1.373
Funds	0.131	0.13	0.11	0.17	0.06

Table 6

Figures 5-7 reflect the relationship between yearly return and standard deviation for each portfolio scenario, its mean, and the funds. The figures show that, for all of the scenarios, the mean standard deviation is between 0.2 and 0.4, meanwhile no funds exceed a standard deviation of 0.2. This also entails that the scenario with a majority holding in large cap has a lower standard deviation and vice versa for the simulation with a majority holding mid cap, consequently showing that large cap stocks have a lower risk when compared to the mid cap stocks. An explanation for this tendency could be the value-weighted nature of the market portfolio and index, leading to a larger probability that equity funds use these stocks to hedge against the larger growth opportunity of stocks with a smaller market capitalization. The mean spread of standard deviation for the simulation is 1.26, which is large in comparison to the equity funds and shows that there are numerous risk levels in the simulation. This, however, is to be expected since a zero-intelligent investor is not able to take into account risk when establishing a portfolio, and is thus risk-neutral. Meanwhile, the spread for the equity funds is at a mere 0.047, this could be an effect of the small number of observations in comparison to the simulations. However, the equity fund spread's low-risk level, in comparison to the simulations, which can be due to market standards for such specific equity funds and the forced diversification of the judicial system (SFS, 2004:46).

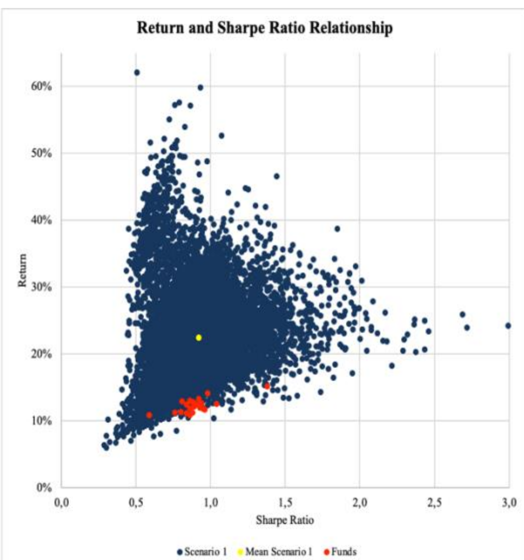

Figure 8

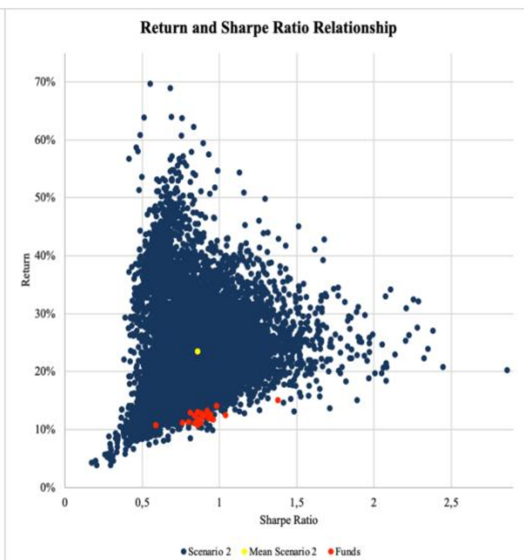

Figure 9

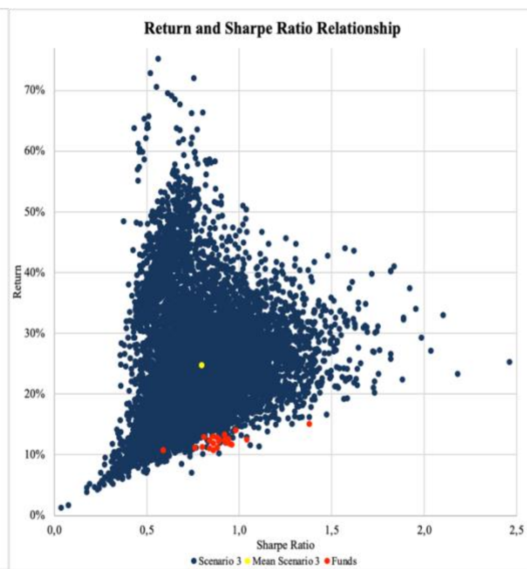

Figure 10

Sharpe Ratio	Mean	Standard Deviation	Median	Min	Max	Spread
Scenario 1	0.921	0.249	0.887	0.287	2.993	2.706
Scenario 2	0.858	0.241	0.828	0.171	2.863	2.692
Scenario 3	0.797	0.225	0.768	0.037	2.462	2.425
Funds	0.899	0.137	0.885	0.589	1.380	0.791

Table 7

Risk is not the sole measure that defines how well a portfolio/fund performs, the relationship between risk and return has to be considered. The simulation and fund results for the Sharpe ratio prove that, on average, funds are more efficient in asset allocation when assuming the Sharpe ratio as a performance measurement. Figures 5-7 show that with increased risk there is increased return. However, comparing this to figures 8-10, high risk and high return might not be sufficient in comparison to lower risk and relatively high return. Hence, the Sharpe ratio is a trade-off between return and risk, meaning that even with high returns, the portfolio does not always have better performance than a portfolio with a lower return. It could be concluded that a large cap heavy portfolio has a higher Sharpe ratio, this can be observed through the relatively lower standard deviation and higher returns in large cap companies throughout the time period. Figures 8-10 reflect the relationship between yearly return and Sharpe ratio for each portfolio scenario, its mean, and the funds. The funds are located on the lower end of the return spread compared to the simulations. However, the funds have a higher mean Sharpe ratio than the simulations. This is correlated with the earlier segment noting the funds' smaller exposure to risk. For all of the scenarios, there are instances where, a single or several, portfolios have a yearly mean return above 60%. This, in relation to the Sharpe ratio, shows that these specific portfolios have a high standard deviation, meaning that in a bear market, these portfolios would be likely to suffer the most among the portfolios.

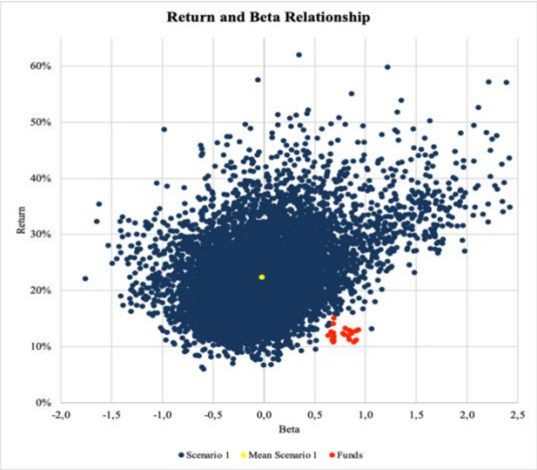

Figure 11

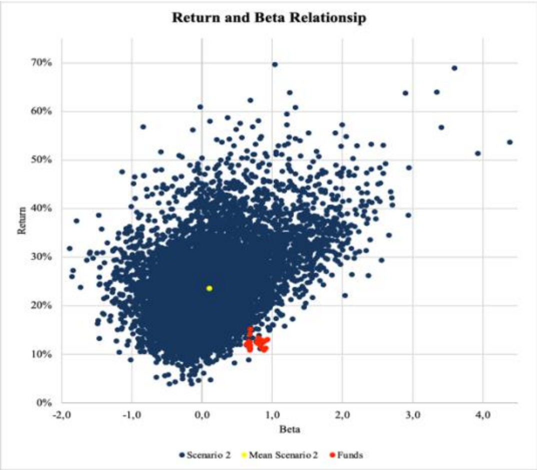

Figure 12

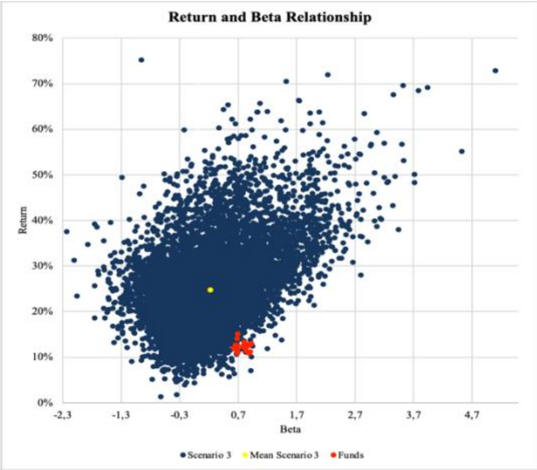

Figure 13

Beta	Mean	Standard Deviation	Median	Min	Max	Spread
Scenario 1	-0.019	0.476	-0.064	-1.763	2.423	4.186
Scenario 2	0.100	0.577	0.032	-1.885	4.383	6.268
Scenario 3	0.225	0.667	0.141	-2.230	5.105	7.335
Funds	0.773	0.096	0.785	0.630	0.930	0.300

Table 8

Figures 11-13 reflect the relationship between yearly return and beta for each portfolio scenario, its mean, and the funds. The beta values of the simulation mean are closer to zero than to one, meaning that the portfolios have a low correlation with the market and thus low systematic risk. This is also motivated by table 3, as the correlation between the simulation scenarios and the market is low. There is a clear distinction between the beta values of the simulation scenarios and the funds. The funds follow the market and thus are more sensitive to systematic risk, see figure 11-13. On the other hand, the portfolio scenarios are on the lower end of the beta values, even negative as in scenario 1. This entails that the simulation scenarios are less correlated with the market and it is therefore less systematic risk. Scenario 3 has the highest beta of the simulations, which indicates that the market portfolio has more exposure towards mid cap listed companies. The equity funds are more correlated with the market portfolio, which is to be assumed due to the nature of the equity funds, i.e. specialization in mid and large cap. The low correlation between the market portfolio and the simulations could be due to the 1/N nature of the simulation strategy. The simulated portfolios value all possible stocks equally, meanwhile, the intelligent investor and market portfolio are selective. The intelligent investor tries to find undervalued companies and the market portfolio weighs companies by market cap. This entails a lower beta for the simulations and a higher beta for the equity funds.

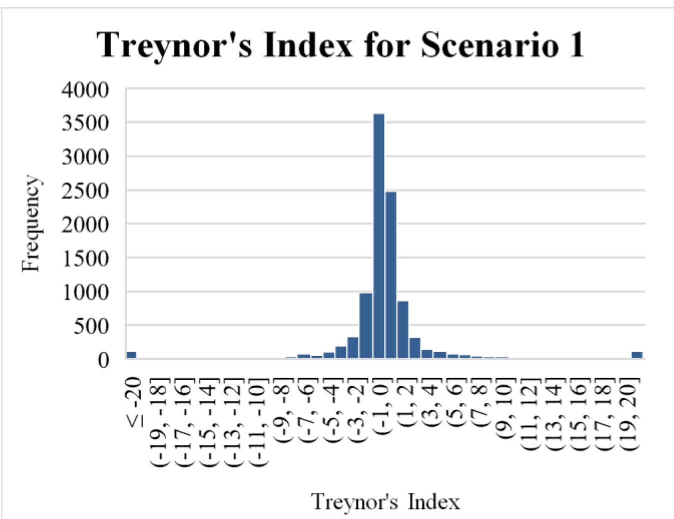

Figure 14

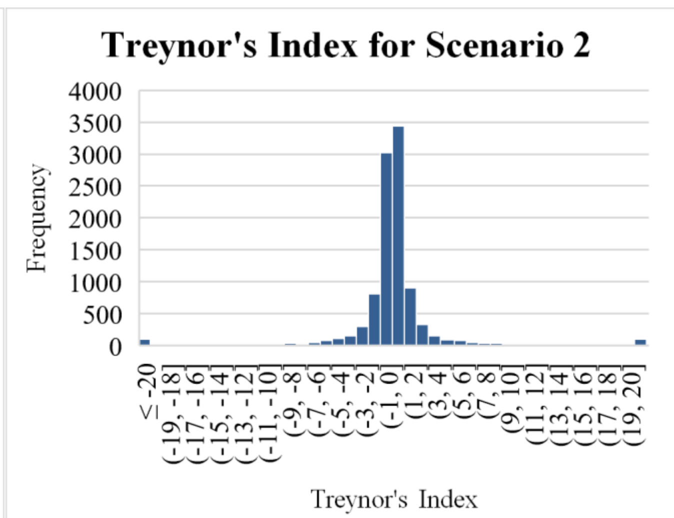

Figure 15

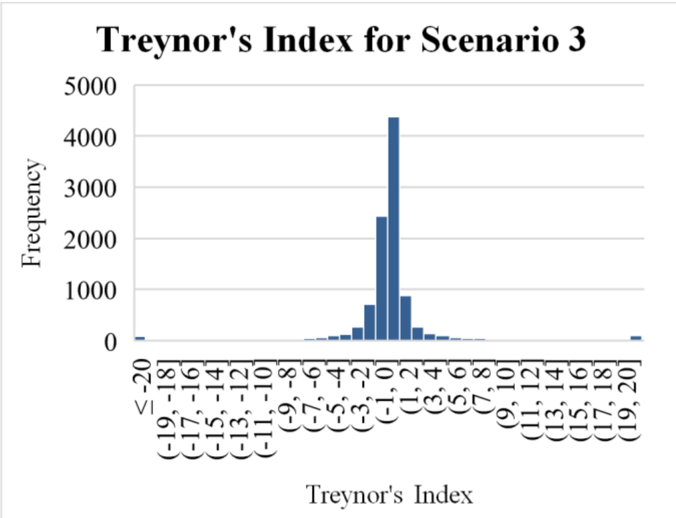

Figure 16

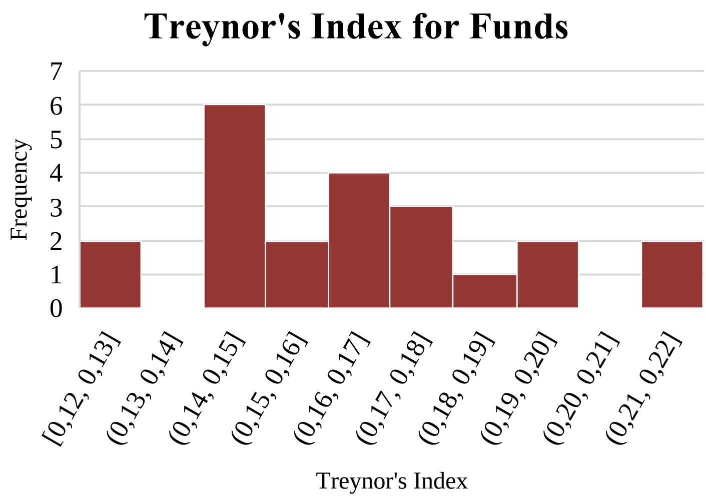

Figure 17

Treynor's Index	Mean	Standard Deviation	Median	Min	Max	Spread
Scenario 1	0.748	67.769	-0.290	-610.296	6200.443	6810.739
Scenario 2	0.542	56.088	0.203	-1565.529	4366.684	5932.213
Scenario 3	0.173	77.079	0.263	-6077.024	3851.644	9928.668
Funds	0.159	0.025	0.160	0.115	0.210	0.095

Table 9

Figures 14-17 show the Treynor's Index for each portfolio scenario, and the funds. As for the trade-off between risk and return for the Sharpe ratio, the same trade-off is used when evaluating Treynor's index. The difference between the results of the Sharpe ratio and Treynor's index is that Treynor's index is in favor of the simulation, indicating a higher systematic risk-adjusted return. The portfolios in scenario 1 produce the highest Treynor's index, implying that a larger asset allocation in large cap equity entails a greater return when taking systemic risk into consideration. This is due to a couple of extreme outliers which is probably the result of a couple of portfolios achieving a massive return and/or having a beta incredibly close to zero, another component of the formula, that results in a couple of unbelievable Treynor's indices.

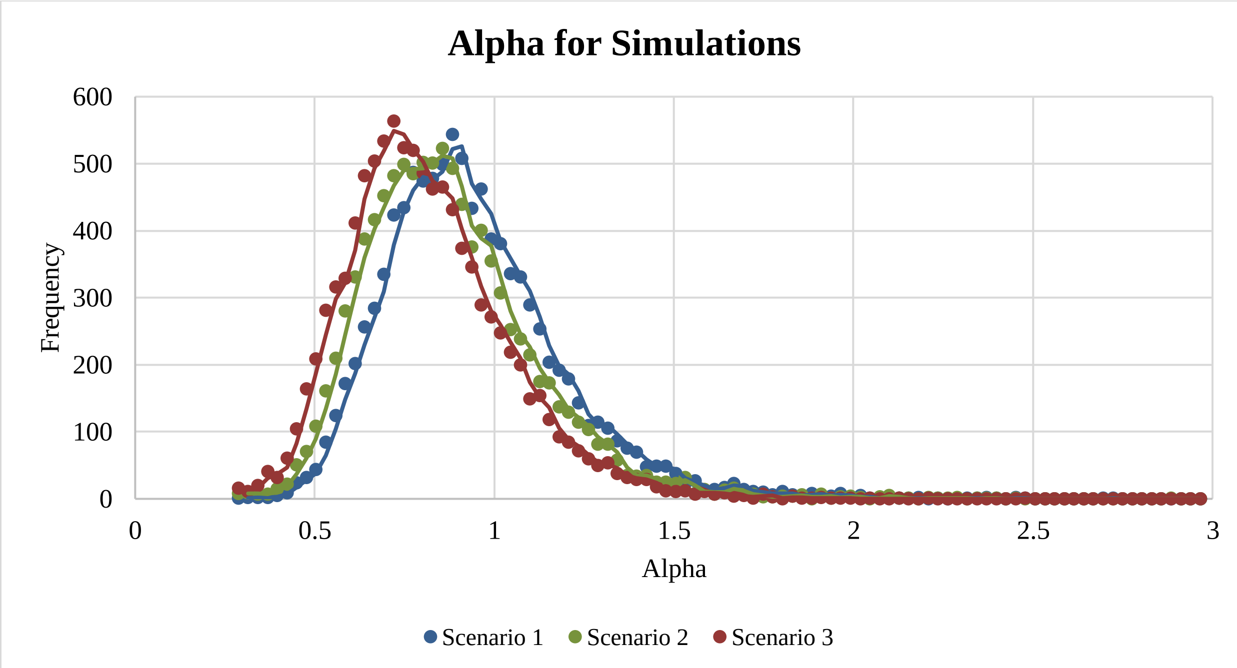

Figure 18

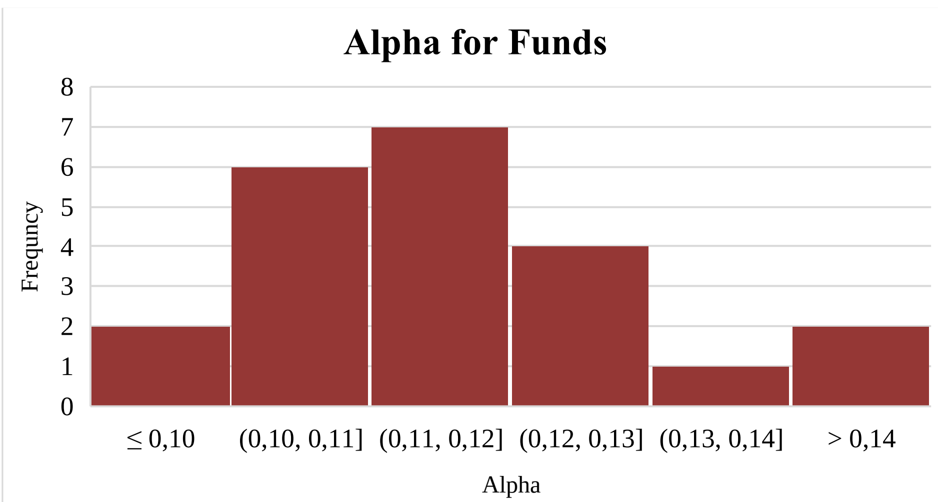

Figure 19

Alpha	Mean	Standard Deviation	Median	Min	Max	Spread
Scenario 1	0.220	0.063	0.213	0.031	0.583	0.552
Scenario 2	0.220	0.073	0.211	0.022	0.636	0.614
Scenario 3	0.221	0.083	0.209	-0.018	0.830	0.848
Funds	0.120	0.042	0.120	0.022	0.266	0.244

Table 10

Figures 18 and 19 show the distribution of alpha for each portfolio scenario and for the funds. The simulations' results show that a greater amount of large cap stocks in the portfolio produces an alpha closer to one. The alpha shows the systematic risk-adjusted return, which means that a higher beta equals lower alpha and is, therefore, an indicator of how well assets have been allocated. Since the beta and market portfolio are incorporated, the alpha shows how well the portfolio has performed in comparison to the market. The alpha values show that all of the strategies outperformed the CAPM predicted return. The actively managed equity funds are expected to outperform the market, however, the random portfolio simulations are all superior in the study. Since the simulated portfolio has higher returns and lower beta than the equity funds, these results are reasonable. The alpha could be interpreted as how well equities have been selected, which in this instance implies that picking randomly, during the ten-year period for large and mid cap equities, is more effective than actively evaluating individual assets. This can be the cause of investor-bias towards certain companies, meaning that equity funds value stocks higher if they have a larger weighting in the market portfolio. Since the alpha is an estimate compared with the market portfolio, various outcomes are dependent on the choice of the period, which should be taken into account as highly relevant. The period between 2010 and 2020 is characterized by a high growth market (Appendix C). The low standard deviation of the equity funds, in comparison with the simulations, will affect the opportunity for higher returns in a booming market. Hence, the low alpha values for the equity funds are reasonable during this period. As stated earlier, the simulated portfolios' performances are dependent on the overall market development during the period, due to that the portfolios are sensitive towards all stock movements rather than the market's movement.

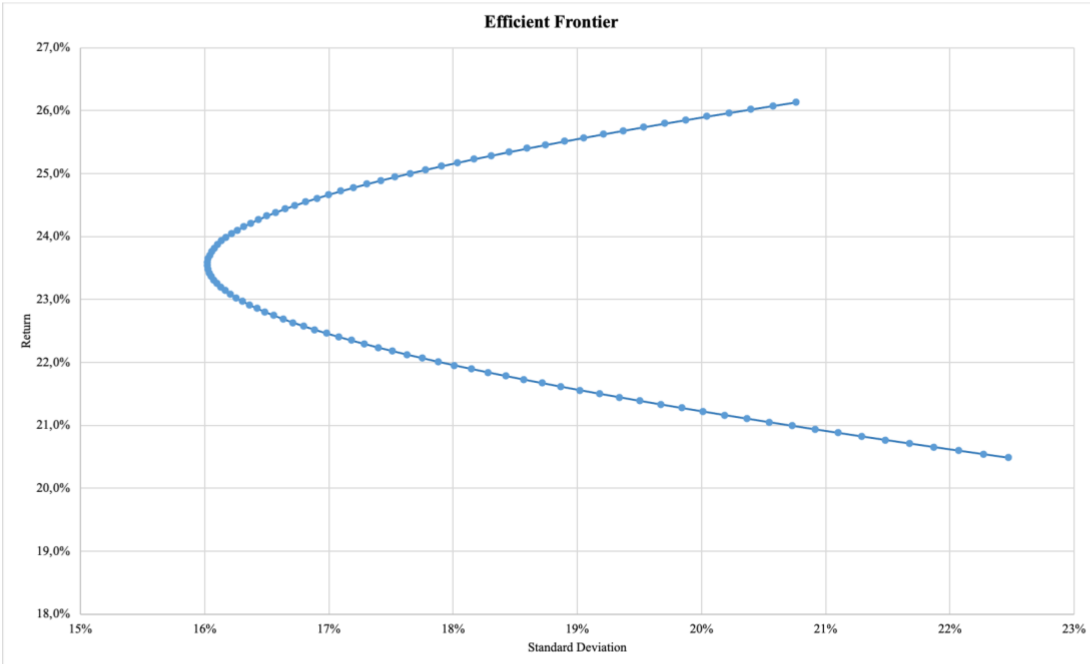

Figure 20

Figure 20 shows all possible combinations of large and mid cap. The figure was generated through every combination in percentage, as an integer, in relation to the expected return for both large and mid cap. This allows for a distinction between mid and large cap heavy portfolios when taking into account return and risk. What can be distinguished is that a portfolio of only large cap equity is less lucrative when compared to a pure mid cap portfolio, which both has higher expected returns and lower risks. However, to minimize the risk exposure the portfolio needs a combination of both large and mid cap companies. For this instance the optimal, when accounting for risk, portfolio is made up of 45% mid cap and 55% large cap, which entails a 16% risk and 23.6% expected return. Below this level, i.e. the global minimum variance portfolio, there is an alternative with the same amount of risk but with a greater expected return. Therefore, the maximum amount of large cap in the portfolio should be 55% when accounting for risk.

5. Discussion

The study aims to examine how well actively managed funds perform in comparison to a randomly generated portfolio from a retail investor's perspective. However, the performances are not perfectly comparable since the simulations fail to include some essential practical factors for a retail investor, such as the Swedish tax rate on capital gains, transaction costs, and the constraint to this particular period which has an effect on the return and thus the performance measurements. However, if external costs were to be included the results would most likely indicate, considering the large difference in return, that the funds reap a lower return on average during the period. Going forward, it would be more interesting, from a retail investor's point of view, to make a more elaborate simulation that takes transaction fees and taxes into account.

The sample criteria established for the equity funds resulted in only 22 funds being recognized as suitable candidates to be compared with the randomly generated portfolios. This is a rather low amount of data objects, especially compared to the 10,000 portfolios, which means that the results could be misleading. One way of extracting a larger amount of data would be to divide ten years into different subperiods, for example adding five, three, and one-year periods. Then the result could be compared to funds that have not existed for 10 years, meaning a larger sample. Another benefit would also be that the survivorship bias from choosing a longer period, such as 10 years, could be avoided to a larger extent. A final way of increasing the fund sample would be to include funds that rely more on derivative trading or other alternative investments, i.e. hedge funds. However, the more the investment possibilities between the funds and the simulated portfolio differ the less comparable will the results be. Furthermore, by including a variation of funds, using different investment strategies, groupings should be expected to occur. depending on the investment strategy of the fund. On the other hand, since the simulations proved to be uncorrelated with the market it could therefore still be interesting from a retail investor's perspective to investigate the alternatives for allocating capital.

Some Swedish companies are registered in foreign stock markets, meaning that they are not part of the data sample used in this study. This also adds to the difference of investment alternatives between the random portfolios and the funds, since some of the funds also invest in these companies. However, the equity funds chosen had the advantage of obtaining holdings in Swedish companies listed on foreign markets, which in one sense impairs the result as this opportunity is not taken into account in the simulation. If small cap companies were included in the sample for common stock it would be reasonable to include funds focusing on small cap companies to a higher extent and it would also result in a larger number of equities to choose from in the simulation. Small cap companies vary to a higher degree in mean return and volatility. They also make up a greater number of assets than the large and mid cap lists combined. This would have enabled more contrasting results and more scenarios to study.

The simulation studied a ten-year period, 2010-2020. The significance of the choice of time period is determinant of the studies outcome and how well the simulation performs compared to the benchmarks. During the period of the study, there was no great financial crisis or event that altered the markets in a powerful manner. However, the period was deemed suitable due to previous studies and the disadvantage of choosing a longer period, whereas there would be less data to collect. These restrictions have created a result that favors the randomly assembled portfolios rather than common equity funds. If certain events would have occurred, e.g. the Dot-Com-Bubble, one could imagine a more favorable outcome for the intelligent investor, meaning the equity funds rather than the random portfolio that ignores risk. While funds have a higher sensitivity towards systematic risk, randomly selecting common stock imposes a higher risk and generates outliers when large market movements occur. The relatively steady growing Swedish stock market observed (judging by OMXS30 development between 2000-2010 and 2010-2020) is most likely a determinant of the outcome of simulations. Since the focus of this thesis is to analyze the difference between actively managed equity funds and randomly assembled portfolios, of different weights, from recent historical data, the period is of significance. Since market cap lists are changing each year, the choice of the time period would also include the change of companies taken into consideration when building the model throughout the years studied. The choice of the time period would also include the change of fund managers and their investment strategy, which would have an impact on how well a standardized investment strategy performs, since the fund manager's philosophy on the market probably changes throughout time.

The script can be improved to account for more factors, such as external costs, but due to time, this is not included in this study. Furthermore, this study's methodology involved a lot of formula calculations and graphs being executed in Excel which is to a high extent fairly manual, this allowed for the possibility of human errors.

6. Conclusion

The results imply that, on average, a randomly assembled portfolio yields a higher return than an actively managed equity fund, at least during the period between 2010-01-01 and 2020-01-01. This exceeded the expectations in the hypothesis, which was rooted in the EMH stance that the return from the funds and portfolios should be comparable. The results, therefore, suggest that funds on average generate a lower return than chance. However, there is not enough evidence to claim it is the better choice of investment, partly because of the practical limitations, such as excluding external costs, but also because of the large spread of returns. Institutional investors' ability to diversify improves their risk-adjusted return, which is present in the results, but only a slightly higher Sharpe ratio is achieved in relation to a randomly selected portfolio. The simulation returns are considerably greater than for the funds, implying that the amount of risk in the simulation is also substantially larger, due to the similar Sharpe ratios. However, if the systematic risk is considered, the funds are more sensitive. Both the CAPM alpha and Treynor's Index show that the simulations are superior in selecting stocks and have a higher systematic risk-adjusted return. Considering that the result is potentially biased towards the period and excludes external factors such as tax and transaction costs, in the end, the retail investors' risk preferences decide if a fund manager adds value or not.

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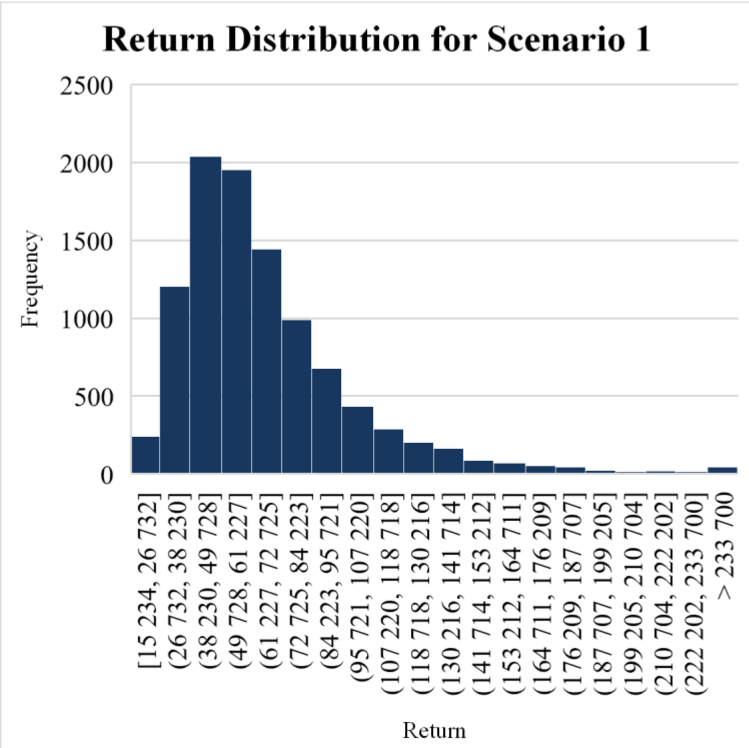
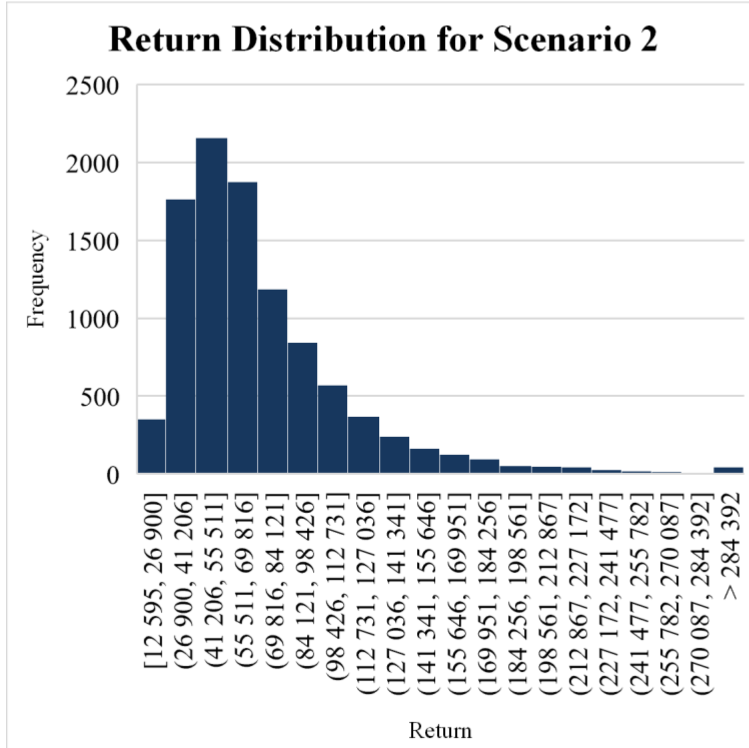
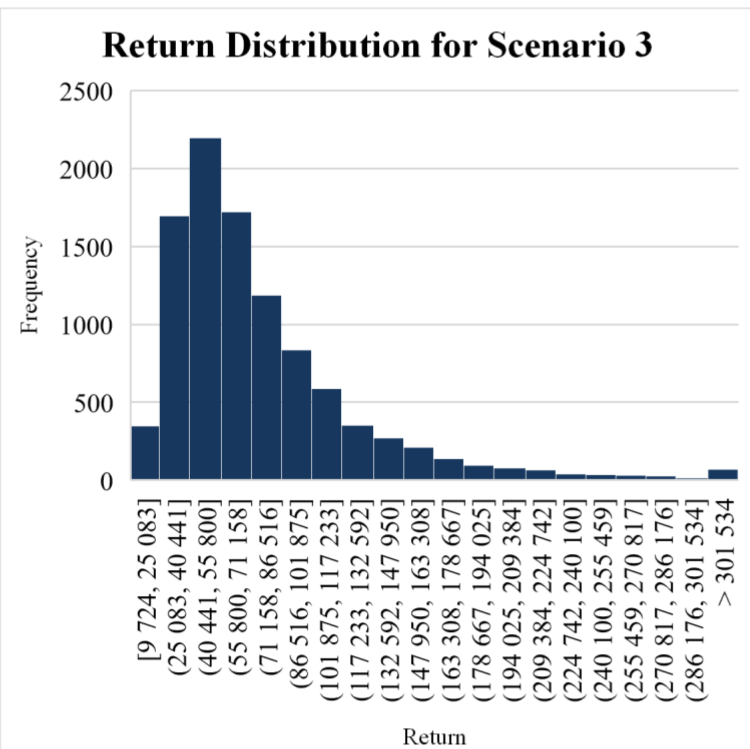
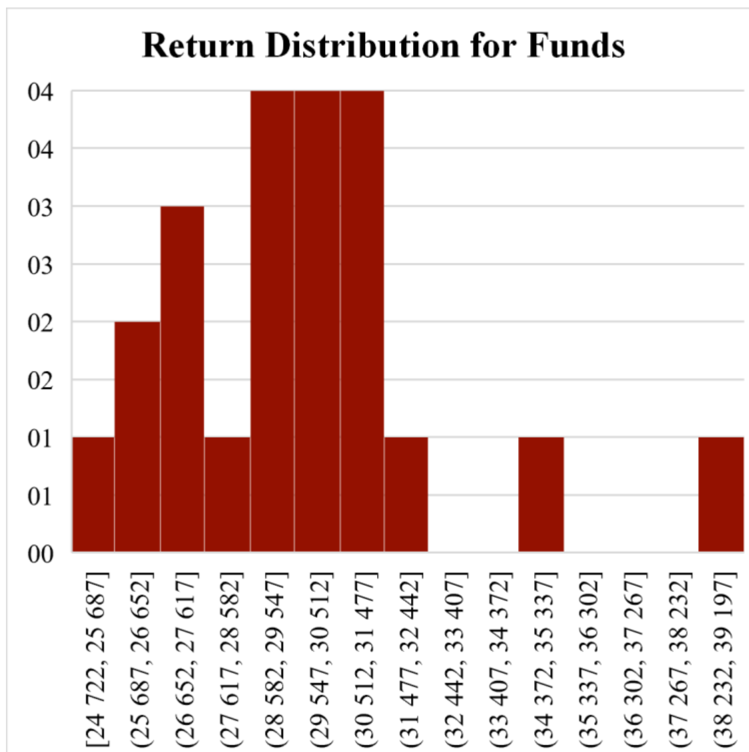
Appendix A

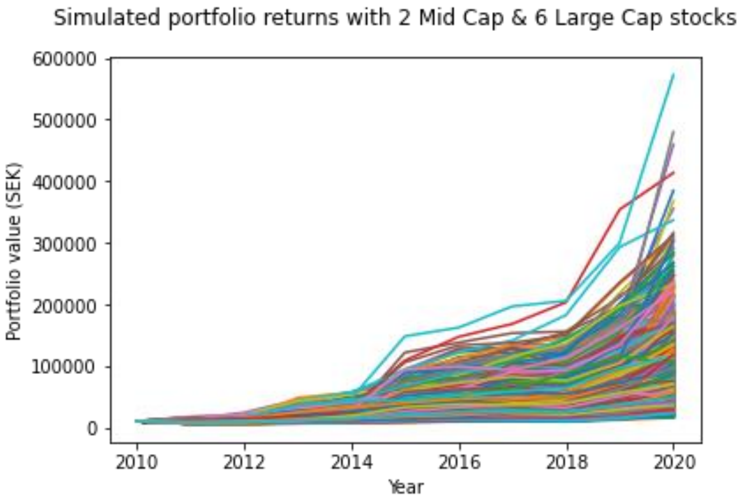

Return Distribution for Scenario 1
Frequency
Return


Return Distribution for Scenario 2
Frequency
Return


Return Distribution for Scenario 3
Frequency
Return


Return Distribution for Funds

Appendix B


Simulated portfolio returns with 2 Mid Cap & 6 Large Cap stocks
Portfolio value (SEK)
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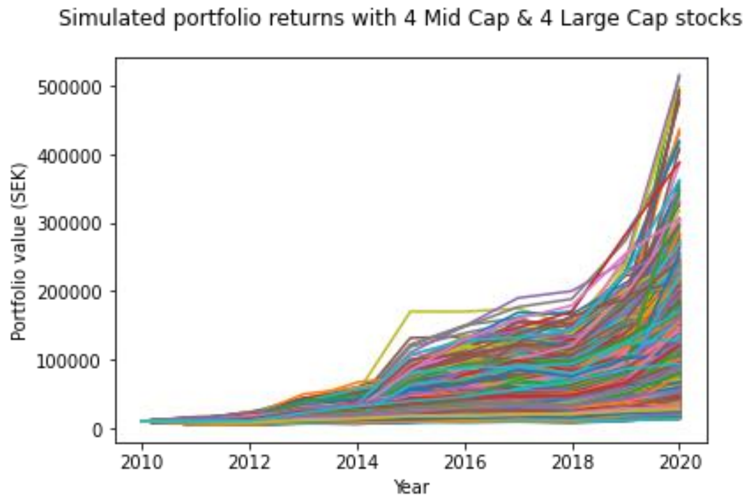
400000
300000
200000
100000
0
2010
2012
2014
2016
2018
2020
Year


Simulated portfolio returns with 4 Mid Cap & 4 Large Cap stocks
Portfolio value (SEK)
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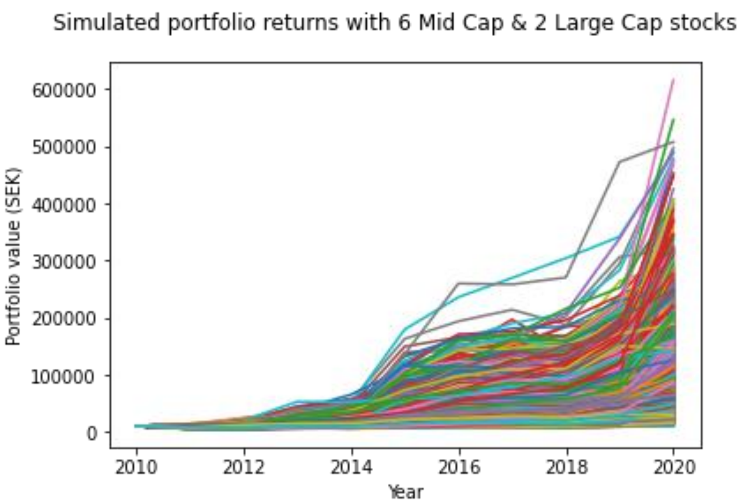
400000
300000
200000
100000
0
2010
2012
2014
2016
2018
2020
Year


Simulated portfolio returns with 6 Mid Cap & 2 Large Cap stocks
Portfolio value (SEK)
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400000
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200000
100000
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2010
2012
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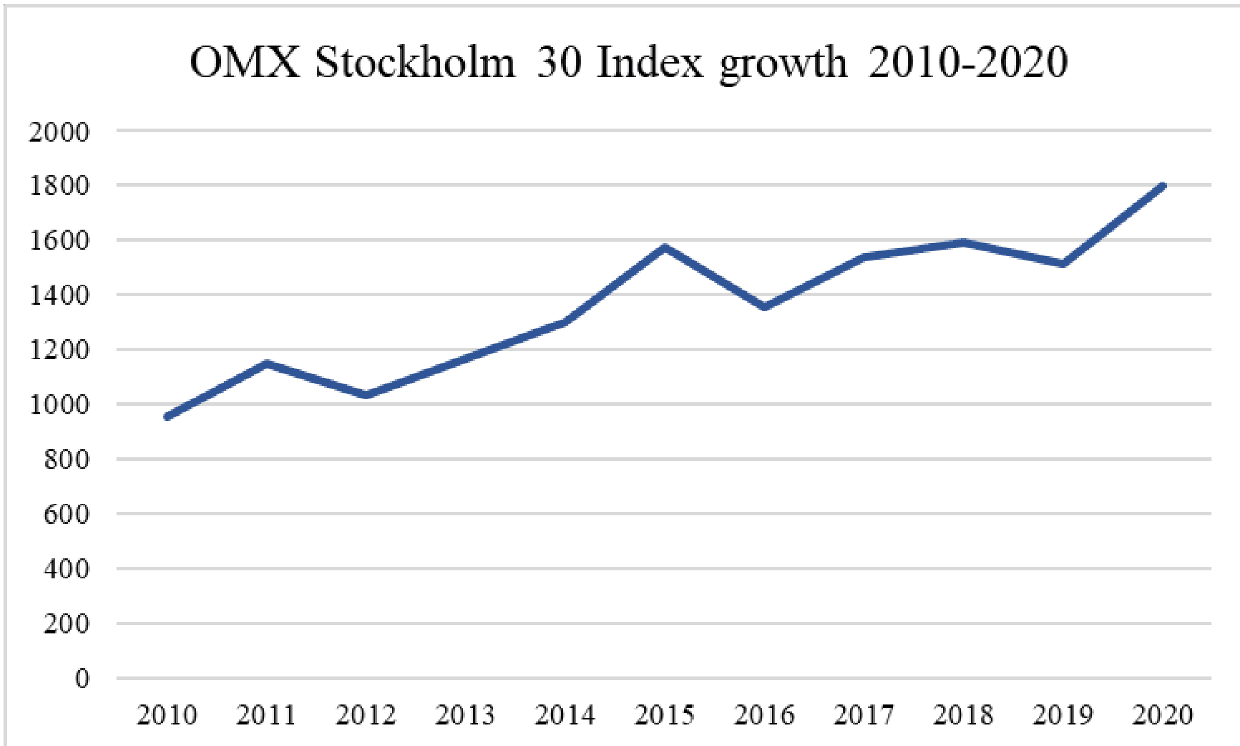
2016
2018
2020
Year

Appendix C



OMX Stockholm 30 Index growth 2010-2020
2000
1800
1600
1400
1200
1000
800
600
400
200
0
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

Appendix D

```
import pandas as pd
import datetime as dt
import numpy as np
import matplotlib.pyplot as plt
import csv
import random
large_cap = []
with open('LargeCapCSV_Finaldata_yearly.csv', 'r') as file:
   reader = csv.DictReader(file)
   for row in reader:
     large_cap.append(dict(row))
mid_cap = []
with open('MidCapCSV_Finaldata_yearly.csv', 'r') as file:
   reader = csv.DictReader(file)
   for row in reader:
     mid_cap.append(dict(row))
     #print(dict(row))
def random_mid_cap_stock(year):
 selected_stock = random.choice(mid_cap)
 while(selected_stock[str(year)] == '0'):
     selected_stock = random.choice(mid_cap)
 return selected_stock
def random_large_cap_stock(year):
 selected_stock = random.choice(large_cap)
 while(selected_stock[str(year)] == '0'):
     selected_stock = random.choice(large_cap)
 return selected_stock
### ÄNDRA VARIABLER HÄR ###

PORTFOLIO_START_YEAR = 2010
PORTFOLIO_END_YEAR = 2020

TOTAL_STOCKS_IN_PORTFOLIO = 8
INITIAL_INVESTMENT_SIZE = 10000 # SEK

NR_MID_CAP_STOCKS = 4
NR_LARGE_CAP_STOCKS = 4

NR_SIMULATIONS = 10000
class Portfolio:
  def __init__(self):
   self.portfolio_size = {PORTFOLIO_START_YEAR:INITIAL_INVESTMENT_SIZE}
   self.nr_mid_cap = NR_MID_CAP_STOCKS
   self.nr_large_cap = NR_LARGE_CAP_STOCKS
   self.start_year = PORTFOLIO_START_YEAR

   self.mid_cap_stocks = {}
   self.large_cap_stocks = {}
  def add_mid_cap_stocks(self, year, stocks):
```

```
   self.mid_cap_stocks[year] = stocks
  def add_large_cap_stocks(self, year, stocks):
   self.large_cap_stocks[year] = stocks

  def y_size(self, year, sum):
    self.portfolio_size[year] = sum
def generate_returns():
 p = Portfolio()
 for year in range(PORTFOLIO_START_YEAR, PORTFOLIO_END_YEAR):
   portfolio_size = p.portfolio_size[year]
   size_per_stock = portfolio_size / TOTAL_STOCKS_IN_PORTFOLIO
   next_Y_portfolio_size = 0
   for i in range(NR_MID_CAP_STOCKS):
     stock = random_mid_cap_stock(year)
     curr_price = float(stock[str(year)])
     #print("curr_price : " + str(curr_price))
     nr_curr_stocks =  size_per_stock / curr_price
     #print("nr_curr_stocks : " + str(nr_curr_stocks))
     next_y_price = float(stock[str(year+1)])
     #print("next_y_price : " + str(next_y_price))
     next_Y_portfolio_size += ((nr_curr_stocks*next_y_price))
     #print(next_Y_portfolio_size)

   for i in range(NR_LARGE_CAP_STOCKS):
     stock = random_large_cap_stock(year)
     curr_price = float(stock[str(year)])
     #print("curr_price : " + str(curr_price))
     nr_curr_stocks =  size_per_stock / curr_price
     #print("nr_curr_stocks : " + str(nr_curr_stocks))
     next_y_price = float(stock[str(year+1)])
     #print("next_y_price : " + str(next_y_price))
     next_Y_portfolio_size += ((nr_curr_stocks*next_y_price))
     #print(next_Y_portfolio_size)
   p.y_size(year+1, next_Y_portfolio_size)

 return p.portfolio_size
df = pd.DataFrame()
final_return_values = []
for i in range(NR_SIMULATIONS):
 returns = generate_returns()
 df[i] = list(returns.values())
 final_return_values.append(list(returns.values())[-1])

fig = plt.figure()
fig.suptitle("Simulated    portfolio    returns    with    "    +
str(NR_MID_CAP_STOCKS) + " Mid Cap & " + str(NR_LARGE_CAP_STOCKS) + "
Large Cap stocks")
plt.xlabel('Year')
plt.ylabel('Portfolio value (SEK)')
plt.plot(list(returns.keys()), df)
plt.show()
```

```
plt.xlabel('Year')
plt.ylabel('Average portfolio value (SEK)')
plt.plot(list(returns.keys()), df.mean(axis=1))
plt.show()

print("Mean    portfolio    return    (final    year's    value):    ",
round(np.mean(final_return_values),2))
print("Quantile (25%): ",np.percentile(final_return_values,25))
print("Quantile (75%): ",np.percentile(final_return_values,75))

plt.hist(final_return_values,bins=100)
plt.axvline(np.percentile(final_return_values,25),          color='r',
linestyle='dashed', linewidth=2)
plt.axvline(np.percentile(final_return_values,75),          color='r',
linestyle='dashed', linewidth=2)
plt.xlabel('Final portfolio value (SEK)')
plt.ylabel('# portfolios')
plt.show()
```

Appendix E

Tickers							
AAK	EQT	MYCR	THULE	BETSB	EOLUB	KOPY	RAYB
ADDTB	ERICB	NCAB	TRELB	BINV	EWRK	LEO	REJLB
AFRY	ESSITYA	NCCB	TRIANB	BMAX	EXPRS2	LIME	RENEW
ALFA	EVO	NDA	TROAX	BONAVA	EXS	LINC	RESURS
ALIFB S!	FABG	NENTB	VITB	BONAVB	FASTAT	LOGIA	RFAST
ANODB	FAG	NEWAB	VITR	BONEX	FG	LOGIB	RROS
ARJOB	FOIB	NIBEB	VNV	BRE2	FINGB	LYKOA	RUG
ASSAB	FPARA	NOLAB	VOLCARB	BRGB	FMMB	MANG	SAS
ATCOA	GARO	NP3	VOLO	BRINB	FNM	MCAP	SCST
ATRLJB	GETIB	NYF	VOLVB	BTSB	FNOVAB	MEKO	SEDANA
AXFO	HEBAB	OEMB	WALLB	BULTEN	FPIP	MILDEF	SEMC
AZA	HEM	PEABB	WIHL	BUSER	G5EN	MINEST	SEYE
BALDB	HEXAB	PLAZB	XACTHDI	CALTX	GAPW	MMGRB	SFAST
BEIAB	HMB	PNDXB	XACTVIN	CAMX	GENO	MNTC	SHOT
BEIJB	HMS	RATOB	ABSO	CANTA	GHP	MSONA	SIGNUP
BFG	HOLMB	RVRC	ACAD	CATA	GPG	MSONB	SIVE
BHG	HPOLB	SAABB	ACAST	CATB	GREEN	MTGA	SOLT
BICO	HTRO	SAGAA	ACCON	CCC	GRNG	MTGB	STEFB
BILIA	HUFVA	SAND	ACQSPAC	CEVI	HAYPP	NELLY	STRLNG
BILL	HUSQB	SAVE	AGROUP	CHECK	HLDX	NETEL	STUDBO
BIOAB	ICA	SBBB	AJAB	CIB	HNSA	NETIB	SVOLA
BIOGB	INDT	SCAB	ALCA	CIBUS	HOFI	NMAN	SVOLB
BIOT	INDUA	SDIPB	ALIG	CLAB	HUM	NOBI	SYNACT
BOL	INSTAL	SEBA	AMAST	CLASB	HUMBLE	NOBINA	SYNSAM
BOOZT	INTRUM	SECTB	AMBEA	COLL	IDUNB	NORBB	SYNT
BRAV	INVEB	SECUB	ANNEB	COOR	IMMNOV	NOTE	TEQ
BUFAB	JM	SF	AQ	CPACSPA(	INWI	NPAPER	TETY
BURE	KARO	SHBA	ARISE	CRADB	IPCO	NWG	TFBANK
CARY	KFASTB	SINCH	AROS	CS	IRLABA	NYTTO	THUNDR
CAST	KINDSDI	SKAB	ASPIRE	CTEK	ISOFOL	OP	TOBII
CATE	KINVB	SKFB	ATIN	CTM	ITAB	OPTI	TRACB
CINT	KLED	SKISB	ATT	CTT	ITABBTAI	ORES	TRAINB
COIC	LAGRB	SOBI	AWRD	DIST	IVACC	OVZON	TRAINBTA
COREA	LATOB	SSABA	AZELIO	DOXA	IVSO	PACT	TRANS
CREDA	LIAB	STORB	BACTIB	DSNO	JOMA	PAGERO	VBGB
DIOS	LIFCOB	SWECB	BAHNB	DUNI	K2AB	PIERCE	VEFAB
DOM	LOOMIS	SWEDA	BALCO	EAST	KABEB	PLEJD	WBGRB
DUST	LUNDB	SWMA	BEGR	EG7	KAMBI	PRFO	XANOB
EKTAB	LUNE	SYNCB	BELE	ELANB	KAR	PRICB	XBRANE
ELUXB	MCOVB	SYSR	BERGB	ELOSB	KJELL	PROB	XVIVO
EPIA	MIPS	TEL2B	BESQ	ELTEL	KNOW	PSCAND	ZZB
EPROB	MTRS	TELIA	BETCO	ENEA	KOBRB	QLINEA	