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Degree of Active Management and Performance of Storebrand's ESG-labeled Mutual Funds

Master Thesis

by
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MSc in Finance

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ABSTRACT

This thesis investigates whether Storebrand's ESG labeled mutual funds can outperform their benchmarks, and how likely that is. We analyze five active mutual funds that have high scores on Storebrand's proprietary sustainability index. We apply performance and active management measures that are well known in the finance literature. Simulation methods are also conducted to calculate the probability of outperformance. In addition, we apply the Black-Litterman framework to calculate the loss in expected risk-adjusted returns as a result of a smaller investment universe. We find that the higher fees of Storebrand's high-ESG mutual funds significantly harm performance, and lower the probability of outperformance. Finally, the exclusion of certain stocks or sectors can have notable impact on the Sharpe Ratio.

Acknowledgements

This thesis marks the end of our Master of Science in Finance at BI Norwegian Business School. Despite the Covid-19 pandemic, it has been two exciting years of intense learning of what we find most interesting: financial markets.

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1 Introduction

There has been a growing emphasis on environmental, societal, and governmental (ESG) issues in the recent decade. This movement is incontestably evident in finance, as investors are increasingly aware of how their money is managed when they invest in mutual funds. As Hartzmark and Sussman, 2019 discover, investors value sustainability, although there are disputes about whether high-sustainability funds outperform low-sustainability funds. In this thesis, we aim to contribute to the literature on whether ESG-labeled mutual funds provide excess returns above their benchmarks. The higher cost of ESG-labeled funds compared to passive funds is also discussed. This has led to the following research question:

How likely is it that Storebrand's ESG mutual funds will outperform their benchmarks net of fees?

In this thesis, we focus on Storebrand's ESG funds. Storebrand has been a leading institution in the marketing of sustainability and ESG. They have created an index of sustainability scores, and all of their ESG-related mutual funds have earned high sustainability scores.

The background for this thesis is partly due to the increased marketing of ESG funds and partly due to the higher cost of ESG funds marketed to individuals and institutions compared to the cost of general funds without the ESG label.

One argument that is widely used in ESG marketing is that the investor is doing good by valuing sustainability and, at the same time, can expect higher returns. We are curious whether this is true and, if so, how. Furthermore, ESG funds, labeled both as active and index-near, have relatively higher fees than their non-ESG counterparts. Therefore, it is interesting to examine if the ESG funds labeled as active are sufficiently active and deliver enough alpha to compensate for their higher fees.

ESG fund providers, such as Storebrand, tend to practice exclusion screening. That is, they divest or do not invest in so-called "sin stocks" or companies that contribute negatively to ESG issues. The exclusion of certain stocks or sectors, will decrease the investment universe, in which the mutual funds can invest. Therefore, in order to supplement to our primary research question, we investigate how risk-adjusted performance might change due to the exclusion of sectors with high-level emissions.

Getting insight into these questions would interest investors who consider investing in ESG funds, in general, and Storebrand's ESG funds, in particular. Investors would thus be in a better position to evaluate the likelihood that ESG funds will outperform their non-ESG labeled counterparts and make better and more rational investment decisions.

2 Literature Review and Theory

This section provides the reader with an overview of the current state in the finance literature regarding the debate on active versus passive management in mutual funds. We also review articles on ESG factors' effect on fund performance, and their implications are discussed. The Capital Asset Pricing Model is also discussed.

2.1 Review on the Literature Between Active vs Passive Management

There have been disputes within the finance literature on whether active management is able to outperform its benchmarks, especially after adjusting for its risk and costs. Fama, 1970, argues with his Efficient Market Hypothesis (EMH) that mutual funds should not be able to deliver excess returns over the market. Despite the research that suggests investing in actively managed mutual funds might be suboptimal, Gruber, 1996, provides a possible explanation of why investors buy actively managed funds. Gruber argues that funds are bought and sold at Net Asset Value (NAV). Hence, the management's ability may not be priced in. His reasoning thus arises because some sophisticated investors might recognize that a fund has superior management and might be able to benefit from this. Thus, investing in an actively managed mutual fund might be more rational than previously considered.

Since the scope of our thesis relates much to the active management of mutual funds, we find it necessary to define both active and passive investing. Passive investing aims at establishing a well-diversified portfolio of assets that represent the broad market and do not attempt to find over- or undervalued assets (Bodie et al., 2018). This is usually done by creating or buying an index fund, which can be done through Exchange Traded Funds (ETFs). An index fund is designed to replicate the performance of a broad index of stock, for example, the S&P500. Passive index funds are usually much cheaper than their active counterpart. Active investing contrasts with passive investing and often involves humans or computers making investment decisions. Active managers often rely on research, classified as fundamental or quantitative analysis. Either way, active investing incorporates other strategies aiming to deliver performance above benchmarks to generate excess returns. Due to the extra efforts and research for an active manager, they usually charge a substantially higher fee than their passive counterparts.

Malkiel, 2003, associates the EMH with the "random walk," a term in finance that represents the idea that prices move randomly from one point in time to another. The random walk model has proved challenging to beat, especially in forecasting exchange rates, as Meese and Rogoff, 1983, documented. The random walk model assumes that price changes are unpredictable and that the market reflects all available information. Furthermore, Malkiel, 2003, postulates that passive management would still be effective in an inefficient market because after one accounts for the additional expenses of active management, most investors seem to underperform the market.

Sorensen et al., 1998, believe that active managers are likely to perform better during bear markets, and passive managers are likely to perform better during bull-market years. In conclusion, Sorensen and colleagues argues that optimal allocation still allocates a remarkable weight to index-tracking products.

Kosowski et al., 2006, applied a bootstrap technique to investigate the performance of U.S. mutual funds. Their findings reveal that luck cannot solely explain mutual funds' performance. A "sizable minority," as they put it, was able to select stocks skillfully enough to more than compensate for their costs.

French, 2008, compares the cost of active investing to the scenario of passive investing. He estimates that 0.75% of the value of all NYSE, Amex, and NASDAQ stocks in 2006 was used to pay fees related to mutual funds, hedge funds, and funds of funds. In the passive investing scenario, investors pay fewer fees. Hence, he estimates that the cost of passive investing was only 0.09% of the aggregate market cap in 2006. This implies that the average annual cost of price discovery is 0.66%. French goes on to claim that active investing is a negative-sum game. Furthermore, overconfidence may lead to more active investing, regardless of whether the investor is skillful. In conclusion, French believes that the typical investor would increase his annual returns by 67bps over the 1980-2006 period if he were to follow a passive investing strategy.

2.2 Review on ESG Effect in Financial Markets

ESG factors have been increasingly important for investors in recent decades. Investors want to invest in more sustainable assets and are more conscious of ESG when investing in new assets. This has been a remarkable market opportunity for providers of ESG-friendly financial assets, but it also allows for opportunistic ways to make money, a concept known as ESG washing. Unfortunately, insufficient regulation in the ESG investment area has made it hard for investors to differentiate between assets and funds with vigorous ESG documentation and those making deceptive statements about their ESG practices. Candelon et al., 2021, prove that this is undoubtedly the case. Furthermore, they find that some managers present themselves as socially responsible but do not invest accordingly.

Statman, 2000, found that socially responsible stocks and mutual funds did better than their conventional counterparts over the 1990-98 period, but their risk-adjusted returns were not statistically significant. Bauer and colleagues' results conform with what Statman found (Bauer et al., 2005). Their results indicate that ethical mutual funds did not provide statistically different risk-adjusted returns than their conventional counterparts in the 1990-2001 period.

Borgers et al., 2015, find that weightings to socially sensitive stocks are smaller for funds that focus on attracting socially conscious investors. However, the document that exposures to socially sensitive stocks are not adequate across their universe of mutual funds to induce variability in their returns. Borgers and colleagues' investigations were done on U.S. equity mutual funds from 2004 to 2012.

El Ghoul and Karoui, 2017, study corporate social responsibility (CSR) reverberations on fund performance and flows. Their sample is on equity mutual funds over the 2003-2011 period. Their article discovered that CSR is negatively related to risk-adjusted performance, return volatility, R-squared, number of stocks, and the expense ratio, given their determinants of CSR. Furthermore, they argue that high-CSR funds may have trouble captivating performance-chasing investors due to relatively poor and persistent performance in high-CSR funds.

To summarize, it is evident that some fund managers act opportunistically and practice ESG-washing. This may be because ESG-friendly funds often tend to have higher fees than their conventional counterparts, and ESG-washing may help attract fund inflows. In addition, evidence in the literature indicates that some ESG-friendly funds might have done better than conventional funds. However, ESG-friendly funds seem not to provide statistically different risk-adjusted returns. In conclusion, there is vagueness and uncertainties related to whether ESG-friendly funds outperform conventional funds.

2.3 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) was introduced in the 1960s by Treynor, 1961, Sharpe, 1964, Lintner, 1965, and Mossin, 1966. They built on the work introduced by Markowitz in 1952. CAPM states that the expected return of an asset is related to the ex-ante expected return of the market and adjusting for how the asset relates to the systematic risk or non-diversifiable risk. The CAPM equation is given by Equation (1):

$$r_i = r_f + \beta_i(r_m - r_f) \tag{1}$$

where the beta is given by:

$$\beta = \frac{cov(r_i, r_m)}{\sigma^2(r_m)} \tag{2}$$

where $cov(r_i, r_m)$ is the covariance between asset i and the market, and $\sigma^2(r_m)$ is the variance of the market.

Thus, we see that the beta functions as a measure of how responsive the asset is to the market and hence denotes how exposed the stock or asset is to the overall market or benchmark.

We can illustrate the equations above by presenting the Security Market Line (SML) in Figure 1. The SML is a graphical way to illustrate the CAPM. It shows the expected return of an asset as a function of the beta, or systematic market risk, which is assumed to be non-diversifiable. Proponents of the EMH often advocate that asset prices quickly react to news and are reasonably priced. Moreover, advocates of EMH typically believe that active management is a “wasted effort” (Bodie et al., 2018). It is then given that, in market equilibrium, assets will lie on the SML. On the other hand, opponents of the EMH will typically argue that assets tend to be mispriced and that assets can and do deviate from their fair or intrinsic market values. Given that crises and market anomalies do occur, it is hard to advocate in favor of the EMH.

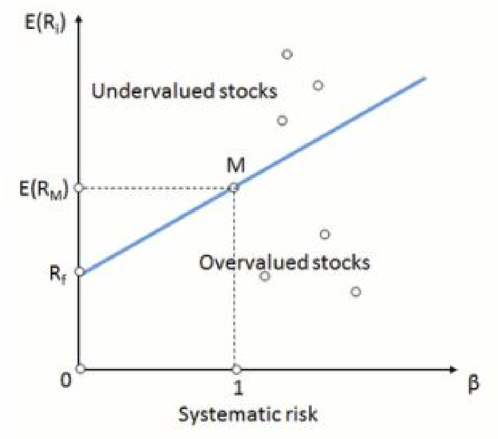

Figure 1: The Security Market Line

Beta, or systematic risk is shown on the x-axis, while expected return is shown on the y-axis.

2.3.1 Jensen’s Alpha

Jensen’s Alpha was introduced in 1968 by Michael Jensen, and builds on the work of the CAPM model. The alpha is calculated by running the following regression:

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_j(r_{m,t} - r_{f,t}) + \epsilon_{j,t} \tag{3}$$

where the subscript t designates an interval of time w.r.t. the starting and ending dates (Jensen, 1968). If a portfolio manager is skilled, his portfolio will earn a higher risk premium given its level of risk. Moreover, if a portfolio manager earns the same return as implied by his given risk level, the above equation will be equal to zero. Hence, to allow for higher returns implied by the risk level, we introduce the alpha, j, the possibility of a non-zero constant in Equation (3). If a portfolio manager is skilled, the alpha in Equation (3) will be positive. As Jensen, 1968, states, the alpha denotes the average return per interval of time over or under than its beta would suggest.

Jensen found that the 115 mutual funds he investigated in 1945-1964 were, on average, unable to deliver positive alpha, even when considering returns gross of fees. Those are findings that conform to the EMH (Fama, 1970). It is noteworthy that the alpha and CAPM itself have been criticized several times, often for their simplicity and especially regarding to which extent EMH is valid, on which CAPM builds its assumptions.

2.3.2 The Black-Litterman Framework

The Black-Litterman model is an asset allocation model, introduced by Fisher Black and Robert Litterman in 1990. It is a method to construct portfolios with risky assets. The Black-Litterman model differentiates itself from regular Markowitz portfolio optimization in that it allows the investor to consider subjective market views and incorporate this into the model.

The model uses equilibrium returns as the neutral starting point, which is the returns that clear the market. The assumption regarding equilibrium returns is derived from the CAPM, which substitutes an unstable estimate, the first order moment, ie., the mean vector, the expected return. Instead, new estimates are derived using inputs from second order moments, i.e., covariance, which are thought to be more robust than first order moments. A reverse optimization method is used to calculate the implied equilibrium returns for any risky assets considered. The generated set of equilibrium expected returns construct the market portfolio when applied in a portfolio optimizer with a given risk level. Thus, the only expected return assumption one needs is one of the broad market.

3 Methodology

This section highlights the methodology we use to answer our research question. We use a range of performance and active management measures well-documented in the finance literature. We explain their relevance, and show how they are calculated.

3.1 Performance and Active Management Measures

3.1.1 Subtraction Alpha

The first measure we consider is the Subtraction Alpha (SA). This difference shows what an investor would get beyond by simply investing in the benchmark. If the SA is positive or negative, then this is a sign that the portfolio has deviations from its benchmark. Moreover, if the differential return is positive, this would indicate that the portfolio manager can deliver returns in excess of the benchmark's, and vice versa if negative. The SA is the differential return between a portfolio and its benchmark, and is calculated as follows:

$$SA = R_p - R_b \tag{4}$$

3.1.2 Sharpe Ratio

In 1966, William F. Sharpe introduced the reward-to-variability ratio, better known as the Sharpe Ratio (SR), as a measure of the performance of mutual funds, investment security, or portfolio. The ratio measures the performance, i.e., its returns, compared to a risk-free asset while adjusting for its risk. The risk-free asset is the risk-free rate in the finance literature, symbolizing the return an investor would get by taking no (theoretical) risk. We often use volatility, or standard deviation, to assess the risk of an investment security. The Sharpe Ratio formula is shown in Equation (5):

$$SR = \frac{E[R_A - R_f]}{\sigma_A} \tag{5}$$

where E = expected value notation, R_A = asset return, R_f = risk free rate, σ_A = standard deviation of the asset's excess return.

We also consider the Sortino Ratio, which is very similar to the Sharpe Ratio. The Sortino Ratio is calculated using the same formula as the Sharpe Ratio, but only using negative returns when calculating the volatility. The rationale is that investors only care about downside volatility, as upside volatility is considered positive.

3.1.3 Tracking Error

Tracking Error (TE) measures the volatility of the portfolio's active returns. It is defined by the difference in standard deviation between the asset return and its benchmark return. The formula is as follows:

$$TE = \sigma(R_p - R_b) = \sigma(R_A) \tag{6}$$

where σ = standard deviation, R_p = the mutual fund's or portfolios return, R_b = return of the benchmark.

Petajisto, 2013, finds that the average TE for closet-indexers is around 3.5%, while moderately active funds usually lie around 6%. This is, however, often seen in conjunction with Active Share, where a low value of Active Share and low Tracking Error represent closet-indexers. In addition, the European Securities and Markets Authority (ESMA) presented a statement regarding closet indexers and defined that funds with a TE of less than 4% were classified as potentially being closet-indexers (ESMA, 2016). Hence, we will use the 4% threshold in our analysis of whether the mutual funds analyzed are potentially being closet-indexers or not.

3.1.4 Information Ratio

The information ratio (IR) measures a portfolio's returns beyond the benchmark returns, adjusted for the volatility of those returns. The IR is therefore considered as a measure of a manager's ability to produce excess returns relative to a benchmark but also accounting for the Tracking Error or the volatility of the portfolio and the benchmark.

The SR and IR are closely related but have notable differences. Pedersen, 2019, discusses that the SR gives credit for all excess returns, while the IR gives credit for the risk-adjusted abnormal return. The former is a return that is excess of the risk-free rate, while the latter is a return that is excess of the benchmark return. The IR is calculated as follows:

$$IR = \frac{E[R_p - R_b]}{\sigma(R_p - R_b)} \tag{7}$$

As we see, the denominator corresponds to the Tracking Error.

Jacobs and Levy, 1996, states that a good manager might have an IR of 0.5, while an exceptional manager might have one of 1.0. However, whether this came from theory or empirical evidence was not stated.

3.1.5 R-Squared

Another popular measure used in finance academics is the R-squared. This measure allows us to see how the benchmark returns explain mutual fund returns. The maximum R-squared is 1. Thus, a higher R-squared means that the benchmark returns explain more of the mutual funds' returns. As such, a high R-squared would indicate a lack of active management.

The R-squared is found by running a regression, and the R-squared is given to us by our statistical software. However, the mathematical formula for R-squared is as follows:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{8}$$

The numerator in Equation (8) shows the sum of the squared distance between the actual value of the dependent variable y_i and the estimated value $\hat{y}_i$. The denominator shows the sum of the squared distance between the actual value and the mean $\bar{y}_i$.

Another way of interpreting the R-squared in finance is by taking one minus the R-squared. Since the R-squared measures how much returns of the mutual fund are explained by benchmark returns, taking one and subtracting the R-squared tells us how much of the returns are explained by active management of the mutual fund.

$$R_{active} = 1 - R^2 \tag{9}$$

ESMA, 2016, extended its statement regarding classifications of closet-indexers and stated that an R-squared of more than 0.95 could potentially be closet indexers. Thus, we have a second criterion in addition to the TE threshold on whether to classify mutual funds as closet-indexers or not.

3.1.6 Probability of Outperformance

We also consider the method of Bjerksund and Døskeland, 2015, to calculate the probability that a mutual fund will outperform its benchmark. First, we would find the difference between the cost of the mutual fund and that of the passive fund. Second, we would want to determine how probable it is that the active return surpasses this cost found in the first step. If we assume that the active return is normally distributed, this can be expressed mathematically in Equation (10):

$$P(R_A > Cost_{Diff}) = 1 - F\left(\frac{(Cost_{diff} - 0\%) * H}{TE\sqrt{H}}\right) \tag{10}$$

F is the cumulative distribution function for a standard normally distributed variable. TE is the tracking error, and H is the investment horizon. 0% in the equation comes from assuming that the expected excess return for actively managed funds equals 0%. Bjerksund and Døskeland, 2015, postulates that it is not an unreasonable assumption, given evidence on mutual fund performance in the literature.

3.1.7 Active Share

Another measure of active management is Active Share (AS). The measure was first introduced by Cremers and Petajisto, 2009. This measure shows how much of the portfolio holdings deviate from its benchmark holdings. Cremers and Petajisto emphasize that Active Share is best utilized with Tracking Error to span two dimensions of active management. In their article, Cremers and Petajisto find that AS predicts fund performance. Funds with higher AS tend to outperform their benchmarks before and after expenses. Hence, a high AS is necessary to generate alpha above the benchmark. Active Share is defined with Equation (11):

$$AS = \frac{1}{2}\sum_{i=1}^{N} |w_{p,i} - w_{b,i}| \tag{11}$$

where $w_{p,i}$ is the weight of stock i in the fund's portfolio, $w_{b,i}$ is the weight of the same stock in the fund's benchmark index.

In this thesis, we failed to calculate a time series on Active Share on our mutual funds and benchmarks due to insufficient data. We were able to extract some data from Bloomberg and Refinitiv Eikon. However, the data was insufficient to connect the respective holdings and provide an accurate and reliable calculation of Active Share. Furthermore, the license to extract the appropriate data far exceeds the budget for this thesis. Hence, we unfortunately decided to skip the calculation of Active Share in this thesis.

4 Data

This chapter gives an overview of how we collected the data needed to conduct our analysis. We also present some descriptive statistics regarding our data. Finally, we conduct some diagnostic testing.

4.1 Data Collection

In order to answer our research question, we need the Net Asset Value (NAV) of the mutual funds we have chosen and their respective benchmarks, as well as the risk-free rate. Therefore, we collected all necessary data regarding our mutual funds from a Bloomberg Terminal. In addition, to perform our Black-Litterman analysis, we collected weekly data on sector prices on the Norwegian Stock Exchange, from January 2005 through May 2022.

4.1.1 Fund Selection

Since this thesis aims to analyze whether Storebrand's sustainable mutual funds can outperform its benchmark, we selected mutual funds that are marketed as ESG-friendly or sustainable. Those include five actively managed mutual funds that aim to deliver returns over their benchmark. An overview of the fund selection, their benchmark, and fee structure is provided in the table below, as well as Storebrand's proprietary sustainability score and active share for each fund.

Fund Name	Benchmark	Annual Fee	Sustainability Score	Active Share	AUM (mNOK)
Storebrand Global Solutions A	MSCI All Countries	0,75 %	9	96 %	9056
Storebrand Norge A	Oslo Børs Fondsindeks	1,50 %	8	39 %	952
Storebrand Norge Fossilfri	Oslo Børs Fondsindeks	1,50 %	8	33 %	1779
Storebrand Verdi A	Oslo Børs Hovedindeks	1,50 %	7	33 %	1794
Storebrand Vekst A	Oslo Børs Hovedindeks	1,50 %	7	77 %	606

Table 1: Overview of Selected Mutual Funds

Overview of the selected mutual funds with their respective benchmarks, fee structure, sustainability scores, reported Active Share and AUM. Active Share retrieved as of 31.12.2021. AUM retrieved as of 30.04.2022.

When analyzing net returns for benchmarks, we assume an annual fee of 0.20%, which is equal to the usual cost of an index funds in Norway and worldwide.

A short summary of each mutual fund as well as Storebrand's own Sustainability Score is provided below.

Storebrand Global Solutions is a fossil-free, actively managed equity fund that invests in stocks positioned to solve challenges related to the UN's sustainability goals. This means that the fund invests in firms with solutions relating to climate, sustainable cities, and responsible consumption. The fund's goal is to deliver long-term excess returns over its benchmark. Furthermore, the fund invests in the global market, including emerging markets. Lastly, the fund follows Storebrand's proprietary standard for sustainable investments, which means the exclusion of several firms.

Storebrand Norge invests in big, medium, and small Norwegian firms and is diversified across sectors. The fund contains a selection of stocks not found in Storebrand's broader funds. In addition, the fund follows Storebrand's standard for sustainable investments, which means the exclusion of several firms.

Storebrand Norge Fossilfri is an actively managed fund that mainly invests in stocks listed on the Oslo stock exchange. The fund excludes firms in the energy sector that make up 20% of the Oslo stock exchange because they are in the energy sector. This is because the fund does not invest in firms with their primary business related to oil- and gas extraction. The fund does, however, invest in firms that operate in solar and hydropower. The fund's goal is to deliver returns over its benchmark. Norge Fossilfri follows Storebrand's standard for sustainable investments, which excludes several firms.

Storebrand Verdi is a factor fund investing in value stocks at the Oslo stock exchange. The manager of the fund has the potential to overweight the large firms in the Norwegian market. It is stated that the fund, over time, will be overweight in big and medium firms compared to the fund's benchmark. Verdi follows Storebrand's standard for sustainable investments, which means the exclusion of several firms.

Storebrand Vekst is a factor fund investing in growth stocks at the Oslo stock exchange. The manager takes on selective bets, especially on the smaller firms in the Norwegian market. As a result, the fund, over time, will be overweight towards medium and small enterprises compared to the fund's benchmark. In addition, the fund follows Storebrand's standard for sustainable investments, excluding several firms.

Storebrand's Sustainability Score measures both risk and opportunities in conjunction with ESG. The scores are measured from one (poor) to ten (best) and are based on the sustainability score of the companies in the fund. The score is used to optimize portfolios towards better companies and compute Storebrand's fund label, making it easier to pick the most sustainable fund products.

The sustainability score is computed for over 4500 companies and is scaled from 0 to 100. It consists of two components: ESG risk and SDG opportunities, each representing 50% of the total score. ESG risk consists of data from Sustainalytics ESG Rating and measures companies' exposure to and governance of financial-related sustainability risk. The SDG component analyzes ESG data sources to identify companies with products and services that contribute positively towards accomplishing financial-related sustainability objectives.

4.1.2 Time Period

In this thesis, we are using monthly data up until the end of March 2022. The starting point for each fund differs as some mutual funds are older than others. Nonetheless, we have collected data for the whole period the fund has existed. For Global Solutions, we have monthly data since December 2000 and Fossilfri since April 2017. For the three funds, Storebrand Norge A, Vekst and Verdi, we have monthly data since September 1999.

Thus, we have an extended sample that includes several market crashes along the way. This may lead to some extreme observations in our results and may thus produce a different view than otherwise would, also depending on the market environment one experiences now and the time horizon for investment for the investor. However, financial crashes and financial crises are part of financial markets' nature and occur occasionally. Therefore, simply eliminating market crashes due to outliers is certainly not desirable.

The performance measures are very susceptible to changes in the period due to the abovementioned factors. Thus, we always use the same period for the mutual fund and their respective benchmark when evaluating it.

4.1.3 Risk-Free Rate

Due to the scope of our thesis and our fund selections, we have used the ten-year yield on Norwegian government bonds as a proxy for the risk-free rate in our calculations, as we believe it is the most accurate representation of the risk-free rate for a Norwegian investor, as well as the mutual funds are Norwegian and the benchmarks alike. The only exception is Storebrand Global Solutions, a global fund owning international companies with a global benchmark. We used the US ten-year government yield as the risk-free rate in this case. Going forward, when we mention "excess returns," we refer to returns over the risk-free rate.

4.2 Descriptive Statistics

In this section we will provide some statistical analysis on the returns of our chosen funds.

Funds and Benchmarks	Expected Return	Standard Deviation	Skewness	Kurtosis	Max Drawdown
Storebrand Global Solutions A	15,40 %	11,68 %	-0,51	3,26	10,77 %
Storebrand Norge A	8,95 %	21,40 %	-1,49	8,50	59,52 %
Storebrand Norge Fossilfri	12,06 %	13,03 %	-0,46	6,61	18,14 %
Storebrand Verdi A	10,85 %	19,68 %	-1,30	7,79	54,90 %
Storebrand Vekst A	10,65 %	24,60 %	-0,53	6,87	69,80 %
MSCI All Countries*	14,66 %	10,34 %	-0,63	3,22	9,62 %
Oslo Børs Fondsindeks**	8,87 %	21,26 %	-1,53	8,80	62,11 %
Oslo Børs Hovedindeks*	9,15 %	20,31 %	-1,32	7,39	58,25 %

Table 2: Descriptive Statistics of the Mutual Funds

Descriptive statistics of our chosen funds and their benchmarks. Data is gross of fees. Mean and standard deviation are annualized. *Benchmarks are marked with an asterisk. **The information for Oslo Børs Fondsindeks is computed with the same sample period as for Storebrand Norge A.

We observe that our data is skewed to the left. Much of this is probably due to our sample containing several market crashes, and stocks tend to decline more rapidly than they increase. As the saying goes: "Up the stairs, down the elevator." Negative skewness is, therefore, to be expected. We also notice a relatively high kurtosis, which is also expected given our sample period and for the aforementioned reasons. Norge A has a lower expected return than their benchmark, even before adjusting for fees. Global Solutions, Norge Fossilfri, Vekst, and Verdi exhibit slightly higher expected returns than their benchmarks, although the data is gross of fees. All mutual funds also exhibit marginally higher volatility than their benchmark, except for Storebrand

Verdi, which has an annualized volatility of 19.68% compared to its benchmark with 20.31%.

Table 3 below provides a correlation matrix of the funds and their benchmarks. Because the funds differ dramatically in terms of observations and period, we have used the correlation of the last five years to capture the correlations between all the funds. It may be worth mentioning that correlations can change during different macroeconomic environments, and correlations in financial assets usually tend to increase in the case of market turmoil. Nevertheless, as we can see, the correlations between some of the funds are pretty high.

	Oslo Børs Fondsindeks (1)	**Oslo Børs Hovedindeks (2)**	**MSCI All Countries (3)**	**Norge A (4)**	**Global Solutions (5)**	**Verdi (6)**	**Vekst (7)**	**Fossilfri (8)**
1	100 %							
2	99 %	100 %						
3	56 %	54 %	100 %					
4	97 %	96 %	52 %	100 %				
5	49 %	45 %	86 %	49 %	100 %			
6	95 %	96 %	47 %	94 %	39 %	100 %		
7	86 %	84 %	52 %	89 %	47 %	76 %	100 %	
8	90 %	87 %	55 %	91 %	57 %	83 %	83 %	100 %

Table 3: Correlation Matrix

Correlation matrix of the funds and their respective benchmarks, last five years.

Storebrand Norge A has a 0.97 correlation with its benchmark, which is amongst the highest of the mutual funds. Further, the correlations from the mutual funds and their benchmarks range from 0.84 to 0.97, whereas Storebrand Vekst has the lowest correlation of 0.84.

4.3 Diagnostic Testing

Some diagnostic testing is done to ensure we obtain valid and reliable results from our regressions in section 5. There are five classic Ordinary Least Squares (OLS) assumptions to confirm not having spurious regressions:

$$E(u_i) = 0 \tag{12}$$

$$Var(u_i) = \sigma^2 < \infty \tag{13}$$

$$Cov(u_i, u_j) = 0 \tag{14}$$

$$Cov(u_i, x_i) = 0 \tag{15}$$

$$u_t \sim N(0, \sigma^2) \tag{16}$$

In order to have valid estimations, all five assumptions must hold. Equations (12)-(16) show the mathemathical formulations of the assumptions. However, we will skip elaborating on those assumptions as it adds little value to our thesis objective. The results from our calculations relating to the diagnostic tests are documented in the Appendix.

To summarize, we checked whether the mean of residuals equals zero, which is confirmed by our calculations. To test for heteroscedasticity, we applied White's test. The null hypothesis is that the data is heteroscedastic. Results show that the data is somewhat heteroscedastic, which means that estimators may not be as precise. Some heteroscedasticity is however common in financial time series. To check for autocorrelation, we employed the Durbin-Watson (DW) test. The DW test statistic ranges between zero and four. A value of two indicates that there is no autocorrelation in the data. Values ranging between zero and two indicate positive autocorrelation and vice versa for values between two and four. Our results show that our data may have slightly positive autocorrelation, as the test statistic is slightly below two for four of the five funds. We proceeded with the fourth OLS assumption to check whether the correlation between the residuals equals zero, and this was indeed the case. The last regression assumption is the assumption about normality, where we applied the Bera-Jarque test to see if the skewness and kurtosis match that of a normal distribution. The null hypothesis is that the data does have a normal distribution. We reject the null hypothesis for all our funds, as the distribution does not match a normal distribution. However, this is expected given a large amount of data and that financial crises often tend to create large sigma events.

5 Analysis

In this section, we use historical data to analyze the performance and degree of active management of the mutual funds. We will use two methods to compute the probability that the mutual funds will outperform their benchmarks net of fees. Lastly, we will perform an exercise based on the Black-Litterman framework to investigate the risk-adjusted effects the average investor can expect when decreasing their investment universe, which is the case Storebrand is doing for their mutual funds by applying exclusionary screening methods.

5.1 Performance Measures

We start this section of performance measures by looking at the historical performance of each mutual fund, both gross and net of fees, compared to their benchmarks. The historical performance is illustrated in the line chart to the left-hand side in Figure 2. This provides a compelling way to explain and view the impact of fees on the returns of the funds.

Every fund performs above its benchmark net of fees, except Norge A, where a profound effect of hefty fees is clearly illustrated. However, this statement only holds for the last observations, as fund performance tends to dip below its benchmark from time to time during the whole period. Thus, the net return for an individual investor will differ significantly, depending upon the investor's timing and holding period. We will later analyze how the holding period matters for an individual investor and consider different holding periods and the probability of outperformance that an investor can expect.

The first performance measure we consider is the Subtraction Alpha (SA). The bar charts to the right-hand side in Figure 2 below show the monthly

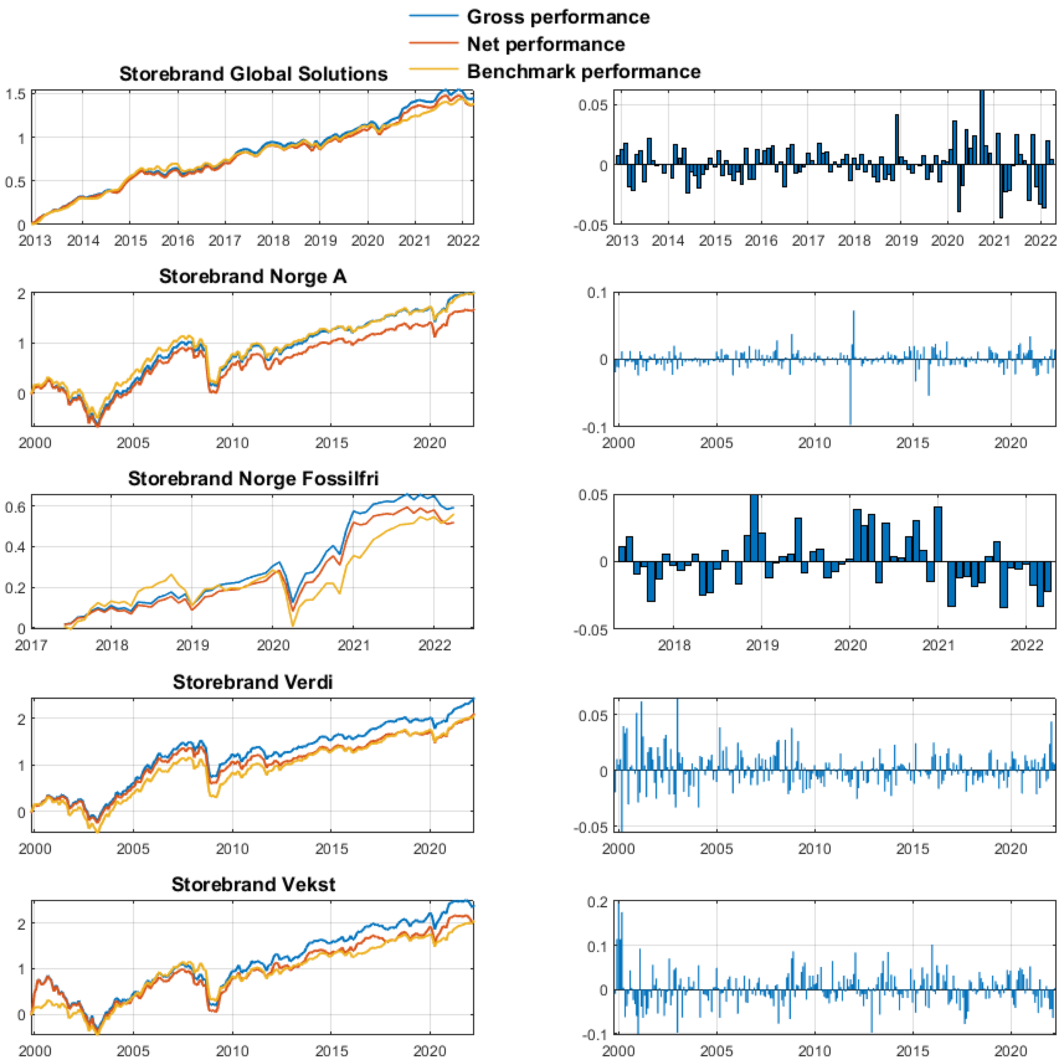

Figure 2: Historical Mutual Fund Performance and Subtraction Alphas

Left side: Overview of the evolution of price for the mutual funds and their benchmarks, gross and net of fees. Right side: Corresponding subtraction alphas for the respective mutual fund.

differential returns of our funds compared to their accompanying benchmarks. This gives a straightforward way to see how the funds perform monthly relative to their benchmarks. The SA seems not to contain any persistent pattern, which means that the level of randomness is relatively high when it comes to alpha generation. This is aligned with what Gallefoss et al., 2015 find, namely that some Norwegian mutual funds can give significant returns over their benchmark for up to one year, but not over a longer time horizon.

To further evaluate the historical performance of our mutual funds, we provide Sharpe Ratios, Tracking Errors, Information Ratios, and Sortino Ratios in Table 4. Calculations are net of fees.

Fund Name	Sharpe Ratio	Tracking Error	Information Ratio	Sortino Ratio
Storebrand Global Solutions A	1,08	5,6%	0,03	1,68
Storebrand Norge A	0,19	4,5%	-0,27	0,21
Storebrand Norge Fossilfri	0,70	6,6%	-0,10	0,79
Storebrand Verdi A	0,31	5,3%	0,08	0,34
Storebrand Vekst A	0,24	13,4%	0,04	0,30
MSCI All Countries*	1,20			
Oslo Børs Hovedindeks*	0,28			
Oslo Børs Fondsindeks*	0,25			
Oslo Børs Fondsindeks**	0,60			

Table 4: Performance Measures

Overview of the funds' Sharpe Ratio, Tracking Error, Information Ratio and Sortino Ratio. All numbers are reported net of fees. *Benchmarks marked with an asterisk. **SR of Oslo Børs Fondsindeks when computed with same time period as Norge Fossilfri.

First and foremost, we consider the Sharpe Ratio. The SR of the mutual funds' corresponding benchmarks is 1.2 for MSCI All Countries, and 0.28 for Oslo Børs Hovedindeks. The SR for Oslo Børs Fondsindeks is 0.25, using the period corresponding to Norge A. It is worth mentioning that the Sharpe Ratio of Oslo Børs Fondsindeks is 0.6 when using the period that corresponds to that of Norge Fossilfri. So, the performance measures depend strongly on the time period in which it is measured, which is important for like-for-like comparisons. Global Solutions, Norge A and Vekst A, posit a lower SR than their benchmarks. Verdi A and Norge Fossilfri have marginally higher Sharpe ratios than their benchmarks. However, the SR alone cannot tell whether a fund is sufficiently actively managed or is consistently outperforming. Nevertheless, three out of five mutual funds delivered poorer risk-adjusted returns than their corresponding benchmark, net of fees.

Next, we turn our eyes to the Tracking Error (TE). We stated earlier in section 3.1.3 that our criteria for labeling a fund as a closet-indexer was a TE of 4%. As we see, all our funds posit higher TEs than 4%. However, Norge A is just slightly above 4%, with a TE of 4.5%. Vekst A posits the highest

TE, netting out 13.4%. This may be because the fund seeks to replicate the growth factor, and the OSEBX is an index heavily tilted toward energy and value stocks.

Turning our eyes to the Information Ratio (IR), it is clear that all our funds show very low IR values, even negative ones. We stated earlier that a good manager has an IR of 0.5. None of our funds are above this threshold. A negative IR implies that the managers could not produce any returns over their benchmark. Thus, even though the funds dodged the 4% threshold for TE, it is questionable whether they delivered any returns over their benchmark after adjusting for the volatility of those actively managed returns.

We see that Global Solutions delivers the highest Sortino among the mutual funds, as with the SR. The high Sortino might be explained by the low maximum drawdown of Global Solutions, as the volatility of the negative returns will be relatively low.

5.2 Regression Results

We ran linear regressions for the mutual funds and their benchmark, where the excess returns of the mutual fund are the dependent variables, and the excess returns of the corresponding benchmarks are the explanatory variables. The regression results in Table 5 below are calculated using returns gross of management fees. The intercept has been annualized.

We observe that all the mutual funds generate positive alpha. However, only Storebrand Verdi A delivers a significant one. So, there is no statistical evidence that the mutual funds can generate superior returns over time compared to their benchmarks, even gross of fees. Furthermore, all the estimated

Fund Name	Alpha	t-stat	Beta	t-stat	R-squared
Storebrand Global Solutions A	0,0088	0,44	0,99	19,25	0,77
Storebrand Norge A	0,0020	0,21	0,98	75,81	0,96
Storebrand Norge Fossilfri	0,0308	1,17	0,78	15,61	0,81
Storebrand Verdi A	0,0223	2,06	0,94	61,21	0,93
Storebrand Vekst A	0,0137	0,48	1,02	25,25	0,70

Table 5: Gross of Fees Regression Results

Regression results for our mutual funds using returns gross of management fees. Alphas are annualized.

beta coefficients are close to 1, except for Norge Fossilfri, with a beta of 0.78. Additionally, all the beta coefficients are highly statistically significant. We note that Vekst A has a beta higher than 1. According to CAPM, the expected return should be higher than that of the market, or other assets with lower beta. However, from Table 1, we see that the expected return of Vekst A is in fact lower than Verdi A, with the same benchmark, despite Verdi A having a lower beta.

We defined earlier in section 3.1.5 the 0.95 thresholds for R-squared as being a closet-indexer. Here, Norge A has an R-squared of 0.96. This implies that only 4% of the returns are due to active management, and thus could be defined as a closet-indexer. Verdi A also posits a somewhat high R-squared, with a value of 0.93. The rest of the funds do not have any meaningful high R-squared in our stated sense.

We also ran the regressions net of fees, and we immediately observed the change in alpha. Results are reported in Table 6. None of the alphas are significant, and the alpha for Norge A even turned negative. Thus, when accounting for fees, it is apparent that none of the mutual funds deliver statistically significant alpha over its respective benchmarks. We will build further

Fund Name	Alpha	t-stat	Beta	t-stat	R-squared
Storebrand Global Solutions A	0,0032	0,16	0,99	19,25	0,77
Storebrand Norge A	-0,0110	-1,15	0,98	75,81	0,96
Storebrand Norge Fossilfri	0,0174	0,66	0,78	15,61	0,81
Storebrand Verdi A	0,0092	0,85	0,94	61,21	0,93
Storebrand Vekst A	0,0007	0,03	1,02	25,25	0,70

Table 6: Net of Fees Regression Results

Regression results for our mutual funds using returns net of management fees. Alphas are annualized.

on this finding when considering the probability of outperformance and using simulations to calculate outperformance probabilities.

5.3 Probability of Outperformance

The charts in Figure 3 below display the probability that the funds will outperform an index fund that tracks their benchmark, taking fees into account, for different levels of Tracking Error and horizon of investment. Using the Bjerksund and Døskeland, 2015 method, as introduced earlier, we see that probabilities at t = 1 start under 50%. From here on, it is only decreasing. Much of this is due to the assumption that we consider the case of no excess return above the benchmark. Given our findings of no statistically significant alpha in our regression, we consider this assumption to be reasonable.

Figure 3 is separated into two parts because Global Solutions is the only fund with a different fee level than the others. Hence, the curve will be the same for the four other mutual funds, given the assumptions on which we have built. For example, since Global Solutions has a tracking error of 5.6%, its probability of outperformance will be roughly 30% if your holding period is five years. Overall, the probability of outperformance is very low. In this model, we see with clarity the importance of having a high Tracking Error to justify a

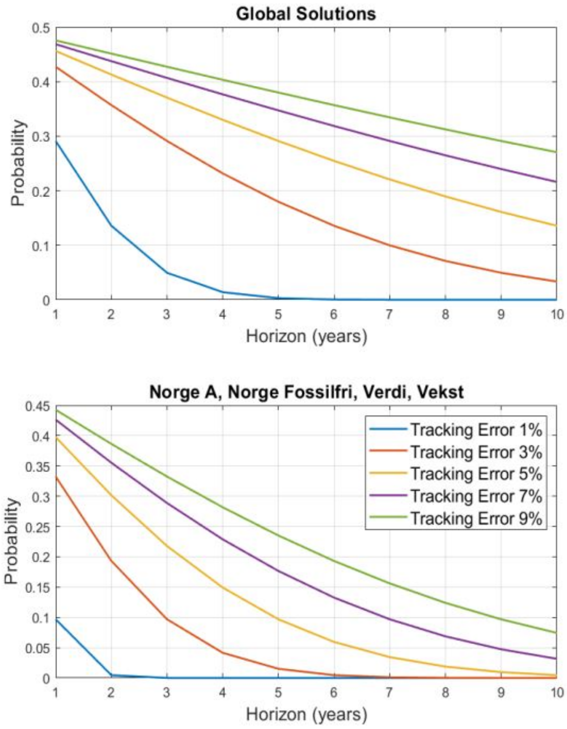

Figure 3: Probability of Outperformance

The probability that Global Solution will outperform its benchmark for different levels of tracking error and investment horizon.

higher fee structure. To conclude this section, given the assumptions we have built on, we have results that indicate in favor of passive index investing.

5.4 Monte Carlo Simulations using the Geometric Brownian Motion Model

We complement our analysis by performing Monte Carlo simulations on our funds and benchmarks, using a net of fees returns. We do so by employing a Geometric Brownian Motion model, which allows us to simulate sample price paths.

The Geometric Brownian Motion (GBM) is the most fundamental model of the value of a financial asset (Glasserman, 2004). It is a logarithmic augmentation of the stochastic continuous-time process Brownian Motion with drift.

To be considered a GBM, a stochastic process St must satisfy the following stochastic differential equation (SDE):

$$dS_t = \mu S_t dt + \sigma S_t dt W_t \tag{17}$$

W_t is a Wiener process, μ is the drift constant, or percentage expected return in our case, and σ, the percentage volatility constant. The first part of the equation models the deterministic part, or trend, whereas the latter segment is the stochastic motion, used to model the random events that eventuate during the trend.

We proceed with the model by specifying the correlation between Gaussian random variates drawn to generate the Wiener processes to account for comovement between the mutual funds and their respective benchmarks. Correlation structures are calculated between single funds and their respective benchmarks such that we utilize their whole period. By including the correlation structure between the mutual funds and the benchmarks, our simulations are more likely to represent real-world possibilities based on the historical correlation structure. Hence, we assume that the correlation between the mutual funds and their respective benchmarks is constant, although correlations may change over time in the real world. After running N simulations, we can proceed by calculating the probability of outperformance of our mutual funds as follows:

$$x_t = \begin{cases} 1, & \text{if } S_t > B_t \\ 0, & \text{otherwise} \end{cases}$$

where S_t is the simulated price of the mutual fund at time t, and B_t is the simulated price of the respective benchmark at time t. An illustration of simulated price paths is documented in the Appendix. The probability of outperformance is given by:

$$P(outperformance) = \frac{\sum_{i=1}^{N} x_t}{N} \tag{18}$$

We proceed in our Monte Carlo process by calculating our drift and volatility constants, net of fees. The volatility is assumed to be constant and we use the historical standard deviation as input. For the drift, we simply used the expected returns and assumed them to be constant.

Then, we ran 10,000 simulations over ten years, corresponding to 120 months. By applying the methodology described above, we calculated the probability that a mutual fund will perform above its benchmark for one, three, five, seven, and ten years. The results can be seen in Figure 4.

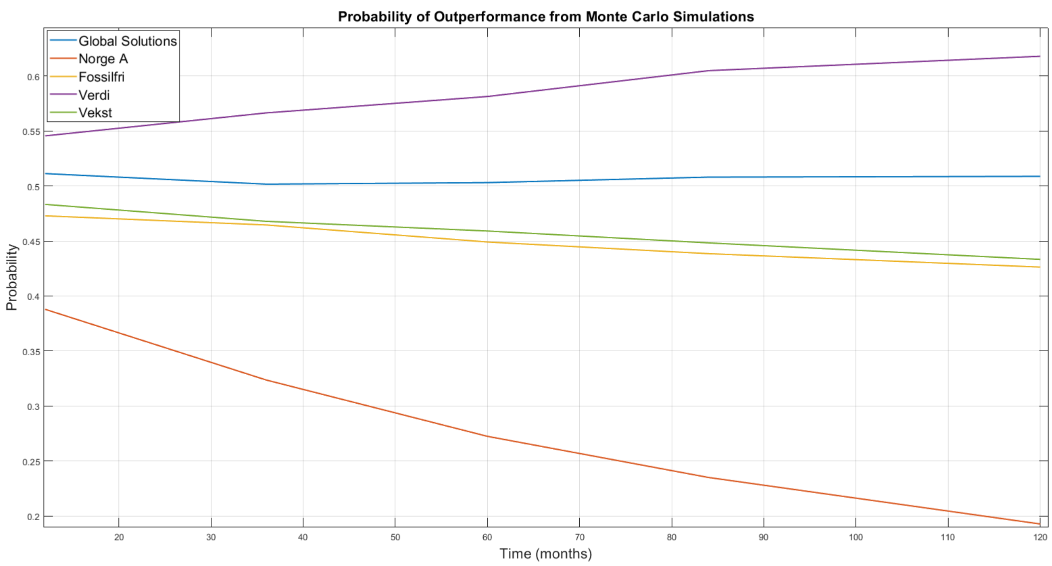

Figure 4: Probability of Outperformance from Monte Carlo Simulations

Plot of simulated probability of outperformance for 120 months for each mutual fund, where drift is set as the expected returns less the management fee.

From Figure 4, we observe that Storebrand Verdi is the only fund with an increasing probability of outperformance over time and has the highest probability of outperforming among all our simulated mutual funds over time. Storebrand Global Solutions shows a relatively flat probability of outperformance over time, around 50%. As for the last three funds, Vekst, Fossilfri, and Norge A show decreasing probability of outperformance. Most notably, Storebrand Norge A has only a 20% probability of outperforming its benchmark after ten years. It is fair to say that this correlates with our earlier findings regarding Norge A. This is also true for Fossilfri and Vekst, where performance measures were of questionable quality.

We also examine what happens with the probability of outperformance when we, based on our previous findings of no significant alphas, set the gross drifts for each mutual fund and benchmark equal to the expected return of the respective benchmarks, i.e., the mutual fund return will equal the market/benchmark return. Then, we adjust for management fees to obtain the net drift used in the GBM. We proceed by doing the same simulation as above and get the following output displayed in Figure 5.

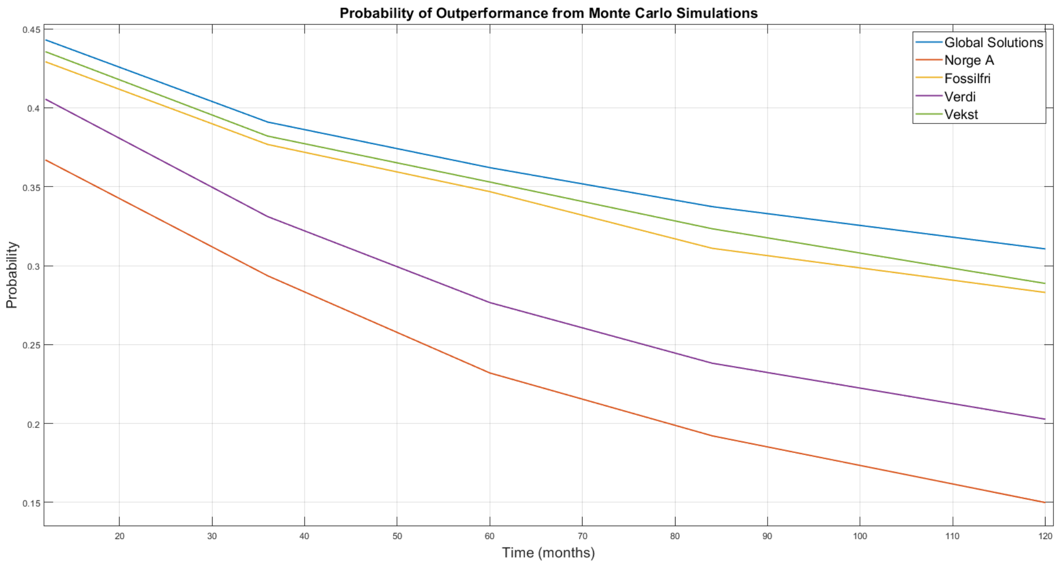

Figure 5: Probability of Outperformance from Monte Carlo Simulations with Equal Drift

Probability of outperformance with gross drift set to be equal for mutual fund and respective benchmarks, and subtracting management fees.

As we can see, Figure 5 looks very similar to that of Figure 3. This is mainly due to the fact that we allow no outperformance over its benchmark. As stated before, this assumption seems reasonable as alphas are not significant, and the randomness of the alphas generated by all mutual funds seems to be quite random.

Figure 6 illustrates the average simulated value of each mutual fund and corresponding benchmark for every time horizon we analyzed, based on the method used for Figure 5. We observe that all the benchmarks consistently outperform and are increasingly dispersed over time. Global Solutions is closer to its benchmark due to a lower fee than the other four funds. To quantify how much alpha each mutual fund must generate to break even with its benchmarks net of fees, we calculated the Compounded Annual Growth Rate (CAGR) for each time horizon. The results are displayed in Table 7.

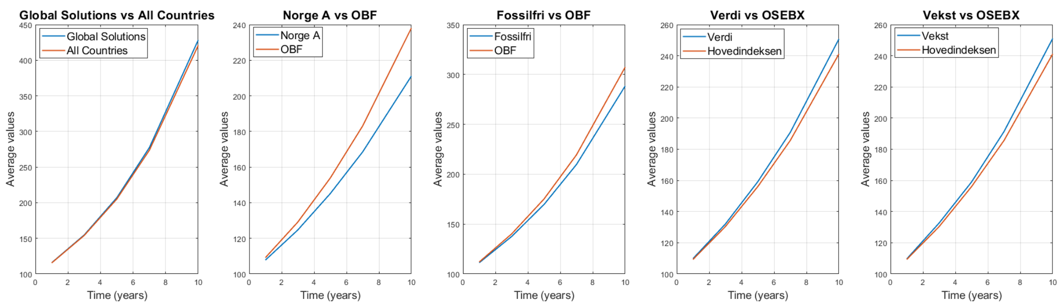

Figure 6: Simulated Average Mutual Fund and Benchmark Prices

Average fund and benchmark values for every given time period.

The table shows that all funds must deliver an annual compounded alpha larger than the difference between the active mutual fund (1.50%) and the passive index fund fee (0.20%). Vekst A is the only fund that needs to generate an alpha approximately equal to the difference in fees. Given our previous findings of no significant alphas, the results from this analysis suggest that

Fund Name	1 year	3 years	5 years	7 years	10 years
Storebrand Global Solutions A	0,66 %	0,76 %	0,73 %	0,72 %	0,74 %
Storebrand Norge A	1,52 %	1,43 %	1,43 %	1,45 %	1,47 %
Storebrand Norge Fossilfri	1,50 %	1,45 %	1,46 %	1,47 %	1,46 %
Storebrand Verdi A	1,38 %	1,46 %	1,48 %	1,48 %	1,49 %
Storebrand Vekst A	1,36 %	1,09 %	1,30 %	1,25 %	1,28 %

Table 7: Required Alpha for Each Time Horizon

Overview of required annualized alpha, calculated as CAGR, for each mutual fund to justify their higher fees.

the mutual funds will struggle outperforming or even breaking even with their benchmarks net of fees.

5.5 Black-Litterman: Implications of a Smaller Investment Universe

In this section, we investigate how the risk-adjusted performance of the Norwegian Market Portfolio, measured as the Sharpe Ratio (SR), changes if the energy sector is excluded, as it is the sector with the highest emission-level. This exercise is interesting because Storebrand performs exclusion of certain stocks and/or sectors based on ESG criteria. The expected risk-adjusted return of their investable investment universe will thus be lower than the risk-adjusted returns of the broad market.

We use the Black-Litterman framework to calculate returns for each of the sectors we are considering (Black and Litterman, 1990). We do not consider any investor views when performing our analysis.

The crucial assumptions for this approach is that financial markets are highly competitive, there are no systematic arbitrage opportunities, and markets clear. Further, we base on the notion that realized mean returns are not good estimates for future expected returns, as suggested by Pástor and Stambaugh, 2012. Thus, using second order moments (covariance and variance) as inputs will give more robust estimates for the return process than simply using first order moments, such as expected returns.

In order to solve the problem we need to make an assumption of the expected return on the broad market. We assume an expected market return of 10%, and a risk-free rate of 2% in our calculations. We use the weekly sector data on the Norwegian Stock Exchange, from January 2005 through May 2022. Sector weights are observed market capitalizations as of January 2020.

Below, in Table 8, we applied the reverse optimization method to calculate the implied equilibrium returns for our respective sectors, given their market weightings, the correlation matrix, and their annualized volatility. The equilibrium returns are calculated using the formula below:

$$\Pi = \lambda \Sigma w_{mkt} \tag{19}$$

Π is the implied equilibrium return vector, λ is the risk-aversion parameter, which simply is the return divided by the portfolio variance, and w_{mkt} is the observed market capitalization weights.

Sector	Implied Return	Volatility	Market Weights
Basic Materials	11,0%	29,8%	0,07
Consumer Discretionary	8,9%	28,2%	0,01
Consumer Staples	7,8%	24,3%	0,14
Energy	11,7%	27,6%	0,33
Financials	11,1%	27,0%	0,18
Healthcare	6,6%	28,0%	0,01
Industrials	9,1%	22,7%	0,08
Real Estate	4,1%	19,3%	0,02
Technology	8,5%	25,4%	0,02
Telecom	8,2%	25,3%	0,14
Utilities	7,2%	26,2%	0,01

Table 8: Implied Equilibrium Returns

Implied returns for sectors, in which the market will clear given the market weights and an expected market return of 10%.

After we obtained the implied market returns for each sector, we used those returns as input for the portfolio optimization calculations to obtain new market weights when Energy sector weight is set to zero. Those new weights produce the highest return for a given level of risk, and can thus be said to be the most efficient portfolio given our inputs. The new optimized weights are reported in Table 9. To calculate the optimal portfolio (highest SR) we solve the following problem:

$$\max_{w} SR = \frac{w^T \bar{R}}{(w^T \Sigma w)^{1/2}} \tag{20}$$

$$s.t.\ w^T \mathbf{1} = 1$$

$\bar{R}$ is a vector of excess returns, w is a vector of market capitalization weights, Σ is the covariance matrix, and $\mathbf{1}$ is a vector of ones.

Also, we do not allow for short sales:

$$w_i \geq 0 \tag{21}$$

Sector	Optimized Weights
Basic Materials	0,17
Consumer Discretionary	0,00
Consumer Staples	0,15
Energy	0,00
Financials	0,29
Healthcare	0,01
Industrials	0,15
Real Estate	0,03
Technology	0,04
Telecom	0,14
Utilities	0,02

Table 9: Optimized Weights Excluding Energy

Optimized weights when excluding Energy from the market portfolio.

To calculate the expected excess return of the new portfolio we use Equation (22):

$$E[\bar{R_p}] = E[R_p] - R_f = w^T E[\bar{R}] \tag{22}$$

where $E[\bar{R}]$ is a vector of the excess expected returns of the assets in the portfolio.

We further compute the volatility of the portfolio, using Equation (23):

$$\sigma_p = (w^T \Sigma w)^{1/2} \tag{23}$$

Lastly, we can compute the SRs. Table 10 summarizes the results from our two portfolios. The cost of excluding the Energy sector is illustrated with the decrease in SR from 0.36 to 0.35. Thus, the analysis confirms that by decreasing the investment universe in a CAPM world, the portfolio with the best risk-adjusted performance is the market portfolio. It further suggests that, since Storebrand excludes certain stocks from their investment universe, their mutual fund investors cannot expect risk-adjusted returns as good as the market portfolio that can be obtained by buying a passive index fund.

	Excess Return	**Volatility**	**Sharpe Ratio**
Market Portfolio	8,0%	22,5%	0,355
Market Portfolio excl. Energy	7,4%	21,3%	0,349

Table 10: BL Results Gross of Fees

Excess returns, standard deviation, and Sharpe Ratios for the market portfolio and the market portfolio excluding the Energy sector.

Table 10 does however not consider any management fees. In our earlier calculations, we have used 0.20% as management fee for passive index investing, which is consistent with what most index tracking ETFs charge. Four out of five of our mutual fund sample has a management fee of 1.50%. It is thus also reasonable to consider the SR net of management fees. We consider the case where we have an active mutual fund excluding the energy sector, and charge an annual 1.50% management fee.

	Excess Return	**Volatility**	**Sharpe Ratio**
Market Portfolio	7,8%	22,5%	0,346
Active Mutual Fund excl. energy	5,9 %	21,3%	0,278

Table 11: BL Results Net of Fees

Excess returns, standard deviation, and Sharpe Ratios for the market portfolio and for an active mutual fund excluding the Energy sector when subtracting management fees.

Table 11 shows the effect management fees have on risk-adjusted performance. We observe a lower SR for both portfolios. However, the portfolio excluding the energy sector declines substantially due to the higher fees.

Using the two new SRs, we can compute the alpha that the active portfolio needs to generate to achieve the same SR as the market portfolio net of fees.

We start with computing the excess return of the portfolio to make the SR equal to that of the market, using Equation (24).

$$E[R_a] = SR_{mkt} * \sigma_p \tag{24}$$

By applying the formula above, we get that the excess return needed for an actively managed mutual fund excluding the Energy sector, must be 7.4% to have the same risk-adjusted return as the market.

Using Equation (24), we compute the annualized alpha the actively managed mutual fund must thus deliver to justify the higher fees.

$$\alpha_p = E[R_a] - E[\bar{R_p}] \tag{25}$$

We then get an alpha of $1.4\%(= 7.4\% - 5.9\%)$ to obtain the SR of the market. Values are subject to rounding. For this to be reasonable, one requires a skilled portfolio manager able to outperform in the long run.

Since the Norwegian Stock Exchange is characterized by having significant overweight in the energy sector, the results could differ somewhat when performing the same analysis for the global market, where the energy sector make up less of the total market than that of the Norwegian market. It also depends on which ESG-criterias are employed for exclusion, as certain exclusion criterias spill over to other sectors as well other than just the energy sector. Nevertheless, we identified that exclusion of sector(s) will lower expected risk-adjusted returns.

6 Conclusion

In this thesis, we investigated the historical performance of some of Storebrand's actively managed high-ESG-labeled mutual funds. We have analyzed the degree of active management of those funds and the impact management fees have on fund performance. Additionally, we used two methods to compute the probability that the mutual funds will outperform their benchmarks net of fees. Lastly, we applied Black-Litterman to look at the potential implications of a smaller investment universe due to exclusion screening.

We find that, even though some of the funds can outperform from one time to another gross of fees, none of the funds can deliver persistent and significant alpha to make up for their higher fees. Additionally, the periodic alphas generated show no persistence and thus seem quite random. Using the R-squared and Tracking Error thresholds we defined earlier, we cannot conclude that any of the funds are closet-indexers, with the exception of Norge A with an R-squared of 0.96, and with a relatively low Active Share and tracking error. However, we observe that some of the funds are close to being defined as closet-indexers. Using the CAPM regression, we find that all the funds have an estimated beta-coefficient close to 1, indicating that the covariance between fund returns and benchmark returns is very high. The only exception is for Norge Fossilfri, with a relatively lower beta. In addition, no alphas are found to be statistically significant, net of fees.

Both methods for the probability of outperformance suggest that the likelihood of mutual fund outperformance net of fees is low and decreases with time. We also find that a higher Tracking Error, i.e., a higher degree of active management, is essential to increase the probability of outperformance for any given time horizon. Furthermore, the average simulated fund value and benchmark value are increasingly dispersed with time, where the benchmark outperforms consistently. Thus, the required annual alpha that the fund managers must deliver to justify their higher fees must be substantially higher than the difference between the active management fee and the index fund fee. The required annual alpha to justify for higher fees is also evident from our BL analysis of the sectors at Oslo Børs. Our findings are consistent with that in highly competitive financial markets, a smaller investment universe caters to a lower risk-adjusted performance.

In conclusion, the higher fee structure of high-ESG-labeled funds is a caveat that harms fund performance and probability of outperformance. Our results indicate that investors with risk-adjusted return objectives would be better off investing in passive indexes, as the mutual funds analyzed here show low or no persistence in generating excess returns above its benchmark, net of fees.

We mentioned under section 3.1.7 that we failed to calculate a time series on Active Share for Storebrand's mutual funds due to insufficient data. Thus, for those who have access to a panel data series of mutual fund and benchmark compositions, it would be interesting to investigate to what degree active mutual funds are, in fact, actively managed. Furthermore, the GBM is widely accepted to describe how asset prices evolve. However, we must be cautious about concluding firmly from the results, as we assume that drift, volatility, and correlation are constant. These assumptions are naturally poor to rely on in practice. To improve the reliability of the results and increase the randomness in the simulated price paths, we suggest that one could use the Heston Model to implement stochastic volatility. This model is more likely to capture the volatility clustering in asset returns that is historically evident and would make the sample paths more realistic.

A APPENDIX

A.1 Additional Tables

	Zero Mean of Residuals (1)	Heteroscedasticity (2)	Autocorrelation (3)		Stochastic Regressors (4)	Normality (5)
Fund Name	**Mean of Residuals**	**White's Test p-val**	**DW-Stat**	**DW p-val**	**Correlation of Residuals**	**Bera-Jarque p-val**
Storebrand Global Solutions A	-1,9E-18	0,6934	1,9297	0,7075	-7,2E-16	0,0070
Storebrand Global Solutions A	-1,7E-18	0,0595	1,9081	0,4412	-1,8E-16	0,0010
Storebrand Norge Fossilfri	4,7E-19	0,7473	1,4509	0,0319	2,1E-17	0,0460
Storebrand Verdi A	-2,0E-18	0,0600	2,0363	0,0005	-7,5E-17	0,0010
Storebrand Vekst A	-1,6E-18	0,1063	1,5769	0,7734	-3,0E-16	0,0010

Table A1: Diagnostic Tests Results

Diagnostic tests results for each mutual fund.

A.2 Additional Figures

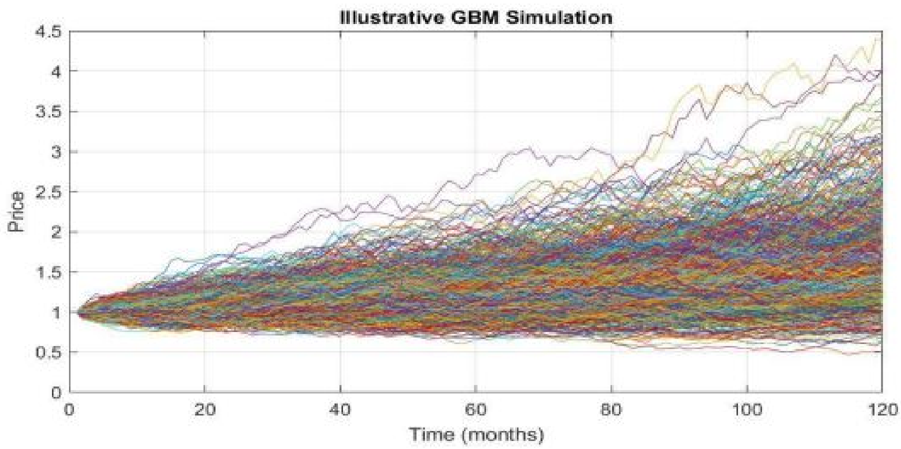

Figure A1: Price Paths from Monte Carlo Simulations

Illustrative Monte Carlo simulations using the Geometric Brownian Motion Model.

A.3 Additional Formulas

$$CAGR = \left(\frac{EV_t}{BV_t}\right)^{1/t} - 1 \tag{A.26}$$

where EV_t is the ending value, or the average simulated benchmark value at a given time t. BV_t = beginning value, or the average simulated mutual fund value at a given time t.

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