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Ethical Investing – A Study of Performance

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Abstract:

This thesis sets out to measure the effect of taking ethical considerations when investing. We analyze the effect over a period from January 2002, and throughout the first half of 2015, by first comparing the risk-adjusted performance of ethical mutual funds with conventional mutual funds, and by later examining the return on single stocks against a measure of ethical behavior. By applying well known models in financial theory we find no significant difference in performance between ethical and conventional mutual funds. However, weak evidence of a slight insignificant underperformance exists. When analyzing the stocks we find that companies with higher ESG-scores have slightly outperformed companies with lower ESG-scores, with the US data being statistically significant. We also find weak evidence indicating that negative screening contributes to a loss in return for ethical investors. We finally conclude that investors who invest ethically do not sacrifice return.

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Contents

1. Introduction

In the last decade, there have been a rising number of investors considering their investments not only from the financial perspective in terms of how much return they will yield, but also what kind of impact their investments have on society. Several issues, such as the large carbon dioxide emissions' effect on the environment, the terrible working condition of millions of people around the globe and gender equality, to name a few, have received large media and political attention. As a result, investors seem to reflect, to a larger extent, on how they put their money to work.

The movement of investors that consider investing with their values and seeking financial return without contributing to the above-mentioned issues is called "ethical" or "socially responsible" investments (SRI). There are several ways for an investor to influence the ethics of the business world through his investments. One can refrain from investing in certain companies or sectors, which are known for not following certain principles, or in general not contributing to a more ethical business environment. Other alternatives are seeking influence in the companies where he invests by having his voice heard on general assemblies, but this generally requires a large investment in order to make an impact. The most dominant way for investors to invest with their values is to restrict their investments to companies that are superior in upholding some ethical standard.

Finding information on which companies are ethical and fulfil the individual investor's ethical requirements in order to qualify for making an investment is difficult. There is no legislation that requires companies to disclose how ethical their business is, and no audit standards exist for this issue. Acquiring such information, on an investment universe that is getting larger and larger is highly time-consuming. The most efficient way of incorporating ethical standards in your investments, especially for less capitalized retail investors, are investing in mutual funds that apply some sort of ethical or SRI strategy. These funds investigate the companies in their investment universe, and evaluate potential investments according to their individual ethical criteria alongside the more traditional financial analyses, before making an investment.

Critics of the ethical and SRI trend have argued that inclusion of social and environmental considerations in the investment-process is hampering returns, and that investors in this sense are sacrificing financial return to compensate for a more ethical profile of their investments.

They argue that by limiting your investment universe by applying ethical screens, you will achieve less diversification, and thereby achieve lower risk-adjusted returns.

Supporters of ethical investing counter with the argument that investing in companies that have a wider, and more long-term perspective on their business, will have a better fundament for delivering strong financial results in years to come, and that ethical investors thereby will outperform investors who do not take ethical criteria into consideration. They also argue that companies with a thorough approach to their business ethics will avoid certain risks in the future, such as lawsuits and scandals.

The million dollar question remains: Does ethical investing hurt financial return? Answering this question could potentially be very important for the future of ethical investing. If the answer to this question is yes, ethical investing will appeal only to investors who are prepared to sacrifice financial wealth in order to keep their conscience clean. If on the other hand ethical investing deliver superior return, this investment strategy will move further into the spotlight and ethical considerations will stand out as something everyone should undertake while investing. This might evidently lead to a corporate world where business ethics and financial results are equally important. Lastly, if there is no significant difference between the returns achieved by applying ethical screens in your investment decision-making process or not, ethical investing will at least appear as a legitimate alternative to consider for investors. Investors can “do well while doing good”.

This thesis aims to uncover whether it is possible for equity investors to invest ethically without sacrificing financial return, in comparison to conventional investing, in two of the most developed markets for ethical investing, namely the UK and the US.

1.1 Problem Formulation

This thesis will try to uncover the return prospective of following an ethical investing strategy. We will through the testing of a large dataset of both ethical mutual funds and ethical companies, and their comparable counterparties, analyze from an investor’s perspective if investing with your values is hampering or enhancing your possible financial return, or whether it has no effect. As the market for ethical investing is growing, this is potentially a crucial question for the future of ethical investing.

Three possible hypotheses exist, each with a possible theoretical explanation. We will now present the three possible hypotheses and elaborate slightly on why they might be valid. In a later section we will elaborate on previous research studies on the topic and shed light on the empirical evidence on each of the possible hypotheses. This could implicate what we are likely to find from our analyses, and our findings could add some insight to the debate, both directly from our findings, but also from how they might differ from the findings in previous research. In a later section we will also elaborate more thoroughly on the main arguments of the two blocks; the supporters and opponents of ethical investing.

Hypothesis 1: "*Following an ethical investing approach is reducing your risk-adjusted returns*."

This hypothesis is reflective of the opponents of ethical investing. One common argument stems from modern portfolio theory, and state that any approach which constrains the investment universe will lower diversification benefits, and thereby lower the risk-adjusted return of a portfolio (Sharpe W. , 1965). From a company perspective, this hypothesis will be true if the costs of being ethical are higher than the benefits. If this hypothesis proves true, the supporters of ethical investing are losing out financially by following their values when investing. However, the benefit of "doing good" might exceed the costs of lower returns depending on the preference of the individual investor.

Hypothesis 2: "*Following an ethical investing approach is increasing your risk-adjusted returns.*"

Supporters of ethical investing believe that investing ethically will also be profitable from a financial perspective. They usually argue that ethical investing implements a longer term perspective, which will result in superior returns over time (Camejo, 2002). One argument is that restricting owning companies which do not fulfil certain ethical criteria will lead them to exclude future non-performers and this effect will offset the loss of diversification. An alternative explanation could be that investors on average underestimate the effect of being ethical, and such companies are underpriced. From a company perspective, this hypothesis will be true if the cost of being ethical is lower than the benefit.

Hypothesis 3: "*Following an ethical investing approach is neither reducing, nor increasing your risk-adjusted returns.*"

This last hypothesis could be true for many reasons. One of them is if the loss of diversification by investing ethically is negligible. This could be the fact if the ethical screen applied leads to exclusion of very few assets, and thereby only a very small fraction of the investment universe. Another explanation is if the loss of diversification is exactly offset by the ability to exclude future non-performers. This explanation is a combination of the two main arguments of the supporters and the opponents of ethical investing. From a company perspective this would imply that the costs of being ethical are exactly offset by the benefits.

This is a brief presentation of the three possible hypotheses that this thesis will try to answer. A more thorough elaboration of the main arguments of supporters and opponents of ethical investing will be presented in section 3.2.

1.2 Delimitations

Since we could not obtain any full list of funds that inhibited the level of ethical investment philosophy that we required, our datasets are to a large extent a result of manual screening. The funds included are therefore a result of a personal interpretation of the fund's prospectus, or is included on the basis of a rating of the funds ethical policy from a third party. The data would have been more reliable if it all stemmed from the same source, but as a list of all funds that invested domestically in either of the markets and which inhibit a strict level of ethical investing does not exist, we were left with our manual screening process.

Our dataset of ethical mutual funds is quite small, consisting of a total of 22 ethical funds. One could argue that this makes our results less applicable for generalization. However, as we chose to look only at equity funds investing domestically, which was alive throughout the period of research this seriously reduced the number of funds available. Also, we have been thorough in our screening, so that only funds with substantial records of ethical considerations are classified as ethical enough for our dataset, which limits the number of applicable funds.

Even though the funds included should only invest domestically and within equity, some of the funds in our analysis have very small portions of their assets invested in foreign assets and/or other asset classes. Finding funds with 100% of their assets in domestic equity was not possible.

One could argue that our fund analysis lacks credibility since only monthly data is used when analyzing the performance of the funds. However, an analysis of neither weekly nor daily data was possible since many of the funds did not report their net asset value (NAV) at such frequency, and was therefore left with zero return in many of the weekly/daily data points. Also, we were not supplied with the factor data for the UK on a weekly basis. Hence, a weekly analysis would have required us to make the factor portfolios ourselves, which would distinguish it from what we have done in the rest of the analyses and consequently make the thesis less consistent. This issue is also relevant to our analysis of the ESG portfolios.

In our stock analysis we rely heavily on the ESG-scores from Asset4. By doing this we assume that these scores reflect how the market participants consider companies when evaluating them on their level of ethical behavior. If it is so, that the Asset4 data is not a good proxy for the market's perception of ethical behavior, our stock analysis bares little credibility.

Tax considerations, transaction costs and mutual fund fees are not taken into account, even though these will affect the returns realized by individual investors.

Finally, our paper includes explanation of the theory and concepts we use in our analysis, in section 4. The reader is though expected to be proficient in basic math, statistics and finance.

1.3 Methodology

1.3.1 Fund analysis

We started the research by finding as many mutual funds as possible that invest domestically in the UK and the US, and which were regarded as ethical. To ensure that these funds actually qualified to be included in our study, we performed a manual screening where we excluded those funds that did not meet a certain standard of ethical screening. We also had a data screening where we excluded funds that DataStream did not provide sufficient data for. Further, we found two comparable funds, which is not classified as ethical, for each ethical fund, and used these as a benchmark for assessing the relative performance of the ethical funds. The comparable funds went through a similar screening process, and were matched to the ethical funds by size, age and fund style.

When the funds had been chosen, we made two portfolios of the different types of funds; one portfolio with ethical funds and one portfolio with conventional funds. We equally weighted each of the funds in these portfolios and rebalanced monthly. Both the ethical- and the conventional funds were included in their portfolio on a basis of when the ethical funds were incepted.

In order to measure the performance of the two portfolios, we started off by looking at light performance measures which do not adjust for risk. Further to adjust for the risk in the portfolios we calculated their Sharpe and Treynor ratio. Further, we formed a third portfolio, which was a portfolio going long the ethical portfolio, and short the conventional portfolio. To test the three portfolios further, we used the CAPM model to estimate Jensen's alpha, which is a measure of the risk-adjusted abnormal return the portfolios have achieved over the period investigated. To adjust for more risk factors, we included both the Fama-French three-factor model, and the Carhart model. Finally, to cross-check our results from the first set of regressions, we did two-year rolling regressions on the same sets of data. As a robustness check we divided our sample-period into two sub-samples and ran the previous regressions on each of the sub-samples individually.

1.3.2 Individual stock analysis

Since we felt that our analysis of the mutual funds was not sufficient to conclude, we decided to analyze the relationship between single stock performance and scores indicating a level of ethical behavior. For this analysis we used UK and US company data from the same period as we did with the fund analysis, from 01.01.2002 until 30.06.2015. We included all stocks in the UK and the US included in the Asset4 ESG database, but excluded companies based on a data screen. The overall ESG-score given by Asset4 includes an "Economical" score in addition to the traditional "Environmental", "Social" and "Governance" scores. We decided to exclude the "Economical" score and were left with an equally weighted score of the stocks' "Social", "Environmental" and "Corporate Governance" score.

As an introductory analysis we did a portfolio approach where we created portfolios based on the stocks' ESG-score. One portfolio consisted of the top 35%, one of the bottom 35% and one of the companies in the middle. Further, we created a long-short portfolio which was long the top 35% and short the bottom 35%, and tested the risk-adjusted performance of these portfolios.

To pin down the “ethical-effect” we chose to perform a Fama-MacBeth cross-sectional regression of the data, where we included the ESG scores, a dummy variable for negative screening, data to control for risk factors, and dummy variables to control for industry effects. The “ethical-effect” would then be measured by the factor loading estimated for the ESG score.

Lastly, we ran the Fama-MacBeth regression with keeping the Environmental, Social and Governance score separated to see if there were any differences in the effect each of the three scores had on returns.

1.4 Data

In our study we have chosen a fairly long sample period, stretching from 01.01.2002 until 30.06.2015. We chose 2002 as the starting year of our analysis, as the Asset4 ESG data did not exist before this. 30.06.2015 was chosen because more recent factor data for the UK was not available when we started our research.

To collect data on the mutual funds we used several sources. To find the ethical funds we used Bloomberg Terminals and SocialFunds.com, while to find comparable funds we used Morningstar’s mutual fund screener. Data regarding the funds’ style, assets under management (AuM) and geographical scope were also collected from Morningstar. The manual screen of the fund’s investment philosophy was done by reading the individual fund’s prospectus.

Factor data and risk free interest rate for the US was provided by Kenneth French’s website, while this data for the UK was provided by University of Exeter Business School and their Xfi Center of Finance and Investments.

The stocks to be used in our stock analysis were initially the stocks that Asset4 had included in their database for the UK and the US, but the number of stocks was reduced following a data screening process.

The stock data and return data for the funds were collected from Datastream 5.1 by Thomson Reuters.

For the mutual funds monthly data was used, while for the individual stocks weekly data was used in the Fama-MacBeth regression and monthly data was used in the portfolio approach.

2. Previous Research

Given the recent decades rise in ethical investing, a lot of research has been conducted on this topic. Primarily three different approaches have been used; investigating ethical indices' performance, investigating ethical mutual funds' performance and investigating the performance of companies with a high score on ethical criteria.

Most studies on the performance of ethical indices have concluded that such indices has a growth bias compared to traditional indices, and controlling for that, there is no significant difference in performance between ethical and traditional indices (Kurtz & DiBartoloemo, 2011) (Managi, Okimoto, & Matsuda, 2012) (Schröder, 2007). In the following sections we will elaborate more on the studies on mutual funds and stocks, which will be the focus of our thesis.

2.1 Mutual Funds

2.1.1 UK

Mallin et al. (1995) claim that their study is the first to compare the performance of ethical and conventional funds in the UK market. They conduct this study over the period 1986-1993, using the Sharpe ratio, Treynor ratio and Jensen's alpha in the CAPM model. They investigate 29 ethical funds, and 29 conventional funds. Each ethical fund is matched by a conventional fund with approximately the same size and inception date. They argue that this approach overcome the pit-falls of previous studies to that date, which had compared ethical funds to a broad index and thereby were unable to attribute differences in performance to the "ethical element" or simply a difference in factor exposure (as most ethical funds were more exposed to small caps). The authors found weak evidence of ethical funds outperforming the conventional funds on a risk-adjusted basis, when taking all three measures into account.

Bauer et al. (2005) find a slight, but not statistically significant, outperformance of UK ethical funds investing domestically compared to their conventional peer group for the period 1990-2001, using a Carhart four-factor model. They also find that ethical funds have high exposure to small cap stocks, and this exposure is significantly higher than the conventional funds. Ethical funds also showed significantly less exposure to the market factor than the conventional funds, and a significant exposure to growth stocks for the ethical funds.

Dividing the sample into three sub-periods, the results show significant outperformance of UK ethical funds compared to conventional ones in one of three sub-periods (the period 1994-1997).

Using Fama-French three factor- and Carhart four factor models, Gregory et al. (2007) investigate the performance of 32 ethical funds relative to 160 conventional funds, matched by size, age and style. Their static regressions show no significant difference between ethical and conventional UK domestic funds, in the period observed (January 1983-December 2002). When applying a rolling regression on the same models, the ethical funds show a positive average alpha compared to a negative average alpha for the conventional funds. However, none of these results are statistically significant. The authors conclude that ethical investors do not lose out compared to ordinary investors. They also conclude that ethical investors can enhance their risk-adjusted performance in domestic funds by investing in previous "winners", as their analysis demonstrated a persistency pattern for ethical funds.

2.1.2 US

From a Carhart four factor model, Bauer et al. (2005) found outperformance of US ethical funds, investing domestically, relative to their conventional peers. However, this outperformance was not statistically significant. Also, both the ethical- and conventional funds showed negative alphas. The US ethical funds showed significantly less exposure to the market factor and to small stocks, than the conventional funds. The ethical funds were also less exposed to value stocks than the conventional funds. Dividing the sample period into three sub-periods, the US ethical funds showed significant underperformance in the first sub-period (1990-1993), but the comparative performance improved over time, and in the last sub-period the ethical funds outperformed the conventional ones, although this outperformance was not statistically significant. Bauer et al. therefore concluded that the US ethical funds experienced a learning-effect, and after a catch-up period they were able to deliver similar returns as the conventional funds.

Bello (2005) investigates the performance of US ethical funds, which invest domestically, in the period 1994-2001. Using the CAPM model and the Sharpe ratio he concludes that there is no significant difference between his ethical funds, and their conventional peers (matched by

AuM). He also concluded that there is no significant difference in diversification effect between the two groups.

Statman (2000) found in his study of 32 ethical funds and 62 conventional funds in the period 1990-1998 that on average both types of funds showed negative alphas using the CAPM model. His group of ethical funds performed better than the conventional ones, but the results were not statistically significant.

Hamilton et al. (1993) investigated the performance of 32 ethical funds in the period 1981-1990. They found that there was no significant difference between the ethical funds and the conventional benchmark made up of 170 conventional funds. They divided their funds in two groups; one of funds founded before 1985, and one of funds founded after. The 170 conventional funds were randomly chosen. Finally, they concluded that "...social responsibility factors have no effect on expected stock returns..." (Hamilton, Jo, & Statman, 1993).

2.2 Single Stocks

Studies on ethical companies' financial performance relative to all other companies, or non-ethical companies usually starts out by defining ethical and non-ethical companies from a research agency rating companies on ESG-factors. Different research has used different agencies and groups of comparables.

2.2.1 UK

Brammer et al. (2006) examine the financial performance of companies scored differently on ethical performance. They obtain data on ethical performance and, among other, sort equal-sized portfolios of high-, medium- and low-scoring companies. They assume an initial investment taking place in June 2002, and evaluate the relative performance on a 1-, 2- and 3-year holding period. They measure the three portfolios against an equally-weighted benchmark and the FTSE All-Share Value-Weighted index. They find that the highest-scoring portfolio underperform all other, and conclude that there is "not a monotonic fall in performance as the ethical score rises, but rather a distinction between the highest and lowest scores." On a side-note they find that looking only at the employment-dimension, the highest scoring companies show stronger financial performance than the lower-scoring. This might be related to Edmans' (2011) findings of a possible "employee-satisfaction premium."

The authors also run a series of Fama-MacBeth cross-sectional regressions, trying to isolate the effect of different ethical performance indicators on financial performance. The resulting evidence is, among other, that a higher score results in lower returns, however not statistically significant. Finally, the study concludes that their findings are in line with the argument that expenditure on ethical aspects is destructive of shareholder value.

2.2.2 US

Statman and Glushkov (2008) studied the performance of US companies during the period 1992-2007, and found that investments tilted towards companies with a high score on different ethical criteria from KLD Research & Analytics (now MSCI Research & Analytics) outperformed conventional investments. However, they found that this outperformance was largely off-set by the return-disadvantage by not investing in "sin" companies such as producers of tobacco, alcohol, gambling and firearms. This "sin premium" is in line with Hong and Kacperczyk's (2009) study on "sin" companies, shunned by many investors.

Kempf and Osthoff (2007) compared several screening strategies, and concluded that a trading strategy based on the best-in-class approach, going long a portfolio with good scores on ethical criteria from KLD Research & Analytics, and short a portfolio of stocks with poor scores yielded an annual alpha of up to 8.7%, from the Carhart model during the period 1992-2004.

2.3 Previous Research Summary

A variety of research is conducted on ethical mutual fund performance in the US and the UK. Although the results differ somewhat, the overall take away seems to be that there is no significant difference in performance of ethical funds, compared to conventional funds. That being said, the picture looks a little brighter in the UK than in the US.

We will follow a similar methodology as Statman (2000) in constructing the group of comparable conventional funds; two conventional funds for each ethical fund. Statman matched them by size, while we took, as Gregory et al. (2007), both size, age and investment style into account. As Mallin et al. (1995), we investigate performance with Sharpe ratio, Treynor ratio and Jensen’s alpha. However, we include multi-factor models as well, in a similar manner as Bauer et al. (2005).

The studies on stock market performance of companies with a high score on ethical criteria also show mixed results. However, there seems to be weak evidence of underperformance by ethical companies in the UK, and outperformance in the US.

In a similar manner as Kempf and Osthoff (2007), we will investigate the differences in return between portfolios of companies ranked highly- and poorly on ethical criteria. As Brammer et al. (2006) we will apply a Fama-MacBeth regression in our stock analysis. However, we will both consider one score of ethicality, an overall score, and how the three different components of the ESG score (E, S and G) affect financial performance, while they only investigated sub-categories of ethicality which differs from ours. As Statman and Glushkov (2008) we will look at the effect of exclusion of certain companies, but while they did so with a portfolio approach, we will incorporate this in our Fama-MacBeth model.

Finally, this thesis distinguishes itself from the previous research mentioned above, as our analyses are conducted on a different and more recent time period. Also, our ESG scores are provided by Asset4’s database, while the previous research relies on ethical scores from other sources such as KLD.

3. Ethical Investing

3.1 Definitions

Ethical investing and SRI concepts evolved from periods of war, when certain groups refused to participate, and did not approve of the inhuman ways of sorting out disagreements (Schueth, 2003). In UK the Quakers, a religious Christian movement, emerged during the Civil War. Among other, they refused to participate in war, and travelled both in the UK and abroad to preach their beliefs. Centuries later some Quakers went into banking, and the first British ethical fund was launched in 1984 by Friends Provident, a life insurance company founded by the Quakers. In the US, the modern ethical investing emerged with the opponents of the Vietnam War, and the world's first modern ethical fund arose in 1971 – the PAX fund (EIRIS Foundation). Since then the landscape of ethical investing has changed considerably, and is still evolving. As a result, there is no uniform definition of ethical investing and SRI.

Defining ethical investing is not an easy task. Ethical investing and SRI are often used interchangeably, and the term SRI is in fact used both for "Socially Responsible Investing" and "Sustainable Responsible Investing". It is obvious that more clear-cut definitions are needed in order to proceed towards the purpose of this thesis. We will now elaborate on the different definitions of ethical investing and SRI, and then conclude on how the terms are defined for the purpose of this thesis, as well as some other important concepts.

3.1.1 Investment Companies

One of the most common ways for investors to ensure investing ethically is by investments in ethical mutual funds. We therefore feel the urge to elaborate a bit on the different types of investment companies, in order to define what we are referring to when talking about mutual funds, and ensure the understanding of these.

Investment companies are financial intermediaries, which pool assets from individual investors (retail and/or institutional) and invest them in a potentially wide range of securities. Each investor has a claim on the portfolio of the investment company in proportion to the amount they have invested (Bodie, Kane, & Marcus, 2014). In such way, investment companies give small investors the benefit of large-scale investing, and make it possible for less educated investors to grow their savings professionally, by leaving investment decisions to experienced professionals. The large pooling of assets creates possibility for better diversification, as a small investor with limited funds would have to hold extremely small positions in order to achieve sufficient diversification, which would make transaction costs very high relative to the invested amount in each position. For performing this service, the investment companies charge fees. Different investment companies operate with different fee-structures, but usually there is some fixed fee charged yearly and some fee which is tied to the performance of the portfolio.

More practically, when an investor invests in an investment company he buys a share of the investment company. Each share is called the net asset value (NAV) and is the difference between the market value of assets and the liabilities of the investment company, divided by the number of shares outstanding (Bodie, Kane, & Marcus, 2014). Hence, NAV reflects the underlying portfolio of the investment company and will increase when the assets in the portfolio performs well.

Several types of investment companies exist, but in this thesis the only type involved is managed investment companies. Managed investment companies are named so, because the securities in their portfolios are continuously bought and sold, and not fixed. Further, there are two types of managed investment companies; close-end and open-end funds. Common for both types are the fact that the board of directors hires a management company to manage the portfolio. Often the managing company is the company that organized the fund, but sometimes the fund will hire an outside portfolio manager. The management company usually has a contract to manage several funds. The difference between open-end and closed-end funds is that open-end funds stand ready to redeem or issue new shares, while closed-end funds do not. In other words, a closed-end fund is owned by the same shareholders for the entire life of the fund, and they may not sell or increase their shares during the life time of the fund, unless they find other investors to take- or sell them their positions. In an open-end fund, investors sell or buy their shares from the investment company at NAV, but this may involve charges (Bodie, Kane, & Marcus, 2014).

In this thesis, all investment companies in the dataset are open-end funds. The most common name of open-ended managed investment companies is “mutual fund”. In this thesis we will refer to our open-end managed funds as “mutual funds” or simply “funds”. There are several types of mutual funds, such as money market funds, sector funds, bond funds, international funds, balanced funds and index funds, but in this thesis we will only consider equity funds. Equity funds are funds with a mandate to primarily own stock, although they may hold small fractions of money-market securities to ensure liquidity, or other securities (Bodie, Kane, & Marcus, 2014). Also, in this thesis we do not consider international funds (funds which invest globally or in several markets), but strictly funds which invest domestically. Our rationale for considering domestic funds only is among others to ensure that our factor models are an as accurate as possible description of the mutual funds considered.

3.1.2 Ethical and Socially Responsible Investing

Ethical investing and Socially Responsible Investing usually refer to the same process and are used interchangeably in the literature. Both terms capture the incorporation of "non-financial" or "extra-financial" considerations into the investment decision-making process. Such considerations are usually environmental, social or governance (ESG) issues, but could in principle be anything an individual investor finds important, as what is considered ethical is highly subjective. Socially Responsible Investing is the most common term in the US, while ethical investing is more of a European term (Hancock, 2002). We define ethical investing as Hudson (2006): "An approach to investing driven by the value system of the key investment decision-maker".

3.1.3 Sustainable Responsible Investing

According to The Forum for Sustainable and Responsible Investing in the US (US SIF), Sustainable Responsible Investing is an investment discipline that considers ESG criteria to generate long-term competitive financial return and positive societal impact. US SIF also acknowledge that ethical investing and Sustainable Responsible Investing are used interchangeably and that there is no general definition of how it differs (US SIF - The Forum for Sustainable and Responsible Investment). In our opinion, based on a variety of articles and literature we have read, both terms focus on doing good deeds, in line with personal values. However, Sustainable Responsible Investing seems to be a concept which to a greater extent grasps longer-term prospects about the planet we are leaving behind for future generations, whereas ethical investing is, put simply, not doing others any harm. The former can be illustrated by the definition of the sustainable component of the term, which developed from the Brundtland report (1987); "meeting the present need without compromising the possibility of future generation to meet theirs". The Brundtland report was published as a UN initiative which sought to propose solutions to the poverty- and environmental problems facing the earth.

Sustainable investment strategies usually focus on megatrends, such as resource scarcity, changing demographics and carbon dioxide emissions. When following such strategy one will aim to identify companies that are positively exposed to these megatrends. Examples could be companies in renewable energy, such as solar panel producers, or companies that come up with innovative solutions to food manufacturing, and can produce more with less. Krosinsky and Robins (2008) defines Sustainable Responsible Investing as “an approach to investing driven by the long-term economic, environmental and social risks and opportunities facing the global economy”.

3.1.4 ESG

ESG is an acronym for Environmental, Social and Governance and is a term widely used in the literature on both ethical investing and Sustainable Responsible Investing. The ESG factors are a sort of framework or check list widely used in ethical investing, and is often implicitly a part of the ethical criteria set forward by the ethical funds. Most of the strategies, which are elaborated on in section 3.3, followed by ethical funds are based on ESG criteria. One might argue that considering ESG factors is the backbone and starting point of ethical investing. Most of the agencies performing ethical scoring of companies base their scores on a variety of different sub-criteria within each of the E, S and G factors. Examples of the environmental sub-criteria are biodiversity loss, waste management and changes in land use. Social sub-criteria might be human rights, labor standards and workplace health and safety. Examples of the governance sub-criteria could be board structure, executive pay and business ethics (such as bribery and corruption).

For the remainder of this thesis, we will consistently use the terms ethical and ethical investing, in order to avoid unnecessary confusion.

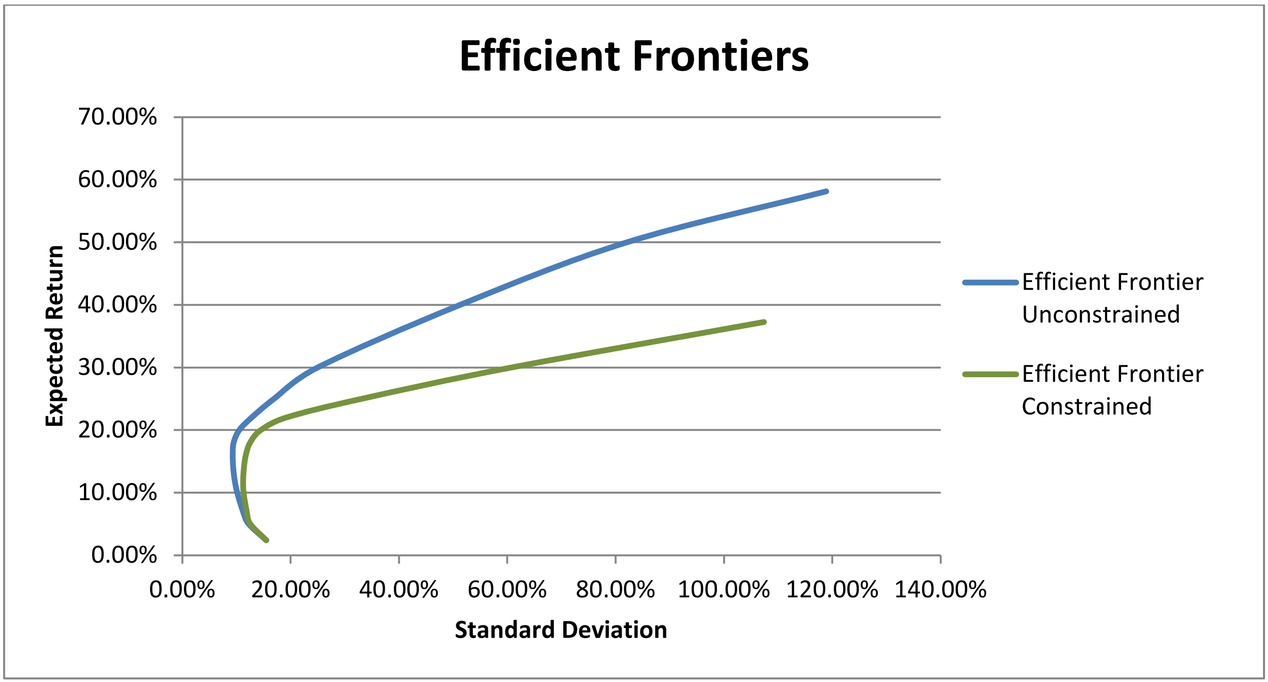
3.2 Arguments in the Debate

The debate has long been raging between supporters and opponents of ethical investing. In this section we will present the main argument for and against ethical investing, and illustrate the validity of the arguments.

Critics of ethical investing are referring to Markowitz' portfolio theory, or mean-variance optimization which he published in 1952, to illustrate how ethical investing can never be optimal (Rudd, 1981) (Sharpe W. , 1965). In the market place two categories of risk exist. The unsystematic, or firm-specific risk, which is specific to one asset or a small group of assets, and the systematic risk which is the overall market risk. Efficient markets reward investors for taking on systematic risk, but not for unsystematic risk as this can be diversified away. Diversification is the concept of adding two or more assets, which does not move in lockstep; hence they are not perfectly correlated, in a portfolio. The effect being that the portfolio is subject to less risk, with variance as the risk measure (Bodie, Kane, & Marcus, 2014).

The critics of ethical investing argue that by reducing the number of investable assets, as is done in ethical investing, the diversification effect will be decreased, which will lead to lower risk-adjusted returns. An investor without constraints can invest in all possible assets. An ethical investor however, shuns specific assets or industries and is thereby constrained. At best, they can do as good as an unconstrained investor, if the unconstrained investor does not hold the shunned stocks due strictly to financial considerations, while most times they will do worse. In Markowitz' framework, for a given level of expected return, the variance is minimized. For the sake of simplicity, let's assume that investors consider only risky assets. If every combination of risky assets is plotted in the risk-return space, the opportunity set will be evident. The upward slope of the hyperbola is the efficient frontier. Portfolios on the frontier are superior to other portfolios in the opportunity set, with respect to risk-adjusted return (Bodie, Kane, & Marcus, 2014). To illustrate, and prove the point of the critics of ethical investing, we have performed a mean-variance optimization on a subset of the UK market. We have constructed portfolios to create the efficient frontier for an unconstrained universe, and for a universe of the top performing companies on ESG only. A risk-free asset is not included, and short selling is not allowed in this basic illustration.

Figure 1 – Efficient Frontiers



As can be seen from Figure 1, the investors who can invest in the entire universe are better off than investors constrained by ethical performance. The unconstrained frontier consistently shows higher returns for the same level of risk than the frontier constrained by ethical criteria. This illustrates and proves the arguments proclaim by critics of ethical investing.

So how do the supporters of ethical investing argue their case, that this investment discipline is more than a charity case? They acknowledge the financial theory, and are aware of the diversification effect. However, they claim that the companies excluded from their investment universe will be poor-performers compared to the ethical companies they hold (Camejo, 2002). This statement is undermined by lots of arguments.

One argument is that companies that take their ESG factors seriously are less prone to scandals and lawsuits. For example, a company that does not consider the environmental effect of their operations could face huge fines for environmentally damaging operations. This will not happen if the firm has already mitigated such risk, by constantly tracking and improving their environmental performance. One recent example could be the Volkswagen scandal. If the Volkswagen group was 100% focused on ethicality and ESG factors of their operations, they probably would not have cheated with their emissions, and the huge scandal which made their stock price plunge would never have happened.

It is obviously not the case that all companies which are not paying a close watch on their ESG factors are deemed to experience huge scandals at some point, but supporters of ethical investing believe that considering such factors implement a longer-term perspective (Camejo, 2002), which will be evident in the future financial performance.

It is also argued that ethical companies are better at acquiring and keeping employees, as employees of a company to a great extent expect that their employer is not operating in an un-ethical matter (Consumers Overwhelmingly Want CSR, 2010). In other words, by operating ethically you have better shots at attracting the brightest minds, and your workforce is more likely to be happy and motivated, which again will lead to higher productivity and superior performance.

3.3 Ethical Mutual Fund Strategies

There is a variety of ethical- and sustainability themed mutual funds offered, however they vary a lot in how they define their investment universe. What is seen as ethical is highly subjective, and the asset manager may define it as he pleases. By taking a strict approach to defining applicable companies to invest in, the manager will please a larger number of ethical investors, but also limit his investable universe, making it more difficult to achieve diversification and outperform more conventional mutual funds. A looser definition of ethical criteria might give the manager more flexibility in his stock picking, but might also scare ethically concerned investors away, and be regarded as not truly ethical.

There should be no doubt that a flawless ethical company does not exist. There will be pros and cons with all companies from an ethical perspective. An oil company might have a lot of social- and governance practices implemented, but they are nevertheless part of an industry that is presumed as not especially environmental friendly by most investors. A green-tech company on the other hand, can be seen favorably from the environmental perspective, as they seek to solve the problem of carbon dioxide emissions by finding new sources of energy, but they might have a poor governance structure. Which company is applicable for an asset manager in an ethical mutual fund?

Each ethical mutual fund has its own individual criteria for ethical screening. Some funds do this screening in-house, while others rely on external experts to help them in the screening process. This has triggered an emergence of independent research agencies which focus is solely on analyzing and ranking the ethical performance of companies. Some of these agencies have also collaborated with index providers to offer ethical indices, comprising only companies that achieve a high score on the ethical criteria set forward from the agency. Examples of such indices are FTSE4Good and Dow Jones Sustainable Index (DJSI). Either way, one could argue that every fund that is serious with their ethical approach should provide detailed information to possible investors, about how they undertake their ethical screening, and which ethical criteria they are screening against.

We will now elaborate on the seven different strategies of ethical investing, defined by the key organizations promoting ethical investing (US SIF, EUROSIF and UN PRI), and further introduce a narrower approach to ethical investing, defined by us.

3.3.1 ***Negative screening***

Negative screening, or exclusion, involves restricting investments in certain companies or industries, usually based on negative exposure to some ESG-criteria (US SIF - The Forum for Sustainable and Responsible Investment, 2014). The most common is excluding companies involved in the production or distribution of tobacco, armaments, alcohol, pornography and gambling services. Some funds also exclude companies involved in animal testing, intensive farming and companies deriving profits from oppressive regimes (Robins & Krosinsky, 2008). Companies operating in environmentally damaging industries, such as fossil fuels, and companies with history of breaching human rights are also excluded by some funds. Common for all of these screens are that they ensure that the fund does not profit from issues that do not comply with their ethical principles.

An important decision for the fund manager, in addition to defining which screens to incorporate, is a cut-off point of how exposed a company can be to one of the exclusionary criteria in order not to be considered as an applicable investment. Companies operating in other industries than the ones comprising the negative screen might still derive revenues from them. Imagine a company producing navigational systems, receiving an order to deliver devices to a producer of fighters, like Lockheed Martin. The revenues stemming from the order might be a small fraction of total revenues, but could the company still risk mutual fund investors selling their shares if they accept the order? Each ethical mutual fund has its own criteria, but as far as we have seen, the most common cut-off point is that less than 5-10% of revenues can stem from operations that are not meeting the screening criteria, in order to be applicable.

3.3.2 ***Positive screening/Best-in-class***

Positive screening is the search for companies with extraordinary performance on some defined ethical criteria. Companies with extensive reporting and full disclosure on ethical issues such as emission, gender equality and working conditions, with substantial measures taken to ensure operating within defined ethical and social criteria, superior to the average company, would usually come out favorable in a positive screening process. Mutual funds following a positive screening process would define a universe of strong performing companies on a set of ESG criteria, before evaluating the more traditional financial performance and valuation of the company (Robins & Krosinsky, 2008). This strategy could incentivize companies to take specific actions concerning ESG issues, in order to pass the positive screening of ethical mutual funds, and thereby potentially lower their cost of equity capital. Such actions might also lead to positive media coverage, and a stronger brand, which again might lead to better financial performance.

A best-in-class approach is similar to positive screening, the difference being that it evaluates the ethical performance relatively to their industry peers (Robins & Krosinsky, 2008). In that way a mining company, which might not come out on top of a positive screening process due to the challenging working conditions of their miners, could be included in the investable universe of an ethical mutual fund, if they have taken measures superior to other mining companies to ensure the safety and health of their workers. A best-in-class strategy encourages companies to achieve ethical performance superior to their peers, and thereby incorporate ESG-criteria in their operation. When following a best-in-class strategy, the nature of their industry or products are not considered, and they might be an applicable investment, as they are analyzed relative to industry peers. Hence, many ethical mutual funds following this strategy could incentivize companies that would usually not take any serious action on implementing ESG criteria in their operation, to do so.

3.3.3 ***Norms-based screening***

Norms-based screening is screening of investments against minimum standards of business practice based on international norms (US SIF - Forum for Sustainable and Responsible

Investment, 2015). From this definition it can be argued that the norms-based screening strategy is a light form for negative screening, except the criteria screened against are not based on subjective, personal beliefs or values, but rather based on a consensus of what could in an absolute minimum be expected of ethics in a corporation. Further, one could probably argue that of what could in an absolute minimum be expected of ethics in a corporation. One could probably argue that this mild form of incorporating ethical criteria in investing would not be sufficient to satisfy a strictly ethical investor.

3.3.4 Integration of ESG factors

ESG integration in the investment process is defined as “the systematic and explicit inclusion by investment managers of ESG risks and opportunities into traditional financial analysis” (US SIF - Forum for Sustainable and Responsible Investment, 2015). In other words, by following a strategy of integration of ESG factors, you consider a variety of criteria under each of the three factors, and determine how a company is performing or possibly exposed to these criteria. Then you assess whether what you uncover is a possible risk or opportunity for the company going forward, and consider this information to complete your view of the company as a possible investment, alongside more traditional financial information. This strategy is fairly basic, and for many ethical investors this is more the building block for constructing negative- or positive screening, than a strategy itself.

However, by defining ESG factor integration as a strategy, US SIF, EUROSIF and UN PRI can raise the awareness, and measure the number of asset managers which take more than plain financial considerations in their investment analysis. As this approach goes mainstream, companies are forced to consider their stance on the different ESG factors, which might eventually lead to an improvement in environmental, social and governance standards by companies.

3.3.5 Sustainability themed

Some mutual funds are sustainability themed. This means they have a specific theme for their investing, such as renewable energy or water (US SIF - Forum for Sustainable and Responsible Investment, 2015). Instead of seeking an overall ethical approach, the fund targets one narrow industry or megatrend, and invests solely in companies exposed to this particular theme. Popular examples are mitigating the threats of resource scarcity or carbon dioxide emission the globe is facing in the future. The financial performance of such funds will, to a greater extent than for the other strategies, be highly linked to the performance of entire industries or sectors.

3.3.6 Impact/Community investing

Impact investing is a concept of targeted investment in private markets (usually) aimed at solving environmental or social problems (US SIF - Forum for Sustainable and Responsible Investment, 2015). Impact investments also seek financial return alongside the superior aim of positive societal impact. According to Global Impact Investing Network (GIIN), close to zero public equity funds with an impact investing strategy exist (GIIN - Global Impact Investing Network). Investing vehicles with an impact investing strategy are more often Private Equity or Venture Capital, and banks providing bonds to finance specific operations with the goal of solving societal issues.

Community investing is closely linked with impact investing, except the funds are specifically directed at underserved and poor individuals or communities (US SIF - Forum for Sustainable and Responsible Investment, 2015). Neither community investing is commonly undertaken through equity funds. More common ways of community investing is trough deposits at community development banks and institutions or through direct loans (GIIN - Global Impact Investing Network, 2015).

Even though Impact/Community investing is defined as one of seven strategies to pursue ethical- or sustainable investing by US SIF, UN PRI and EUROSIF, in their market updating publications EUROSIF do not report this strategy. In this thesis we are focusing on investments in public equity, either directly or through mutual funds. Hence, this strategy is obviously not relevant for our mission.

3.3.7 Corporate engagement and shareholder action (Engagement)

Engagement funds include funds that seek to influence the companies invested in, by regularly holding talks and visit the companies in their portfolio and by using their votes at general assemblies to influence them in a more ethical direction (Robins & Krosinsky, 2008). A record of their votes would usually subsequently be published for the investors to see (US SIF - The Forum For Sustainable And Responsible Investment, 2013). A fund might seek to invest in companies that they believe are not ethical, and try to change that through their ownership, or they might invest in already ethical companies and further enhance the ethical considerations undertaken. Either way, such an approach is clearly more time-consuming, and it might take several years before their actions pay off. For ethically concerned investors, active ownership and influence is probably best considered together with other ethical strategies, and not as the sole strategy of a mutual fund, which is also emphasized by Krosinsky and Robins (2008). Ethically concerned investors would most likely not like to participate in ownership of unethical companies, even if the aim is to influence and encourage them in a more ethical direction. They would probably prefer investing in already ethical companies, and thereby incentivize non-ethical companies to consider their ethics in order to be an applicable investment for the growing numbers of ethical investors. Table 2 illustrates some of the tools used by funds following an engagement strategy.

Table 1 – Active Ownership and Engagement in Public Companies

Active ownership and engagement in public companies
Voting proxies and filing shareholder resolution
Dialoguing with company executives
Conducting letter-writing and e-mail campaigns
Attending and speaking at annual shareholder meetings
Publishing research reports or industry analyses
Participating in multi-stakeholder dialogues

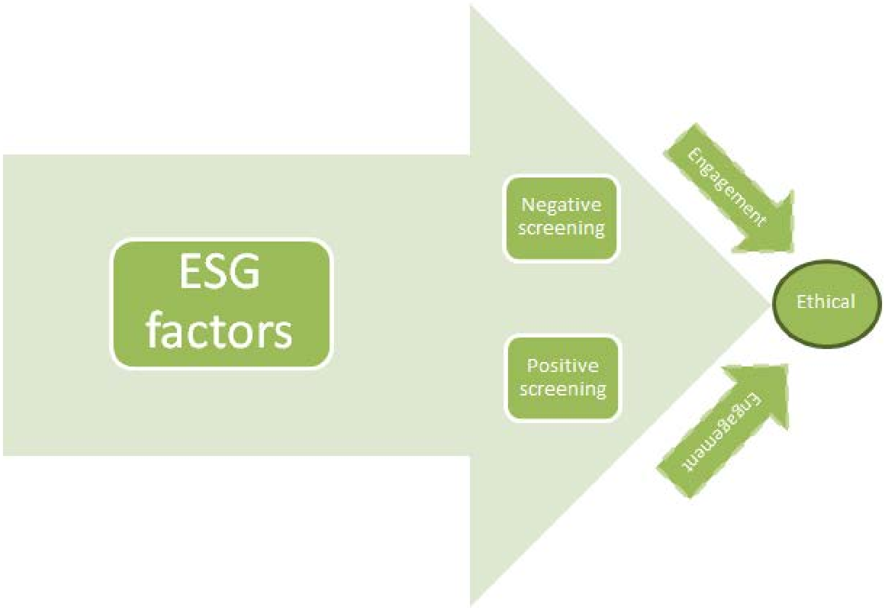
Source: (US SIF - The Forum For Sustainable And Responsible Investment, 2013)

It should be stressed that the seven strategies introduced are not mutually exclusive and are often used in combination. On that note we have established our own framework for ethical strategies followed, in order for an ethical fund to be classified as ethical in our dataset, which will be elaborated on in the following section.

3.3.8 Our approach to an ethical strategy

We have tried to put ourselves in the shoes of the "average" ethical investor and design a capture-all approach which would yield a firm base for us to put together a credible sample of ethical mutual funds, which most ethical investors would approve of. Figure 2 shows a graphical illustration of the approach.

Figure 2 – Our Approach



Considering ESG factors is the foundation of building negative and/or positive screens, which will define the investable universe. We believe truly ethical investors appreciate the fact that the ESG factors are used to take some active choices regarding the investable universe. We have not defined what the negative- or positive screening consist of, but there should be some screening involved. Further an engagement strategy could be used, to further actively ensure ethical performance by the companies under ownership. The dashed lines symbolizes that an engagement strategy does not have to be in place, but it would further enhance the ethical profile of the investment strategy.

3.4 Market Development

Since its launch in 2006 the number of signatories to UN's Principles of Responsible Investments (UN PRI) has risen from 100 to 1,380, with AuM totaling more than 59 trillion dollars in April 2015 (UN PRI - United Nations Principles for Responsible Investment). The signatories have complied with the six principles set forward by UN PRI, which can be seen in table 2. Although agreeing to comply with UN PRI's principles alone is not enough for all of their mutual funds to be deemed ethical in our study, the rise in signatories and AuM clearly underlines the increasing importance of ethical considerations within the financial industry. As mentioned earlier, the early beginning of ethical investing traces years back. The correct use of money is even evident in the New Testament (Hancock, 2002). It is, however, first in the past decade that ethical investing has established itself as a legitimate investment approach for the masses. In recent years ethical investing has gotten serious media-, political- and investor attention.

Table 2 – UN PRI's Six Principals for Responsible Investments

UN PRI's Six Principles for Responsible Investments
We will incorporate ESG issues into investment analysis and decision-making processes
We will be active owners and incorporate ESG issues into our ownership policies and practices
We will seek appropriate disclosure on ESG issues by the entities in which we invest
We will promote acceptance and implementation of the Principles within the investment industry
We will work together to enhance our effectiveness in implementing the principles
We will each report on our activities and progress towards implementing the Principles

Source: (UN PRI - United Nations Principles for Responsible Investment)

We will now elaborate further on the development of ethical investing in two of the main financial markets, which are also the forerunners of ethical investing, namely the two markets of focus in this thesis; the US and the UK.

3.4.1 UK

Since the early traces from the Quakers, the UK market for ethical investing has developed considerably. Today UK is one of the leaders of ethical investing, with several important global NGOs and ethical investing thinkers, such as UN PRI, located within its borders (Eurosif, 2014). According to EIRIS there was more than 15 billion pounds of public assets invested in UK-domiciled ethical retail funds in 2015. It has seen remarkable increase from the 3 trillion pounds invested in 2000 (EIRIS Foundation). Regardless of the remarkable growth, ethical investments only accounted for 2% of the total market in 2015. This is still enough to account for 14.5% of the European market, only behind France (34.9%) as the leader in Europe. Equity funds are by far the most popular, as 74% of the UK funds are pure equity funds, with balanced funds (13%) and fixed income funds (12%) fighting for the second position (Vigeo, 2015).

In their report from 2014 EUROSIF publish the AuM in each six of their seven defined strategies (introduced in section 3.3) for the year of 2013. As mentioned previously, they do not report the size of the Impact/Community investing strategy. As the strategies are not mutually exclusive, and no calculation of the magnitude of the overlapping numbers is provided, these numbers do not give a clear picture of the overall UK market. It does however illustrate which strategies are most popular, and form a basis of comparison between countries. Engagement and ESG integration is by far the strategies employing most money under management, with negative screening as the third most popular strategy. Engagement was also the fastest growing strategy between the years of 2011 and 2013, with a Cumulated Annual Growth Rate (CAGR) of almost 32%. Negative screening was the second fastest growing strategy with a CAGR of more than 20% (Eurosif, 2014). It should also be noted that as ESG integration was not reported in 2011, we have no measure of the growth of this strategy during that period.

Ethical investing has also gotten political attention in the UK, and in 2010 the Financial Services Authority introduced the UK Stewardship code, which consists of good practice standards on engagement with companies. There is mandatory disclosure of commitment to the Stewardship code, on a "comply or explain" basis (Eurosif, 2014).

3.4.2 US

The US market for ethical investments is not surprisingly the world's biggest, with 6.57 trillion dollars under management in one of the seven defined strategies in the beginning of 2014 (GSIA - Global Sustainable Investment Alliance, 2015). Seen relative to UK this number seems enormous, but we should keep in mind that this number accounts for both retail and institutional investors in funds, compared to the 15 billion pounds invested in retail funds referred to in the UK. Regardless, the US ethical market is the world's biggest, and ethical investing is also a relatively more important segment of the market than in the UK, as its market share was reported 17.9% in 2014 (GSIA - Global Sustainable Investment Alliance, 2015).

In the "*Global Sustainable Investment Review 2014*" published by Global Sustainable Investment Alliance (GSIA) and US SIF, they report the size of the different strategies in the same manner as the EUROSIF report referred to in the section above. The numbers are reported as of the beginning of 2014. ESG integration is the most dominant strategy, closely followed by negative screening. Engagement is the third most popular strategy. ESG integration saw a CAGR of more than 102% from the beginning of 2012 to the beginning of 2014, with negative screening as the second fastest growing strategy with a CAGR of more than 25%. The Positive screening/Best-in-class strategy however, experienced a decline with a CAGR of close to -10% (GSIA - Global Sustainable Investment Alliance, 2015).

3.4.3 Differences between UK and US

What is considered ethical is obviously open for personal interpretation, but on a general basis there are some differences worth mentioning between the US and the UK, or more generally between the US and Europe. It can be argued that the exclusion of companies involved in the production of hand weapons is more of a European phenomenon, as guns are more common and accepted in the US. Specifically, in some American states it is considered a right to own guns for protection, and there is nothing unethical about it.

Figure 3 and 4 illustrates the differences in the six strategies published by EUROSIF. The numbers are gathered from EUROSIF's "*European SRI Study 2014*" and GSIA's *Global Sustainable Investment Review 2014"* for the UK and the US respectively. It should be noted that there might be some differences in measurement of the different strategies across the two countries, but these numbers should nevertheless provide some basis for comparison.

Figure 3 – Size of Different Strategies, UK

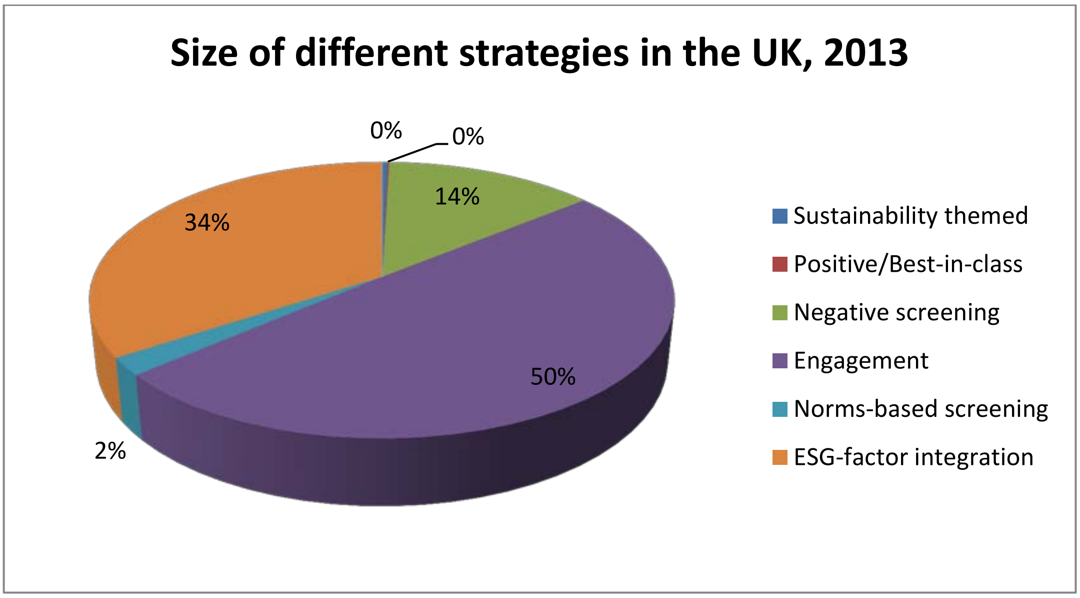
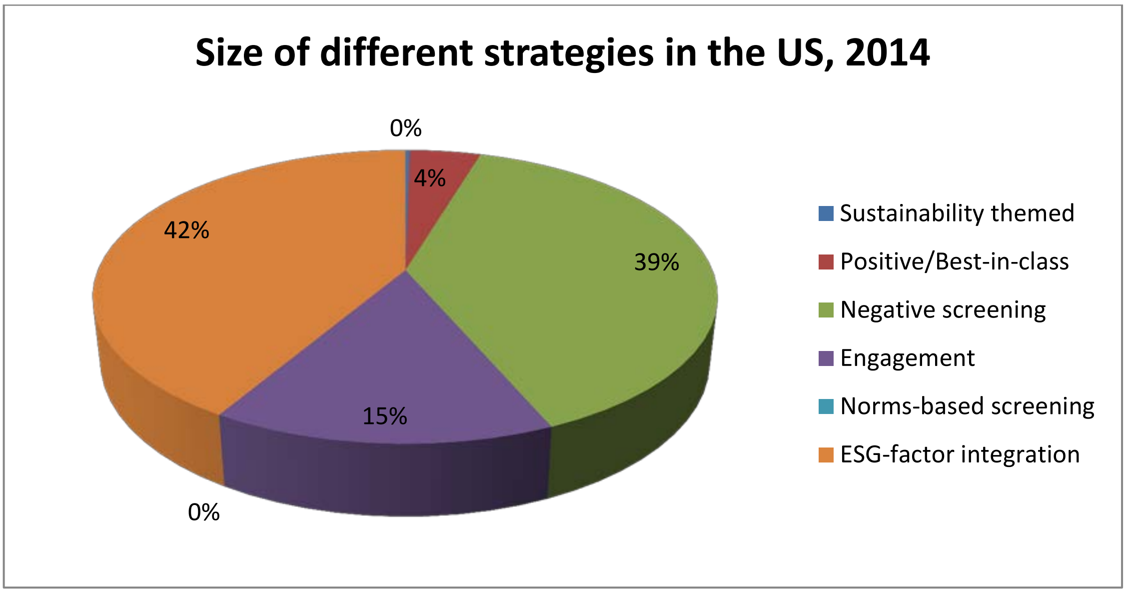


Figure 4 – Size of Different Strategies, US



As can be seen, negative screening is a much more popular strategy in the US than in the UK, while engagement has a much stronger standing in the UK than in the US.

3.5 Evidence of ethical investing in practice

Up till this point we have mainly considered theory, and based our description of the ethical investment industry on facts and statistics from NGOs. As good as this might be such summary- and overall information is on an aggregated level. As an addition, we believe it could be useful to take a more practical approach, and we had the opportunity to conduct an interview with Jan Tore Andresen, director in Nordea Asset Management Norway, on how Nordea conduct their ethical investments. Specifically, Nordea Asset Management Norway offer an equity mutual fund called “Nordea Stabile Aksjer Global Etisk” (which translates into “Nordea Stable Stocks Global Ethical”) which has recently been awarded “Best Global Mutual Fund” by Morningstar Norway, and has also received similar awards internationally for their superior performance. The interview is presented in its entirety in the box below.

Interview with Nordea (Andresen, 2016)

First of all, congratulations on your award winning fund "Nordea Stabile Aksjer Global Etisk" (NSAGE). Why did you decide to launch an ethical mutual fund in the first place?

"Some institutional investors have very strict ESG requirements, such as The Red Cross, Churches and Unions. NSAGE was set up in collaboration with a Norwegian investment consultant back in late 2008 as more of a business case than a need for an ethical version of the Global Stable Stock fund. The fund has several negative filters to ensure that even the strictest of our investors when it comes to ethicality will be able to invest in the fund."

Your fund has achieved superior returns compared to the overall market, but also compared to other conventional mutual funds. Do you think some of the performance can be attributed to the "ethical factor" of your fund, or is the performance mainly driven by good stock picking, and an overall success in your industry-, factor-, and geographic allocations?

"The AIMR GIPS Composite[1] *has done well with approximately 3.5 % in annual excess return since its launch (10 years +). We have not tried to isolate the ethical effect of the performance of NSAGE, so it is hard to say whether this has had an influence on the performance of this particular fund."*

"The investment philosophy of NSAGE is based on identifying companies with historic stable earnings and stable expected future earnings growth, which have attractive valuations. We fall into the "Low volatility" category, but actually it is more of a "high quality and stable growth of earnings" approach. We believe that companies which address ESG issues in a proper manner will have better ability to deliver sustainable growth in earnings than companies which ignores ESG. We do not believe in a best-in-class approach, but what is important to us is that the company addresses the ESG area proactively. Hence, synergies between the ethical component of the fund's strategy, and the strategy's pursuit of stable earnings might exist, and might have contributed to the overall success in performance of NSAGE, although we have not conducted such investigation."

[1] AIMR GIPS Composite refers to the group of Nordea stocks following the same particular investing strategy as the fund in question (Nordea Stabile Aksjer Global Etisk). In this case it does not refer to funds labelled as ethical, but funds following a similar strategy in their factor- and geographic allocation as Nordea Stabile Aksjer Global Etisk.

How do you incorporate the ethical element in your investment process? Is it mainly a negative screening strategy which prohibits you from investing in certain industries and stocks, or do you pick strictly stock of firms that perform superior on some sort of ethical measure (such as ESG ratings etc.)?

"In NSAGE there is pure negative screening conducted. For example the fund will not make investments in companies which derive any profit from the production or distribution of controversial weapons (such as cluster munitions and landmines)."

Do you have some specific ethical criteria your investments must fulfill in order to be applicable for your ethical portfolio?

"No, but the portfolio managers use ESG tools from research providers like MSCI Inc. to incorporate the ESG-effect on the future ability to generate stable earnings growth. If the ESG analysis gives warning signals, this will be taken into consideration. We also have our own ESG team which contributes in this task."

When excluding certain companies, is such exclusions based on your own assessment of their ethicality, or do you rely on outsiders such as ESG specialists?

"Our exclusions in NSAGE are mainly based on external expertise, but we also have our own blacklist in Nordea, which is applicable to all Nordea funds."

Do you believe that ethical mutual funds on average and in the long-run will deliver better risk-adjusted returns for your investors than conventional funds? Or is your ethical fund offers mainly an alternative for your more ethical conscious investors, so that they can invest with Nordea and still keep their conscious clean, although they may earn better returns on their money elsewhere (in a conventional fund, which is not deemed "ethical")?

"Good questions. In Nordea we have what we call the "Star fund family". This "family" of funds does not incorporate negative screening, but rather include only companies which pass a certain threshold of ESG ratings in the portfolio. The Star funds are in such sense incorporating more of a positive screening strategy; hence NSAGE is not a part of this family. A good evaluation of a company's ESG performance is ensured through a combination of engagement, thematic research, field trips and ESG analysis. The reason for establishing such funds is the belief that being aware of and adaptable to ESG challenges will be a key

enabler for a company to survive the tremendous geopolitical challenges ahead, and the success of such will expose their business to less risk. Not only will this create a solid foundation for better long-term returns, but hopefully also make the world a little bit better."

"In the Star funds each investment must be accepted by our own ESG team, and the ESG aspect is integrated in the portfolio management. We believe that our clients want good return that is delivered in a sustainable manner. An issue is of course that the investment universe and the flexibility of the portfolio manager is somewhat constrained, for the better or worse performance wise."

Why isn't a bigger fraction of your mutual fund offering classified as "ethical"?

"The Star family will be more visible going forward with the launch of an additional member of the Star family; Global Stars. We will also launch another fund with "ETISK" (translation: "ethical") in the name this upcoming summer."

Why do you think ethical investment solutions, such as ethical mutual funds, have seen such a rise in popularity in the recent years/decade?

"The huge attention to global warming as well as an increased transparency in the world has probably led to an increased focus on ESG issues, and is likely to have contributed to the rise in demand for products such as ethical mutual funds."

Where do you see the industry of ethical investing heading in the future? Can we hope for a future where all mutual funds take ethical considerations? And will this lead to an overall better business ethic worldwide?

"I think every asset management company must take ESG considerations going forward. The best way is to make this an integrated part of the financial portfolio management without using blacklists, and of course to try to make change happen in companies that you want to invest in, that not yet has sufficient ESG proactivity."

4. Theory

4.1 Return Properties

The return on a security is the sum of the change in price of the security between two different dates, and the income received by the holder of the security in that time period. Such return is known as the Holding Period Return (HPR), as it reflects the return the security has made in the period of holding, regardless of the length of that period. More formally the HPR can be calculated as follows:

$$R_t = \frac{P_t + D_t}{P_{t-1}} - 1$$

Where:
R_t is the HPR
P_t and P_{t-1} is the price of the security at time t and t-1 respectively
D_t is the dividend received at time t

This way of calculating HPR assumes the dividend is paid at the end of the period, and ignores potential reinvestment income between the receipt of the dividend and the end of the holding period (Bodie, Kane, & Marcus, 2014). In our analysis, we have calculated our returns from the Total Return Index in DataStream, which incorporates the dividends at the time they were distributed, and assumed they are reinvested. The dividend component of the HPR is therefore incorporated in the P_t variable. Hence, our returns are calculated as:

$$R_t = \frac{P_t}{P_{t-1}} - 1$$

This way of calculating returns is known as simple returns. An alternative is using logarithmic returns. They are calculated as follows:

$$r_t = \ln(\frac{P_t}{P_{t-1}})$$

Where:
ln is the Natural Logarithm.

Using logarithmic returns are quite popular in finance, for a number of reasons. Logarithmic returns are normally distributed also when calculating returns over more than one period, whereas simple returns are not. The reason for this property is that logarithmic returns are additive, which means you can simply add up logarithmic returns for sub-periods to calculate the return over the entire period. Simple returns on the other hand are multiplicative. If we assume returns are normally distributed, then they still will be when they are added together, but not if they are multiplied. Having normally distributed returns are usually favored since they are symmetric (equally likely to have a positive, as a negative, deviation from the mean), and more “stable” (Bodie, Kane, & Marcus, 2014).

On the other hand, simple returns aggregate across assets, which make portfolio calculation merely a weighted average of the individual securities’ returns. Also, the relation between logarithmic- and simple return averages over a time period is dependent on the variance of the return. This complicates the financial theory that investors who take a particular level of risk should be rewarded by an appropriate level of return. Thus, as the logarithmic return of a series of returns depends on the variance of that series, the relationship between risk and return could to some extent be complicated (Huson & Gregoriou, 2010).

When calculating returns on short time intervals the difference between simple and logarithmic returns are trivial. For the sake of completeness and harmony, and the fact that there are pros and cons with both sorts of returns, we have applied simple return calculation as that is how Fama and French have calculated their returns, which we have used for our factor models.

In our research we are working with weekly and monthly returns, but when reporting the returns we annualize them. The concept of compounding is explained with the following equation:

$$R_{annual} = \left[1 + R_{period}\right]^{number\ of\ periods} - 1$$

4.2 CAPM

The Capital Asset Pricing Model is a single factor equilibrium model for expected return. The model assumes that the expected return that investors require on their investments should be linearly related to the assets covariance with the market portfolio. The model was first introduced by Sharpe (1964) and Lintner (1965b), who built further on the groundwork on portfolio optimization by Markowitz (1959). The model rests on a set of assumptions that states that all investors… (Elton, Gruber, Brown, & Goetzmann, 2010)

- *Face no transaction costs – no cost of buying or selling an asset.*
- *Can trade any fraction of an asset – Assets are infinitely divisible.*

- *Face no personal income tax – the investors do not care how the returns are obtained, dividends vs. capital gains.*
- *Are price takers - individuals cannot affect prices by trading.*
- *Maximize their economic utility – investors solely take the relationship between the return and standard deviation into consideration when investing.*
- *Can short sell an unlimited amount of shares.*
- *Can borrow and lend an unlimited amount at the same risk free interest rate.*
- *Are faced with the same inputs to analyze the relationship between risk and return – same expected return, standard deviations and covariance matrix. They therefore have homogenous expectations of the market.*
- *Can trade all assets in the universe – this means that all assets, including human capital, can be bought or sold in a market place.*

It is clear that many of these assumptions are unrealistic, and do not hold in the real world market. The model is though still attractable, and widely used in the performance measuring of stocks and mutual funds.

4.2.1 The Sharpe-Lintner-Mossin CAPM:

The standard version of the model was independently developed by Sharpe, Lintner and Mossin, and therefore also has gotten the name the Sharpe-Lintner-Mossin model. The model can be written as:

$$E[R_i] = R_f + \beta_{im}\left(E[R_m] - R_f\right)$$

Where:
R_i is the return of asset i
R_f is the return of the risk free asset
β_{im} is the beta of asset i with the market m
R_m is the return of the market portfolio

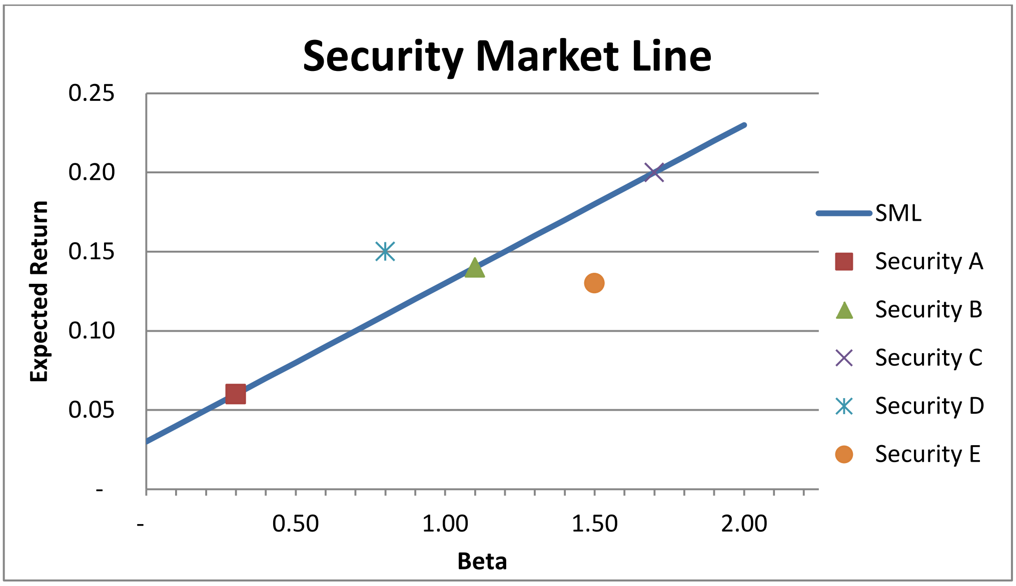
The model therefore explains that the expected return of any asset should be the risk free interest rate, plus the beta of the stock times the market risk premium. The beta measure is in the heart of the model, and should capture the difference in expected return that an investor requires for holding the specific asset. The beta is measured by applying the following formula:

$$\beta_{im} = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

Whereas before

The asset's expected return is therefore related to the asset's covariance with the market portfolio. This means that an asset with a high covariance with the market, that fluctuates more than the market, should also yield a higher expected return than an asset with a low covariance. We further see that if we pick the market portfolio itself to be R_i, the beta will equal 1 – which indicates that the weighted average of the beta of all the stocks in the market portfolio should equal 1. This relationship can be further visualized by studying the security market line (SML).

Figure 5 – Security Market Line



The expected return is linearly related to the beta of the asset. In a perfect equilibrium market, all assets should plot exactly on the line like security A, B and C, and the only thing that should make them differ in the expected return is the differences in beta. If a stock plots above the SML, like security D, this means that the stock is underpriced – in equilibrium the efficient portfolio will then shift and investors will increase their share in that stock, lowering its expected return and bringing it back on the line. On the other side, if a security plots below the security market line, like security E; this means that this asset is overpriced. In equilibrium investors will therefore shift their portfolios to contain less of this security, which will decrease its price, and increase its expected return, bringing it back onto the line.

As mentioned, the model is widely used for performance measurement, but it has also met a lot of skepticism in the academic environment. Several papers have found that there is actually no relationship between the beta and the average return, and that this relation was only prominent for a period in the middle of the 20^{th} century (Fama & French, The Cross-Section of Expected Stock Returns, 1992). Also, the CAPM might not actually be testable, because in order to test the model we would have to find the true market portfolio. The true market portfolio will consist of not only all the stocks and bonds in the universe, but of all the available assets in the universe such as real estate, precious metals, stamp collections etc. The return of the true market portfolio is therefore unobservable (Roll, 1977)

4.2.2 Practical Application of CAPM:

For statistical testing it is most common to use the excess return form of the CAPM:

$$Z_{it} = \alpha_{im} + \beta_{im} Z_{mt} + e_{it}$$

Where:
Z_{it} is the excess return of asset i in period t
α_{im} is the intercept of asset i with market m
β_{im} is the beta of asset i with the market m
Z_{mt} is the excess return of the market portfolio in period t
e_{it} is the error term of asset i in period t

The implication of the CAPM is that in equilibrium, α of all assets should equal to zero, and all the variation in returns should be explained by the beta. The firm-specific residual e_{it} is assumed uncorrelated across all assets, including the market portfolio. An asset's total risk will therefore be the sum of the firm-specific risk and the market risk:

$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma^2(e_i)$$

At a portfolio level the return of a portfolio Q, with weights in k different assets is equal to:

$$R_Q = \sum_{k=1}^{N} w_k \alpha_k + \sum_{k=1}^{N} w_k \beta_k R_M + \sum_{k=1}^{N} w_k e_k = \alpha_Q + \beta_Q R_M + e_Q$$

From this relation we can see that since the firm-specific risk is uncorrelated between assets, it can be eliminated by diversifying the investments across enough stocks. The market risk will though not be eliminated, but will become a weighted average of the betas of the assets held in the portfolio. The alpha of the portfolio will be the weighted average alpha of the assets in the portfolio, and it is therefore favorable to buy assets that yield a positive alpha and short assets with a negative alpha. Though, in the CAPM world opportunities like this should not arise, as the market portfolio will shift and all investors therefore will increase/decrease their position in these assets.

4.3 Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT) was primarily developed by Stephen Ross in 1976. Like the CAPM, APT derives a relationship between risk and return, but there are some differences. APT relies on three propositions (Bodie, Kane, & Marcus, 2014):

- Security returns can be described by a factor model
- There are sufficient securities to diversify away idiosyncratic risk
- Well-functioning security markets do not allow for the persistence of arbitrage opportunities

4.3.1 Factor Models

The first proposition refers to the theory of factor models. A factor model is a model that describes the uncertainty in returns of a security as a function with two groups of components; one or more macroeconomic components and one or more firm-specific components. To consider the most basic example, a factor model with only one macroeconomic factor, the single-factor model:

$$R_i = E(R_i) + \beta_i F + e_i$$

Where:
$R_i$is the excess return of asset i
F is the deviation of the common factor from its expected value
β_i is the sensitivity of firm i to that factor
e_i is the firm-specific disturbance

The common factor F is constructed such that its expected value is zero, in order to capture only new information. Hence, it will only capture the discrepancy from the expected value, and this discrepancy will affect the excess return of the security according to the security's sensitivity to this factor. For example, if we are looking at a stock, which has a risk premium of 10% and a sensitivity of 1.2 to the GDP growth. GDP growth is expected to come in at 3%. Hence, if the GDP growth does in fact come in at 3%, only the already expected return of the security and the firm-specific events will describe the excess return of the security. If the GDF growth comes in at 4% on the other hand, the excess return on the security will equal 11.2% plus the effect of the firm-specific events. The firm-specific term, the e_is, are assumed to be uncorrelated across stocks and with the common factor F (Bodie, Kane, & Marcus, 2014).

This was an example of a single-factor model, but a more compelling example is a model where more than one factor describes excess returns. Interest rate levels and inflation are, in addition to GDP growth rate, examples of common macroeconomic factors applied in multifactor models. The logic and the model specification is the same as in the single-factor model. A multifactor model could look something like this:

$$R_i = E(R_i) + \beta_{iGDP} GDP + \beta_{iIR} IR + e_i$$

For a model that describes excess returns with both GDP growth and interest rate level. Different stocks will have different sensitivity to each of the common factors, and since we are often operating with several factors, these sensitivities (the betas) are often called factor betas or factor loadings (Bodie, Kane, & Marcus, 2014).

4.3.2 Diversification

The second proposition refers to the concept of diversification. Ross states that a sufficient number of securities has to exist, such that idiosyncratic, or firm-specific, -risk is diversifiable. The theory is that a portfolio comprising several securities which are less than perfectly correlated, that is they have a correlation coefficient less than 1, will enable you to eliminate the firm-specific risk of each security. In a specific time-period some securities will experience positive firm-specific shocks, while other will experience negative firm-specific shocks. In the overall portfolio these shocks will average out, and be negligible on a portfolio level, if the portfolio is well-diversified.

More formally, the excess return on a portfolio P, consisting of n stocks, with weights $w_i, \sum w_i = 1$ is given by:

$$R_P = E(R_P) + \beta_P F + e_P$$

Where the portfolio beta and expected risk premium is the weighted average of the individual securities' beta and expected risk premium. The portfolio variance can be divided into a systematic and nonsystematic component:

$$\sigma_P^2 = \beta_P^2 \sigma_F^2 + \sigma^2(e_P)$$

Where:
σ_F^2 is the variance of the factor
$\sigma^2(e_p)$ is the nonsystematic risk of the portfolio

The nonsystematic risk of the portfolio is given by:

$$\sigma^2(e_P) = \sum w_i^2 \sigma^2(e_i)$$

As can be seen, the nonsystematic variance of the portfolio is simply the weighted sum of the nonsystematic variance of the individual securities in the portfolio. This is because the firm-specific term (e_i) of each of the individual securities is assumed uncorrelated. If we assume the portfolio is equally weighted, we can illustrate the effect of diversification with a simple formula:

$$\sigma^2(e_P) = \sum \left(\frac{1}{n}\right)^2 \sigma^2(e_i) = \frac{1}{n} \sum \frac{\sigma^2(e_i)}{n} = \frac{1}{n} \overline{\sigma^2}\ (e_i)$$

As can easily be seen, when n is large, the nonsystematic variance of the portfolio approaches zero. This is the effect of diversification. The effect of diversification holds also for a portfolio which is not equally weighted (Bodie, Kane, & Marcus, 2014).

4.3.3 No Arbitrage

The last proposition is the argument that there is no persistence of arbitrage. The concept of arbitrage is when an investor can earn a risk-less profit with no wealth invested. In other words, when a profit can be made by going short one security and the proceeds of the short trade is used to fund a long trade in another security. Such trades are usually made to exploit an apparent mispricing. An example of arbitrage could be that the same security is listed on two different market places, but have a different price. The law of one price states that two equivalent assets should have the same price, and a violation of the law of one price is an arbitrage opportunity. One could then buy the low-priced security and short the high-priced security, using the short proceeds to finance the long position. An immediate riskless profit is obtained and this profit is the difference between the two prices (without considering transaction costs). This strategy could be scaled up, by taking positions worth millions of dollars, and the prices would converge. The huge long position would pressure the lowest price upwards, and the short position would pressure the highest price downwards, and the prices would find itself in equilibrium again.

Assuming that arbitrageurs in the marketplace quickly exploit arbitrage opportunities, such opportunities will not exist for long and the market will be efficient. This is the condition Ross is referring to in his third and final proposition for the APT.

Let's imagine a single-factor market with a factor *F*, which is a well-diversified portfolio *M*, such as the market factor, for instance. The excess return of any security is:

$$R_i = \alpha_i + \beta_i R_M + e_i$$

And that of a well-diversified portfolio is therefore:

$$R_P = \alpha_P + \beta_P R_M$$

$$E(R_P) = \alpha_P + \beta_P E(R_M)$$

Since the nonsystematic risk is diversified away in the well-diversified portfolio, as proven in the previous section. Hence, the residual risk of both *M* and *P* is zero, and the only risk is the one stemming from its sensitivity to the common factor. Knowing that, we can eliminate all the risk of portfolio *P* by creating a zero-beta portfolio *Z* from *P* and *M* by selecting the weights $w_p$and $w_M = 1 - w_p$ such that the beta of portfolio *Z* equals zero. The portfolio *Z* is riskless, and its alpha is $w_p\alpha_p$. As the portfolio is riskless, its risk premium- the alpha- must be zero. Otherwise arbitrage profits could be made (Bodie, Kane, & Marcus, 2014).

Following the argument above, the expected excess return of any well-diversified portfolio *P* must be:

$$E(R_P) = \beta_P E(R_M)$$

And this proves that APT relates to the SML of the CAPM through the "no-arbitrage" argument and well-diversified portfolios. One shortcoming of APT is that creating well-diversified portfolios is not possible for every investor. Some portfolios consisting of hundreds of stocks might still have some residual risk. It is obvious that retail investors might not always be able to hold well-diversified portfolios, and hence the equation above will be less accurate. At some point the deviation from the equation will be so large that it is difficult to maintain full confidence in the APT. However, as we have seen in section 4.2 CAPM has shortcomings as well, and the APT is valuable.

Both CAPM and APT are equilibrium models, but they are based on a different argument. In the CAPM world, all investors are assumed to be mean-variance optimizers. This has the implication that once a mispricing is evident, all investors will tilt their portfolios slightly towards the underpriced security and away from the overpriced security. In order to eliminate the mispricing, a large number of investors would have to make this adjustment in their portfolio, in order for the dollar volume to be sufficient to move the prices back to equilibrium. In APT however, there is sufficient that a few arbitrageurs take action. As no initial wealth is needed, they can scale their trade so that the dollar volume is sufficient to move prices back to equilibrium, which makes it a stronger argument that the one applied in the CAPM theory (Bodie, Kane, & Marcus, 2014).

4.3.4 Multifactor APT

As briefly mentioned above, APT can easily incorporate more than one factor. A factor portfolio is a well-diversified portfolio, which by construction has a beta of 1 on one of the factors, and zero on any other. Such portfolio is uncorrelated with other risk factors than the one it tracks. With a large number of securities, and a small number of factors, the creation of such portfolio is possible. Each factor portfolio earns a risk-premium, which contributes to the security's total risk-premium. The factor exposure of each security is as before given by the factor loadings on the different factors. A multifactor model takes the form as the one with GDP and Interest Rate shown previously, but could be extended to incorporate several factors. The logic applied in the single-factor model applies also for the multifactor model (Bodie, Kane, & Marcus, 2014).

4.3.5 Fama-French Three-Factor Model

The introduction of multifactor models naturally leads us to the three-factor model of Eugene Fama and Kenneth French from their paper *"Common risk factors in the returns of stocks and bonds (1993)"*. This model is one of the dominant approaches today for describing security returns. Fama and French found that a simple CAPM model proved to be poor at explaining the returns of securities. In their study they uncovered two firm-characteristic factors which, in addition to the market factor, gave a better model to explain returns, namely the SMB and the HML factors. CAPM seems to explain approximately 70% of variability in returns, while the Fama-French three-factor model explains approximately 95% of the variability in returns (Fama Jr., 2006). The model takes the following form:

$$R_{it} = \alpha_i + \beta_{iM}R_{Mt} + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + e_{it}$$

Where:
R_{it} is the return on security i in period t, in excess of the risk-free rate
α_i is the return of security i not explained by the factors
β_{iM}, β_{iSMB} and β_{iHML} is secutrity i's sensitivity to the market-, SMB- and HML factor respectively
R_{Mt} is the return on the market factor in period t, in excess of the risk-free rate
SMB_t and HML_t is the return on the SMB and HML factor respectively in period t
e_{it} is the error-term, which incorporates the nonsystematic risk of security i in period t

SMB is an acronym for Small Minus Big, while HML is an acronym for High Minus Low. The SMB factor is the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks, where small and large refers to the market cap. The HML factor is the return on a portfolio of stocks with high book-to-market ratio in excess of the return on a portfolio of stocks with low book-to-market ratio (Bodie, Kane, & Marcus, 2014). In other words, the SMB factor seeks to incorporate the size-effect, which is an anomaly found in empirical research that small stocks outperform large stocks (Banz, 1981). The HML factor seeks to incorporate the value anomaly, that value stocks outperform growth stocks (Stattman, 1980) (Rosenberg, Reid, & Lanstein, 1985). In their paper Fama and French argue that even though these factors do not seem like obvious risk factors, they might proxy for some yet-unknown fundamental risk variables. Since the publication of their paper, the theoretical grounds for including these factors have been heavily debated. Some argue that small stocks and value stocks are more risky, and therefore should earn a risk-premium; while other argues that there are behavioral explanations for these anomalies. A further discussion of the theoretical grounds for incorporating these factors in a model for security returns is beyond the scope of this thesis.

A number of studies have concluded that the Fama-French three-factor model performs poorly when applied to less developed markets, such as emerging markets. The major problem is that the SMB factor behaves differently in emerging markets, and some have proposed to replace this factor with a factor which proxies for accounting manipulation (Foye, Mramor, & Pahor, 2013). As this thesis are looking at two of the world's most developed markets, the US and the UK, this critique has no implication for our research.

4.3.6 Carhart Four-Factor Model

Another anomaly in finance is the momentum anomaly. Titman and Jagadeesh (1993) confirmed the momentum anomaly by showing that stocks that has performed well in the past will outperform stocks that have performed poor in the past, in the subsequent 3-12 months (Jegadeesh & Titman, Returns to Buying Winners and Selling Losers: Implication for Stock Market Efficiency, 1993). As a response Mark Carhart extended the Fama-French three-factor model to also include a fourth factor- the momentum factor (Carhart, 1997):

$$R_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iMOM} MOM_t + e_{it}$$

Where:
β_{iMOM} is security i's sensitivity to the momentum factor
MOM_t is the return on the momentum factor at time t
The remaining components are as in the Fama-French three-factor model

The momentum factor in the model is the return on a portfolio of the best performing stocks in the last 12 to 2 months (you do not consider the last two months' return), minus the return on a portfolio of the worst performing stocks in the same time-period. Carhart found in his study that much of what appeared to be alpha of many mutual funds when using the three-factor model could be explained by their exposure to momentum stocks (Bodie, Kane, & Marcus, 2014). Fama and French later acknowledge that their three-factor model does not capture the momentum effect (Fama & French, Multifactor Explanations of Asset Pricing Anomalies, 1996).

A theoretical justification of why the momentum factor is an actually risk factor for a security is perhaps even harder to make, than for the two factors in the Fama-French model. Supporters of behavioral finance have argued that irrationality of investors is what causes the momentum anomaly to persist. Among the behavioral explanations are the "hot hands fallacy", namely that individuals believe that a certain event is more likely to occur if it has occurred in the near past, and that investors underreact to news, and hence such news would be slowly incorporated into prices which could cause us to discover a momentum in empirical research (Jegadeesh & Titman, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, 2001).

4.4 Fama-MacBeth Regression

In testing the CAPM, Fama-MacBeth (1973) introduced a new regression methodology which takes into use «rolling» cross sectional regressions. This model distinguishes itself by allowing for variation of the variables in the cross section, by running a series of cross sectional regressions for each time period, and then later aggregates the coefficients for each variable. The model is therefore well suited for testing if, and by how much, different variables are considered as «priced» (Cuthbertson & Nitzsche, 2004).

The model was used originally used to test the CAPM, and was meant to uncover whether the risk premium associated with the betas were positive, if there were any non-linear relationship between the returns and the beta, if non-systematic risk was priced, and if there were any other unknown variables that were priced. The model as proposed in Fama-MacBeth (1973) is a two stage model where the first stage estimates the betas of the different assets:

$$\beta_{it} = \frac{Cov(R_{mt}, R_{it})}{Var(R_{mt})}$$

Where:
β_{it} is the two year rolling beta for asset i
R_{mt} is the return of the market portfolio in the two-year period prior to t
R_{it} is the return of asset i in the two-year period prior to t

The beta is denoted with an «it» since the beta of the different assets is time-varying. In the original paper they are estimated over a two-year period, and then grouped in portfolios to minimize the estimation errors. The betas are then used in the second regression, to estimate the coefficients which describe how the beta is priced in the market. The second hand regression is given by:

$$R_{pt} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t}\hat{\beta}_{p,t-1} + \hat{\gamma}_{2t}\hat{\beta}^2_{p,t-1} + \hat{\gamma}_{3t}\bar{\sigma}^2{}_{p,t-1}(\hat{\varepsilon}_i) + \hat{\eta}_{pt}$$

Where:
R_{pt} is the return of portfolio p in period t
γ is the coefficients, the priced effect in period t
$\beta_{p.t-1}$ is the two-year rolling beta of portfolio from the period prior to t
$\sigma^2_{p,t-1}$ is the variance of the error-terms from the 1st-pass regression
$\hat{\eta}_{pt}$is the error term in the 2nd-pass regression, for portfolio p in period t

This regression is then run for every period, and the coefficients are then aggregated by taking the average of the time series of the individual coefficients. On the assumption that the returns are normally distributed, we can conduct inference by performing simple t-tests on these averages.

Even though the methodology was originally used as a test of CAPM, its applications can be used to test a theory of whether particular factors are priced in the market. The academic theory suggests using either macroeconomic factors, or traded portfolios as risk factors (Campbell, Lo, & MacKinlay, 1996). However, several papers (Brammer, Brooks, & Pavelin, 2006) (Hong & Kacperczyk, 2009) use observed firm-specific variables in their models, which, as we will discuss more in section 5, is also what we are doing.

4.5 Performance Measures

4.5.1 Sharpe Ratio

The Sharpe ratio is a performance measure which was originally developed by William Sharpe in his 1966 paper, “Mutual Fund Performance”. The ratio was originally called the “reward-to-variability ratio”, and was used to measure the performance of mutual funds. Since then Sharpe revised the ratio in his 1994 paper “The Sharpe Ratio”, after it had gotten considerable attention.

Sharpe builds on the previous work done by James Tobin, and shows that under certain conditions all efficient portfolios will lie along a straight line called the Capital Market Line (Sharpe W. F., Mutual Fund Performance, 1966)

$$E(R_i) = R_f + b\sigma_i$$

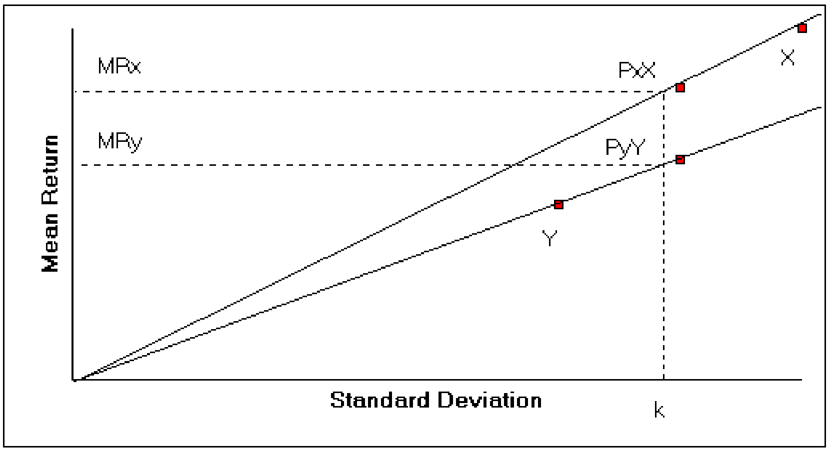
Where:
R_i is the return of asset i
R_f is the return of the risk free asset
b is the risk premium
σ_i is the standard deviation of asset i

Since investors are assumed to be risk averse, the risk premium must be positive, and it should therefore be a positive relationship between the risk and the expected return that an investor face. Then, by assuming that an investor can borrow or lend at the same risk free interest rate, an investor could, by maintaining his funds between the portfolio and the risk free asset, obtain the following return:

$$R = R_f + \left[\frac{R_i - R_f}{\sigma_i}\right]\sigma$$

The optimal portfolio is therefore the portfolio that gives an as high $\left[\frac{R_i - R_f}{\sigma_i}\right]$ as possible. This portfolio might not be the one that gives the highest return, but since the investor can borrow and lend money, the investment can be scaled to adopt the preferred relationship between risk and return (Sharpe W. F., Mutual Fund Performance, 1966). This can be visualized in the following plot:

Figure 6 – Capital Market Line, Source: (Sharpe W. F., The Sharpe Ratio, 1994)



Portfolio X has a higher Sharpe ratio than portfolio Y, indicated by a steeper line. If the preferred standard deviation is k, we could scale both of the investments to achieve this, increasing leverage in Y and decreasing leverage in X. We then see that portfolio X yielded a higher return for the given standard deviation than portfolio Y. The ratio can be expressed as ex-ante, by using the expected return and standard deviation, but it can also, as is most common, be expressed as ex-post by using the realized return and standard deviation over a specific time period (Sharpe W. F., Mutual Fund Performance, 1966).

The ex-post Sharpe ratio, as used in this thesis, is then given by:

$$SR_i = \left[\frac{R_i - R_f}{\sigma_i}\right]$$

Where:
SR_i is the Sharpe ratio of asset i
R_i is the return of asset i
R_f is the return of the risk free asset
σ_i is the standard deviation of asset i

Even though the Sharpe ratio is widely used, and has proved well in the ex-post performance measure of mutual funds, it has several shortcomings that should be addressed. Sharpe himself addresses the concern that the ratio does not incorporate the correlation between current assets held and the asset being evaluated. The ratio must therefore be supplemented with other measures in certain applications (Sharpe W. F., The Sharpe Ratio, 1994). Also, the inputs used to generate the ratio might not be stationary, and therefore a good predictor of what the forthcoming variables look like. A fund which has had success with managing a small amount of money might have to change its investment strategy when getting more AuM. This could distort their ability to generate positive risk adjusted returns. Lastly, the Sharpe ratio might not actually reward what should be rewarded. Days with exceptionally good return will increase the standard deviation as much as days with poor return, and could actually lead to a lower Sharpe ratio than if they were not included (Harding, 2002).

4.5.2 Treynor Ratio

The Treynor ratio was introduced by Jack Treynor in 1965, and was originally known as the "reward-to-volatility ratio". The ratio builds on many of the same concepts as the Sharpe ratio, but distinguishes itself by focusing on how the asset's performance is related to its covariance with the market, instead of its variability in terms of standard deviation.

Treynor plots the returns of mutual funds against the performance of the overall market, in a plot called the characteristics line. He then shows that the long term performance of mutual funds tend to be fairly stable when measured against the market portfolio, and argues that changes in the slope of the line between the fund and the market reveals the sensitivity of the fund's portfolio towards shifts in the market return (later known as beta of the portfolio). He also argues that deviations from this line can arise from two scenarios (Treynor, 1965):

1. That the fund is not fully diversified such that firm-specific risk causes fluctuations in its return.
2. That the funds management is placing bets, by increasing the volatility when they are optimistic and decreasing it when they are pessimistic.

Fund performance can therefore be compared by studying the tilt and intercept of the characteristics line. If two funds contain the same level of variability they will therefore have the same slope of the line and run parallel, but the one that has the highest intercept will have had excess returns over the other fund, and therefore performed better. Since the slope of the different funds will vary, it is hard to eyeball which of the funds that give a greater risk-adjusted return (Treynor, 1965). Treynor therefore proposed a ratio to capture this relationship, but that has later been developed into what we now know as the Treynor ratio:

$$TR_i = \left[\frac{R_i - R_f}{\beta_i}\right]$$

Where:
TR_i is the Treynor ratio of asset i
R_i is the return of asset i
R_f is the return of the risk free asset
β_i is the beta of asset i

An investor who is risk averse and can choose between investments and loan in a money-fixed claim, a risk free asset, will therefore always choose the fund that has a higher Treynor ratio, because this will enable the investor to get a higher return for any preferred level of market risk.

Even though the Treynor ratio is very similar to the Sharpe ratio, it inhibits some important differences compared to the latter. The Treynor ratio has proven to be a better forward looking measure, as the beta of a fund seems to be more persistent variable than the volatility (Sharpe W. F., Mutual Fund Performance, 1966). It also uses the market index as a benchmark, and is therefore better suited at measuring the outperformance of the market. It is though assumed that the portfolio measured is a well-diversified portfolio, such that it is merely the second scenario that influences the differences in the ratio. The Treynor ratio is therefore only suitable to use for portfolio evaluation, while the Sharpe ratio also works well on single securities. Lastly, the critique by Roll (1978), as pointed out earlier regarding CAPM, also applies to the Treynor ratio (Kidd, 2011).

4.5.3 Jensen's Alpha

In 1968 Michael Jensen published his paper *"The Performance of Mutual Funds in the period 1945-1964"*. He was interested in not only the return of the mutual funds, but also their risk. In order to assess the risk-adjusted performance of the mutual funds, he needed a measure of such. The result is what is now known as Jensen's alpha. Jensen's alpha is the intercept in a model, and simply captures the return on a security or a portfolio of securities, which is not explained by the risk factor controlled for in the model. If the alpha equals zero, the security is priced according to the model applied, no abnormal return is earned, and the security plots on the Security Market Line (see section 4.2) (Cuthbertson & Nitzsche, 2004). This would be consistent with efficient markets. In his paper, Jensen used the CAPM model (which is explained in section 4.2). Thus his risk-adjusted measure was the CAPM-alpha, which is the excess return on a security after controlling of its exposure to the market:

$$\alpha_i = r_{it} - r_{ft} + \beta_i\left[r_{mt} - r_{ft}\right] + e_{it}$$

Where:
r_{it} is the return on security i, in period t
r_{ft} is the risk-free rate in period t
β_i is security i's sensitivity to the market
r_{mt} is the return on the market portfolio in period t
e_{it} is the error-term, which captures the firm-specific risk

The alpha-measure may also be applied on models with more explanatory variables, or factors, than a simple CAPM model. The three-factor alpha measures the return on a security after controlling for three factors (most commonly market, size and value, as described in section 4.3.5) and the four-factor alpha measures the return on a security after controlling for a fourth factor (most commonly the momentum factor, as described in section 4.3.6). Adjusting the equation above to incorporate more than one factor is straight forward.

For a mutual fund's return, Jensen's alpha can be interpreted as the manager's ability to outperform the market. Securities or portfolios which show positive alpha have performed better than the market, or better than expected given the factor exposure of the security or portfolio. Positive alpha is fundamentally what investors are seeking when investing.

In this thesis, we will apply Jensen's alpha as a risk-adjusted return measure in different models, to assess the different performance of ethical funds versus conventional funds, and to assess the performance difference between portfolios of stocks with different ethical rating. Wherever "alpha" is stated, we are referring to Jensen's alpha.

4.6 Ordinary Least Square

Throughout this paper our analysis relies heavily on the use of regressions to try to pin down the effect of ethical investing. We therefore feel that a thorough understanding of the estimation method used in these regressions, Ordinary Least Square (OLS), is of importance.

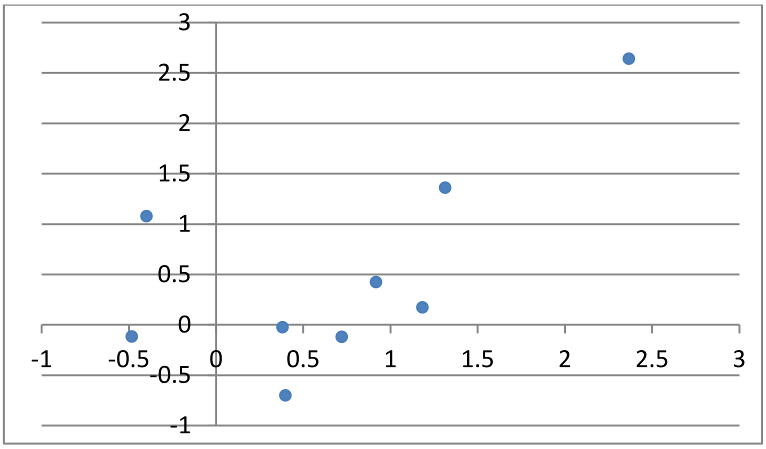
OLS is an estimation method used to assess the relationship between two variables. It is used in several different fields of study, and is considered the "language spoken" when economists and statisticians are talking about regression analysis (Stock & Watson, 2013). In financial data it can, for instance, be used to measure the performance of mutual funds, and to measure the impact of company specific factors on stock returns, which is what we use it for. In the heart of OLS is the linear model which describes this relationship that we want to measure. The basic version with one regressor can be written as:

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

Where:
Y_i is the dependent variable
X_i is the independent variable
β_0 is the intercept of the regression line
β_1 is the factor loading and the slope of the regression
u_i is the error term.

The relationship in this formula can also be visualized in a scatter plot:

Figure 7 – XY Plot



We clearly see that there is a relationship between the X variable and the Y variable, but to decide by drawing a line of what would be the best fitted line in this relationship, would be difficult without making significant errors. The errors that our prediction of the relationship would make are given by:

$$u_i = Y_i - \beta_0 - \beta_1 X_i$$

With the same notation as previously

OLS use these errors, and estimates the β_0 and β_1 by finding the line that can be drawn through the scatterplot that minimizes the sum of the squared errors of the relationship between the dependent and the independent variable. The errors are squared since positive and negative errors else would cancel each other out, and to insure that both negative and positive errors would be equally weighted. Another takeaway from the squaring of the errors is that large errors will get a heavier weight (Stock & Watson, 2013).

Taking the first order derivative of the squared errors with respect to the β_0 and β_1, and setting this equal to zero gives the following:

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_I - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1\bar{X}$$

The line $\hat{\beta}_1 X$ will now be a straight line, with an intercept of $\hat{\beta}_0$. Together they form what is called the regression population line.

A multiple regression, which we use in the other models than CAPM, is just an extension of the single variable regression model. It allows for estimating the effect on the dependent variable of a change in one of the independent variables, while holding the other independent variables constant (Stock & Watson, 2013). The multiple regression function can be written as:

$$Y_i = \beta_0 + \beta_1 X_i \ldots \beta_k X_{ki} + u_i$$

With the same notation as previously, *k* equals the number of independent variables

The estimation of the factor loadings will be a bit different than in the single regression model, but rests on the same minimization of the sum of the squared residuals. By applying matrix algebra the estimated parameters can be given by:

$$\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \ldots \\ \hat{\beta}_k \end{pmatrix} = (X'X)^{-1}X'Y$$

With the same notation as previously, except the variables are now in matrix form

4.6.1 OLS Assumptions

The OLS relies on a set of assumptions that are called the least square assumptions. The estimated variables will only be consistent and unbiased when these conditions are met. The assumptions differ some from single to multiple regression, where the 4th assumption is only relevant for a multiple regression model (Stock & Watson, 2013):

1. The conditional distribution of the error terms, given the independent variable, has a mean of zero – the Y_i will sometimes lie below the population regression line, and sometimes above, but on average it will lay on the line. Hence, the expected value of the error term, u_i, is zero.
2. The dependent and the independent variables are independent and identically distributed (i.i.d.). – Each of the variables has an independent and identical distribution, unaffected by time or unit.
3. Large outliers are unlikely – this third assumption goes back to the squaring of the residuals. Since the error terms are squared, large errors will have a big influence on the estimation. They should therefore be kept out of the analysis.
4. There are no perfect multicollinearity – if one of the independent variables in a multiple regression is perfectly correlated with another independent variable, we have perfect multicollinearity. The covariance matrix will then be singular, and impossible to invert, and estimation cannot be done.

Gauss and Markov also state a set of assumptions that are required for the OLS to be BLUE (Best Linear Unbiased Estimator). These are very similar to the least square assumptions, only slightly stronger. These assumptions have become what is known as the Gauss-Markov theorem.

5. Data

After having identified what models to use, and what kind of data we wanted to analyze, we needed to gather data to conduct the quantitative research needed to answer the problem formulation. The following part discusses the data we used, and how we screened the data to form our dataset. We also explain how the analyses was performed, by the use of the models presented in the in the theory section.

5.1 Fund Data

5.1.1 Ethical Funds

To start of our fund analysis, we needed to find funds that fit our criteria with respect to an ethical investment philosophy, but also funds that were only investing domestically in either the US of the UK. Initially we used Bloomberg's Fund Screen Engine and searched for funds tagged as either "Socially Responsible", "ESG" or "Environmental". Even though "Environmental" might be out of our scope, we used this as well, as the fund style might be reported wrongly. Further, we narrowed the search down by only looking at equity funds, and that was geographically focused either in the US or the UK. This search gave us 75 funds in the US, and 28 funds in the UK that we could further investigate.

As we saw that many of the funds that Bloomberg provided us with, were funds that did not have a name that gave any indication of being especially ethical, we felt a manual screen was needed to ensure that our sample included only funds that had strict ethical policies for the investments. By reading the description Bloomberg provided, we could get a slight indication of whether the funds had any focus, or if the general style they were given was merely wrong. Therefore, based on the description provided by Bloomberg, we excluded the funds that did not have any information about any ethical investment approach in their description. An example of this was the Norwegian fund DNB USA, which had the following description:

"DNB USA is an open-end fund established in Norway. The Fund's objective is long-term capital appreciation. The Fund invests in equities and equity-related securities issued by larger companies listed on any of the exchanges in the United States." (Bloomberg)

Many of the funds also only stated that they did not invest in particular industries; gambling, alcohol, pornography etc. As discussed earlier, this is called a negative screening, and is not uncommon. We therefore required our funds to have a stricter investment philosophy than this. For the US funds we used a rating called “The Heart Rating”, which is maintained by investment advisor Natural Investments, to evaluate the degree of ethical investing in our funds. This rating gives funds a score from one to five hearts, where one heart means that they rank within the lowest percentile group (0-20%), and five hearts that they rank within the top percentile group (81-100%) (Natural Investments LLC).

We tried to find a similar rating for the UK funds, but did not find anything as detailed as “The Heart Rating”. Therefore we ended up using a table provided by EIRIS, which states what types of issues the different funds have a policy regarding. These issues are mostly related to negative screening criteria, but it also incorporates “Positive Business Focus” and “Equal Opportunities” (EIRIS Foundation). We therefore used this as a guideline, but also read through the prospectus of each fund, to see to what extent they evaluate the firms they invest in.

After this extensive screening process we ended up with 13 funds from the US, and 9 funds from the UK. The full list can be seen in Appendix 1 and 2.

5.1.2 Comparable Funds

As we wanted to do a comparative analysis of the funds, we had to find comparable funds for which we could measure the performance of the ethical funds against. Several papers have highlighted the effect of fund characteristics, like AuM and age, on fund performance (Chen, Hong, Huang, & Kubik, 2004) (Ferreira, Keswani, Miguel, & Ramos, 2012). We therefore decided to match the characteristics of each of the ethical funds with the comparable funds’ characteristics in the best suitable manner. The comparable funds also had to be matched with respect to investment style, value/growth stock and large/small cap, followed by the ethical funds. Further, to reduce the randomness in the performance of the comparable funds, we chose to assign two comparable funds for each of the ethical funds. The comparable funds were then equally weighted in a portfolio which we measured the ethical fund against.

To identify funds that matched our criteria we used Morningstar’s Mutual Fund screener. This allowed us to easily select the set of characteristics we needed, and were provided a list of mutual funds that fit those. For the age and AuM we, of course, could not find a perfect fit, but chose funds that were fairly close. For the investment style we matched most of the funds perfectly, but for those funds we did not manage to find a similar fund, we found two comparable funds which were at each of their side. For example, for the fund Premier Ethical we could not find two funds with the same investment style, which was “Mid Blend”. We solved this by choosing one comparable fund with the style “Large Blend” and one with the style “Small Blend”.

The entire list of comparable funds can be found in Appendix 1 and 2, together with the ethical funds.

5.2 Stocks

5.2.1 ESG Data

As we wanted to do an analysis which assessed the difference in performance of companies that were ranked differently on something that could reflect the degree of ethical behavior, we had to collect data on different stocks. There are several databases and organizations that rank companies on a level of sustainable business or ethical behavior. It was therefore important for us to analyze the differences between them, and find the one we thought best suited our analysis. We therefore elaborate on some of these:

Dow Jones Sustainability indices are a group of indices that are constructed by the most ethical companies in different geographical regions. In these indices companies are taken in and out based on a questionnaire that the companies fill out (RobecoSAM Ag, 2015). With this approach we would not get a score for each company, only a “dummy score” which classify them either ethical or not ethical. Data is also a bit hard to obtain, since we would have to file an application to get the full list of companies that have been in the indices through time.

MSCI also ranks companies on ethical performance. They use a slightly different approach, but also construct portfolios of the most ethical companies. They have 140 analysts that assess companies on a set of 1000 different data points, were the end result is a ranking on an AAA to CCC basis (MSCI ESG Research Inc., 2016). This is in general a good feature, which would allow us to differentiate between companies on a more refined scale. However, the MSCI ratings are not freely available, and in order to access them a purchased membership is needed.

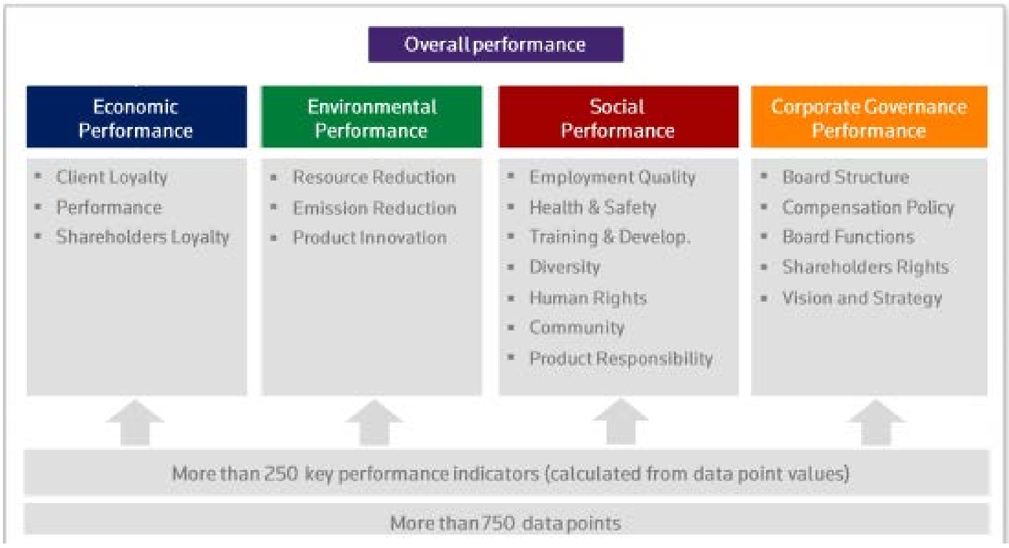
EIRIS is an organization that specializes in responsible investing and ESG research. They rank the world's 3000 largest companies in both established and emerging markets. They specialize in making the ESG criteria easy to include in an investment decision, and works to establish a complete picture of corporate sustainability performance and use a scale from A to E (EIRIS Foundation). Even though this data is used in a few other studies, it requires a common research initiative to be established with EIRIS to be acquired.

The provider of ESG data that we ended up with was Asset4. Since this is an important part of our analysis, we elaborate further on Asset4 below.

5.2.2 Asset4

Asset4 is a leading provider of ESG data. More than 750 data points, based on four different pillars (environmental, social, governance and economic), form the basis for an overall individual ESG score for the 5000 companies covered. The coverage includes, among others, the entire MSCI World, MSCI Europe, STOXX 600, NASDAQ 100, RUSSEL 1000, S&P500 and FTSE 100, and the coverage goes back to fiscal year 2002. The scores are updated yearly (Thomson Reuters, 2012). A graphical illustration of the Asset4 framework for ESG rating can be seen in Figure 8 below.

Figure 8– Asset4 ESG, Source: (Thomson Reuters, 2012)



In 2009 Thomson Reuters acquired Asset4, and their ESG database is now accessible in Datastream. For our purpose, one of the pillars, namely the economic pillar is disturbing the picture. By linking the economic performance to the overall score we expect correlation between the explanatory ESG variable and the dependent variable stock returns. Therefore we have calculated an overall ESG score by averaging the environmental-, social- and governance score and hence neglecting the economic score. This way we believe the score reflect what we want to measure, namely ethical performance, and provide a basis for investigating how this is linked with financial performance.

To acquire the companies covered by Asset4 in the US and the UK we used the Datastream codes LA4CTYUS and LA4CTYUK. These gave us a list of 996 companies from the US, and 312 companies from the UK.

5.2.3 Stock Selection

Even though we now had a list of companies from both the US and the UK that were all given a rating on the Asset4 ESG ranking, we had to further narrow the scope of stocks.

Since not all the stocks had ESG data for all the years of our analysis, we decided a minimum of years of ESG coverage in order to be applicable for the dataset. The cut-off point we sat was at least ten years of coverage. We were then left with a total of 756 stocks. For the purpose of our Fama-MacBeth regression we needed to have scores for the entire time period investigated, as we wanted to have a balanced panel. The companies which lacked a score in some periods were given the score they had or were given in the closest time period. This was done for the first few years for the companies that was not covered from the beginning in 2002, but was taken up for coverage at a later stage. Also, some companies had not yet received their score for 2015 when we collected our data. Such companies were given the score they had in 2014 in this period. Although the scores are only updated on a yearly basis, we have used weekly data in our analysis. This means that the stocks in the dataset receive a score the first day of each year, and keep this score every week until the score is updated. We chose to use weekly data in order to have a larger dataset and thereby, hopefully, improve the significance of the results.

Further, as we wanted to have a balanced panel, we required all stocks to have price data from 31.12.1999. The rationale for this was that we wanted to perform a rolling regression to obtain the betas for each of the stocks at each period of time. Also, since we wanted to mimic the Carhart model, and control for firm size, price-to-book value and momentum, we also required the stocks to have sufficient data to calculate these factors during the entire period from 2002.

Many of the stocks left in our dataset were highly illiquid, and we felt that this would bias our analysis towards zero return. This could be especially crucial if the illiquidity would be correlated in some way with the ESG score. Based on this, we decided to exclude the companies that lacked trading on more than 10 % of the weeks in our time period.

Lastly, we excluded companies that were considered as outliers, as will be further explained in section 6.5.

After the full screening we were left with 458 companies from the US and 207 companies from the UK.

5.2.4 Fama-French and Carhart Factors

In order to perform the Fama-French three-factor- and the Carhart four-factor tests we needed returns for each of the factors SMB, HML and MOM, in addition to the market risk premium. SMB is designed to capture the effect of the size of the company. The SMB returns are calculated form the return on a portfolio of the 50% smallest stocks listed, minus the return on a portfolio of the 50% largest stocks. HML tries to capture the effect of being a growth or a value stock, where growth stocks tend to have low book-to-market values and value stocks tend to have high book-to-market values. HML returns are calculated from the return on a portfolio of stocks with the 30% highest book-to-market values, minus the return on a portfolio of stocks with the 30% lowest book-to-market values. The MOM factor is meant to capture the effect of momentum, as one known anomaly is that recent winner stocks tend to outperform recent losers. The return on this factor is calculated by the return on a portfolio consisting of the 30% of stocks with the highest return in the last 12-2 months, minus the return on a portfolio of the stocks the 30% lowest return in the last 12-2 months. Finally, the market risk premium is calculated as the value-weighted return of all listed stocks in the particular market over the risk-free rate. The risk-free rate is the 1 month Treasury bill in the particular market (Fama & French, Common Risk Factors In The Returns On Stocks And Bonds, 1993). We collected the factor returns for the US from Kenneth French’s website. As French does not publish such data for the UK, we collected this data from the University of Exeter Business School and their “Xfi Centre for Finance and Investment.”

5.3 Setting up the Models

5.3.1 Fund Portfolios (incl. Rolling Regressions)

After we had selected the funds we wanted to include in our analysis, we calculated the returns of each of the different funds. To do this for the US funds, we used the Total Return Index in DataStream to retrieve the accumulated growth in value of capital that was invested in each of the funds. The Total Return Index is calculated as follows:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY_t}{100 * N}\right)$$

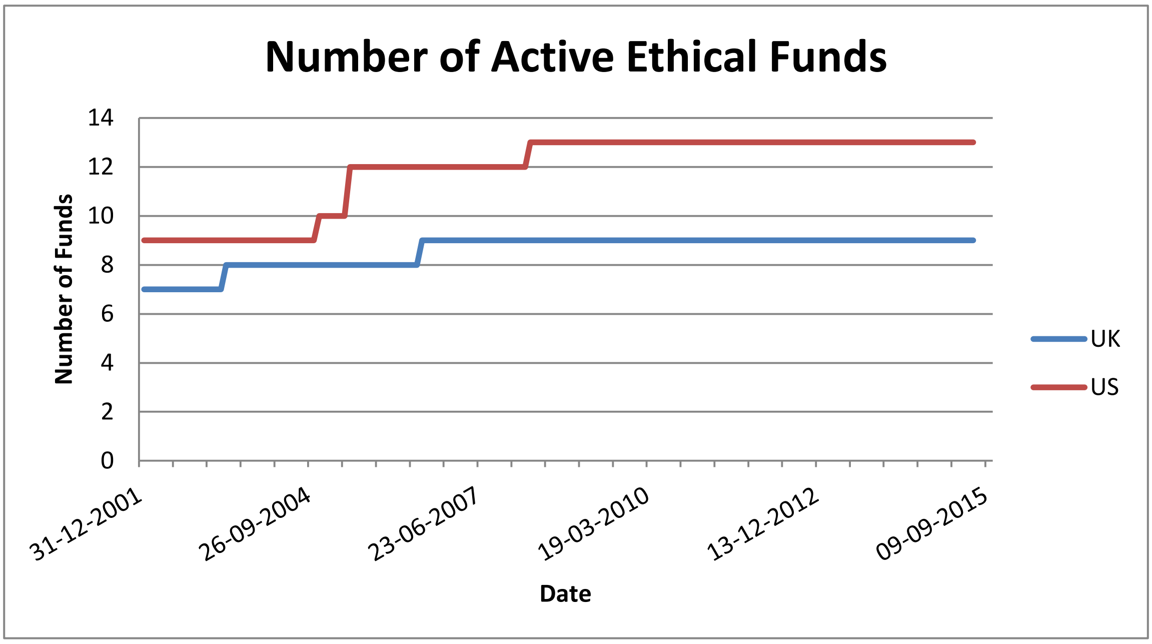
Where:
RI_t and RI_{t-1} is the return index in period t and t-1 respectively
PI_t and PI_{t-1} is the price index in period t and t-1 respectively
DY_t is the dividend yield in period t
N is the number of working days each year

As can be seen, the return index incorporates the dividend, so it should reflect the total return an investor who invests in the fund will experience, given that the dividends are reinvested in the fund.

For the UK we had to use the Total Return Index – Net. This is a similar measure, but includes tax credits which were applied to dividends in the UK prior to 2004. This will then incorporate the total price appreciation the fund would have had, and make it comparable to the US funds.

The portfolios were then created based on an equally weighted approach, where we averaged the return of the funds that were active. This also means that the portfolios were rebalanced for every new month. As mentioned previously, we activated the comparable funds on a basis of when the ethical fund that it was comparable to was established. The plot below shows how many ethical funds that were active at different times.

Figure 9 – Number of Active Ethical Funds



The third portfolio was created as a long-short portfolio, which was long the ethical portfolio and short the comparable portfolio.

When performing the rolling regression to assess how the portfolios had performed on a risk-adjusted basis through time, we used the same set of data. The only difference now is that we ran a series of two year regressions, one for each month from 2004 to the end of our study. From this we got a vector of alphas that we could plot to get a visual interpretation of the risk-adjusted performance of the portfolios through time.

5.3.2 Stock - ESG Portfolios

To start of our analysis of the link between ESG performance and stock returns, we wanted to do a portfolio approach were we compare companies that had scored well with companies that had scored poorly.

To do this we first gathered data on the returns and Asset4 ESG scores of the stocks that we had selected, explained in part 5.2.3. The returns were calculated in the same way as we did for the fund analysis, and the ESG scores were acquired from DataStream and adjusted in the way explained previously (the "Economic" score was left out). One may argue that since the Asset4 score does not penalize stocks that are within harmful industries, and hence would be screen out of the funds' portfolios in a negative screening, we should not include these stocks in our regression. Though, since there are differences between these companies as well, where some are more ethical than others, even though they work within harmful industries, we wanted to include these as well.

To create each of the portfolios we averaged the return for the stocks that had the 35% highest ESG scores and made a portfolio of these, and the stocks that had the 35% lowest scores and made a portfolio of these as well. We then created a long-short portfolio which was long the portfolio with good scores and short the portfolio with poor scores. This portfolio was rebalanced every week to assure that at all times the 35% largest/lowest ESG scoring stocks were included.

5.3.3 Stock - Fama-MacBeth

To further try to pin down the effect that an ethical investment philosophy has on the financial performance of ethical funds, we wanted to perform a Fama-MacBeth regression. This would allow us estimate the effect of ESG on stock performance by looking at how the returns were affected by different ESG scores, and also look at the effect that the exclusion of some industries have on the performance of ethical investments. By doing this we could incorporate both of the two important screening criteria that the ethical funds use when they evaluate which companies to invest in.

To perform the analysis we used the group of stocks that were left after the screening process (explained in part 5.2.3). We set up the model to control for the Fama-French and Carhart factors, but instead of calculating this on a portfolio level, we gathered the real values that each company had for each of these risk factors. This is the same as what is done in several papers (Brammer, Brooks, & Pavelin, 2006) (Hong & Kacperczyk, 2009).

We chose to normalize some of the values that we used in our regression, so that big outliers would not impact the regression as heavily as they otherwise would. We did this by taking the natural logarithm of the market cap of each company, and also by taking the natural logarithm of the price-to-book value. Since some of the stocks inhibited negative price-to-book values, and it is not possible to take the natural logarithm of a negative value, we took the natural logarithm of the absolute value of the price-to-book value. We then used the negative value of this for the companies that had a negative price-to-book value.

To measure the effect of negative screening we had to incorporate a dummy variable, which gave the companies that were considered as working within industries that are considered harmful, a variable “1” and those not “0”. We did this by using the datatype “Ethical Exclusion Alert” in Datastream. This identified the companies that had more than 5% of their total revenues stemming from either the production or distribution of tobacco, alcohol, armaments, gambling or pornography. Some companies retained their dummy variable during the entire period, while other had only temporary periods of involvement with these industries, and therefore had a change in their dummy variable during the period of our research.

Since we feared that some industries had performed especially well during the period in which we have conducted our research, and that the ESG scores might be particularly good in some industries, we felt that it was important to control for industry effects. We did this by including dummy variables for each industry based on the International Building Code Level 1, which contains 10 different industry classes. The stocks were therefore given a “1” for the industry they belonged to. To avoid the dummy-variable trap and by that get perfect multicollinearity, we did not include a dummy variable for one of the industries, the financial industry, and were therefore left with nine dummy variables.

To perform the Fama-MacBeth regression we used the “pmg” function in the “plm” package in R. This function does in general not perform the Fama-MacBeth regression, but as proposed by Govani Millo we can enforce a Fama-MacBeth regression on this function by swapping the index (Millo, 2014). This means that we make the time index into the entity index, and vice versa.

The following equation describes our final Fama-MacBeth model:

$$r_{i,t} - r_{rf,t} = \gamma_0 + \gamma_1 ESG_{i,t} + \gamma_2 Negative\ Screen_{i,t} + \gamma_3 Beta_{i,t} + \gamma_4 \ln(Market\ Cap)_{i,t-1} + \gamma_5 \ln(PTBV)_{i,t-1} + \gamma_6 Momentum_{i,t-1} + \gamma_7 Industry\ Dummy\ 1_{i,t} \dots \gamma_{15} Industry\ Dummy\ 9_{i,t} + \varepsilon_{i,t}$$

Where:
$r_{i,t}$ is the return of asset i in period t, $r_{tf,t}$ is the return of the risk free asset in period t
γ is the estimated coefficients
$ESG_{i,t}$ is the ESG score of asset i in period t
$Negative\ Screen_{i,t}$ is the dummy variable of negative screening of asset i in period t
$Beta_{i,t}$ is the beta of asset i in period t
$ln(Market\ Cap)_{i,t}$ is the natural logarithm of the Market Capitalization of asset i in period t-1
$ln(PTBV)_{i,t-1}$ is the natural logarithm of the Price to Book Value of asset i in period t-1
$Momentum_{i,t-1}$ is the last 12 month return of asset i in period t-1
Industry Dummy is a dummy variable that describes which industry asset t is in in period t
$\varepsilon_{i,t}$ is the error-term of asset i in period t

6. Econometric Considerations

As discussed in the part about Ordinary Least Square, there is a set of assumptions that needs to be fulfilled for our models to produce unbiased and consistent estimators, or to become BLUE as Gauss and Markov states. We therefore devote this part to test and discuss whether our data is in conflict with the most critical econometric assumptions.

6.1 Autocorrelation

Autocorrelation, or serial correlation, means that the value of the residuals in a data-series depends on previous values of the residuals, and that we in a way can predict future error terms by looking at today's. The problem with autocorrelation is that the variance the OLS uses does not take into account the variance between the cross-product between the correlated errors, and the variance will therefore be biased in a downward direction (Wooldridge, 2012). This will lead to a higher t-value, and a higher possibility for a type one error.

Autocorrelation can be found in cross-sectional data, but is most usual to find in time series data (Stewart, 1991). Since this is what we in general work with, we find it important to test our models for this.

There are several ways to test for autocorrelation, but the Durbin-Watson test and the LM test (Breusch-Godfrey) are the most commonly used. When testing our data we chose to use the LM test. The reason for this is that when applying the Durbin-Watson test, one has to test separately for negative and positive autocorrelation. This is a nice feature if further act depends on whether it is positive or negative; else, as in our case, it is does not yield any additional useful information. Also, the Durbin-Watson test can end up being inconclusive, which of course is not preferable (Stewart, 1991).

The LM test can be run for different order of autocorrelation, but the most standard one is with one lag. The model then looks like:

$$u_t = \phi_1 u_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim IID(0, \sigma^2); t = 1, .., n$$

Where:
u is there error terms from the first regression
ø is the estimated coefficients in the second regression

If $\phi_1$is significantly different from 0, we can reject H_0 (that there is no autocorrelation). If higher order of lag is tested, an F-test to check whether they are all equal to zero has to be performed.

To perform the LM test we used R, and it’s built in function “bgtest” which is included in the “lmtest” package.

Table 3 – Table of p-values from test of Serial Correlation

Breusch-Godfrey test for serial correlation				
Data	**Model**	**Regression**	**US**	**UK**
Fund Portfolios	CAPM	Ethical	0.0725*	0.1951
		Conventional	0.0002***	0.9764
		Long-Short	0.2078	0.0003***
	Fama-French	Ethical	0.3556	0.2259
		Conventional	0.0153**	0.0024***
		Long-Short	0.3068	0.0033***
	Carhart	Ethical	0.3491	0.1437
		Conventional	0.0000***	0.0063***
		Long-Short	0.7887	0.0078***
ESG Portfolios	CAPM	Top 35 %	0.9305	0.0098***
		Bottom 35 %	0.1592	0.0291**
		Long-Short	0.0257**	0.3328
	Fama-French	Top 35 %	0.2502	0.1478
		Bottom 35 %	0.0063***	0.3579
		Long-Short	0.0441**	0.2059
	Carhart	Top 35 %	0.5148	0.1204
		Bottom 35 %	0.0004***	0.5123
		Long-Short	0.0157**	0.3121

Where:
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*

As the table explains, there are a lot of the data that contains serial correlation. Looking at the fund portfolios, we can see that all of the models contain some level of serial correlation. The long-short portfolio for the UK got highly significant serial correlation in all models. For the US it is mostly the conventional fund portfolio that contains serial correlation. In the ESG-portfolios there is less serial correlation than for the fund portfolios, with most of this being in the US data. Here, the UK data only contain serial correlation within the CAPM model, while for the US the long-short portfolio contains serial correlation in all models.

6.2 Heteroscedasticity

Heteroscedasticity can be defined shortly as: *when* $Var(u|x)$ *depends on* x (Wooldridge, 2012). In other words, this means that the variance of the residuals in our regression varies for different values of x. Heteroscedasticity in a model will not cause the model to produce biased estimates of the parameters. But it will, as with autocorrelation, cause the variance term of the parameters to be biased and no longer t-distributed (Wooldridge, 2012).

Multiple ways to test for heteroscedasticity have been proposed. We have chosen to use the Breusch-Pagan test, since the interpretation of it is fairly simple, and fairly similar to the LM test for autocorrelation. It starts out with setting up an auxiliary model that describes the squared residuals as a function of the independent variables in the first regression:

$$E(u_t^2) = \delta_1 + \delta_2 Z_{2t} + \cdots + \delta_p Z_{pt}$$

Where:
u is the error terms in the first hand regression
Z is the independent variables from the first regression
δ is the estimated coefficients from the second regression

We then run a regression on this model. The test statistic, which will be asymptotically chi-distributed with p-1 degrees of freedom, then comes out of:

$$LM(H) = \frac{TSS - RSS}{\frac{TSS}{n}} = \frac{ESS}{\frac{TSS}{n}} = nR^2 \quad \sim^a \chi^2_{p-1}$$

Where:
TSS is the total sum of squares
RSS is the residual sum of squares
ESS is the explained sum of squares
n is the sample size

The function we used in R to perform this test is called “bptest” and is also in the “lmtest” package.

Table 4 – Table of p-values from test of Heteroscedasticity

Breusch-Pagan test for heteroscedasticity				
Data	**Model**	**Regression**	**US**	**UK**
Fund Portfolios	CAPM	Ethical	0.8923	0.1543
		Conventional	0.8648	0.0378***
		Long-Short	0.7321	0.4629
	Fama-French	Ethical	0.7230	0.0177**
		Conventional	0.2602	0.0013***
		Long-Short	0.4163	0.4127
	Carhart	Ethical	0.7150	0.0031***
		Conventional	0.2188	0.0001***
		Long-Short	0.7966	0.4634
ESG Portfolios	CAPM	Top 35 %	0.4552	0.8068
		Bottom 35 %	0.1054	0.7902
		Long-Short	0.4293	0.8797
	Fama-French	Top 35 %	0.7763	0.3990
		Bottom 35 %	0.0262**	0.1702
		Long-Short	0.1127	0.1057
	Carhart	Top 35 %	0.7084	0.3796
		Bottom 35 %	0.2024	0.1482
		Long-Short	0.2935	0.1134

Where:
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*

As we can see from the table, there exists heteroscedasticity in some parts of our dataset. For the UK fund data all of the models contain heteroscedasticity, though not the long-short portfolio. For the US data, we see that the only regression which contains heteroscedasticity is the "Bottom 35 %" for the Fama-French model on the ESG portfolios.

6.3 Heteroscedasticity and autocorrelation-consistent (HAC) standard errors

We saw in both the test for autocorrelation and the test for heteroscedasticity that at least some of our models inhibit them. This means that our regressions will not be BLUE. Even though autocorrelation and heteroscedasticity will not make the OLS coefficient estimates inconsistent, they will, as mentioned, have an effect on the standard errors. It is therefore important that the standard errors are adjusted to get reliable test statistics.

The most commonly used tool to adjust for autocorrelation and heteroscedasticity is the one proposed by Newey and West in their 1987 paper, the Newey-West variance estimator. This estimator gives the variance of the coefficients by (Stock & Watson, 2013):

$$\tilde{\sigma}^2_{\hat{\beta}_j} = \hat{\sigma}^2_{\hat{\beta}_j}\hat{f}_T$$

Where:
$\hat{\sigma}^2_{\hat{\beta}_j}$ is the estimator of the variance of β_j in the absence of autocorrelation.
$\hat{f}_T$ is an estimated variable

As our models vary in their test results; some of them inhibit autocorrelation, some heteroscedasticity, some both and some neither, we have chosen to use the Newey-West HAC standard errors on all of them. As the adjustment will increase the standard errors for the estimated coefficients, this will only make the models that do not inhibit autocorrelation or heteroscedasticity more conservative.

6.4 Multicollinearity

Multicollinearity is an issue in econometrics which arises when two or more of the explanatory variables in a regression are perfectly or highly correlated. Its presence will cause the OLS to have a hard time telling which of the explanatory variables that are influencing the dependent variable (Koop, 2007). The fourth OLS assumption states that there should be no perfect multicollinearity, which means that two or more explanatory variables should not be perfectly correlated, but it does not say anything about imperfect multicollinearity. The presence of imperfect multicollinearity is though the most frightening one, since the statistical software will often not warn about this, opposed to perfect multicollinearity where the regression will not run because of a singular matrix. Imperfect multicollinearity will cause the variances of each of the estimated coefficients to be large, which again will make it hard to get statistically significant results (Koop, 2007).

In our research we are in general applying models which are widely used in the academic theory, it is therefore safe to assume that these models do not contain multicollinearity. But for the Fama-MacBeth approach, which we are using to measure the “priced”-effect of higher ESG score and negative screening, we are building the model much by ourselves. It is therefore important to check whether any of the explanatory variables are highly correlated, and if so, test for multicollinearity.

As we can see from the correlation matrices in appendix 3 and 4, the ESG score is quite heavily correlated with market capitalization. Even though theory states that the correlation needs to be very high for it to become a problem (Koop, 2007), we still feel that it is important to run a test on the data to check whether multicollinearity is present.

One way to test for multicollinearity is by running the VIF (variance inflation factor) -test. Without going too much into the quantitative details of the test; the test first runs a series of regressions for each of the explanatory variables, where each explanatory variable is the dependent variable of the other explanatory variables. The variance inflation factors for each of the explanatory variables are then calculated by:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Where:
VIF_i is the VIF value of the explanatory variable i
R^2_i is the r-squared from the auxiliary regression of explanatory variable i

A rule of thumb is that multicollinearity exist if the VIF is higher than 10 (Kutner, Nachtsheim, & Neter, 2004).

Table 5 – Table of VIF values from test of Multicollinearity

#	ESG	Neg. Screen	Beta	Market Cap	PTBV	12 Month Return	D1	D2	D3	D4	D5	D6	D7	D8	D9
(1)	1.90	1.14	1.24	2.12	1.15	1.04	1.21	1.58	1.67	1.16	1.99	1.16	1.22	1.11	1.22
(2)	1.71	1.02	1.08	1.79	1.08	1.04									
(3)	1.70	1.02	1.08	1.79	1.06										
(4)	1.04	1.01	1.04												
(5)	1.01	1.01													

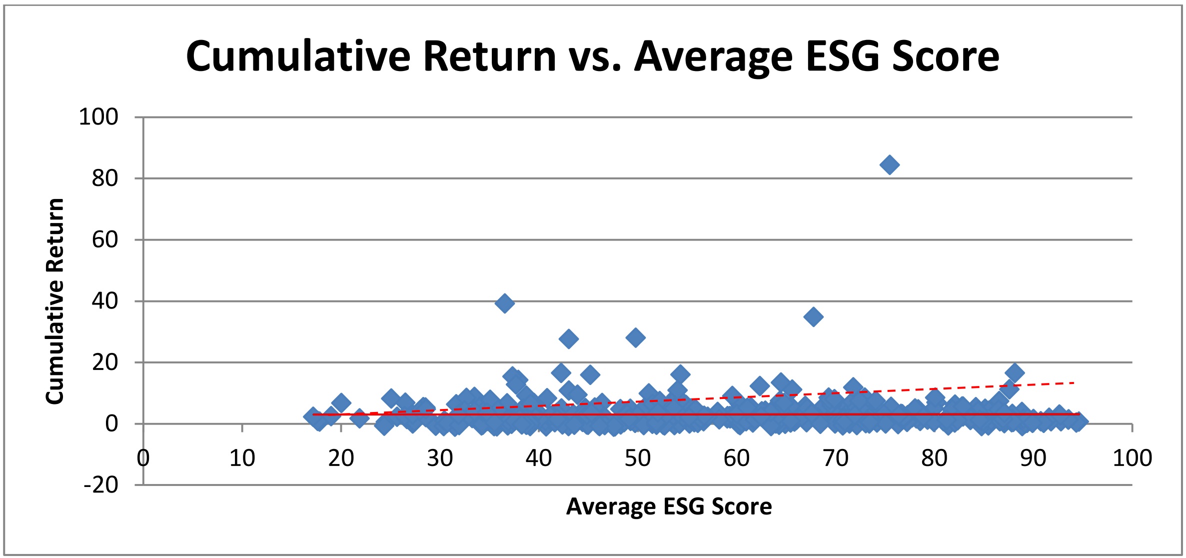
As expected from the correlation matrices, the ESG-score and the Market Capitalization are the two explanatory variables that get the highest VIF-scores (including D5). Though, none of them are anywhere close to our rule of thumb, 10, and we therefore can reject the hypothesis that our models contain multicollinearity.

6.5 Outliers

From the discussion regarding the OLS approach to get the estimated coefficients, we remember that each of the observations is given an equal weighting in the regression. This can be a problem if some of the observations are non-typical, and distinguish itself from the rest of the “crowd”, since the observation will then have a large effect on the estimated coefficients, especially since we use the squared error terms for the estimation (Gujarati, 2014). These observations are known as outliers.

By looking at the plot of the total returns and average ESG score of the stocks in the US, we can better understand the effect.

Figure 10 – Cumulative Return vs. Average ESG Score



As we can see from the plot, there are a few stocks that have had extreme return over the period that we conduct our research. The stippled line is an example of what the estimated regression line could look like if we include the outliers, compared to the solid line without the outliers included. To be sure that these observations does not have the effect illustrated in the plot, and become what is known as influence points; we set a cut-off point of stocks with positive and negative returns that we exclude from our dataset. Hence, we exclude stocks that have had above 2500%- and below -95% accumulated return in the period from 2002 until July 2015. We do the same for the UK data. This led us to exclude a total of 11 stocks, 9 in the US and 2 in the UK.

Outliers are also searched for in the fund data, but no extreme events have been detected.

6.6 Sample Selection Bias

Sample selection bias occurs when the sample selection is not truly random, and thereby is not a true representation of the population. More technically, sample selection includes correlation between one or more regressors and the error term, which causes the OLS estimator to be biased (Stock & Watson, 2013).

In research on financial performance one common issue of sample selection bias is survivorship bias. Survivorship bias is the bias in returns which stems from the inclusion of only “successful” securities in the dataset. By only including securities which are alive at the end of the time period, one will omit securities which have been delisted, shut down or went into bankruptcy. Survivorship bias may be especially relevant for studies of mutual funds. Most investors considering a specific mutual fund will investigate the historical performance of the fund. Hence, providers of mutual funds will be reluctant to let poor-performing funds stay alive. A common practice is to either shut such funds down or merge them with a well-performing fund (Elton, Gruber, & Blake, Survivor Bias and Mutual Fund Performance, 1996). In this way, the poor historical performance is buried, and we are left with a slightly misleading picture of historical mutual fund performance. In a sample which suffers from survivorship bias, the returns will typically be overstated. This is documented by Malkiel (1995) who found an annual overestimation of 1.5% in US mutual fund’s performance, over a time period of ten years, if survivorship bias was not controlled for.

Our sample of mutual funds includes solely funds that are alive from the time they are included in the dataset, until the end of the time period investigated. In other words, our dataset is prone to survivorship bias. This bias could have been solved by including funds; both ethical and conventional which were liquidated or merged during the period, in the dataset. However, finding data on dead funds is not a simple task. We have used Morningstar’s fund screener to construct a portfolio of comparable mutual funds. Morningstar do not report information on dead funds, and we were thereby not able to conduct a reasonable comparison of dead funds. More importantly, we do not believe the possible survivorship bias in our sample is a big problem. As the aim of this thesis is to uncover whether there are return differences between ethical investing and conventional investing, and not how profitable ethical investing is, survivorship bias will not affect our conclusion. As both our ethical and conventional funds are alive through the time period, both samples will be subject to survivorship bias. Hence, the only effect of this will be that the reported returns and alphas might be slightly overstated, for both groups of funds. The interpretation of the differences between the two groups will still be valid. The same logic applies to our dataset of individual stocks.

6.7 Errors-in-Variables

Errors in variables (EIV) arise when one of the variables are measured imprecisely. If the dependent variable, which in our case is the fund or stock return, is measured with error, the variance of the regression and the coefficients will increase. However, the coefficients will not be biased. A more serious problem is if there is measurement error in the explanatory variables. This could arise for several reasons (Stock & Watson, 2013).

In our case, it is most likely to happen if some of the data we have gathered are misstated or if there are typographical errors in the data gathered from the records from funds and/or companies. One could also imagine that the data gathered from Asset4 could be subject to some errors. Asset4 gather an extreme amount of data from each of the companies covered. From all this data each company is given an environmental, social and governance (and economic) score. It seems plausible that some of this large data could be misstated, or based on estimates that might not be correct. This, in turn, could affect the ESG score we apply in our stock analysis. In our Fama-MacBeth regression, we need to estimate the market beta, as the true market beta for each company is not observable. Hence, the market beta is estimated with error. According to Shanken (1992), this makes our Fama-MacBeth regression subject to EIV. Shanken concludes that this will lead to an overstatement in the precision of our coefficients. Carmichael and Coen (2008) also states that since the true risk factors for any stock are not observable, models such as CAPM, Fama-French three-factor model and Carhart four-factor model will be subject to EIV.

Errors in a variable would lead us to estimate coefficients and draw inference on a variable that is not the true variable. This could lead to correlation between the observed variable and the error term, and the coefficient will be biased and inconsistent. For example, if the measurement error simply adds a completely random element to the true value of the variable, the coefficient will be biased toward zero (Stock & Watson, 2013). Needless to say, this could lead us to draw conclusions that do not exist in reality, or fail to draw conclusions that could have been made, had the variables been observed correctly. There are several methods to correct for EIV, with pros and cons with each of them. Examples are the creation of portfolios to minimize the measurement errors (Blume & Friend, 1973) or the Shanken-correction (Shanken, 1992). However, we have decided to follow a common procedure of not correcting our estimates, which is a reasonable approximation (Campbell, Lo, & MacKinlay, 1996).

7. Analysis and Results

In this section we will present the results from our analysis, and elaborate on the findings and their implications. We will start out by presenting the analysis of the funds, before moving on to the stock analysis. We divide between the US and the UK, before summarizing and comparing the results between the two markets. During the discussion of the results, we will also consider the robustness of the results in light of the robustness checks we have performed.

7.1 Fund Analysis

7.1.1 Descriptive Statistics and Performance Measures

7.1.1.1 UK

Table 6 - Descriptive Statistics and Performance Measures, UK Funds

Portfolio	Mean Return	Standard Deviation	Sharpe Ratio	Treynor Ratio
Ethical Funds	0.0665	0.1439	0.2829	0.0427
Conventional Funds	0.0710	0.1477	0.3052	0.0452
Market Proxy	0.0621	0.1421	0.2563	0.0364

Where:
Mean Return is the annualized geometric mean of the returns.
Standard Deviation is the annualized standard deviation of the returns.
Sharpe- and Treynor ratio are the ratios as explained in section 4.5.
Market Proxy is the proxy used in the factor data from University of Exeter
The period analyzed is from January 1st 2002 until June 30th 2015.

As we can see from the table above, both the ethical- and the conventional funds have outperformed the market proxy. The conventional funds have though had a higher return than the ethical funds, with a yearly outperformance of 0.45%-points. The ethical funds have had less variability in returns, and do therefore have a lower standard deviation than the conventional funds. Both types of funds however, have had slightly higher standard deviations than the market. Despite this, the conventional fund portfolio has the highest Sharpe ratio in the period of research. Moreover, the ethical fund portfolio has higher Sharpe ratio than the market proxy. Even somewhat closer, the Treynor ratio of the conventional funds has also been better than the ethical funds, but also on this measure they have both outperformed the market.

7.1.1.2 US

Table 7 - Descriptive Statistics and Performance Measures, US Funds

Portfolio	Mean Return	Standard Deviation	Sharpe Ratio	Treynor Ratio
Ethical Funds	0.0615	0.1529	0.3109	0.0468
Conventional Funds	0.0660	0.1553	0.3348	0.0507
Market Proxy	0.0729	0.1487	0.3953	0.0588

Where:
Mean Return is the annualized geometric mean of the returns.
Standard Deviation is the annualized standard deviation of the returns.
Sharpe- and Treynor ratio are the ratios as explained in section 4.5.
Market Proxy is the proxy used in the factor data for Kenneth French
The period analyzed is from January 1^{st} 2002 until June 30^{th} 2015.

In the US market, both the ethical- and conventional funds underperform the market in terms of return, and their returns are more volatile as can be seen from the higher standard deviation. As a result, both types of funds underperform the market proxy on both the Sharpe- and Treynor ratio. This indicates that the active management has not payed off in the period, and an investor would have been better of holding a passive position in the market index. When assessing the performance of the two types of funds against each other, it is obvious from the descriptive statistics, that the ethical funds underperform the conventional ones in terms of return. Regardless of their slightly lower volatility the ethical funds also underperform on both ratios. In fact, also in the US, the ethical funds have underperformed the conventional ones with 0.45%-points yearly in the period of research.

7.1.1.3 Summary

The conventional funds outperform the ethical funds in both markets. In the US market, both types of funds underperform the market proxy, unlike in the UK where both types of funds outperform the market proxy. From this it seems that the active portfolio management is more successful in the UK than in the US, but that the effect of investing ethically is the same, namely they underperform conventional investments. Quite strikingly, the relative underperformance of ethical funds is exactly equal in both markets- 0.45%-points annually. In both markets the ethical funds show slightly lower standard deviations than the conventional funds, but they still underperform conventional funds on both the Sharpe- and Treynor ratio.

7.1.2 CAPM

From the looks of the descriptive statistics, ethical investing in mutual funds seems less profitable than investing in conventional mutual funds. However, this is not an analysis thorough enough to draw any conclusions. Financial theory says that exposure to certain factors could drive investment return, and in order to investigate the performance of ethical funds more thoroughly, we will now apply some models which incorporate different risk factors. Out- or underperformance will be captured by Jensen's alpha, and first up is the CAPM model, which assumes exposure to the market factor as the only source of systematic risk.

7.1.2.1 UK

Table 8 – CAPM, UK Funds

Portfolio	Alpha	Yearly Alpha	Beta	R-Squared
Ethical Funds	0.000556	0.006692	0.952***	0.882
Conventional Funds	0.000785	0.009463	0.996***	0.916
Long-Short	-0.000230	-0.002757	-0.043***	0.071

Where:
Alpha is the monthly return that cannot be explained by the exposure to the market factor (Beta)
Yearly Alpha is the annualized monthly alpha
Beta is the average exposure to the market factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

From the results when applying the CAPM we can see that both the ethical and the conventional portfolio exhibit positive alphas, though none of them are statistically significant. The long-short portfolio has a negative alpha, indicating the same as we see from the results; that the ethical portfolio has underperformed on a risk-adjusted basis compared to the conventional funds. On a yearly basis this underperformance is 0.276%-points, though neither this alpha is statistically significant, with a p-value of 0.66. The ethical fund portfolio has had a lower beta than the conventional fund portfolio, indicating that the ethical companies might inhibit lower market risk than the rest of the market. We also see that the R-squared of the ethical funds are lower than that of the conventional funds, which indicate that the ethical funds track the market portfolio to a less degree than the conventional funds.

7.1.2.2 US

Table 9 – CAPM, US Funds

Portfolio	Alpha	Yearly Alpha	Beta	R squared
Ethical Funds	-0.000925	-0.011044	1.015***	0.974
Conventional Funds	-0.000595	-0.007117	1.026***	0.964
Long-Short	-0.000331	-0.003965	-0.011	0.000

Where:
Alpha is the monthly return that cannot be explained by the exposure to the market factor (Beta)
Yearly Alpha is the annualized monthly alpha
Beta is the average exposure to the market factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

When applying the CAPM model to explain the return of the different portfolios of funds in the US, we can see that both types of funds have a negative alpha. This indicates that both fund portfolios are underperforming the market, and that the active management of the funds is unsuccessful. The portfolio of ethical funds underperforms the portfolio of conventional funds, which can be seen both from the lower alpha and in the negative alpha obtained by the long-short portfolio. More specifically, the ethical fund portfolio underperforms the conventional portfolio with approximately 0.03%-points on a monthly basis during the period of investigation, which equals approximately 0.4%-points yearly. However, none of the alphas are statistically significant on common confidence levels, and we can therefore not reject the hypothesis that there is no statistical difference between the ethical and conventional funds. We can also observe that the conventional funds take on slightly more market risk, which is evident from the higher beta coefficient, although the difference in market exposure between the two types of funds is not statistically significant either.

7.1.2.3 Summary

As with the descriptive statistics, the CAPM analysis unveils an underperformance of ethical funds compared to their conventional counterparties in both markets. The most notable differences between the two markets is that active management is more successful in the UK, which shows positive alphas for both types of funds compared to negative alphas for both types of funds in the US. However, none of the alphas are statistically significant and we can therefore not draw any conclusions from this, as we cannot reject that both types of funds have an alpha of zero, in both markets. It could also be mentioned that it seems that the portfolio managers in the US take on slightly more market risk than in the UK, and in both markets the ethical funds exhibit less market risk than the conventional funds. In the UK this difference in market risk between funds is significant. This is in line with what Feldman et al. (1997) found on environmental performance. Their study states that improving the environmental performance can lower the firm's beta with about 13% (Feldman, Soyka, & Ameer, 1997). Our findings for the US is in line with Bello (2005) who found no significant difference between ethical and conventional funds using the CAPM model, and with Statman (2002) who found negative alphas for both types of funds, but not statistically different from zero. For the UK market, our findings are somewhat conflicting with Mallin et al. (1995) who found weak evidences of outperformance of UK ethical funds. However, all these papers have studied different time periods than this thesis, and somewhat different results should not be surprising.

7.1.3 Fama-French

We move on to the Fama-French analysis, where we incorporate two more risk factors in the model, namely the exposure to small stocks and value stocks. These factors are historically known to be a source of higher expected return than their large- and growth stocks counterparties.

7.1.3.1 UK

Table 10 – Fama-French, UK Funds

Portfolio	Alpha	Yearly Alpha	Beta	SMB- Factor	HML-Factor	R squared
Ethical Funds	-0.000293	-0.003530	0.932***	0.335***	-0.036	0.942
Conventional Funds	0.000086	0.001032	0.981***	0.274***	-0.033	0.955
Long-Short	-0.000379	-0.004539	-0.048***	0.060**	-0.002	0143

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Yearly Alpha is the annualized monthly alpha
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
R-squared is how much of the variability in the returns which is explained by the model

Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

Analyzing the results of the Fama-French model on the UK data reduces the alpha compared to the CAPM model. The alpha of the ethical portfolio is now negative, while the alpha of the conventional fund portfolio is now only slightly positive. The long-short portfolio's alpha is still negative, indicating that the ethical fund portfolio is still underperforming compared to the conventional fund portfolio. The underperformance amounts to 0.45%-points on a yearly basis, but this is not statistically different from zero since the p-value is 0.41. As with the CAPM, the beta of the ethical fund portfolio is lower than the conventional fund portfolio, indicating a lower degree of market risk. The SMB-factor is also slightly higher for the ethical funds, which can be interpreted as a greater exposure to small stocks in the ethical funds' portfolio. The HML-factor of the two portfolios is not significantly different from each other.

7.1.3.2 US

Table 11 – Fama-French, US Funds

Portfolio	Alpha	Yearly Alpha	Market Factor	SMB Factor	HML Factor	R squared
Ethical Funds	-0.001089***	-0.012990***	0.998***	0.150***	-0.128***	0.983
Conventional Funds	-0.000867	-0.010355	0.997***	0.207***	-0.124***	0.978
Long-Short	-0.000223	-0.002673	0.001	-0.057**	-0.004	0.038

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Yearly Alpha is the annualized monthly alpha
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

When we use the Fama-French model to explain the return of the different portfolios of funds in the US, a more diverse picture of the performance is evident. The ethical funds show a significant negative yearly alpha of approximately 1.3%, while the conventional fund portfolio has a negative alpha of approximately 1% yearly. However, the conventional alpha is not statistically significant and we cannot rule out that this is actually zero. The long-short portfolio reveals an underperformance of approximately 0.27%, but not significant. In other words, in terms of performance the only thing we can say with certainty is that the ethical fund portfolio has a negative risk-adjusted performance, after controlling for the Fama-French factors. There is little difference in exposure to the market factor between the two types of funds, while the conventional funds are slightly more exposed to small stocks than the ethical funds. Both the ethical- and conventional funds are significantly more exposed to value firms, but there is no significant difference in exposure between the two types of funds.

7.1.3.3 Summary

Adding the Fama-French factors allows us to state that the ethical portfolio in the US show a negative alpha, which is significant. This cannot be said about the conventional portfolio, as the alpha of this portfolio is still not statistically significant. None of the alphas in the UK are significantly different from zero, and we cannot draw any conclusions of performance in this market. This is in line with Gregory et al.'s (2007) findings for the period of 1983-2002. What is more interesting is that the ethical portfolio in the UK is more exposed to small stocks, while the ethical portfolio in the US is less exposed to small stocks, compared to their conventional counterparties. Both these results are in line with the findings of Bauer et al. (2005). In the US we have significant exposure to growth stocks for both ethical- and conventional funds, but there is no significant difference between the two. This is in conflict with Bauer et al. (2005) who found a significant growth bias for ethical funds compared to the conventional funds. In the UK there is no significant bias towards neither value nor growth stocks.

7.1.4 Carhart

Our last factor model is the Carhart model, which incorporates a fourth factor- the momentum factor.

7.1.4.1 UK

Table 12 – Carhart, UK Funds

Portfolio	Alpha	Yearly Alpha	Beta	SMB-Factor	HML-Factor	Momentum-Factor	R squared
Ethical Funds	-0.000842	-0.010057	0.938***	0.354***	-0.002	0.050*	0.945
Conventional Funds	-0.000557	-0.006664	0.988***	0.298***	0.005	0.060***	0.958
Long-Short	-0.000284	-0.003403	-0.050***	0.057*	-0.008	-0.009	0.141

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Yearly Alpha is the annualized monthly alpha
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
MOM Factor is the average exposure to the momentum factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

Finally, by applying the Carhart model on the UK data we see that the alphas of both the ethical and the conventional portfolio decline. Now both the alphas are negative, revealing that the effect of active management is not paying off. The long-short alpha is even more negative than with the previous models, with a yearly alpha of -0.34%, which is still not statistically significant because of a p-value of 0.57.

The beta relationship and the factor exposure is merely the same as in the Fama-French model. The momentum factor is slightly positive and statistically significant on different levels for both of the portfolios, but negative for the long-short portfolio. This is an indication that the funds are investing in companies that exhibit a positive momentum, and that there is no significant difference in momentum exposure between the two types of funds. The R-squared for both of the funds are very high, revealing that the model explains the variation in returns well.

7.1.4.2 US

Table 13 – Carhart, US Funds

Portfolio	Alpha	Yearly Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor	R squared
Ethical Funds	-0.001093**	-0.013037**	0.999***	0.150***	-0.127***	0.001	0.983
Conventional Funds	-0.001056*	-0.012599*	1.02***	0.193***	-0.112**	0.051**	0.980
Long-Short	-0.000037	-0.000444	-0.025	-0.043*	-0.015	-0.050***	0.180

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Yearly Alpha is the annualized monthly alpha
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
MOM Factor is the average exposure to the momentum factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

When adding the fourth factor in the Carhart model in the US, the picture is, as with the UK data, quite similar as the one we had when applying the Fama-French model. The ethical funds still show a significant negative yearly alpha of approximately 1.3%, while the conventional fund portfolio has a negative alpha of approximately 1.25% yearly. Unlike in the Fama-French model, also the conventional portfolio alpha is now statistically significant, however on a lower confidence level than the ethical portfolio. The long-short portfolio reveals an underperformance of approximately 0.04%, but still not significant. This analysis shows that after controlling for the four factors in the Carhart model, both types of funds underperform on a risk-adjusted basis. The long-short portfolio does, however show that there is not necessarily any difference in returns between the two types of funds. The ethical funds have slightly less small stock exposure than the conventional ones, and the difference is significant. Furthermore, the ethical portfolio show slightly less exposure to growth stocks, and slightly less exposure to the market factor, but these factor loadings are not statistically significant. The ethical portfolio shows virtually no exposure to the momentum factor, opposed to the conventional portfolio which has a small positive exposure. This leads to a small negative exposure to the momentum factor for the long-short portfolio.

7.1.4.3 Summary

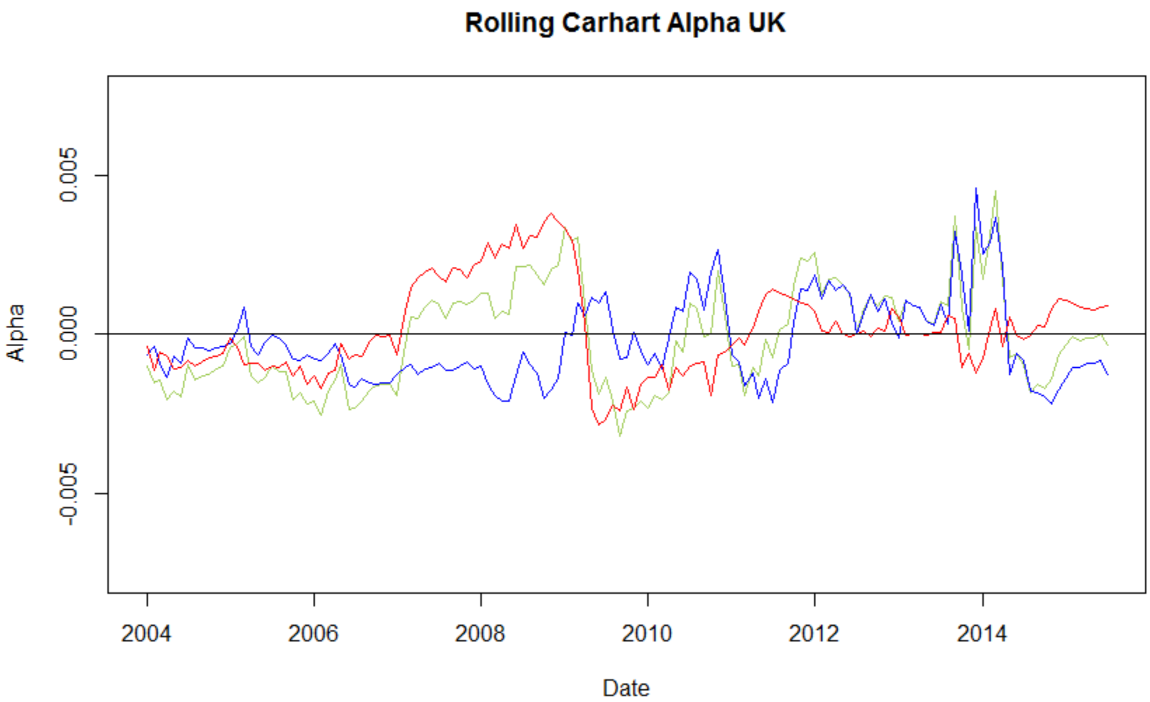
The interpretation of the results from the Carhart model is fairly similar as in the Fama-French model. The main difference is that both types of funds now show negative alpha in the UK, but they are not significant and we cannot rule out that there is no significant difference between ethical funds and conventional funds in the UK. In the US both types of funds show significant, negative alphas, but there is no significant difference between them. From these analyses we can say that we have no proof that investors lose out by investing ethically in neither of the two markets. In the UK the ethical fund portfolio is significantly more exposed to small stocks, while in the US the ethical portfolio is significantly less exposed to small stocks. This is in line with Bauer et al.'s (2005) findings. In the US, the ethical portfolio shows significantly less exposure to momentum stocks, while in the UK no such relation is evident.

7.1.5 Rolling Regression

The rolling regression was performed on all the three models, but is only presented for the Carhart model as the results from all three models were very similar and because this is the most comprehensive model. The rolling regression is performed in a similar manner as Gregory et al. (2007).

7.1.5.1 UK

Figure 11 – Rolling Regression, UK Funds

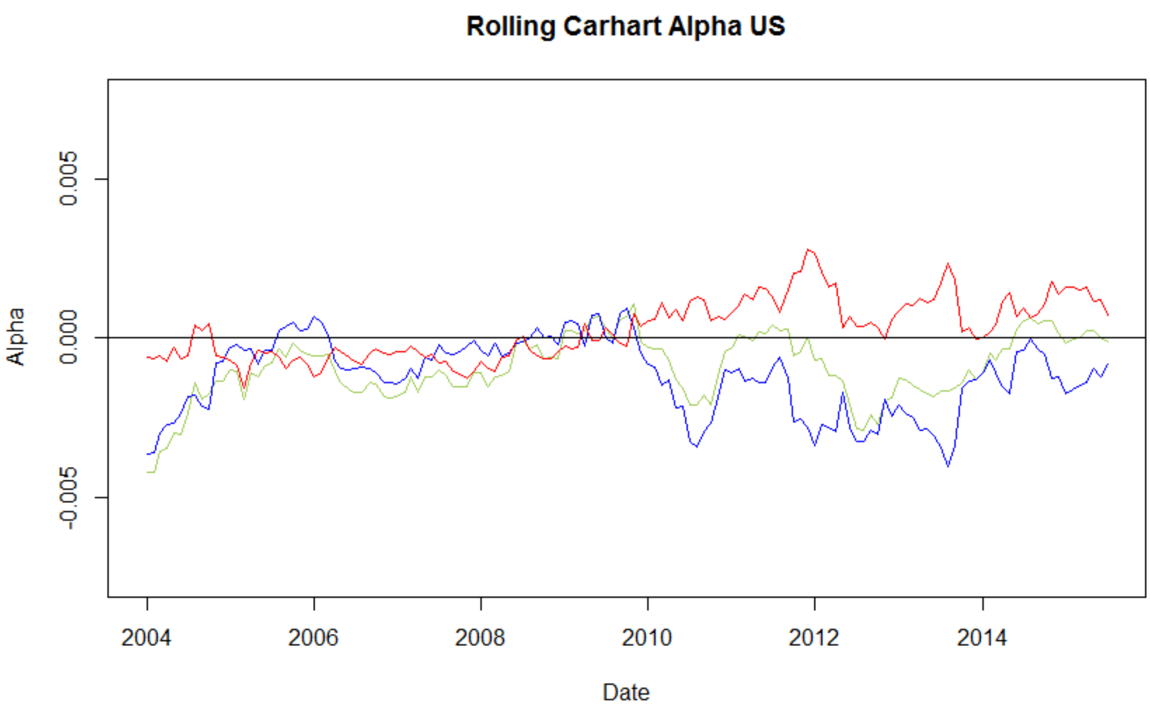


Where:
The green line illustrates the alpha of the portfolio of ethical funds
The blue line illustrates the alpha of the portfolio of conventional funds
The red line illustrates the alpha of a portfolio which is long the ethical portfolio and short the conventional portfolio

The takeaway from the previous analysis is that the comparable fund portfolio outperformed the ethical fund portfolio over the interval studied, however not statistically significant. The red line indicates that there is a considerable variation in this outperformance. We see that the comparable funds outperformed the ethical funds in the first period, but the ethical funds then outperformed the comparable funds significantly in a period after. It though seems like the ethical funds underperformed their counterparts during the financial crisis, before being reasonably equal in performance during the later periods. In essence, it seems like there are periods of out- and underperformance by the ethical funds, and it could therefore be beneficial to perform the previous study on sub-samples of the original interval.

7.1.5.2 US

Figure 12 – Rolling Regression, US Funds



Where:
The green line illustrates the alpha of the portfolio of ethical funds
The blue line illustrates the alpha of the portfolio of conventional funds
The red line illustrates the alpha of a portfolio which is long the ethical portfolio and short the conventional portfolio

As in the UK market, the alphas of the different portfolios change during the period also in the US. This indicates that assuming the factor loadings are constant over time is an assumption which does not hold in practice. The red line indicates that the ethical portfolio outperforms the conventional portfolio on a risk-adjusted basis in the latest part of the period. More specifically, the relative performance of the ethical funds is starting to catch up during the period of the financial crisis. It seems that our results from the Carhart analysis in section 7.1.4 would paint a different picture if we had analyzed only the later part of the time period. Whether this indicates that the ethical funds have gained the necessary experience, and thus could be expected to perform better in the coming years is not possible to say from this simple analysis. At least the improved performance over the conventional portfolio could be an insight that we should not take it for granted that ethical funds will underperform the conventional ones, as could be weakly interpreted from the previous analyses on the US market. However, we should keep in mind that we cannot observe the statistical significance in this plot, and we could very well still be left with the conclusion that there is no significant difference in returns, no matter the time period. At least we have learned that the factor loadings do change over time, which will influence the alpha value of the funds, and relatively to the conventional portfolio the ethical portfolio have been better off in more recent time in the US.

7.1.5.3 Summary

From the two plots it is obvious that the factor loadings are not constant over time in any of the two markets, which causes the alpha to vary over time. In the US more than the UK it seems like the ethical funds are catching up, and in fact outperform the conventional funds in the later periods of our sample. In the UK the pattern is not as clear, but it seems that there is even more variation in the factor loadings in the UK market than in the US. As mentioned, we do not observe the statistical significance in these plots, and we cannot draw any conclusions on whether there is a significant difference between the two types of funds. One interesting thought is that when looking at the plot of the US data, the improved relative performance of the ethical fund portfolio starts during the financial crisis. This could be explained by the fact that during times with high risk aversion in the markets, investors tend to fly to “safe havens”. Ethical companies could be seen as safer than less ethical companies, especially in the light of the scandalous behavior of the big American banks, revealed in the financial crisis, which caused a meltdown of the financial system. This pattern is mainly evident in the US, but knowing that the global financial crisis in 2008 emerged from the US, it could make sense that this pattern is mainly observable in the US. This theory would be in line with what is proposed by Kadiyala (2009); that investors tend to move their investments to less risky securities, such as ethical companies or funds, in times of crisis. This would pressure the price of such securities upwards, and would lead to higher returns in the specific period, but lower expected returns going forward. The observed variability in the alphas indicates that the results of Gregory et al. (2007) could also be evident in our data, namely that the ethical funds outperform the conventional ones when allowing factor loadings to change during time. In order to investigate the effect of looking at different time intervals, and to serve as a robustness test of our finding in the first part of analyses we should divide our time interval into sub-periods and see whether the picture changes.

7.1.6 Study of sub-samples

As the results from the rolling regression indicated, the underperformance of the ethical funds has not been stationary during the period of research. To perform a robustness check of our previous analysis, we therefore performed the same analysis individually over the first and the second half of our interval. The results, as can be seen on the next page, will be presented but not discussed separately for each of the models, but we will instead elaborate on them collectively and how they are related to the previous results.

The results for the UK are in general very similar to what they were in our initial analysis. The Long-Short portfolio has a negative alpha in both of the periods for all the models, except when performing the Carhart model on the first half. The positive alpha is though not statistically significant, and it is reasoned by that the conventional fund portfolio exhibit a considerably positive covariance with the momentum portfolio.

For the US the picture is different. Here we see that the alpha of the long-short portfolio is negative during the first half, but positive in all of our models during the second half of our research. Applying the Carhart model gives us a statistically significant alpha, with a p-value of 0.055. These results are in line with what is visualized in the rolling regression for the US. The explanation for this development can be that the fund managers have gained more experience within ethical investing. If that is the case, we might expect ethical funds to continue their outperformance. Another explanation could be that the increased interest in ethical investing lately has led to an increased stock price for ethical companies and therefore these stocks have seen a higher return lately. If that is the case, then ethical stocks will have lower expected returns going forward, as the prices are expected to fall back to their equilibrium prices, and the outperformance of ethical funds would not be expected to persist.

Table 14 – First and Second Half, UK Funds

UK	First Half						Second Half					
	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor
CAPM	Ethical	-0.000447	0.927				Ethical	0.001394	0.973			
	Conventional	-0.000117	0.978				Conventional	0.001575	1.010			
	Long Short	-0.000330	0.018				Long Short	-0.000181	-0.037			
FF	Ethical	-0.000793	0.904	0.400	0.000		Ethical	-0.000090	0.967	0.295	-0.068	
	Conventional	-0.000393	0.960	0.320	-0.000		Conventional	0.000290	1.008	0.248	-0.064	
	Long Short	-0.000400	-0.055	0.080	0.000		Long Short	-0.000380	-0.041	0.047	0.004	
Carhart	Ethical	-0.000723	0.903	0.399	-0.002	-0.005	Ethical	-0.000598	0.962	0.341	0.019	0.097
	Conventional	-0.000923**	0.966	0.327	0.018	0.037	Conventional	-0.000113	1.004	0.285	0.005	0.077
	Long Short	0.000200	-0.063	0.072	-0.020	-0.042	Long Short	-0.000485	-0.042	0.056	0.014	0.020

Table 15 – First and Second Half, UK Funds

US	First Half						Second Half					
	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor
CAPM	Ethical	-0.001579**	1.027				Ethical	-0.000181	1.005			
	Conventional	-0.000337	1.014				Conventional	-0.000925	1.034			
	Long Short	-0.001243**	0.014				Long Short	0.000744	-0.029			
FF	Ethical	-0.001223*	0.982	0.136	-0.150		Ethical	-0.000786	0.998	0.172	-0.118	
	Conventional	-0.000434	0.966	0.193	-0.106		Conventional	-0.001891***	1.037	0.208	-0.186	
	Long Short	-0.000788	0.016	-0.057	-0.044		Long Short	0.001105**	-0.039	-0.036	0.068	
Carhart	Ethical	-0.001567***	1.020	0.118	-0.150	0.063	Ethical	-0.000864	0.987	0.177	-0.140	-0.037
	Conventional	-0.001151	1.043	0.155	-0.105	0.130	Conventional	-0.001906***	1.035	0.209	-0.191	-0.007
	Long Short	-0.000417	-0.024	-0.037	-0.044	-0.068	Long Short	0.001042*	-0.048	-0.032	0.051	-0.030

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor, HML Factor is the average exposure to the value factor, MOM Factor is the average exposure to the momentum factor
Long-Short is a portfolio which is long the ethical portfolio and short the conventional portfolio.
**** indicates significance on a 1% confidence level, ** indicates significance on a 5% confidence level, * indicates significance on a 10% confidence level*
The first period is from January 1st 2002 until August 31st 2008
The second period is from September 1st 2008 until June 30th 2015

7.2 Stock Analysis

In our stock analysis we intend to measure the effect of ethical business practice on stock returns. We follow two approaches to measure this effect – first with a portfolio approach, and then secondly with a comprehensive Fama-MacBeth regression.

7.2.1 Portfolio Approach

In the introductory analysis on the effect of higher ESG scores on stock performance, we constructed portfolios based on the companies' ESG scores, and then measured the risk-adjusted return on these portfolios with the same models as in the fund analysis. The results are presented for each of the markets individually, and then summarized collectively.

7.2.1.1 UK

The CAPM model estimates the alpha of the long-short portfolio to be negative and statistically significant on a 10% confidence level, as can be seen from Table 16. This means that the portfolio of the stocks with the 35% lowest ESG scores (lower portfolio), have outperformed the portfolio of stocks with the 35% highest ESG scores (upper portfolio). We can also see that the beta of the lower portfolio is higher than the beta of the upper portfolio, which indicate that the companies with a low ESG score in general exhibit more market risk than the stocks with a higher score.

Looking at the results from the Fama-French model, the results are similar with respect to the alpha and the beta. The alpha of the long-short portfolio is though lower than before, but it is statistically significant on a higher level. The SMB-factor is significantly smaller for the upper portfolio, than for the lower one. This indicates that the companies that on average are ranked well on the Asset4 ESG score are big companies, while the ones that are ranked poorly in general are smaller companies. The HML-factor is also higher for the lower portfolio than the upper, indicating that the lower portfolio on average consists of more value stocks than the upper portfolio.

When applying the last model, the Carhart model, the alpha of the long-short portfolio is further reduced. Also, the alpha is again statistically significant on a 10% confidence level, and it seems like companies with a high ESG-score underperform companies with a low ESG-score in the UK. The upper portfolio has a significant negative coefficient on the momentum factor indicating that the highest ESG scoring companies are negatively exposed to the momentum factor.

Table 16 – ESG Portfolios, UK

UK	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor	R-Squared
CAPM	Top 35%	0.004286***	1.022***				0.869
	Middle	0.006305***	1.134***				0.782
	Bottom 35%	0.008194***	1.120***				0.673
	Long-Short	-0.003908*	-0.098				0.022
FF3	Top 35%	0.003486***	0.990***	0.330***	0.015		0.921
	Middle	0.004901***	1.044***	0.610***	0.139**		0.921
	Bottom 35%	0.006085***	1.004***	0.898***	0.144**		0.934
	Long-Short	-0.002599**	-0.014	-0.569***	-0.129**		0.596
Carhart	Top 35%	0.004271***	0.982***	0.302***	-0.032	-0.073*	0.925
	Middle	0.005187***	1.041***	0.600***	0.122**	-0.027	0.921
	Bottom 35%	0.006430***	1.000***	0.886***	0.124***	-0.032	0.934
	Long-Short	-0.002159*	-0.019	-0.584***	-0.156**	-0.041	0.598

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
MOM Factor is the average exposure to the momentum factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the Top 35% portfolio and short the Bottom 35% portfolio
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

7.2.1.2 US

The CAPM model estimates the alpha of the long-short portfolio to be negative, which indicate that the top 35% portfolio, have underperformed the bottom 35% portfolio in the interval studied, although the alpha is not statistically significant. The beta of the upper portfolio is lower than for the lower portfolio, indicating that stocks of companies with a high ESG-score on average exhibit less market risk than firms with a lower ESG-score.

The Fama-French model increases the estimated alpha of the long-short portfolio significantly, and the alpha is now positive, but not statistically significant. The higher SMB-factor for the lower portfolio indicates that the firms with lower ESG-score in general are smaller companies. For the HML-factor we see that the lower portfolio has a higher covariance with the HML portfolio than the upper portfolio, which means that it on average should consist of more value stocks than the upper portfolio.

Including the momentum factor, by applying the Carhart model, does not change the conclusion regarding the US market dramatically. The alpha of the long-short portfolio declines, but is still positive without being statistically significant. The lower portfolio got a more negative covariance with the momentum portfolio than the upper portfolio does, with all the coefficients being highly statistically significant. It might also be worth mentioning that for both the CAPM and Carhart models, the middle portfolio seems to be the best performing portfolio. In other words it seems like, in the US, having an average ESG score gives the best financial performance. However, we have not performed any analysis on this, and we do not know if the alpha of the middle portfolio is statistically different from any of the other two portfolios.

Table 17 – ESG Portfolios, US

US	Portfolio	Alpha	Market Factor	SMB Factor	HML Factor	MOM Factor	R-Squared
CAPM	Top 35%	0.003013***	1.079***				0.955
	Middle	0.003449***	1.232***				0.908
	Bottom 35%	0.003240**	1.245***				0.899
	Long-Short	-0.000228	-0.166***				0.186
FF3	Top 35%	0.002641***	1.038***	0.113***	0.183***		0.966
	Middle	0.002633**	1.143***	0.327***	0.238***		0.937
	Bottom 35%	0.002257**	1.138***	0.373***	0.327***		0.941
	Long-Short	0.000384	-0.100***	-0.261***	-0.144**		0.360
Carhart	Top 35%	0.002944***	0.996***	0.134***	0.164***	-0.082***	0.971
	Middle	0.003224***	1.061***	0.369***	0.201***	-0.160***	0.952
	Bottom 35%	0.002851**	1.056***	0.416***	0.290***	-0.160***	0.957
	Long-Short	0.000093	-0.060**	-0.282***	-0.126**	0.078**	0.401

Where:
Alpha is the monthly return that cannot be explained by the exposure to the factors
Market Factor is the average exposure to the market factor
SMB Factor is the average exposure to the size factor
HML Factor is the average exposure to the value factor
MOM Factor is the average exposure to the momentum factor
R-squared is how much of the variability in the returns which is explained by the model
Long-Short is a portfolio which is long the Top 35% portfolio and short the Bottom 35% portfolio
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*
The period analyzed is from January 1st 2002 until June 30th 2015.

7.2.1.3 Summary

In this introductory analysis of the effect that ethical behavior, measured by ESG-score, has on stock market performance, we have found conflicting results between the two markets. In the UK the takeaway is that companies with a higher ESG-score have underperformed companies with a low ESG-score, with the results being statistically significant. In the US we have found the opposite: The best scoring companies on ESG outperformed the lowest scoring companies. However, none of the long-short alphas from the US were statistically significant, and we therefore cannot state that there is a significant difference in stock market performance between companies with different ESG scores in the US.

In both markets the portfolio of the higher scoring companies has a lower beta than the portfolio with the lower scoring companies, however this result is only significant in the US. This is partly in line with what we found in our study of the ethical mutual funds and, as mentioned, is found in previous studies as well (Feldman, Soyka, & Ameer, 1997).

A similar relationship between the two markets also arises for the SMB- and HML-factors. In both markets the lower portfolio has a higher covariance with the SMB portfolio, than the upper portfolio. An interpretation of this could be that the lower portfolio is made up of more small stocks than the upper portfolio, and from this that small stocks on average have lower ESG-scores than bigger companies. This is also found in previous research (Brammer, Brooks, & Pavelin, 2006), and makes sense since big companies in general are more in the "spotlight", and therefore have better incentives for having a strict policy of ethical business practice. For the HML-factor we find that higher scoring companies on ESG on average are more tilted towards growth stocks, than companies with a lower ESG score.

One thing we found puzzling from our portfolio approach analysis on single stocks is the fact that all portfolios show significant positive alphas in all models. With three portfolios totaling 665 stocks we find this result rather surprising. With stocks moving in and out of the different portfolios dependent on their ESG score at every given time of rebalancing, this result is different to investigate, but we suspect that it might be influenced by the fact that our portfolios are equally weighted, giving more weight to smaller stocks than the portfolios used to control for the different risk factors, which are value-weighted. One last thing to be mentioned is that the results of our portfolio approach could be dependent on the cut-off point for the different portfolios, meaning that an approach with, for example, portfolios with 25% of the highest- and lowest scoring stocks on ESG might give different results and interpretations. This underlines the need for further analysis.

7.2.2 Fama-MacBeth

The Fama-Macbeth approach was conducted to measure the priced effect of a higher ESG score and the effect of negative screening. This was done to mimic the investment philosophy of the ethical mutual funds, and to isolate effect of ethical investing, regardless of portfolio manager abilities. The approach is similar to Brammer et al. (2006), but also distinguishes itself from their study, as we are looking both to capture the ethical effect as a whole, but also to divide the ESG score into three individual elements (E, S and G) and assess how the different components affect financial performance. Brammer et al. (2006) on the other hand are looking at different dimensions of ethical aspects only, and these dimensions are Environmental, Community and Employment, and thus differ from our analysis. Also, they did not incorporate a variable to capture the effect of negative screening.

The results of our Fama-MacBeth regression will be presented for each of the two markets, and discussed individually before being summarized in a last part.

7.2.2.2 UK

Table 18 – Fama-MacBeth, UK

UK	*Intercept*	*ESG*	*Negative Screen*	*Beta*	*Market Cap*	*PTBV*	*Momentum*	*Dummy1*	*Dummy2*	*Dummy3*	*Dummy4*	*Dummy5*	*Dummy6*	*Dummy7*	*Dummy8*	*Dummy9*
(1)	*0.00663 (0.00136)****	*0.00001 (0.000009)*	*0.00049 (0.00038)*	*0.00024 (0.00080)*	*-0.00080 (0.00018)****	*-0.00041 (0.00013)****	*-0.00037 (0.00103)*	*0.00099 (0.00090)*	*0.00099 (0.000632)*	*0.00027 (0.00056)*	*0.00158 (0.00093)**	*-0.00016 (0.00056)*	*0.00066 (0.00098)*	*0.001149 (0.00092)*	*0.00115 (0.00090)*	*0.00110 (0.00080)*
(2)	*0.00663 (0.00133)****	*0.00001 (0.00001)**	*0.00032 (0.00037)*	*-0.00005 (0.00080)*	*-0.00075 (0.00018)****	*-0.00043 (0.00014)****	*0.00039 (0.00108)*									
(3)	*0.00706 (0.0014)****	*0.00001 (0.000001)*	*0.00042 (0.00037)*	*0.00033 (0.00093)*	*-0.00079 0.00020)****	*-0.00040 (0.00016)***										
(4)	*0.00400 (0.00089)****	*-0.00003 (0.00001)***	*0.00007 (0.00037)*	*0.00025 (0.00096)*												
(5)	*0.00415 (0.00114)****	*-0.00002 (0.00001)***	*0.00008 (0.00038)*													

Where:
Intercept is the return which is not explained by the other variables
ESG is the score of each company given by Asset4
Negative Screen is a dummy variable, which gives a company "1" if it operates outside of ethical guidelines, and "0" if not
Beta is the exposure to the market factor
MarketCap is the natural logarithm of the market capitalization
PTBV is the natural logarithm of the Price-to-Book value of the firm
Momentum is the exposure to the momentum factor
Dummy1 is a dummy variable, which gives a company "1" if the company is in the "Basic Materials" industry and "0" if not
Dummy2 is a dummy variable, which gives a company "1" if the company is in the "Consumer Goods" industry and "0" if not
Dummy3 is a dummy variable, which gives a company "1" if the company is in the "Consumer Services" industry and "0" if not
Dummy4 is a dummy variable, which gives a company "1" if the company is in the "Health Care" industry and "0" if not
Dummy5 is a dummy variable, which gives a company "1" if the company is in the "Industrials" industry and "0" if not
Dummy6 is a dummy variable, which gives a company "1" if the company is in the "Oil & Gas" industry and "0" if not
Dummy7 is a dummy variable, which gives a company "1" if the company is in the "Technology" industry and "0" if not
Dummy8 is a dummy variable, which gives a company "1" if the company is in the "Telecommunications" industry and "0" if not
Dummy9 is a dummy variable, which gives a company "1" if the company is in the "Utilities" industry and "0" if not
The number in parentheses is the standard error of the coefficient
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*

Starting from the fifth and least comprehensive model, regression (5), we see that the coefficient for the ESG score is negative and also statistically significant on a 5% level. The interpretation of this could be that an increased ESG score will lead to a lower expected return. We also analyze the effect of negative screening, and we can see from the results that the regression yields a positive coefficient, though not statistically significant. This indicates that the model estimates that firms which operate within harmful industries on average yield a higher return in any given period than companies which do not. For the ethical funds this implies that they do not only experience lower returns because they are investing in firms with a high ethical standard, but also because they are avoiding certain industries which would give rise to a higher return.

By including the market risk in the regression (4), we see that the results for the ESG and negative screen remain similar. The coefficient for the beta is positive, and in line with the CAPM theory, which suggests that market risk should be priced positively.

By including the Fama-French factors in the regression (3), we see that the results change. The coefficient for the ESG score is now positive, and the effect of the negative screening increased dramatically. The market cap is priced negatively, implying a small cap premium, and that the big companies have underperformed small companies. An interpretation of the change of sign could be that many of the companies which are highly rated on ESG are also large companies, which is in line with the correlations referred to in section 6.4. This seems reasonable, as large companies get more attention and media coverage, and the benefit of a high ESG score is possibly more valuable for a large company. Also, the costs of focusing on ESG factors are probably lower for a large company relative to a smaller company. If most companies with high ESG scores are also large companies, and large companies have yielded lower returns in the stock market during the period of research (which would be in line with the Fama-French model) then controlling for market capitalization would be important in order to isolate the effect of ESG scores. This seems evident from our results. The price-to-book value has a negative coefficient meaning that the firms with a high price-to-book value, namely growth stocks, have in general performed worse than value stocks. This is also in line with the Fama-French theory.

In the regression (2), when including the momentum factor, there are no significant changes in the variables of interest. We though see that the coefficient for the ESG score is now significant on a 10% level. The momentum factor is positively priced, and in line with theory.

In regression (1), which is the most comprehensive one, we also control for industry effects. This is done to assure that if the ESG score, and especially the negative screen dummy, is correlated with any particular industry, our results will not be driven by this effect. The coefficient of the industry dummies is an indication of how well that industry has performed. As can be observed the fourth dummy, health care, is the industry with the highest coefficient, indicating that the health care industry has performed well in the interval studied. Further, we can see that the coefficient for the ESG score is still positive, though no longer statistically significant. Also, the negative screen dummy got a positive coefficient larger than in any of the other regressions. The effect of ethical investing from this model therefore seems to be ambiguous. On one side, the most ethical firms, or at least the ones with the highest ESG score, seem to yield a higher return than those less ethical, but the industries that are harmful and therefore excluded from the investment universe of the ethical funds seem to outperform other firms.

7.2.2.1 US

Table 19 – Fama-MacBeth, UK

US	Intercept	ESG	Negative Screen	Beta	Market Cap	PTBV	Momentum	Dummy1	Dummy2	Dummy3	Dummy4	Dummy5	Dummy6	Dummy7	Dummy8	Dummy9
(1)	0.00774 (0.00151)***	0.00002 (0.000005)***	0.00049 (0.00038)	0.00041 (0.00084)	-0.00084 (0.00014)***	-0.00060 (0.00013)***	-0.00049 (0.00100)	-0.00048 (0.00081)	0.00028 (0.00056)	0.00054 (0.00059)	0.00111 (0.00067)*	-0.00007 (0.00067)	0.00046 (0.00124)	0.00024 (0.00087)	-0.00014 (0.00103)	-0.00055 (0.00083)
(2)	0.00861 (0.00152)***	0.00002 (0.000005)***	0.00030 (0.00038)	0.00030 (0.00093)	-0.00090 (0.00015)***	-0.00061 (0.00016)***	-0.00044 (0.00110)									
(3)	0.00919 (0.00160)***	0.000006 (0.00160)***	0.00056 (0.00038)	0.00066 (0.00101)	-0.00095 (0.00016)***	-0.00061 (0.00018)***										
(4)	0.00106 (0.00080)	-0.000005 (0.000005)	0.00053 (0.00038)	0.00131 (0.00110)												
(5)	0.00315 (0.00145)**	-0.00001 (0.00008)	0.00043 (0.00039)													

Where:
Intercept is the return which is not explained by the other variables
ESG is the score of each company given by Asset4
Negative Screen is a dummy variable, which gives a company “1” if it operates outside of ethical guidelines, and “0” if not
Beta is the exposure to the market factor
MarketCap is the natural logarithm of the market capitalization
PTBV is the natural logarithm of the Price-to-Book value of the firm
Momentum is the exposure to the momentum factor
Dummy1 is a dummy variable, which gives a company “1” if the company is in the “Basic Materials” industry and “0” if not
Dummy2 is a dummy variable, which gives a company “1” if the company is in the “Consumer Goods” industry and “0” if not
Dummy3 is a dummy variable, which gives a company “1” if the company is in the “Consumer Services” industry and “0” if not
Dummy4 is a dummy variable, which gives a company “1” if the company is in the “Health Care” industry and “0” if not
Dummy5 is a dummy variable, which gives a company “1” if the company is in the “Industrials” industry and “0” if not
Dummy6 is a dummy variable, which gives a company “1” if the company is in the “Oil & Gas” industry and “0” if not
Dummy7 is a dummy variable, which gives a company “1” if the company is in the “Technology” industry and “0” if not
Dummy8 is a dummy variable, which gives a company “1” if the company is in the “Telecommunications” industry and “0” if not
Dummy9 is a dummy variable, which gives a company “1” if the company is in the “Utilities” industry and “0” if not
The number in parentheses is the standard error of the coefficient
**** indicates significance on a 1% confidence level*
*** indicates significance on a 5% confidence level*
** indicates significance on a 10% confidence level*

When looking at the results for the US, we once again start from the regression (5), and look at the simplest model. This model takes only ESG score and whether the company is considered as operating in a non-ethical way (which is captured in the "Negative Screen") into consideration. From this it seems that companies which focus on ESG factors lose out financially in the stock market, and that the costs from such focus outweighs the benefits. It also seems like investors would lose out by excluding companies which do not operate within ethical standards. However, it should be noted that none of these coefficients are statistically significant.

When including the exposure to the market factor, the overall takeaway remains the same, even though the ESG-coefficient declines somewhat, and the negative screen coefficient increase somewhat. The coefficients are still not significant on common levels of confidence. The market beta coefficient is positive, which is in line with CAPM theory.

One interesting point is evident once including the two remaining Fama-French factors, size and price-to-book. The ESG coefficient is now positive, indicating that companies which focus on ethical standards of operations do actually profit from this in the stock market. Also, the positive ESG coefficient is now significant on a 1% confidence level. The interpretation of the change in sign is the same as discussed for the UK market in the previous section. Companies excluded in the negative screen still earn positive returns; hence the effect of excluding such companies is still negative for ethical investors. However, the negative screening effect is yet again not statistically significant. Both the market cap and the price-to-book coefficients are negative, and significant. This is in line with Fama-French's theory.

No big changes in our interpretation are evident when including the momentum factor. The momentum coefficient is negative, which contradicts with the theory of Carhart. However, the coefficient is not significant.

When including dummy variables to control for industry effects in regression (1), the result is still that the ESG coefficient is positive and significant, and the negative screen coefficient is positive, but not significant. From these results we can conclude that in the US market, for the period investigated, investors who incorporate a positive ethical screening strategy, including the best ethical performers in their portfolio, would earn better returns than investors who include similar companies with lower ESG scores. We cannot conclude with certainty that excluding companies which are not considered to operate ethically hurt returns, but weak evidence indicate it does. It also seems that incorporating such positive screening strategy would give exposure to large stocks; at least when basing the judgement of ethicality on ESG scores from research agencies like Asset4.

7.2.2.2 Summary

In both the UK and the US, our analysis indicates that the higher the ESG score, the better the stock market performance. However, our most comprehensive model only shows a statistically significant effect in the US. This is in line with the overall takeaway from most of the previous research in section 2.2. In both markets there is also a weak indication that exclusion of certain, non-ethically operating, companies hurt investment returns. This would be in line with Statman and Glushkov (2008), who found that exclusion of “sin” companies largely offset the outperformance of ethical companies. In our results, this effect is however not statistically significant, and we cannot with confidence conclude that investors lose out by making such exclusions. From our results we have strong implications that high-scoring companies on ESG are large companies, in both markets. Our model behaves in line with theory when pricing value stocks and small stocks with a risk premium which is statistically significant. The market risk premium is also priced according to theory, however this is not statistically significant. The only risk premium which contradicts theory is the momentum factor, which receives a negative risk premium in our most comprehensive model. This premium is not significant on common levels of confidence. The model mainly behaves in line with theory, which should be seen as a sign of quality and in our opinion makes the results trustworthy.

The bottom line from our Fama-MacBeth regressions is that there is a positive relation between ESG score and stock market return in the US, while in the UK there is no significant difference between the return of companies with different ESG scores. In neither of the markets there are clear statistical implications of lower expected returns from excluding certain companies.

7.2.3 Fama-MacBeth for Individual Factors

In the previous analysis we analyzed the effect on stock returns for an overall ESG score, calculated as the average of the Environmental, Social and Governance score that each company had received from Asset4. However, it might be that the effect of the three factors is not the same, such that the different scores influence return in a different manner. To analyze this effect we set out to perform the previous regression, but to analyze the scores (E, S and G) individually.

7.2.3.1 UK

As the interpretation of the explanatory variables listed after Negative Screen is already elaborated on, and these in general are the same as the previous analysis, we will not discuss these further.

From regression (5) and (4) we see that there is a positive coefficient for the environmental as well as the social score, meaning that a high score within these two contributed to a higher return. The governance score on the other side has a negative coefficient, meaning that scoring well on governance leads to a lower return. None of these coefficients are though statistically significant on any common level. The negative screen dummy has, unlike in the previous analysis, a negative coefficient, but this is not statistically significant either.

Looking from regression (3) until (1), we see that now both the coefficients for the negative screen dummy and for the governance score turns positive as well. This can be interpreted as a higher score within all the three categories will on average yield a higher stock market return, and that the stocks which fall into the negative screen have outperformed other stocks on average. Even though the coefficients are not statistically significant, the results are in line with the results from the first analysis where we applied the average of the of the ESG scores.

Table 20 – Fama-MacBeth Individual Scores, UK

UK	Intercept	Env.	Social	Gov.	Negative Screen	Beta	Market Cap	PTBV	Momentum	D1	D2	D3	D4	D5	D6	D7	D8	D9
(1)	0.005865 (0.001435) ***	0.000003 (0.000006)	0.000002 (0.000007)	0.000005 (0.000006)	0.000402 (0.000386)	0.000236 (0.000795)	-0.000681 (0.000169) ***	-0.000444 (0.000129) ***	-0.000544 (0.001029)	0.0009 (0.0009)	0.0011 (0.0006) *	0.0003 (0.0006)	0.0016 (0.0009) *	-0.0001 (0.0006)	0.0006 (0.0009)	0.0012 (0.0009)	0.0011 (0.0009)	0.0013 (0.0008)
(2)	0.005813 (0.001400)	0.000001 (0.000006)	0.000004 (0.000007)	0.000009 (0.000009)	0.000252 (0.000377)	-0.000104 (0.000792)	-0.000637 (0.000169)	-0.000465 (0.000138)	0.000217 (0.001083)									
(3)	0.006293 (0.001452) ***	0.000001 (0.000007)	0.000007 (0.000007)	0.000006 (0.000010)	0.000360 (0.000378)	0.000338 (0.000926)	-0.000679 (0.000182) ***	-0.000447 (0.000162) ***										
(4)	0.002264 (0.000902) **	0.000001 (0.000007)	0.000004 (0.000007)	-0.000002 (0.000010)	-0.000061 (0.000389)	0.000042 (0.000931)												
(5)	0.002347 (0.001012) **	0.000002 (0.000007)	0.000004 (0.000008)	-0.000004 (0.000010)	-0.000064 (0.000398)													

Where:
Intercept is the return which is not explained by the other variables
Env is the environmental score of each company given by Asset4
Social is the social score of each company given by Asset4
Governance is the governance score of each company given by Asset4
Negative Screen is a dummy variable, which gives a company "1" if it operates outside of ethical guidelines, and "0" if not
Beta is the exposure to the market factor
MarketCap is the natural logarithm of the market capitalization
PTBV is the natural logarithm of the Price-to-Book value of the firm
Momentum is the exposure to the momentum factor
Dummy1 is a dummy variable, which gives a company "1" if the company is in the "Basic Materials" industry and "0" if not
Dummy2 is a dummy variable, which gives a company "1" if the company is in the "Consumer Goods" industry and "0" if not
Dummy3 is a dummy variable, which gives a company "1" if the company is in the "Consumer Services" industry and "0" if not
Dummy4 is a dummy variable, which gives a company "1" if the company is in the "Health Care" industry and "0" if not
Dummy5 is a dummy variable, which gives a company "1" if the company is in the "Industrials" industry and "0" if not
Dummy6 is a dummy variable, which gives a company "1" if the company is in the "Oil & Gas" industry and "0" if not
Dummy7 is a dummy variable, which gives a company "1" if the company is in the "Technology" industry and "0" if not
Dummy8 is a dummy variable, which gives a company "1" if the company is in the "Telecommunications" industry and "0" if not
Dummy9 is a dummy variable, which gives a company "1" if the company is in the "Utilities" industry and "0" if not
The number in parentheses is the standard error of the coefficient
**** indicates significance on a 1% confidence level, ** indicates significance on a 5% confidence level, * indicates significance on a 10% confidence level*

7.2.3.2 US

The results from the US reflect much of the same intuition as the first Fama-MacBeth analysis, but with some interesting additional insights.

The result from regression (5) indicates that there is a negative relationship between return and the social- and governance score, while the effect of a higher environmental score does not seem to affect returns at all. The coefficient of the negative screen dummy is positive, but none of the coefficients are statistically significant.

Regression (4) gives a small change in the coefficients. The coefficient of the social score is now positive, while the coefficients for the environmental and governance scores are negative. All the scores are though very small, and neither of them are close to being statistically significant.

From regression (3) to (1) we see that a somewhat different pattern arises. The effect of a higher social score is positive and larger than before, while also being highly statistically significant. We see that the coefficient for the environmental score is also positive, while the effect of a higher governance score is negative, but none of them are statistically significant at any common confidence level. As in all the previous regressions the effect of the negative screening is positive, indicating that stocks within harmful industries outperform other stocks on average, but again this is not statistically significant.

Table 21 – Fama-MacBeth Individual Scores, US

US	*Intercept*	*Env.*	*Social*	*Gov.*	*Negative Screen*	*Beta*	*Market Cap*	*PTBV*	*Momentum*	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*
(1)	*0.008758 (0.001604) ****	*0.000005 (0.000005)*	*0.000017 (0.000005) ****	*-0.000007 (0.000006)*	*0.000459 (0.000381)*	*0.000434 (0.000841)*	*-0.000881 (0.000149) ****	*-0.000601 (0.000141) ****	*-0.000480 (0.001002)*	*-0.0005 (0.0008)*	*0.0002 (0.0006)*	*0.0005 (0.0006)*	*0.0011 (0.0007)*	*-0.0001 (0.0006)*	*0.0005 (0.0012)*	*0.0002 (0.0009)*	*-0.0002 (0.0010)*	*-0.0006 (0.0008)*
(2)	*0.009524 (0.001614) ****	*0.000003 (0.000005)*	*0.000017 (0.000005) ****	*-0.000006 (0.000006)*	*0.000249 (0.000381)*	*0.000304 (0.000937)*	*-0.000935 (0.000157) ****	*-0.000616 (0.000165) ****	*-0.000424 (0.001101)*									
(3)	*0.010156 (0.001711) ****	*0.000005 (0.000006)*	*0.000017 (0.000006) ****	*-0.000006 (0.000006)*	*0.000507 (0.000386)*	*0.000666 (0.001020)*	*-0.000983 (0.000168) ****	*-0.000616 (0.000187) ****										
(4)	*0.001066 (0.000869)*	*-0.000003 (0.000005)*	*0.000001 (0.000006)*	*-0.000003 (0.000007)*	*0.000574 (0.000384)*	*0.001340 (0.001100)*												
(5)	*0.003431 (0.001514) ***	*0.000000 (0.000005)*	*-0.000006 (0.000008)*	*-0.000008 (0.000007)*	*0.000462 (0.000392)*													

Where:
Intercept is the return which is not explained by the other variables
Env is the environmental score of each company given by Asset4
Social is the social score of each company given by Asset4
Governance is the governance score of each company given by Asset4
Negative Screen is a dummy variable, which gives a company "1" if it operates outside of ethical guidelines, and "0" if not
Beta is the exposure to the market factor
MarketCap is the natural logarithm of the market capitalization
PTBV is the natural logarithm of the Price-to-Book value of the firm
Momentum is the exposure to the momentum factor
Dummy1 is a dummy variable, which gives a company "1" if the company is in the "Basic Materials" industry and "0" if not
Dummy2 is a dummy variable, which gives a company "1" if the company is in the "Consumer Goods" industry and "0" if not
Dummy3 is a dummy variable, which gives a company "1" if the company is in the "Consumer Services" industry and "0" if not
Dummy4 is a dummy variable, which gives a company "1" if the company is in the "Health Care" industry and "0" if not
Dummy5 is a dummy variable, which gives a company "1" if the company is in the "Industrials" industry and "0" if not
Dummy6 is a dummy variable, which gives a company "1" if the company is in the "Oil & Gas" industry and "0" if not
Dummy7 is a dummy variable, which gives a company "1" if the company is in the "Technology" industry and "0" if not
Dummy8 is a dummy variable, which gives a company "1" if the company is in the "Telecommunications" industry and "0" if not
Dummy9 is a dummy variable, which gives a company "1" if the company is in the "Utilities" industry and "0" if not
The number in parentheses is the standard error of the coefficient
**** indicates significance on a 1% confidence level, ** indicates significance on a 5% confidence level, * indicates significance on a 10% confidence level*

7.2.3.3 Summary

After looking at the analysis from the UK and the US, we can draw the conclusion that they do not distort the results we have from the first Fama-MacBeth analysis. The results for the UK are in line with the previous analysis, with all of the factors pulling in the same direction, though without being statistically significant.

The results from the US are more interesting, as we get a positive statistically significant coefficient for the effect of the social score on financial return. This is in line with Brammer et al. (2006) who found that a higher score on employment, which would fall into our social category, affects stock market return positively, though in the UK market. Also, the governance score of the US analysis has a negative coefficient, but since this is small and not statistically significant, it is difficult to state that improving the governance structure in a firm will lead to a lower return. To summarize it seems like it is the social score that influences the previously found positive effect of a higher ESG-score the most.

8. Conclusion

The market for ethical investing has seen significant growth in the later period. Despite this growth, ethical investing remains a small fraction of the overall market, especially in the UK. As we have seen incorporation of ESG factors in the investment process is increasingly widespread, and the UN PRI principles for responsible investments have seen a huge rise in signatories. This is indisputable evidence of the increasing popularity and importance of ethical investing. The crucial factor to determine the future importance of this segment is its financial performance. This thesis contributes to the literature of ethical investing by looking at a more recent time period, studying the risk and return characteristics of ethical funds in both the US and the UK. This thesis also takes it a step further and looks at the performance on stock level, in order to control for portfolio manager abilities and the subjective nature of the ethical criteria set forward by the different ethical funds. Each ethical fund has its own ethical criteria, and although the funds to a large extent report their criteria and their stance on different ethical issues, it is difficult to assess how successful each fund is at incorporating sufficient ethical criteria. By looking at ESG scores rated by an independent agency, which has this as their primary purpose, we seek to study the effect of ethical investing in an unambiguous and more objective way. As far as our knowledge goes, this thesis is the first to use the Asset4 ESG database to investigate the performance of ethical investments.

Despite the range of ethical strategies that exist, we developed our own approach in order to ensure a dataset of ethical funds which should be sufficiently ethical for the average ethical investor. By looking at funds which use ESG factors to employ a negative and/or positive screening strategy, potentially enhanced by shareholder engagement and active ownership, we ended up with a dataset of US and UK ethical equity funds investing domestically. This dataset was analyzed with several well-known financial models in order to compare the risk-adjusted performance of ethical funds and conventional peers.

Our analysis of ethical mutual funds indicates that investors in ethical mutual funds do not sacrifice return to follow their values when putting their money to work. Although our descriptive statistics show lower returns for the ethical funds than the conventional funds, and lower Sharpe and Treynor ratios, we find no significant underperformance in risk-adjusted returns of ethical funds in neither market, as none of the alphas of the long-short portfolios are significantly different from zero. However, there is weak evidence of underperformance of

0.3% and 0.04% in the UK and the US respectively after controlling for market risk, size, book-to-market and stock price momentum. In both markets the ethical funds show significant exposure to small stocks, the difference being that the UK ethical funds show significantly more exposure to small stocks than their peers, while the US ethical funds show significantly less. Our rolling regression indicated that the factor loadings of the funds are not stable over time, and hence that the alphas vary over time. Our robustness check uncovered a significant outperformance of US ethical funds over their conventional peers in the second half of our time period. Whether this could indicate a future period of continued outperformance by US ethical funds is difficult to conclude upon.

Through the Asset4 database we gathered a large dataset of stocks with an ESG score. This enabled us to investigate whether a higher ESG score, which should indicate a more ethical company, affect stock market performance. This was analyzed with two different approaches. First a portfolio approach, where the best and worst scoring companies are grouped in two different portfolios. Secondly a Fama-MacBeth regression was performed to investigate the effect of both ESG score and negative screening, after controlling for a wide range of variables. Finally, we split the ESG score into three individual scores to analyze whether any of the three factors (Environmental, Social or Governance) affect financial performance differently than the other.

Our portfolio approach confirms that a portfolio of the (35%) highest scoring companies on ESG at all times underperform a similar portfolio of the lowest scoring companies in the UK. In the US we cannot with confidence conclude that there is any difference in performance of the two portfolios, although we have weak evidence of outperformance by the highest scoring portfolio. Our Fama-MacBeth approach shows that a higher ESG score leads to significantly better stock market performance in the US. In the UK no such conclusion can be made, although we see weak evidence of the same. We cannot conclude that investors lose out when employing negative screening, however weak evidence indicate that they do. By splitting the ESG score into three individual components we learn that the social score is the most important score in affecting stock market performance positively for US companies. For the UK companies we cannot conclude that any of the three components are more important than the other. What is clear from both of our stock analysis approaches is that the highest scoring, and thus most ethical companies, are large companies.

To summarize, there is little evidence of any risk-adjusted difference in financial performance between ethical and conventional investing in the UK. This is in line with hypothesis 3; ethical investors can do equally well while doing good. There is no clear reason for investors in the UK not to invest ethically, at least not from a risk-return perspective. In the US hypothesis 3 is true for the funds, while the stock analysis uncovers that there might even be possible to outperform conventional investing by investing ethically, which would be in line with hypothesis 2. Our robustness check confirms this, as the ethical funds have outperformed conventional funds in the later years. However, our findings suggest that there is some discrepancy between how the mutual funds and the ESG-rating agencies assess ethicality, as the ethical funds are biased towards small stocks, while the highest scoring companies on ESG are large companies. All our analyses points in the direction that ethical investments perform better in the US than in the UK. This might have to do with a more mature industry in the US, and might explain why the ethical investing segment is a larger fraction of the overall market in the US than in the UK. The bottom line is however, in line with what the majority of previous research has found ethical investing does not hurt your financial return, which should be good news for the thriving trend of ethical investing.

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Appendices

Appendix 1 - List of UK Mutual Funds

UK Funds	
Ethical	**Conventional**
Jupiter Environmental Income	Wesleyan Growth Trust Acc
	Allianz UK Equity Income Fund Class A Shares Income
Eden Tree Amity UK A	Aberdeen UK Mid-Cap Equity Fund A Inc
	Man GLG UK Income
Premier Ethical R Income	Baring United Kingdom Growth
	Schroder Institutional UK Smaller Companies
Kames Ethical Equity A	Invesco Funds Series - Invesco UK Equity Fund A annual distribution
	Invesco Funds Series - Invesco UK Equity Fund A annual distribution
Aberdeen Responsible United Kingdom Equity A Accumulation	TM UBS (UK) - UK Equity Net Inc
	Lazard UK Omega Retail Inc
Alliance Trust Sustainable Future UK Growth 1 Acc	Allianz UK Mid-Cap Fund Class A Shares Accumulation
	Marlborough UK Multi-Cap Growth Fund A Inc
Aviva Investors United Kingdom Ethical A Accumulation	JP Morgan UK Dynamic A - Net Accumulation
	Architas MM UK Equity Fund Class R Acc
Standard Life United Kingdom Ethical Retail Accumulation	Baillie Gifford UK Equity Alpha Fund Class A Acc
	Barclays United Kingdom Lower Capital A Distribution
F&C Responsible United Kingdom Equity Growth 1 Income	Kames UK Equity A Acc
	AXA General Trust Acc

Appendix 2 - List of US Mutual Funds

US Funds	
Ethical	Conventional
Calvert Capital Accumulation A	Eagle Mid Cap Stock Fund Class A
	Baron Opportunity Retail
Calvert Small Cap Value A	Columbia Select Smaller-Cap Value A
	Wasatch Small Cap Value
Domini Social Equity A	Cambiar Opportunity Inv
	BlackRock Large Cap Core Inv A
Dreyfus Premier Third Century Z	Prudential Jennison Conservative Gr C
	Voya Large Cap Growth A
Dreyfus Socially Resp Growth S	Deutsche Large Cap Growth
	BMO Large Cap Growth
Green Century Equity	Value Line Large Companies Focused
	Chase Growth N
Integrity Growth & Income Fund	Commerce Growth
	Eaton Vance Atlanta Capital Focused Gr I
Neuberger Berman Socially Responsive Trust	Vantagepoint Growth Investor
	USAA Agressive Growth
Parnassus Endeavor Fund	Transamerican Capital Growth
	ASTON/Montag & Caldwell Growth I
Pax World Growth	AB Core Opportunities
	Rainer Large Cap Equity Original
Pax World Small Cap Fund	Aberdeen Small Cap A
	Columbia Acorn USA A
Sentinel Sustainable Core Opportunities Fund A	BlackRock Flexible Equity Investor A
	Virtus Growth & Income A
Sentinel Sustainable Growth Opp Fund A	Bridgeway Aggressive Investors 1
	Westport Select Cap R

Appendix 3 - Correlation Matrix UK:

UK	*ESG*	*Neg. Screen*	*Beta*	*Market Cap*	*PTBV*	*MOM*	*Dummy1*	*Dummy2*	*Dummy3*	*Dummy4*	*Dummy5*	*Dummy6*	*Dummy7*	*Dummy8*	*Dummy9*
ESG	1.00														
Neg. Screen	0.08	1.00													
Beta	0.19	-0.03	1.00												
Market Cap	0.63	0.12	0.21	1.00											
PTBV	0.02	0.04	-0.12	0.16	1.00										
MOM	-0.08	-0.00	-0.05	0.01	0.16	1.00									
Dummy1	0.07	-0.08	0.15	0.10	0.06	0.01	1.00								
Dummy2	0.15	0.12	-0.14	0.04	0.02	0.02	-0.08	1.00							
Dummy3	-0.10	0.07	-0.10	-0.05	0.01	-0.01	-0.11	-0.17	1.00						
Dummy4	0.10	-0.05	-0.06	0.17	0.11	-0.02	-0.04	-0.06	-0.08	1.00					
Dummy5	-0.01	0.17	-0.00	-0.20	0.04	0.01	-0.14	-0.22	-0.30	-0.10	1.00				
Dummy6	-0.03	-0.07	0.06	0.07	-0.01	0.01	-0.05	-0.08	-0.10	-0.03	-0.13	1.00			
Dummy7	-0.13	-0.07	0.08	-0.13	0.07	0.03	-0.05	-0.08	-0.10	-0.03	-0.13	-0.05	1.00		
Dummy8	-0.05	-0.00	-0.04	0.06	0.01	-0.01	-0.04	-0.06	-0.08	-0.02	-0.10	-0.03	-0.03	1.00	
Dummy9	0.15	-0.06	-0.17	0.15	0.06	-0.01	-0.04	-0.06	-0.08	-0.03	-0.11	-0.04	-0.04	-0.03	1.00

Appendix 4 - Correlation Matrix US:

US	*ESG*	*Neg. Screen*	*Beta*	*Market Cap*	*PTBV*	*MOM*	*Dummy1*	*Dummy2*	*Dummy3*	*Dummy4*	*Dummy5*	*Dummy6*	*Dummy7*	*Dummy8*	*Dummy9*
ESG	1														
Neg. Screen	0.02	1.00													
Beta	-0.09	-0.02	1.00												
Market Cap	0.50	0.04	-0.24	1.00											
PTBV	0.10	0.01	-0.16	0.22	1.00										
MOM	-0.02	0.02	0.08	0.04	0.12	1.00									
Dummy1	0.15	0.03	0.05	-0.04	0.03	0.01	1.00								
Dummy2	0.07	0.06	-0.08	-0.04	0.08	0.00	-0.08	1.00							
Dummy3	-0.04	0.02	-0.01	-0.00	0.04	0.02	-0.09	-0.14	1.00						
Dummy4	-0.00	-0.07	-0.16	0.08	0.11	-0.00	-0.07	-0.10	-0.12	1.00					
Dummy5	0.07	0.24	0.09	-0.04	0.05	0.00	-0.10	-0.15	-0.18	-0.13	1.00				
Dummy6	-0.02	-0.06	0.03	0.06	-0.07	0.02	-0.07	-0.10	-0.12	-0.08	-0.13	1.00			
Dummy7	0.07	-0.09	0.19	0.00	0.06	-0.01	-0.08	-0.12	-0.14	-0.10	-0.16	-0.10	1.00		
Dummy8	-0.03	0.01	-0.05	0.03	-0.04	-0.02	-0.03	-0.04	-0.05	-0.03	-0.05	-0.03	-0.04	1.00	
Dummy9	0.13	-0.06	-0.23	-0.01	-0.10	-0.02	-0.06	-0.09	-0.10	-0.07	-0.11	-0.07	-0.09	-0.03	1.00