Norwegian School of Economics
Bergen, Spring 2023

The 2015 Paris Climate Agreement and stock market performance

An empirical analysis of the stock market reaction across different industries in Europe and the United States

Tobias Immer and Chris Alexander Stokvik

Supervisor: Svein-Arne Persson

Master thesis, Economics and Business Administration
Majors: Financial Economics, Business Analysis and Performance Management

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgments

With this master thesis, we complete the final step in our Master of Science in Economics and Business Administration with majors in Business Analysis and Performance Management and Financial Economics at the Norwegian School of Economics.

Finding an exciting research topic, literature research, data wrangling, statistical programming, and finally, the actual writing process has been challenging but also very enriching. We both feel that out of the countless assignments we have completed on the path to our bachelor’s and master’s degrees, this thesis has definitely been the project where we have learned the most, especially what is the most important when doing scientific research. We hope to contribute to the existing research in sustainable finance by analyzing the stock market reaction in Europe and the United States to one of the most important climate-related events in recent history, the 2015 Paris Climate Agreement.

We want to express our sincere gratitude to our supervisor Svein-Arne Persson for the help at all stages of the research process. Your input and feedback have been invaluable and have helped us to hopefully make a small but meaningful contribution to research. We also want to extend our gratitude to the Norwegian School of Economics for teaching us the necessary knowledge about crucial concepts in Finance, Econometrics, and other related areas to be able to conduct this research. Finally, we would also like to thank our families and friends for their support and encouragement throughout this thesis and our studies.

Declaration of Authenticity

We hereby declare that we wrote this thesis on our own and did not use any unnamed sources. To the best of our knowledge, this thesis contains no material previously published or written by another person except where this is clearly marked as a citation. The work in this thesis has not been previously submitted for examination. We agree that this thesis may be checked for plagiarism using plagiarism detection software. We are aware that failure to comply with the rules of good scientific research can have serious consequences.

Norwegian School of Economics

Bergen, May 31st, 2023

Chris Alexander Stokvik

Tobias Immer

Abstract

Aggregated market behavior: We used cumulative average abnormal returns (CAARs) to analyze the aggregated market behavior. There were negative average abnormal returns (AARs) in the days leading up to the announcement and positive AARs in the days following the announcement. The U.S. and European markets were both negative leading up to the event, but the U.S. had a stronger reaction with larger CAARs. In the U.S., the two closest windows to the announcement day (-5:-1, -2:-1) were negative and significant, while in Europe, only one window was significant (-5:-1). Both markets turned positive after the announcement of the PA when the terms of the agreement became known. Thus, the announcement day ($t_0 = 14.12.2015$) was a clear shifting point in the market sentiment for the period around the Paris Agreement in both markets. Our interpretation of this shift is that the market viewed the terms of the Paris Agreement as good for business.

Industry market behavior: We used the cumulative abnormal return (CAR) of each industry to analyze the market behavior of each industry. Most industries followed the same pattern as the aggregated market, with a negative CAR before the announcement and a positive CAR after. We expect emissions-heavy industries to have a stronger market reaction. In the windows looking exclusively before the announcement (-15:-1, -7:-1, -5:1, -2:-1), many "brown" industries are among the industries with the biggest negative CARs (Oil, Gas & Consumable Fuels, Construction Materials, Metals & Mining, and Automobiles). The "brown" industries are also among those with the biggest positive CARs in the after windows. This positive CAR in the after period reduces the net effect in the whole period, measured in the equal windows (-15:15, -10:10, -5:5, -2:2) with an equal number of days before and after the announcement. The equal windows have small CARs and low significance levels. Accordingly, it is not possible to say anything conclusive about the market reaction of these industries over the entire period.

Beta change: We looked at the beta change of individual industries to measure changes in systematic risk for each industry. We found significant beta changes in eight industries with synchronized behavior in both markets. Two industries, Metals & Mining and IT Services, had an increased beta, which is associated with increased risk. The six industries with reduced beta and reduced risk were: Containers & Packaging, Construction Engineering, Airlines, Communication equipment producers, Electronics equipment producers, and the Entertainment industry.

Contents

Glossary of Abbreviations

AAR	Average abnormal return
AR	Abnormal return
CAAR	Cumulative average abnormal return
CAR	Cumulative abnormal return
CCS	Carbon Capture and storage
CMA	Conservative Minus Aggressive
COP	Conference of the Parties (United Nations climate change conference)
ETF	Exchange Traded Fund
GHG	Green House Gas
HML	High Minus Low
PA	Paris Agreement
RMW	Robust Minus Weak
SMB	Small Minus Big
UMD	Momentum factor

List of Figures

List of Tables

1. Introduction

The 2015 Paris Climate Agreement, negotiated at the Conference of the Parties 21 (COP 21), was a major milestone in humanity's fight against climate change due to its more binding nature than previous climate agreements for developed and developing countries. While the 2015 Paris Climate Agreement set important targets for reducing carbon emissions and achieving climate neutrality, achieving these targets will be no easy task. Companies with a fossil fuel-based business model will either have to adapt or cease operations altogether in the medium and long term. On the other hand, substantial investments in areas such as renewable energy, electricity grids, electric vehicle charging, home insulation, or public transport will be needed. The International Energy Agency (2021) estimates the necessary worldwide investments to amount to 5 trillion U.S. dollars annually until 2030 and 4.5 trillion U.S. dollars annually until 2050. Bloomberg New Energy Finance (2022) estimates the total investment needed to reach worldwide carbon neutrality by 2050 at around 194.2 trillion U.S. dollars. Investing in renewable energy on this scale will not be easy, and governments will not be able to shoulder the burden alone. Instead, the private sector will have to play a significant role in raising the capital for these large green investments. All forms of private financing, from the stock and bond markets to bank loans and private equity, will be required. This thesis will focus on the stock market and its contribution and response to the green transition. Specifically, the stock market's reaction to the 2015 Paris Climate Agreement will be studied.

Conducting an event study on stock returns relating to the Paris Climate Agreement 2015 allows us to examine how the stock market reacts to the announcement. It provides insights into whether and how investors incorporate information related to climate change and environmental policies into their valuation of companies. Analyzing stock returns surrounding the Paris Climate Agreement can offer insights into investor sentiment and confidence regarding climate change policies. It can indicate whether investors view such international agreements positively or negatively and how it affects their investment decisions. The study will evaluate the efficiency of financial markets by examining how quickly and accurately market participants incorporate new information by measuring market movement over time with multiple event windows. The Paris Climate Agreement seeks to reduce greenhouse gas emissions, which can have varying impacts across industries and sectors. We have analyzed how different industries and sectors are affected by climate change policies, potentially revealing winners and losers. By conducting an event study on stock returns concerning the Paris Climate Agreement, we can contribute to understanding the financial implications of climate change policies, investor behavior, market efficiency, and the relationship between sustainability efforts and market value. This research can be valuable for investors, policymakers, and companies looking to assess the impact of climate change-related events on financial markets and investment decision-making.

1.1 Research objective

This thesis seeks to contribute to a deeper understanding on the effect of the 2015 Paris Climate Agreement on the U.S. and European stock markets. We aim to answer the following research questions:

1.) *Is there a difference between the stock market reaction in the U.S. and Europe?*
2.) *How did different industries in the U.S. and European stock markets react to the 2015 Paris Climate Agreement?*
3.) *Which industries are impacted the most by the 2015 Paris Climate Agreement?*

2. Background

2.1 International regulation of greenhouse gas emissions

Climate change is one of the most severe threats to human prosperity in the decades to come. To this date, climate change has already cost countries around the world trillions of U.S. dollars, with developing countries being hit the hardest, and the cost is expected to increase dramatically (Naddaf, 2022). The cost of climate change in the United States since 1980 is estimated at 2.2 trillion U.S. dollars (Krieger, 2022), while alone in 2022, it cost the American economy more than 165 billion U.S. dollars (Cleetus, 2023). Due to the dangers of unmitigated climate change and high social and economic costs, global climate change mitigation is necessary and without any alternative. Since climate change cannot be mitigated effectively by just a few willing countries, a coalition to reduce carbon emissions and eventually reach climate neutrality is necessary. Since the Club of Rome raised the question of whether there is a limit to growth because of resource depletion in the early 1970s, the world has already come a long way, and the issue is taken more seriously (Club of Rome, 2022).

International climate negotiations, called Conferences of the Parties (COP), are essential to global climate change mitigation efforts. The first Conference of the Parties (COP 1) took place in 1995 in Berlin (Population Reference Bureau, 2000). However, COP 3 in Kyoto, which led to the signing of the Kyoto Protocol, was the first Conference of the Parties with binding emission reduction targets (Population Reference Bureau, 2000). The Kyoto Protocol required developed countries to lower their carbon emissions by 5.2% below 1990 levels during the first commitment period from 2008 to 2012 (Council on Foreign Relations, 2022). The biggest weakness of the Kyoto Protocol was that it did not include any obligations to reduce carbon emissions in developing countries (Council on Foreign Relations, 2022). Large carbon emitters such as China and India were not obliged to lower their emissions. This was most likely one of the main reasons why the U.S. withdrew from the Kyoto Protocol process by failing to ratify the agreement (Council on Foreign Relations, 2022). President George W. Bush's rationale was that the Kyoto Protocol placed the entire burden of reducing emissions on developed economies. He said he opposed “the Kyoto Protocol because it exempts 80 percent of the world, including major population centers such as China and India, from compliance, and would cause serious harm to the U.S. economy” (Shepherd, 2021). In 2005 the Kyoto Protocol took effect after countries accounting for more than 55% of global emissions had ratified the agreement (Council on Foreign Relations, 2022). In 2007 leading up to COP 13 in Bali, negotiations for a second commitment period of the Kyoto Protocol started but were largely unsuccessful (Council on Foreign Relations, 2022).

At COP 15 in Copenhagen, negotiators failed to agree on a binding agreement. The goal of limiting global warming to two degrees Celsius was agreed upon, but no commitments or obligations were made to reach this goal (Council on Foreign Relations, 2022). COP 15 in Copenhagen can therefore be regarded as a failure. At COP 18 in Doha, a second commitment period of the Kyoto Protocol was agreed upon. However, Japan, Canada, New Zealand, and Russia decided not to make any commitments for the second commitment period of the Kyoto Protocol (Council on Foreign Relations, 2022).

Until the breakthrough at COP 21 in Paris, little progress had been made. In the 2015 Paris Climate Agreement, the parties agreed to “limiting global temperature increase to well below two degrees Celsius while pursuing efforts to limit the increase to 1.5 degrees” (United Nations, 2022). Signatory countries are required to commit to legally binding national targets called Nationally Determined Contributions (NDCs). However, there is no enforcement of the targets by the United Nations or any other body (Council on Foreign Relations, 2022). In 2017, the Trump administration notified the United Nations of its intention to withdraw from the 2015 Paris Climate Agreement as soon as the U.S. was eligible to do so (United Nations, 2020). In 2020 the U.S. formally withdrew from the 2015 Paris Climate Agreement but rejoined in 2021 under the new Biden administration.

2.2 Climate risk for firms and investors

Climate change will significantly impact the economy in most sectors. It can harm firms when their supply or demand sides are negatively hit. For instance, firms in the agriculture and hydropower sectors could suffer from droughts caused by climate change. Firms can also be impacted indirectly by climate change when governments impose regulations to mitigate climate change by introducing restrictions on production technologies and carbon emissions. These factors can lead to lower expected future cashflows and, therefore, to lower firm values since the assets have lost a substantial part of their value. According to Caldecott (2017), assets that have lost a large part of their value due to government regulations (e.g., emissions trading system) or technological change (e.g., increased competitiveness of renewables) can be referred to as stranded assets. This can be the case for fossil fuel extraction projects, power plants, steel factories, low energy efficiency real estate, and fossil fuel-powered cars.

Welsby et al. (2021) estimate that for the Paris Climate Agreement's 1.5 degrees Celsius target, 58% of oil reserves, 56% of natural gas reserves, and 89% of coal reserves considered economic today would have to remain unextracted. McGlade & Ekins (2015) estimate that for the below two degrees Celsius target, the non-extractable amount is slightly lower, with 33% of oil reserves, 49% of natural gas reserves, and 82% of coal reserves. It should be noted that the assumption in this scenario was that Carbon Capture and Storage (CCS) plays an important role. Without CCS, the unextractable amount is slightly higher. According to Kepler-Cheuvreux, the lost revenues from fossil fuel extraction under a two-degree Celsius warming scenario would be 19.3 trillion U.S. dollars for oil, 4 trillion U.S. dollars for natural gas, and 4.9 trillion U.S. dollars for coal (Lloyd's, 2017). With these numbers in mind, it becomes clear that with fossil fuel assets in the trillions of U.S. dollars that cannot be extracted if the climate goals have any realistic chance of being reached, the financial markets are confronted with a considerable challenge. If also considering existing assets such as airplanes, ships, and low-energy efficiency real estate, that are economically viable only with affordable fossil fuels, it is clear that specific industries will be severely impacted in their operations and on the financial markets.

2.3 Efficient market hypothesis

The efficient market hypothesis states that market prices fully reflect all available information. The implication is that it is impossible to consistently beat the market when adjusted for risk since the market price should reflect all the available information. The theory was primarily developed by Fama (1965) and describes how price setting works in a marketplace when new information is incorporated into security prices.

Any new information that could be used to predict stock performance should already be reflected in the stock prices. If any information indicates that a stock is over or underpriced, investors will sell or buy the stock and immediately cause a price change that brings the price to a fair level, where only ordinary rates of return can be expected. Ordinary rates are rates that do not produce higher returns than their risk implies. Market efficiency refers to the time it takes until new information affects the price. The shorter it takes until the new information is reflected in the price, the higher the market's efficiency. If prices are immediately bid to a fair level, given all available information, prices must increase or decrease only in response to new information. New information must be unpredictable by definition. If it could be predicted, the prediction would be part of today's information and thus be incorporated into the stock price.

Random walk

The unpredictability of the prices is one of the "random walk" arguments, which suggests that prices are random. This randomness was first discovered after the first extensive time-series computations on market data (Kendall & Hill, 1953). Kendall & Hill (1953) hoped to find a pattern that could be used to predict future stock prices but found only random behavior. However, randomness does not mean that stock prices are irrational; they are just unpredictable. The randomly changing stock price results from investors competing to discover relevant information on which to buy or sell before the rest of the market becomes aware of the information (Bodie et al., 2018, p. 334).

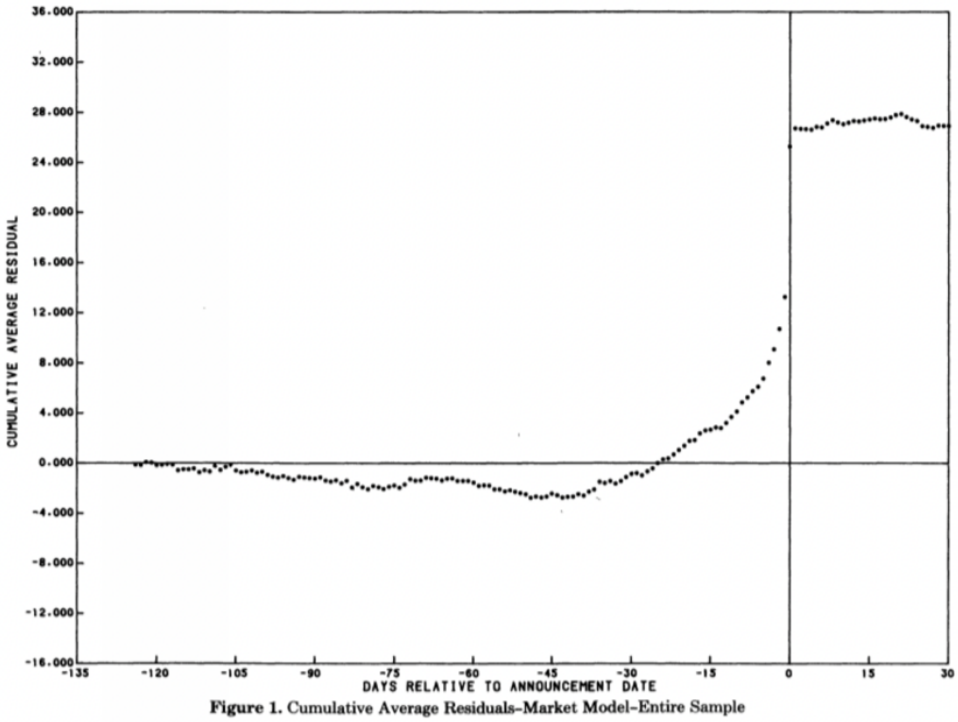

Figure 1: Cumulative average residuals, (Keown & Pinkerton, 1981)

Figure 1 Notes: The figure shows the cumulative returns leading up to a merger announcement and after. It can be seen that the returns increased already before the merger was publicly announced, which could potentially be illegal insider trading. Keown & Pinkerton (1981) state that planned mergers are often relatively loosely guarded secrets among experienced financial market participants. The new information is mostly incorporated into the share price on the day of the announcement and a few days before. After the announcement day, there is little reaction.

Competition among investors leads to market efficiency as their price expectations form the market price through buying and selling. This pattern can be seen in Figure 1. Keown & Pinkerton (1981) found that after the announcement day ($t = 0$), the market has a relatively stable price indicating market efficiency. This is because the market knows the takeover bid price, which is essential information for price setting. Still, the days leading up to the merger or acquisition announcement had high returns. There might have been some information leakage, which indicates different degrees of information in the market. Since there may be different degrees of information in the market, there are different forms of the efficient market hypothesis, depending on the type of information the market has access to.

The weak form of the efficient market hypothesis assumes that stock prices reflect all information that can be gathered through examining the market trading data, such as historical prices and volumes, since this information is widely available.

The semi-strong form assumes that the stock price reflects all publicly available fundamental data about the firm, such as accounting data, products, R&D, earnings forecasts, management quality, and market data.

The strong form of efficiency demands that the stock price reflects all information, including information not available to the public, only company insiders. This view is a bit extreme, but as we can see from Keown & Pinkerton (1981), confidential information tends to leak and be priced into securities. This can also be the result of good analyst work and does not necessarily have to be information leakage. For instance, keeping track of where key executives travel can give some indication of negotiations. Grossman & Stiglitz (1980) infer that investors will only be incentivized to spend resources to analyze and uncover new information if the activity is likely to generate a positive return. If a fund has \$10 billion assets under management (AUM) and generates an increased return of 1% after hiring active management, that will create a value of \$100 million, which leaves a large budget to hire staff to search for unexploited inefficiencies in the market.

Many other factors also affect the price setting and contribute to the unpredictability of prices. Even professional analysts are not immune to bias and other unaware external influences. Both sports and weather have been shown to affect the market return on stock indexes. Saunders (1993) shows that rain in New York City was correlated with negative returns on the New York Stock Exchange. Edmans et al. (2007) found that negative outcomes for national teams in sports events affected the returns on a national level the day after. This shows that even in a marketplace dominated by professional actors whom you would expect to be rational and take relatively long-term views, these factors can create significant abnormal returns even though the weather and sports results are independent of the firm’s results.

Selection bias can also be a problem when assessing market efficiency. Selection bias refers to the fact that when investors find valuable information that can generate abnormal returns, they are unlikely to share that information with the public (Bodie et al., 2018, p. 338). Instead, they quietly exploit this information advantage themselves to generate abnormal returns. The result is that most of the time, only information that cannot generate high abnormal returns becomes public. Since the information presented to the public is preselected and biased, it is impossible to tell whether an investor has beaten the market due to luck or by exploiting an information advantage.

2.4 Abnormal returns

An abnormal return is the difference between a security's actual return and its expected return (Bodie et al., 2018, p. 175). Abnormal returns often occur because new information about a security has been made available to the public, resulting in higher returns than is expected under "normal" circumstances. The equation for abnormal return is

$$Abnormal\ return = r_t - (\alpha + \beta * r_{Mt}), \qquad (1)$$

r_t = securities return in time period t,
α = intercept (the average rate of return the stock would realize in a period with zero market return),
β = sensitivity to the market return,
r_{Mt} = market return.

To find the abnormal return, one must choose a model to obtain the expected or normal return. In the equation for abnormal return, this is the part inside the parenthesis which is subtracted from a security's actual return r_t. In this case, the CAPM is used, although it should be mentioned that other asset pricing models can also be used. The general approach is to use a proxy for what the stock return might have been in the absence of the event. There are several options to achieve this. The most basic approach is the return of the security minus the return on a broad market index. Another way is to use other similar securities as a proxy. The more accurate approach is an asset pricing model such as the CAPM to estimate normal returns. We have used a multifactor model like the Fama-French five-factor model plus the momentum factor to estimate normal returns. This approach adds more independent variables to the regression, such as firm size characteristics and firm book-to-market ratio. This can potentially make the estimation of abnormal returns more accurate.

One problem with calculating abnormal returns for events is information leakage or the fact that the event date is hard to determine precisely. Then we might see a drift in the returns before $t = 0$, either positive or negative, depending on whether it's good or bad news. One can do two things to reduce the effect of pre-event drift on the calculations. The first is to include a holdout period before the event so that the holdout period is not included in the calculation of the normal returns. The other measure one can adopt is to focus the analysis on cumulative abnormal returns (CARs), the sum of the abnormal returns for the event window. The cumulative abnormal return captures the return for the entire period, and it is possible to have an event window longer than just one day. A multi-day event window can be helpful if it takes a few days before the market reacts by not being efficient immediately.

2.5 Beta

Beta is a measure of a security's systematic risk. More precisely, a stock's beta is the ratio of its volatility due to market risk to the volatility of the whole market. Investors in financial markets are only compensated for the systematic risk, not for the idiosyncratic risk, because they can hold a large portfolio of different stocks to diversify. Systematic risk refers to the risk that affects all the securities of a particular asset class, such as interest rate increases or inflation (Corporate Finance Institute, 2022). Idiosyncratic risk is inherent to a specific security (Corporate Finance Institute, 2022). In the case of a stock, idiosyncratic risk could materialize when a firm loses its technological advantage in a particular area or an important product experiences technical difficulties. The formula for beta is

$$\beta_i = \frac{Cov(r_i, r_M)}{\sigma_M^2}. \tag{2}$$

A beta of one indicates that a stock's returns move parallel with the market, while a lower beta indicates lower volatility. Betas larger than one mean higher volatility and, therefore, higher returns when the market is doing well but also higher losses when the market is in a downturn. In the event study setting of the 2015 Paris Climate Agreement, changes in beta can indicate the change in firm or industry-specific risk. It enables us to conclude which sectors experienced increased risk after the 2015 Paris Climate Agreement and which sectors now have a lower risk.

3. Literature Review

The stock market response to climate and environment-related events and policy announcements has been well-researched in recent years. This branch of research differentiates itself from the research field of classical ESG and stock performance studies, which essentially seek to answer the question of whether stocks with higher ESG ratings perform better. In this type of study, the intrinsic sustainability performance of the firm and its impacts on stock returns are the center of the research objective. However, this master thesis and the previous research it builds on analyze the short-term impact of climate-related events on stock returns using the event study methodology. Stocks are often classified into different sectors or green versus brown stocks. This helps to understand if different sectors or green stocks compared to brown stocks were impacted differently by climate policy-related events such as the 2015 Paris Climate Agreement. This literature review section will present the most influential research and important findings. The literature overview will begin with studies on the impact of the 2015 Paris Climate Agreement on the stock market. After this, essential results of studies done on other major climate negotiations and agreements will be presented. Finally, studies researching the impact of local environmental legislation on the stock market in different regions will be presented.

Diaz-Rainey et al. (2021) research the stock market response of oil and gas sector stocks to four policy events related to the 2015 Paris Climate Agreement and the election of Donald Trump in 2016. Specifically, they analyze the 2015 Paris Climate Agreement itself, the ratification of the Paris Climate Agreement, the election of Donald Trump in 2016, and the withdrawal of the U.S. from the Paris Climate Agreement in 2017, which came into effect in 2020. With a CAAR of -8.4%, Diaz-Rainey et al. (2021) find a high negative impact on the Oil and Gas sector following the 2015 Paris Climate Agreement. In particular, the Exploration and Production sector (CAAR -12.2%) and the Drilling sector (CAAR -10.5%) were strongly impacted. In addition, Diaz-Rainey et al. (2021) find a more substantial impact on firms with U.S.-centered operations.

Kruse et al. (2020) classify American firms according to green and brown revenue share and carbon intensity. Following the Paris Agreement, they find a positive CAAR of up to 10% for the greenest firms. The effect is less pronounced for green firms with a lower share of green revenues. The effect is weaker and less significant for brown firms, which could mean that the stock market reacts strongly to opportunities but does not punish brown firms.

Monasterolo & de Angelis (2020) analyze the impact of the Paris Climate Agreement on various green, brown, and market ETFs from Europe, the U.S., and other developed markets. They focus on abnormal returns, changes in beta, and optimal portfolio weights of green and brown stocks. The most important findings are that the Paris Agreement was associated with lower systematic risk (beta) among the green indices. This holds for the U.S., EU, and global markets and possesses high statistical significance. In addition, Monasterolo & de Angelis (2020) find that the optimal weight of green indices based on Markowitz portfolio optimization is higher after the Paris Agreement than before. However, the findings about abnormal returns are statistically not significant.

Mukanjari & Sterner (2018) find only moderate negative effects with low statistical significance of the Paris Agreement on abnormal returns of fossil fuel stocks in the coal, oil, and natural gas sectors. However, they find statistically significant positive CAARs of 12.91% for the solar industry and 4.20% for the alternative energy sector at the 1% significance level for the (0:2) event window. However, the abnormal returns for the wind power sector are small and not statistically significant. For the U.S. presidential election, Mukanjari & Sterner (2018) find statistically significant negative CAARs for the solar, wind power, alternative, and nuclear energy sectors. For the solar industry, the CAAR was -6.76%, for the wind power sector -7.46%, for the alternative energy sector -3.55%, and -3.73% in the nuclear energy sector.

Some studies also compare the effects of the Paris Climate Agreement (COP 21) on stock returns to previous and subsequent international climate negotiations. Schuetze et al. (2020) research the stock market impact of all climate negotiations from COP 15 in Copenhagen in 2009 to COP 22 in Marrakesh in 2016. For COP 15 in Copenhagen, where no agreement on a successor to the Kyoto Protocol was reached, they found no statistically significant CAARs for any event window. At COP 16 in Cancun, where an extension of the Kyoto Protocol was agreed upon, a positive CAAR of 0.89% for green stocks was observed at the 5% significance level. At COP 17 in Durban, negotiators agreed to postpone a binding climate treaty until 2015. A highly significant CAAR of -2.08% was observed for green companies, which is not surprising given the disappointing results of COP 17. After COP 18 in Doha, green companies experienced a positive and statistically significant CAAR of 1.64%; no statistically significant effect was observed for brown stocks. COP 19 in Warsaw, where it was agreed to keep up efforts to decrease carbon emissions, was associated with a slightly negative statistically significant CAAR of -0.33% for brown companies. For the Paris Agreement, Schuetze et al. (2020) find a statistically highly significant negative CAAR of -1.4% for brown stocks. Schuetze et al. (2020) also find that the positive and negative effects for green and brown companies are more pronounced in emerging markets than in developed countries. This is particularly the case for green companies in emerging markets.

Jiang & Luo (2018) research the impact of the COP 15 Copenhagen climate conference on the Chinese stock market. They analyze the impact of eight events on carbon-intensive and non-carbon-intensive stocks connected to the Copenhagen climate conference. The Copenhagen climate conference failed to reach legally binding emission reduction targets and is therefore widely regarded as a failure (Parker & Karlsson, 2017). This is reflected in the results of their study, as carbon-intensive stocks have a higher mean return and CAAR than non-carbon-intensive stocks. Specifically, they find a mean return of 0.25% for carbon-intensive stocks vs. 0.09% for non-carbon-intensive stocks. They find a 1.24% CAAR for carbon-intensive companies and a 0.5% CAAR for non-carbon-intensive companies. Overall, they conclude that carbon-intensive firms benefit more from the low level of ambition in climate change mitigation, demonstrated through the non-binding nature of the agreements reached during COP15 in Copenhagen. Jiang & Luo (2018) think that the Fairness principle of the Kyoto Protocol and the principle of Common But Differentiated Responsibilities will play an essential role in China's future climate change mitigation ambitions. Since China has, proportional to its population, lower historical carbon emissions than most developed countries, China will be allowed a longer time to lower its carbon emissions. In the meantime, it is possible that carbon-intensive Chinese firms could gain an advantage over their Western competitors. This theory was at least partially substantiated by the higher returns of carbon-intensive firms Jiang & Luo (2018) found in their study.

Other studies also examine local environmental legislation, such as a carbon tax, air pollution restrictions, and chemical waste handling. Ramiah et al. (2013) research the effect of 19 announcements on environmental legislation in Australia on Australian stocks. The announcements are mostly linked to the implementation of Australia's carbon emission reduction measures through the Carbon Pollution Reduction Scheme (CPRS). The sector most affected by the CPRS was the Alternative energy sector, with a statistically significant CAR of -31.18%. The low ambition of the CPRS and the reported Australian carbon emission reduction targets can most likely explain this. Overall, the results for the different sectors are mixed and inconclusive. However, Ramiah et al. (2013) find a significant increase in risk showing the pattern of a diamond risk structure. The alternative energy, auto parts, and mining sectors experienced a statistically significant increase in short-term risk. The beverage, health care, and industrial transportation sectors witnessed a decline in short-term risk. This can be explained by the low impact of carbon emission reduction targets on these sectors or by sectors benefiting from increasingly restrictive carbon emission legislation.

Borghesi et al. (2022) analyze the impact of European green policy announcements, for instance, the European Green Deal, on sectoral stock returns. They construct green and brown portfolios and differentiate by sector, country, and type of green policy announcement. Borghesi et al. (2022) find positive and statistically significant cumulative abnormal returns (CARs) of +2.5% for the green and +1.7% for the brown portfolios. The different types of green policy announcements are adaptation, air pollution, biodiversity, climate change mitigation, other climate change issues, waste and recycling, and water. Borghesi et al. (2022) find the largest and most significant effects of policy announcements related to climate change mitigation. The positive CAR is larger for the green portfolio but still present for the brown portfolios. However, green policies related to adaption and waste & recycling resulted in negative CARs for the green and brown portfolios. For these types of green policy announcements, the CAR was lower in the green portfolio than in the brown portfolio. The analysis by sector revealed only relatively inconclusive results. One notable result is that green stocks in the energy, industrial, financial, and consumer discretionary sectors outperformed brown stocks. The results also differ at the country level. While the general pattern with higher CARs for green portfolios remains intact, some countries have a higher gap between green and brown portfolios than others. The countries with the largest gap between green and brown CARs are Switzerland and Italy. Smaller differences between CARs can be observed in Germany and Belgium.

Pham et al. (2020) research the reaction of the French stock market to environmental legislation. They distinguish between water, soil, and air pollution regulations and the European Union Emissions Trading System. Overall, the reaction to the water, soil, and air regulations was more negative and homogenous for most sectors than to the European Union Emission Trading System, where the effect varies across industries. For the water, soil, and air regulation events, only the sectors of Oil and gas producers (+3.26%) and banks (+1.8%, +5.74%) showed positive and statistically significant cumulative abnormal returns. The sectors alternative energy (-17.18%, -19.63%, -18.29%) and food and drug retailers (-9.84%, -11.33%, -10.86%) reacted the most negatively with statistically significant cumulative abnormal returns. However, it should be noted that all the other sectors except those with a positive reaction had statistically significant cumulative abnormal returns of at least -2.5%. The number of industries positively and negatively affected by legislation related to the European Union Emission Trading System is about the same. The sectors Fixed line telecommunications (+17.46%), and mobile telecommunications (+17.13%) had the highest cumulative abnormal returns. Oil equipment & services (-9.68%, -5.98%, -8.64%), electricity (-5.64%, - 6.82%, -9.91%, -4.99%), and oil and gas producers (-4.11%, -5.29%) had the largest negative cumulative abnormal returns. Concerning risk, water, soil, and air pollution legislation resulted in three different outcomes. The systematic risk for polluting firms increased, decreased for green firms, and stayed the same for some firms. On the other hand, the European Emissions Trading System produced a diamond risk structure for each individual event. The risk returned to the previous level a short while after the event.

In a similar study, Pham et al. (2019) analyzed the effect of environmental regulation events on the Singapore stock market. The environmental regulation studied centers around implementing Singapore's international climate commitments into law and practical measures such as a carbon tax. Pham et al. (2019) find evidence that relatively carbon-intensive sectors such as chemicals (-5.20% AR), forestry and papers (-4.92% AR), industrial engineering (-2.34% and -1.36% AR), industrial metals and mining (-4.14% AR) and electrical equipment and services (-2.49% and -2.74%) were negatively affected by the announced environmental legislation and experienced statistically significant negative abnormal returns. In addition, green sectors, such as the alternative energy sector, experienced a positive CAR of 43.1%.

Literature overview

authors	scope	region	approach	findings
(Diaz-Rainey et al., 2021)	Four policy events associated with the Paris Agreement and the election of Donald Trump (Paris Agreement, Paris Agreement ratification, Trump election and withdrawal of U.S. from Paris Agreement)	U.S. and worldwide	Oil and gas sector stocks differentiated according to if U.S. headquarter or not	Negative CAAR of -8.4% in the Oil and Gas sector after the Paris agreement. Exploration and Production sector (CAAR -12.2%) and the Drilling sector (CAAR -10.5%) strongly impacted. Larger impact on firms with U.S.-centered operations.
(Kruse et al., 2020)	Paris Agreement	U.S.	Green and brown firms differentiated by green revenue share and carbon intensity	Positive CAAR of up to 10% for the greenest firms. Brown firms are not punished however.
(Monasterolo & de Angelis, 2020)	Paris Agreement	Developed markets (U.S., EU and others)	ETFS in some green and some brown sectors	Lower systematic risk (beta) among the green indices in all the markets analyzed. Higher optimal weight of green indices after the Paris agreement than before in a portfolio constructed based on Markowitz portfolio optimization
(Mukanjari & Sterner, 2018)	Paris Climate Agreement and Donald Trump election	USA	Different enery sector ETFs based on energy source (coal, oil, wind, solar etc.)	Positive CAARs of 12.91% for the solar industry and 4.20% for the alternative energy sector two days after the Paris agreement. For the fossil energy sectors only moderate effects with low statistical significance. After Donald Trump's election negative CAARs for the solar (-6.76%), wind power (-7.46%), alternative (-3.55%), and nuclear energy sectors (-3.73%).
(Schuetze et al., 2020)	Paris Agreement and many other COPs	Worldwide	Stocks classified as green or brown	Statistically signifcant negative CAAR of -1.4% for brown stocks and positive but not significant CAAR for green stocks after the Paris Agreement

authors	scope	region	approach	findings
Jiang and Luo (2018)	Copenhagen Climate Summit (failed to reach legally binding emission reduction targets and is widely regarded as a failure)	China	Polluting vs green stocks	Higher CAAR for carbon intensive stocks than non-carbon-intensive stocks. 1.24% CAAR for carbon-intensive companies and 0.5% CAAR for non-carbon-intensive companies.
Ramiah et al. (2013)	19 announcements of environmental regulation mostly linked to carbon pricing in Australia from 2005–2011	Australia	Different industries	Mixed results. Alternative energy sector with a CAR of -31.18%. Significant increase in risk with the pattern of a diamond risk structure. Notably an increase in short-term risk in the alternative energy, auto parts, and mining sectors. Decrease in short-term risk in the beverages, health care, and industrial transportation sectors
(Borghesi et al., 2022)	73 green policy announcements classified into different categories.	Europe. Specifically Belgium, Switzerland, Germany, Denmark, Finland, France, Ireland, Italy, Netherlands, Spain, UK, and Sweden.	Green and brown portfolios differentiated by sector	CARs of +2.5% for the green and +1.7% for the brown portfolios. Policy announcements concerning climate mitigation have the largest impact.
(Pham et al., 2020)	European Union Emissions Trading System events and water, soil and air regulation events	France	Different sectors	High sensitivity of French stock market to emissions trading event. Low sensitivity to the water, soil and air events. chemicals, oil and gas industries have negative reactions while other polluting sectors have positive abnormal returns
(Pham et al., 2019)	Singapore legislation (Carbon tax)	Singapore	Different sectors	Carbon-intensive sectors such as chemicals (−5.20% AR), forestry and papers (−4.92% AR), industrial metals (−4.14% AR), industrial engineering (−2.34% and −1.36% AR) and industrial metals and mining (−4.14% AR) and electrical equipment and services (−2.49% and −2.74%) negatively affected showing statistically significant negative abnormal returns. Green sectors, i.e. the alternative energy sector, show positive CAR of 43.1%.

4. Data

4.1 Obtaining the data

The data used in this thesis is comprised of time series data from the SP500 and the STOXX 600 indices obtained from the CRSP/Compustat Merged Database (Wharton Research Data Services, 2023). We chose a date range from November 2014 until January 2016 for the two indices. In addition, we use the Global Industry Classification Standard (GICS) from Standard & Poor’s & MSCI (2023) to determine which company belongs to which industry.

Furthermore, we obtained data for the Fama-French five-factor models from Kenneth R. French’s factor database (French, 2023). We used specific Fama-French factors for each of the indices analyzed. For the SP500 and the STOXX 600, the Fama-French North American and European Five Factors with daily data were used. In addition, index-specific daily factors with the Momentum Factor also from Kenneth R. French’s factor database were added to our model.

4.2 Descriptive Statistics

The following section provides an overview of the performance of some important industries and companies in the SP500 and the STOXX 600. The aim is to provide a more intuitive understanding of the different industries’ and companies’ performance in these two indexes.

4.2.1 SP500

Table 1 shows the number of firms in each industry for the SP500 stock index. It can be seen that the number of firms per industry varies substantially. Equity Real Estate Investment Trusts (REITs) have the highest number of firms, while there are eight sectors with only one firm. The average number of firms per industry in the SP500 is eight, and the median is five.

Industry	Number of firms	Industry	Number of firms
Equity Real Estate Investment Trusts (REITs)	27	Communications Equipment	5
Insurance	23	Food and Staples Retailing	5
Capital Markets	21	Household Products	5
Semiconductors and Semiconductor Equipment	21	Media	5
Oil, Gas and Consumable Fuels	20	Road and Rail	5
IT Services	19	Air Freight and Logistics	4
Banks	18	Consumer Finance	4
Health Care Equipment and Supplies	18	Electrical Equipment	4
Hotels, Restaurants and Leisure	17	Metals and Mining	4
Electric Utilities	16	Textiles, Apparel and Luxury Goods	4
Health Care Providers and Services	16	Automobiles	3
Software	16	Distributors	3
Chemicals	14	Diversified Telecommunication Services	3
Machinery	14	Industrial Conglomerates	3
Food Products	12	Interactive Media and Services	3
Life Sciences Tools and Services	12	Internet and Direct Marketing Retail	3
Specialty Retail	12	Multiline Retail	3
Multi-Utilities	10	Trading Companies and Distributors	3
Aerospace and Defense	9	Auto Components	2
Electronic Equipment, Instruments and Components	8	Construction Materials	2
Pharmaceuticals	8	Energy Equipment and Services	2
Biotechnology	7	Tobacco	2
Entertainment	7	Construction and Engineering	1
Household Durables	7	Gas Utilities	1
Containers and Packaging	6	Independent Power and Renewable Electricity Producers	1
Professional Services	6	Leisure Products	1
Technology Hardware, Storage and Peripherals	6	Personal Products	1
Airlines	5	Real Estate Management and Development	1
Beverages	5	Water Utilities	1
Building Products	5	Wireless Telecommunication Services	1
Commercial Services and Supplies	5		

Table 1: SP500 industries and number of companies

Figure 2 shows the returns of selected sectors of the SP500 during a (-15,+15) window. Specifically, the sectors shown are Automobiles, Entertainment, IT Services, Metals and Mining, and Oil, Gas and Consumable Fuels. The daily returns vary between -5% and +5%, with the Oil and Gas sector showing the highest volatility. The vertical red line signals the first trading day after the signing of the Paris Agreement. The behavior of the returns does not show a very consistent pattern. After the agreement, there is an increase in returns followed by slightly negative or close to zero returns. A significant increase can again be observed the week after the agreement, with the Metals and Mining and the Oil, Gas and Consumable Fuels sectors having the highest returns of about 5% for a single day.

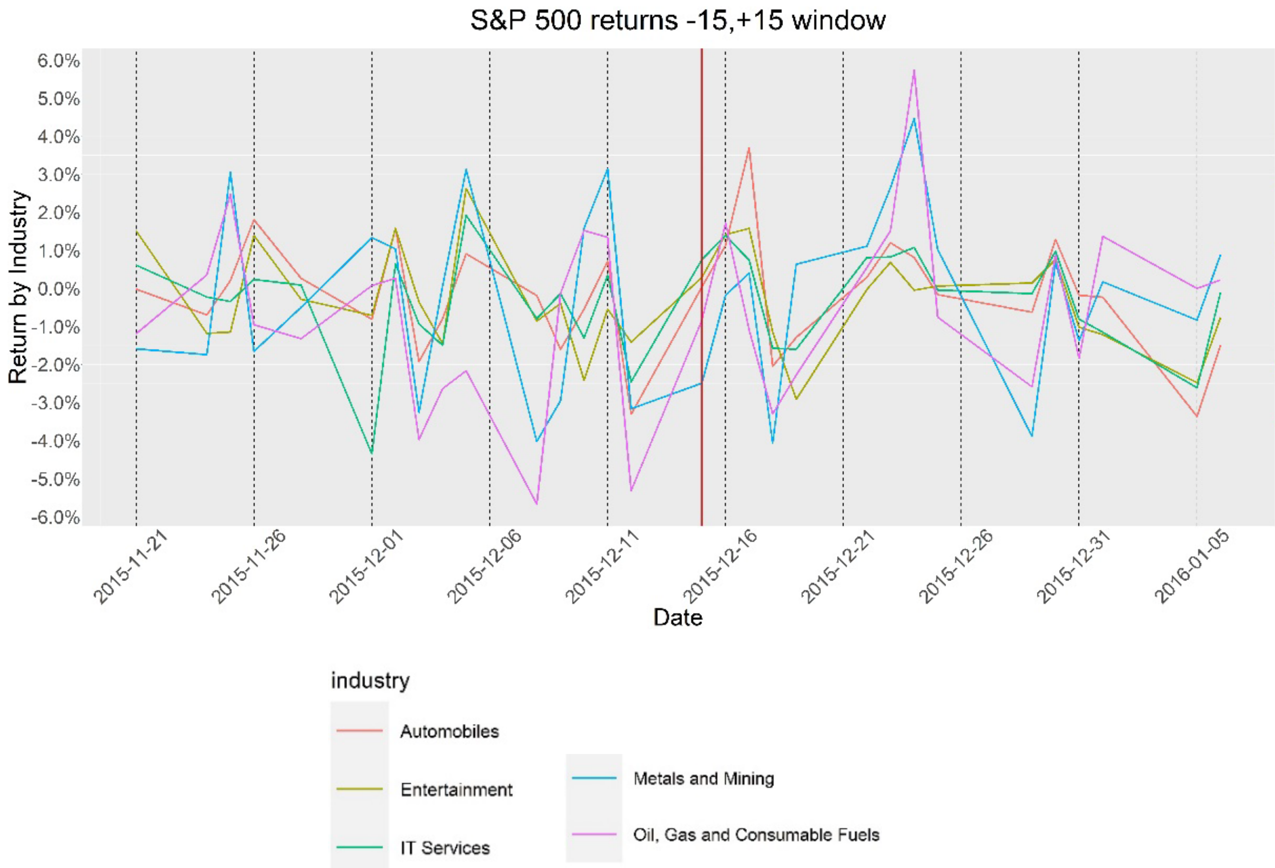

Figure 2: SP500 returns in selected sectors

Figure 3 shows the daily returns of firms in the Oil, Gas and Consumable Fuels industry. It can be seen that the returns were volatile before the event date. After the event, the reaction is initially moderate until negative returns can be observed for many firms. In the week after, relatively high positive returns can be seen.

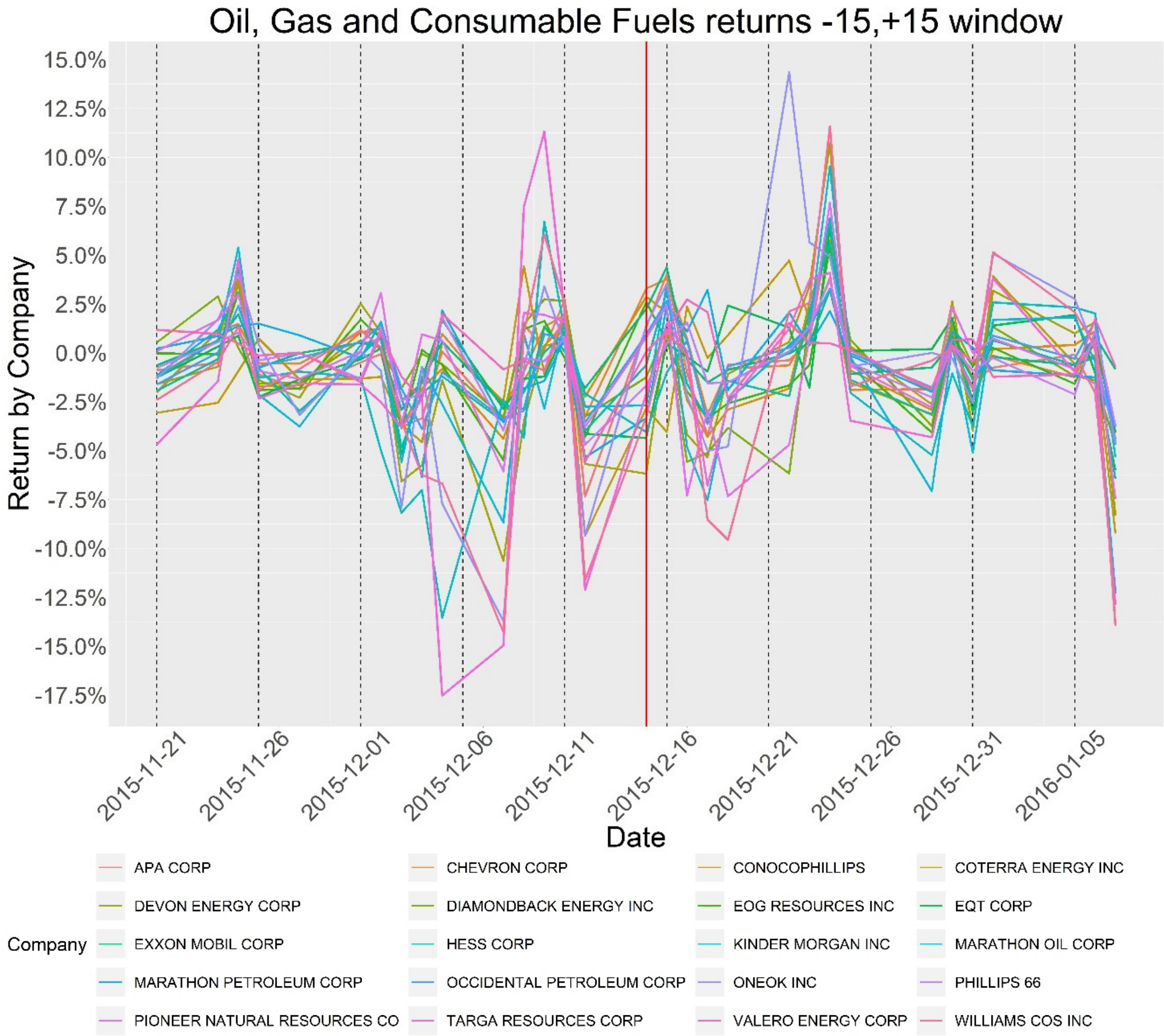

Figure 3: SP500 Oil, Gas and Consumable Fuels returns -15,+15 window

Figure 4 shows the returns in the Metals and Mining industry. With only four firms, there are fewer firms in this industry than in the Oil, Gas and Consumable Fuels industry. Before the event date, the returns are stable for two firms, while the others are more volatile. After the event date, the reaction is moderate before some negative returns can be observed. Later, most firms had stable returns, while Freeport McMoran Inc had high positive returns.

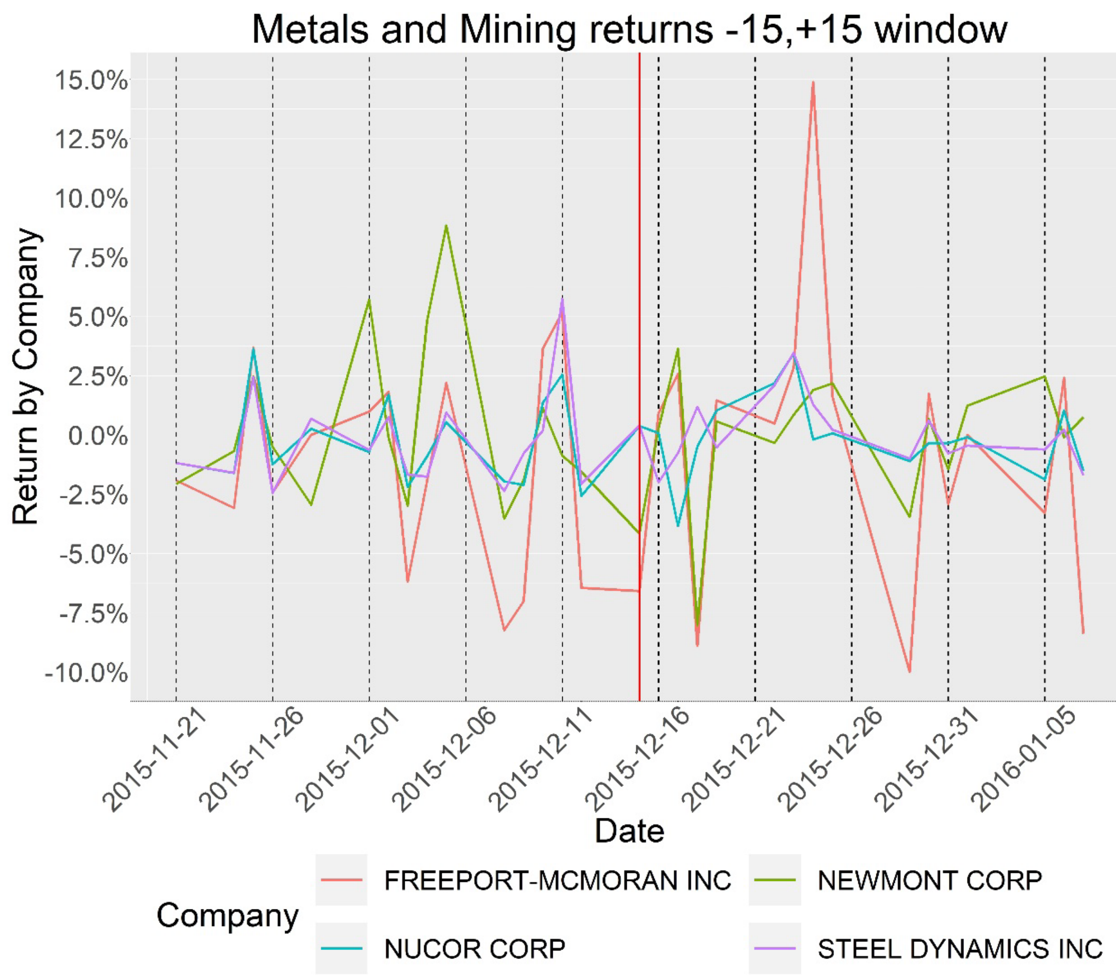

Figure 4: SP500 Metals and Mining returns -15,+15 window

Figure 5 shows returns in the automotive industry. The three firms in this industry are Ford, General Motors, and Tesla. A positive reaction to the Paris Agreement can be observed in the beginning. This is followed by moderately negative returns. All the firms follow a relatively similar path and seem to have a high degree of correlation. Tesla has the most positive reaction to the Paris Agreement. This is not surprising, as an electric automotive firm like Tesla will likely benefit the most from the ongoing low-carbon transition.

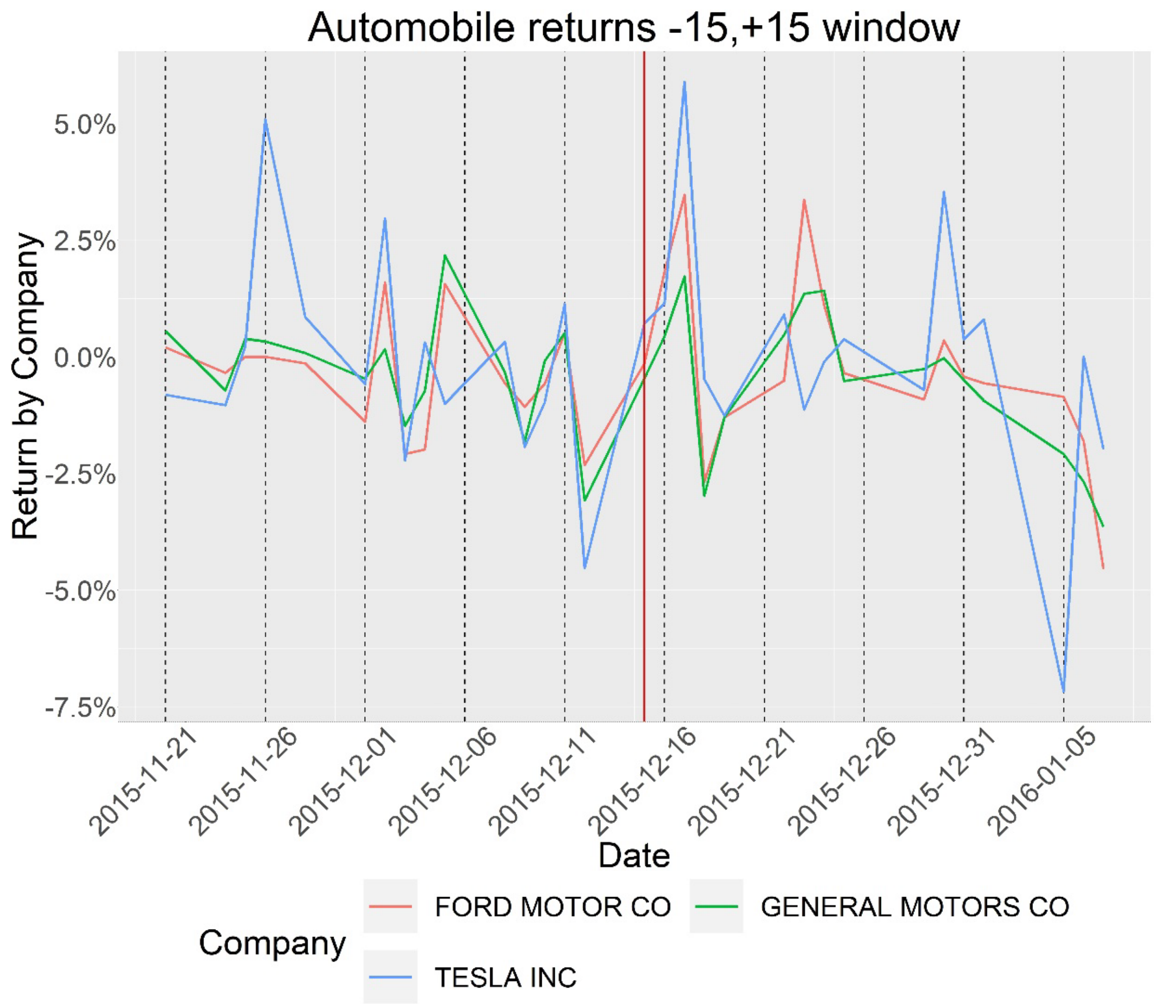

Figure 5: SP500 Automobile returns -15,+15 window

Figure 6 shows the returns of firms in the IT Services industry before and after the Paris Agreement. Slightly negative returns can be observed in the days before the agreement before the returns recover. After the event date, there is a short increase, and then the returns fall once again. It should be noted that many of the firms listed in the IT Services sector are actually payment service companies, such as PayPal or Mastercard.

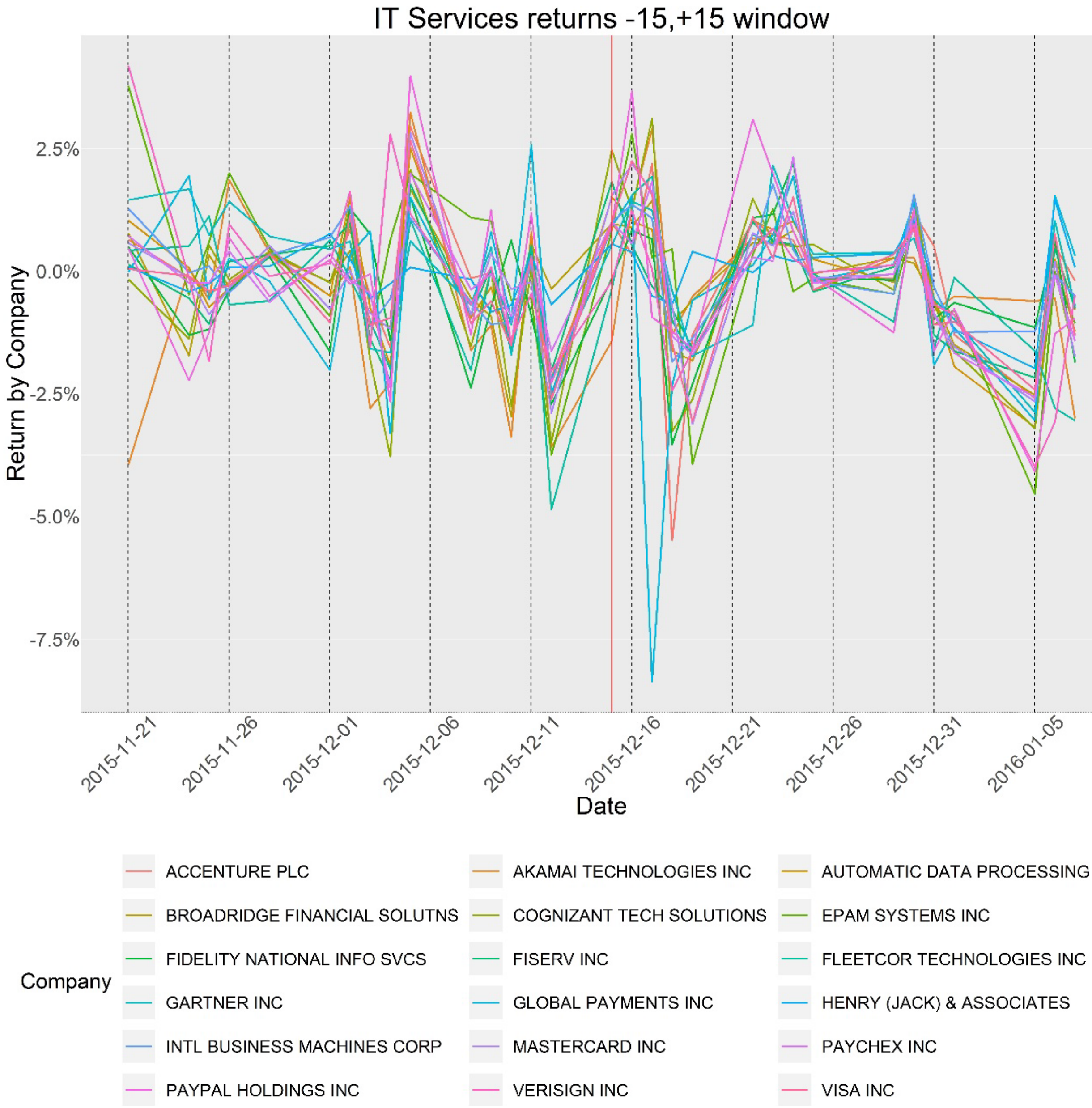

Figure 6: SP500 returns IT Services sector -15,+15 window

4.2.2 STOXX 600

Table 2 shows the number of firms in each industry for the STOXX 600 index. The Banking sector has the highest number of firms in any industry, with 44 firms. The three sectors Household Products, Leisure Products, and Thrifts and Mortgage Finance include only one firm. The average number of firms per industry in the STOXX 600 is ten and the median is eight.

Industry	Number of firms	Industry	Number of firms
Banks	44	IT Services	7
Insurance	36	Multi-Utilities	7
Chemicals	29	Transportation Infrastructure	7
Machinery	27	Automobiles	6
Metals & Mining	27	Construction Materials	6
Diversified Telecommunication Services	25	Health Care Providers & Services	6
Capital Markets	24	Interactive Media & Services	6
Hotels, Restaurants & Leisure	23	Airlines	5
Media	20	Auto Components	5
Energy Equipment & Services	19	Containers & Packaging	5
Equity Real Estate Investment Trusts (REITs)	18	Independent Power and Renewable Electricity Producers	5
Aerospace & Defense	16	Life Sciences Tools & Services	5
Oil, Gas & Consumable Fuels	16	Personal Products	5
Real Estate Management & Development	16	Electronic Equipment, Instruments & Components	4
Pharmaceuticals	15	Gas Utilities	4
Construction & Engineering	14	Industrial Conglomerates	4
Electric Utilities	14	Multiline Retail	4
Food & Staples Retailing	13	Wireless Telecommunication Services	4
Professional Services	12	Communications Equipment	3
Semiconductors & Semiconductor Equipment	12	Consumer Finance	3
Textiles, Apparel & Luxury Goods	12	Entertainment	3
Commercial Services & Supplies	11	Internet & Direct Marketing Retail	3
Food Products	11	Road & Rail	3
Trading Companies & Distributors	11	Technology Hardware, Storage & Peripherals	3
Biotechnology	10	Distributors	2
Diversified Financial Services	10	Diversified Consumer Services	2
Beverages	9	Marine	2
Electrical Equipment	9	Paper & Forest Products	2
Health Care Equipment & Supplies	9	Tobacco	2
Specialty Retail	9	Household Products	1
Air Freight & Logistics	8	Leisure Products	1
Household Durables	8	Thrifts & Mortgage Finance	1
Software	8		
Building Products	7		

Table 2: STOXX 600 industries and number of companies

Figure 7 shows the returns of selected industries in the STOXX 600. Before the Paris Agreement, slightly negative returns can be observed. After the Paris Agreement, there are moderately positive returns.

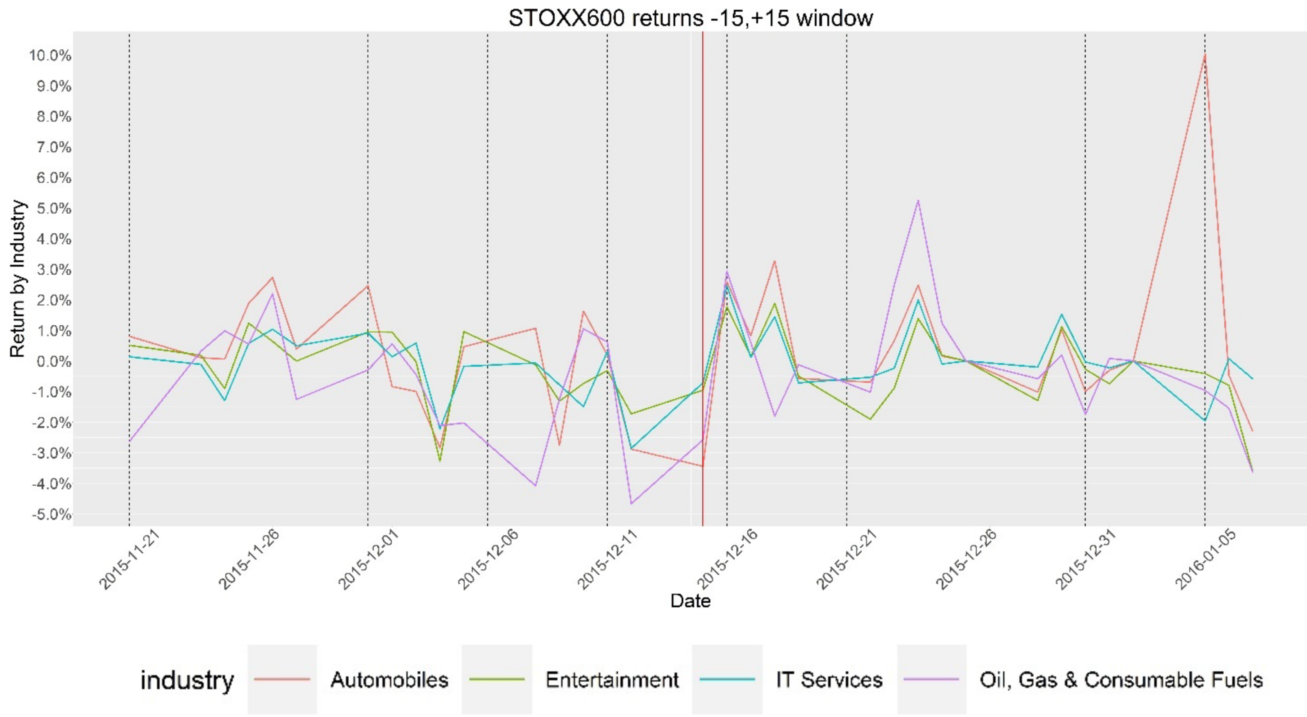

Figure 7: STOXX 600 returns -15,+15 window

Figure 8 shows the performance of firms in the Oil, Gas and Consumable Fuels industry listed in the STOXX 600 index. Positive returns can be seen in the beginning after the Paris Climate Agreement. However, it should also be noted that the returns of some companies are significantly negative after a few days; in the following week, most companies show positive returns.

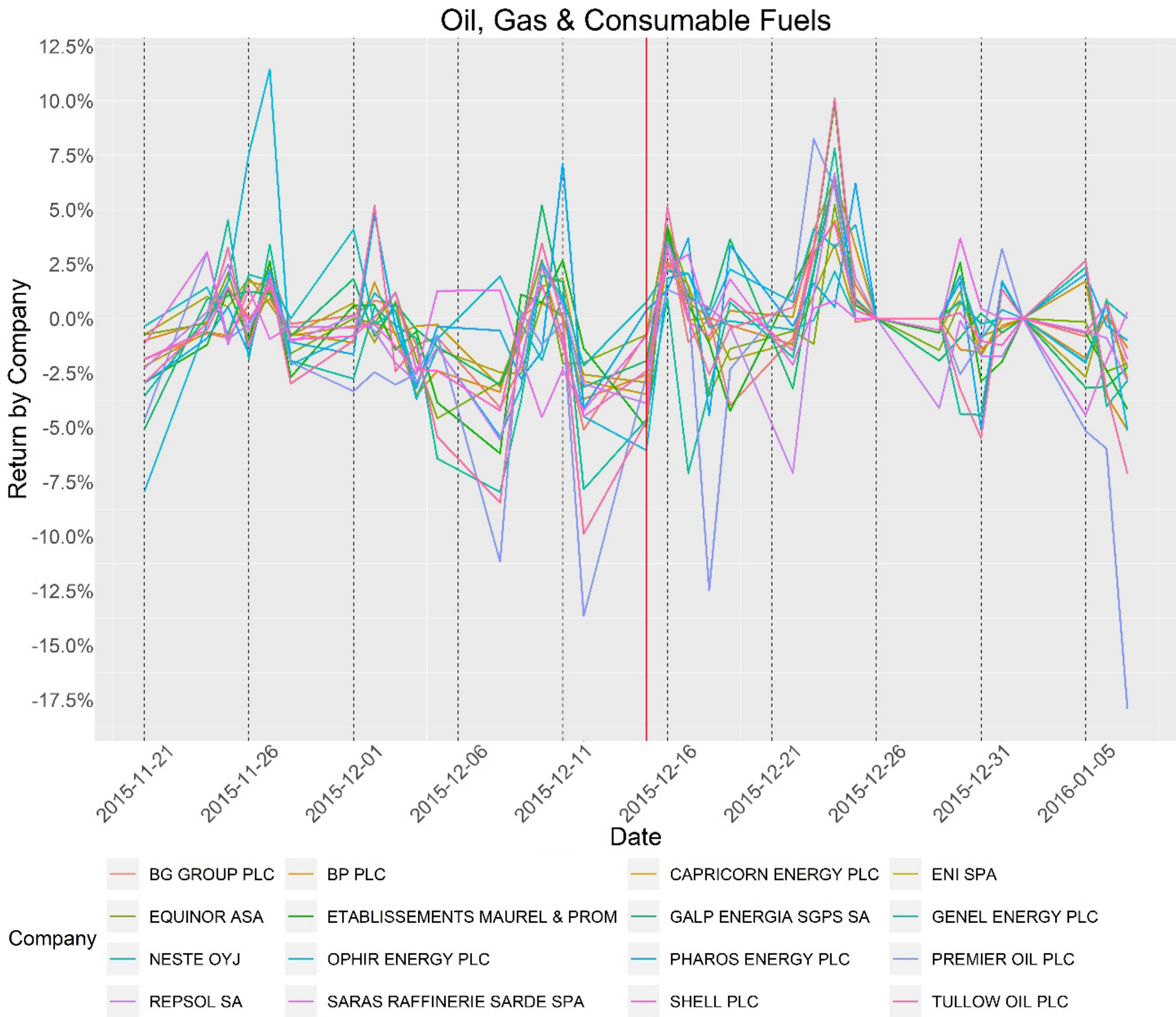

Figure 8: STOXX 600 Oil, Gas & Consumable Fuels returns

Figure 9 shows the returns of the largest European car manufacturers. After some negative returns just before the Paris Climate Agreement, positive returns can be observed after the agreement.

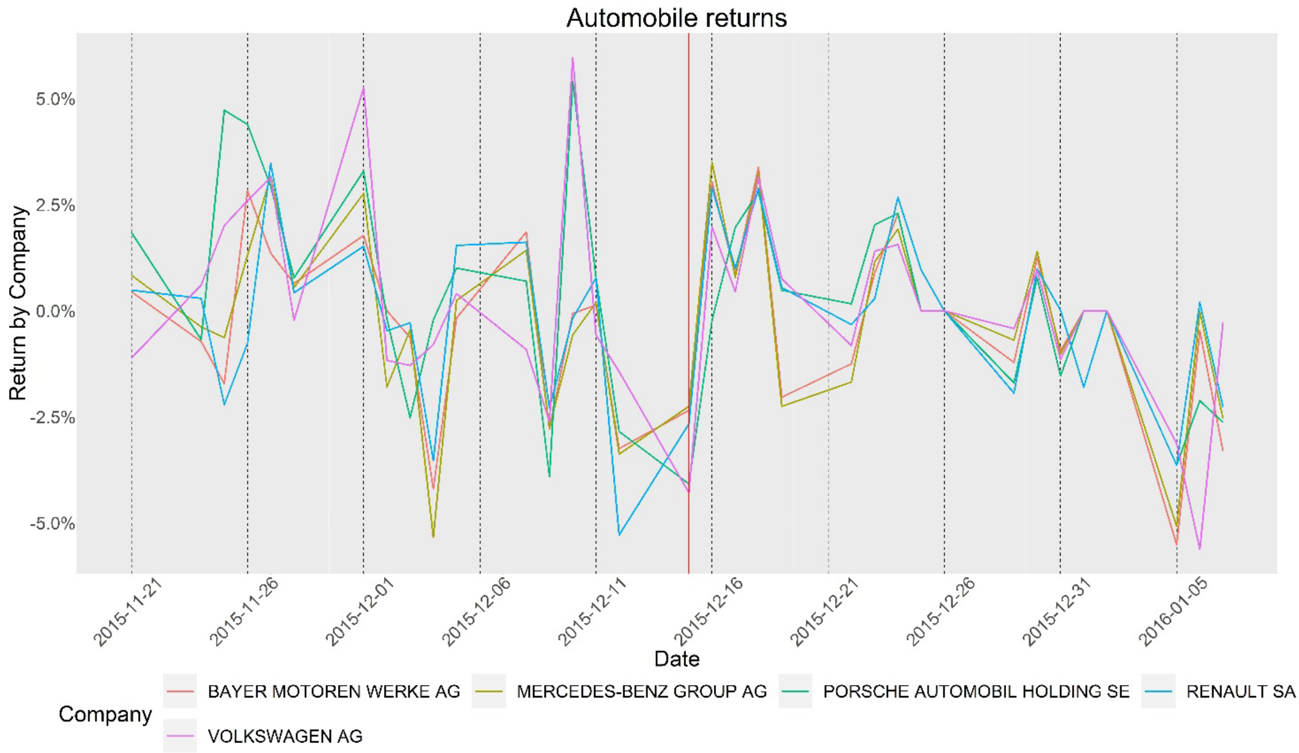

Figure 9: STOXX 600 Automobile returns

Figure 10 shows the returns of IT Services firms listed in the STOXX 600. In the days right before the Paris Agreement, many firms had moderately negative returns. After the agreement, the returns increased again.

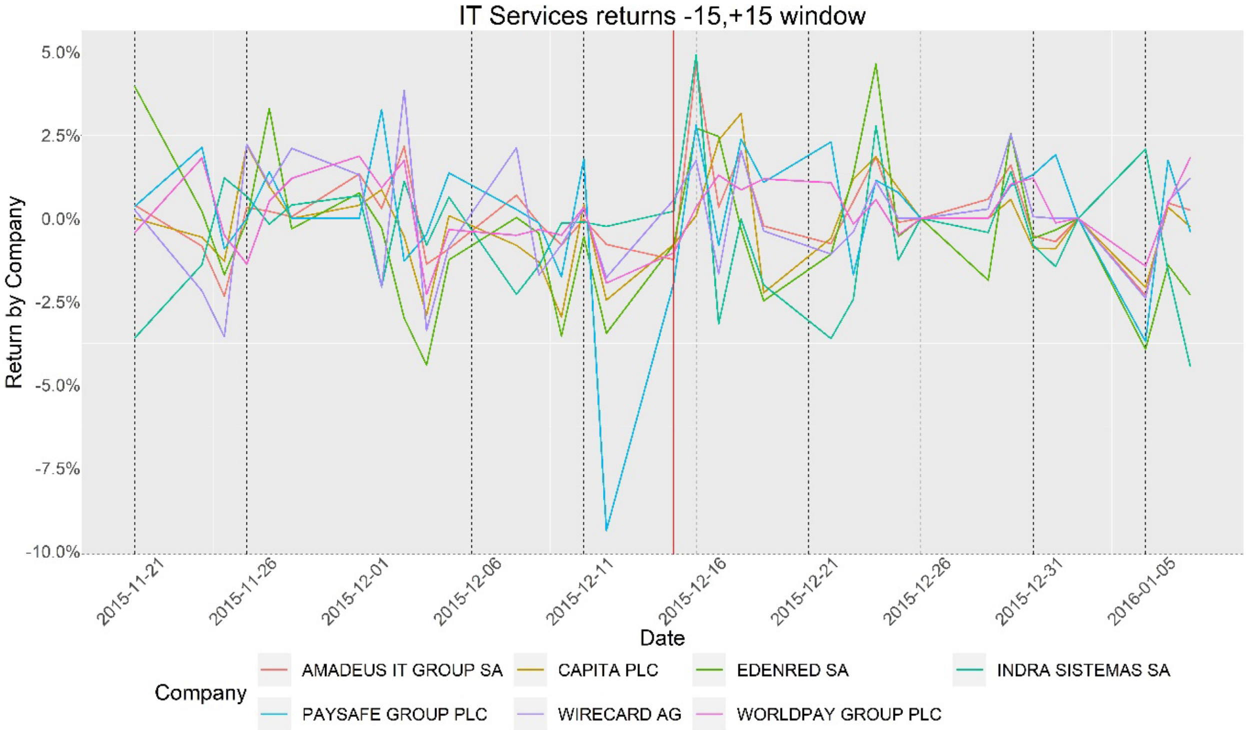

Figure 10: STOXX 600 IT Services returns -15,+15 window

Descriptive statistics can help gain an intuitive understanding of the underlying effects. However, more sophisticated models that use asset pricing models and abnormal returns are needed to obtain reliable results and make correct inferences.

4.3 Data wrangling

Our study's core data is the stock price information of index-listed corporations from two different markets. The columns gvkey (company identifier), datadate (date), conm (company name), and gind (industry identifier) are the most critical variables in our analysis. We join the Global Industry Classification Standard (GICS) dataset to classify each company by industry. After this step, we compute daily returns for each industry. In order to do this, we first calculate lagged prices before computing daily returns. We calculate simple and logarithmic returns and compare the two by calculating the difference. We used logarithmic returns since the two calculation methods provide almost the same values with only minor differences. This approach is in line with the majority of research using the event study methodology. The daily return using simple and logarithmic returns are

$$Daily\ Return = \frac{P_t}{P_{t-1}} - 1 \qquad (simple\ returns), \qquad (3)$$

$$Daily\ Return = ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (logarithmic\ returns). \qquad (4)$$

gvkey	datadate	tic	conm	prccd	gind	industry	PRClagged	returnArithmetic	return	Returndifference
004213	20150424	ECL	ECOLAB INC	115.59	151010	Chemicals	115.85	-2.244281e-03	-2.246804e-03	2.522174e-06
004213	20150427	ECL	ECOLAB INC	116.09	151010	Chemicals	115.59	4.325634e-03	4.316305e-03	9.328662e-06
004213	20150428	ECL	ECOLAB INC	112.97	151010	Chemicals	116.09	-2.687570e-02	-2.724346e-02	3.677557e-04
004213	20150429	ECL	ECOLAB INC	114.41	151010	Chemicals	112.97	1.274675e-02	1.266619e-02	8.055595e-05
004213	20150430	ECL	ECOLAB INC	111.98	151010	Chemicals	114.41	-2.123940e-02	-2.146820e-02	2.288016e-04
004213	20150501	ECL	ECOLAB INC	113.95	151010	Chemicals	111.98	1.759243e-02	1.743947e-02	1.529554e-04
004213	20150504	ECL	ECOLAB INC	113.97	151010	Chemicals	113.95	1.755156e-04	1.755002e-04	1.540106e-08
004213	20150505	ECL	ECOLAB INC	112.36	151010	Chemicals	113.97	-1.412652e-02	-1.422725e-02	1.007291e-04
004213	20150506	ECL	ECOLAB INC	112.50	151010	Chemicals	112.36	1.245995e-03	1.245219e-03	7.756076e-07
004213	20150507	ECL	ECOLAB INC	113.28	151010	Chemicals	112.50	6.933333e-03	6.909408e-03	2.392503e-05
004213	20150508	ECL	ECOLAB INC	114.79	151010	Chemicals	113.28	1.332980e-02	1.324174e-02	8.806013e-05

Figure 11: Return computation on company level

Large outliers with very high or low values can be a problem in regression analysis. In a preliminary analysis, we found some outliers in the daily returns on a company level. Hence, we decided to remove the largest outliers by winsorizing at the 0.1% and 99.9% levels. To prevent the loss of valuable observations, we decided that winsorizing on a relatively low level was the best option. After winsorizing, we analyzed the data again and the most extreme outliers were gone. Subsequently, we compute the average daily return in each industry. This is the actual return we use in the event study.

	industry	datadate	averageReturnSector
	All	All	All
126881	Independent Power and Renewable Electricity Producers	20170313	-0.0117276942
126882	Independent Power and Renewable Electricity Producers	20170314	-0.0018165309
126883	Independent Power and Renewable Electricity Producers	20170315	0.0277920173
126884	Independent Power and Renewable Electricity Producers	20170316	-0.0008845644
126885	Independent Power and Renewable Electricity Producers	20170317	0.0140599856
126886	Independent Power and Renewable Electricity Producers	20170320	-0.0229489330
126887	Independent Power and Renewable Electricity Producers	20170321	0.0088889474
126888	Independent Power and Renewable Electricity Producers	20170322	-0.0133632278
126889	Independent Power and Renewable Electricity Producers	20170323	0.0026869698
126890	Independent Power and Renewable Electricity Producers	20170324	0.0044623010

Figure 12: Return computation on an industry level

Now we prepare the data for the calculation of abnormal returns using the Fama-French Five-factor model. We merge this data with the average return by industry. Now we have daily average returns for each sector and the necessary information for computing abnormal returns using the Fama-French five factors in one dataset. After this, we create the event window dummy variable, which later in the regression is used to identify the estimation period, the holdout period, and the event period.

	datadate	mktrf	smb	hml	rmw	cma	rf	umd
13440	20170424	0.0118	0.0028	0.0050	-0.0007	0.0016	3e-05	0.0094
13441	20170425	0.0065	0.0039	-0.0007	-0.0037	0.0031	3e-05	0.0011
13442	20170426	0.0004	0.0075	0.0031	0.0023	0.0001	3e-05	-0.0021
13443	20170427	0.0005	-0.0020	-0.0097	0.0020	-0.0057	3e-05	0.0023
13444	20170428	-0.0030	-0.0076	-0.0061	0.0011	-0.0019	3e-05	-0.0008
13445	20170501	0.0021	0.0025	-0.0012	-0.0018	-0.0051	3e-05	0.0098
13446	20170502	0.0003	-0.0047	-0.0021	0.0039	-0.0035	3e-05	-0.0059
13447	20170503	-0.0019	-0.0052	0.0021	-0.0004	0.0013	3e-05	-0.0002
13448	20170504	0.0002	-0.0013	-0.0035	0.0036	-0.0071	3e-05	-0.0001
13449	20170505	0.0046	0.0011	0.0000	-0.0022	0.0065	3e-05	-0.0030
13450	20170508	-0.0004	-0.0020	0.0026	0.0013	0.0008	3e-05	0.0001
13451	20170509	-0.0005	0.0040	-0.0080	0.0034	-0.0037	3e-05	0.0005
13452	20170510	0.0020	0.0025	0.0002	-0.0031	0.0039	3e-05	0.0005
13453	20170511	-0.0026	-0.0043	-0.0016	-0.0025	-0.0002	3e-05	0.0013
13454	20170512	-0.0018	-0.0038	-0.0060	-0.0027	-0.0033	3e-05	0.0031
13455	20170515	0.0053	0.0025	0.0021	-0.0031	0.0004	3e-05	0.0007
13456	20170516	-0.0003	0.0010	-0.0009	-0.0025	-0.0012	3e-05	0.0083
13457	20170517	-0.0197	-0.0096	-0.0060	0.0053	0.0029	3e-05	-0.0155
13458	20170518	0.0040	0.0001	-0.0039	-0.0034	-0.0060	3e-05	0.0057
13459	20170519	0.0070	-0.0033	0.0040	-0.0009	0.0079	3e-05	-0.0025
13460	20170522	0.0056	0.0025	-0.0030	-0.0004	-0.0031	3e-05	0.0036

Figure 13: Fama-French Five factor model implementation

5. Methodology

This section gives an overview of the event study methodology. Then we show how our study approaches the research question of how stock market investors in different markets and industries worldwide react to the 2015 Paris Climate Agreement. We present the essential steps in the data-wrangling process, regression equations, and results, and an assessment of the statistical significance and robustness of our results.

5.1 Research design

The research design is a general plan for approaching the chosen research question (Saunders et al., 2019, p. 174). Our study will be an exploratory study of the market reaction to the Paris Agreement. The purpose of this research is to gain a more detailed understanding of the market in general and how the different industries in the market behaved during before and after the Paris Agreement. Since our analysis is exploratory, we will use a critical value of 10%. This is higher than the normal 5%, but since our research is exploratory it is less important to be certain in our significance testing. Our research consists of analyzing big datasets of market data. Since our analysis relates to numerical analysis, we use the quantitative method. The quantitative method allows us to use an empirical analysis to test the significance of market responses.

5.2 Research strategy

The research strategy is how our research project will answer the research question (Saunders et al., 2019, p. 177). In our research project, we use the experiment strategy to study the significance of market responses. To do this, we formulate a hypothesis, and we test this hypothesis by checking whether the behavior of the market response during the PA was statistically significantly different from the normal market variations.

5.3 Event study

The event study methodology, which according to MacKinlay (1997), was first developed by Ball & Brown (1968) and Fama et al. (1969), can help determine whether financial markets react to public announcements of new events in a statistically significant way. Event studies can therefore determine the efficiency of the financial markets. According to Brown & Warner (1980), security returns that are systematically and persistently nonzero after a particular financially relevant event are inconsistent with the efficient market hypothesis. In addition, the event must be unexpected for the financial market. There should be no other events during the event window that could confound the results and be responsible for the stock price change (Binder, 1998; McWilliams & Siegel, 1997).

5.3.1 Event window

Following over two weeks of complex negotiations, French Foreign Minister Laurent Fabius, who presided over the meetings, announced the Paris Agreement's approval on the 12th of December, 2015. Our study's event day ($t = 0$) is the 12th of December, 2015. It should be noted that since the 12th of December, 2015, was a Saturday, it is not a trading day. Choosing an appropriate event date is probably one of the most crucial research decisions when using the event study methodology. While a too-short event window might risk missing the effects of the event on the stock price, long event windows have a higher risk of confounding events, which can distort the results. Moreover, empirical research has shown that a short event window can, in most cases, capture an event's important effects (Ryngaert & Netter, 1990). For instance Busse & Clifton Green (2002) find that it takes only a few minutes for new information to be reflected in the stock price. Mitchell & Netter (1989) found that new information about federal tax rules in the U.S. took about 90 minutes to be reflected in the stock price. Since with long event windows, it is more challenging to avoid confounding events, event windows should be long enough to capture an event's effect but short enough to prevent confounding effects. Ryngaert & Netter (1990) suggest that the event window length should reflect the event's nature and consider the likelihood of information leakage. To prevent information leakage from impacting the results, it is good practice to start the event window slightly before the actual start of the event window. Therefore we decided to use a (-3,3) window as our baseline event window, which starts on Wednesday, the 9^{th} of December, and ends on Wednesday 16^{th} of December. Kruse et al. (2020) use the trading volume of SP500 and SP500 Energy Futures as a proxy to determine if there was information leakage before the

2015 Paris Climate Agreement. They argue that if the agreement came as a surprise, this would cause increased trading activity. Kruse et al. (2020) observed an increase in trading activity only on Monday, the 14th of December 2015. This means that the Paris Climate Agreement, most likely in particular the binding nature of the agreement, was mostly a surprise to the market.

In addition to various significance tests, we try out multiple longer event windows as a conservative form of robustness checks. According to Kruse et al. (2020), this makes it easier to assess the robustness of the results. Kruse et al. (2020) explain that if the effect of the event is only present in the first two days, the likelihood of type II errors is higher. Explained in simple terms, the likelihood of failing to reject a false null hypothesis is increased. This would mean accepting that there is no difference between the return and the abnormal return when in reality, there is a difference.

5.3.2 Computing abnormal returns

The first step before calculating abnormal returns is to calculate the expected or normal returns. Several models can be used to achieve this, including the Capital Asset Pricing Model (CAPM) and the Fama-French factor models. According to MacKinlay (1997), the Capital Asset Pricing Model takes the form

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}. \tag{5}$$

The expected return using the CAPM is

$$E(R_{it}) = \widehat{\alpha_i} + \widehat{\beta_i} R_{mt} + \varepsilon_{it}. \tag{6}$$

Consequently, the estimated abnormal return is

$$\widehat{AR_{it}} = (r_{it} - r_{ft}) - E(r_{it} - r_{ft}). \tag{7}$$

Next, we can calculate the estimated average abnormal return AAR for all the different industries,

$$\widehat{AAR_t} = \frac{1}{N} \sum_{i=1}^{N} \widehat{AR_{it}}. \tag{8}$$

By aggregating the estimated average abnormal returns over time, we obtain the estimated cumulative average abnormal return

$$\widehat{CAAR_t} = \sum_{t=1}^{t=2} \widehat{AAR_t}. \tag{9}$$

While the CAPM is a very useful model used in many studies, in line with many other studies such as Kruse et al. (2020), we use the Fama-French factor model. Specifically, we use the Fama-French Five Factor model since we think it will give us the most accurate results. When choosing which model to use for expected returns, we tried out the different models and found that the differences in the statistical significance of the regression results were only minor. Therefore, the choice between the different models for expected returns is not crucial since they all provide valid results showing only minor deviations. Normal returns using the Fama-French Five Factor model are estimated as

$$R_{it} = \alpha_i + \beta_{i1} R_{mt} + \beta_{i2} SMB + \beta_{i3}\ HML + \beta_{i4}\ RMW + \beta_{i5}\ CMA + + \beta_{i6}\ UMD + \varepsilon_{it}. \tag{10}$$

Once we have obtained the normal returns, according to Kruse et al. (2020), we can compute abnormal returns as

$$\widehat{AR}_{it} = R^e_{it} - (\widehat{\alpha}_i + \widehat{\beta_{i1}} R_{mt} + \widehat{\beta_{i2}}\, SMB + \widehat{\beta_{i3}}\, HML + \widehat{\beta_{i4}}\, RMW + \widehat{\beta_{i5}}\, CMA + \widehat{\beta_{i6}}\, UMD) + \varepsilon_{it}. \tag{11}$$

The calculation of AAR and CAAR with the Fama-French Five Factor model uses similar formulas as above with the CAPM model.

5.3.3 Econometric model

Our econometric model takes the following form. It consists of a Fama-French Five-factor return estimation combined with an event dummy which turns one during the event window. This way, we can capture the effects of the Paris Agreement on each industry. We run this regression for each industry using the LmList function in R. Once the event dummy for the Paris Climate Agreement is added, normal returns are

$$R_{it} = \alpha_i + \beta_{i1} R_{mt} + \beta_{i2} SMB + \beta_{i3} HML + \beta_{i4} RMW + \beta_{i5}\ CMA + \beta_{i6}\ UMD + \beta_{i7}\ D_{Paris} + \varepsilon_{it}. \tag{12}$$

5.3.4 Assumptions in multiple linear regression

The Gauss-Markov Theorem justifies why in most cases, it is best to use the ordinary least squares (OLS) method as long as the Gauss-Markov assumptions are not violated (Wooldridge, 2013, p. 101). The five relevant assumptions are called Multiple Linear Regression assumptions (MLRs). If all five MLR assumptions hold, "the OLS estimator $\hat{\beta}_j$ for β_j is the best linear unbiased estimator (BLUE)" (Wooldridge, 2013, p. 102). But what does the term BLUE mean exactly? According to Wooldridge (2013, p. 102), "an estimator $\tilde{\beta}_j$ of β_j is linear if, and only if, it can be expressed as a linear function of the data on the dependent variable":

$$\tilde{\beta}_j = \sum_{i=1}^{n} w_{ij} y_i . \qquad (13)$$

Furthermore, $\tilde{\beta}_j$ is an unbiased estimator of β_j, if $E(\tilde{\beta}_j) = \beta_j$. This has to hold for any $\beta_0, \beta_1, \dots, \beta_k$. Finally, best in BLUE means that the estimator should have the smallest variance (Wooldridge, 2013, p. 102).

The first Gauss-Markov assumption MLR.1 is "Linearity in Parameters" (Wooldridge, 2013, p. 105). MLR.1 demands that the relationship between the independent and dependent variables in the population is linear. The model takes the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + u . \qquad (14)$$

This does not mean that there can be no transformations to x using logarithms or interaction terms with other variables. However, the estimator β cannot be transformed.

The second assumption MLR.2 is "Random Sampling". The data used in the empirical analysis has to be drawn randomly from the population and takes the following form

$$\{(x_{i1}, x_{i2}, \dots, x_{ik}, y_i): i = 1, \dots, n\}. \qquad (15)$$

The relationship between dependent and independent variables follows the model stated in MLR.1.

The third assumption MLR.3 is "No Perfect Collinearity". It means that "in the sample (and therefore in the population), none of the independent variables is constant, and there are no exact linear relationships among the independent variables" (Wooldridge, 2013, p. 105). It should be mentioned, however, that the independent variables can be correlated. They should just not be perfectly correlated. Some degree of correlation among the independent variables is normal and acceptable in multiple regressions.

The fourth assumption MLR.4 is "Zero Conditional Mean". This means that "the error u has an expected value of zero given any values of the independent variables" (Wooldridge, 2013, p. 105). In other words, no information about the mean of unobserved factors is revealed by the included independent variables. According to Wooldridge (2013, p. 105), mathematically "Zero Conditional Mean" means

$$E(u|x_1, x_2, \ldots, x_k) = 0. \tag{16}$$

The fifth assumption is MLR.5 "Homoskedasticity". According to Wooldridge (2013, p. 105), MLR.5 means that "the error u has the same variance given any value of the explanatory variables". Expressed mathematically, this means

$$Var(u|x_1, \ldots, x_k) = \sigma^2. \tag{17}$$

5.3.5 Test of multiple linear regression assumptions in our data

Assumption MLR.1 "Linearity in Parameters"

We plot the dependent and independent variables in a diagram to check for linearity in the parameters. If we see the datapoints move in a straight line, the relationship is constant.

SP500 "Linearity in Parameters"

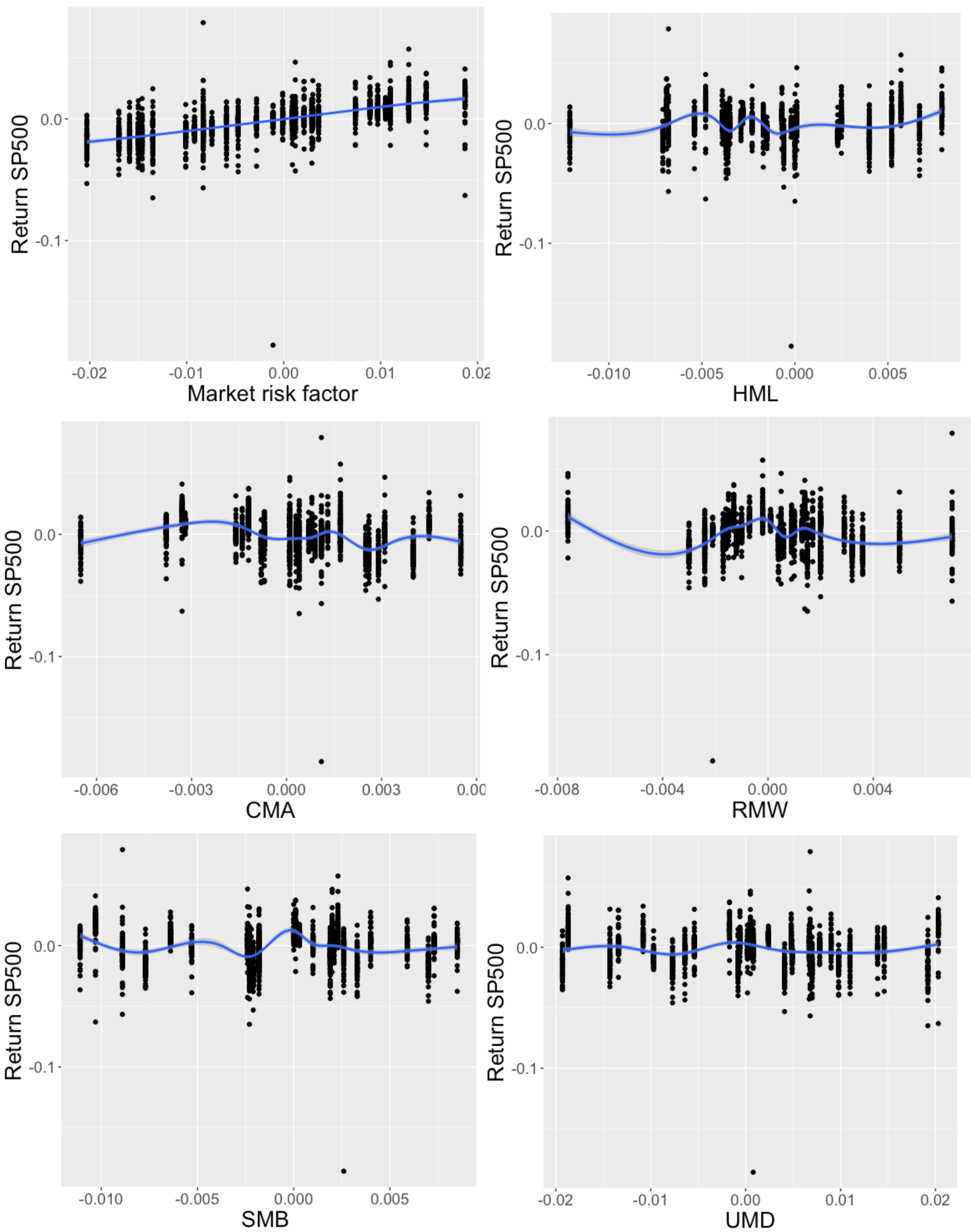

Figure 14: SP500 returns and five factors relation

STOXX 600 "Linearity in Parameters"

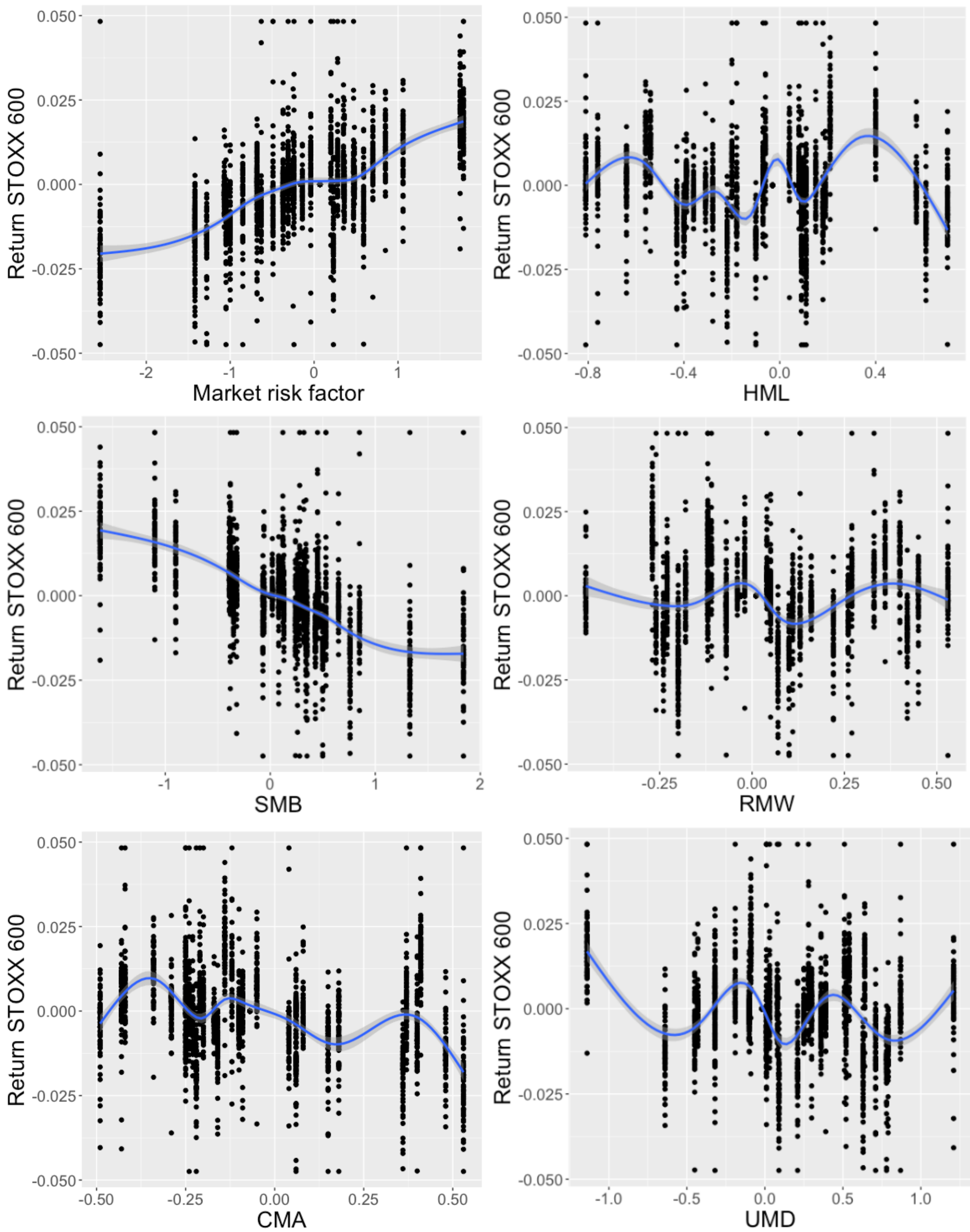

Figure 15: STOXX 600 returns and five factors relation

Based on the charts, we conclude that we have linearity in the parameters, even though the parameters deviate somewhat from a straight line. We see a clear relationship for all factors, but for the European market, the relationship is less linear. We used five factors especially created for both markets, but Europe's less linear relationship could mean that the model's predicting power is decreased.

Assumption MLR.2 “Random Sampling”

Our selection of data is the SP500 and the STOXX 600. These indices represent a large part of the total market capitalization of their representative markets. The SP500 has a total market capitalization of 34.8 trillion U.S. dollars, representing 86% of the U.S. equity market, which is 40.5 trillion (Morningstar, 2023). The STOXX 600 index has a market capitalization of 12.8 trillion Euros, while the total equity market is 14.6 trillion Euros representing an 87% share (Deutsche Börse Group, 2023). Our chosen indexes represent such a large part of the total population that it is almost the entire population we try to test. This limits our exposure to biased samples. However, the composition of the indexes favors big corporations, and by using these indexes, we have a bias toward big corporations' market behavior. For the random sampling assumption to be fulfilled, the sample must accurately represent the population it should represent. Since the indexes we have chosen are such a big part of the overall population and because they are well-diversified but biased toward big companies, we view them as a good representation of the total population. The random sampling assumption is therefore fulfilled.

Assumption MLR.3 “No Perfect Collinearity”

Table 3 and Table 4 show the correlation between independent variables in our econometric analysis of the SP500 and the STOXX 600 indexes. We can see that there is some degree of correlation between the independent variables, but they are far from being perfectly correlated. The highest correlation in the SP500 is 0.556 and -0.843 in the STOXX 600. The correlation seems to be much higher in the STOXX 600 than in the SP500. However, even in the STOXX 600, most values are below 0.65. We can therefore say that our variables do not suffer from “Perfect Collinearity”. A typical mistake would be to include two dummy variables that have an exact linear relationship in the same regression model. Such a regression model would run into the dummy variable trap distorting the results and making them invalid. An example of this could be if we included two dummies for the Paris Agreement, one for the period before the agreement and one for the period after.

	mktrf	smb	hml	rmw	cma	umd
mktrf	1	0.285	0.061	–0.386	–0.214	–0.126
smb	0.285	1	–0.013	–0.365	–0.086	–0.151
hml	0.061	–0.013	1	–0.122	0.556	–0.37
rmw	–0.386	–0.365	–0.122	1	0.074	0.101
cma	–0.214	–0.086	0.556	0.074	1	–0.164
umd	–0.126	–0.151	–0.37	0.101	–0.164	1

Table 3: Correlation matrix of independent variables SP500

	Mktrf	SMB	HML	RMW	CMA	UMD
Mktrf	1	–0.642	0.394	–0.308	–0.03	–0.348
SMB	–0.642	1	–0.264	0.188	–0.029	0.212
HML	0.394	–0.264	1	–0.843	0.492	–0.496
RMW	–0.308	0.188	–0.843	1	–0.479	0.409
CMA	–0.03	–0.029	0.492	–0.479	1	–0.012
UMD	–0.348	0.212	–0.496	0.409	–0.012	1

Table 4: Correlation matrix of independent variables STOXX 600

Another method to assess whether multicollinearity is a problem is the variance inflation factor (VIF). It measures how much the variance of the estimated regressors increases due to high correlation between the regressors (Wooldridge, 2013, p. 98). According to (Wooldridge, 2013, p. 98), a VIF which is higher than 10 is cause for concern and suggests that multicollinearity is a serious problem. As can be seen in Table 5, all the VIFs for our SP500 and STOXX 600 econometric models are below five. Hence, we can conclude that it is unlikely that our model is affected by multicollinearity.

	Variance inflation factor					
	Mktrf	**SMB**	**HML**	**RMW**	**CMA**	**UMD**
SP500	1.174	1.276	2.294	1.349	2.090	1.598
STOXX 600	2.316	2.321	4.899	2.582	1.503	3.102

Table 5: Variance inflation factor SP500 and STOXX 600

Assumption MLR.4 “Zero Conditional Mean”

A violation of the “Zero Conditional Mean Assumption” could lead to omitted variable bias. According to Stock & Watson (2020), omitted variable bias occurs when an omitted variable is correlated with an independent variable and is a determinant of the dependent variable. In our analysis, we cannot completely rule out the possibility that there are omitted variables that are correlated with the error term. Such variables could, for instance, be oil prices or currency exchange rates. However, in econometric analysis, it is rarely possible to say for certain that there are no such omitted variables and give a guarantee that omitted variable bias is not a problem.

Assumption MLR.5 “Homoskedasticity”

If the “Homoskedasticity” assumption is violated, this can cause the test statistics and standard errors to be invalid (Wooldridge, 2013, p. 296). However, heteroskedasticity does not cause bias or make the estimated coefficients invalid. We use the Breusch-Pagan test to find out if our data suffers from heteroskedasticity. According to Wooldridge (2013, p. 276), the null hypothesis is that assumption MLR.5 holds,

$$H_0: Var(u|x_1 x_2, \dots, x_k) = \sigma^2. \tag{18}$$

If this null hypothesis cannot be rejected at the chosen significance level, it is the usual practice to assume that heteroskedasticity is not a problem. For the SP500 and STOXX 600, the Breusch-Pagan test had p-values of 0.4224 and 0.3615. Hence, we cannot reject the null hypothesis of homoskedasticity at a sufficiently small significance level and assume that heteroskedasticity is not an issue in our model.

5.3.6 Significance testing

Significance testing is essential to event studies, allowing researchers to assess the reliability of estimated abnormal returns with a high degree of confidence. The main goal of hypothesis testing in event studies is to determine whether the abnormal returns associated with the event are statistically significant or merely the result of chance (Giaccotto & Sfiridis, 1996). This process involves developing a null hypothesis that there is no relationship between the event and the abnormal returns (AR) and testing it against an alternative hypothesis H_0 that there is a significant relationship (Schimmer, 2023). The null hypothesis and the alternative hypothesis are

$$H_0: \mu = 0, \tag{19}$$

$$H_1: \mu \neq 0. \tag{20}$$

In our research, we performed a regression to calculate the abnormal returns. We used a t-test to test the statistical significance, representing the change in the dependent variable (AR) associated with a change in the independent variable. We also use different versions of the abnormal return to test different dimensions of the data. The t-test is used to determine whether the observed coefficient is significantly different from zero ($H_1 : \mu \neq 0$), suggesting a relationship between the independent and dependent variables. For the t-statistics, the null hypothesis is defined as the abnormal return having no significant relationship with the independent variable, which can be expressed mathematically as H_0: $E\left(AR_{i,t}\right) = 0$. According to Schimmer (2023), the corresponding t-statistics are

$$t = \frac{\bar{X}-\mu}{\frac{\hat{\sigma}}{\sqrt{n}}} = \frac{AR_{i.t}}{S_{AR_i}}. \tag{21}$$

In the t-test, x̄ is the sample mean, and μ is the population mean (the value we compare x̄ to). $\hat{\sigma}$ is the sample standard deviation, and n is the sample size. According to Ubøe (2008, p. 266), for the t-test in multiple regression to be valid, the data must fulfill the following three assumptions:

- Independence
- Normality
- Homogeneity of variance

Independence assumption

We use autocorrelation to test the independence of observations. This analysis assesses whether there is any correlation between observations in time series data. An autocorrelation threshold must be set independently when used in any study, according to the specific data type (Kutner, 2005, p. 482). We use a 20% threshold since Martin (2021) finds that the SP500 has up to 20% autocorrelation when affected by a market shock. Thus, we consider any autocorrelation above this threshold to violate the independence assumption. In appendix

Table 33 and Table 34, we have the autocorrelation for industries in both markets. Below there is a list of industries that failed the test and are therefore excluded from our data since we can't trust the t-test on these industries since they don't fulfil the assumption required.

Failed Autocorrelation-test

Trading Companies & Distributors
Multiline Retail
Specialty Retail
Life Sciences Tools & Services
Electronic Equipment, Instrument
Diversified Telecommunication Services
Electric Utilities
Multi-Utilities
Consumer Finance
Diversified Telecommunication Services

Normality assumptions

We perform a Shapiro-Wilk test for the normality assumption to check the distribution within each industry's abnormal returns for the period. If the returns are normally distributed, we can use them for t-tests. The normality assumption has to be fulfilled for the t-test results to be valid. It states that the population from which the sample is drawn follows a normal (Gaussian) distribution. The normality assumption is important because it allows for accurate inference and hypothesis testing based on the t-distribution. Departures from normality, especially in small samples, can affect the validity and reliability of the t-test results.

SP500	-15:15	-15:-1	-5:-1	1:5	1:15
Industry	p-value	p-value	p-value	p-value	p-value
Oil, Gas & Consumable Fuels	47%	51%	8%	68%	73%
Construction Materials	27%	16%	29%	52%	59%
Metals & Mining	39%	21%	17%	15%	46%
Aerospace & Defense	**8%**	28%	**9%**	39%	10%
Airlines	92%	94%	21%	21%	73%
Automobiles	46%	88%	79%	62%	72%
Banks	69%	48%	26%	54%	99%
IT Services	23%	23%	89%	24%	31%
Semiconductors & Equipment	69%	61%	98%	31%	82%
Containers and Packaging	88%	77%	23%	36%	52%

Table 6: SP500 - Shapiro-Wilk test for normality

STOXX 600	-15:15	-15:-1	-5:-1	1:5	1:15
Industry	p-value	p-value	p-value	p-value	p-value
Oil, Gas & Consumable Fuels	87%	43%	32%	92%	46%
Construction Materials	20%	99%	77%	35%	12%
Metals & Mining	65%	97%	18%	65%	27%
Aerospace & Defense	87%	67%	36%	37%	47%
Airlines	63%	79%	89%	61%	17%
Automobiles	63%	23%	18%	71%	18%
Banks	11%	10%	31%	74%	24%
IT Services	30%	16%	73%	86%	14%
Semiconductors & Equipment	11%	43%	79%	88%	56%
Containers and Packaging	100%	96%	82%	99%	91%

Table 7: STOXX 600 - Shapiro-Wilk test for normality

We have performed the Shapiro-Wilk test on the remaining 52 industries in two markets for five windows. The only industry that failed was Aerospace and Defence. This industry is therefore excluded from our analysis.

Homogeneity of Variance Assumption

The homogeneity of variance assumption is also known as the assumption of equal variances. It states that the variances of the populations being compared are equal. In other words, the variability within each group or condition being compared is roughly the same. Violating the homogeneity of variance assumption can affect the validity of the t-test. When the assumption is violated, the probability of making a Type I error (incorrectly rejecting the null hypothesis when it is true) can be inflated. In other words, the significance level of the t-test may no longer accurately reflect the actual probability of observing a significant result. The test power of the t-test is reduced when there are unequal variances, making it more challenging to detect true differences between groups. To ensure the validity and reliability of the t-test results, we assess the homogeneity of variance assumption using Levene's test. The test calculates the variance within each group and checks if the variance within the groups is significantly different. Our results from Levene's test show no significant difference in variance among the groups since both markets had p-values above our 10% significance level. The p-value for the U.S. is 0.35, while Europe's is 0.17. Since the European market is close to our critical value of 10%, indicating that the variance between the industry's abnormal returns has some difference in variance but not significantly different. The low p-value can lead us to reject the null hypothesis too often and conduct a Type I error.

5.3.6.1 Aggregated market analysis - significance tests

For analyses of the aggregated market, we needed to use a specialized hypothesis test that avoids the limitations of the t-test so that the aggregated market response significance test would have higher reliability. Stock returns have been shown to have “fat tails”. This indicates that the extreme values deviate from the normal distribution, which makes the t-test on stock returns less reliable, as it assumes a normal distribution. We have therefore incorporated a nonparametric significance test which has been shown to be more robust for non-normally distributed data.

Among the commonly used significance tests in event studies are the Patell-test (Patell, 1976; Patell & Wolfson, 1979) and the BMP test (Boehmer et al., 1991). The Patell-test is well suited for testing the significance of the cumulative abnormal returns but weak under event-induced volatility and cross-sectional correlation and requires a normal distribution of the data. Boehmer, Musumeci, and Poulsen introduced the BMP test, which builds on the Patell-test. The BMP test uses a standardized cross-sectional method that is more reliable under event-induced variance, which happens when event clustering occurs (Harrington & Shrider, 2007). In our thesis, we use the adjusted BMP test to assess the significance, and consequently, we will first present the BMP test and then its adjusted version. According to Schimmer (2023), the BMP-test statistics for testing the null hypothesis of the average abnormal returns on day *t* are

$$H_0: E(AAR) = 0, \tag{22}$$

$$Z_{BMP_t} = \frac{ASAR_t}{\sqrt{N}\, S_{ASAR_t}}. \tag{23}$$

The $ASAR_t$ is the sum of the standardized abnormal returns over the sample, with the expectation of zero AR. According to Marks & Musumeci (2017), the formulas for $ASAR_t$ and $SAR_{i.t}$ are given as

$$ASAR_t = \sum_{i=1}^{N} SAR_{i.t}, \tag{24}$$

$$SAR_{i.t} = \frac{AR_{i.t}}{S_{AR_{i.t}}}. \tag{25}$$

And according to Schimmer (2023), the standard deviation $S^2_{ASAR_t}$ is given as

$$S^2_{ASAR_t} = \frac{1}{N-1} \sum_{i=1}^{N} \left(SAR_{i,t} - \frac{1}{N} \sum_{l=1}^{N} SAR_{l,t}\right)^2. \tag{26}$$

The BMP test statistic and the null hypothesis for the cumulative average abnormal return specified by Boehmer et al. (1991) are

$$H_0: E(CAAR) = 0, \tag{27}$$

$$Z_{BMP_t} = \sqrt{N}\, \frac{\overline{SCAR}}{S_{\overline{SCAR}}}. \tag{28}$$

According to Schimmer (2023), the average standardized cumulative abnormal return across the number of firms (N) $\overline{SCAR}$, and the standard deviation $S^2_{\overline{SCAR}}$ are given as

$$\overline{SCAR} = \frac{1}{N} \sum_{i=1}^{N} SCAR_i, \tag{29}$$

$$S^2_{\overline{SCAR}} = \frac{1}{N-1} \sum_{i=1}^{N} (SCAR_i - \overline{SCAR})^2. \tag{30}$$

Schimmer (2023) states that $SCAR_i = \frac{CAR_i}{S_{CAR_i}}$ with S_{CAR_i} denoting the forecast-error-corrected standard deviation, which in the market model would be

$$S^2_{CAR_i} = S^2_{AR_i} \left[L_i + \frac{L_i^2}{M_i} + \frac{\left(\sum_{t=T_1+1}^{T_2} (R_{m.t} - \bar{R}_m)\right)^2}{\sum_{t=T_0}^{T_1} \left(R_{m,t} - \overline{\overline{R_m}}\right)^2} \right]. \tag{31}$$

The BMP test has been found to be too liberal in data containing cross-sectional correlation, with the result of rejecting a true H_0 too often (Kolari & Pynnönen, 2010). This means that it returns a high t-value too often so that H_1 is accepted. We therefore use an adjusted version of the BMP-test, which is more robust to the cross-sectional correlation of abnormal returns (Kolari & Pynnönen, 2010). Cross-sectional correlation is the correlation of two variables at the same time (Frees, 1995). This is relevant for our study because we investigate events that affect multiple firms simultaneously. The Adjusted BMP test uses the standardized abnormal returns ($SAR_{i,t}$) as given in the first BMP test equation and defines $\bar{r}$ as the average of the sample's cross-correlation of the estimation-period abnormal return. According to Kolari & Pynnönen (2010) the test statistic and null hypothesis for the average abnormal return are

$$H_0: E(AAR) = 0, \tag{32}$$

$$Z_{adj.BMP_t} = Z_{BMP_t} * \sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}}. \tag{33}$$

When looking at the aggregated market response, we test the CAAR. If one assumes the square-root rule holds for the standard deviation of different return periods, the test can be used on cumulative average abnormal returns. Kolari & Pynnönen (2010) define the null hypothesis and test statistic as

$$H_0: E(CAAR) = 0, \tag{34}$$

$$Z_{adj.BMP_t} = Z_{BMP_t} * \sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}}. \tag{35}$$

The drawback of the BMP and Adjusted BMP tests is that they perform best under normal distribution. Therefore, we have included a nonparametric test that does not require normally distributed data. The nonparametric test we use is the Generalized Rank Test from Kolari & Pynnönen (2011). The test is based on the idea of comparing the ranks of the response variable between two groups, where the groups are defined based on the values of the predictor variables. Specifically, the test compares the average ranks of the response variable in the two groups using a permutation-based approach.

The first calculation is to adjust for event-induced volatility. According to Kolari & Pynnönen (2011), the Rank test reduces the whole event window into one observation by standardizing cumulative abnormal returns of firms i in the event window with

$$SCAR_i = \frac{CAR_i}{S_{CAR_i}}. \tag{36}$$

The S_{CAR} is the standardized deviation of the predicted error in the CAR of firm i (Kolari & Pynnönen, 2011):

$$S^2_{CAR_i} = S^2_{AR_i}\left[L_i + \frac{L_i^2}{M_i} + \frac{\left(\sum_{t=T_1+1}^{T_2}(R_{m.t} - \bar{R}_m)\right)^2}{\sum_{t=T_0}^{T_1}\left(R_{m,t} - \overline{\overline{R_m}}\right)^2}\right]. \tag{37}$$

Under the null hypothesis the $SCAR_i$ has an expectation of zero. To account for event-induced volatility following Kolari & Pynnönen (2011), we standardize with the cross-section's standard deviation and obtain

$$SCAR_i^* = \frac{SCAR_i}{S_{SCAR}}, \tag{38}$$

$$S^2_{SCAR} = \frac{1}{N-1}\sum_{i=1}^{N}(SCAR_i - \overline{SCAR})^2, \tag{39}$$

$$\overline{\overline{SCAR_0}} = \frac{1}{N}\sum_{i=1}^{N} SCAR_i. \tag{40}$$

By using the $SCAR_i^*$ we find the Generalized standard abnormal return (GSAR), which according to Schimmer (2023), is defined as

$$GSAR_{i.t} = \{SCAR_i^* \; for\ t\ in\ event\ window\ SAR_{i.t} \; for\ t\ in\ estimation\ window\ \}, \tag{41}$$

$$K_{i.t} = \frac{rank\ (GSAR_{i.t})}{L_1+2} - 0.5. \tag{42}$$

The null hypothesis for the Rank T-test on the cumulative average abnormal return is $H_0\colon E(CAAR_0) = 0$ and $L_1 + 1$ is the standardized rank (Schimmer, 2023). The Rank T-test statistics according to Kolari & Pynnönen (2011) are

$$RANK\ T = Z \cdot \left(\frac{L_1 - 1}{L_1 - Z^2}\right)^{1/2}, \tag{43}$$

$$Z = \frac{\overline{\overline{K_0}}}{S_{\overline{\overline{K}}}}, \tag{44}$$

$$S_{\overline{\overline{K}}}^{2} = \frac{1}{L_1+1} \sum_{t \in CW} \frac{N_t}{N} K_t^{-2}, \tag{45}$$

$$\overline{\overline{K_t}} = \frac{1}{N_t} \sum_{i=1}^{N_t} K_{i.t}. \tag{46}$$

The null hypothesis for average abnormal returns on a single day is $H_0 : E(AAR_0) = 0$ and the corresponding test statistics according to Kolari & Pynnönen (2011) are

$$RANK\ T = Z \cdot \left(\frac{L_1 - 1}{L_1 - Z^2}\right)^{1/2}, \tag{47}$$

$$Z = \frac{\overline{\overline{K_0}}}{S_{\overline{\overline{K}}}}, \tag{48}$$

$$S_{\overline{\overline{K}}}^{2} = \frac{1}{L_1+1} \sum_{t \in CW} \frac{N_t}{N} K_t^{-2}, \tag{49}$$

$$\overline{\overline{K_t}} = \frac{1}{N_t} \sum_{i=1}^{N_t} K_{i.t}. \tag{50}$$

6. Results

In this section, we present the results of the event study. Firstly, we examine the aggregated stock market reactions for the U.S. market with the SP500 and Europe with the STOXX 600. We use different returns statistics and significance tests to investigate the robustness of the abnormal returns and our interpretations of the data. Secondly, we look at a more detailed level how the industries in the different markets reacted to the PA and whether there are differences between industries. Thirdly, we look at the beta change to see if industry-specific systematic risk changes. Lastly, we link the industry's cumulative abnormal returns to changes in the industry’s beta to summarize the industry’s market response.

We use a portfolio approach for the industry market response. The only drawback is if the number of constituents in one industry is low since this increases the effect of single-firm returns/idiosyncratic risk affecting the industry response and decreasing reliability. We anticipate that climate regulation will affect industries associated with higher emissions more. Therefore, we expect to see a negative market response in the event window because of the climate risk focus during the negotiations.

6.1 Aggregated market response

Summary of the Aggregated market response

Our most important finding is that the market sentiment changed on the day the Paris Agreement was announced. Both markets had significant negative cumulative average abnormal returns (CAAR) windows before the announcement. After the announcement, both markets had positive but not significant CAARs. The U.S. market had bigger CAARs, so the U.S. market response to the announcement was stronger.

Aggregated market response

The market reaction to the Paris Agreement is analyzed by looking at each industry's abnormal return (AR) and then at the average abnormal return (AAR) of the cross-section, which is the equally weighted average AR of all industries in that market index. We look at how the cumulative average abnormal return (CAAR) evolved during the event window to see how the overall market reacted to the event and perform significance tests of the AAR and CAARs of different event windows.

We use the returns for the 51 industries the indexes contain, and these industries compose an equally weighted index. The aggregated data for the market response will be a proxy for the market index, and the returns will deviate from the original market indexes, which are market value-weighted, not equally weighted. This difference in index construction will most likely cause a deviation in the AAR of the market value-weighted index compared to our equally weighted index. If an industry subgroup of the index has a small market weight in the original market index and a higher AR than the average, this will put upward pressure on the AAR of the whole market in our market index proxy. This happens if there are many small industries with high AR that get increased market weighting since we use equal weighting, not market weighting. This difference in index design will decrease the validity of the aggregated market response.

We look into CAARs for different event windows around the event day ($t_0 = 14.12.2015$), where -15:15 means we have an event window 15 days before and 15 days after t_0. We look at different event windows to see how consistent the results are so that we don't conclude on one event window, which might deviate from the rest. Multiple event windows will make our inference from the results more reliable since a single day's return will have less impact on the total results. However, a too-long window might "even out" the event effect since the market has other factors affecting the returns. The longer windows can lead to more "random walk" of the market returns, so it would be harder to test the significance of the abnormal returns, since a longer window possibly has a larger variance interval. The effect of having a too-long event window is that the test is not sensitive enough to the abnormal returns created by the event since it evened out and might cause a type II error, rejecting H_1 when it is actually true.

We have divided our event windows into three categories. The first is an equal number of days before and after the window, and the second and third look exclusively at the days before and after the announcement. A window with an equal number of days before and after the event is most suitable for short windows since the equal number of days before and after the event means a large number of days in the window. These long windows make it harder to make any statistical inference with confidence. This can also be seen in Table 8. As the event window widens, the p-values increase and the statistical significance decreases despite having the same CAAR size.

The other two categories of event windows look exclusively in each direction, with the center being ($t_0 = 14.12.2015$). These event windows are suitable for seeing how the aggregated market responded before and after the agreement. They also indicate how the market priced in the expectations of the agreement and how they reacted to the terms of the agreement.

6.1.1 SP500 - Aggregated market response

We look at the U.S. stock market and use the constituents of the SP500 as a proxy for the market response in the U.S. The Global Industry Classification Standard (GICS) we use contains 69 different industries, but in our period of analysis, the SP500 has only constituents from 62 of these industries and 11 failed assumptions tests leaving 51 industries. The reason these industries are not included in the SP500 may be that there are no firms in these industries that have high enough market capitalization to be included in the market value-weighted SP500 index.

SP500 - Cumulative average abnormal return

We performed two significance tests on 14 different event windows, and three windows showed significant CAAR at our 10% significance level. We observed a change from negative CAAR on the event window, looking at the period exclusively before and then turning to positive on the event window exclusively after the agreement.

SP500 CAAR Significance test					
	Event window	CAAR	Adj BMP	Rank T	Average-P
			p-value	p-value	p-value
Equal before and After	-15:15	-2.20%	56%	48%	52%
	-10 : 10	-1.30%	67%	49%	58%
	-5 : 5	-1.40%	54%	45%	50%
	-2 : 2	-2.00%	30%	18%	24%
Exclusively Before	-15 -1	-4.82%	14%	10%	12%
	-10:-1	-3.40%	21%	13%	17%
	-7:-1	**-4.78%**	**3%**	**3%**	**3%**
	-5:-1	**-3.86%**	**4%**	**3%**	**4%**
	-2:-1	**-2.25%**	**2%**	**3%**	**2%**
Exclusively After	1:2	1.03%	44%	25%	35%
	1:5	2.40%	31%	18%	25%
	1:7	3.25%	19%	14%	17%
	1:10	3.61%	16%	9%	13%
	1:15	2.02%	59%	50%	54%
	Average Equal	-1.73%	52%	40%	46%
	Average Before	-3.82%	9%	6%	8%
	Average After	2.46%	34%	23%	29%

Table 8: SP500 CAAR Significance test

The aggregated market response for the SP500 results shows that the windows with equal days before and after the event have very low significance. When we look at the windows with one direction exclusively, we start to find the reason why. The pre-announcement period has only windows with a negative CAAR, and three of those are significant. The period "-7:-1" has the highest negative CAAR of -4.78% with a p-value of 3%, while the most significant one is "-2:-1" with a negative CAAR of -2.25% and a p-value of 2.5%. The shorter window has a more significant CAAR because the abnormal returns are divided on fewer days.

When we look at the exclusively after window, it becomes clear why the "equal before and after" windows have a low significance. The after-windows have only positive CAARs, and the before-windows have only negative CAARs. This means that the equal before and after windows had a negative return before and it was reduced after the announcement. This gives a lower net AR for the equal window, and the length of the window is longer, so the low AR and the high number of days reduced the significance. That the before and after response is consistently different in all windows, with only negative before and only positive after, is a clear indicator that the market sentiment changed on the announcement day, even if the after windows are not significant.

SP500 - Average abnormal return (AAR) per day

We have analyzed the daily AAR through an event window of 31 days, with 15 days before and 15 days after the event date ($t_0 = 14.12.2015$). In Figure 16, you can see a graphical distribution of the AAR, while in Table 9, you can see the AAR for the whole period and the daily significance.

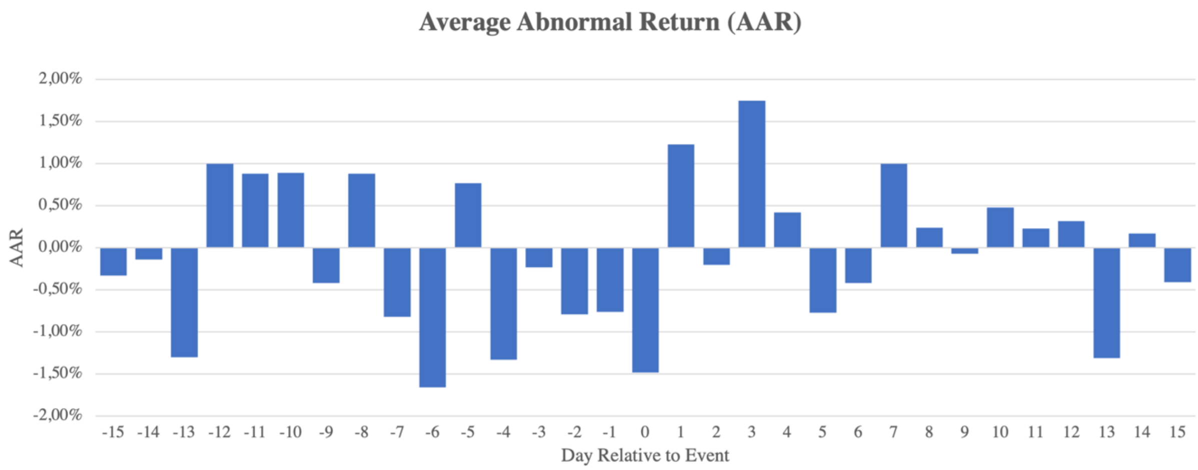

Figure 16: SP500 average abnormal return (AAR) per day

For the SP500, we found that the announcement day ($t_0 = 14.12.2015$) has the largest AAR with -1.48% and a p-value of 3.2% on our main indicator of significance, the "Average", which is the average p-value of the adjusted BMP and Rank T-test.

In Table 9, we look at the development of the AAR and CAAR throughout the -15:15 windows and call the CAAR status on a single day so far in the period the Rolling-CAAR (R-CAAR). With the R-CAAR, we can distinguish between a CAAR looking at one specific window and how the R-CAAR develops in the period 15 days before and 15 days after the announcement.

Day	AAR	R-CAAR	Adj BMP	Rank T	Average
			p-value	p-value	p-value
-15	-0.3%	-0.3%	77%	79%	78%
-14	-0.1%	-0.5%	71%	64%	68%
-13	-1.3%	-1.8%	**8%**	**5%**	**6%**
-12	1.0%	-0.8%	20%	11%	16%
-11	0.9%	0.1%	26%	14%	20%
-10	0.9%	1.0%	29%	19%	24%
-9	-0.4%	0.6%	60%	41%	51%
-8	0.9%	1.5%	48%	29%	38%
-7	-0.8%	0.6%	38%	23%	30%
-6	-1.7%	-1.0%	**7%**	**4%**	**6%**
-5	0.8%	-0.3%	31%	16%	24%
-4	-1.3%	-1.6%	**6%**	**4%**	**5%**
-3	-0.2%	-1.8%	78%	67%	72%
-2	-0.8%	-2.6%	39%	29%	34%
-1	-0.8%	-3.4%	30%	19%	25%
0	-1.5%	-4.8%	**4%**	**3%**	**3%**
1	1.2%	-3.6%	16%	**7%**	11%
2	-0.2%	-3.8%	78%	56%	67%
3	1.8%	-2.1%	**7%**	**5%**	**6%**
4	0.4%	-1.6%	78%	77%	78%
5	-0.8%	-2.4%	49%	25%	37%
6	-0.4%	-2.8%	42%	24%	33%
7	1.0%	-1.8%	16%	**10%**	13%
8	0.2%	-1.6%	50%	41%	45%
9	-0.1%	-1.7%	85%	68%	77%
10	0.5%	-1.2%	43%	28%	36%
11	0.2%	-1.0%	65%	59%	62%
12	0.3%	-0.6%	53%	42%	47%
13	-1.3%	-1.9%	23%	13%	18%
14	0.2%	-1.8%	83%	90%	87%
15	-0.4%	-2.2%	65%	57%	61%

Table 9: SP500 AAR and R-CAAR for different windows and significance tests

Table 9 Notes: Day = Day relative to event day (t_0 = 14.12.2015). AAR = average abnormal returns for the cross-section of industries on that individual day. R-CAAR = the cumulative AAR from the start of the period day -15 until that individual day. Adjusted BMP and Rank T are significance tests, while average is the average p-value of those two tests.

From the data, we can see an indication of a negative trend after day -7, which was a few days after the beginning of the COP 21 conference (30.11.2015). From the beginning of the conference (day -10) to the announcement day (day 0), there was a negative AAR on seven out of the nine days. To look further into this, we ran a “-9:-1” window before the announcement, with a CAAR of -3.4%, but it was not significant at the 10% level. This indicates that there was no immediate change after the start of the conference.

The highest R-CAAR value during the period is day -8 with 1,46%. We can see a relatively big negative AAR at days -7 and -6 in Figure 17. It looks like the beginning of a negative AAR trend that continues until day 0, with the most negative R-CAAR on day 0 at -4.84%. This can be seen in Figure 17 as the orange area bottoms out at day 0. This trend is supported in Table 8 This trend is supported in Table 8 CAAR significance tests, as all three windows looking at this time period and exclusively in the direction before the event (-7:-1, -5:-1, -2:-1) were significant, with a low p-value between 2.5% and 3.7%. The AAR turns positive after the announcement (day 0), and the R-CAAR gradually decreases. The days between day 0 and day +10 have a CAAR of +3.6% but were also not significant at the 10% level.

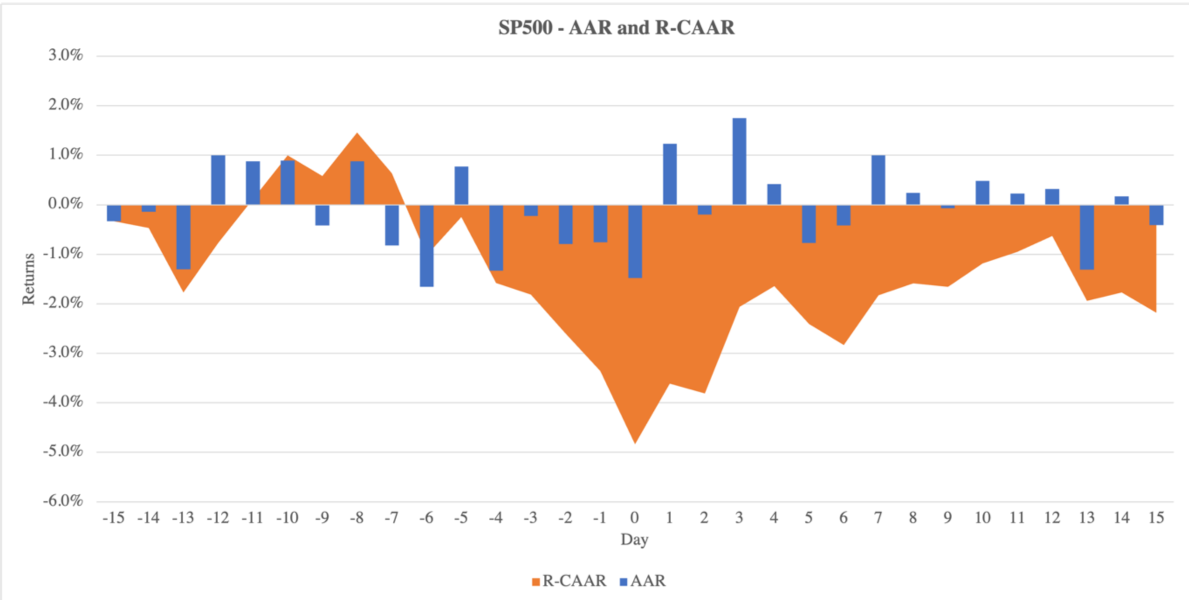

Figure 17: SP500 AAR and R-CAAR -15,+15 window

Figure 17 Notes: R-CAAR is the orange area in the figure, which represents the development of the cumulative abnormal return (CAAR) during the period starting at day -15. The blue bars are the average abnormal returns of the cross-section of industries for that single day, when viewed over time they form the development R-CAAR. A negative AAR decreases the R-CAAR, while a positive AAR increases the R-CAAR.

The change in the AAR after the announcement day may indicate that the U.S. market was relieved by the PA and that a stricter agreement had already been priced in. Since our analysis showed that the CAARs looking exclusively in the before direction (-7:-1, -5:-1, -2:-1) in Table 8 were significant, the CAAR windows also support the relieved interpretation. In the opposite direction, windows looking exclusively in the direction after the announcement were not significant at the 10% level. Since the positive CAARs after the announcement were insignificant, it is hard to draw definite conclusions about the market sentiment in both directions.

Table 9 has one AAR after the announcement that is significant AAR (positive) and two positive AARs that were close to the critical value. The AAR is only for single days, so it is hard to use them to interpret the trend of a period when the windows that overlap this period are not significant. Since the recovery is spread out over a longer period, the returns will be less abnormal and therefore have a less significant market response compared to negative returns. This will make our CAAR analysis biased toward negative returns and against positive returns. Therefore, we should not be too quick to reject the positive post-event CAARs, as we have several significant positive post-event AARs in that period.

To summarize the CAAR windows and AAR: the CAAR windows looking at the before windows were significant when looking at the three shortest windows closest to the announcement day. The CAAR windows looking at the after windows were not significant, but they had several significant and positive AARs among them. We can conclude that the U.S. market had a significant negative market reaction before the announcement. In contrast, the post-announcement reaction is less conclusive since the CAAR was not significant. Still, there were several significant AARs, so one cannot completely rule out the possibility that it could be significant.

6.1.2 STOXX 600 – Aggregated market response

In the European market analysis, we use the constituents of the STOXX 600 as a proxy for the European market response. We use the Global Industry Classification Standard (GICS) with 69 different industries to classify the STOXX 600 constituents into different industries. Our European market analysis is based on the aggregated returns from the 51 industries the index contains after our exclusions, based on constituencies and assumptions tests.

STOXX 600 - Cumulative average abnormal return

We performed two significance tests on 14 different event windows, and one had a significant CAAR below the 10% significance level. We also observed a change to a negative CAAR for the shortest event windows looking at the period exclusively before and then turning positive after the announcement for the event windows looking exclusively after the agreement.

STOXX 600 CAAR Significance test					
	Event window	**CAAR**	**Adj BMP**	**Rank T**	**Average**
			p-value	p-value	p-value
Equal before and after window	-15:15	1.77%	48%	43%	46%
	-10 : 10	1.66%	35%	36%	36%
	-5 : 5	-0.40%	57%	67%	62%
	-2 : 2	-0.37%	57%	67%	62%
	-1 : 1	-0.44%	40%	47%	43%
Exclusively before	-15:-1	0.20%	93%	81%	87%
	-10:-1	0.30%	79%	84%	81%
	-7:-1	-0.61%	58%	62%	60%
	-5:-1	**-1.60%**	**8%**	**9%**	**9%**
	-2:-1	-0.79%	12%	11%	11%
Exclusively after	1:2	0.27%	72%	61%	66%
	1:5	1.11%	37%	44%	40%
	1:7	1.10%	45%	53%	49%
	1:10	1.36%	26%	27%	26%
	1:15	0.67%	31%	15%	23%
	Average Equal	0.44%	47%	52%	50%
	Average Before	-0.50%	50%	49%	50%
	Average After	0.90%	42%	40%	41%

Table 10: STOXX 600 CAAR for different windows and significance tests

The lowest p-value is in the -5:-1 window, which has an average p-value of 8.5% and is significant. The following window, -2:-1, has an average p-value of 11.3%, so it's just above the 10% significance level. The fact that the two consecutive windows closest to the event day are the most significant suggests a trend leading up to the event.

No windows were significant for the equal before and after windows, and the lowest strict average p-value was the -10:10 window with a p-value of 36% and a positive CAAR of 1.66%. When we look at one-direction windows, the significance increases. This is because the market reaction with a negative AAR before the announcement is offset by a positive AAR after, so the loss is reduced by the following gain, which nets out the AAR to a small CAAR. The One-direction windows isolate the market response before and after so that we see if they are different and test them for significance.

The small number of consistently significant p-values within a window group like "exclusively before" indicates that the aggregated market response in Europe to the PA is not very strong. The response would be strong if we saw consecutively significant p-values in a window, which would indicate a robust trend. Within a window group (equal, before, after) in Table 10, there is a pattern of consecutive consistent either positive or negative CAARs, indicating a change in the aggregate market response to the PA. This trend begins by turning negative a few days after the conference begins and then turning positive after the PA announcement. Since the windows looking at these periods are not significant, we cannot say for certain that this is not just a random behavior, but the changes in CAAR both after the start of the conference and after the announcement suggest that it is a response to the PA.

STOXX 600 – Average abnormal return per day

This part looks at how the daily AAR developed over the entire period. We have analyzed the daily AAR through an event window of 31 days, with 15 days before and 15 days after the event date ($t_0 = 14.12.2015$).

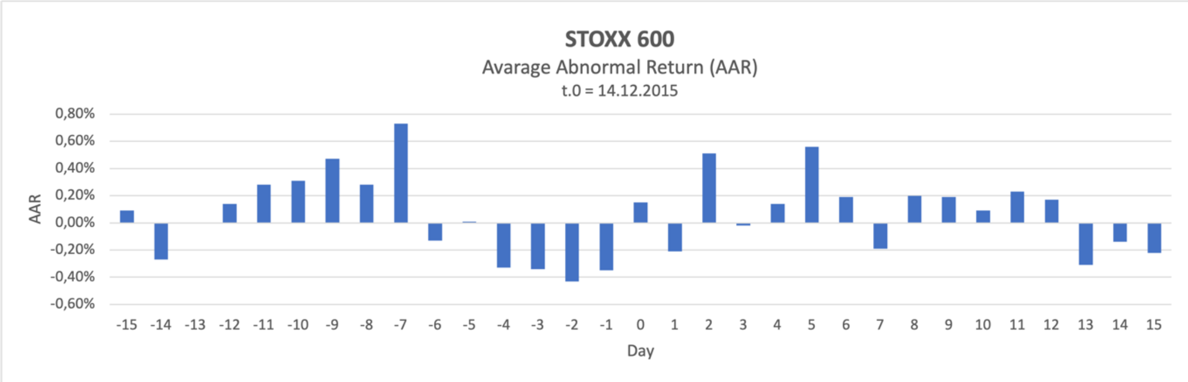

Figure 18: STOXX 600 average abnormal return -15+15 window

The most significant AAR for a single day was day -7, with a positive AAR of 0.73% and an average p-value of 5%. The second most significant was day +2, with an AAR of 0.51% and an average p-value of 8%. These were the only two significant days in the 31-day window.

Day	AAR	R-CAAR	Adj BMP	Rank T	Average
			p-value	p-value	p-value
-15	0.09%	0.09%	98%	86%	92%
-14	-0.27%	-0.18%	23%	20%	21%
-13	0.00%	-0.18%	75%	62%	69%
-12	0.14%	-0.04%	68%	60%	64%
-11	0.28%	0.24%	16%	9%	12%
-10	0.31%	0.55%	51%	46%	48%
-9	0.47%	1.02%	13%	13%	13%
-8	0.28%	1.30%	58%	70%	64%
-7	0.73%	2.03%	**6%**	**3%**	**5%**
-6	-0.13%	1.90%	72%	88%	80%
-5	0.01%	1.91%	84%	72%	78%
-4	-0.33%	1.58%	22%	24%	23%
-3	-0.34%	1.24%	32%	21%	27%
-2	-0.43%	0.81%	19%	25%	22%
-1	-0.35%	0.46%	34%	36%	35%
0	0.15%	0.61%	51%	45%	48%
1	-0.21%	0.40%	38%	40%	39%
2	0.51%	0.91%	**8%**	**8%**	**8%**
3	-0.02%	0.89%	94%	99%	97%
4	0.14%	1.03%	94%	76%	85%
5	0.56%	1.59%	34%	41%	37%
6	0.19%	1.78%	44%	61%	53%
7	-0.19%	1.59%	42%	30%	36%
8	0.20%	1.79%	14%	17%	15%
9	0.19%	1.98%	12%	15%	13%
10	0.09%	2.07%	63%	51%	57%
11	0.23%	2.30%	23%	28%	26%
12	0.17%	2.47%	46%	39%	42%
13	-0.31%	2.16%	32%	22%	27%
14	-0.14%	2.02%	78%	40%	59%
15	-0.22%	1.80%	70%	69%	70%

Table 11: STOXX 600 AARs for different windows and significance tests

Table 11 Notes: Day = Day relative to event day ($t_0 = 14.12.2015$). AAR = average abnormal returns for the cross-section of industries on that individual day. R-CAAR = the cumulative AAR from the start of the period day -15 until that individual day. Adjusted BMP and Rank T are significance tests, while average is the average p-value of those two tests.

In Figure 19 below, we can see a negative trend starting at day -4, where the AAR turns negative, and the highest R-CAAR value during the window is day -7, with an R-CAAR of 2.03%. Then there are a few days of random walk and only -0.1% change. The negative AAR trend continues from day -4 until day 0.

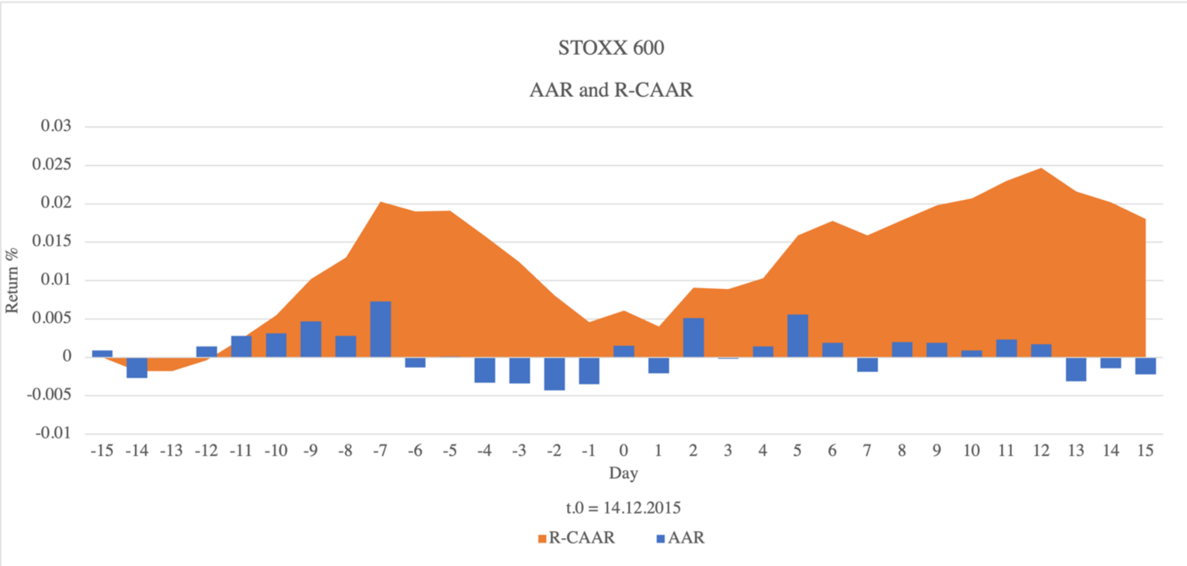

Figure 19: STOXX 600 AAR and R-CAAR Graph -15,+15 window

The negative AAR trend before the announcement is supported in Table 10 CAAR since the two shortest windows looking exclusively in the direction before the event (-5:-1, -2:-1) were significant, and the negative trend seems to bottom out at day one with an R-CAAR of 0.40%. After the announcement (day 0), the trend turns positive consecutively after days one to six and accumulates positive AARs before it peaks on day 12 with an R-CAAR of 2.47%. Although we can see this positive trend, the Table 10 CAARs looking exclusively at windows after the announcement were not significant, so there is weak evidence of a positive trend after the announcement.

6.1.3 Comparison of aggregated market responses

When we compare the responses of the different markets, we see one clear difference and one similar trend. The clear difference is that the U.S. market had a much stronger market response. This can be seen in the average CAAR at the bottom of Table 8 and Table 10. The average CAAR before the announcement was -3.82% in the U.S. and -0.50% in Europe, and after the announcement, the U.S. had 2.46% while Europe had 0.9%. The windows before have a difference in average CAAR of -3.33% with a 664% difference in magnitude, and the window after has a difference in average CAAR of 1.56% and a 173% difference in magnitude. The highly negative market response leading up to the event is clearly shown in Figure 17 and Figure 19 with the orange R-CAAR. The U.S. market had a negative R-CAAR for most of the

31-day window. In the European markets, it was the opposite, with a positive R-CAAR for almost the entire period.

A similar trend is that both markets had a negative trend shortly after the start of the conference (day -10) until the announcement day (day 0), where the sentiment changed, and the AAR turned positive. Prior to the announcement, both markets had a negative trend, with their shortest CAAR windows being significant. After the announcement, the CAAR windows were positive but not significant. Both markets had a significant single-day AAR after the announcement. This creates a V-shape in the R-CAAR diagram, with the lowest point being day 0. The fact that both markets had this V-shape supports our interpretation that the markets were relieved by the PA and that it wasn't just external factors affecting a single market that coincidently happened at the same time as the PA. But since our analysis includes only two markets, it's hard to draw any inference with confidence from the reactions in the two markets.

6.2 Industry market response

This part of our analysis aims to identify industries with abnormal returns related to the Paris Agreement (PA), which might indicate a sensitivity to climate regulations. When looking into the industry-specific returns, we use the cumulative abnormal return (CAR), similar to the CAAR used in the aggregated market response. The main difference is that the CAR looks at the entity level, which is the industry level for our analysis, while the CAAR looks at the average CAR of the entire cross-section of entities.

We use the same data and industry classification as in the aggregated analysis but at a lower level since we look at the entity/industry level. We have included the most significant CARs for different industries in the SP500 and STOXX 600. Our analyses use the GICS industry classification, which includes 69 different industries, but only used 51 industries with valid data. We have summarized the findings by including industries that are significant at the 10% level in two or more event windows. We have two different types of windows, one where we look at an equal number of days before and after the announcement and another where we look exclusively in one direction to look for a trend or market sentiment for the period these windows look at.

SP500 - Cumulative abnormal return (CAR)

Equal before and after CAR windows

In this group of CAR windows, we look at the entire period to see wide window industry effects with an equal number of days before and after to see if there is a significant change in return around the negotiations or announcement of the PA.

SP500	-15:15		-10:10		-5:5		-2:2	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	-7%	51%	-5%	52%	-7%	24%	-3%	47%
Oil, Gas & Consumable Fuels	-4%	69%	-3%	70%	-7%	33%	-4%	35%
Construction Materials	-3%	69%	-5%	39%	-2%	70%	**-9%**	**0%**
Metals & Mining	1%	93%	7%	36%	6%	27%	-6%	11%
Machinery	-5%	41%	-4%	49%	-3%	41%	-2%	38%
Air Freight & Logistics	-2%	73%	-1%	75%	-1%	73%	-1%	52%
Airlines	7%	41%	8%	24%	5%	31%	1%	83%
Road & Rail	-4%	53%	-3%	50%	-6%	11%	0%	77%
Automobiles	8%	41%	1%	94%	2%	73%	-4%	30%
Hotels, Restaurants & Leisure	5%	30%	5%	14%	3%	32%	1%	63%
Internet & Direct Marketing Retail	**15%**	**8%**	8%	25%	-2%	70%	-3%	42%
Banks	**16%**	**8%**	**23%**	**0%**	9%	12%	-2%	60%
Software	-4%	50%	-2%	71%	**-6%**	**10%**	**-5%**	**5%**
Semiconductors & Equipment	-12%	13%	**-11%**	**8%**	**-11%**	**2%**	**-13%**	**0%**

Table 12: SP500 industry-level CARs for different windows and significance tests

For all four windows, the semiconductor & equipment industry seems to have the biggest negative and most significant response in the period around the PA. They have consistent negative CAR in all four windows and significant CARs at the 10% level in three out of four windows. On the other side of the spectrum, we see that the Banking industry has the highest positive CAR of all industries, with a CAR of 16% in the longest window (-15:15) at 8% p-value and CAR of 23% at 0% p-value. Industry 2 , 3, and 4 in Table 12 are the ones we view as most vulnerable to climate risk. In the shortest window -2:2, we see CARs with low p-values among these three industries. The Construction Materials industry has a CAR of -9% with a p-value of 0%, and the Metals and Mining industry has a negative CAR of -6% and a p-value of 11%. The Oil Gas and Consumable Fuels industry has only a insignificant and weak negative behavior.

One-direction CAR windows

In Table 13 and Table 14 we look at four CAR windows for before and after directions exclusively, meaning we only look at days before or after. The idea is to isolate the market response and see how the CARs of different industries evolved before and after the announcement.

SP500	-15:-1		-7:-1		-5:-1		-2:-1	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	-5%	51%	-8%	12%	-5%	21%	-3%	16%
Oil, Gas & Consumable Fuels	-7%	39%	**-9%**	**7%**	**-7%**	**9%**	**-6%**	**3%**
Construction Materials	-7%	14%	**-13%**	**0%**	**-8%**	**1%**	**-4%**	**4%**
Metals & Mining	**-17%**	**1%**	**-10%**	**4%**	-6%	15%	**-6%**	**2%**
Machinery	-1%	77%	**-6%**	**8%**	-4%	18%	**-3%**	**8%**
Air Freight & Logistics	-3%	47%	**-5%**	**8%**	-3%	21%	-2%	20%
Airlines	0%	100%	-1%	78%	-1%	82%	-2%	36%
Road & Rail	-5%	31%	**-8%**	**1%**	**-7%**	**1%**	0%	93%
Automobiles	6%	39%	-2%	64%	-3%	46%	**-5%**	**5%**
Hotels, Restaurants & Leisure	2%	62%	-2%	32%	-1%	55%	0%	91%
Internet & Direct Marketing Retail	8%	20%	0%	97%	-2%	61%	-1%	70%
Banks	2%	75%	-5%	26%	**-8%**	**6%**	-2%	45%
Software	4%	38%	-2%	52%	-3%	35%	-2%	31%
Semiconductors & Equipment	-7%	21%	**-13%**	**0%**	**-11%**	**0%**	-2%	25%

Table 13: SP500 One-direction CAR before windows

SP500	1:2		1:5		1:7		1:15	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	1%	76%	-1%	71%	3%	50%	-4%	55%
Oil, Gas & Consumable Fuels	1%	59%	1%	74%	**9%**	**10%**	5%	53%
Construction Materials	-2%	25%	**7%**	**1%**	**8%**	**3%**	**8%**	**8%**
Metals & Mining	-1%	75%	**13%**	**0%**	**20%**	**0%**	**20%**	**0%**
Machinery	1%	73%	1%	81%	2%	49%	-2%	60%
Air Freight & Logistics	1%	63%	2%	39%	4%	14%	2%	63%
Airlines	2%	28%	**6%**	**8%**	6%	18%	9%	15%
Road & Rail	1%	42%	1%	60%	2%	48%	1%	85%
Automobiles	1%	71%	5%	20%	7%	19%	4%	57%
Hotels, Restaurants & Leisure	1%	37%	**4%**	**4%**	**4%**	**8%**	3%	27%
Internet & Direct Marketing Retail	-2%	33%	0%	97%	2%	59%	9%	12%
Banks	2%	44%	**16%**	**0%**	**17%**	**0%**	**15%**	**3%**
Software	**-4%**	**1%**	-3%	16%	-4%	17%	-7%	11%
Semiconductors & Equipment	-3%	19%	0%	97%	1%	80%	-2%	69%

Table 14: SP500 One-direction CAR after windows

The most important finding in the one-direction CAR windows is that the market reaction is different before and after. The four windows before have only red numbers, which are negative and significant at the 10% level. In the after windows, where all but one of the significant values are positive. The only negative is software, which is negative in seven out of eight windows. This is in line with the findings from the CAAR windows in Table 8 and Table 10, where the CAARs looking exclusively in one direction have higher CAARs and are more significant.

The Metals and Mining industry has the most volatile and most significant CARs, with -17% in the 15 days leading up to the announcement (-15:-1) and 20% up in the 15 days preceding the announcement (1:15). The second most volatile industry is Construction and Materials, with -13% in the seven days leading up to the announcement (-7:-1) and positive with 8% in the seven days preceding the announcement (1:7). We also see a large negative development in the "Oil, Gas, and Consumable Fuels" industry with -12% in the seven days leading up to the PA (-7:-1), and a significant increase of 9% in the seven days after the PA (1:7). Due to the following recovery the net effect measured in the equal before and after window is only -4% in the longest window -15:15. This is in contradiction to Diaz-Rainey et al. (2021) who find a strong negative CAR for the industry after the PA. Mukanjari & Sterner (2018) find a moderately negative CAR with low significance which is in line with our findings.

According to the U.S. Department of Energy, cement production accounts for 0.5% of total U.S. emissions, while iron and steel account for 2,1% (Nimbalkar, 2020). These emissions would be allocated to the Construction & Material, Metals & Mining industries. These industries' high emissions could be the reason why these industries experienced negative returns leading up to the PA. The Oil, Gas and Consumable Fuels industry has much higher emissions as a by-product of their products, with just the U.S. transportation sector alone emitting 36% of U.S. emissions.

One reason for the difference in returns after the PA could be that the agreement is more at odds against fossil fuel energy producers (Oil, Gas and Consumable Fuels) since it demands a transition away from fossil fuels as a primary energy source. At the same time, steel and cement producers might not see the PA as a direct threat to their current business models. According to Nimbalkar (2020), it is possible to produce carbon-neutral steel with current technology. However, in steel production, coal is not just used as an energy source but also as an essential part of the chemical reaction in the production process. The role of coal in the chemical reaction can be replaced with green hydrogen, while renewable electricity or other forms of green energy can be used as a heat source. So far, coal has been a more price-competitive energy source. Nimbalkar (2020) expects the transition from coal to low-carbon sources in the steel industry to take at least 20 years since that's the expected lifetime of the production equipment. For cement, it's a similar story as with steel. A large part of the emissions arise from the choice of energy source in the production process to heat the limestone (Busch et al., 2022). If firms in the industry choose greener energy sources, the emissions will be substantially reduced. Heating limestone releases large quantities of $C0_2$, so they still have an emissions problem, but it's on a scale that can be solved through carbon capture and storage. At the moment, with current $C0_2$ prices, it's not economical to do carbon capture and storage. The main takeaway is that steel and cement production have an emissions problem. Still, for the most part, they can use other energy sources to decrease their climate risk. At the same time, the Oil, Gas and Consumable Fuel industry's business model is more at odds with global climate goals since it's harder to avoid the emissions caused by the consumption of its products.

STOXX 600 - Cumulative abnormal returns

Equal before and after CAR windows

In this group of CAR windows, we look at equal amounts of days within a window before and after.

STOXX 600	-15:15		-10:10		-5:5		-2:2	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	-4%	65%	-3%	72%	-7%	23%	-1%	76%
Oil, Gas & Consumable Fuels	1%	91%	0%	96%	-5%	33%	-2%	68%
Construction Materials	1%	78%	-1%	75%	0%	93%	**-7%**	**0%**
Metals & Mining	13%	12%	11%	12%	7%	17%	-4%	25%
Machinery	-3%	53%	-1%	89%	2%	47%	-1%	76%
Air Freight & Logistics	0%	94%	1%	77%	0%	94%	0%	95%
Airlines	**13%**	**7%**	**12%**	**4%**	**7%**	**9%**	2%	40%
Road & Rail	-1%	91%	-2%	73%	-5%	11%	0%	88%
Automobiles	**14%**	**4%**	6%	32%	4%	35%	-2%	61%
Hotels, Restaurants & Leisure	**8%**	**1%**	**8%**	**0%**	**3%**	**5%**	**2%**	**7%**
Internet & Direct Marketing Retail	**20%**	**1%**	**10%**	**10%**	-1%	80%	-2%	59%
Banks	**23%**	**0%**	**27%**	**0%**	**9%**	**4%**	0%	91%
Software	-1%	88%	1%	80%	**-5%**	**9%**	**-3%**	**7%**
Semiconductors & Equipment	-8%	20%	-7%	14%	**-10%**	**1%**	**-11%**	**0%**

Table 15: STOXX 600 industry-level CARs equal before and after windows

The semiconductor & equipment industry had one of the strongest negative responses in the period around the PA. The industry had two significant and negative CARs in the two shortest windows at the 1% level. This shows that the negative market response grew stronger as we got closer to the event day, which makes it more likely that the PA was the main explanatory factor for the change.

On the other hand, the Banking sector has the highest positive CAR with +23% in "-15:15" and +27% in "-10:10". Both are significant at the 1% level. The windows closer to the event "-5:5" saw less change, only +9% with a p-value of 4%. While the shorter window "-2:2" saw 0% CAR, so it seems to have stabilized close to the event date. Hotels, restaurants and Leisure was the only European industry that was positive and significant in all equal windows.

One-direction CAR windows

Here we look in one direction exclusively to isolate the market response before and after.

STOXX 600	-15:-1		-7:-1		-5:-1		-2:-1	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	-2%	76%	-4%	42%	-4%	30%	-1%	58%
Oil, Gas & Consumable Fuels	-3%	64%	-5%	32%	-6%	18%	-2%	46%
Construction Materials	-5%	16%	**-4%**	**9%**	**-4%**	**7%**	**-2%**	**10%**
Metals & Mining	**-12%**	**4%**	-3%	54%	-3%	48%	-1%	77%
Machinery	2%	55%	0%	97%	-1%	74%	0%	85%
Air Freight & Logistics	0%	89%	-1%	66%	-1%	79%	0%	99%
Airlines	2%	65%	**6%**	**8%**	4%	17%	1%	68%
Road & Rail	-4%	37%	-4%	19%	**-5%**	**2%**	0%	82%
Automobiles	**11%**	**4%**	3%	30%	3%	26%	0%	88%
Hotels, Restaurants & Leisure	3%	13%	**2%**	**10%**	1%	65%	1%	46%
Internet & Direct Marketing Retail	**10%**	**8%**	5%	14%	1%	85%	0%	91%
Banks	8%	16%	**12%**	**0%**	-5%	12%	-1%	75%
Software	**6%**	**9%**	**4%**	**7%**	1%	49%	2%	20%
Semiconductors & Equipment	-3%	45%	**-7%**	**3%**	**-8%**	**0%**	**-7%**	**0%**

Table 16: STOXX 600 industry-level CARs One-direction after windows

STOXX 600	1:2		1:5		1:7		1:15	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	1%	83%	-1%	84%	2%	75%	-7%	27%
Oil, Gas & Consumable Fuels	1%	68%	2%	62%	6%	19%	1%	84%
Construction Materials	**3%**	**2%**	**4%**	**3%**	**5%**	**4%**	**7%**	**4%**
Metals & Mining	-1%	52%	**13%**	**0%**	**17%**	**0%**	**18%**	**0%**
Machinery	0%	86%	-1%	78%	0%	99%	4%	23%
Air Freight & Logistics	0%	100%	1%	77%	2%	26%	1%	71%
Airlines	1%	47%	4%	14%	4%	32%	**9%**	**9%**
Road & Rail	1%	57%	1%	66%	1%	77%	1%	88%
Automobiles	-1%	81%	4%	25%	3%	41%	5%	35%
Hotels, Restaurants & Leisure	1%	46%	**3%**	**3%**	2%	14%	3%	21%
Internet & Direct Marketing Retail	**-3%**	**13%**	-1%	75%	0%	95%	**9%**	**9%**
Banks	1%	55%	**15%**	**0%**	**14%**	**0%**	**13%**	**2%**
Software	**-5%**	**0%**	**-5%**	**2%**	**-2%**	**1%**	**-8%**	**2%**
Semiconductors & Equipment	**3%**	**2%**	-1%	59%	-6%	62%	-4%	36%

Table 17: STOXX 600 industry-level CARs One-direction after windows

The Construction materials industry is one of the most significant windows market responses, with clear change on the announcement day from a negative market response before and a positive afterward. The semiconductor industry has a negative CAR in seven out of eight windows. It was only positive in the shortest window immediately after the announcement day before it turned negative again. Two of the industries we suspect are climate regulations sensitive, “Energy Equipment & Services” and “Oil, Gas & Consumable Fuels”, had a very weak response with no significant days in the European market. These findings are in line with Mukanjari & Sterner (2018) who found a moderately negative CAR with low significance, and Kruse et al. (2020) which found little punishment for brown industries.

Banks had a very volatile market response throughout the whole period. One interesting observation about the banking industry CAR is that it changes so abruptly within an exclusive direction window. It was significant and positive in “-7:-1” with a CAR of 12%. Two days later in the “-5:-1” window it was negative with a CAR of -5% and almost significant with a p-value of 12%. This is a 17% difference in AR for two days, which is very volatile for AR. The AR is already the deviation from the normal market volatility. After the announcement, the CAR turned slightly positive with 1% CAR but not significant. In the next window “1:5”, the CAR was very positive with +15% and a p-value of 0%, and this high-level CAR persisted for all three longest after windows. The number of constituents in the banking industry is 44 in Europe, the highest number of constituents for any industry in Europe. Therefore, we would expect a diversification effect on the industry CAR since the single-firm idiosyncratic risk is very small.

Comparison of market responses

In Table 18 and Table 19, we look at the difference in CAR. We use the SP500 as a base and subtract the STOXX 600 response to examine the difference. We count the negative and positive differences to get an aggregated picture of the market response on an industry level. In the before windows (4 left), a negative CAR difference means that the SP500 had a higher CAR, while a negative p-value means the SP500 had a lower p-value. In the after window (4 right), it’s the opposite.

Difference: SP500 - STOXX600	-15:-1		-10:-1		-5:-1		-2:-1	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	-3%	-25%	3%	-34%	-1%	-9%	-2%	-42%
Oil, Gas & Consumable Fuels	-3%	-25%	-4%	-20%	-2%	-9%	-4%	-44%
Metals & Mining	-5%	-2%	-6%	-29%	-4%	-33%	-5%	-74%
Construction & Engineering	-4%	-1%	-5%	-41%	2%	22%	-1%	-25%
Machinery	-3%	22%	-5%	-81%	-3%	-56%	-3%	-77%
Air Freight & Logistics	-2%	-42%	-5%	-58%	-2%	-58%	-2%	-78%
Airlines	-2%	35%	-6%	71%	-5%	66%	-3%	-33%
Road & Rail	-1%	-6%	-3%	-30%	-2%	-1%	0%	11%
Hotels, Restaurants & Leisure	-2%	49%	-4%	80%	-2%	-10%	-1%	45%
Internet & Direct Marketing Retail	-2%	13%	-4%	27%	-2%	-24%	-1%	-21%
Banks	-6%	59%	-6%	18%	-3%	-7%	-1%	-29%
Software	-2%	29%	-5%	75%	-4%	-15%	-3%	11%
Semiconductors & Equipment	-4%	-24%	-6%	-11%	-4%	0%	5%	25%
Negative	13	7	12	8	12	11	11	9
Positive	0	6	1	5	1	2	2	4

Table 18: CAR difference - before window

Difference: SP500 - STOXX600	1:2		1:5		1:7		1:15	
Industry	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
Energy Equipment & Services	0%	-7%	-1%	-14%	2%	-25%	3%	28%
Oil, Gas & Consumable Fuels	0%	-10%	-1%	12%	2%	-9%	3%	-31%
Metals & Mining	1%	23%	0%	0%	3%	0%	2%	0%
Construction & Engineering	1%	-24%	1%	-9%	2%	-11%	2%	-12%
Machinery	1%	-13%	1%	3%	2%	-50%	-6%	36%
Air Freight & Logistics	1%	-37%	1%	-37%	2%	-12%	1%	-8%
Airlines	1%	-19%	2%	-6%	2%	-14%	0%	7%
Road & Rail	0%	-15%	0%	-6%	1%	-29%	0%	-4%
Hotels, Restaurants & Leisure	1%	-9%	1%	1%	2%	-5%	1%	6%
Internet & Direct Marketing Retail	1%	20%	1%	21%	2%	-36%	0%	3%
Banks	1%	-11%	1%	0%	2%	0%	2%	1%
Software	1%	1%	1%	14%	-2%	16%	1%	9%
Semiconductors & Equipment	-6%	17%	2%	38%	7%	19%	2%	33%
Negative	1	9	3	5	1	9	1	5
Positive	12	4	10	7	12	3	12	8

Table 19: CAR difference - after window

The biggest difference was the consistency of the market response before and after the Paris Agreement. In the U.S., we see that in the before period, all significant industries were negative, and after the event, all significant industries except one observation were positive. We can see that the difference between before and after is very clear. In Europe, the picture was less clear. In the period before the announcement, six industries were significant and had a positive CAR, while eight had significant and negative CARs.

In the eight windows, the SP500 had a stronger CAR response 90.9% of the time, with 131 out of 141 observations. The limitations of these statistics are that they only look at a sample, not the entire population, and we also include non-significant numbers. Therefore, the magnitude and significance are not taken into account. Overall, the numbers show a stronger response both in the CARs magnitude and the number of significant CARs in the SP500. We can say with a high degree of certainty that the SP500 reacted more strongly than the STOXX 600 in the before period. In the after-period, the response was also stronger in the SP500, but it was less significant in both markets, so we can only say with a lower degree of certainty that the market responses were different. For the Oil, Gas & Consumable Fuels industry, this is in line with Diaz-Rainey et al. (2021), who found that Oil and Gas sector firms with U.S.-centered operations experienced more negative industry CARs after the Paris Agreement than other markets. In our study, we also find that the Oil, Gas, and Consumable Fuels industry in the U.S. has a negative CAR of -4% (-15:15), while in Europe, it had a positive CAR of 1% for the whole period (-15:15).

6.3 Betas

This part analyzes how the betas changed during and after the Paris Agreement (PA). Beta measures how much a security moves relative to the market, known as systematic risk. More movement relative to the market is associated with more risk. We look at the beta change during the PA negotiations and afterward to measure how systematic risk changed for different industries. For the estimation of beta changes, we use the 250 days base period beta before the negotiations started to see if the beta changed for four different windows and then test them for significance. Since increased beta can be both positive and negative for risk-neutral investors, at the end of the thesis, we will look at the beta change and industries' CARs as an indicator if the change in beta was good or bad for the investor.

6.3.1 Beta change – SP500

For the SP500 index, we analyzed 62 different industries and looked at four windows where only 11 industries had a significant change in beta at the 10% level. Six of the eleven industries had a negative change in beta. The reduction in beta indicates that these industries had a perceived decrease in systematic risk. On the other hand, we had five industries with an increase in beta, indicating a perceived increase in the systematic industry risk.

SP500	Change in Beta				-7:-1	-5:5	1:-7	8:58
Industry	-7:-1	-5:5	1:7	8:58	p-val.	p-val.	p-val.	p-val.
Energy Equipment & Services	**16%**	**15%**	**16%**	**17%**	**0%**	**0%**	**0%**	**0%**
Oil, Gas & Consumable Fuels	**11%**	**9%**	**10%**	**12%**	**3%**	**5%**	**3%**	**4%**
Chemicals	4%	4%	4%	6%	27%	24%	27%	28%
Construction Materials	3%	2%	2%	6%	35%	35%	38%	31%
Containers & Packaging	**-6%**	**-6%**	**-6%**	**-3%**	**9%**	**10%**	**9%**	**9%**
Metals & Mining	**24%**	**21%**	**21%**	**22%**	**0%**	**0%**	**0%**	**0%**
Building Products	1%	1%	1%	5%	50%	44%	49%	36%
Construction & Engineering	**-10%**	**-12%**	**-11%**	**-8%**	**1%**	**1%**	**1%**	**1%**
Electrical Equipment	3%	2%	2%	6%	36%	39%	39%	31%
Machinery	5%	4%	4%	7%	22%	23%	23%	22%
Commercial Services & Supplies	6%	6%	6%	6%	17%	13%	15%	25%
Air Freight & Logistics	1%	1%	1%	5%	48%	42%	47%	35%
Airlines	**-11%**	**-10%**	**-11%**	**-6%**	**1%**	**1%**	**1%**	**3%**
Road & Rail	-5%	-3%	-4%	-2%	12%	21%	15%	12%
Auto Components	6%	5%	5%	7%	16%	17%	18%	22%
Automobiles	**12%**	**12%**	**12%**	**14%**	**1%**	**1%**	**1%**	**1%**
Internet & Direct Marketing Retail	**-14%**	**-15%**	**-15%**	**-11%**	**0%**	**0%**	**0%**	**0%**
IT Services	**23%**	**23%**	**23%**	**23%**	**0%**	**0%**	**0%**	**0%**
Software	0%	-1%	-1%	1%	37%	36%	37%	32%
Communications Equipment	**-9%**	**-10%**	**-9%**	**-6%**	**2%**	**2%**	**2%**	**2%**
Technology Hardware, Storage	-2%	-3%	-3%	1%	23%	24%	22%	33%
Electronic Equipment & Instruments	**-11%**	**-11%**	**-11%**	**-7%**	**1%**	**1%**	**1%**	**2%**
Semiconductors & Equipment	3%	3%	3%	5%	33%	33%	32%	34%
Media	-2%	-2%	-2%	1%	28%	30%	27%	32%
Entertainment	**-6%**	**-30%**	**-6%**	**-2%**	**8%**	**0%**	**8%**	**15%**
Electric Utilities	0%	0%	0%	3%	41%	45%	40%	49%
Average	1%	0%	1%	3%	25%	25%	25%	27%
SD	6.5%	7.4%	6.4%	5.9%				

Table 20: SP500 changes in industry betas

Table 20 Notes: The table shows the change in beta for selected industries in the SP500. The bold industries are significant at the 10% level or higher. The p-values are given in the right part of the table. In the lowest row, the standard deviation of the change in beta can be seen.

Among the industries with a significant increase in beta, we see that four out of five belong to industries associated with high emissions: Energy Equipment & Services, Oil, Gas & Consumable Fuels, Metals and Mining, and Automobiles. This could indicate that the PA increased investors' attention to climate risk, which is in line with the findings of (Pham et al., 2019). The last of the five industries with increased beta is IT Services, which is not an industry typically related to emissions or climate risk. This industry had 19 constituents, so it's also less likely that the increased industry beta originates from one single firm's volatility. The deviation of the IT Services sector from our expectations is a good example that other factors also play in, and even though the PA was one of the most important events in this period, it's not the only thing that affected company and industry returns.

At the other end of the spectrum, we have the companies with a reduced beta, which indicates a reduced risk. We found six industries with a significant reduction in beta and five of these industries we believe could potentially benefit from restrictions on emissions: Containers & Packaging, Construction & Engineering, Internet & Direct marketing Retail, Communications equipment, Electronics Equipment, Instruments & Components, and Entertainment.

6.3.2 Beta change - STOXX 600

For the STOXX 600 index, we analyzed 62 different industries and looked at four windows in which 16 industries had a significant change in beta at the 10% significance level. 14 of the 16 industries experienced a reduction in beta. For the significant companies, we see that the beta change was consistently positive or negative in all four windows.

STOXX 600	Change in beta				-7:-1	-5:5	1:-7	8:58
Industry	**-7:-1**	**-5.5**	**1:7**	**8:58**	**p-val.**	**p-val.**	**p-val.**	**p-val.**
Energy Equipment & Services	3%	2%	3%	4%	43%	50%	49%	21%
Oil, Gas & Consumable Fuels	2%	2%	2%	4%	49%	42%	40%	21%
Chemicals	1%	1%	1%	0%	31%	40%	29%	43%
Construction Materials	-1%	-1%	-1%	1%	16%	18%	15%	44%
Containers & Packaging	**-7%**	**-7%**	**-7%**	**-5%**	**0%**	**1%**	**0%**	**4%**
Metals & Mining	**9%**	**8%**	**8%**	**6%**	**3%**	**4%**	**5%**	**9%**
Building Products	**-4%**	**-4%**	**-4%**	**-3%**	**2%**	**4%**	**2%**	**10%**
Electrical Equipment	**-8%**	**-8%**	**-8%**	**-4%**	**0%**	**0%**	**0%**	**8%**
Machinery	-1%	0%	-1%	2%	19%	24%	16%	41%
Airlines	**-9%**	**-7%**	**-8%**	**-5%**	**0%**	**0%**	**0%**	**5%**
Road & Rail	**-5%**	**-4%**	**-5%**	**-4%**	**2%**	**3%**	**2%**	**8%**
Auto Components	**-7%**	**-8%**	**-7%**	**-5%**	**0%**	**0%**	**0%**	**4%**
Automobiles	3%	3%	3%	1%	44%	46%	45%	49%
Household Durables	**-3%**	**-1%**	**-3%**	**-4%**	**7%**	**16%**	**6%**	**6%**
Diversified Financial Services	-6%	-6%	-6%	-2%	1%	1%	1%	18%
Capital Markets	**-7%**	**-7%**	**-7%**	**-5%**	**0%**	**1%**	**0%**	**4%**
Insurance	1%	1%	1%	0%	35%	34%	32%	39%
IT Services	**11%**	**11%**	**11%**	**9%**	**1%**	**1%**	**1%**	**1%**
Software	**-7%**	**-6%**	**-7%**	**-6%**	**0%**	**1%**	**0%**	**3%**
Communications Equipment	**-13%**	**-13%**	**-13%**	**-6%**	**0%**	**0%**	**0%**	**2%**
Electronic Equip. & Instruments	**-14%**	**-12%**	**-14%**	**-10%**	**0%**	**0%**	**0%**	**0%**
Semiconductors & Equipment	5%	6%	5%	5%	22%	16%	27%	13%
Media	-2%	-1%	-2%	0%	11%	16%	10%	33%
Entertainment	**-8%**	**-18%**	**-19%**	**-4%**	**0%**	**0%**	**0%**	**8%**
Interactive Media & Services	-9%	-6%	-8%	-3%	0%	1%	0%	15%
Electric Utilities	-7%	-7%	-6%	-3%	1%	0%	0%	11%
Average	-2.4%	-2.2%	-2.6%	-1.0%	15%	16%	14%	23%
SD	5.4%	5.8%	5.7%	3.3%				

Table 21: STOXX 600 changes in industry betas

Of the two industries with a significant increase in beta, one of the two belongs to an industry associated with high emissions; Metals and Mining. This industry had seven constituents, it's also less likely that the increased beta originates from a single firm's volatility.

On the other end, we have the companies with a reduced beta, which indicates a reduced risk. We found 14 industries with a reduction in beta that was significant, and five of those industries we believe could potentially benefit from restrictions on emissions: "Containers & packaging", "Construction & Engineering", "Internet & Direct marketing Retail", "Communications equipment", "Electronics Equipment, Instruments & Components", and "Entertainment". In contrast in Europe we didn't find any link with resource industries and increased beta like Pham et al. (2019) did.

6.4 Summary of industries with strongest market response

In the last part of the results section, we summarize the industry CAR and beta change to conclude on the market response of the different industries, this is our answer to research question three. We will do this by checking if the CARs are positive or negative. The negative CAR is viewed as negative since it decreases the stock value with negative returns. We also look at the change in beta. If the beta change is positive, industry return volatility increased more than the market. The increased beta is viewed as riskier, but if the increased risk is due to positive returns that are higher than the market, investors benefit from the increased volatility. Therefore, we look at the direction of the CAR (positive/negative) and the change in beta together to better understand whether the market response for the industry is good or bad.

Since this event study deals with the Paris Agreement in the context of GHG emissions regulations, we will look more closely at industries with higher perceived climate risk. Ideally, we would like to examine the correlation between CAR, beta change, and industry emissions. Unfortunately, emissions reporting was voluntary at the time, so one-third of our constituent companies did not report. As a result, we were unable to perform the analysis between beta change and emissions for all constituent companies in the index.

Based on our inspection of the companies' missing emissions data, we suspect that the largest polluters are also the ones not reporting. Therefore, we found the results less valid when aggregating industry emissions from those who reported. We looked at other ways of aggregating an industry score on emissions. ESG emissions scores are given to individual firms according to their relative performance on an industry-specific benchmark. Since the ESG emissions scores are industry-specific, it's not a valid measure of emissions and climate risk to compare different industries against each other, only within each industry. We have therefore chosen not to classify the different industries according to any objective measurement of emissions or climate risk. Instead, we only discuss the results according to a brief investigation of the industry constituents' business activities and our evaluation of the different industries' climate risks.

Oil, Gas & Consumable Fuels

The overall industry market response is weak and negative since only a few observations are significant. The industry had a volatile market response in the U.S., with one of the biggest CARs of all industries in absolute terms.

One-direction exclusively windows

	-7:-1		-5:-1		-2:-1		1:2		1:5		1:7	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	**-9%**	**7%**	**-7%**	**9%**	**-6%**	**3%**	1%	59%	1%	74%	**9%**	**10%**
STOXX 600	-5%	32%	-6%	18%	-2%	46%	1%	68%	2%	62%	6%	19%
Difference	-4%	-25%	-2%	-9%	-4%	-44%	0%	-10%	-1%	12%	2%	-9%

Table 22: Summary one-direction windows - Oil Gas & Consumable Fuels

SP500, n = 20,
STOXX 600, n = 16

The one-direction exclusively windows have synchronized behavior, being positive and negative simultaneously in both markets, which makes the market response more substantial. The industry had a negative market response leading up to the announcement. After the announcement, the industry market response turned positive. This is also in line with the development of the general market, but the volatility is higher for the industry. The industry is one of the most directly affected by the PA as its products cause high emissions, which directly violates the PA goal. Since the PA threatens the business model of these companies, it is no surprise that the market response in the U.S. was initially negative and significant. Surprisingly, the market reaction was not significant in Europe, but it moved in the same direction as the U.S. market. After the PA, the CAR became positive, and surprisingly, such a "brown" industry became positive and even significant in one of the after windows.

Equal before and after window

	-15:15		-10:10		-5:5		-2:2	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	-4%	69%	-3%	70%	-7%	33%	-4%	35%
STOXX600	1%	91%	0%	96%	-5%	33%	-2%	68%
Difference	-5%	-22%	-4%	-26%	-1%	0%	-2%	-33%

Table 23: Summary equal windows - Oil Gas & Consumables Fuels

Looking at the equal before and after CAR windows, we can see the total response from the beginning of the period until the end. The industry had negative CARs in all windows except one. This means that by the end of the period, it had a net loss in abnormal returns (AR), even though the stock prices increased after the announcement. That means it didn't regain the entire initial loss. Since these windows look at the net effect of the whole period, it's an important indicator of the industry trend. A negative trend in the two shortest windows -5:5 and -2:2 indicates an initially negative response. The two longest windows -15:15 and -10:10, are neither synchronized between the markets nor significant, so it's impossible to say anything conclusive about the longer-term market response. With the shortest windows, it's only possible to say anything about the short-term effect around the announcement, which is negative. In addition, these short windows are also not significant. Therefore, we can't put too much weight on the direction of the windows.

Change in beta

	-7:-1	p-val.	-5:5	p-val.	1:7	p-val.	8:58	p-val.
SP500	**11%**	**3%**	**9%**	**5%**	**10%**	**3%**	**12%**	**4%**
STOXX 600	2%	49%	2%	42%	2%	40%	4%	21%
Difference	8%	-46%	7%	-38%	8%	-37%	8%	-17%

Table 24: Summary change in beta - Oil Gas & Consumable Fuels

Beta increased over the period and persisted at the same elevated level, which is negative since it's associated with more risk. The U.S. market had a greater beta change in all periods, which is natural since it also had larger CARs and was consequently more volatile. The number of constituents in both markets is relatively high and similar. Therefore, there should be little risk of one firm affecting the aggregated industry results, so the reliability of the results should be high.

The overall conclusion about the Oil, Gas and Consumable Fuels industry's market response around the PA is that the industry experienced a weakly negative reaction. The reaction was only significantly negative before the announcement. Since the after period was positive but not significant it marks a weakly positive response and supports our conclusion of the negative reaction. The equal before and after windows were negative in all periods except one in Europe, and the beta increased and persisted at a higher level. All three results indicate a negative market response. Although they have weak significance, they all point in the same direction, which gives the conclusion about a negative market response more confidence. Nevertheless, this conclusion does not possess a high degree of certainty.

Construction Materials

The market reaction of the industry is inconclusive, except for a negative reaction before the announcement and a positive reaction after. The CARs were among the highest of all industries, especially when looking at both periods and markets combined. The beta change was small and not synchronized, although the industry CAR was very volatile. One drawback to our analysis of this industry is the low number of constituents. In the U.S., there were only two firms in the industry, which makes our findings less reliable, as the results are very susceptible to single-firm returns affecting the aggregated industry results.

One-direction exclusively windows

	-7:-1		-5:-1		-2:-1		1:2		1:5		1:7	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	**-13%**	**0%**	**-8%**	**1%**	**-4%**	**4%**	-2%	25%	**7%**	**1%**	**8%**	**3%**
STOXX 600	**-4%**	**9%**	**-4%**	**7%**	**-2%**	**10%**	**3%**	**2%**	**4%**	**3%**	**5%**	**4%**
Difference	**-9%**	**-9%**	**-5%**	**-6%**	**-2%**	**-6%**	**-5%**	**24%**	**3%**	**-2%**	**2%**	**-1%**

Table 25: Summary one-direction window - Construction Materials

SP500, n = 2
STOXX 600, n = 6

The construction materials industry had a very strong market reaction, being the only industry with negative and significant CARs in the three shortest windows before the announcement in both markets. The European market had a weaker response than the U.S., so it’s unusual to be significant in both markets and periods. In the post-announcement period, it was positive and significant in the three shortest windows in both markets, except for one observation. The direction of the CARs was synchronized in both markets for all but one observation. This suggests that the market views the effect of climate regulations similarly for both markets.

Equal before and after windows

	-15:15		-10:10		-5:5		-2:2	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	-3%	69%	-5%	39%	-2%	70%	-9%	0%
STOXX600	1%	78%	-1%	75%	0%	93%	-7%	0%
Difference	-4%	-9%	-4%	-36%	-1%	-23%	-2%	0%

Table 26: Summary equal windows - Construction Materials

Since there is a substantial gain in the after period, we look at the equal windows to see the net effect for the period. The only significant findings are in the shortest window -2:2, where both markets were significant and negative, so the significant negative market response was only for a short period. In the U.S., all equal window CARs are negative, which indicates that the overall U.S. market response was negative. In Europe, there was also just one significant equal window CAR of -7%, and it was also the shortest one, "-2:2". The other equal window CARs ranged from -5% to 1%, and the lowest p-value was 39%, so it's impossible to say anything conclusive about the direction of the industry's CARs. The equal windows are very wide since they include an equal number of days before and after, making it harder to obtain significant results and increasing the chance of a type I error.

Change in beta

	-7:-1	p-val.	-5:5	p-val.	1:7	p-val.	8:58	p-val.
SP500	3%	35%	2%	35%	2%	38%	6%	31%
STOXX 600	-1%	16%	-1%	18%	-1%	15%	1%	44%
Difference	4%	18%	3%	17%	3%	23%	5%	-13%

Table 27: Summary One-direction windows - Construction Materials

The beta change had no significant observation in both markets, and the direction was not synchronized between the markets, so it's not possible to conclude on a beta market response. The overall industry market response is not very conclusive. It is only possible to say anything conclusive in the one-direction windows, where it was significant and negative before the announcement and significantly positive after. The positive reaction after the announcement, which regained almost all of the previous losses, resulted in a small net change in the CAR for the period. That the positive returns after the announcement nulled out the initial losses can be seen in the longest (-15:15, -10:10) equal before and after windows' small CARs. Since they are not significant, it’s not possible to say anything conclusive about the longer-term market response with the net effect on CARs in the equal before and after windows being close to zero. With no significant observations, the betas also didn’t have any conclusive market response nor behave synchronized in both markets. So overall, the market response didn’t go in one specific direction except in the shortest window -2:2. This is most likely because of the negative overall market returns before the announcement and then delayed positive returns after the announcement. That is most likely why the longer windows, such as -5:5, are not significant, because then the recovery has started, which creates a small net effect in the equal windows.

Metals and Mining

The overall market response of the industry tends toward a positive response. The equal window’s short period response -2:2 was negative, but positive in all other windows.

One-direction windows

	-7:-1		-5:-1		-2:-1		1:2		1:5		1:7	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	**-10%**	**4%**	-6%	15%	**-6%**	**2%**	-1%	75%	**13%**	**0%**	**20%**	**0%**
STOXX 600	-3%	54%	-3%	48%	-1%	77%	-1%	52%	**13%**	**0%**	**17%**	**0%**
Difference	-7%	-49%	-4%	-33%	-5%	-74%	1%	23%	0%	0%	3%	0%

Table 28: Summary one-direction windows - Metals and Mining

SP500, n = 4
STOXX 600, n = 27

In the one-direction windows, the before period was synchronously negative in all windows and markets. The shortest ones (-2:-1, 1:2) were negative in both markets. Normally the announcement day is a turning point, so the after period is positive. For the Metals & Mining industry, there seems to be a lag in the market's adoption of a positive sentiment for the industry. When the market sentiment turned, it increased very substantially, with the two longest windows, 1:5 and 1:7, turning positive and p-values close to zero. A deviation from our expectations is that the market response was more significant for the after CARs than for the before CARs. This supports our interpretation that the overall reaction was positive.

Equal before and after windows

	-15:15		-10:10		-5:5		-2:2	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	1%	93%	7%	36%	6%	27%	-6%	11%
STOXX600	13%	12%	11%	12%	7%	17%	-4%	25%
Difference	-13%	81%	-4%	23%	-1%	10%	-2%	-14%

Table 29: Summary equal windows - Metals and Mining

For the equal before and after windows, the -2:2 window is negative. We can see the effect of the positive after period in the longer equal before and after windows, as the net effect for the whole period was positive for the three longest window -15:15, -10:10, -5:5. The market response for the longer windows was not significant so we can't trust them too much. However, they are positive in both markets and in all three longest windows, indicating a positive response even though they are not significant.

Change in beta

	-7:-1	p-val.	-5:5	p-val.	1:7	p-val.	8:58	p-val.
SP500	**24%**	**0%**	**21%**	**0%**	**21%**	**0%**	**22%**	**0%**
STOXX 600	**9%**	**3%**	**8%**	**4%**	**8%**	**5%**	**6%**	**9%**
Difference	15%	-3%	13%	-4%	13%	-5%	16%	-9%

Table 30: Summary change in beta - Metals and Mining

The betas increased, indicating that the industry returns were more volatile than the market. Since the net change of CAR was positive for the entire period, this increased beta is not necessarily bad, as it leads to higher positive returns than the market.

Automobiles

The auto industry had a weak market reaction, so it is impossible to say anything conclusive except that the beta in the U.S. market increased, indicating higher risk for the industry.

One-direction exclusively windows

	-7:-1		-5:-1		-2:-1		1:2		1:5		1:7	
	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.	CAR	p-val.
SP500	-2%	64%	-3%	46%	-5%	5%	1%	71%	5%	20%	7%	19%
STOXX 600	3%	44%	4%	21%	0%	88%	0%	81%	4%	25%	3%	41%
Difference	-5%	20%	-7%	25%	-5%	-83%	1%	-10%	1%	-5%	4%	-22%

Table 31: One-direction windows - Automobiles

SP500, n = 4
STOXX 600, n = 6

The automobile industry is one of the sectors we anticipated would have high negative returns. The rationale was that car producers will have to invest substantially in new technologies and products to be aligned with the PA. The market response was mixed. In the before-period, it was not a synchronized response. The U.S. market had small negative CARs but only one significant observation, while Europe had positive but non-significant CARs in the before-period. Both markets had positive CARs in the after-period, but none were significant.

Change in beta

	-7:-1	p-val.	-5:5	p-val.	1:7	p-val.	8:58	p-val.
SP500	**12%**	**1%**	**12%**	**1%**	**12%**	**1%**	**14%**	**1%**
STOXX 600	3%	44%	3%	46%	3%	45%	1%	49%
Difference	9%	-42%	10%	-45%	9%	-44%	13%	-48%

Table 32: Summary change in beta - Automobiles

Betas increased in both markets but more substantially in the U.S. The increased beta could be due to the fact that the U.S. automobile industry has only three constituent firms. Hence, there is a high risk of one single firm's volatility affecting the industry returns, thereby decreasing the reliability of the results. Although the U.S. beta change is significant, the reliability is lower.

The overall market response to the industry is hard to determine since the CARs didn't behave synchronized in the before-period, and the after-period was synchronized but had no significant observations. The beta change increased, with a synchronized response in both markets and all periods, indicating increased risk. When we look at the equal before and after windows to see the net effect on the industry CARs, it's +1.4% in the longest window (-15:15). Since the longest CAR window is positive, this means that the initial loss in the before period is fully recovered by the gains in the after-period. So the results are mixed, the increased beta suggests increased risk and a negative market response, but it's only significant in one market. The positive CAR suggests a positive response, but they are not significant. Therefore, it is not possible to say that the industry had a positive or negative market response in the period related to the PA.

6.5 Our contribution to research and limitations

Contribution

Our thesis contributes to the existing literature with a granular and detailed analysis of the stock market reaction in the U.S. and European markets on an industry level. Our research differentiates itself from previous research with a very detailed analysis of the stock market reaction over time. We analyze the stock market reaction at many different points before and after the event and therefore gain a good understanding of how the stock market reaction develops over time. We look at the stock market reaction both in terms of returns and risk. We are able to show changes in industry-specific risk with a detailed analysis of changes in beta following the 2015 Paris Climate Agreement.

Limitations

Validity and reliability are two quality characteristics that tell us about the limitations and trustworthiness of our research. Reliability is based on whether there is consistency in the measurements, while validity shows the extent to which the research measures what it is supposed to measure (Saunders et al., 2019, p. 214).

6.5.1 Validity

Internal and external validity are two concepts essential to consider when conducting research.

1. Internal Validity refers to the extent to which a research study provides accurate and valid conclusions about the causal relationship between variables within the study (Saunders et al., 2019, p. 181).

To ensure high internal validity in our research, we have examined the assumptions that must be fulfilled for our OLS model and significance tests to perform reliably. Our data and model fulfilled all the necessary assumptions, but some results were close to the threshold. Especially the homogeneity of variance assumption tested with Levene's test had a p-value close to the critical value. The low p-value could reduce the reliability of the significance test for the European market.

2. External validity refers to the extent to which the findings of a research study can be generalized or applied to a broader population, settings, or contexts beyond the specific study sample. It assesses whether the results obtained from a particular study can be validly extrapolated to other populations, situations, or conditions (Saunders et al., 2019, p. 181).

Our research uses real-world data, and our sample consists of 86% of the target population we want to examine. The results should therefore be representative of the market behaviors we want to examine. Our inability to perform the analysis we wanted on a market-weighted index is one of our biggest threats to external validity, as it increases the weighting of industries with small market capitalization, leading to divergence of aggregated market behavior if many of the smaller industries behave differently from the industries with bigger market capitalization.

6.5.2 Reliability

Reliability in scientific research refers to the consistency, stability, and repeatability of measurement and data collection procedures. It focuses on the extent to which the results of a study or measurement can be trusted and replicated under similar conditions (Saunders et al., 2019, p. 202). We have three main strategies to maintain the reliability of our findings.

1. We use indexes that contain a high percentage of our target population to reduce the risk of sampling error. This reduces the likelihood that somebody would get different results if they replicated our research.

2. The second is that we analyze two markets of relatively similar character. Therefore, we chose the U.S. market and Europe since both are big markets with well-diversified industries. If both markets behaved synchronized, it is more likely that the market behavior was a response to the Paris Agreement.

3. The third strategy to increase reliability is the use of multiple event windows. If we had chosen just one window, it would have made the results less robust. When using just one event-window, it is possible to choose dates selectively to increase the significance of one window. By using more windows, we limit the possibility of one single window misrepresenting the market's response. There is a tradeoff between reliability and internal validity when using multiple windows, especially with the smallest windows. The smaller windows have less ideal results in the assumptions tests and are therefore less reliable. Even though the smallest windows have less reliability, we think the increased windows will make our overall assessment of market response more reliable. This strategy is in in line with our exploratory research strategy, which focuses more on gaining more knowledge about a topic, but being less certain in the conclusions.

7. Conclusion

7.1 Aggregated market behavior

For the first research question, we looked at the aggregated market behavior using cumulative average abnormal returns (CAAR) to see if we could identify a distinctive market response in the period around the Paris Agreement (PA). We have found that the market behavior for the entire period, measured by the equal before and after windows (-15:15, -10:10, -5:5, -2:2) is consistently negative in the U.S. market, while the European market is negative in the shortest windows (-5:5, -2:2), but Europe has positive CAARs in the longest windows (-15:15, -10;10). That means that the overall U.S. market behavior for the whole period is negative, while in Europe, the market behavior is negative in the short run close to the announcement day but positive in the longer run. None of the equal before and after windows in either market are significant, so we cannot draw any definitive conclusions about a market reaction from them. That is, the market behavior may just be a "random walk" within its normal variations since the significance is so low.

We found a shift in the market sentiment on the announcement day of the Paris Agreement (PA), with large negative average abnormal returns (AAR) in the days before the announcement and positive AAR in the days after the announcement. To analyze this shift in market sentiment, we look at a period exclusively before or after the announcement to isolate the market reaction for each period. The U.S. and European markets were both negative leading up to the event, but the U.S. had a stronger reaction with larger CAARs. In the U.S., the two closest windows to the announcement day (-5:-1, -2:-1) were negative and significant, while in Europe, only one window was significant (-5:-1). Both markets turned positive after the PA's announcement, as the specific terms of the agreement became known. Thus, the day of the announcement was a clear turning point in market sentiment for the period around the PA in both markets. Our interpretation of this shift is that the market viewed the terms of the PA as not as bad as expected.

7.2 Industry market behavior

The second research question examined the market behavior of the industries. We used each industry's cumulative abnormal return (CAR) to analyze each industry's market behavior. Most industries followed the same pattern as the aggregated market behavior, with a negative CAR before the announcement and positive CARs after. Since we are looking at a period around the Paris Agreement, which is climate-related, we expect emissions-heavy industries to have a stronger market response and have paid more attention to them. In the windows looking exclusively before the announcement (-15:-1, -7:-1, -5:1, -2:-1), many "brown" industries are among the industries with the largest negative CARs (Oil, Gas & Consumable Fuels, Construction Materials, Metals & Mining). The "brown" industries are also among the ones with the biggest positive CARs in the after windows. This positive CAR in the after period reduces the net effect over the whole period. The equal before and after windows have small CARs and low significance levels. Accordingly, it is difficult to say anything conclusive about the market response of these industries over the entire period. One can only conclude that they had a negative reaction before and a positive reaction after the announcement. This assessment is in line with the findings of Mukanjari & Sterner (2018) who only find a moderately negative CAR with low significance. We expected them to have a persistently lower level after the announcement because they are heavy emitters, but we could not conclude that from the data. One of the "brown" industries, Metal & Mining, was positive in both markets when looking at the net effect in the longest equal window (-15:15), and the CAR in Europe was 13% with a p-value of 12%, so it was close to being significant. This positive market reaction is surprising since most of the companies are steel producers, which are large emitters of greenhouse gases.

In the longest equal window (-15:15), the Internet & Direct Marketing, Retail, and Banking industries had positive CARs and stood out by being significant in both markets. This time window gives us the net effect of the longest window. We use it to measure more long-term return change than just looking at the days closest to the announcement date. Since these two industries had a significant and synchronized reaction in both markets, they likely had a positive market reaction caused by the agreement. In the shorter equal windows (-5:5, -2:2), the Consumer Finance, Software, and Semiconductor & Equipment industries also had a significant and synchronized market reaction in both markets. Since they were only significant in the short windows, it is only possible to say something about the initial market reaction to the PA, which was negative.

Many other industries had single observations of significant CARs, however, this is less reliable as a market response for the industry because it is only a small sample of firms, and other market forces could be affecting that industry in that particular market. We gave special weight to CARs that were significant in both markets. Ideally, we would have a higher number of markets, but due to the limitation of the thesis, we only had two. The mentioned industries were the only ones with significant CARs in both markets.

7.3 Beta change

For the beta changes, we wanted to look at changes in risk for individual industries. We found significant beta changes in eight industries with synchronized behavior in both markets. Two had increased beta, which is associated with increased risk. These industries were Metals & Mining and IT Services. The six industries with decreased beta and reduced risk were: Containers & Packaging, Construction Engineering, Airlines, Communication equipment producers, Electronics equipment producers, and Entertainment. From the type of industries that had a change in beta, it is hard to find one group of industries that was at a disadvantage or benefited from the PA. We would have expected the "brown" industries to see an increase in beta in both markets, but that did not happen. Only the U.S. market saw a significant increase in beta for our list of brown industries (Oil, Gas & Consumable Fuels, Metals & Mining, and Automobiles). This is in line with Pham et al. (2019) and Ramiah et al. (2013) who find resource heavy industries had increased short-term risk. In addition, we found the construction materials industry saw an increase in beta in the U.S., but it was not significant. The only significant "brown" industry in Europe was Metals and Mining.

7.4 Future research

We have examined different market responses for specific industries to one event related to climate regulations. Future research could analyze industry-specific market reactions for multiple events and see if the reaction is similar for other later climate regulation events. For instance, possible events that could be researched using a similar research methodology include the election of Donald Trump in 2016 and the U.S. withdrawal from the Paris Climate Agreement announced by the Trump administration in 2017. As our research examines the reaction of each industry to the Paris Climate Agreement in detail using many different windows, undertaking a similar analysis would have exceeded the scope of our thesis. Similarly, it could also be interesting to extend the analysis to other regions, such as the Japanese, Chinese, or Latin American stock markets. In addition, it would also be an exciting idea to study the response of each industry using trading volume rather than returns. Differences in trading volume across industries could provide insights into the climate sensitivity of investors in different industries. Moreover, it could also be interesting to undertake an event study researching the volatility in the various industries, possibly using hourly or even more granular stock price data.

8. References

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*(2), 159–178. https://doi.org/10.2307/2490232

Binder, J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting*, *11*(2), 111–137. https://doi.org/10.1023/a:1008295500105

Bloomberg New Energy Finance (2022). *BloombergNEF*. https://about.bnef.com/new-energy-outlook/

Bodie, Z., Kane, A., & Marcus, A. J. (2018). *Investments*. McGraw-Hill Europe.

Boehmer, E., Masumeci, J., & Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, *30*(2), 253–272. https://doi.org/10.1016/0304-405X(91)90032-F

Borghesi, S., Castellini, M., Comincioli, N., Donadelli, M., Gufler, I., & Vergalli, S. (2022). European green policy announcements and sectoral stock returns. *Energy Policy*, *166*, 113004. https://doi.org/10.1016/j.enpol.2022.113004

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/10.1016/0304-405X(80)90002-1

Busch, P., Kendall, A., Murphy, C. W., & Miller, S. A. (2022). Literature review on policies to mitigate GHG emissions for cement and concrete. *Resources, Conservation and Recycling*, *182*, 106278. https://doi.org/10.1016/j.resconrec.2022.106278

Busse, J. A., & Clifton Green, T. (2002). Market efficiency in real time. *Journal of Financial Economics*, *65*(3), 415–437. https://doi.org/10.1016/S0304-405X(02)00148-4

Caldecott, B. (2017). Introduction to special issue: Stranded assets and the environment. *Journal of Sustainable Finance & Investment*, *7*(1), 1–13. https://doi.org/10.1080/20430795.2016.1266748

References

Cleetus, R. (2023, January 10). *Climate Change in 2022: Multiple Billion-Dollar Disasters and Unbearable Human Costs*. The Equation. https://blog.ucsusa.org/rachel-cleetus/climate-change-2022-multiple-billion-dollar-disasters-unbearable-human-costs/

Club of Rome. (2022). *The Limits to Growth+50*. Club of Rome. https://www.clubofrome.org/ltg50/

Corporate Finance Institute. (2022). *Idiosyncratic Risk*. Corporate Finance Institute. https://corporatefinanceinstitute.com/resources/risk-management/idiosyncratic-risk/

Council on Foreign Relations. (2022). *Timeline: UN Climate Talks*. Council on Foreign Relations. https://www.cfr.org/timeline/un-climate-talks

Deutsche Börse Group. (2023). *STOXX® EUROPE 600 INDEX*. https://www.stoxx.com/document/Bookmarks/CurrentFactsheets/SXXGR.pdf

Diaz-Rainey, I., Gehricke, S. A., Roberts, H., & Zhang, R. (2021). Trump vs. Paris: The impact of climate policy on US listed oil and gas firm returns and volatility. *International Review of Financial Analysis*, *76*.

Edmans, A., García, D., & Norli, Ø. (2007). Sports Sentiment and Stock Returns. *The Journal of Finance*, *62*(4), 1967–1998. https://doi.org/10.1111/j.1540-6261.2007.01262.x

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business*, *38*(1), 34–105.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, *10*(1), 1–21. https://doi.org/10.2307/2525569

Frees, E. W. (1995). Assessing cross-sectional correlation in panel data. *Journal of Econometrics*, *69*(2), 393–414. https://doi.org/10.1016/0304-4076(94)01658-M

French, K. R. (2023). *Kenneth R. French—Data Library* [Database]. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Giaccotto, C., & Sfiridis, J. M. (1996). Hypothesis testing in event studies: The case of variance changes. *Journal of Economics and Business*, *48*(4), 349–370. https://doi.org/10.1016/0148-6195(96)00019-7

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, *70*(3), 393–408.

Harrington, S. E., & Shrider, D. G. (2007). All Events Induce Variance: Analyzing Abnormal Returns When Effects Vary across Firms. *Journal of Financial and Quantitative Analysis*, *42*(1), 229–256. https://doi.org/10.1017/S002210900000226X

International Energy Agency. (2021). *Net Zero by 2050—A Roadmap for the Global Energy Sector*. https://iea.blob.core.windows.net/assets/deebef5d-0c34-4539-9d0c-10b13d840027/NetZeroby2050-ARoadmapfortheGlobalEnergySector_CORR.pdf

Jiang, Y., & Luo, L. (2018). Market reactions to environmental policies: Evidence from China. *Corporate Social Responsibility and Environmental Management*, *25*(5), 889–903. https://doi.org/10.1002/csr.1505

Kendall, M. G., & Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11–34. https://doi.org/10.2307/2980947

Keown, A. J., & Pinkerton, J. M. (1981). Merger Announcements and Insider Trading Activity: An Empirical Investigation. *The Journal of Finance*, *36*(4), 855–869. https://doi.org/10.1111/j.1540-6261.1981.tb04888.x

Kolari, J. W., & Pynnönen, S. (2010). Event Study Testing with Cross-sectional Correlation of Abnormal Returns. *The Review of Financial Studies*, *23*(11), 3996–4025. JSTOR.

Kolari, J. W., & Pynnönen, S. (2011). Nonparametric rank tests for event studies. *Journal of Empirical Finance*, *18*(5), 953–971. https://doi.org/10.1016/j.jempfin.2011.08.003

Krieger, E. (2022, October 19). *Billion Dollar Losses, Trillion Dollar Threats: The Cost of Climate Change | E2*. https://e2.org/reports/cost-of-climate-change/

Kruse, T., Mohnen, M., & Sato, M. (2020). *Are financial markets aligned with climate action? New Evidence from the Paris Agreement*.

Kutner, M. H. (Ed.). (2005). *Applied linear statistical models* (5th ed). McGraw-Hill Irwin.

Lloyd's. (2017). *Stranded Assets—Lloyd's*. https://www.lloyds.com/strandedassets

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, *35*(1), 13–39.

Marks, J. M., & Musumeci, J. (2017). Misspecification in event studies. *Journal of Corporate Finance*, *45*, 333–341. https://doi.org/10.1016/j.jcorpfin.2017.05.003

Martin, I. (2021). On the Autocorrelation of the Stock Market. *Journal of Financial Econometrics*, *19*(1), 39–52. https://doi.org/10.1093/jjfinec/nbaa033

McGlade, C., & Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 °C. *Nature*, *517*(7533), Article 7533. https://doi.org/10.1038/nature14016

McWilliams, A., & Siegel, D. (1997). Event Studies in Management Research: Theoretical and Empirical Issues. *The Academy of Management Journal*, *40*(3), 626–657. https://doi.org/10.2307/257056

Mitchell, M. L., & Netter, J. M. (1989). Triggering the 1987 stock market crash: Antitakeover provisions in the proposed house ways and means tax bill? *Journal of Financial Economics*, *24*(1), 37–68. https://doi.org/10.1016/0304-405X(89)90071-8

Monasterolo, I., & de Angelis, L. (2020). Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement | Elsevier Enhanced Reader. *Ecological Economics*, *170*, 106571. https://doi.org/10.1016/j.ecolecon.2019.106571

Morningstar. (2023) Morningstar, Inc. https://www.morningstar.com/indexes/spi/spx/quote

Mukanjari, S., & Sterner, T. (2018). *Do markets trump politics? Evidence from fossil market reactions to the Paris Agreement and the US election.*

Naddaf, M. (2022). Climate change is costing trillions—And low-income countries are paying the price. *Nature (London)*. https://doi.org/10.1038/d41586-022-03573-z

Nimbalkar, S. (2020). *Potential Decarbonization Strategies and Challenges for the U.S. Iron & Steel Industry* (p. 22). Oak Ridge National Laboratory.

Parker, C. F., & Karlsson, C. (2017). The European Union as a global climate leader: Confronting aspiration with evidence. *International Environmental Agreements: Politics, Law and Economics*, *17*(4), 445–461. https://doi.org/10.1007/s10784-016-9327-8

Patell, J. M. (1976). Corporate Forecasts of Earnings Per Share and Stock Price Behavior: Empirical Test. *Journal of Accounting Research*, *14*(2), 246–276. https://doi.org/10.2307/2490543

Patell, J. M., & Wolfson, M. A. (1979). Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics*, *1*(2), 117–140. https://doi.org/10.1016/0165-4101(79)90003-X

Pham, H., Nguyen, V., Ramiah, V., Mudalige, P., & Moosa, I. (2019). The Effects of Environmental Regulation on the Singapore Stock Market. *Journal of Risk and Financial Management*, *12*(4). https://doi.org/10.3390/jrfm12040175

Pham, H., Nguyen, V., Ramiah, V., Saleem, K., & Moosa, N. (2019). The effects of the Paris climate agreement on stock markets: Evidence from the German stock market.

Applied Economics, *51*(57), 6068–6075. https://doi.org/10.1080/00036846.2019.1645284

Pham, H., Ramiah, V., & Moosa, I. (2020). The effects of environmental regulation on the stock market: The French experience. *Accounting & Finance*, *60*(4), 3279–3304. https://doi.org/10.1111/acfi.12469

Population Reference Bureau. (2000). *The Conference of Parties to the UN Framework Convention on Climate Change*. PRB. https://www.prb.org/resources/the-conference-of-parties-to-the-un-framework-convention-on-climate-change/

Ramiah, V., Martin, B., & Moosa, I. (2013). How does the stock market react to the announcement of green policies? *Journal of Banking & Finance*, *37*(5), 1747–1758. https://doi.org/10.1016/j.jbankfin.2013.01.012

Ryngaert, M., & Netter, J. (1990). Shareholder Wealth Effects of the 1986 Ohio Antitakeover Law Revisited: Its Real Effects. *Journal of Law, Economics, & Organization*, *6*(1), 253–262.

Saunders, E. M. (1993). Stock Prices and Wall Street Weather. *The American Economic Review*, *83*(5), 1337–1345.

Saunders, M., Philip, L., & Thornhill, A. (2019). *Research Methods For Business Students* (Eight).

Schimmer, B. (2023). *Apps for event studies and news analytics*. Eventstudytools. https://www.eventstudytools.com/API-ARC

Schuetze, F., Aleksovski, D., & Mozetic, I. (2020). Stock Market Reactions to International Climate Negotiations. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3718277

Shepherd, M. (2021). *Clearing The Air—The U.S., India, China And The Paris Agreement*. Forbes. https://www.forbes.com/sites/marshallshepherd/2021/01/22/clearing-the-airthe-us-india-china-and-the-paris-agreement/

Standard & Poor's, & MSCI. (2023). *GICS - Global Industry Classification Standard*. https://www.msci.com/our-solutions/indexes/gics

Stock, J. H., & Watson, M. W. (2020). *Introduction to econometrics* (Fourth edition.; Global edition.). Pearson.

Ubøe, J. (2008). *Statistikk for økonomifag* (3rd ed., Vol. 2). Gyldendal Norske Forlag.

United Nations. (2020). *UN and partners express regret over US departure from Paris climate accord | UN News*. https://news.un.org/en/story/2020/11/1076882

United Nations. (2022). *Key aspects of the Paris Agreement | UNFCCC*. https://unfccc.int/most-requested/key-aspects-of-the-paris-agreement

Welsby, D., Price, J., Pye, S., & Ekins, P. (2021). Unextractable fossil fuels in a 1.5 °C world. *Nature*, *597*(7875), Article 7875. https://doi.org/10.1038/s41586-021-03821-8

Wharton Research Data Services. (2023). *Security Daily*. WRDS. https://wrds-www.wharton.upenn.edu/pages/get-data/center-research-security-prices-crsp/annual-update/crspcompustat-merged/security-daily/

Wooldridge, J. M. (2013). *Introductory econometrics: A modern approach / Jeffrey M. Wooldridge.* (5th ed.). South-Western Cengage Learning.

9. Appendix

Independence assumption – Autocorrelation

	SP500				
Industry	**-15:15**	**-15:-1**	**-5:-1**	**1:5**	**1:15**
Energy Equipment & Services	4%	4%	1%	1%	4%
Oil, Gas & Consumable Fuels	3%	3%	2%	3%	3%
Chemicals	-18%	-18%	-18%	-18%	-18%
Construction Materials	-13%	-12%	-13%	-14%	-13%
Containers & Packaging	-17%	-17%	-16%	-15%	-17%
Metals & Mining	-7%	-7%	-5%	-5%	-6%
Aerospace & Defense	-9%	-9%	-7%	-7%	-9%
Building Products	-5%	-5%	-4%	-4%	-5%
Construction & Engineering	0%	0%	2%	0%	0%
Electrical Equipment	-13%	-13%	-14%	-14%	-13%
Machinery	-8%	-8%	-9%	-9%	-8%
Trading Companies & Distributors	-26%	-26%	-25%	-23%	-26%
Air Freight & Logistics	-11%	-11%	-11%	-11%	-11%
Airlines	-10%	-10%	-8%	-8%	-11%
Road & Rail	-10%	-9%	0%	0%	-9%
Auto Components	-2%	-1%	-1%	-1%	-2%
Automobiles	6%	6%	6%	7%	6%
Leisure Products	-13%	-12%	-13%	-12%	-13%
Distributors	-9%	-9%	-9%	-8%	-9%
Internet & Direct Marketing Retail	6%	6%	0%	-1%	6%
Multiline Retail	-30%	-30%	-28%	-28%	-30%
Specialty Retail	-25%	-25%	-24%	-24%	-25%
Life Sciences Tools & Services	-26%	-26%	-24%	-24%	-26%
Banks	-11%	-12%	-10%	-10%	-11%
Diversified Financial Services	-10%	-10%	-10%	-9%	-10%
Consumer Finance	-21%	-20%	-21%	-21%	-21%
Insurance	-16%	-16%	-16%	-16%	-16%
IT Services	2%	2%	2%	2%	2%
Software	-18%	-18%	-19%	-19%	-18%
Communications Equipment	-9%	-8%	-8%	-8%	-8%
Technology Hardware, Storage	7%	7%	5%	5%	7%
Electronic Equipment, Instruments	-26%	-26%	-25%	-24%	-26%
Semiconductors & Equipment	-7%	-7%	-7%	-7%	-7%
Media	-12%	-11%	-13%	-13%	-13%
Entertainment	-1%	-1%	-12%	-12%	-1%
Interactive Media & Services	-6%	-6%	-6%	-6%	-6%
Electric Utilities	-20%	-20%	-20%	-20%	-20%
Gas Utilities	-15%	-15%	-14%	-14%	-15%
Multi-Utilities	-21%	-21%	-21%	-21%	-21%

Table 33: Appendix - SP500 Autocorrelation

	STOXX 600				
Industry	**-15:15**	**-15:-1**	**-5:-1**	**1:5**	**1:15**
Energy Equipment & Services	6%	6%	5%	5%	6%
Oil, Gas & Consumable Fuels	9%	9%	10%	9%	9%
Chemicals	-4%	-5%	-5%	-5%	-4%
Construction Materials	0%	0%	-1%	-1%	0%
Containers & Packaging	-5%	-5%	-6%	-5%	-5%
Metals & Mining	12%	12%	11%	10%	12%
Building Products	-1%	-1%	-1%	-1%	-1%
Construction & Engineering	3%	4%	8%	7%	4%
Machinery	8%	8%	7%	7%	8%
Air Freight & Logistics	-2%	-2%	-2%	-2%	-2%
Airlines	5%	6%	5%	5%	6%
Road & Rail	8%	7%	9%	10%	9%
Auto Components	2%	2%	2%	2%	2%
Automobiles	10%	10%	10%	11%	10%
Household Durables	-7%	-7%	-6%	-5%	-7%
Leisure Products	-11%	-11%	-12%	-11%	-11%
Distributors	-1%	-1%	-1%	-2%	-1%
Internet & Direct Marketing Retail	15%	14%	12%	12%	14%
Multiline Retail	**-25%**	**-25%**	**-25%**	**-24%**	**-25%**
Specialty Retail	-12%	-13%	-13%	-12%	-12%
Banks	4%	3%	5%	5%	5%
Diversified Financial Services	6%	5%	5%	7%	6%
Consumer Finance	-11%	-11%	-9%	-10%	-11%
Capital Markets	5%	5%	5%	5%	5%
Insurance	1%	1%	1%	1%	1%
IT Services	3%	3%	3%	3%	3%
Software	-10%	-10%	-11%	-11%	-11%
Communications Equipment	-7%	-7%	-7%	-7%	-7%
Technology Hardware, Storage	4%	5%	3%	3%	4%
Electronic Equipment, Instruments	**-26%**	**-26%**	**-25%**	**-24%**	**-25%**
Semiconductors & Equipment	-10%	-10%	-11%	-11%	-11%
Media	-10%	-10%	-10%	-10%	-10%
Entertainment	0%	0%	-8%	-8%	-6%
Interactive Media & Services	-6%	-6%	-6%	-6%	-6%
Electric Utilities	-4%	-4%	-3%	-3%	-4%
Gas Utilities	-1%	-1%	-1%	-1%	-1%
Multi-Utilities	-4%	-3%	-3%	-3%	-3%

Table 34: Appendix - STOXX 600 Autocorrelation