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In the view of a carbon tax:

How carbon emission and climate change action are priced in US stocks

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ABSTRACT

This paper tries to link carbon emission and climate change action to the performance of US-listed stocks. More and more countries have a carbon pricing policy, but the United States are lagging. This paper shows that cleaner stocks do not convincingly outperform dirtier stocks over the period from 2005 until 2017. In addition, there is a positive price for carbon risk and climate risk. The positive price for carbon risk implies that there is a positive relation between carbon-intensity and expected returns. The positive price for climate risk, proxied by Carbon Disclosure Project scores, implies a positive relation between unsustainability and expected returns. Therefore, this paper encourages the American government to implement a carbon pricing system. By implementing this policy, the government can dispirit carbon-intensive production and advocate sustainable solutions.

Keywords: pricing carbon, sustainability, climate, carbon emissions, stock returns.
JEL Classification: G12; G18; Q54

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1. Introduction

Temperatures are rising, arctic ice is melting and sea levels are rising. Global warming is real and is amplified by human actions. The more carbon dioxide we release in the atmosphere, the faster global warming will deteriorate the environment. More and more countries try to fight this phenomenon by implementing policies to reduce emissions, think of Europe's Emissions Trading System (ETS) and China's national carbon market (Harvey & Min, 2017). Though China's market is still in an early phase, the country shows progress in pricing carbon. However, the world's biggest economy is trailing. The United States lack a general carbon policy.

This means that American corporations are not restricted in their emissions. Nevertheless, one would expect companies and its investors to take the environment into account. This paper investigates the assessment of CO2-emissions and sustainability with the following research question:

- ***How do stocks of dirtier US companies perform compared to those of cleaner companies?***

Since the inauguration of Donald Trump, his policy measures have been heavily criticized. The current American president always had his doubts on the existence of global warming. For years he has been releasing questionable statements regarding the subject. This scepticism resulted in dubious policy measures, with most notably the withdrawal from the Paris Climate Agreement (Shear, 2017). This agreement was signed by 195 parties and was meant to fight global warming together by limiting greenhouse gas emissions. However, the White House inhabitant found US sovereignty of greater importance. In a recent interview, he admitted climate change was not a hoax. However, he followed this up by claiming the changes of global warming will change back in the future. According to the head of state, it is unsure if these changes are due to actions of mankind. This makes it not worth it to spend immense amounts of money to try and influence the phenomenon (Holden, 2018).

America is well behind in taking action in favour of the environment, but there are signs that this might change in the near future. In June of 2017, the Climate Leadership Council (CLC) introduced a plan to tax carbon emissions. The Consensus Climate Solution, as the plan is called, contains a $40 tax per metric tonne of CO2. Revenues are then to be used as a dividend to American people as a compensation for climate damage. US oil and gas companies seem to support this tax. One of the reasons for this could be the deregulations that the CLC proposes, which makes the plan questionable (Klug, 2017). The price of pollution might go up, but large companies could profit nonetheless as emission limits could disappear.

In more recent news, a tax of 24$ per metric tonne of CO2-emission was proposed by a Republican politician. However, few politicians backed the plan because they feared the tax would be harmful to American families and businesses (Morgan, 2018). This brings back the idea of sharing the tax revenues with the American people.

Either way, it does not seem assumable that the US government is going to implement a carbon pricing policy to fight global warming anytime soon. Because the authorities do not take action, it is of great interest how American people think of this problem. In this paper, I try to figure out if investors in US-listed companies consider eco-friendliness and sustainability as important factors in their portfolio decisions.

While the USA is lagging in the fight against global warming, the rest of the world seems to acknowledge the severity of the situation. A growing group of world leaders and influential people collaborate and start initiatives to take measures into their own hands. Recently, the Global Commission on Adaption was launched in the Netherlands. This commission, led by the Secretary-General of the UN Ban Ki-Moon, CEO of the World Bank Kristalina Georgieva and the so-called philanthropist Bill Gates, has the goal to spark the international political will to take action after the demotivating news of America's withdrawal. Involving seventeen countries like China and Indonesia, the commission is to make a global impact. In addition, over 380 billion US dollar was spent to decrease CO2-emissions in 2015-2016. Remarkably, 63% of this sum was invested by the private sector (Carrington, 2018).

The latter shows an increased willingness to invest in a greener and more sustainable future by companies, in addition to governments. This leads to the question whether individuals are willing to help in the battle against global warming. Of course, one can take shorter showers and use more durable light bulbs, but another way to help is to invest in green industries. For example, investing in renewable energy would be more environmentally responsible than investing in oil and gas companies.

This thought is confronted by a lot of scepticism. Pavel Molchanov, senior vice president of financial services firm Raymond James, claims that someone who strives for decarbonisation can better install solar panels than sell dirty stocks. However, the manager of the Guinness Atkinson Alternative Energy Fund, Edward B.M. Guinness, claims investing in clean energy does have impact. More investments can lead to expanding green companies (Gray, 2018). In addition, Deutsche Bank analysed over 2,000 empirical studies regarding socially responsible investing, from which 90% suggested they gained superior returns (Brown, 2017).

These considerations make the research question very relevant. If it turns out that the dirtiest stocks outperform the cleaner stocks, I could say investors are more concerned about financial gains than environmental responsibility. Investors are assumed to not only be risk-averse, but also rational. Therefore, investors maximize utility. If the dirtiest portfolio performs best, this would imply that they are willing to take the risk that comes with investing in dirtier stocks for higher returns. However, I expect to see a trend in performance. Due to all the commotion about global warming, the uncertainty about carbon policy in the US and the surging demand for green investments, I expect the cleaner portfolio to improve performance over the years.

I will measure this by comparing the performance of three different US-listed portfolios. These portfolios will be ranked by their scope 1 plus scope 2 CO2 emissions over the previous year. I will describe risk-adjusted stock returns with the help of the Carhart four factor model in a sampling period of thirteen years. To further explain the differences in return, I will add two additional factors. These factors are based on emissions and on climate change action. With this model, I shall find an alpha for each portfolio to rank the relative stock performances. This ranking will then be compared to the predicted ranking.

This paper shows that the cleanest stocks slightly outperform the dirtiest ones, with medium stocks performing the worst. However, with the help of proxies for carbon and climate risk, it seems that carbon-intensity and unsustainability could pay off. A positive price of risk for both over the full sample indicates that more exposure to these risks leads to higher expected returns. These results contribute to the current literature, as the carbon risk proxy has been tested in a country without a carbon pricing system. In addition, a climate risk proxy is introduced that also significantly explains a part of the stock returns. The outcomes of this research advocate for a carbon pricing policy in the United States. It seems that the market does not deal with the externalities of pollution itself, which calls for a government intervention.

In the next section, I will review previous literature on environmental links to financial performance. Forthcoming from earlier papers, I will compose three hypotheses that will help to answer the research question. Section 3 describes the data and methodology that are used. The section thereafter shows the results of the empirical models. Section 5 will include a conclusion and a comprehensive discussion on the paper and ideas for future research.

2. Literature review and hypotheses

2.1.1 Environmental performance and financial performance

The main goal of this paper is to show if investors in US-listed stocks take different environmental factors into account. Ambec and Lanoie (2008) reviewed previous papers that link better environmental performance to better financial performance. According to their research, increasing environmental performance could lead to new opportunities to gain revenues. Firms could have better access to public markets, as sustainability is a much-discussed topic in politics. The public sector could therefore be more interested in greener companies. Not only the public sector is increasingly interested in environment-friendly products, also the individual consumer. Think of the amount of hybrid cars and solar panels that are sold nowadays. Society is concerned about climate change, which offers opportunities to companies to sell differentiated products. Furthermore, investing in sustainable production could also lead to a decrease in costs. Companies with tradable stocks can reduce cost of capital by investing in green innovation, because of its potential importance in investors' sentiment. As huge ecological blunders by large multinationals lead to decreasing stock prices, positive ecological news could steer the stock returns in the opposite direction.

Konar and Cohen (2001) blamed small samples for the ambiguous results in previous literature. They used manufacturing firms of the S&P 500 in their measure of the environmental performance impact on market value. However, they were also encountered by the lack of environmental performance data. Their environmental measure consisted of the amount of toxic chemicals released and the number of environmental lawsuits against a firm. Financial performance in their paper is measured with Tobin's q, which is calculated by dividing the market value of a company by its replacement value. The authors divide market value in tangible and intangible value. As the tangible value of a company is calculated as the replacement costs, Konar and Cohen could measure changes in the value of intangible assets with Tobin's q. They found that in their sample, poor environmental performance significantly impacts a company's intangible asset value in a negative way. This impact was estimated at about 9% of the replacement costs of tangible assets.

2.1.2 Socially responsible investing

Kempf and Osthoff (2007) investigated the profitability of socially responsible investing (SRI), which consists of both social and environmental criteria. For these kind of investments, SRI mutual funds exist. They used three screens for stock portfolios; negative, positive and best-in-class. If the negative screen is used, investors do not invest in controversial businesses like tobacco and nuclear power. Using the positive screen, no such exclusions are taken into account. However, these investors do rate companies based on criteria like environment and human rights and choose companies with the best ratings. The best-in-class screen is comparable to the positive screen but has a better-balanced portfolio across industries. The authors used the Carhart four factor model to measure the effect of the different screening policies. By buying stocks with a high SRI rating and selling those with a low rating, investors are able to receive high abnormal returns in S&P 500 stocks. However, only the positive and best-in-class screening portfolios have this result, where the latter showed the highest alpha. Furthermore, the abnormal returns in the best-in-class screening was mostly impacted by the factors community, diversity and employee relations, while environment came in fourth. The environment result was positive, but not significant individually.

Derwall, Guenster, Bauer and Koedijk (2005) also looked at SRI portfolio performance. However, their focus was on the environmental aspect, such as sustainability and eco-efficiency. Their sample existed of two portfolios with Innovest ratings, splitting the sample into high-ranked and low-ranked companies. The performance of both portfolios was measured with the help of a Carhart four factor model. The authors showed that the high-ranked portfolio outperformed the less eco-efficient portfolio over a period of eight years. Furthermore, they proved that market-sensitivity, industry bias or investments style do not explain the performance differences.

These papers show some evidence for profitable stock investments in more socially aware companies. The environment seems to be a factor of increased importance in the last few years, with CO2 emissions being a useful measure for this. The first hypothesis to be answered is:

- *H1: The lower the relative CO2-emissions in a portfolio, the higher the abnormal returns.*

I will test this hypothesis in a sample that consists of three portfolios with each 40 companies. The portfolios are ranked based on their recent average emissions relatively to their revenues. To give a better view on the development over time, the sample is split in three different periods. The first period will be from 2005 until 2012, which contains the first two phases of the ETS system. The second phase will be from 2013 until November 8th of 2016. Barack Obama was president in this period, as he launched his climate action plan in June of 2013. The last phase will be from November 8th of 2016 until the end of 2017, as this contains the first period after Donald Trump got elected. Furthermore, the aforementioned Consensus Climate Solution was introduced in this period and Trump left the Paris agreement. All three periods contain important events regarding the environment. Therefore, I expect a different impact of emissions on stock prices in each interval. To model the returns, I use the Carhart four factor model. As environmental awareness is increasing, I expect this hypothesis to hold in the last sub-sample.

By answering the first hypothesis, I try to figure out if there are visible differences in returns of these portfolios. The model is risk-adjusted for market returns, the outperformance of small stocks over big stocks, the outperformance of high book-to-market stocks versus low book-to-market stocks and momentum of stocks. In the case of increasing importance for companies to be greener, one would expect that carbon risk is priced.

2.2.1 The social cost of emitting carbon

Emitting carbon comes at a cost. Nordhaus (1992) pioneered in this subject by constructing a model to tie together climate change and economic results. He concluded that a rise of three degrees Celsius in global temperatures impacts 1.3% of global output. This calls for a reduction of CO2 emissions. Nordhaus prices the marginal cost of reducing carbon emissions at 5.3$ per tonne in the 90s, which is a mild estimate compared to later research.

Tol (2008) gathered 211 estimates from 47 different studies to get an overview of the social cost of carbon. He stated that there is a huge uncertainty about the exact marginal costs of carbon emissions to society. This uncertainty heavily impacts conclusions. An important note is that until 2008, estimates showed a downward trend. However, the estimates are still at a very high level. If people should pay a price for carbon that is equal to its social cost, this tax would exceed the annual income for most of them. Overall, it is justified to reduce CO2 emissions, as all estimates of social cost exceed zero. The mean of the estimates is 23$ per tonne of CO2, but there are also estimates of over 78$ per tonne.

Ackerman and Stanton (2012) estimated the social cost of carbon in another setting. They stated that estimates of 21$ per tonne of CO2, made by a US government group of researchers, are marginal costs that will lead to no enhancements of the situation. In their scenario, the world’s net emissions should be zero or even negative before the end of the 21st century. In the worst-case scenario, the costs in 2010 would already be 900$ per tonne of CO2. The authors aimed for a maximum feasible speed of abatement and measured climate damage by way of temperature increases. With this method, their most ambitious scenario still led to costs of 150-500 by 2050.

2.2.2 Carbon risk

Carbon emission costs are on the rise. One would expect investors to take this into account, even if there is no carbon pricing policy in the US yet. Blyth, Bradley, Bunn, Clarke, Wilson and Yang (2007) assessed investment risks of private carbon-intensive companies when there is uncertainty about carbon policy. By using real option methodology, the authors showed that carbon is priced in investment decisions and that uncertainty about policy could increase this price by a minimum of 16%.

Public companies are also challenged by carbon risk. Busch and Hoffmann (2007) tried to show how corporations could manage carbon constraints from both the input as the output side. Looking at the input side, they stated that carbon policy was not the only risk factor. An important factor for production is the availability of resources. Companies should take the depletion of fossil fuel sources into account. On the output side, policy should again be assessed. Furthermore, climate change is accelerated by increasing carbon emissions. This could lead to physical damage of plant property or damage to human health. All these factors have an impact on the value chain of a corporation. The authors concluded that companies must be aware of their carbon impact and the companies' exposure to the aforementioned risks. By doing so, management can adjust strategy to integrate these factors.

Over the last few years, more and more companies have been trying to hedge against policy and climate uncertainties by using an internal price for carbon. By putting a price on emissions, companies become more aware of carbon risk when they make investment decisions. As companies consider this price as a cost, they hedge against bad outcomes. Furthermore, it could be an incentive to invest in more sustainable projects. This kind of risk management shows a trend of corporations to find a way to deal with the growing environmental concerns, which should also affect stock investors' strategy.

2.2.3 Carbon emission and stock returns

Oestreich and Tsiakas (2015) linked carbon emission to stock returns in the German market around the implementation of the ETS. They compared dirty firms with medium and clean firms to investigate this effect of carbon emissions. By using the CAPM model, the Fama-French three factor model and the Carhart four factor model, they found a high and significant carbon premium. This means that dirtier companies gathered higher abnormal returns compared to cleaner companies. This finding disappeared after March 2009, as this was the end of the period where the market knew for sure that there would be free allowances allocation. Furthermore, they added a dirty-minus-clean factor to all three models to explain the carbon premium. This was calculated by the expected returns of the dirty stocks portfolio minus the clean stocks portfolio. They found that this factor could largely explain variation in stock returns until March 2009.

These findings imply that large polluters' stocks gain higher returns when there is no price for carbon. The reason for this could be that investors being exposed to more risk should be compensated by higher returns. However, most economic models assume risk-averse investors. These considerations lead to the second hypothesis:

- *H2: By adding a carbon risk factor, the difference in abnormal returns of the cleanest and dirtiest portfolio will increase.*

The same Carhart model is used to answer this hypothesis, but it will be complemented by the dirty-minus-clean (DMC) factor of Oestreich and Tsiakas (2015). Again, the same sample and sub-samples will be used. Where in Europe risky investments led to higher excess returns in times with guaranteed free allowances, it is interesting to investigate the existence of a carbon premium and carbon risk in the US stock market. In the first subsample from 2005 until 2012, this might be still very high due to the idea that an EU system has a limited impact on US-listed companies. However, Obama's climate plan and recent talks of a carbon tax could change the investors' sentiment in subsample 2 from 2013 until November 8th of 2016. I expect a decreasing carbon premium on stocks and increasing carbon risk, with the last subsample from November 8th of 2016 until the end of 2017 showing the highest level of carbon risk. Firstly, the existence of carbon risk is tested over the full sample with a DMC factor comparable to the one of Oestreich and Tsiakas (2015). To answer the hypothesis, an out-of-sample carbon risk factor is created.

2.3.1 Sustainability and Corporate Social Responsibility

If the view on a carbon risk factor is clear in the US stock market, there may be more ways to value environmental factors. In addition to carbon emissions, it is also of importance to assess a company's sustainability. Oberndorfer, Schmidt, Wagner and Ziegler (2013) investigated if being included in a sustainability index impacts a stock's performance. By using German stocks that were part of the Dow Jones STOXX sustainability world index, they found that this inclusion is penalized in the German market. On average over the course of six days, the authors found cumulative abnormal returns of almost minus two percent. This, however, was a joint result when a company is also included in the Dow Jones STOXX sustainability index. In the separate analysis with only the world index, the results were even more negative than two percent. This implies that corporate sustainability does not lead to financial gains.

Lee and Faff (2009) compared leading and lagging Corporate Social Responsibility (CSR) Dow Jones portfolios. CSR rates companies based on their performance on environment, labour and human rights, sustainable procurement and ethics. In contrast to earlier research, also mentioned in this section, they found that the leading CSR portfolio underperformed the lagging portfolio. This can be explained as before: the more risk exposure, the higher the demanded return. Lee and Faff substantiated this explanation by showing that significant parts of the differences in returns could be explained by idiosyncratic risk differences. Von Arx and Ziegler (2008) argued that there is a positive effect between CSR and stock returns within industries, especially in the US. These are seemingly contradicting results. However, it is important to note that the latter showed evidence for within industry performance differences.

2.3.2 CDP ratings

While the CSR rating is based on both the environment as society, this paper focuses on the environmental factor. A measure for sustainability based on the environment in specific is the Carbon Disclosure Project (CDP) rating, which will be further explained in the methodology. According to Luo, Lan and Tang (2012), more and more companies disclose carbon information to the CDP due to social, legal and economic influences. In their Global 500 sample, mostly carbon-intensive corporations are willing to release such information. It seems that they are aware of the seriousness of climate change and are thus willing to act on it. Most of the companies that did not disclose carbon numbers were either small companies with limited processing resources or companies in a less polluting sector. However, one could question the reliability of such information. Luo and Tang (2014) measured the link between carbon disclosure and the true carbon administration of firms. Based on Australian, American and UK companies, they found a positive association between performance and carbon disclosure. At a 99% confidence interval, carbon reduction positively impacts the disclosure level. This suggests, in line with the signalling theory, that companies with a better carbon performance have a higher level of accuracy of their carbon disclosure to the CDP. However, their best model for all three countries had an adjusted R-squared of 12.3%. This shows that the model could not accurately explain the variance in carbon disclosure levels.

Liu, Zhou, Yang and Hoepner (2017) link both carbon disclosure as carbon performance to the financial performance of 62 UK companies. With CDP and Datastream data, they found that carbon emissions negatively affect firm value. This shows that investors in UK stock take carbon risk into account. However, there is a positive link between carbon emissions and the disclosure of carbon information. In addition, the level of carbon disclosure is positively related to the financial performance of a company. The latter finding can thus be seen as a mitigation of the negative carbon emission effect. These results in the UK make for an interesting case in the US, where there is no general carbon policy:

- *H3: Avoiding climate risk pays off, which is represented by a negative climate risk factor.*

To answer this hypothesis, a final factor is added to the earlier model. Inspired by the DMC factor, I created a climate risk factor. This factor represents the difference in returns between the 22 stocks with the worst climate performance and the 18 stocks with the best climate performance. If better climate performance leads to higher expected returns, the worst-minus-best factor should be negative over the full sample.

Table 1: Meta-literature table.

Author(s)	Time-Period	Region	Method	Results
Nordhaus (1992)	1860-1989	Global	DICE model	Impact global warming is 1.3% of global output.
Konar and Cohen (2001)	1989	S&P500, US	Tobin's q	Poor environmental performance negatively affects firm value at approximately 9% of the replacement value of tangible assets.
Wagner et al. (2001)	1995-1999	Global	Meta-analysis	Significant relationship environmental & financial performance, differs per sector.
Derwall et al. (2005)	1995-2003	Innovest, US	CAPM, FF 3 factor & Carhart 4 factor model	Most eco-efficient companies outperform less eco-efficient companies. Without transaction cost this differs 3.55%.
Blyth et al. (2007)	2007	US private companies	Real options	Uncertainty about policy increases price of carbon by 16-37%.
Busch and Hoffmann (2007)	1992-2006	Macroeconomic, sector and company level	Meta-analysis	Importance to determine a firm's exposure to carbon risk and to adjust strategy, as best-in-class stocks outperformed their sector peers by 2.3% annually.
Kempf and Osthoff (2007)	1992-2004	S&P 500, DS400, US	Carhart 4 factor model	By going long in high SRI stocks and going short in low SRI stocks, one can get abnormal returns by up to 8.7% annually.
Ambec and Lanoie (2008)	1970-2007	Global	Meta-analysis	More recent papers show an association between environmental and economic performance, in the sense that reduction costs can be completely offset.
Tol (2008)	1982-2006	Global	Meta-analysis	Downward trend in estimates social costs of carbon, but still big due to uncertainty at 23$ per tonne.
Von Arx and Ziegler (2008)	2002-2006	US and Europe	CAPM, FF 3 factor & Carhart 4 factor model	CSR partly explains stock returns. It has a positive effect and is more robust in the US compared to Europe.
Lee and Faff (2009)	1998-2002	Global, DJSI and DJGI	Carhart 4 factor model with 2 added factors.	Leading CSP firms do not underperform the market, but lagging CSP firms outperform both the leading firms as the market by approximately 0.01% monthly. This is due to a lower idiosyncratic risk.
Ackerman and Stanton (2012)	2010-2050	Global	DICE model	The most optimistic scenario shows way higher social costs of carbon than calculated before. Worst case scenario could rise to over 1,000$ per tonne of CO2.
Luo, Lan and Tang (2012)	2008-2009	Global 500	Theoretical model and regression	Carbon disclosure is explained by economic, social and legal influences.
Oberndorfer et al. (2013)	1999-2002	DJSI, German companies	FF 3 factor and GARCH	Inclusion in DSJI world leads to strong negative CAR of up to 2% in six days.
Luo and Tang (2014)	2009-2010	US, UK and Australia	Regression model	Firms that perform well environmentally are more likely to disclose emission information.
Oestreich and Tsiakas (2015)	2003-2012	Germany	Carhart 4 factor model	In the EU ETS, a significant carbon premium of up to 17% existed in the first few years.
Liu et al. (2017)	2010-2012	UK, FTSE100	Regression model	Carbon emission negatively affects financial performance, which is positively related to carbon disclosures. The latter is positively related to carbon emissions.

3. Research design

3.1.1 Data Sample

This paper focuses on stocks that are listed in the US. The sample exists of 120 stocks, which are all listed on NASDAQ or NYSE. These are the two biggest American exchanges. NASDAQ divided each stock in a certain sector, including NYSE-listed stocks. As this made it easier to gather a representative sample, the whole sample is gathered from NASDAQ's website (https://www.nasdaq.com/screening/industries.aspx). The NASDAQ sectors are described in table 2. According to Konar and Cohen (2001), the banking and insurance sector is mostly non-polluting and is therefore omitted in this sample. The sector descriptions are comparable to the Fama and French 12 industry portfolio. Appendix A provides the summary statistics of the sectors.

Table 2: Sector descriptions.

Sector	Description
Basic Industries	Producers of basic goods, which are used in further productions. For example: chemicals, cosmetics, package goods and metals.
Capital Goods	Manufacturing companies, such as car and machinery manufacturers.
Consumer Durables	Durable form of basic goods, such as containers or specialty chemicals.
Consumer Non-Durables	Producers of consumer goods for frequent consumption, such as beverages or packaged foods.
Consumer Services	Companies that provide services to consumer like retailers or TV.
Energy	Producers of energy, in this sample only fossil fuel producers.
Healthcare	Producers of medical instruments, pharmaceuticals and other healthcare related goods.
Public Utilities	Service companies to provide utilities like water, gas and electricity.
Technology	Technological goods and services.
Transportation	Transportation of goods and people.

Note: Fama and French divide Basic Industries into chemicals and allied products and other. They divide Consumer Services into shops, telecommunication and other. Technology is assigned to business equipment, while Transport is assigned to other.

To give the most credible representation of US stocks, I retrieved a sample with at least 7 stocks per sector. Ideally, I would get a sample with every sector having the same amount of stocks. However, the supply of carbon emission data is limited. Therefore, I picked stocks from companies that disclose their emission levels to end up with 120 stocks. All these companies have a high market capitalization, as they need to have the resources to be able to report their emissions. This approach possibly leads to a selection bias, which is unavoidable due to the limited data supply. The full sample is divided in three groups of 40, based on their emissions relative to their revenues. They will be referred to as the cleanest, medium and dirtiest portfolio based on their relative emissions. Table 3 shows the representation of each sector within the portfolios. As there is no carbon data over the full sample, I calculate their relative emissions based on the most recent data. Companies in this sample disclose their scope 1 and scope 2 CO_2-emissions in their sustainability reports. In addition, I also created three groups based on carbon emissions only. By doing this, I try to single out the effect of the emissions. By making a ratio relative to their revenues, companies could seem less pollutive due to extremely high revenues and vice versa.

Table 3: Sector representation per portfolio.

Portfolio	Sector									
	Health	Tech	CG	BG	CS	CND	CD	Energy	PU	TT
Cleanest	14(12)	11(10)	8(6)	2(3)	3(4)	2(5)	0	0	0	0
Medium	4(5)	5(5)	3(4)	2(2)	6(3)	6(2)	7(7)	0(5)	5(5)	2(2)
Dirtiest	0(1)	0(1)	0(1)	10(9)	2(4)	0(1)	2(2)	10(5)	11(11)	5(5)

Note: Health represents the healthcare sector. Tech represents the technology sector. CG represents the capital goods sector. BG represents the basic goods sector. CND represents the consumer non-durables sector. CD represents the consumer durables sector. Energy represents the energy sector. PU represents the public utility sector. TT represents the transportation sector. The sector representation for the carbon-only portfolios is given within brackets.

3.1.2 Sampling period

The time period to be tested is from 2005 until 2017, with three sub-periods. From 2005-2012, the EU underwent the first two phases of its ETS, which was the first international carbon trading market. This could be a sign to American companies that carbon risk should be considered. Furthermore, some American multinationals are directly affected by the system as they own subsidiaries in the EU. However, I expect the link between pollution and financial performance in this period to be the weakest.

At the end of 2012, Barack Obama was re-elected as the US president. Because of this, he could finally issue his long-awaited Climate Action Plan to reduce carbon emissions in 2013. He aimed to cut emissions at the national power plants (Broder & Landler, 2013). Such a reduction in emissions would lead to higher prices of fossil fuels and energy. This would then increase production or service costs in all American sectors. Therefore, I expect carbon emissions to have a stronger impact on financial performance in the period from 2013 until October 2016.

On November 8th of 2016, Donald Trump was elected president. One of his promises in his campaign was to repeal the plan of his predecessor, eventually called the Clean Power Plan. This action was ultimately announced almost a year after the start of the elections by the Environmental Protection Agency (EPA). Even though this could slow down the transition to clean energy, American industries were happy with this announcement (Friedman & Plumer, 2017). Because this leads to less regulations for carbon emissions, I expect the link between environmental performance and stock prices to be weakened in the period from November 8th of 2016 until December 2017.

3.2.1 Methodology H1

The main theory to be quantitively tested in this paper will be that more polluting companies are being outperformed by the cleaner ones. Liu et al. (2017) showed a negative effect of carbon emissions on financial performance in the UK. I transfer this theory to the US, using the same model as Oestreich and Tsiakas (2015). The first hypothesis reads:

- *H1: The lower the relative CO2-emissions in a portfolio, the higher their abnormal returns.*

The model that is used to answer hypothesis 1 looks as follows:

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{j,t}$$

This Carhart four factor model consists of four factors to explain monthly excess stock returns, which is denoted by the return of stock j by $r_{j,t}$ minus the risk-free rate $r_{f,t}$. The risk-free rate in this model is the one month T-bill rate, just as Von Arx and Ziegler (2008). The constant α_j , or the Carhart alpha, can be interpreted as the abnormal excess returns of a stock. Portfolios can be ranked based on these alphas, which are expected to increase as emissions decrease. This model is risk-adjusted for four factors. Firstly, there is the variable excess market return $r_{m,t}$ minus $r_{f,t}$, where the first part stands for the market return. This model uses the S&P 500 returns as a proxy for market return. After taking market risk into account, there are three other market anomalies this model tries to capture. The first one is that small caps usually outperform stocks of bigger companies, which is captured by the small-minus-big factor (SMB). This is measured by subtracting the average return of big company portfolios from small company portfolios. The SMB factor is expected to give a positive coefficient. In addition, stocks of companies with high book-to-market ratios usually outperform low book-to-market ratio stocks. This is captured by the high-minus-low factor (HML). This factor is measured by taking the average return of value portfolios minus growth portfolios' average return. Value stocks are known to have high book-to-market ratios, where growth stocks are known to have low book-to-market ratios. Again, this factor is expected to have a positive coefficient. Finally, stocks tend to show short-run persistence in returns. A rising stocks tends to continue going up for a while and vice versa. This momentum is captured in the model by the factor MOM, which consists of the return going long in positive momentum portfolios minus going short in negative momentum portfolios (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html). The final independent factor is also expected to give a positive coefficient. The betas in the model represent coefficients and ε_t is an error term to capture the residual.

The first hypothesis implies that if I run the regression for all three portfolios, the cleanest portfolio will get the highest intercept and vice versa. If there is no evidence in support of the first hypothesis in the full sample, there might be evidence in the subsamples. If the cleaner portfolio does indeed have a higher alpha, this suggests a discount on stocks of carbon-intensive sectors.

3.2.2 Methodology H2

In addition to the first test, I will investigate the existence of a carbon risk factor in US industries. Oestreich and Tsiakas (2015) found evidence for the hypothesis that companies that were allowed to emit more carbon gained higher abnormal returns. Also, more exposure to carbon risk increased the expected returns as they found a positive price for carbon risk. However, the authors only found this phenomenon when there was a guaranteed free allocation of emission allowances. Because the USA has no similar system, there is less control on emissions. As American companies are less restricted in their CO2-emissions, I expect a positive price for carbon risk. However, if carbon risk is considered, the expected returns of dirtier companies should go up. Therefore, their abnormal returns are expected to go down.

The second hypothesis reads:

- *H2: By adding a carbon risk factor, the difference in abnormal returns of the cleanest and dirtiest portfolio will increase.*

The equation for the second hypothesis looks as follows:

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 DMC_t + \varepsilon_{j,t}$$

With this formula, I try to find evidence for a carbon risk factor in daily stock returns with the help of DMC. This variable is the expected return of a portfolio with ‘dirty’ and ‘clean’ companies and will be added to the Carhart four factor model. More specifically, it is equal to going long in the dirtiest portfolio and going short in the cleanest portfolio. The variable is used as a proxy for carbon risk. Firstly, the DMC factor will be used as a dependent variable to investigate a possible carbon premium. The independent variables will be the four Carhart factors. Thereafter, the DMC factor will be regressed on the full sample, like the formula above. In addition, I will construct an out-of-sample proxy for carbon risk. This factor, DMCos, consists of the daily stock returns of the ARCA oil and gas index minus the daily stock returns of the New Alternatives Fund. The former index can be seen as one of the most carbon-intensive funds to invest in, while the New Alternatives Fund focuses on renewable energy and the environment. This out-of-sample factor can be regressed on the separate portfolios, while the DMC factor from this sample can only be regressed on the full sample Carhart model.

The second hypothesis implies that when I find evidence that there is a significant carbon risk factor, all alphas should go down compared to the previous hypothesis. A significant carbon risk factor leads to higher required returns for carbon-intensive stocks, which should result in the biggest decrease in abnormal returns. However, the cleanest and medium portfolio are also exposed to carbon risk. Therefore, their abnormal returns should also end up being lower. However, the gap between the alpha of the dirtiest portfolio and the one of the cleanest portfolio should increase. This addition to the first model should affect the alphas in such a way that they come closer to their predicted ranking. If the variable is significant and the R-squared goes up, it implies that the model gives a better explanation of the excess stock returns.

3.2.3 Methodology H3

When the stock returns are assessed based on their emissions, I finally investigate the importance of climate change action. While I reckon carbon emission is the strongest measure of environmental performance, I also think investors value a company's openness and willingness to become more sustainable. A way to measure the latter is the CDP score for companies. This score is based on several environmental factors. In short, it is based on the level of detail of a company's response, its awareness of the environmental issues and its advancement in acting to fight climate change.
CDP ranks companies from A to D-, with an F given to companies that did not disclose enough information. The CDP states that each of its questionnaires requires an individual scoring methodology, making it too cumbersome to further explain the ratings. The CDP takes size and sector into account for example. Therefore, oil companies could score better than food companies, regardless of its higher emissions. Table 4 shows a description of the ratings and a corresponding score, which is used in the ranking of the companies. This ranking is then used to create a climate risk proxy.

Table 4: Description of CDP scores.

Rating	Category	Description	Score
A and A-	Highest	Implementation of current best practices.	5
B and B-	High	Taking action on the issues of climate change.	4
C and C-	Medium	Knowledge and awareness of impact on climate change.	3
D and D-	Low	Disclosing numbers about climate change issues.	2
F	Lowest	Failed to disclose enough information.	1

Note: Scores are used to calculate the average climate performance per company.

The third hypothesis reads:

- *H3: Avoiding climate risk pays off, which is represented by a negative climate risk factor.*

To answer the third hypothesis, the earlier model is complemented by a climate risk factor:

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 DMC_t + \beta_6 WMB_t + \varepsilon_{j,t}$$

The third hypothesis implies that the CDP score has a positive effect on excess returns. Therefore, I expect the WMB variable to be negative and significant. This corresponds to a negative price for climate risk. The WMB variable, or the worst-minus-best variable, represents the return of the 22 worst scoring companies minus the return of the 18 best scoring companies. The worst scoring companies will have an average score of 2 or less, while the best scoring companies score 4.5 or better on average. This variable is comparable to the DMC factor. CDP scores are not available over the full time period, so I ranked the companies based on their average score since 2010. When there is not enough data, the average will be taken over less years. This will credibly represent a company's engagement in climate change for the last few years. These scores will be gathered from the Carbon Disclosure Project website. A final regression in this paper will also include an interaction term DMC*WMB. With this term, I can check if WMB influences the effect of DMC on excess returns and vice versa. By adding this factor, I expect alphas to go down as the final model should be better able to describe the stock returns. I will use daily stock data and S&P 500 returns, retrieved from Yahoo Finance. These returns are in logarithm form, which are calculated for day t as the natural logarithm of the return of day t divided by day t-1. Because of the high level of observations, the impact of possible outliers is expected to be negligible. Furthermore, the one month T-bill data is gathered from FRED in logarithm form. To match the risk-free data with the other data, I transformed all data into full percentages. This means one percent will be 1 instead of 0.01.

The Carhart model factors will be retrieved from the data library of Kenneth R. French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). For missing values, I will carry forward the last observation. Before I will run the regressions, I will check the dependent variables for autocorrelation and heteroskedasticity. For autocorrelation, the Breusch-Godfrey test is used. For heteroskedasticity on the other hand, the Breusch-Pagan test will be performed. The results of this test can be found in Appendix B. Both autocorrelation as heteroskedasticity could lead to spurious results. If both are found to be present, I will run the regression with Newey-West standard errors for robustness. The number of lags for this regression is chosen based on the lowest information criteria. If only heteroskedasticity is present, I will use White standard errors for robustness. These tests can also be found in Appendix B. All tests are performed in Stata. The risk of endogeneity is of less importance, as this paper aims to predict alpha instead of a causal relationship between independent variables and the dependent variable.

4. Results

Before I will discuss the results of the regression, I present the descriptive statistics of the most important variables in table 5.

Table 5: Descriptive statistics.

	Mean	*SD*	*Median*	*Min*	*Max*	*Skewness*	*N*
EXCRd	0.0221	1.3871	0.0765	-12.2301	14.0259	-0.3406	3271
EXCRm	0.0161	1.2072	0.0704	-11.0000	9.2224	-0.5932	3271
EXCRc	0.0245	1.1897	0.0540	-9.1919	11.8021	-0.1283	3271
DMC	-0.0025	0.6663	0.0032	-3.9599	3.6046	-0.0859	3271
DMCos	-0.0058	1.1982	-0.0022	-7.9939	8.9786	0.2931	3271
WMB	0.0026	0.5814	0.0002	-8.6065	3.5171	-0.9225	3271

Note: SD is the standard deviation. N is the number of observations. EXCRd is the excess return of the dirtiest portfolio. EXCRm is the excess return of the medium portfolio. EXCRc is the excess return of the cleanest portfolio. DMC is the dirty-minus-clean portfolio. DMCos is the out-of-sample dirty-minus-clean portfolio. WMB is the worst-minus-best portfolio. Numbers are whole percentages.

These statistics imply a better performance on average for the cleanest portfolio, followed by the dirtiest and the medium. In addition, the cleanest portfolio has the lowest standard error. Furthermore, both the dirty-minus-clean factors are negative. This indicates a premium for investing in cleaner companies. However, the mean of the worst-minus-best factor is positive and could hint at a premium for investing in less sustainable companies.

4.1 Results H1

The first hypothesis to be answered reads:

- *H1: The lower the relative CO2-emissions in a portfolio, the higher the abnormal returns.*

Table 6: Results for the cleanest portfolio (EXCRc) as dependent variable.

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0181***	0.0175**	0.0207***	-0.0002
	(0.0051)	(0.0073)	(0.0070)	(0.0127)
EXCRsp	0.9837***	0.9685***	1.0360***	1.0069***
	(0.0085)	(0.0110)	(0.0086)	(0.0348)
HML	-0.2073***	-0.2031***	-0.2146***	-0.2230***
	(0.0170)	(0.0231)	(0.0180)	(0.0252)
SMB	0.1584***	0.1813***	0.0954***	0.1579***
	(0.0160)	(0.0219)	(0.0152)	(0.0347)
MOM	-0.0337***	-0.0483***	-0.0022	-0.0536*
	(0.0092)	(0.0119)	(0.0107)	(0.0322)
Adj. R^2(%)	93.97	94.32	93.96	81.37
SD type	White	White	Normal	White
N	3271	2012	971	288
F-statistic	4948.33	3460.35	3770.87	324.60

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

The first results are presented in table 6. The cleanest portfolio gains abnormal returns of 0.018% per day with 99% significance over the full sampling period. Furthermore, there is a significant upward trend visible between subsample one and two. This could describe the growing interest traders have in clean stocks but is of lesser power as the last subsample from November 8th of 2016 until the end of 2017 did not give the right result. In addition, the HML factor is negative in the full sampling period as well as in all the subsamples of the clean portfolio. This suggests that either the sample consists mainly of low book-to-market stocks, also called growth stocks, or that value stocks with a high book-to-market ratio are simply outperformed by the growth stocks. The latter would defy the theory of mostly better performing value stocks. On the other hand, the cleanest portfolio consists of 62.5% health and technology companies. As these are sectors subject to a high level of innovation, one could expect these stocks to be growth stocks. In contrary to the HML factor, the SMB factor of the clean portfolio is significantly positive in every subsample. This suggests that either the sample consists mainly of small-cap stocks or that the small-cap stocks outperform the large-cap stocks. The former is not credible as all stocks are from companies within the top 50 largest companies within the sector in the US, according to NASDAQ. Therefore, according to theory, the latter explanation is expected to be true. Finally, the MOM factor is significantly negative. This is either due to the fact that the sample consists of mostly losing companies or that winning companies do not profit from momentum. The latter seems to be more credible, as the sample outperforms the market. Also, the clean portfolio regression seems to capture the variation in returns well. The adjusted R-squared of the full period is 0.9397, which means the regression explains almost 94% of the variation in excess stock returns. Since this is the adjusted R-squared, it is unbiased and it corrects for the sample size and the number of independent variables.

Table 7: Results for the dirtiest portfolio (EXCRd) as dependent variable.

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0147	0.0358***	-0.0110	-0.0052
	(0.0093)	(0.0119)	(0.0137)	(0.0229)
EXCRsp	1.0673***	1.1277***	1.0334***	0.9685***
	(0.0088)	(0.0010)	(0.0168)	(0.0591)
HML	-0.0185	-0.1065***	0.3147***	0.2668***
	(0.0180)	(0.0211)	(0.0349)	(0.0448)
SMB	0.1109***	0.0901**	0.1413***	-0.0291
	(0.0167)	(0.0198)	(0.0296)	(0.0480)
MOM	-0.0130	0.0790***	-0.3241***	-0.1424***
	(0.0118)	(0.0139)	(0.0208)	(0.0418)
Adj. R^2(%)	85.19	89.02	82.59	56.32
SD type	Normal	Normal	Normal	Normal
N	3271	2012	971	288
F-statistic	4701.70	4076.01	1151.30	93.53

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

The dirtiest portfolio also seems to outperform the market but this result lacks significance, as table 7 shows a positive alpha for the full sample. However, the results of subsample one are highly significant, both statistically as economically. In this period from 2005-2012, this portfolio gained abnormal returns of 0.0358% per day. As this result is much higher than the full sample result, it implies a decrease in stock performance in the following subsamples for the dirtiest portfolio. This can be seen in the alphas of subsample two and three and is according to expectations, but these results are unfortunately not significant. The HML, SMB and MOM factor have the same sign as in the cleanest portfolio over the full sampling period. The HML factor being negative is not in line with theory and is something I cannot explain. The dirtiest portfolio consists mainly of public utilities, energy and basic goods companies, which are expected to have a high book-to-market ratio. The SMB factor is positive and should be explained by the theory of small-cap stocks outperforming large-cap stocks. Finally, the momentum factor is negative which shows that winning companies tend to do worse instead of to profit from momentum. The adjusted R-squared implies that 85.19% of the variation in the dirtiest portfolio returns can be explained by the model.

Table 8: Results of the medium portfolio (EXCRm) as dependent variable.

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0097*	0.0101	0.0112	-0.0059
	(0.0056)	(0.0075)	(0.0087)	(0.0166)
EXCRsp	0.9488***	0.9461***	0.9557***	0.9628***
	(0.0102)	(0.0118)	(0.0107)	(0.0574)
HML	-0.0567***	-0.0788***	0.0322	-0.1326***
	(0.0181)	(0.0229)	(0.0223)	(0.0389)
SMB	0.2143***	0.2723***	0.0736***	0.1443***
	(0.0186)	(0.0230)	(0.0189)	(0.0443)
MOM	-0.0730***	-0.0896***	-0.0505***	-0.0356
	(0.0105)	(0.0133)	(0.0133)	(0.0423)
Adj. R^2(%)	92.96	94.26	89.49	69.45
SD type	White	White	Normal	White
N	3271	2012	971	288
F-statistic	3532.63	2796.06	2066.77	109.67

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

The medium portfolio is the least interesting portfolio. However, the alpha of this model was expected to be between the alphas of the other two portfolios. Instead, table 8 shows that this portfolio gains the lowest abnormal returns of approximately 0.01% at a 90% confidence level. The alphas of the subsamples lack significance. Over the full period, the independent variables have the same sign as the ones of the other two portfolios. Furthermore, this regression seems to capture the variance of stock returns well as its adjusted R-squared is almost 93%.

Table 9: Results for carbon-only portfolios as dependent variable.

	Full sample			Subsample 1			Subsample 2			Subsample 3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Alpha	0.0134* (0.0069)	0.0103 (0.0065)	0.0188*** (0.0053)	0.0266*** (0.0086)	0.01602* (0.0092)	0.0208*** (0.0072)	-0.0042 (0.0111)	0.0078 (0.0088)	0.0172** (0.0077)	0.0072 (0.0159)	-0.0176 (0.0151)	-0.0090 (0.0136)
EXCRsp	0.9723*** (0.0125)	1.0251*** (0.0121)	1.0024*** (0.0090)	1.0119*** (0.0073)	1.0421*** (0.0148)	0.9882*** (0.0114)	0.9533*** (0.0136)	1.0341*** (0.0108)	1.0378*** (0.0094)	0.8835*** (0.0501)	1.0632*** (0.0392)	0.9914*** (0.0352)
HML	-0.0180 (0.0243)	-0.0835*** (0.0256)	-0.1809*** (0.0175)	-0.0816*** (0.0153)	-0.1347*** (0.0298	-0.1721*** (0.0262)	0.2269*** (0.0283)	0.0975*** (0.0224)	-0.1921*** (0.0197)	0.1548*** (0.0384)	0.0145 (0.0296)	-0.2581*** (0.0267)
SMB	0.0494** (0.0209)	0.1978*** (0.0245)	0.2364*** (0.0156)	0.0524*** (0.0144)	0.2160*** (0.0326)	0.2754*** (0.0225)	0.0338 (0.0240)	0.1243*** (0.0190)	0.1523*** (0.0167)	-0.0772 (0.0547)	0.1764*** (0.0318)	0.1739*** (0.0286)
MOM	-0.0104 (0.0124)	-0.0658*** (0.0152)	-0.0425*** (0.0093)	0.0473*** (0.0101)	-0.0453** (0.0196)	-0.0608*** (0.0131)	-0.2117*** (0.0168)	-0.1657*** (0.0134)	0.0007 (0.0117)	-0.0916* (0.0487)	-0.1030*** (0.0277)	-0.0369 (0.0249)
Adj. R^2(%)	89.64	92.32	93.98	92.62	93.33	94.58	84.99	91.12	92.94	59.93	78.12	80.02
SD type	White	Newey, lag(4)	White	Normal	Newey, lag (3)	Newey, lag(3)	Normal	Normal	Normal	Newey, lag(3)	Normal	Normal
N	3271	3271	3271	2012	2012	2012	971	971	971	288	288	288
F-statistic	2712.54	3164.13	4833.51	6312.62	2580.43	3197.99	1374.46	2488.67	3193.29	91.58	257.22	288.28

Note: (1) represents the dirtiest carbon portfolio. (2) represents the medium carbon portfolio. (3) represents the cleanest carbon portfolio. Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B).
* equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

To make sure these differences in performance are due to the carbon-intensity of the portfolios, I also created portfolios based on carbon only. The results of these regressions are visible in table 9. Because of this, results will be more credible as very dirty companies could have been in the medium group due to enormous revenues. However, these regressions give the same implications. Looking at the alphas of the portfolios, the full period abnormal returns differ not more than 0.002 percentage point in all three groups. Furthermore, the dirtiest portfolio has a 90% significant alpha over the full sampling period that is nearly 0.0015 percentage point lower than that of the cleanest portfolio. Again, only the first subsample is significant. Also, it implies a decrease in performance in the subsequent periods. However, with this sorting, all portfolios perform best in the first subsample. This could be due to the survivorship bias, as the crisis at the end of the 00's led to many companies going bankrupt. However, the effect of a possible survivorship bias is of less importance, as the aim here is to compare the three portfolios. Therefore, all three portfolios are potentially encountered by this bias. Furthermore, the chance of the presence of a survivorship bias is smaller in the investigation of individual stocks compared to mutual fund research. Again, the independent variables have the same sign as in the earlier regression and R-squared results did not change much. By adding this regression, I think my results are more reliable. However, I cannot accept hypothesis one reading:

- *H1: The lower the relative CO2-emissions in a portfolio, the higher the abnormal returns.*

Firstly, in neither approach do I get three significant alphas for the whole period. Furthermore, the worst performing portfolio is the medium portfolio instead of the dirtiest one. Lastly, I expect that there is a decreasing trend in performance of the dirtier portfolio. The problem is that the results are not significant and can thus not support my hypothesis enough. They indicate that the cleaner portfolio outperforms the dirtier one, but the lack of significant forces me to reject the first hypothesis.

4.2 Results H2

The results in this subsection are used to answer the following hypothesis:

- *H2: By adding a carbon risk factor, the difference in abnormal returns of the cleanest and dirtiest portfolio will increase.*

To make a stronger and more convincing case for cleaner stocks outperforming dirtier stocks, I implemented the carbon risk factor of Oestreich and Tsiakas (2015). Before I added the carbon risk factor to the earlier regressions, I follow their approach by regressing the four factors on the dirty-minus-clean portfolio. The latter would be the dependent variable in this setting. The aim of this is to find out if there is a carbon premium to be found in the data.

Table 10: Results for the DMC portfolio as dependent variable.

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	-0.0033	0.0183	-0.0316**	-0.0050
	(0.0112)	(0.0148)	(0.0157)	(0.0281)
EXCRsp	0.0837***	0.1592***	-0.0026	-0.0384
	(0.0106)	(0.0203)	(0.0192)	(0.0728)
HML	0.1888***	0.0965**	0.5293***	0.4898***
	(0.0216)	(0.0418)	(0.0400)	(0.0551)
SMB	-0.0474**	-0.0913**	0.0459	-0.1870***
	(0.0201)	(0.0357)	(0.0340)	(0.0591)
MOM	0.0207	0.1273***	-0.3219***	-0.0888*
	(0.0142)	(0.0249)	(0.0239)	(0.0515)
Adj. R^2(%)	6.85	9.86	39.48	25.26
SD type	Normal	White	Normal	Normal
N	3271	2012	971	288
F-statistic	61.08	26.90	159.19	25.25

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

Table 10 represents the DMC portfolio results. Over the full sample, the alpha of this portfolio is negative but insignificant at -0.0033. The only significant result is the alpha of subsample two. In the period from 2013 until November 8th of 2016, a negative alpha of -0.0316 was found on a 5% significance level. This could imply that there is a negative carbon premium, which would mean that going long in the dirtiest portfolio while going short in the cleanest portfolio gains negative abnormal returns. As you go long in the dirtiest portfolio, you gain the returns of these stocks. While going short in the cleanest portfolio would cost you the returns of these stocks, as you must buy back the stocks you shorted. These returns together form the DMC portfolio, which appear to be negative. In addition, the DMC portfolio gains positive abnormal returns in subsample one from 2005 until 2012. This indicates that the dirty portfolio outperformed the clean one in the first period only, which is credible as there is a growing interest in sustainable investing. However, this coefficient again lacks significance. Subsample two results in negative abnormal returns for this portfolio at a 95% confidence level. Even though these results are in line with the first hypothesis, they are not very valuable due to its weak statistic power. In addition, the adjusted R-squared over the full sample is under 7 percent.

As cleaner investments seem to be more profitable, one would expect that more exposure to carbon risk would result in higher expected returns. I try to measure this by using the DMC variable as a proxy for carbon risk over the whole sample. A positive coefficient implies a positive correlation between exposure to carbon risk and expected return.

Table 11: Results of regressing the DMC factor on the full sample (EXCR).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0147***	0.0185***	0.0142***	-0.0028
	(0.0037)	(0.0052)	(0.0054)	(0.0090)
EXCRsp	0.9852***	0.9913***	1.009003***	0.9871***
	(0.0064)	(0.0045)	(0.0067)	(0.0262)
HML	-0.1275***	-0.1433***	-0.0765707***	-0.1276***
	(0.0138)	(0.0092)	(0.0151)	(0.0249)
SMB	0.1696***	0.1943***	0.093007***	0.1285***
	(0.0133)	(0.0086)	(0.0118)	(0.0218)
MOM	-0.0436***	-0.0378***	-0.0521953***	-0.0594***
	(0.0082)	(0.0061)	(0.0090)	(0.0176)
DMC	0.1767***	0.1432***	0.2279589***	0.2000***
	(0.0082)	(0.0078)	(0.0111)	(0.0250)
Adj. R^2(%)	96.94	97.36	96.22	88.72
SD type	White	Normal	Normal	White
N	3271	2012	971	288
F-statistic	8351.20	14827.22	4939.68	440.21

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMC is the dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

The first thing visible when looking at the alphas in table 11 is that the whole sample gains abnormal returns of 0.0147% per day from 2005 until 2017. Again, one could argue that this is due to the survivorship bias. However, the abnormal gains are also visible in the second time period from 2013 until November 8th of 2016, which is less known for financial depressions. Furthermore, the excess return of the S&P 500 is a significant explanatory variable for predicting the excess returns of stocks. It does not occur often that an S&P 500 company files bankruptcy. In addition, the signs of the independent variables are the same as in the earlier regressions. The most important factor in this table however is the DMC factor. This factor, which can be interpreted as the price of carbon risk, is positive and highly significant in the full sample at 0.1767. It is also positive and highly significant in all the subsamples. This means that companies in this sample with higher exposure to carbon risk are expected to gain higher returns. Furthermore, the price of carbon risk is much higher in the last two periods compared to the first, which was only 0.1432. An explanation for this could be that in the later periods, there has been more focus on being sustainable and green. Also, there is growing uncertainty about the supply of fossil fuels. This trend of sustainability and uncertainty makes it riskier to invest in dirty stocks. For investors to do so, they require higher returns to compensate for the risk. As dirtier companies have higher expected returns, their abnormal returns should be lower. On the other hand, cleaner companies experience lower carbon risk, so their abnormal returns should not change much after adding a carbon risk factor. Therefore, this positive price of carbon risk over the full sample might explain why the cleaner portfolio gained the highest abnormal returns. This calls for a measure to investigate the price of carbon risk separately per portfolio.

To implement the DMC factor in the three portfolios, I created the factor myself by subtracting the returns of the New Alternatives Fund from the NYSE ARCA oil and gas index. I could not use the aforementioned DMC factor per portfolio as this was calculated as the returns of two of these portfolios. Therefore, I created an out-of-sample DMCos variable. By adding this variable, I can answer the second hypothesis.

Table 12: Results of the dirtiest portfolio excess returns(EXCRd) as dependent variable, including the out-of-sample dirty-minus-clean factor(DMCos).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0163*	0.0320***	-0.0049	-0.0013
	(0.0086)	(0.0112)	(0.0134)	(0.0204)
EXCRsp	0.9993***	1.057***	0.9975***	0.8990***
	(0.0154)	(0.0105)	(0.0171)	(0.0525)
HML	-0.0313	-0.0961***	0.2659***	0.1514***
	(0.0305)	(0.0199)	(0.0347)	(0.0543)
SMB	0.1626***	0.1527***	0.1551***	-0.0157
	(0.0271)	(0.0191)	(0.0289)	(0.0754)
MOM	-0.0351**	0.0355***	-0.2754***	-0.0968*
	(0.0163)	(0.0134)	(0.0214)	(0.0580)
DMCos	0.1846***	0.1502***	0.1120***	0.1321***
	(0.0109)	(0.0096)	(0.0156)	(0.0411)
Adj. R^2(%)	87.39	90.21	83.45	59.34
SD type	White	Normal	Normal	Newey, lag(3)
N	3271	2012	971	288
F-statistic	1666.76	3707.38	979.35	69.26

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMCos is the out-of-sample dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

The addition of this out-of-sample factor led to several changes to the base model. First of all, this carbon risk factor is highly significant in all three portfolios. Except for subsample three of the cleanest portfolio, presented in table 14, the factor is also highly significant in all subperiods. Furthermore, the R-squared results of the cleanest and the dirtiest portfolio regressions are higher compared to the base model. Table 12 shows that the dirty portfolio adjusted R-squared increased with more than 2 percentage points to 87.39%, where the adjusted R-squared of the cleanest portfolio rose with 0.36 percentage point to 94.33%. Even though the R-squared of the medium portfolio in table 13 is slightly lower at 93.26%, the significance of the factor implies that its addition strengthens the regressions. The alpha of the dirty portfolio is now significant at a 90% level at 0.0163 after the addition of the carbon risk proxy. However, the change in this alpha is not as expected. The alpha increases by approximately 0.0015 percentage point, where a decrease was expected. The alpha represents the abnormal returns of the portfolio, which is the difference between the realized returns and the expected returns. As the dirtiest portfolio is exposed to the highest level of carbon risk, the expected return of this portfolio is also expected to increase the most. Following this reasoning, the alpha of this portfolio was expected to drop the most. I do not have an intuitive argument for the alpha to increase, but it could possibly be due to the fact that the first alpha was not significant and that this estimate comes closer to the true value. However, the alpha of the first period did in fact go down and is highly significant in both cases. As the other two periods are not significant, it could be a sign in support of the hypothesis. Nonetheless, the lack of significance results in a lack of power.

Table 13: Results of the medium portfolio excess returns(EXCRm) as dependent variable, including the out-of-sample dirty-minus-clean factor(DMCos).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0092*	0.0116	0.0074	-0.0085
	(0.0055)	(0.0073)	(0.0085)	(0.0166)
EXCRsp	0.9708***	0.9740***	0.9782***	1.010***
	(0.0099)	(0.0121)	(0.0109)	(0.0443)
HML	-0.0525***	-0.0830***	0.0626***	-0.0546
	(0.0182)	(0.0229)	(0.0222)	(0.0374)
SMB	0.1976***	0.2476***	0.0650***	0.1353***
	(0.0177)	(0.0227)	(0.0185)	(0.0349)
MOM	-0.066***	-0.0724***	-0.0808***	-0.0663**
	(0.0106)	(0.0141)	(0.0137)	(0.0312)
DMCos	-0.0597***	-0.0595***	-0.0698***	-0.0893***
	(0.0072)	(0.0093)	(0.0010)	(0.0212)
Adj. R^2(%)	93.26	94.50	89.99	71.16
SD type	White	White	Normal	Normal
N	3271	2012	971	288
F-statistic	2914.48	2278.70	1744.90	142.60

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMCos is the out-of-sample dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

As the medium and cleanest portfolio are less exposed to carbon risk, their alpha is expected to be less impacted. However, these portfolios are in fact exposed to carbon risk and are thus expected to get lower abnormal returns. Table 13 and table 14 show the results of the respective portfolios. In the case of the cleanest portfolio, the result is as expected. The constant has only decreased by approximately 0.0005 percentage point. The medium alpha is expected to have a bigger decrease due to its higher exposure to carbon risk but decreased by about the same. Though there is hardly a distinction between the two changes, they both are in the right direction. Overall, the difference between the abnormal returns of the dirtiest and cleanest portfolio decreases with both alphas being significant. This does not support the second hypothesis.

Table 14: Results of the cleanest portfolio excess returns(EXCRc) as dependent variable, including the out-of-sample dirty-minus-clean factor(DMCos).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0175***	0.0194***	0.0190***	-0.0008
	(0.0050)	(0.0070)	(0.0070)	(0.0128)
EXCRsp	1.0072***	1.0046***	1.046***	1.0168***
	(0.0078)	(0.0104)	(0.0090)	(0.0307)
HML	-0.2029***	-0.2084***	-0.2011***	-0.2065***
	(0.0162)	(0.0216)	(0.0182)	(0.0343)
SMB	0.1406***	0.1493***	0.0916***	0.1560***
	(0.0155)	(0.0215)	(0.0152)	(0.0363)
MOM	-0.0261***	-0.0260**	-0.0157	-0.0601*
	(0.0091)	(0.0122)	(0.0112)	(0.0311)
DMCos	-0.0636***	-0.0769***	-0.0311***	-0.01886
	(0.0059)	(0.0077)	(0.0082)	(0.0243)
Adj. R^2(%)	94.33	94.74	94.04	81.39
SD type	White	White	Normal	White
N	3271	2012	971	288
F-statistic	4935.14	3559.78	3061.34	363.36

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMCos is the out-of-sample dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

While the results regarding the abnormal returns miss convincing power, the risk factor itself does provide stronger information. Over the full sampling period, this factor has strong statistical and economic significance for the dirty portfolio at 0.1846. As it has a strong positive coefficient, one can say that there is a strong positive price of carbon risk for companies in this portfolio. This means that the higher the carbon exposure of a firm is, the higher the expected return. In other words, the better the relative performance of the ARCA index compared to the clean mutual fund, the higher the expected returns in the dirty portfolio. This can be explained by the fact that the ARCA index excess returns over the clean mutual fund is used as a proxy for carbon risk. It makes sense for dirty companies to gain higher returns when the oil and gas index does too, because of the high carbon connection between the two.

On the other hand, both the cleanest and medium portfolio have a negative price of carbon risk. This implies that companies within these groups that have higher carbon exposure have lower expected returns compared to the less exposed stocks within these groups. In addition, the cleanest portfolio has an even more negative coefficient for carbon risk than the medium portfolio over the full period. This result is consistent with expectations, as cleaner companies are expected to profit when the New Alternatives Fund outperforms the ARCA index. Again, intuition supports this result as clean company performance is linked with clean mutual fund performance based on their low carbon-intensity. However, abnormal returns still decreased because of the fact that even the cleaner companies in this sample are exposed to carbon risk.

Based on these results, I can now answer the second hypothesis:

- *H2: By adding a carbon risk factor, the difference in abnormal returns of the cleanest and dirtiest portfolio will increase.*

Overall, the DMC factor is positive over the whole sample. This implies that it is indeed profitable to invest in more carbon-intensive stocks. When taking carbon risk into account with an out-of-sample proxy, the abnormal returns of the dirtiest and cleanest sector converge. Therefore, the second hypothesis is rejected.

4.3 Results H3

While carbon-intensity does not seem to negatively impact returns over the full sample, the abnormal returns of the cleanest portfolio are still the highest. Therefore, I try to find out if a company's awareness of climate change and its willingness to act against it can explain part of the abnormal returns. I constructed the worst-minus-best factor as a proxy for climate risk, comparable to the dirty-minus-clean factor. The absence of climate change awareness and willingness to act against global warming is expected to result in increased risk over the years, because of the increasing importance of sustainability and uncertainty about climate policy. As investors are expected to be risk-averse and thus more interested in more sustainable stocks, I expect that more exposure to climate risk lowers the expected returns. The results in this section are used to answer the following hypothesis:

- *H3: Avoiding climate risk pays off, which is represented by a negative climate risk factor.*

Table 15: Results of the worst-minus-best portfolio (WMB) as dependent variable.

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0029	0.0076	-0.0050	-0.0065
	(0.0096)	(0.0139)	(0.0137)	(0.0227)
EXCRsp	-0.0530***	-0.0570**	0.0854***	-0.0102
	(0.0200)	(0.0244)	(0.0167)	(0.0588)
HML	0.0028	0.0032	0.0451	0.2010***
	(0.0379)	(0.0447)	(0.0378)	(0.0503)
SMB	0.1705***	0.1274***	0.2161***	0.2752***
	(0.0317)	(0.0428)	(0.0295)	(0.0485)
MOM	0.0378**	0.0735***	-0.0571**	-0.1497***
	(0.0169)	(0.0231)	(0.0226)	(0.0418)
DMC	0.2615***	0.2141***	0.2949***	0.1987***
	(0.0233)	(0.0302)	(0.0279)	(0.0480)
Adj. R^2(%)	11.16	9.45	26.77	31.67
SD type	Newey 0	Newey 1	Normal	Normal
N	3271	2012	971	288
F-statistic	40.42	22.08	71.92	27.60

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMC is the dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

In imitation of the DMC factor of Oestreich and Tsiakas (2015), I started by using the worst-minus-best factor as the dependent variable. The alpha of this regression can be seen as a premium for unsustainability. The resulting alpha for the full sample in table 15 implies that this premium exists in the full sample. Furthermore, there is a negative trend visible throughout the subsamples, with the second and third subsample resulting in a negative alpha. The negative trend corresponds to expectations, as companies have a growing interest in sustainability. Unfortunately, the alphas are all insignificant. This makes the implications not very powerful.

Regarding the independent variables, the momentum factor is positive and highly significant over the full sample for the first time. This means that stocks from this portfolio manage to profit from momentum, which was expected to be visible in earlier regressions. This positive factor also means that losers are expected to stay in the losing column. Remarkably, the coefficient of the excess return of the S&P 500 is negative and highly significant over the full sample. The implication to be made here is that the returns of this portfolio are going in the opposite direction of S&P 500 returns. There is no logical explanation for this, but it could be due to the fact that this regression captures very few of the variation in the portfolio returns. The adjusted R-squared of this model is 11.16%, which shows that this model has weak predictive power.

However, it is interesting to look at the DMC factor here. It is highly significant in the full sample as well as all the subsamples. The outcome in this regression is fairly high, with a coefficient of around 0.26 over the full sample. Compared to the DMC coefficient over the full sample, it has increased by 0.085. This strong increase is as expected, as the WMB portfolio was expected to be more exposed to carbon risk than the full sample. Therefore, it could indicate that the high coefficient in the full sample regression is mostly because of the dirtier and less sustainable companies.

Table 16: Results of regressing both DMC as WMB on the full sample (EXCR).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0146***	0.0181***	0.0144***	-0.0030
	(0.0037)	(0.0051)	(0.0054)	(0.0090)
EXCRsp	0.9879***	0.9942***	1.0052***	0.9868***
	(0.0035)	(0.0045)	(0.0067)	(0.0262)
HML	-0.1277***	-0.1435***	-0.0786***	-0.1215***
	(0.0072)	(0.0091)	(0.0150)	(0.0262)
SMB	0.1609***	0.1878***	0.0835***	0.1368***
	(0.0067)	(0.0086)	(0.0120)	(0.0241)
MOM	-0.0455***	-0.0416***	-0.0497***	-0.0639***
	(0.0047)	(0.0061)	(0.0090)	(0.0186)
DMC	0.1634***	0.1322***	0.2150***	0.2060***
	(0.0060)	(0.0079)	(0.0117)	(0.0244)
WMB	0.0509***	0.0510***	0.0440***	-0.0303
	(0.0037)	(0.0085)	(0.0128)	(0.0271)
Adj. R^2(%)	96.99	97.40	96.26	88.74
SD of alpha	Normal	Normal	Normal	White
N	3271	2012	971	288
F-statistic	17580.29	12576.78	4164.72	372.97

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMC is the dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

To answer the final hypothesis, I added the WMB factor to the full sample regression as a proxy for climate risk. Table 16 shows that the alpha is still highly significant, but it slightly decreased. This could be a sign that this model is better able to describe the excess returns. Another sign of this is the increased adjusted R-squared, which is 96.99% over the full sample. The four Carhart factors do not change much and are still highly significant. Furthermore, the DMC factor decreased in every test. This means the price of taking carbon risk decreased when I also take climate risk into account, which possibly captures a part of the carbon risk factor. The climate risk factor is significant and positive in the full sample as well as the first two subsamples, which implies a positive price for climate risk. Companies that are more exposed to climate risk will then exhibit higher expected returns. This indicates that being more sustainable will not result in higher returns. In addition, the worst scoring companies outperform the best scoring companies in the full sample as well as in the first two subsamples. Only the last subsample gives a negative coefficient. This would be in support of the expectation that there is an increasing stock performance of sustainable companies visible. However, this indications lack power due to a lack of significance.

Table 17: Results of regressing DMC, WMB and DMC*WMB on the full sample (EXCR).

	Full sample	Subsample 1	Subsample 2	Subsample 3
Alpha	0.0154***	0.0192***	0.0122**	-0.0007
	(0.0038)	(0.0052)	(0.0057)	(0.0091)
EXCRsp	0.9881***	0.9947***	1.0056***	0.9848***
	(0.0035)	(0.0045)	(0.0067)	(0.0261)
HML	-0.1279***	-0.1441***	-0.0789***	-0.120***
	(0.0072)	(0.0091)	(0.0150)	(0.0265)
SMB	0.1603***	0.1869***	0.0852***	0.1355***
	(0.0068)	(0.0086)	(0.0121)	(0.0240)
MOM	-0.0456***	-0.0418***	-0.0491***	-0.0647***
	(0.0047)	(0.0061)	(0.0090)	(0.0189)
DMC	0.1635***	0.1326***	0.2159***	0.2064***
	(0.0060)	(0.0079)	(0.0117)	(0.0248)
WMB	0.0511***	0.0516***	0.0449***	-0.0310
	(0.0068)	(0.0085)	(0.0128)	(0.0270)
DMC*WMB	-0.0074	-0.0118	0.0161	-0.0247
	(0.0066)	(0.0081)	(0.0121)	(0.0290)
Adj. R^2(%)	96.99	97.41	96.27	88.73
SD type	Normal	Normal	Normal	White
N	3271	2012	971	288
F-statistic	15070.24	10786.49	3572.83	314.82

Note: Alpha is the constant. EXCRsp is the excess return of the S&P 500. HML is the high-minus-low factor. SMB is the small-minus-big factor. MOM is the momentum factor. DMC is the dirty-minus-clean factor. N is the number of observations. Below each coefficient the standard deviation is given within brackets. SD type tells which kind of standard error is used, based on tests on heteroskedasticity and autocorrelation (Appendix B). * equals a 10% significance level, ** equals a 5% significance level and *** equals a 1% significance level.

Finally, the interaction effect of DMC*WMB has been added to the model to check for a joint effect. Table 17 presents the results of this regression. Surprisingly, the alpha of the full sample has gone up. This implies that the interaction term is not a good explanatory variable for the excess returns of the full sample. This thought is amplified by the fact that none of the interaction term coefficients is statistically significant. As the addition of the WMB factor decreased the coefficient of the DMC factor, I expected a significant joint effect. However, its economic significance is also negligible. As the interaction term barely impacts the WMB coefficient on the full sample, I can reject the third hypothesis:

- *H3: Avoiding climate risk pays off, which is represented by a negative climate risk factor.*

There is a positive price for carbon risk. Over the whole sample, it pays off to invest in the worst scoring stocks over the best scoring stocks. This result is consistent with the results for hypothesis 2. In both cases there is a positive price of risk for unsustainable investing. These unexpected results could be due to the fact that the US lacks a carbon pricing system and that investors in US-listed stocks do not mind taking carbon risk and climate risk to gain higher returns.

5. Conclusion and discussion

As other countries implement carbon pricing policies, the United States stay behind. European companies are incentivized to lower their emissions by the European Union. American companies on the other hand still have relatively much freedom in their emission levels. In lack of a carbon pricing policy, I expected investors to consider carbon risk and to support sustainable stocks. This paper answers the following research question:

- ***How do stocks of dirtier US companies perform compared to those of cleaner companies?***

The results for the first hypothesis indicated that cleaner stocks may outperform dirtier stocks. In addition, there seems to be a slightly negative trend in dirty stock performance. However, the difference in performance was small at around 0.0035%. In addition, the alpha of the dirtiest portfolio was insignificant. Also, the medium carbon-intensity stocks performed the worst. These results could not point out a convincing case of cleaner companies outperforming dirtier companies. To build a stronger case, I added the dirty-minus-clean factor. This factor turned out to be strongly significant and positive. Having economic significance, a convincing positive price of carbon risk is found in the sample. The coefficient was the highest in subsample two from 2013 until November 8th of 2016, in which Obama introduced his climate plan. This implies that taking carbon risk paid off most in that period, which could be explained by the risk-return payoff. To measure the price of carbon risk per portfolio, an out-of-sample DMC factor was introduced. As expected, it was strongly significant and positive in the dirtiest portfolio. Also having great economic significance, this shows that these stocks perform better if they have higher exposure to carbon risk. In addition, the out-of-sample DMC factor was negative and significant for the medium and cleanest portfolio. Carbon risk exposure turned out to be negatively impacting expected returns in these portfolio, which was as expected. However, by adding this factor, the difference in abnormal returns between the dirtiest and cleanest portfolio got smaller. This supports the finding that the difference in performance is not convincing. Finally, a proxy for climate risk was added to see if considering sustainability improved stock performance. The addition of the climate risk factor lowered the alpha of the full sample by a minimum amount of 0.0001% per day and increased the adjusted R-squared by 0.05%, implying a very small enhancement of the model. The climate risk factor was positive and statistically significant, indicating that more exposure to climate risk leads to higher expected returns. This final result is in line with the result of hypothesis two, as again the dirtier companies seem to have an advantage.

Most importantly, this paper shows that investing in unsustainable and carbon-intensive companies can lead to higher expected returns. Even though this is not visible in the abnormal returns of the dirtiest portfolio, the addition of proxies for carbon and climate risk show a positive link between risk and return. This finding can be explained by the fact that the US has not implemented a carbon pricing system. Earlier investigations in other countries showed how environmental performance could enhance financial performance. However, this paper shows a negative relationship between environmental performance and financial performance in the US and therefore advocates the implementation of a carbon pricing system. The stock market clearly does not take care of externalities of pollution with an invisible hand, so it needs the help of the government. The government should act to make carbon-intensive stocks less attractive to investors and thus encourage dirty companies to invest in sustainability.

By focusing on a country without carbon pricing policy in a time of increased environmental importance, this paper complements current literature. In addition, an out-of-sample DMC factor and a new proxy for climate risk are introduced and led to significant results. These factors show a significant positive price for risk over the sample, which calls for policy changes.

This research was limited by the lack of emission data. Hopefully, the importance of our environment grows in the United States. With that, organizations like the CDP can put more pressure on companies to disclose emission numbers. With more available data, the problem of selection bias could be avoided and bigger portfolios could be created. Bigger portfolios will give the opportunity to measure performance differences within a portfolio. Furthermore, I expect that more data supply makes it possible to show the link between emission and stock performance more clearly. If there is more convincing evidence of the profitability of investing in carbon in the US, there will be more pressure on the government to implement a better policy to decrease pollution. Oestreich and Tsiakas (2015) showed that the price of carbon risk went down after the EU stopped giving away free carbon allowances. This implies that if the US makes its companies pay for their carbon emission, the price of taking risk would go down. Eventually, such policy will possibly decrease the carbon-intensive stock investors. Less investors will make companies more aware of climate problems and more willing to act on it.

Furthermore, it would be interesting to do a similar research with more data on Trump’s tenure. Because my last subsample consisted of just a little over 13 months of data, the results of this were parsimonious. With more data, I think one can show a more significant trend in the data. In addition, further research could implement an out-of-sample worst-minus-best factor. With this, one can insert this climate risk proxy in the separate portfolios. Also, another sustainability measure could be implemented like corporate social responsibility. Finally, the model could be strengthened with more control variables like volatility or liquidity. As more control variables could possibly increase robustness, I expect that this could lead to more convincing results.

Finally, the same hypotheses could be tested by using a different methodology. For example, a difference-in-difference methodology could expose the difference in performance more clearly. If high carbon-intensive companies within a sector are assigned to the treatment group and low carbon-intensive companies to the control group, performances could be compared. In addition, this methodology could illuminate the effect of a carbon pricing policy. If one would make an American portfolio and a European portfolio with similar stocks, the impact of such policy on stock performance could be investigated. By showing the financial impact of the ETS on stock performance, US politicians could propose a more well-advised policy.

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Appendix

Appendix A:

Appendix A1: Summary statistics for sector averages.

Sector	*Mean*	*SD*	*Median*	*Min*	*Max*	*Skewness*	*N*
Basic Industries	0.0333	1.7280	0.1034	-13.4649	13.8069	-0.3397	3271
Capital Goods	0.0396	1.4257	0.0942	-10.0175	11.4987	-0.2139	3271
Consumer Durables	0.0390	1.2899	0.0787	-9.4231	8.2405	-0.4184	3271
Consumer Non-Durables	0.0387	1.3496	0.0905	-15.0405	12.1232	-0.8854	3271
Consumer Services	0.0357	1.4402	0.0625	-11.4886	10.7697	-0.3701	3271
Energy	0.0296	1.9036	0.0887	-17.1073	18.0519	-0.4809	3271
Healthcare	0.0450	1.0585	0.0748	-7.5585	11.6235	-0.1440	3271
Public Utilities	0.0326	1.2565	0.0943	-8.7974	12.7255	0.0938	3271
Technology	0.0461	1.4500	0.0820	-9.5776	11.6242	-0.1697	3271
Transportation	0.0463	1.6790	0.0867	-10.5668	10.9449	-0.2356	3271

Note: SD is the standard deviation. N is the number of observations. Numbers are whole percentages.

Appendix B:

Appendix B1: Test results for autocorrelation and heteroskedasticity in hypothesis 1 regressions.

Dependent variable	Full sample		Subsample 1		Subsample 2		Subsample 3	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
EXCRc	0.1391	0.0033	0.1849	0.0010	0.9704	0.3167	0.9129	0.0430
EXCRm	0.6864	0.0103	0.4309	0.0005	0.9959	0.6439	0.9596	0.0095
EXCRd	0.7299	0.2691	0.2003	0.0705	0.7793	0.8972	0.0686	0.2801
EXCRcc	0.0751	0.0000	0.0158(3)	0.0000	0.3795	0.6692	0.5457	0.3868
EXCRmc	0.0118(4)	0.0000	0.0003(3)	0.0000	0.0861	0.3770	0.9524	0.0678
EXCRdc	0.6489	0.0000	0.7699	0.0968	0.5816	0.3126	0.0039(3)	0.3819

Note: Breusch-Godfrey (1) and Breusch-Pagan (2) p-values of regressions for hypothesis 1. If there is autocorrelation (p<0.05 for (1)), the number of lags is within brackets for the Newey-West standard errors. The number of lags is chosen based on information criteria. If there is only heteroskedasticity (p<0.05 for (2)), White standard errors are used.

Appendix B2: Test results for autocorrelation and heteroskedasticity in hypothesis 2 regressions.

Dependent variable	Full Sample		Subsample 1		Subsample 2		Subsample 3	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
DMC	0.5916	0.2678	0.7206	0.0000	0.6973	0.5299	0.1844	0.4737
EXCR	0.4061	0.0040	0.8368	0.0507	0.6451	0.1463	0.8387	0.0006
EXCRc	0.4081	0.0000	0.6636	0.0000	0.9026	0.5421	0.9404	0.0370
EXCRm	0.3978	0.0012	0.1744	0.0002	0.9776	0.2467	0.9959	0.2382
EXCRd	0.9584	0.0049	0.3167	0.4575	0.9568	0.8387	0.0429(3)	0.0009

Note: Breusch-Godfrey (1) and Breusch-Pagan (2) p-values of regressions for hypothesis 1. If there is autocorrelation (p<0.05 for (1)), the number of lags is within brackets for the Newey-West standard errors. The number of lags is chosen based on information criteria. If there is only heteroskedasticity (p<0.05 for (2)), White standard errors are used.

Appendix B3: Test results for autocorrelation and heteroskedasticity in hypothesis 3 regressions.

Dependent Variable	Full Sample		Subsample 1		Subsample 2		Subsample 3	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
WMB	0.0180(0)	0.0000	0.0054(1)	0.0000	0.3668	0.8552	0.9593	0.1072
EXCR	0.4812	0.2578	0.9024	0.8390	0.5974	0.1675	0.6911	0.0011
EXCR(+)	0.4860	0.2606	0.9163	0.8471	0.6015	0.1034	0.7085	0.0009

Note: Breusch-Godfrey (1) and Breusch-Pagan (2) p-values of regressions for hypothesis 1. If there is autocorrelation (p<0.05 for (1)), the number of lags is within brackets for the Newey-West standard errors. The number of lags is chosen based on information criteria. If there is only heteroskedasticity (p<0.05 for (2)), White standard errors are used. The EXCR(+) model is the final model including the interaction effect.