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THE IMPACT OF THE REMOVAL OF HIGH POLLUTING COMPANIES FROM A WELL-DIVERSIFIED PORTFOLIO ON ITS PERFORMANCE

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PREFACE AND ACKNOWLEDGEMENTS

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I present this thesis with the hope that it adds meaningful insights to the field of institutional asset management, pension funds, and the ethical dimensions of ESG considerations.

ABSTRACT

Excluding high-polluting companies from a portfolio is a way for investors to adjust their investment strategy in response to rising concerns about climate change and additional regulations. This study examines the impact of removing polluting companies from a well-diversified portfolio compared to a portfolio that includes them. Polluting companies are identified using the PMC factor (defined by Huij et al., 2023). To compare the performance of the two portfolios, the Sharpe ratio and asset pricing models, including, and excluding a transition risk factor, have been applied. The results of the study confirm that excluding polluting companies does not have a negative impact on portfolio performance.

Keywords: Climate change, investment, carbon risk, climate finance, asset pricing, exclusion

JEL Classification: G11, G12, Q54

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CHAPTER 1 Introduction

Climate change is currently one of the world's biggest concerns. Global warming has a major impact on the world and its inhabitants. This is reflected in rising sea levels, extreme weather, changing habitats, and possible food and water shortages (Rijksoverheid, n.d.). To limit the problems arising from this climate change as much as possible, agreements are being made worldwide. A well-known example of this is the Paris Climate Agreement of 2015. In this agreement, EU member states have agreed to work towards climate neutrality. They want to achieve this by emitting 55% less CO_2 in 2030 and emitting no net greenhouse gases in 2050 (Rijksoverheid, n.d.). The increasing concerns about climate change and the resulting agreements are affecting many aspects of society, including the financial sector. Worldwide, companies must adhere to increasingly strict regulations to combat climate change. Polluting companies must therefore change. This is one of the reasons why also financial institutions must increasingly focus on climate change. During the Paris climate agreement, non-governmental parties were called upon to work against global warming. Institutional investors are keeping a closer eye on the greenhouse gas emissions of publicly traded companies. They are also forming alliances, such as Climate Action 100+, to work together with companies to reduce their carbon emissions (Bolton and Kacperczyk, 2021, p.2). An example of actions taken is the signing of the climate agreement in 2019 by Dutch financial institutions. By doing so, they are required to report on the climate impact of their investments and financing starting from 2020. Furthermore, by signing this agreement, they must make plans to reduce CO_2 emissions (Klimaatakkoord, 2019). Despite the U.S. withdrawal from the Paris Agreement in 2019 and the maybe partially credible commitments of other remaining signatories, it is expected that significant reductions in CO_2 emissions will be implemented in the coming decade (Bolton and Kacperczyk, 2021, p.2). Due to the changing climate and efforts to mitigate its effects, institutional investors must change their investment portfolios, not just because they want to, but because they are obligated to. This often involves excluding firms with a high carbon emission footprint from their investment portfolio. This investment choice can impact the level of pensions, among other things. Therefore, it is important to ask the following question:

> *How does the removal of high polluting companies from a well-diversified portfolio impact its performance?*

Policy makers must understand the impact of excluding these types of stocks. Generally, institutional investors have two options when it comes to high polluting companies: divest or remain involved. By excluding stocks of polluting companies from their investment portfolio, ownership of the shares is shifted to another party. In this way, the institutional investors try to distance themselves from polluting companies. Investors can also choose to remain as shareholders in the polluting company and use their voting rights to change the behavior of the company (Swinkels, 2021). Although the effectiveness of divesting is questionable (Blitz and Swinkels, 2020), institutional investors seem to prefer this approach over engagement. A recent example involves Dutch pension funds selling their shares in the meat industry due to its negative impact on the climate. ABP, for instance, sold its shares in the Brazilian meat company Minerva, while the Pension Fund for Healthcare and Welfare (PFZW) did the same with their shares in Marfrig (Groot and Sie, 2023).

Excluding stocks from a portfolio due to a lack of social responsibility is not a new practice. Several studies have already analyzed the impact of this practice on investor performance. For instance, Swinkels and Blitz (2021) conducted research on the exclusion of sin-stocks and its impact on portfolio risk and return, which they investigated using the Fama-French five-factor model. They found that excluding sin-stocks would result in a lower expected return, which could be explained by the advantageous characteristic factors of these stocks. Another article, specifically on high polluting companies, is Huij et al. (2023). They introduce a carbon beta, a climate risk measure based on a regression of stock returns on the returns of a pollutive-minus-clean portfolio. The higher a share's beta for this factor, the higher the carbon risk of the security. The pollutive-minus-clean (PMC) portfolio takes a long position in the most polluting 30% of firms and a short position in the least polluting 30% of firms. The authors reveal that the level of carbon risk to which an investor is exposed can explain additional returns on an investment. Nowadays, companies, including institutional investors, must consider sustainable investing in the areas of climate, working conditions, and good governance. Environmental, Social, and Governance (ESG) criteria are used to measure how responsible a company is run. Alessandrini and Jondeau (2019) executed a study in which they excluded certain stocks from a portfolio based on their ESG scores. They removed companies that had the lowest scores. The research found that removing these low-scoring companies could enhance the ESG profile of passive portfolios without compromising overall performance.

In practice we see that investment funds are for example hesitant to invest in companies in the weapons industry, where it cannot be ruled out that human rights are violated. This can lead to financial difficulties for companies in this industry, as there is less interest in buying their shares or providing loans by providers of capital. The war in Ukraine by Russia is causing a growing demand for weapons and equipment. Although high returns can currently be achieved in this industry, institutional investors are not investing in weapons (Boermans, 2023) and Bauer et al. (2023) analyzed the performance of more climate friendly (green) and less climate friendly (brown) stocks during the energy shock caused by the war of Russia in Ukraine.

They discovered that during the first half of 2022, brown stocks had higher returns than green stocks. They think this change in performance is likely due to unexpected demand shift in the energy and defense industries, which are both considered brown sectors. This war is a good example of a shock in the financial world that impacts the returns of green and brown investments.

Another recent example of an economic shock is the Covid-19 crisis. Wang et al. (2022) conducted a study that looked at the impact of Covid-19 on investor behavior. They wanted to determine how Covid-19 affected investment behavior in the United Kingdom. The study showed that Covid-19 has led to investors becoming more cautious and less tolerant of risks which might influence their investment decisions regarding polluting versus clean stocks.

In this master's thesis, I take the perspective of an investor in the U.S. I will examine what the impact of excluding high polluting firms from a well-diversified portfolio is on its Sharpe ratio and whether the difference in returns between a well-diversified portfolio including high polluting companies and another well diversified portfolio without these stocks can be explained by the carbon beta of Huij et al. (2023). Determining polluting companies can be done in various ways. Bolton and Kacperczyk (2021) evaluated companies based on the 3 scopes of emissions. Scope 1 refers to emissions directly produced by an organization, while scope 2 refers to indirect emissions produced by the energy the organization purchases and uses. Scope 3 includes emissions not directly produced by the organization but by assets indirectly controlled or responsible for throughout its value chain. For Bolton and Kacperczyk (2021), data for scopes 1 and 2 are available for their sample, while scope 3 is estimated. On the other hand, Huij et al. (2023) only use the first two scopes of emissions. They indicate that scope 3 emissions are challenging to monitor, require voluntary reporting, and are of significant magnitude. When comparing emissions between firms, scope 3 emissions have much lower correlations than scope 1 and 2 emissions and are double counted for firms in the same value chains. Pástor et al. (2022) determine polluting companies based on ESG scores and specifically look at the E-scores. However, Bauer et al. (2023) argue that using ESG scores is not the right way to estimate polluting companies because ESG scores are subject to significant variation across data providers and are subject to retroactive revisions. The market-based nature of Huij et al.'s (2023) carbon beta considers not only greenhouse gas emissions but also other factors that assess the ability to deal with transition risk. Huij et al. (2023) argue that when evaluating a company's ability to reduce greenhouse gas emissions, it is important to consider factors beyond its current emissions, such as the availability of clean technology, the quality of management, innovation ability, competition, and financial health. To define polluting companies in this master’s thesis Huij et al.’s (2023) PMC beta is used. Companies with a PMC beta in the highest 10% (30% or 50%) are considered polluting companies (as defined by Huij et al., 2023) The PMC beta will be estimated for every firm that is part of the S&P500 index from 2008 to 2022.

This master’s thesis specifically examines the effect of excluding high polluting companies on the performance of a well-diversified portfolio of a passive investor. I assume that the S&P500 index represents a well-diversified portfolio for such an investor because it is common to use this index as proxy for the U.S. market portfolio (Berk and DeMarzo, 2020). Comparable studies so far have always looked at all companies for which the required data was available and not at a specific investor portfolio (Blitz and Swinkels, 2021; Bolton and Kacperczyk, 2021; Huij et al., 2023; Bauer et al., 2023).

I will also investigate whether there is an impact of the 2015 Paris Agreement on the effect of excluding high polluting firms from a well-diversified portfolio on its performance. In 2020, Monaterolo and De Angelis conducted a similar study and found that, after the Paris Agreement, low-carbon assets had less systematic risk than before 2015, while high-carbon assets became riskier. Other shocks to the economy, such as the Covid-19 crisis and the Russian-Ukrainian War, will also be taken into consideration.

The results of this master's thesis indicate that there is no significant difference in the Sharpe ratios between the portfolios with and without polluting companies. This suggests that the anticipated impact of less diversification on risk levels due to excluding polluting companies is not substantial enough to create a significant performance difference. Furthermore, the study reveals that the difference in returns between the two portfolios is partially explained by the addition of the PMC risk factor to the asset pricing models. This implies that the PMC factor plays a role in explaining abnormal returns. The effects of the 2015 Paris Agreement, Covid-19, and the Russian Ukrainian war on portfolio performance are explored as well. The results indicate that the Paris Agreement did not significantly affect the Sharpe ratios and abnormal returns of the portfolios. Additionally, the expected impacts of Covid-19 and the Russian Ukrainian war on portfolio's abnormal returns were not observed, and the level of perceived carbon risk did not change significantly during the Russian Ukrainian war.

The structure of the master's thesis is outlined as follows: Chapter 2 provides a brief literature review on the impact of excluding stocks from portfolios on their performance. In Chapter 3, the data and in Chapter 4 the method is described. Chapter 5 presents the results and discusses the empirical findings including robustness checks. Finally, Chapter 6 concludes.

CHAPTER 2 Literature Review

In this chapter empirical literature on excluding stocks from portfolios and the impact on their performance is discussed. In Section 2.1 the different categories of firms being excluded will be described. Then in Section 2.2 empirical literature is divided in a section where the Sharpe ratio is applied as a measure to describe the difference between the performance of a well-diversified portfolio and a portfolio where certain firms are excluded from. In Section 2.3 the performance of the two before mentioned portfolios will be compared based on the loadings of systematic risk factors and abnormal returns Finally, Section 2.4 elaborates on the expected impact on the performance of polluting stocks due to the 2015 Paris Agreement, Covid-19, and the Russian Ukrainian war. Several hypotheses have been formulated based on the empirical literature.

Table 1: Summary empirical papers about excluding stocks and the impact on performance
This table gives an overview of the empirical papers regarding excluding stocks and the impact on performance. In this table the author(s) (Publication year), time period, region, method, control variables and results are given.

Author(s) (Publication year)	**Time period**	**Region**	**Method**	**Control variables**	**Results**
Hong and Kacpeczyk (2009)	1965-2006	U.S.	Time-series return regression model to determine abnormal returns	Size, book-to-market, momentum	Sin stocks perform better than their comparables, with an alpha of 26 bps a month.
Humphrey and Tan (2014)	Jan 1996 – Dec 2010	U.S.	Regression model to determine abnormal returns	4 factors of Fama and French	No significant differences
Alessandrini and Jondeau (2019)	Jan 2007 - Dec 2017	U.S., Europe, Pacific and emerging countries	Regression model to determine abnormal returns	5 factors of Fama and French	Improvement of portfolio performance when excluding firms with low ESG scores.
Monasterolo and De Angelis (2020)	1999 – 2018	EU, U.S., global financial markets	Quantitative research method to analyze the stock market reaction to the Paris Agreement.	5 factors of Fama and French, region	After 2015 Paris Agreement low-carbon assets seen as less risky and high-carbon assets as riskier than before 2015.
Blitz, Van Vliet, and Baltussen (2020)	1929-2018	U.S.	Summary of findings from previous research studies.	5 factors of Fama and French	Empirical evidence for the 'low-risk effect'.
Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2020)	Jan 2010 – Dec 2017	Global	Panel regression based on the BGS (Brown-Green-Score) to analyze if carbon risk has a positive or negative effect on returns.	Fundamentals, county, industry, time, and firm fixed effects.	BMG factor explains returns variation, but no carbon risk premium. Brown firms have higher returns, but green firms outperform due to fast improvement.
Bolton and Kacperczyk (2021)	2005-2017	U.S.	Cross-sectional return regression model to determine abnormal returns	Size, book-to-market, momentum, variables that predict returns, and firm characteristics	Firms with higher emissions generate higher returns.
Bolton and Kacperczyk (2022)	2005-2018	Global	Cross-sectional return regression model to determine abnormal returns	Size, book-to-market, momentum, value of PPE, profitability, investment over assets	Companies with higher carbon emissions have higher stock returns (carbon premium).
Pástor, Stambaugh, and Taylor (2022)	Nov 2012 – Dec 2020	U.S. (Asia, Europe, and North America)	Cross-sectional return regression model to determine abnormal returns	5 factors Fama and French, momentum factor of Pástor and Stambaugh (2003), factors of Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2021)	Green-minus-brown alpha between 47 to 71 bps per month (t-statistics between 1.99 and 2.91), statistically significant.
Hsu, Li and Tsou (2022)	1991-2016	U.S.	"Cross-sectional variation in the relation between stock returns and	Size, book-to-market, investment rate, ROE,	High-minus-low emission portfolio annual return of 4.42%

			industrial pollution" (Hsu et al. 2022, p.2)	tangibility, WW index, book leverage, and industry dummies	
Bauer, Huber, Rudebusch, and Wilms (2023)	Jan 2010 – Dec 2021	U.S. (and G7 countries)	Panel regression of stock returns to determine abnormal returns	3 factors of Fama and French, firm characteristics	The superior performance of green stocks in the U.S. is attributed to a combination of lower risk and higher risk-adjusted returns compared to brown stocks.
Huij, Laurs, Stork, and Zwinkels (2023)	Jan 2004 – Dec 2020	U.S.	Regression of stock returns on a PMC portfolio to assess asset-level climate transition risk exposure.	5 factors of Fama and French	Introduction of the Polluting Minus Clean (PMC) factor. The carbon risk premium increases by 1.15% per standard deviation of carbon beta.

2.1 Excluding companies from portfolios

As mentioned in the introduction, institutional investors generally have two ways of dealing with companies that are not considered responsible. Firstly, an investor may choose to remain invested in the company and exert influence on its management through voting rights. Alternatively, an investor may choose to sell the shares of the company and distance themselves from irresponsible business practices. This master's thesis examines the impact of excluding certain stocks from a well-diversified portfolio. In practice different methods have been applied to define "unresponsible" stocks. In Sections 2.1.1 to 2.1.3 the following categories of unresponsible stocks will be discussed: sin stocks, stocks with a low ESG rating and high polluting stocks.

2.1.1 Sin stocks

Excluding specific stocks from a portfolio, partly due to external pressure, is not a new concept. Previous studies have focused on excluding sin stocks for example. When it comes to excluding stocks for responsible investing, sin stocks are the most traditional stocks to consider. These are stocks of companies that are active in sectors such as tobacco, weapons, alcohol, gambling, and adult entertainment (Blitz and Swinkels, 2021). Previous studies suggest that excluding sin stocks would result in lower returns and higher levels of risk. This is partly due to the inability to fully diversify the portfolio, and partly due to the exclusion of stocks that achieved relatively high average returns.

Hong and Kacperczyk (2009) initiated the literature on sin stocks. The authors investigated the impact of social norms on the stock market by examining sin stocks, which according to their definition include gambling, alcohol, and tobacco stocks. These stocks were expected to be neglected due to rising litigation risk associated with social norms. The authors compared the returns of an equal-weighted portfolio of sin stocks with a portfolio of comparable stocks with similar characteristics. They found that sin stocks perform better than their comparables in the sample period 1965 to 2006 in the U.S. (see Table 1). Humphrey and Tan (2014) tested this by simulating stock investment funds. Their research showed that excluding sin stocks has no significant effect on the performance or risk of the portfolio. Blitz and Swinkels (2021) focus on specific sin industries when excluding stocks from a portfolio. They suggest that these popular exclusions of stocks can often result in a negative impact on portfolio returns due to the fact that these exclusions often conflict with rewarded risk factors such as value, profitability, and low risk. While sin itself may be a priced factor as well, they had no empirical evidence to support this claim yet.

2.1.2 ESG

When discussing socially responsible investing, it's not only about reducing investments in "sin stocks". Due to regulations related to climate change, there is an increasing emphasis on investing in a manner that considers environmental, social, and governance (ESG) aspects (Alessandrini and Jondeau, 2019). The study conducted by Alessandrini and Jondeau (2019) excluded certain stocks from a portfolio based on their ESG scores. The companies with the lowest scores were removed from the portfolio. According to Alessandrini and Jondeau (2019), passive portfolios' ESG profile can be improved without reducing overall performance.

It is also possible to investigate only one aspect of ESG. For example, Pástor et al (2022) determined polluting firms based on the Environmental pillar score and weight of the ESG ratings of MSCI. Based on the ESG database, Görgen et al. (2020) also examined only the environmental aspect by looking at polluting companies and investigated carbon risk. In their article, they observe two contrasting effects: brown firms are linked to higher average returns, while decreases in the greenness of firms are associated with lower announcement returns. This research also mimics a carbon risk factor that can explain the variation in systematic returns, but it did not find any risk premium associated with it.

2.1.3 Polluting companies

To assess carbon risk, Huij et al. (2023) also introduced a carbon risk factor (measured by carbon beta). The higher the beta of the share for that factor, the higher the carbon risk the investor runs on that investment. They study greenhouse gas emissions and examine two scopes of The Greenhouse Gas Protocol. The first scope includes direct emissions from a company's production process, while the second scope covers indirect emissions related to the purchase of electricity, heat, or steam. All other emissions along a company's value chain are accounted for in the third scope. Because of incomplete data Huij et al. (2023) only take scope 1 and 2 into account. They have found that an additional return on an investment can be explained by the level of carbon risk that the investor is exposed to. Bolton and Kacperczyk (2021) also used scopes of The Greenhouse Gas Protocol to analyze how carbon emissions affect stock returns. They linked the emission levels, year-to-year changes, and emission intensities of companies to their stock returns within each of the three scopes. Their primary finding is that stock returns have a positive correlation with the level (and changes) of carbon emissions. According to Bolton and Kacperczyk (2021) this aligns with the idea that investors are factoring in a carbon risk premium at the firm level.

Pástor et al. (2022) discovered that a value-weighted portfolio of green stocks outperformed brown stocks by 174% over the period 2012 to 2021, with a significant alpha ranging from 47 to 71 bps per month. This contradicts Bolton and Kacperczyk's findings that firms with higher carbon emissions earn higher risk-adjusted returns, which according to Pástor et al. (2022) might depend on a different sample and methods. For example, Bolton and Kacperczyk (2021) look at total emissions and do not consider emission intensity (which measures the amount of carbon emissions per unit of sales). The sample of Bolton and Kacperczyk (2021) consisted of observations of stock returns over the period 2005 to 2017.

Görgen et al. (2020) found an insignificantly negative carbon premium when combining multiple carbon-emission-related measures and using a sample period more similar to that of Pástor et al. (2022). Bolton and Kacperczyk examined in 2022 the effects of progress made by countries worldwide in the energy transition and corporate carbon emissions on stock returns. They found that raising investor awareness about climate change increased the perceived level of transition risk. In addition, over the period 2012 to 2020 they discovered a widespread market-based carbon premium in all sectors across three continents: Asia, Europe, and North America. This premium is connected to both direct emissions from production and indirect emissions from firms in the supply chain and is based on the transition risk at the firm level. In this study, a characteristics-based approach was used to explain differences in return, instead of an asset pricing model. The authors of the article state that at that time no asset pricing model considers climate change risk yet. A risk factor that was introduced a year later by Huij et al. (2023).

Bauer et al. (2023) conducted research similar to Huij et al. (2023) and found opposite results, that green stocks have higher realized returns compared to brown stocks. Their findings suggest that there may not be a carbon premium, assuming that average realized returns are good proxies for expected returns. According to Bauer, differences in results may be due to factors such as differences in the sample used. For instance, Huij et al. use a sample period from 2004 to 2020, while Bauer’s sample period is from 2010 to 2022. Bauer’s study is like that of Huij et al. and Görgen et al. (2020) but differs in focus. Huij et al. and Görgen et al. (2020) examine whether carbon is a priced risk factor, while Bauer et al. (2023) primarily document the relative green and brown equity performance.

Hsu et al. (2022) investigated the impact of mandatory disclosures of toxic emissions, as opposed to greenhouse gas emissions, on U.S. stock returns. The authors created a long-short portfolio based on toxic emissions, which generated an annual return spread of 5.52%. The researchers found a “pollution premium” among these returns, which they believe is due to the simple logic that high-emission companies require higher expected returns as compensation because they are more vulnerable to changes in environmental policy regimes.

2.2 The Sharpe ratio

Empirical literature uses the Sharpe ratio to compare the performance of a well-diversified portfolio to that of a portfolio where certain firms have been excluded. The Sharpe ratio adjusts for total risk when measuring performance. It can be calculated by dividing the excess return of a portfolio by a measure of the portfolio’s volatility (Sharpe, 1966). Humphrey and Tan (2014) investigated the impact of excluding sin stocks on the performance of a portfolio. They reviewed the fund performance, by investigating raw returns and the Sharpe ratio. They found no significant differences in performance between the two portfolios, with or without screening for social responsibility. Alessandrini and Jondeau (2019) examined the overall performance of a portfolio both with and without the exclusion of stocks based on their ESG scores. The researchers also found the exclusion had in essence no effect on the portfolio's Sharpe ratio. Based on Lintner's theory (1965), we would expect that excluding stocks from a well-diversified portfolio would have a negative impact on the Sharpe ratio because optimal diversification cannot be achieved anymore due to higher level of total risk. Based on Lintner's theory (1965) the following hypothesis can be formulated:

> Hypothesis 1) The Sharpe ratio of the well-diversified portfolio with polluting companies is higher than the Sharpe ratio of the well-diversified portfolio without polluting companies.

2.3 Systematic risk

The first hypothesis considers excess returns in relation to the total level of risk. In this section systematic risk will be discussed and hypotheses 2.A and 2.B will be formulated. Differences in returns between portfolios with and without polluting stocks will be explained by systematic risk, which is divided into multiple risk factors. Many studies that aim to explain differences in returns by risk factors use the five Fama and French's risk factors (or a variation thereof).

Fama and French's five risk factors are used to divide systematic risk across multiple factors, including market, size, value, profitability, and investment (Fama and French, 2015). Hong and Kasperzyck (2009) used a four-factor model that included the market size, value, and momentum. Their analysis revealed an alpha of 26 basis points per month, leading them to conclude that sin stocks perform better than their comparables. Humphrey and Tan (2014) calculate the four-factor alpha as the intercept from the Carhart (1997) model. Similar to the findings regarding the Sharpe ratio, they did not find significant evidence that excluding sin stocks from the portfolio impacts performance. A similar study conducted by Blitz and Swinkels (2021) examined the impact of excluding sin stocks from a portfolio on performance using Fama and French's five-factor model including the low-risk factor (VOL) of Blitz et al. (2020). Their findings suggest that simply excluding stocks associated with sin industries will generally lead to a lower expected return, as these stocks tend to have favorable factor characteristics. The researchers then investigated the possibility of a potential sin premium. They found support for this hypothesis in two (theoretical) ways. Firstly, sin stocks have higher expected returns when they are avoided by a large group of investors. This could be due to compensation for the reputational risk associated with owning these stocks. An additional risk factor can then be added to the formula: SIN. Secondly, excluding these stocks from investment portfolios would – according to Blitz and Swinkels (2021) – increase the cost of capital, providing an additional argument for the existence of a sin premium. In 2021, Bolton and Kacperczyk utilized risk factors to investigate whether these factors could account for the carbon premium. They discovered that in theory there is a significant carbon premium associated with the level and growth of emissions. However, their regressions indicate that the carbon premium cannot be explained by the known risk factors, such as size, book-to-market, momentum, variables that predict returns, and firm characteristics. Hsu et al. (2022) show that creating a portfolio that is long in companies with high toxic emission intensity within an industry and short on companies with low toxic emission intensity generates an annual return of 4.42%, which remains statistically significant even after accounting for known systematic risk factors. The following hypothesis is proposed:

> Hypothesis 2.A) The difference in returns between the well-diversified portfolio with and without high polluting companies is partially explained by the five-factor model of Fama and French (2015).

Hypothesis 2.A implies that the expected returns of polluting firms are higher than the expected returns of clean firms corrected for the risk factors included in the five-factor model of Fama and French and that alpha is expected to be positive.

As discussed in Section 2.1.3 Huij et al. (2023) introduced a carbon beta and added an extra risk factor to the market, size, and value factors of Fama and French and the Carhart momentum factor: The Polluting Minus Clean (PMC) factor. The PMC portfolio holds a net long (short) position in brown (green) stocks. It is a self-financing portfolio that holds a long position in the most polluting 30% of firms and a short position in the least polluting 30% of firms. By adding this risk factor to the factor model returns should be better explained. This is also suggested by Hsu (2022). Hsu proposes to include a risk factor that is related to environmental policy uncertainty. Building upon this, the second part of the hypothesis is formulated as follows:

> Hypothesis 2.B) Returns that cannot be explained by the five factors of Fama and French (2015) may be attributed to the risk factor PMC, as introduced by Huij et al. (2023).

Hypothesis 2.B implies that when adding the risk factor PMC, the alpha will be reduced to zero.

There is also a possibility that alpha of a portfolio that consists of polluting companies is negative because of negative effects of environmental regulation. The negative effect of environmental regulation on a company's profit is supported by research conducted by Gray and Shadbegian (1998). Environmental laws reduce productivity by requiring companies to devote resources to non-productive activities such as environmental audits, waste management, and litigation. Ambec and Lanoie (2008) further support this theory, finding that companies operating in high polluting industries may face a disadvantage when implementing stricter environmental regulations. As a result of increased compliance costs, companies must choose between raising prices (which could ultimately lead to losing market share) or experiencing lower profitability.

2.4 The 2015 Paris Agreement and other events

After the Paris Agreement in 2015, the assumption is that there is a shift in demand by investors from polluting to clean assets. Because of this shift in demand institutional investors begin selling shares of (high) polluting companies with a possible negative impact on the prices of these shares as a result. On the other side the demand for clean assets increases with a positive impact on prices of those securities (Bauer et al. 2023). If after the 2015 Paris Agreement this indeed is the case, then a well-diversified portfolio without high polluting stocks might generate higher returns than a portfolio including these stocks. However, excluding shares of high polluting companies might also result in losing benefits of diversification. A portfolio without (high) polluting firms might generate higher returns on the one hand but also show higher levels of total risk on the other. Before the 2015 Paris Agreement it is expected that the impact of excluding high polluting companies from a well-diversified portfolio on the returns was less prevalent because the shift in demand then was less strong (or absent), but the loss of the benefit of diversification would still be present. That would imply that the difference between the Sharpe ratio of a well-diversified portfolio with polluting companies and of a well-diversified portfolio without polluting companies would be greater before the 2015 Paris Agreement than after this agreement. To analyze the impact of investors behavior due to the 2015 Paris Agreement on the performance of well-diversified portfolios including versus excluding high polluting companies the following hypothesis will be tested:

> Hypothesis 3) The difference between the Sharpe ratio of a well-diversified portfolio and of the well-diversified portfolio without polluting companies is in the period before 2015 greater than in the period thereafter.

Monasterolo and De Angelis (2020) examine whether financial markets are pricing the Paris Agreement. According to them, low-carbon assets have less systematic risk after the Paris Agreement, while carbon-intensive assets have become riskier. In addition, they find that the weight of low-carbon indices in investors optimal portfolios increases after the Paris Agreement.

Bolton and Kacpercszyk (2021, 2022) found that companies in polluting industries face a carbon transition risk, leading to a carbon premium in their returns compared to green stocks. This premium is expected to increase after the Paris Agreement due to greater investor awareness of climate change. The strength of a country's climate policy also affects the magnitude of the carbon premium, as firms in countries with stricter policies are more likely to transition away from fossil fuels. Bolton and Kacperczyk (2022) examine the carbon premium in recent years, comparing estimated premiums before and after the 2015 Paris Agreement. The analysis reveals no significant premium before the agreement, but a significant and large premium after the agreement. They suggest that investors have only recently become aware of the urgency of climate change. It could also be argued that investors only recently became aware of transition risk they bare when they hold stocks of polluting companies.

Based on the findings by Bolton and Kacperczyk (2022) it can be expected that the unexplained part of the returns when the Fama and French 5-factor model is estimated on the difference in returns between a well-diversified portfolio and a well-diversified portfolio without polluting firms is greater after 2015 then before. Additionally, it is expected that the 5-factor model of Fama and French including the PMC factor will absorb the before mentioned unexplained part of the returns. This translates into the following hypothesis:

Hypothesis 4a) The unexplained part of returns between a well-diversified portfolio with and without high polluting companies is greater after 2015 than before when the Fama and French 5-factor model is estimated.
Hypothesis 4b) The unexplained part of returns between a well-diversified portfolio with and without high polluting companies after 2015 will be better explained by the Fama and French 5-factor model including the PMC factor than before 2015.

In addition to analyzing the difference between the period before and after the 2015 Paris Agreement, the period after 2015 will be analyzed in more detail. The reason is that Covid-19 and the war of Russia in Ukraine might have its impact on returns and levels of risk of polluting versus non-polluting companies.

Wang et al. (2022) showed that Covid-19 has led investors becoming even more cautious and less tolerant of risks. This might have led to have its impact on investment decisions regarding polluting versus clean stocks by investors. It can be expected that the perceived level of carbon risk was higher during Covid-19 period (February 2020-February 2022) than in the period before (from 2015-January 2020) and that due to even more selling pressures during Covid-19 (abnormal) returns of a portfolio including polluting stocks were lower than in the period before Covid-19. This leads to the following hypothesis:

Hypothesis 5: The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the Covid-19 period (February 2020-February 2022) is lower than in the period before Covid-19 (from 2015 to January 2020) and the level of perceived carbon risk is higher.

According to Bauer et al. (2023) the war of Russia in Ukraine led to higher returns for brown than for green stocks due to an unexpected shift in the demand of products from the energy and defense industry. Whether the war also led to a change in the level of perceived carbon risk is unclear. This leads to hypothesis 6:

Hypothesis 6: The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the period that starts with the war of Russia in Ukraine is higher than in the period before this war because it is expected that polluting stocks generates higher (abnormal) returns.

CHAPTER 3 Data

This chapter describes the construction and analysis of the dataset that is used in this research. Section 3.1 gives the data sample including its sources and the construction of the portfolios. In Section 3.2 the descriptive statics of the dependent variables are given. In Section 3.3 the descriptive statistics of the independent variables are given.

3.1 Data sample

In this study it is assumed that a portfolio that consists of the market value weighted constituents of the S&P500 index is a good proxy for the market portfolio in the U.S. The dataset consists of data of companies from the S&P500 index over the period 2008-2022.

For each firm the following items are obtained via DataStream (Eikon): Total Return Index, Market-capitalisation, and Industry. Return data regarding the Fama and French (2015) risk-factors and risk-free interest rates are retrieved from the website of Kenneth R. French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Return data regarding the Huij et al. (2023) risk factor PMC will be downloaded from the website of Remco Zwinkels (https://research.vu.nl/en/persons/remco-zwinkels).

3.2 Descriptive statistics portfolios

A well-diversified portfolio is created by collecting all constituents from the years 2008 to 2022. For each year, the index constituents are identified, and companies with less than 36 observations are removed from the dataset. The All-mP portfolios are then composed based on the PMC beta, which is a proxy for a company's pollution. To create these portfolios, 10%, 30%, and 50% of the companies with the highest PMC beta are removed from the well-diversified portfolio. Excluding 10% of the portfolios is in line with the paper of Swinkels and Blitz (2021). In order to investigate whether the impact is greater when excluding more companies from portfolio All, the hypotheses are also tested when excluding 30% and 50% of firms with the highest beta.

The PMC beta will be estimated for each of the firms included in the S&P500 index over the period 2008-2022. The following model will be estimated:

$$R_{i,t} = a_i + \beta_i^{PMC} PMC_t + \epsilon_{i,t}, \qquad (1)$$

where $R_{i,t}$ is the excess return on stock i in month t, a_i is the intercept, β_i^{PMC} the sensitivity to the factor PMC_t, PMC_t the monthly return on the carbon risk factor, and $\epsilon_{i,t}$ the residual term (Huij et al., 2023).

Table 2 summarizes the descriptive statistics of the portfolios. As more companies are removed from the portfolio, the average monthly return increases (up to 1.718%), but so does the volatility (up to

5.993%) of the portfolio. Additionally, the portfolio with the most excluded companies has the highest and lowest returns (ranging from -21.128% to 22.380%).

Table 2: Descriptive statistics portfolios

The table below presents descriptive statistics for the portfolios All, All-mP 10%, All-mP 30%, and All-mP 50%. Portfolio All includes all companies in a well-diversified portfolio based on the S&P500. Portfolios All-mP 10%, All-mP 30%, and All-mP 50% consist of the same companies as portfolio All, but exclude 10%, 30%, and 50% of the companies with the highest PMC beta, respectively. The mean, standard deviation, minimum, maximum, median of returns for each portfolio are given in percentages, also the skewness and kurtosis are presented.

	All	All-mP 10%	All-mP 30%	All-mP 50%
Mean (%)	1.456	1.504	1.642	1.718
Median (%)	2.189	2.154	2.258	2.107
Maximum (%)	16.779	17.758	20.719	22.380
Minimum (%)	-17.923	-17.412	-19.111	-21.128
Std. Dev. (%)	5.066	5.115	5.724	5.993
Skewness	-0.450	-0.444	-0.394	-0.358
Kurtosis	4.540	4.575	4.726	4.678

3.3 Descriptive statistics asset pricing models

Table 3 presents descriptive statistics for the independent variables used in specific asset pricing models. The differences in returns are explained using different risk factors. The Fama and French (2015) five-factor model, comprising the market, size, value, profitability, and investment risk factors, is used. Additionally, the Carhart (1997) momentum factor is added to the Fama and French factors. To identify polluting companies and to test hypotheses 2B, 4B, 5, and 6, the PMC risk factor is used.

Table 3: Descriptive statistics asset pricing models

The table provides the mean, standard deviation, minimum, maximum, median (in percentages) and the skewness and kurtosis for the risk-free rate (Rf) and risk factors. The risk factors are denoted as RMRF, SMB, HML, RMW, CMA, MOM, and PMC, which represent the market, size, value, profitability, investment, momentum, and polluting factor, respectively.

	RF	RMRF	SMB	HML	RMW	CMA	MOM	PMC
Mean (%)	0.042	1.017	-0.025	-0.140	0.267	0.144	0.148	-0.026
Median (%)	0.010	1.285	0.165	-0.260	0.165	-0.025	0.780	-0.272
Maximum (%)	0.330	13.330	6.360	12.140	6.220	9.680	7.470	8.535
Minimum (%)	0.000	-14.090	-9.810	-10.400	-3.640	-6.470	-25.000	-6.910
Std. Dev. (%)	0.069	4.649	2.405	3.206	1.653	2.125	3.751	2.583
Skewness	1.786	-0.360	-0.104	0.507	0.347	1.045	-2.015	0.555
Kurtosis	5.386	3.500	3.930	4.597	3.654	6.387	13.872	3.966

CHAPTER 4 Method

This chapter discusses the methodology of the research. For each hypothesis, it will be indicated how it will be tested. First, the methodology of the hypotheses related to the differences in Sharpe ratios will be discussed, followed by methodology of the hypotheses related to differences in returns and finally the impact of the 2015 Paris Agreement and other events.

4.1 Differences in Sharpe ratios

Hypothesis 1) The Sharpe ratio of the well-diversified portfolio with polluting companies is higher than the Sharpe ratio of the well-diversified portfolio without polluting companies.

The first hypothesis is based on the expectation that portfolios that include less securities than the market-portfolio – proxied by the market value weighted average of the constituents of the S&P500 – are inefficient. The expectation is based on the fact that portfolios that exclude (high) polluting companies, are less well diversified and are thus expected to have lower Sharpe ratios.

To test this hypothesis, the difference between the Sharpe ratio of a well-diversified portfolio with polluting companies based on the constituents of the S&P500 index (All) and that of a similar portfolio excluding (high) polluting companies (All-mP) will be determined. Both portfolios are market value weighted portfolios.

Sharpe ratios of both portfolios (All and All-mP) will be estimated over the whole sample period and over shorter periods.

The Sharpe ratio is defined as:

$$Sharpe\ Ratio_i = \frac{Portfolio\ Excess\ Return_i}{Portfolio\ Volatility_i} = \left(\frac{E_i - R_f}{\sigma_i}\right) \qquad (2)$$

Where E_i is the average return of portfolio *P* over period *a-b*, R_f is the risk-free return and σ_i the standard deviation of the returns. Expected is that the Sharpe ratio of All is greater than that of All-mP.

To determine whether the difference between the Sharpe ratio of portfolio All and All-mP is significantly different from zero, the test statistic developed by Jobson and Korkie (1981), which has been adjusted by Memmel (2003) will be applied:

$$Z_{JK} = \frac{\hat{S}R_{All} - \hat{S}R_{All-mP}}{\sqrt{\hat{V}}} \qquad (3)$$

Where $\hat{S}R_{All}$ is the Sharpe ratio of the well-diversified portfolio with polluting companies based on the constituents of the S&P500 index. $\hat{S}R_{All-mP}$ is the Sharpe ratio of the similar portfolio excluding (high) polluting companies and $\hat{V}$ the asymptotic variance of the difference in those Sharpe ratios, and calculated as follows (Memmel, 2003):

$$\hat{V} = \frac{1}{T}\left[2 - 2\rho_{All,All-mP} + \frac{1}{2}\left(\hat{S}R_{All}^2 + \hat{S}R_{All-mP}^2 - 2\hat{S}R_{All}\hat{S}R_{All-mP}\rho_{All,All-mP}^2\right)\right] \qquad (4a)$$

Where $\rho_{All,All-mP} = \frac{\sigma_{All,All-mP}}{\sigma_{All}\sigma_{All-mP}}$ is the correlation between the returns of portfolios All and All-mP over the period 2008-2022. $\sigma_{All,All-mP}$ is the covariance between the returns of All and All-mP, σ_{All} and σ_{All-mP} are respectively the standard deviations of the returns of portfolios All and All-mP, and T is the total number of periods for which the returns are observed.

To further examine the differences in Sharpe ratios, differences in the means of the excess returns and the volatility of the returns of the two portfolios are also analyzed. To test whether the difference in means of the excess returns between portfolios All and All-mP is significant, a one-sample t-test is conducted. To test if the standard deviations significantly differ from each other, a Levene's test (1960) is performed.

In addition to the Jobson and Korkie test (1981) a mean-variance spanning test is applied to analyze the performance of the portfolio including polluting companies relative to the performance of the portfolio excluding polluting companies. The following model will be estimated:

$$R_{All,t} = a_i + \beta_{All}R_{All-mP,t} + \epsilon_{i,t} \qquad (4b)$$

Where $R_{All,t}$ is the excess return of portfolio All in month t, a_i is the intercept, $R_{All-mP,t}$ is the excess return of portfolio All-mP in month t and $\epsilon_{i,t}$ is the residual term. If the performance of portfolio All equals the performance of portfolio All-mP it is expected that a_i is 0 and β_{All} is 1.

4.2 Differences in returns

Hypothesis 2.A) The difference in returns between the well-diversified portfolio with and without high polluting companies is partially explained by the five-factor model of Fama and French (2015).

The second hypothesis is based on the expectation that polluting firms might have generated different returns than that of none or less polluting firms. In order to analyze the effect of excluding (high) polluting firms from a well-diversified portfolio on the return of the portfolio, the difference between the returns of All and All-mP will be calculated (defined as "AllMAll-mP"). Next, it will be analyzed whether the returns of this AllMAll-mP portfolio can be explained by the five-factor model of Fama and French (2015). As described in Section 4.1 All-mP is a market value weighted portfolio consisting of the constituents of the S&P500 minus firms that are part of the highest 10%, 30%, or 50% of firms ranked by their estimated carbon beta.

The following model will be estimated:

$$R_{i,t} = a_i + \beta_i^{RMRF}\, RMRF_t \; + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \epsilon_{i,t} \quad (5)$$

Where $R_{i,t}$ is the excess return of the AllMAll-mP portfolio *I* in month *t*, a_i is the portfolio's risk-adjusted outperformance, β's denote sensitivities to the factors: $RMRF_t$, SMB_t, HML_t, RMW_t, and CMA_t are respectively the monthly returns on the market, size, value, profitability, and investment, and $\epsilon_{i,t}$ is the residual term.

Hypothesis 2.B) Returns that cannot be explained by the five factors of Fama and French (2015) may be attributed to the risk factor PMC, as introduced by Huij et al. (2023).

If investments in (high) polluting firms are rewarded by a positive risk premium – as presented by Huij et al. (2023), a positive alpha is expected to be found. Next, the 5-factor model of Fama and French including the PMC factor will be estimated. It is expected that by including the PMC factor the abnormal return will not be found. A risk premium for this factor would be the explanation.

The following model will be estimated:

$$R_{i,t} = a_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{PMC} PMC_t + \epsilon_{i,t} \quad (6)$$

The regressors in this equation are like the regressors in the Equation (5). In Equation (6) the PMC factor is included. This factor, PMC_t, the monthly return on the carbon risk factor.

If a significant positive alpha remains this might, indicate that positive abnormal returns are generated by polluting companies or that the pricing model is incomplete.

4.3 The 2015 Paris Agreement and other events

Hypothesis 3) The difference between the Sharpe ratio of a well-diversified portfolio with polluting companies and of the well-diversified portfolio without polluting companies is in the period before the 2015 Paris Agreement greater than in the period thereafter.

To test the third hypothesis, the difference of the Sharpe ratios between All and All-mP before 2015 Paris Agreement (PA) and after 2015 Paris Agreement will be analyzed. It is expected that the difference after 2015 is smaller than before 2015 because of lower returns for (high) polluting companies during the period after 2015.

To test whether the difference between the differences of the Sharpe ratios is statistically significant different from zero, the difference in returns of All and All-mP before PA and after PA will be calculated. The first and second mentioned set of returns is referred to as AllMAll-mP_beforePA and AllMAll-mP_afterPA, respectively.

For each set the Sharpe ratio will be calculated following Equation (2). To determine whether the difference between the Sharpe ratio of AllMAll-mP_beforePA and AllMAll-mP_afterPA is significantly different from zero, a similar test statistic as presented in Equation (3) will be applied:

$$Z_{JK} = \frac{\hat{S}R_{\mathrm{AllMAll-mP}\,before\ PA} - \hat{S}R_{\mathrm{AllMAll-mP}\,after\ PA}}{\sqrt{\hat{V}}} \tag{7}$$

Where $\hat{S}R_{AllMAll-mP\ before\ PA}$ is the Sharpe ratio of the difference in returns of All and All-mP before PA, $\hat{S}R_{AllMAll-mP\ \ after\ PA}$ is the Sharpe ratio of the difference in returns of All and All-mP after PA and $\hat{V}$ the asymptotic variance of the difference in those Sharpe ratios, and calculated as follows (Memmel, 2003):

$$\begin{aligned}&\hat{V}\\&= \frac{1}{T}\Big[2 - 2\rho_{\mathrm{AllMAll-mP}\,before,PA\ \mathrm{AllMAll-mP}\,after\ PA}\\&+ \frac{1}{2}\big(\hat{S}R^2_{\mathrm{AllMAll-mP}\,before\ PA} + \hat{S}R^2_{\mathrm{AllMAll-mP}\,after\ PA}\\&- \ 2\hat{S}R_{\mathrm{AllMAll-mP}\,before\ PA}\hat{S}R_{\mathrm{AllMAll-mP}\,after\ PA}\rho^2_{\mathrm{AllMAll-mP}\,before\ PA,\mathrm{AllMAll-mP}\,after\ PA}\big)\Big]\end{aligned} \tag{8}$$

Where $\rho_{AllMAll-mP\ before,PA\ LSR\ after\ PA} = \frac{\sigma_{\mathrm{AllMAll-mP}\,before\ PA,\ \mathrm{AllMAll-mP}\ \,after\ PA}}{\sigma_{\mathrm{AllMAll-mP}\,before\ PA}\sigma_{\mathrm{AllMAll-mP}\,after\ PA}}$ is the correlation between the returns of AllMAll-mP_beforePA and AllMAll-mP_afterPA, $\sigma_{\mathrm{AllMAll-mP}\,before\ PA,\mathrm{AllMAll-mP}\,after\ PA}$ is the covariance between the returns of AllMAll-mP_beforePA and AllMAll-mP_afterPA, $\sigma_{AllMAll-mP\ before\ PA}$ and $\sigma_{AllMAll-mP\ after\ PA}$ are the standard deviations of the returns of AllMAll-mP_beforePA and AllMAll-mP_afterPA respectively, and T is the total number of periods for which the returns are observed.

In addition to the Jobson and Korkie test the mean-variance spanning test will be applied (see Equation 4b).

Hypothesis 4a) The unexplained part of returns between a well-diversified portfolio with and without high polluting companies is greater after the 2015 Paris Agreement than before when the Fama and French 5-factor model is estimated.

Hypothesis 4b) The unexplained part of returns between a well-diversified portfolio with and without high polluting companies after the 2015 Paris Agreement will be better explained by the Fama and French 5-factor model including the PMC factor than before the 2015 Paris Agreement.

To test hypothesis 4a, the returns of the portfolio AllMAll-mP are again analyzed. First, the 5-factor model of Fama and French is estimated over the period 2008-2022 but now including a 2015 Paris Agreement Dummy. This dummy (*Dum*) is 1 for all observations after the 2015 Paris Agreement.

$$R_{i,t} = a_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{DUM} Dum + \epsilon_{i,t} \quad (9)$$

It is expected that the unexplained part is greater after the 2015 Paris Agreement than before which implies that the expected sign of β_i^{DUM} is positive.

To test hypothesis 4b, the 5-factor model of Fama and French is estimated including the PMC factor over the period 2008-2022 including an intercept and slope dummy which is 1 for all observations after the 2015 Paris Agreement. The intercept dummy changes the level of alpha, whereas the slope dummy adjusts the coefficient of risk factor PMC. If $PMC_t\ Dum$ is equal to 1, alpha is equal to a_i plus β_i^{DUM} and the coefficient of PMC is then equal to the sum of β_i^{PMC} and β_i^{PMCDum}.

$$R_{i,t} = a_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{PMC} PMC_t + \beta_i^{DUM} Dum + \beta_i^{PMCDum} PMC_t\ Dum + \epsilon_{i,t} \quad (10)$$

Because it is expected that the perceived level of carbon risk after the 2015 Paris Agreement is greater than before the 2015 Paris Agreement, the expected sign of β_i^{PMCDum} is positive. It is expected that the coefficient β_i^{DUM} of the intercept dummy is negative. This is due to the lower returns for high-polluting companies caused by price pressure effects. As described in Section 2.4. The higher slope dummy captures the higher level of perceived risk, and the lower intercept dummy should capture the price pressure effect.

Hypothesis 5: The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the Covid-19 period (February 2020-February 2022) is lower than in the period before Covid-19 (from 2015 to January 2020) and the level of perceived carbon risk is higher.

To test hypothesis 5, the 5-factor model of Fama and French is estimated including the PMC factor over the period 2015-2022 including an intercept and slope dummy which is 1 for all observations starting February 2020 (start of Covid-19) until February 2022. In order to exclude the effect of PA the sample is limited to the period after PA only.

$$R_{i,t} = a_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{PMC} PMC_t + \beta_i^{DUM} Dum + \beta_i^{PMCDum} PMC_t Dum + \epsilon_{i,t} \tag{11}$$

Because it is expected that the perceived level of carbon risk during Covid-19 is greater than in the period 2015 to January 2020, the expected sign of β_i^{PMCDum} is positive. It is expected that the coefficient β_i^{DUM} of the intercept dummy is negative. This is again due to the lower returns for high-polluting companies caused by price pressure effects. The higher slope dummy captures the higher level of perceived risk, and the lower intercept dummy should capture the price pressure effect.

According to Bauer et al. (2023) the war of Russia in Ukraine led to higher returns for brown stocks than for green stocks due to an unexpected shift in the demand of products from the energy and defense industry. This leads to hypothesis 6:

Hypothesis 6: The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the period that starts with the war of Russia in Ukraine is higher than in the period before this war because it is expected that polluting stocks generates higher (abnormal) returns.

To test hypothesis 6, the 5-factor model of Fama and French is estimated including the PMC factor over the period 2015-2022 including an intercept and slope dummy which is 1 for all observations starting February 2022 (start of war) until December 2022.

$$R_{i,t} = a_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{PMC} PMC_t + \beta_i^{DUM} Dum + \beta_i^{PMCDum} PMC_t Dum + \epsilon_{i,t} \tag{12}$$

It is expected that the coefficient β_i^{DUM} of the intercept dummy is positive because during the war certain polluting firms performed unexpectedly better because of the (perceived) shift in demand for its products. Because it is unclear what the impact of the war is on the level of perceived carbon risk the sign of the coefficient of the slope dummy is unclear.

CHAPTER 5 Results

In this chapter the hypotheses as formulated in Chapter 2 will be tested. In Section 5.1 the results regarding differences in Sharpe ratios between a well-diversified portfolio with polluting companies and a well-diversified portfolio excluding polluting companies will be discussed. To test if these differences significantly differ from zero, the Jobson and Korkie test and the mean-variance spanning test are used. Section 5.2 differences in returns between the before mentioned two portfolios will be explained by different asset pricing models, including, and excluding the PMC factor. In Section 5.3 the impact of the 2015 Paris Agreement, Covid-19 and Russian Ukrainian war on the Sharpe ratios and returns will be presented. Section 5.4 gives a brief summary.

5.1 Differences in Sharpe ratios

This section discusses the results regarding the first hypothesis. Which is as follows: (1) *The Sharpe ratio of the well-diversified portfolio with polluting companies is higher than the Sharpe ratio of the well-diversified portfolio without polluting companies.* Table 4 shows the Sharpe ratios for the well-diversified portfolio (All) and this portfolio excluding polluting companies (All-mP). The table displays the exclusion of polluting companies where 10%, 30%, and 50% of the companies with the highest PMC betas are excluded from the well-diversified portfolio, along with the corresponding average excess returns, standard deviations of the returns, and Sharpe ratios.

Table 4: Results difference in Sharpe ratios
This table reports the average excess returns, standard deviations (SD), and Sharpe ratios of the well diversified portfolio (All) and the well diversified portfolio excluding polluting companies (All-mP). Results are given for the exclusion of 10%, 30%, and 50% of the companies which have the highest PMC beta. The differences between the two portfolios (All and All-mP) are shown and the P-values of these differences are given.

	Percentage Exclusion Polluting (PMC)	All	All-mP	Difference	P-value difference
Average excess return	10%	0.0141	0.0146	-0.0005	0.0832
SD-returns	10%	0.0507	0.0511	-0.0005	0.9239
Sharpe ratio	10%	0.2792	0.2859	-0.0067	0.1685
Average excess return	30%	0.0141	0.0160	-0.0019	0.0148
SD-returns	30%	0.0507	0.0572	-0.0066	0.2652
Sharpe ratio	30%	0.2792	0.2796	-0.0004	0.4880
Average excess return	50%	0.0141	0.0168	-0.0026	0.0171
SD-returns	50%	0.0507	0.0599	-0.0093	0.0893
Sharpe ratio	50%	0.2792	0.2798	-0.0006	0.4880

The results show that excluding the 10% most polluting companies from the portfolio does not lead to a significant difference in the Sharpe ratios (p-value = 0.1685)[1]. Even when 30% or 50% of the most polluting companies are excluded from the well-diversified portfolio, there is no significant difference between the Sharpe ratios of the portfolio that contains all companies and the portfolio that excludes these most polluting companies. The expected effect of reduced diversification is not strong enough to significantly differentiate the Sharpe ratios from each other. Therefore, based on the analysis of the differences in Sharpe ratios hypothesis 1 is rejected.

This result is consistent with previous research conducted by Humphrey and Tan (2014), who excluded sin stocks from their portfolio identified by SIC/NAICS or by KLD, and Alessandrini and Jondeau (2019), who excluded companies based on their ESG score. Both studies concluded that excluding certain stocks from a portfolio had no effect on its Sharpe ratio.

Although there are no significant differences between the Sharpe ratios, the differences between the excess returns of the two portfolios are significant. The differences are -0.05%, -0.19%, and -0.26% with p-values of 8.3%, 1.5%, and 1.7% respectively for excluding 10%, 30%, or 50% of the companies which have the highest PMC beta of the portfolio.

These differences imply that the excess return of portfolio All is less than the excess return of portfolio All-mP. As expected, the risk of portfolios All-mP is greater than the risk of portfolios All. But only when excluding 50% of the portfolio this difference is statistically significant at a 10% level.

To further analyze the results, the mean-variance spanning test is performed (see Equation 4b). When excluding 10% of the portfolio based on the PMC beta the results of the mean-variance spanning test does not reveal a difference in the performance either. The estimated intercept (0.000) is not significantly different from zero and β_{All} (0.987) is not significantly different from 1. When excluding 30% and 50% of the portfolio the results confirm that the excess return of the portfolio including polluting companies realize on average lower excess returns than a portfolio excluding polluting companies. In both cases the intercept is 0.000 and not significant, while β_{All} is 0.873 when excluding 30% of the portfolio and 0.822 when excluding 50% of the portfolio. Both coefficients differ significantly from 1 with a significance level lower than 1%.

[1] When returns are not normally distributed, such as with hedge funds, Ardia and Boudt (2015) suggest comparing modified Sharpe ratios instead of standard Sharpe ratios. In their study of hedge fund performance, they found that the percentage of disagreement between the Sharpe ratio and modified Sharpe ratio regarding equal performance ranged from 5% to 14% for hedge funds following non-Relative Value styles, and 22% for those following the Relative Value Style. The level of kurtosis in the sample used in this thesis is around 4.5-4.7, which is less severe than the level observed for the hedge funds analyzed by Ardia and Boudt (2015). They showed a level of kurtosis of 9.34 for the Relative Value Style and an average level of kurtosis of all hedge funds analyzed of 5.82. Still the results should be interpreted taking this in consideration.

5.2 Differences in returns

In this section the results regarding the hypotheses 2.A and 2.B are discussed. Hypothesis 2.A is formulated as: *The difference in returns between the well-diversified portfolio with and without high polluting companies is partially explained by the five-factor model of Fama and French (2015)* and Hypothesis 2.B as: *Returns that cannot be explained by the five factors of Fama and French (2015) may be attributed to the risk factor PMC, as introduced by Huij et al. (2023).* Table 5 presents the results of models estimated following Equations (5) and (6) as presented in Section 4.2. In the models the difference between the returns of portfolios All and All-mP (defined as AllMAll-mP) is the dependent variable. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. In models [1], [3], and [5] the coefficient of factor CMA is statistically significant. In models [3] and [5] the market factor and profitability factor RMW are in addition to the CMA factor significant as well.

Table 5: Results regression five-factor model of Fama and French including and excluding PMC
This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	0.000	0.000	-0.002**	-0.001	-0.002**	-0.002*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.005	-0.012	-0.093***	-0.108***	-0.135***	-0.150***
	(0.008)	(0.008)	(0.015)	(0.016)	(0.021)	(0.023)
SMB	-0.002	0.017	-0.035	0.001	-0.006	0.032
	(0.019)	(0.019)	(0.042)	(0.040)	(0.050)	(0.051)
HML	0.022	-0.007	-0.007	-0.060	0.023	-0.033
	(0.023)	(0.024)	(0.052)	(0.056)	(0.066)	(0.073)
RMW	-0.018	-0.077***	0.090*	-0.022	0.136**	0.018
	(0.024)	(0.024)	(0.054)	(0.061)	(0.065)	(0.072)
CMA	0.060*	0.011	0.239**	0.146**	0.392***	0.294***
	(0.034)	(0.029)	(0.080)	(0.066)	(0.105)	(0.092)
PMC		0.103***		0.195***		0.205***
		(0.019)		(0.041)		(0.058)
Adjusted R^2	0.157	0.302	0.442	0.527	0.515	0.559
Sample size	170	170	170	170	170	170

The results of models [2], [4], and [6] show that factor PMC has explanatory power. The coefficient of PMC is in each of these models significant at the 1% level. In models [3] and [5] the alpha, which represents the abnormal return of the portfolio AllMAll-mP is negative and significantly different from zero. In models [4] and [6] alpha becomes insignificant or less significant by including PMC. As expected, by adding the PMC factor to the model the abnormal returns captured by alpha in models [3] and [5] are (partly) explained by this additional risk factor. These finding confirms hypothesis 2.A and 2.B.

In addition to the five-factor model of Fama and French, the Carhart model (1997) including and excluding PMC is estimated. Table 6 presents the results. As in Table 5 factor PMC has a coefficient that is significant at the 1% level, which again contributes to the explanatory power of the model. Factor momentum is in models [3], [4], [5], and [6] statistically significant. In none of the models, alpha deviates significantly from zero. It seems as if the factor momentum is able to explain part of the abnormal returns as shown in models [3], [5], and [6] of Table 5. In appendix A.1 the results of the five-factor model of Fama and French including momentum and including and excluding PMC are presented. Results are comparable to the results in Table 5.

Table 6: Results regression Carhart model including and excluding PMC

This table shows the results of the regression of AllMAll-mP on the Carhart model including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, MOM_t, and PMC_t are respectively the monthly returns on the market, size, value, momentum, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	0.000	0.000	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.005	-0.010	-0.092***	-0.107***	-0.139***	-0.158***
	(0.009)	(0.008)	(0.017)	(0.017)	(0.023)	(0.024)
SMB	0.000	0.030	-0.074**	0.009	-0.071	0.034
	(0.017)	(0.019)	(0.034)	(0.034)	(0.044)	(0.045)
HML	0.063***	0.023	0.144***	0.034	0.260***	0.120***
	(0.013)	(0.017)	(0.021)	(0.029)	(0.027)	(0.043)
MOM	0.022	0.016	0.077**	0.060**	0.096***	0.074**
	(0.017)	(0.016)	(0.032)	(0.028)	(0.033)	(0.029)
PMC		0.076***		0.209***		0.265***
		(0.020)		(0.041)		(0.060)
Adjusted R^2	0.157	0.267	0.393	0.535	0.427	0.535
Sample size	170	170	170	170	170	170

5.3 Effect of external events

In this section the results are presented regarding the effect of external events on the Sharpe ratios and returns of portfolio All and portfolio All-mP. In section 5.3.1 effects of the 2015 Paris Agreement on the Sharpe ratios of portfolio All and portfolio All-mP are discussed. In sections 5.3.2, 5.3.3, and 5.3.4 the effect on returns of the 2015 Paris Agreement. Covid-19 and the war of Russia in Ukraine are respectively analyzed.

5.3.1 Effect of the 2015 Paris Agreement on Sharpe ratios

In this section hypothesis 3 will be tested: *The difference between the Sharpe ratio of a well-diversified portfolio with polluting companies and of the well-diversified portfolio without polluting companies is in the period before the 2015 Paris Agreement greater than in the period thereafter*. As in Table 4, Table 7 presents the Sharpe ratios of portfolio All and portfolio All—mP. The difference is that in Table 7 results are presented for the period before (Panel A) and the period after (Panel B) the 2015 Paris Agreement (PA). The differences in Sharpe ratios of portfolio All and portfolio All-mP are before as well as after PA for each of the three exclusions (10%, 30%, and 50%) not significantly different from zero. It seems like the anticipated impact of losing diversification by excluding polluting companies is not significant enough to yield meaningful results. The risk of portfolio All-mP is in most cases greater than the risk of portfolio All, but the differences are not significant. The differences in average excess returns are before PA statistically significant at the 1% level. After PA these differences are smaller and less significant. The results confirm the findings from Table 4. In addition to the analysis of the differences between the Sharpe ratios of portfolio All and All-mP the mean-variance spanning test is done. The results show that – before as well as after the 2015 Paris Agreement excluding 10% - the performance of All is equal to All-mP. The estimated intercept is 0.001 before PA and 0.000 after PA. Both coefficients are insignificant. β_{All} is 0.977 before and 1.000 after PA and not significantly different from 1. When excluding 30% or 50% of the portfolio the constant remains close to 0.000 and β_{All} decreases to 0.839 and 0.806 before and 0.921 and 0.843 after PA, respectively. All coefficients differ significantly from 1.

To test whether the difference between the Sharpe ratio of portfolio All and portfolio All-mP, before and after PA is significantly different the test statistic Z_{jk} (see Equation 7) is applied. When for example excluding 10% of the portfolio, the difference in Sharpe ratios before PA is -0.0119 and after PA is -0.0010. According to this test, the differences are not significantly different when excluding 10%, 30%, and 50% of the portfolio based on the PMC beta with p-values of 0.128, 0.203, 0.251, respectively. This means that hypothesis 3 is rejected.

Table 7: Results Sharpe ratio for the period before and after Paris Agreement
This table reports the average excess returns, standard deviations (SD), and Sharpe ratios of the well diversified portfolio (All) and the well diversified portfolio excluding polluting companies (All-mP). Results are given for the exclusion of 10%, 30%, and 50% of the companies which have the highest PMC beta. The differences between the two portfolios (All and All-mP) are shown and the P-values of these differences are given. Panel A (B) shows the results for the period before (after) the Paris Agreement.

Panel A: Results for period before Paris Agreement

	Percentage Exclusion Polluting (PMC)	All	All-mP	Difference	p-value difference
Average excess return	10%	0.0158	0.0167	-0.0009	0.0083
SD-returns	10%	0.0523	0.0533	-0.0010	0.9804
Sharpe ratio	10%	0.3012	0.3131	-0.0119	0.1314
Average excess return	30%	0.0158	0.0187	-0.0029	0.0021
SD-returns	30%	0.0523	0.0615	-0.0092	0.3738
Sharpe ratio	30%	0.3012	0.3036	-0.0024	0.4483
Average excess return	50%	0.0158	0.0193	-0.0036	0.0033
SD-returns	50%	0.0523	0.0633	-0.0110	0.2722
Sharpe ratio	50%	0.3012	0.3054	-0.0042	0.4325

Panel B: Results for period after Paris Agreement

	Percentage Exclusion Polluting (PMC)	All	All-mP	Difference	p-value difference
Average excess return	10%	0.0125	0.0126	0.0000	0.0925
SD-returns	10%	0.0492	0.0491	0.0001	0.9095
Sharpe ratio	10%	0.2545	0.2555	-0.0010	0.4562
Average excess return	30%	0.0125	0.0133	-0.0008	0.1090
SD-returns	30%	0.0492	0.0529	-0.0037	0.5035
Sharpe ratio	30%	0.2545	0.2520	0.0025	0.4404
Average excess return	50%	0.0125	0.0142	-0.0017	0.0755
SD-returns	50%	0.0492	0.0566	-0.0074	0.1885
Sharpe ratio	50%	0.2545	0.2507	0.0038	0.4443

5.3.2 Effect of the 2015 Paris Agreement on returns

In this section the effect of the Paris Agreement on the returns of portfolio AllMAll-mP is analyzed. Hypothesis 4a states: *The unexplained part of returns between a well-diversified portfolio with and without high polluting companies is greater after the 2015 Paris Agreement than before when the Fama and French 5-factor model is estimated* and hypothesis 4b states: *The unexplained part of returns between a well-diversified portfolio with and without high polluting companies after the 2015 Paris Agreement will be better explained by the Fama and French 5-factor model including the PMC factor than before the 2015 Paris Agreement.*

In order to test hypothesis 4a the model as presented in Equation 9 in Section 4.3 is estimated. This model includes an intercept dummy (PA Dummy) which is 1 for all observations after the 2015 Paris Agreement and 0 before. As shown in Table 8 the coefficient of the PA Dummy in models [1], [3], and [5] is insignificant. This implies that the unexplained alpha after PA is not greater than before PA and that hypothesis 4a is rejected.

To test hypothesis 4b the model as presented in Equation 10 in Section 4.3 is estimated. This model includes the intercept dummy PA Dummy as well as PA Dummy as interaction term with PMC. As shown in models [2], [4], and [6] the coefficient of the interaction term is negative and significantly different from zero. This implies that the level of carbon risk after the 2015 Paris Agreement is lower than before, while a higher level was expected. A possible explanation might be that the market is convinced that because of the 2015 Paris Agreement high polluting companies will take actions to realize the goals as defined in the 2015 Paris Agreement. The intercept dummy is insignificant for all models, which means that negative price pressure is not observed in this sample with this model.

These results go against the findings of Monasterolo and De Angelis (2020), who argued that carbon-intensive assets have become riskier after the signing of the 2015 Paris Agreement. Furthermore, Bolton and Kacperczyk (2022) found no significant carbon premium before the Paris Agreement but did find a significant and substantial carbon premium after its signing.

Table 8: Results regression Fama and French five factors, PA Dummy, and PA Slope Dummy including and excluding PMC

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. PA Dummy is 1 for all months after the 2015 Paris Agreement. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	-0.001	-0.000	-0.002*	-0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.005	-0.009	-0.093***	-0.099***	-0.135***	-0.137***
	(0.008)	(0.007)	(0.015)	(0.016)	(0.021)	(0.021)
SMB	-0.002	0.018	-0.035	0.005	-0.006	0.038
	(0.019)	(0.0189)	(0.042)	(0.037)	(0.050)	(0.046)
HML	0.022	-0.003	-0.006	-0.053	0.023	-0.024
	(0.023)	(0.023)	(0.053)	(0.052)	(0.067)	(0.068)
RMW	-0.018	-0.075***	0.090	-0.016	0.136**	0.026
	(0.024)	(0.023)	(0.055)	(0.057)	(0.065)	(0.066)
CMA	0.058*	0.021	0.237***	0.173**	0.392***	0.335***
	(0.035)	(0.030)	(0.081)	(0.068)	(0.107)	(0.093)
PMC		0.160***		0.344***		0.429***
		(0.035)		(0.079)		(0.100)
PA Dummy	0.001	0.000	0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
PA Dummy x		-0.089**		-0.228***		-0.336***
PMC		(0.034)		(0.084)		(0.100)
Adjusted R^2	0.158	0.340	0.438	0.573	0.531	0.608
Sample size	170	170	170	170	170	170

In addition to the five-factor model of Fama and French, the Carhart model including and excluding PMC is estimated with a PA intercept Dummy and/or a PA slope Dummy. The results are presented in Table 9 and are similar to the results as presented in Table 8. The results of model [2], [4], and [6] in Table 9 show again that the coefficient of the interaction term is negative and significantly different from zero hypothesis 4b is again rejected. In appendix A.2, the results of the effect of PA using the five-factor model of Fama and French including momentum and including and excluding PMC are presented. The results are comparable to the results of the other two asset pricing models (five-factor model of Fama and French including and excluding PMC as presented in Table 8 and the Carhart model including and excluding PMC as presented in Table 9).

Table 9: Results regression Carhart model, PA Dummy, and PA Slope Dummy including and excluding PMC

This table shows the results of the regression of AllMAll-mP on the Carhart model including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, MOM_t, and PMC_t are respectively the monthly returns on the market, size, value, momentum, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. PA Dummy is 1 for all months after the 2015 Paris Agreement. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	-0.001	-0.000	-0.001	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
RMRF	-0.005	-0.008	-0.092***	-0.102***	-0.139***	-0.151***
	(0.009)	(0.008)	(0.035)	(0.017)	(0.023)	(0.023)
SMB	0.001	0.031*	-0.073**	0.011	-0.071	0.037
	(0.017)	(0.019)	(0.031)	(0.032)	(0.045)	(0.0425)
HML	0.062***	0.029*	0.143***	0.047*	0.259***	0.138***
	(0.0123)	(0.016)	(0.021)	(0.028)	(0.027)	(0.040)
MOM	0.021	0.014	0.076**	0.057**	0.096***	0.070**
	(0.017)	(0.016)	(0.031)	(0.0278)	(0.033)	(0.030)
PMC		0.134***		0.345***		0.461***
		(0.036)		(0.081)		(0.109)
PA Dummy	0.001	0.000	0.001	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
PA Dummy x PMC		-0.085***		-0.195**		-0.276***
		(0.032)		(0.080)		(0.101)
Adjusted R^2	0.158	0.303	0.392	0.567	0.423	0.556
Sample size	170	170	170	170	170	170

5.3.3 Effect of Covid-19 on returns

In this section the effect of Covid-19 is analyzed for the sample period after the 2015 Paris Agreement. Hypothesis 5 is tested: *The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the Covid-19 period (February 2020-February 2022) is lower than in the period before Covid-19 (from 2015 to January 2020) and the level of perceived carbon risk is higher.* To test hypothesis 5 the model as presented in Equation 11 in Section 4.3 is estimated. The results are presented in Table 10. Because the coefficient of the Covid-19 Dummy is insignificant, the expected price pressure which would result in a lower abnormal return during the Covid-19 period is not present. The slope Dummy in model [2] and [3] is negative and significant at the 5% and 10% level, respectively. This result is in contradiction to what was expected as well. According to Wang et al. (2022), there has been an increase in investors' caution and lower risk tolerance due to the impact of Covid-19. Because it was expected that the level of carbon risk during Covid-19 was greater, a positive slope dummy was expected. Given the results hypothesis 5 is rejected. A possible explanation for the negative slope dummy is that during Covid-

19, the capital market might assume that high polluting firms will take decisions to reduce their negative impact on climate change which results in a lower level of carbon risk for those companies.

Table 10: Results regression Fama and French five factors, PMC, Covid-19 Dummy, and Covid-19 Slope Dummy

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. Covid-19 Dummy is 1 for all months between February 2020 and February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.001)
RMRF	-0.000	-0.059***	-0.109***
	(0.007)	(0.015)	(0.027)
SMB	0.032*	0.014	0.054
	(0.016)	(0.032)	(0.059)
HML	0.019	0.051	0.127**
	(0.016)	(0.031)	(0.054)
RMW	-0.075***	0.006	0.088
	(0.018)	(0.038)	(0.064)
CMA	0.028	0.117***	0.223***
	(0.023)	(0.040)	(0.074)
PMC	0.058***	0.093***	0.075
	(0.015)	(0.033)	(0.056)
Covid-19 Dummy	0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.002)
Covid-19 Dummy x PMC	-0.021	-0.085**	-0.117*
	(0.024)	(0.037)	(0.066)
Adjusted R^2	0.669	0.700	0.691
Sample size	85	85	85

In addition to the five-factor model of Fama and French, the Carhart model including PMC is estimated with a Covid-19 intercept Dummy as well as a Covid-19 slope Dummy. The results in Table 11 confirm that hypothesis 5 should be rejected, because the coefficient of the intercept Dummy is in each model insignificant. The slope Dummy is has the opposite sign as expected and is significant different from zero in models [2] and [3]. In Table A.3 in the Appendix, the results when using the five-factor model of Fama and French including momentum and PMC and the Covid-19 variables are presented. The results are similar to the results of the same model without momentum (see Table 10).

Table 11: Results regression Carhart model. PMC, Covid-19 Dummy, and Covid-19 Slope Dummy
This table shows the results of the regression of AllMAll-mP on the Carhart model including PMC. The variables, $RMRF_t$, SMB_t, HML_t, MOM_t, and PMC_t, are respectively the monthly returns on the market, size, value, momentum, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas. Respectively, Covid-19 Dummy is 1 for all months between February 2020 and February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)
RMRF	0.001	-0.063***	-0.121***
	(0.008)	(0.014)	(0.028)
SMB	0.052***	0.015	0.035
	(0.018)	(0.034)	(0.058)
HML	0.057***	0.111***	0.213***
	(0.015)	(0.023)	(0.043)
MOM	0.030***	0.032	0.025
	(0.010)	(0.025)	(0.053)
PMC	0.046***	0.127***	0.161***
	(0.016)	(0.033)	(0.054)
Covid-19 Dummy	0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.002)
Covid-19 Dummy x PMC	-0.040	-0.094**	-0.116*
	(0.026)	(0.037)	(0.064)
Adjusted R^2	0.631	0.680	0.651
Sample size	85	85	85

5.3.4 Effect of the war of Russia in Ukraine on returns

In this Section the effect of the war of Russia in Ukraine on the Returns of AllMAll-mP is investigated. Most specifically hypothesis 6 is tested: *The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the period that starts with the war of Russia in Ukraine is higher than in the period before this war because it is expected that polluting stocks generates higher (abnormal) returns.* In order to test hypothesis 6, the five-factor model of Fama and French including the PMC factor as presented in Equation 12 in Section 4.3 is estimated. The model includes a War Dummy which equals 1 for all observations starting after February 2022 until December 2022. The expected sign of the intercept dummy is positive because according to Bauer et al. (2023) the war of Russia in Ukraine let to higher returns for brown stocks than for green stocks. In addition to the intercept dummy the model includes an interaction term as well in order to observe whether the perceived level of carbon risk during the period of war is different than in the period before the war.

Table 12: Results regression Fama and French five factors, PMC, War Dummy, and War Slope Dummy
This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t, are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. War Dummy is 1 for all months after February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.001	-0.002
	(0.000)	(0.001)	(0.001)
RMRF	0.001	-0.059***	-0.107***
	(0.006)	(0.018)	(0.030)
SMB	0.030**	0.016	0.053
	(0.015)	(0.036)	(0.067)
HML	0.019	0.043	0.116**
	(0.014)	(0.031)	(0.055)
RMW	-0.080***	-0.017	0.052
	(0.016)	(0.041)	(0.069)
CMA	0.023	0.120***	0.232***
	(0.019)	(0.040)	(0.079)
PMC	0.048***	0.063*	0.033
	(0.015)	(0.036)	(0.059)
War Dummy	0.001	0.002	0.003
	(0.001)	(0.001)	(0.003)
War Dummy x PMC	0.009	-0.008	-0.038
	(0.020)	(0.050)	(0.093)
Adjusted R^2	0.705	0.675	0.675
Sample size	85	85	85

Table 12 presents the results over the period after the 2015 Paris Agreement. The coefficient of the intercept War Dummy is insignificant, which is contradicting hypothesis 6. The coefficient of the interaction term is insignificant as well, which means that the war has no impact on the perceived level of carbon risk. The results for the two other asset pricing models Carhart including PMC and the five-factor model of Fama and French including momentum and PMC are similar to those presented in Table 12. The results are included in appendix A.4 and Appendix A.5.

When comparing the impact of the external events - the 2015 Paris Agreement, Covid-19, and the Russian war in Ukraine - it is noted that the coefficient of the interaction term with PMC for each event is negative. This means that the level of carbon risk during Covid-19 and the Russian Ukrainian war and after the 2015 Paris Agreement is perceived as relatively low. This is opposite to what was expected. It seems that companies during these periods are more focused on climate change than before and that investors expect high polluting companies to take actions to mitigate transition risk. Regarding the 2015 Paris

Agreement, the highest negative coefficient for the interaction term between the Dummy and the PMC factor was found in comparison with Covid-19 and the Russian war in Ukraine, namely -0.089 at a 5% significance level when 10% of the portfolio is excluded. For the Covid-19 Dummy x PMC and the War Dummy x PMC, the coefficients are -0.021 and 0.009 respectively, and the coefficients were not significantly different from 0.

5.4 Robustness checks

This section examines how certain assumptions may impact the results of the analysis regarding the returns of the portfolio containing all firms and the portfolio excluding polluting firms, as explained by the asset pricing models. The first robustness check reevaluates the results if different choices regarding the impact of the Paris Agreement are made. The second analysis examines how the choice regarding the Covid-19 Dummy has its influence on the estimated coefficients. The last paragraph investigates what the impact of the choice of polluting companies is on the results. Instead of the PMC beta the Environmental Pillar Score are used to exclude polluting companies from the well-diversified portfolio.

5.4.1 The 2015 Paris Agreement Dummy

The 2015 Paris Agreement is an agreement between countries around the world to combat climate change. The US participated in the Conference of Parties, where the agreement was made, in 2015. However, in 2017, President Trump decided to withdraw from the Paris Agreement (announcement date: June 1, 2017). When President Biden took office, he decided to rejoin the Paris Agreement in January 2021 (announcement date: January 20, 2021).

To analyze the impact on an alternative setting of the dummy variable, the dummy variable will be set to 0 for the period from December 2008 to December 2015, 1 for the period from December 2015 to June 2017, 0 for the period from June 2017 to January 2021, and 1 for the period from January 2021 to January 2023. This is different from the setting as formulated in Section 4.3 where the dummy variable was set to 0 for the period before the 2015 Paris Agreement (from December 2008 to December 2015) and 1 for the period after the 2015 Paris Agreement (from December 2015 to January 2023).

The results are presented in Table 13 and are similar to the results in Table 8. The main differences between the results in both tables is (i) the lower level of significance of the interaction term in model [2] in Table 13 compared to model [2] in Table 8 and (ii) the higher level of significance of the alpha in models [3] and [5] in Table 13 compared to models [3] and [5] in Table 8. The results confirm that abnormal returns are explained by the PMC factor.

Table 13: Regression Fama and French five factors, PA Dummy, and PA Slope Dummy including and excluding PMC (Robustness check regarding choice period PA Dummy)
This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. PA Dummy is 1 for the period between December 2015 and June 2017 and the period between January 2021 and January 2023. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	-0.001	-0.000	-0.002**	-0.001	-0.002*	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.004	-0.012*	-0.093***	-0.108***	-0.135***	-0.151***
	(0.008)	(0.007)	(0.015)	(0.015)	(0.021)	(0.022)
SMB	-0.002	0.017	-0.035	0.001	-0.006	0.032
	(0.019)	(0.015)	(0.042)	(0.036)	(0.050)	(0.046)
HML	0.020	-0.004	-0.008	-0.050	0.024	-0.017
	(0.023)	(0.016)	(0.052)	(0.049)	(0.066)	(0.064)
RMW	-0.021	-0.075***	0.088	-0.014	0.137**	0.031
	(0.024)	(0.022)	(0.055)	(0.053)	(0.065)	(0.061)
CMA	0.058*	0.015	0.238***	0.160**	0.392***	0.314***
	(0.035)	(0.024)	(0.081)	(0.064)	(0.106)	(0.088)
PMC		0.112***		0.227***		0.253***
		(0.019)		(0.046)		(0.066)
PA Dummy	0.001	0.000	0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
PA Dummy x		-0.031		-0.100*		-0.143*
PMC		(0.025)		(0.055)		(0.074)
Adjusted R^2	0.158	0.301	0.439	0.534	0.513	0.566
Sample size	170	170	170	170	170	170

5.4.2 The Covid-19 Dummy

The impact of Covid-19 related government measures on the performance of portfolios All and All-mP is measured by including an intercept and slope dummy, which is set to 1 for the period from February 2020 to February 2022. Different results may be obtained for other periods. Since government measures were not always identical in each state, the new period in which the dummy is set to 1 is based on the measures taken by California, the largest state by population. The dummy is set to 1 from March 2020 to January 2021 and from March 2021 to June 2021, because these periods were known as kind of "stay at home" order periods.

Results are presented in Table 14. The results deviate slightly from the results in Table 10. If 50% of the portfolio is excluded a significant alpha is presented when using the new setting for the Covid

Dummy. Another difference is that the slope Dummy is not significant in the new setting. Again, the results confirm that hypothesis 5 should be rejected, because the intercept dummy as well as the slope dummy do not have the expected sign nor the level of significance, except in model [3] where the alpha is negative and significantly different from zero. This might be explained by the expected price pressure when excluding 50% of the companies from the well-diversified portfolio based on the PMC beta.

Table 14: Results regression Fama and French five factors, PMC, Covid-19 Dummy, and Covid-19 Slope Dummy (Robustness check regarding choice period Covid Dummy)

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. Covid-19 Dummy is 1 from March 2020 to January 2021 and from March 2021 to June 2021. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	0.000	-0.001	-0.002*
	(0.000)	(0.001)	(0.001)
RMRF	0.000	-0.060***	-0.111***
	(0.006)	(0.014)	(0.024)
SMB	0.033**	0.018	0.056
	(0.014)	(0.030)	(0.054)
HML	0.016	0.042	0.118**
	(0.014)	(0.028)	(0.047)
RMW	-0.077***	-0.011	0.063
	(0.015)	(0.038)	(0.064)
CMA	0.030	0.126***	0.240***
	(0.020)	(0.037)	(0.067)
PMC	0.054***	0.066**	0.0303
	(0.014)	(0.032)	(0.053)
Covid-19 Dummy	0.000	0.001	0.003
	(0.001)	(0.001)	(0.003)
Covid-19 Dummy x PMC	-0.016	-0.031	-0.040
	(0.021)	(0.033)	(0.062)
Adjusted R^2	0.663	0.675	0.676
Sample size	85	85	85

5.4.3 The Environmental Pillar Score

In the previous analysis, companies with high levels of pollution were identified using the PMC beta. The top 10%, 30%, and 50% of companies with the highest PMC betas were excluded from the well-diversified portfolio. In this section an analysis will be conducted by identifying polluting companies based on the ESG score defined in the Environmental Pillar Score instead of PMC betas. The Environmental Pillar Score is the weighted average rating of a company based on the reported environmental information and resulting scores in three environmental categories (Datastream, n.d.).

The identification of the top 10%, 30%, and 50% of polluting companies will be done for the periods before and after the 2015 Paris Agreement. This is because it is expected that Environmental Pillar Scores will differ for firms before and after the agreement, as companies are more climate-oriented after the agreement. The companies with the 10%, 30%, and 50% lowest Environmental Pillar Scores will be removed from the well-diversified portfolio.

Table 15: Results regression five-factor model of Fama and French including and excluding PMC for the period *before* the 2015 Paris Agreement

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the lowest Environmental Pillar Score. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	0.000	0.000	0.000***	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RMRF	0.001	0.001	0.001	0.008	0.006	0.007
	(0.001)	(0.001)	(0.004)	(0.004)	(0.006)	(0.006)
SMB	0.010***	0.010***	0.030***	0.030***	0.067***	0.069***
	(0.002)	(0.002)	(0.008)	(0.007)	(0.011)	(0.011)
HML	-0.00	-0.001	-0.015	-0.014*	-0.006	-0.008
	(0.003)	(0.003)	(0.010)	(0.008)	(0.013)	(0.013)
RMW	0.005	0.006	0.006	0.007	0.013	0.009
	(0.004)	(0.005)	(0.012)	(0.011)	(0.017)	(0.018)
CMA	-0.004	-0.003	-0.032***	-0.032***	-0.070***	-0.072***
	(0.004)	(0.004)	(0.012)	(0.012)	(0.019)	(0.019)
PMC		-0.001		-0.003		0.007
		(0.004)		(0.009)		(0.015)
Adjusted R^2	0.140	0.130	0.367	0.360	0.481	0.476
Sample size	85	85	85	85	85	85

Table 15 shows the results for the period before the 2015 Paris Agreement and Table 16 the results for the period after the 2015 Paris Agreement. The results in Table 15 show, that when excluding 30% and 50% of the companies from portfolio All based on their Environtal Pillar Score, positive (although low) abnormal returns that are significantly different from zero for the period before the Paris Agreement are realized for portfolio AllMAll-mP. This indicates that polluting companies realizes positive abnormal returns before the period of the 2015 Paris Agreement. When adding the PMC factor to the model these abnormal returns remain and are thus not captured by the PMC risk factor. In Table 16 no significant abnormal returns are shown, this might be explained by price pressure effect after the 2015 Paris Agreement. Another difference between the period before and after the 2015 Paris Agreement is the negative coefficient for the PMC factor in Table 16. It seems as if the perceived level of carbon risk in the period after the 2015 Paris Agreement is lower than in the period before the 2015 Paris Agreement. This last finding is in line with the results in Table 8, where the coefficient of the interaction term was negative and significantly different from zero. In Table 8 however the sum of the coefficient of the PMC factor and the coefficient of the interaction term remains positive, which implies that the beta for PMC is positive, while in Table 16 the total beta for this factor is negative.

Table 16: Results regression five-factor model of Fama and French including and excluding PMC for the period *after* the 2015 Paris Agreement

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, and PMC_t are respectively the monthly returns on the market, size, value, profitability, investment, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the lowest Environmental Pillar Score. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RMRF	-0.001	-0.000	0.003	0.008*	0.009	0.018*
	(0.002)	(0.003)	(0.005)	(0.005)	(0.008)	(0.009)
SMB	0.001	0.000	0.007	-0.001	0.033	0.021
	(0.006)	(0.007)	(0.011)	(0.010)	(0.022)	(0.022)
HML	0.003	0.004	0.016	0.027**	0.010	0.025
	(0.006)	(0.007)	(0.012)	(0.012)	(0.022)	(0.023)
RMW	-0.012*	-0.010	-0.036***	-0.020*	-0.035	-0.011
	(0.007)	(0.008)	(0.012)	(0.012)	(0.027)	(0.025)
CMA	-0.018*	-0.016	-0.018	0.000	-0.017	0.009
	(0.010)	(0.011)	(0.018)	(0.017)	(0.039)	(0.032)
PMC		-0.003		-0.034***		-0.049**
		(0.006)		(0.011)		(0.022)
Adjusted R^2	0.135	0.1261	0.215	0.312	0.136	0.186
Sample size	85	85	85	85	85	85

If the results from Tables 15 and 16 are compared with the results that are presented in Table 5, the main difference is that while in Table 5 the introduction of the PMC factor absorbs alpha (see model [3], [4], [5] and [6] of Table 5). This is not the case in Tables 15 and 16. This means that if the Environmental Pillar Score is used to exclude polluting firms from the well-diversified portfolio hypothesis 3 cannot be confirmed. A possible explanation for the contradicting results is that the average Environmental Pillar Score is not a valid estimate for the categorization of polluting versus not polluting companies (See Bauer et al., 2023 and the discussion in Chapter 1).[2]

[2] When the Sharpe ratios of the portfolio All is compared to the Sharpe ratios of the portfolio All-mP, the results indicate that excluding polluting companies has a marginally negative impact on this performance measure for the period before the Paris Agreement. In the period after the Paris Agreement the exclusion of polluting companies has a marginally positive impact on the Sharpe ratio. In both periods the differences seem to be mainly caused by differences in excess returns of both portfolios.

CHAPTER 6 Conclusion

This research tries to answer the following question:

How does the removal of high polluting companies from a well-dviersified portfolio impact its performance?

The thesis examines the effect of excluding high polluting companies on the performance of a well-diversified portfolio of a passive investor. It is assumed that the S&P500 index represents a well-diversified portfolio for such an investor. Based on the PMC betas the polluting companies are being identified. The PMC beta represents the climate transition risk a company is exposed to. Companies with the highest PMC beta are considered to be the most polluting companies. To create portfolios All-mP 10%, 30%, and 50% of the portfolio is being excluded using the PMC beta. All-mP is a well-diversified portfolio where the high polluting companies are excluded from. The impact of the exclusion is analyzed by comparing the performance of a well-diversified portfolio with (All) and without (All-mP) high polluting companies. Measures to analyze the difference in performance are the Sharpe ratio and unexplained returns, that is the alpha of the asset pricing models. Six hypotheses are being tested, see Table 17.

Table 17: Overview of the hypotheses
The table below presents an overview of the hypotheses tested in this master's thesis. The hypothesis, time period, method, results and if the hypothesis is accepted or rejected are shown per hypothesis. The results shown are the results when 10% of the portfolio is excluded based on the highest PMC score, unless mentioned otherwise. For hypothesis 2.A., 2.B., 4.A., 4.B., 5 and 6 the results are given when using the Fama and French 5-factor model. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Hypothesis	Time period	Method	Results	Accepted or Rejected
1. The Sharpe ratio of the well-diversified portfolio with polluting companies is higher than the Sharpe ratio of the well-diversified portfolio without polluting companies	2008-2022	Comparison Sharpe ratios	Difference Sharpe ratio of All and All-mP = -0.0067 (p-value = 0.1685)	Rejected
2.A. The difference in returns between the well-diversified portfolio with and without high polluting companies is partially explained by the five-factor model of Fama and French (2015)	2008-2022	Asset pricing models	Alpha = 0.000, when excluding 30% or 50% Alpha is in both cases -0.002**	Accepted
2.B. Returns that cannot be explained by the five factors of Fama and French (2015) may be attributed to the risk factor PMC, as introduced by Huij et al. (2023).	2008-2022	Asset pricing models	Coefficient of PMC factor = 0.103*** and Alpha = 0.000, when excluding 30% or 50% the coefficient of PMC factor is 0.195*** and 0.0205***, and Alpha is -0.001 and -0.002*, respectively	Accepted
3. The difference between the Sharpe ratio of a well-diversified portfolio with polluting companies and of the well-diversified portfolio without polluting companies is in the period before the 2015 Paris Agreement greater than in the period thereafter.	2008-2022	Comparison Sharpe ratios	Difference in Sharpe ratios before PA is -0.0119 and after PA is -0.0010 (p-value difference = 0.128)	Rejected

4.A. The unexplained part of returns between a well-diversified portfolio with and without high polluting companies is greater after the 2015 Paris Agreement than before when the Fama and French 5-factor model is estimated.	2008-2022	Asset pricing models	Coefficient of the PA Dummy = 0.001 (insignificant)	Rejected
4.B. The unexplained part of returns between a well-diversified portfolio with and without high polluting companies after the 2015 Paris Agreement will be better explained by the Fama and French 5-factor model including the PMC factor than before the 2015 Paris Agreement.	2008-2022	Asset pricing models	Coefficient of the PA Dummy = 0.000 (insignificant) Coefficient of the interaction term PA Dummy x PMC = -0.089**	Rejected
5. The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the Covid-19 period (February 2020-February 2022) is lower than in the period before Covid-19 (from 2015 to January 2020) and the level of perceived carbon risk is higher.	2015-2022	Asset pricing models	Coefficient of the Covid-19 Dummy = 0.000 (insignificant) Coefficient of the interaction term Covid-19 Dummy x PMC = -0.021 (insignificant), when excluding 10%. When excluding 30% or 50% the coefficient of the interaction term Covid-19 Dummy x PMC is -0.085** and -0.117*, respectively.	Rejected
6. The unexplained part of returns between a well-diversified portfolio with and without high polluting companies in the period that starts with the war of Russia in Ukraine is higher than in the period before this war because it is expected that polluting stocks generates higher (abnormal) returns.	2015-2022	Asset pricing models	Coefficient of the War Dummy = 0.001 (insignificant) and coefficient of the interaction term War Dummy x PMC = 0.009 (insignificant).	Rejected

The first hypothesis, which states that the Sharpe ratio of a well-diversified portfolio with polluting companies is higher than the Sharpe ratio of a well-diversified portfolio without polluting companies, was rejected. The results show that there is no significant difference between the Sharpe ratios of the well-diversified portfolio with polluting companies and the portfolio excluding polluting companies. The anticipated impact of less diversification on the level of risk is not substantial enough to create a significant difference between the Sharpe ratios of the portfolio with all companies and the portfolio without polluting companies. The results of both the Jobson and Korkie test and the mean-variance spanning test confirm that there is no significant difference between the performance of the two portfolios. This finding is in line with Humphrey and Tan (2014) and Alessandrini and Jondeau (2019). These studies excluded particular stocks from their portfolios based on different criteria, such as SIC/NAICS or ESG scores, and both concluded that doing so did not impact their portfolio's Sharpe ratio.

Hypothesis 2a, which states that the difference in returns between the well-diversified portfolio with and without high polluting companies is partially explained by the five-factor model of Fama and French (2015), was confirmed. By adding the PMC risk factor as introduced by Huij et al. (2023), abnormal returns that were revealed by the five-factor model of Fama and French were explained by this added factor. Therefore, hypothesis 2b was also confirmed.

Furthermore, the effect of the 2015 Paris Agreement on the Sharpe ratios and (abnormal) returns of the portfolios was examined. The results show that the Paris Agreement of 2015 had no significant effect on the difference between the Sharpe ratio of the portfolios. It was expected that the difference between the Sharpe ratio of the well-diversified portfolio and the well-diversified portfolio excluding polluting companies was greater before than after the 2015 Paris Agreement. The reasoning was as follows: although the loss of diversification would persist after 2015 (leading to higher risk for the portfolio that excluded polluting companies compared to the portfolio that included all companies and leading to a lower Sharpe ratio for the former portfolio), the exclusion was also expected to have a positive effect on the returns of the portfolio excluding polluting companies. This was due to price pressure caused by investors selling high polluting companies, which would raise the average excess return for the portfolio without polluting companies and improve its Sharpe ratio. Because the results did not reveal this, hypothesis 3 is rejected.

The results regarding the effect of the Paris Agreement on the returns of the portfolio with and without polluting companies show that the intercept dummy is not significantly different from zero which means that the unexplained returns (i.e., the alpha of asset pricing model) after the Paris Agreement is not statistically different than before the Paris Agreement.

When estimating the models including the PMC factor, the 2015 Paris Agreement Dummy and the interaction term of this dummy with PMC, a negative and significantly different from zero interaction term is found. This indicates that the level of carbon risk after the Paris Agreement is perceived as lower than before. This contradicts Monasterolo and De Angelis (2020), who stated that carbon-intensive assets have become riskier after the signing of the 2015 Paris Agreement. The expected negative price pressure is not observed because the intercept dummy is insignificant for all models. Only when excluding 30% and 50% of the portfolio an insignificant negative coefficient for the intercept dummy is found. This contradicts the findings by Bolton and Kacperczyk (2022) who found no significant carbon premium before the Paris Agreement, but a significant and large carbon premium after its signing. Hypotheses 4a and 4b are rejected.

Besides the 2015 Paris Agreement also the impact on returns of two other external events was examined, Covid-19 and the Russian Ukrainian war. The results indicate that the expected price pressure due to Covid-19, resulting in lower abnormal returns (measured by an intercept dummy) during that period is not present. Wang et al. (2022) found that the impact of Covid-19 has led to an increase in investor caution and a decrease in risk tolerance. Therefore, due to the higher expected level of perceived carbon risk during the pandemic, a positive slope dummy was anticipated. However, the coefficient of the interaction term (Covid-19 Dummy x PMC) gives a contradicting sign to what was expected. A negative instead of a positive slope dummy which significantly differs from zero was found. Hypothesis 5 is rejected.

The expected result of hypothesis 6 is that the Russian Ukrainian war has a positive impact on the alpha due to an unexpected shift in demand of products from the energy and defense industry (Bauer et al. 2023). The results in this master's thesis do not confirm the findings by Bauer et al. (2023). The coefficient of the intercept War Dummy was insignificant. Similarly, the coefficient of the interaction term (War Dummy x PMC) was also insignificant, indicating that the war did not have a significant impact on the perceived level of carbon risk.

Besides the application of alternative asset pricing models (i.e., Carhart model and the Fama and French five-factor model including a momentum factor) which confirm the results using the Fama and French five-factor model, additional robustness checks are being done for the 2015 Paris Dummy, Covid-19 Dummy and the exclusion of companies based on the Environmental Pillar Score instead of the PMC beta. The conclusions do not change significantly by adjusting the setting of the 2015 Paris Agreement Dummy. This applies for the Covid-19 Dummy as well. The use of Environmental Pillar Scores instead of PMC betas to select polluting companies, results in findings that differ from the results if PMC betas are used. By adding the PMC factor, previously found abnormal returns do not disappear using the Environmental Pillar Scores as selection criterion, which means that the factor PMC does not capture abnormal returns as it did when PMC beta was the selection criterion.

This research contributes to the literature because of the choice of the selection criterion for the exclusion of polluting companies and an application of pricing models including the PMC risk factor as a measure for climate transition risk. Other papers often choose the E-scores or available data for emissions to identify brown companies. The impact of the 2015 Paris Agreement, Covid-19, and the war of Russia in Ukraine also have been considered. The results of this thesis contribute to the empirical literature which gives mixed results on the performance of green stocks compared to brown stocks.

Overall, the findings of this thesis confirm that excluding polluting companies from a well-diversified portfolio does not lead to a major deterioration of the performance of this portfolio.

A recommendation for future research might be applying similar analyses based on the constituents of other (broader) indices. This research used the S&P500 as a proxy for a well-diversified portfolio. If investors use a different benchmark, a different index is recommended to be used instead. Using a different index could also reduce the impact of a selection bias on the results that occur when using the S&P500 as a proxy for a well-diversified portfolio. Because S&P500 firms get a lot of media attention, these firms might sell polluting activities to other firms that are not included in this index or not even listed. In order to analyze the effect of excluding polluting companies from a well-diversified portfolio a broader index gives more opportunities to find out what the effect of this exclusion is, because these broader portfolios contain more high polluting companies.

Another recommendation is to do the analysis for portfolios containing corporate bonds. The selection of brown bonds should then again be based on PMC betas of the issuing firms in the for the investor relevant index. For investors holding a well-diversified portfolio of European firms the analyses could be performed using the STOXX Europe 600 instead of the S&P500.

To compare the excess return per unit of risk, instead of comparing Sharpe ratios a comparison of the modified Sharpe ratios as suggested by Ardia and Boudt (2015) could be done. The test of equality of modified Sharpe ratios considers the performance of investments with non-normal returns.

Because investors are interested in the purchasing power of returns, the analyses could also be done in real terms instead of in nominal terms. The analyses in this thesis have been done in nominal terms.

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APPENDICES

Table A.1: Results regression Fama and French five factors, Momentum, and PMC
This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including momentum and including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, MOM_t, and PMC_t, are respectively the monthly returns on the market, size, value, profitability, investment, momentum, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	0.000	0.000	-0.002**	-0.001	-0.002**	-0.002*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.003	-0.011	-0.086***	-0.101***	-0.127***	-0.143***
	(0.008)	(0.008)	(0.015)	(0.016)	(0.021)	(0.023)
SMB	0.000	0.018	-0.025	0.008	0.004	0.039
	(0.019)	(0.019)	(0.038)	(0.039)	(0.048)	(0.051)
HML	0.035	0.003	0.043	-0.017	0.074	0.011
	(0.024)	(0.025)	(0.052)	(0.056)	(0.068)	(0.076)
RMW	-0.012	-0.073***	0.110**	-0.001	0.156**	0.039
	(0.023)	(0.024)	(0.049)	(0.056)	(0.063)	(0.071)
CMA	0.046	0.003	0.187**	0.107	0.339***	0.254***
	(0.033)	(0.028)	(0.076)	(0.066)	(0.104)	(0.094)
MOM	0.015	0.010	0.057	0.047	0.058	0.047
	(0.017)	(0.014)	(0.035)	(0.030)	(0.036)	(0.032)
PMC		0.102***		0.186***		0.196***
		(0.020)		(0.039)		(0.056)
Adjusted R^2	0.163	0.302	0.464	0.542	0.525	0.565
Sample size	170	170	170	170	170	170

Table A.2: Results regression Fama and French five factors, Momentum, PA Dummy and PA Slope Dummy including and excluding PMC

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including momentum and including PMC in models [2], [4], and [6]. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t MOM_t, and PMC_t, are respectively the monthly returns on the market, size, value, profitability, investment, and momentum, and carbon factors. Models [1] and [2] exclude 10%, models [3] and [4] exclude 30%, and models [5] and [6] exclude 50% of the portfolio based on the highest PMC betas. PA Dummy is 1 for all months after the 2015 Paris Agreement. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level. respectively.

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Alpha	-0.001	-0.000	-0.002*	-0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RMRF	-0.003	-0.008	-0.086***	-0.094***	-0.127***	-0.132***
	(0.008)	(0.008)	(0.015)	(0.016)	(0.021)	(0.021)
SMB	0.001	0.019	-0.025	0.011	0.003	0.043
	(0.019)	(0.019)	(0.039)	(0.037)	(0.049)	(0.047)
HML	0.035	0.003	0.043	-0.016	0.074	0.010
	(0.024)	(0.025)	(0.053)	(0.053)	(0.068)	(0.072)
RMW	-0.013	-0.071***	0.109**	0.002	0.157**	0.043
	(0.023)	(0.024)	(0.050)	(0.052)	(0.064)	(0.066)
CMA	0.045	0.015	0.185**	0.138**	0.339***	0.302***
	(0.034)	(0.030)	(0.078)	(0.069)	(0.106)	(0.095)
MOM	0.015	0.007	0.056	0.040	0.058	0.038
	(0.017)	(0.014)	(0.035)	(0.030)	(0.036)	(0.032)
PMC		0.158***		0.331***		0.416***
		(0.036)		(0.078)		(0.099)
Paris Dummy	0.001	0.000	0.001	-0.000	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Paris Dummy x		-0.086**		-0.218***		-0.326***
PMC		(0.035)		(0.084)		(0.101)
Adjusted R^2	0.163	0.338	0.462	0.583	0.522	0.611
Sample size	170	170	170	170	170	170

Table A.3: Results regression Fama and French five factors, Momentum, PMC, Covid-19 Dummy, and Covid-19 Slope Dummy

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including momentum and including PMC. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, $MOM_{t,}$, and PMC_t, are respectively the monthly returns on the market, size, value, profitability, investment, momentum, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. Covid-19 Dummy is 1 for all months between February 2020 and February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)
RMRF	0.003	-0.056***	-0.108***
	(0.007)	(0.015)	(0.028)
SMB	0.037**	0.019	0.057
	(0.018)	(0.036)	(0.063)
HML	0.032*	0.065**	0.134**
	(0.017)	(0.029)	(0.053)
RMW	-0.066***	0.015	0.092
	(0.021)	(0.040)	(0.069)
CMA	0.018	0.107***	0.218***
	(0.023)	(0.038)	(0.078)
MOM	0.020	0.021	0.011
	(0.012)	(0.023)	(0.047)
PMC	0.057***	0.092***	0.074
	(0.015)	(0.033)	(0.056)
Covid Dummy	0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.002)
Covid Dummy x PMC	-0.025	-0.089**	-0.119*
	(0.025)	(0.039)	(0.070)
		-0.001	-0.001
Adjusted R^2	0.720	0.700	0.690
Sample size	85	85	85

Table A.4: Results regression Carhart model, PMC, War Dummy, and War Slope Dummy
This table shows the results of the regression of AllMAll-mP on the Carhart model including PMC. The variables, $RMRF_t$, SMB_t, HML_t, MOM_t, and PMC_t, are respectively the monthly returns on the market. size. value. Momentum, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. War Dummy is 1 for all months after February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)
RM-RF	-0.001	-0.067***	-0.124***
	(0.010)	(0.016)	(0.029)
SMB	0.056***	0.023	0.039
	(0.019)	(0.039)	(0.065)
HML	0.053***	0.104***	0.206***
	(0.017)	(0.024)	(0.044)
MOM	0.026**	0.024	0.011
	(0.012)	(0.033)	(0.063)
PMC	0.030*	0.085**	0.102
	(0.017)	(0.039)	(0.063)
War Dummy	0.001	0.001	0.003
	(0.001)	(0.002)	(0.004)
War Dummy x PMC	0.012	0.013	0.011
	(0.041)	(0.050)	(0.085)
Adjusted R^2	0.643	0.648	0.636
Sample size	85	85	85

Table A.5: Results regression Fama and French five factors, Momentum, PMC, War Dummy, and War Slope Dummy

This table shows the results of the regression of AllMAll-mP on the five factors of Fama and French including momentum and including PMC. The variables, $RMRF_t$, SMB_t, HML_t, RMW_t, CMA_t, MOM_t, and PMC_t, are respectively the monthly returns on the market, size, value, profitability, investment, momentum, and carbon factors. Models [1], [2], and [3] exclude 10%, 30%, and 50% of the portfolio based on the highest PMC betas, respectively. War Dummy is 1 for all months after February 2022. Robust standard errors are presented between parentheses. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 level. respectively.

Variables	[1]	[2]	[3]
Alpha	-0.000	-0.001	-0.002
	(0.000)	(0.001)	(0.001)
RMRF	0.004	-0.057***	-0.107***
	(0.006)	(0.018)	(0.031)
SMB	0.035**	0.019	0.053
	(0.016)	(0.042)	(0.071)
HML	0.028*	0.050*	0.116**
	(0.015)	(0.028)	(0.051)
RMW	-0.074***	-0.012	0.052
	(0.016)	(0.042)	(0.071)
CMA	0.019	0.116***	0.233***
	(0.019)	(0.038)	(0.076)
MOM	0.016	0.013	-0.000
	(0.011)	(0.031)	(0.056)
PMC	0.049***	0.063*	0.033
	(0.015)	(0.037)	(0.062)
War Dummy	0.001	0.002	0.003
	(0.001)	(0.002)	(0.003)
War Dummy x PMC	0.001	-0.015	-0.038
	(0.020)	(0.053)	(0.100)
Adjusted R^2	0.680	0.672	0.670
Sample size	85	85	85