Do carbon emissions impact stocks' returns: An evidence from EU Emissions Trading Scheme*

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Abstract

We assess the impact of carbon emissions on the stock returns of companies participating in the European Union Exchange Trading System (EU ETS), in which the energy and basic materials sectors are overrepresented. We apply a four factor model to three carbon portfolios defined according to the level of verified CO2 emissions during the 2005-2019 period. We use verified rather than reported emissions to ensure the transparency and reliability of our results. We found that brown firms underperform green firms when allocated allowances were not longer given for free (during the second phase of the EU-ETS). This result is mainly explained by the cash flow effect due to the additional cost faced by the most polluting companies as allowances are no longer allocated for free at this time. More interestingly, we find evidence of a statistically significant green premium (green firms earn higher returns than brown firms) during the Paris Agreement period in 2015. This means that during this period, investors were able to discard greenwashing, and select stocks according to verified CO2 emissions. Policy makers can thus encourage investments in low-emitting firms stocks by advertising the excess returns that such investment brings, or by increasing the cost of allowances, or by expanding "carbon audits" for all firms.

Keywords: Energy, Emissions Trading Schemes, Climate change, Carbon risk, Asset pricing, Ecological transition.

JEL Classification : O13, Q49, Q54, G12, G15

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1 Introduction

Draining savings and orienting investment toward less carbon-emitting firms will be among the greatest challenges in the financial world in the coming decades. In addition to the massive costs of inaction (OECD, 2016), the ability of the financial system to channel money and capital flows toward projects that are more able to limit climate change is now unanimously acknowledged as a crucial element of the success of climate policies (Campiglio et al., 2018; NGFS, 2019). Exposure to transition risk by financial institutions is of special interest (ECB, 2019, Special feature A, Climate change and financial stability). Accordingly, institutional investors are increasingly interested in the level of CO_2 emissions of the firms in which they invest (Krueger et al., 2020). In particular, as the ESRB (2016) report underlines, having a precise measure of firm's contribution to CO_2 emissions is important. On the one hand, to help prevent abrupt fire sales or assets reallocations. On the other hand, to avoid an underestimation of the effetcs of climate change on firms' prospects and assets payoffs, especially by macroprudential policies. In such adverse scenario, we would face an underinvestment is alternative energy sources' infrastrucres and research.

One precise way to evaluate the impact of carbon emissions on investors decisions is to compare the performance of firms according to their level of emissions. In this literature, when we are interested in investment decisions and their determinants, we generally use asset pricing models. More specifically, since our aim is to compare the performance of different asset portfolios, our methodology is based on the use of a factor model. In this strategy, factor models can be used to isolate the abnormal returns. The related literature suggests that any stock return above the risk-free rate provided by a secure investment be justified by an additional risk taken when investing in certain firm category. For example, with the seminal three factor model of Fama and French (1993), the equity risk premium is explained by the exposition to market risk (measured by the coefficient "*beta*", market model or capital asset pricing model (CAPM)), the size of the firm (the small-minus-big (SMB) factor), and its book-to-market ratio (the high-minus-low (HML) factor).

Therefore, our objective is to assess the impact of carbon emissions on stock returns using those type of factor model. For example Bolton and Kacperczyk (2020a) cover the period 2005-2017 and find that carbon emissions explain the stock returns of US firms, even controlling for the other main factors.

More precisely, firms with higher CO_2 emissions earn higher stock returns, which the authors refer to as the *carbon premium*, which means that investors consider high-emitting firms as being riskier, and consequently, they demand higher returns from these firms as a form of compensation. Incidentally, the above authors find that institutional investors exclude certain firms from their portfolios, if they emit too much CO_2. In a related study, Bolton and Kacperczyk (2020b) extend their findings to an international study of 77 countries for the period 2005-2018 and confirm the existence of a carbon premium. However, their approach is not strictly an asset pricing approach, in the sense that the carbon premium is their dependent variable, and is not considered a risk factor (i.e. an independent variable), capable of explaining stock returns. Görgen et al. (2019) go a step further and explicitly build a carbon risk factor (that they label the "brown-minus-green" (BMG) factor) capable to explain stock returns. Using an comprehensive dataset of data on environmental, social, and governance (ESG) disclosures of firms, the above authors build a global carbon risk score based on 1,637 firms from 43 countries (2010-2016). This score is then used to build the carbon factor for almost 40,000 firms in 111 countries. Notably, the auhtors find that this factor has explanatory power and show that the carbon risk factor, although negative and not significant on average (the return of "green firms" is slightly higher on average), has a significantly negative coefficient for the three lowest deciles of carbon scores (firms with a low carbon score are less exposed to the carbon risk factor), and a significantly positive coefficient for the five highest deciles of carbon scores (firms with a high carbon score are more exposed to the carbon risk factor).

However, these previous works have limitations. First, they rely on company-provided estimates of CO_2 emissions. It is possible that following the Paris Agreement[1], companies have become interested in pretending to be "green" by choosing a set of variables, or a methodology, that makes them appear as relatively low-carbon emitters. In short, firms have an interest in "greenwashing" their self-provided CO_2 emissions data (Wu et al., 2020). Furthermore, as Roncalli et al. (2020) emphasize, the carbon risk measure of Görgen et al. (2019) while interesting for understanding and measuring carbon risk, is very data-intensive and require strong hypothesis as a risk factor for explaining stock returns.

Our article aims to overcome these limitations. We propose to investigate the performance of firms according to their level of carbon emissions based on *verified* emissions provided by the exchange market for "pollution rights", or "carbon quotas" i.e., carbon European Union emission trading system (EU ETS). We use 2005-2019 data on European countries from the EU ETS market. The main contribution of our paper is that using such *verified* emissions allows us to assess whether investors can truly have an impact on climate change, by taking into account this carbon risk in their portfolio choice. Moreover, contrary to what exists in the literature, we also propose to integrate a sectoral dimension in our analysis to make our results more robust to the estimation method.

First, we found that during the overall observation period, there is no significant difference in stock returns between brown and green companies. Second, we highlight that brown firms perform significantly worse than non-brown firms during the second phase of the EU-ETS, suggesting that brown firms are more penalized due to paid quotas. Third, after performing rolling windows regression, we found the same result if we consider the Paris Agreement period. Besides, this period is characterised by a statistically and sig-

[1]The Paris Agreement was adopted at the end of the COP21 held in Paris in 2015 and entered into force on November 4, 2016. 197 countries adopted the agreement committing to cooperate together in the fight against global warming by limiting greenhouse gas emissions to 1.5°compared to the pre-industrial era.

nificant green premium (green firms exhibit higher abnormal returns than brown firms). It is important to emphasize that this result holds whereas EU ETS is dominated by firms within the energy and basic materials sector. This means, that, even within industries considered as the most CO2 emitters, some firms can positively signal themselves to investors by showing evidence of reduced CO2 emissions.

The rest of the article is structured as follows. Section 2 presents the related literature, Section 3 exposes the data used and Section 4 presents the methodology. Section 5 presents the results, and Section 6 concludes the paper.

2 Literature and context

It is now acknowledged that climate change has an impact on finance (Campiglio et al., 2018; ECB, 2019; NGFS, 2019; Krueger et al., 2020), and that finance should sustain energetic transition (Millar et al., 2018), subject to the constraint that no prosperity can arise in an economy with costly energy supplies. Thus, it follows that firms engaged in lowering their emissions should direct their investments toward long-term projects. In other words, the "tragedy of horizons" as the Governor of the Bank of England termed it in a famous speech (Carney, 2015), must be overcome. According to Aglietta and Espagne (2016), climate change is not a mere externality against which society can insure itself, but rather a systemic risk meaning that negative feedback loops can arise between finance and climate change. For example, if the financial sector is not able to drive investments toward "2°C portfolios", then the physical damage brought about by climate change can increase the financial fragility of financial institutions, which in turn will be less able to fund low-emitting projects. The subsequent question concerns how to operate this transition in the area of finance?

The above aspects are why factor models are important. Although limited to stock-listed firms, factor models provide a road map about the factors that influence the risk and return characteristics of stock portfolio investments. Then, it would be interesting to build a carbon risk factor that could drive investors toward low-emitting firms.

An important point about factors is that they are simultaneously measuring the extent of exposure to risk, and revealing whether the market has "priced" this risk or not. If we take the renowned paper by Fama and French (1993), their three-factor model takes the market risk factor from the CAPM, the size factor (the SMB factor) and the book-to-market factor (the HML factor). In some configurations, the factor can "exist" (in the sense that for example, small firms' returns are systematically different than those of large firms, or put differently, the factor return is not zero), but its coefficient (its β), when included as an explanatory variable in a regression on excess returns, may not be significant. In such a case, the interpretation is that the market (investors) does not recognize, or does not price, this risk. In contrast, if factor β is significant, then it has an impact on the stock return, and the stock is exposed to this risk factor. Then, investors willing to chase high returns will overweight the stocks exposed to this risk in their portfolios, and investors willing to limit exposure to this risk will underweight or exclude such stocks.

Applied to carbon risk (meaning, here, all aspects related to CO_2 emissions that can impact on returns), the literature shows mixed evidence. In a review of the empirical literature, Campiglio et al. (2019) show some studies in which the carbon risk does not seem to be fully priced, is only for very recent years, or is for some industries. Monasterolo and de Angelis (2020) show that stock markets react to low-carbon firms after the 2015 Paris Agreement but do not seem to penalize high-emitters' assets, which is problematic because, theoretically, the more uncertain we are about the future damage due to climate change, the higher the carbon should be priced today (Daniel et al., 2016). In other words, investors are insufficiently channeling funds toward low-carbon firms. Similarly, Delis et al. (2019) study the loan rate that banks charge to fossil-fuel firms, and compare it to that charged to non-fossil-fuel firms. They confirm a "carbon bubble" before 2015 (banks neglect the fact that fossil fuel reserves become "stranded", i.e. lose value) but not after 2015. Interestingly, in 2015, Harris (2015) builds a carbon factor (the efficient-minus-intensive (EMI) factor) and shows that green firms earn higher returns (because of the higher risk associated with investment in carbon-efficient processes and technologies); however, the factor is not significantly different from zero ($t = 1.14$). Additionally, Görgen et al. (2019) showed that the BMG factor is important, as presented in the previous section. The difference between the returns on high- and low-carbon-scoring firms is -0.25%, which seems to indicate that green firms are riskier, although this difference is not significant (t-stat 1.17). When regressing this factor, however, the above authors find that the coefficient indicates that firms with high (low) carbon scores are more (less) exposed to carbon risk. In the same vein, but without explicitly building a carbon factor, Bolton and Kacperczyk (2020a) and Bolton and Kacperczyk (2020b), as presented in the previous section, show the existence of a "carbon premium"; i.e. high-emitting firms exhibit higher returns, which means that carbon risk factor "exists" in the sense that the factor return is not zero. β (the coefficient for the BMG factor) is constant in Görgen et al. (2019), and Roncalli et al. (2020) propose a model with a dynamic β (without applying it). They propose the use of thresholds on this β to manage portfolios, which typically exclude the stock if it has a coefficient above a certain value because this indicates a high exposure to the carbon risk. The carbon risk factor could also be used to overweight or underweight stocks in a market index to build a "decarbonized" market index. In a theoretical exercise, Andersson et al. (2016) show that long-term passive investors (such as pension funds, life insurance, and sovereign wealth funds) have an interest in replicating such indexes in their portfolios. If markets do not recognize the importance of the level of CO_2 emissions by firms, then the returns from the decarbonized index is the same as those from benchmark indexes, but, once climate-mitigation policies and actions are launched or expected to be launched, markets start pricing carbon risk; consequently, decarbonized indexes surpass their benchmark. On average, holding such decarbonized portfolios is interesting for passive, long-term investors.

However, there are limitations in the previous approaches. First, most of them rely on company-disclosed data. In 2015, the Financial Stability Board (FSB) encouraged company disclosure of data about their carbon emissions, by setting up the Task Force on Climate-related Financial Disclosure (TCFD). Thousands of firms have engaged in this process, and companies such as Truecost have gathered and supplied these data to researchers. However, these data are not verified by an external third party, and thus it is possible that some companies bias their data, i.e. proceed toward "greenwashing" (Wu et al., 2020). Second, studies that build carbon scores (Görgen et al., 2019; Roncalli et al., 2020) are data-intensive and necessarily posit several hypotheses at each step of the building of the score, which renders the factor difficult to replicate. This question of the credibility of company-disclosed carbon data is at the core of regulators' worries concerning this matter, according to the vice president of the ECB: "improved disclosure is essential to pursue this effort in earnest. Disclosure by firms and financial institutions tends to be incomplete and not always consistent. Mandatory and harmonized firm-level reporting of carbon emissions would be a step in the right direction, as it would enable better pricing and monitoring of financial firms' exposures to climate-related risks" (de Guindos, 2020).

The above factors are why the use of *verified* CO_2 emissions provided in the EU ETS to compare the excess returns of firms according to their level of emissions. In the ETS compliance cycle, the data for a given year must be verified by an accredited verifier by March 31 of the following year. Verifiers must be "competent, independent and impartial"[2] and, must, among others, proceed to inspections and site visits, and is responsible for entering verified emissions data into the registry. The advantage of using these data is to reduce the problem of greenwashing, manipulating several company-disclosed databases, and to assess whether real (as opposed to declared) emissions have an impact on investor portfolios. The article of Oestreich and Tsiakas (2015) is the closest to ours, as the authors find that firms with high carbon emissions have higher exposure to carbon risk and exhibit higher expected returns. However, their study is restricted to German firms (2003-2012), whereas we use data on European firms.

One contribution of our analysis is to use emissions verified by an accredited and external authority instead of reporting emissions. We have chosen to carry out our study with this type of data to ensure transparency and to avoid any problems of possible over or underestimation with declarative data. Our carbon analysis is therefore a reliable data source for economic analysis.

[2]See for example the EU ETS website, *ec.europa.eu/clima/policies/ets/monitoring*, accessed October 23, 2020.

3 Data

3.1 European Union Emissions Trading System

Since 2005, the European Union has adopted an emissions trading scheme to reduce greenhouse gas emissions. It is the largest emissions trading scheme in the world with the objective of reducing emissions by 20% in 2020 and by at least 30% by 2030 (objective updated by Law No. 2019-1147 of November 8, 2019, on energy and climate). The system covers approximately 1000 firms from 31 European countries representing 45% of the European Union's greenhouse gases.

The functioning of the ETS is based on the "polluter pays" principle. First, allowances are allocated free of charge by auction. Then, they can be traded (bought or sold) according to the quantity of emissions emitted by the installation. Thus, each year, companies participating in the system must surrender several allowances corresponding to the amount of carbon emissions they have emitted (1 European Union Allowance (EUA) = 1 ton of CO_2). If an installation emits more than it has received allowances, it can either pay a fine (see table for details of fines) or buy additional allowances from companies that have not exceeded the cap.

The EU ETS is divided into 4 phases. The first covers the period 2005-2007, the second from 2008 to 2012, the third from 2013 to 2020 and the fourth phase started in 2021 and ends in 2030 (see table for details on the phases). Currently the system is in its fourth period.

3.2 Carbon emission data

As a reminder, our objective is to analyze the link between carbon emissions and stocks' return. Currently, self-reported data produced on a voluntary basis is common when it comes to a company's greenhouse gas emissions. Since these data are provided on a voluntary basis and are not subject to a clear legal framework, the accuracy and reliability of the data remain an issue.

Carbon emission data are obtained from the EU ETS company database, and displays verified carbon emissions by EU accredited carbon verifiers such as DNV, SGS, Bureau Veritas or TÜV. Thus, the verified emissions correspond to the amount of emissions actually emitted by a facility. The emissions of each facility are monitored and verified by independent third parties in accordance with the monitoring and reporting guidelines published by each member state. Our study is part of an analysis at the company level. The carbon market database provides carbon data information for more than 1,000 firms from 31 European countries and covers 16 sectors of activity. However, we collect yearly verified carbon emission data for 166 companies over the sample period[3].

Table 1 summarizes the descriptive statistics of annual emissions over the observation period (2005-2019).

[3]The number of companies in the sample is limited by the information needed for our analysis,especially stock returns data. As a result, our sample is composed of 166 companies.

Table 1: Descriptive statistics of verified emissions

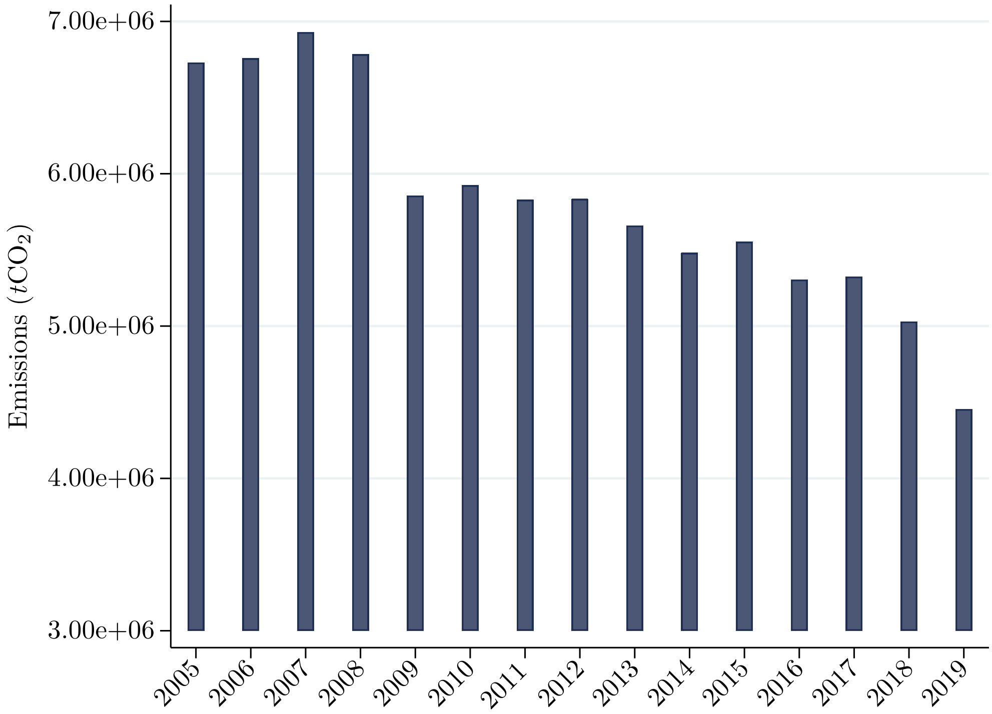
Year	N	Mean	Std.Dev.	p25	p75
2005	166	6729848	1.73e+07	117462	4356134
2006	166	6757043	1.72e+07	127106	4648817
2007	166	6928775	1.73e+07	117538	4389100
2008	166	6783255	1.65e+07	125844	5117255
2009	166	5856253	1.44e+07	108705	4084708
2010	166	5923742	1.45e+07	119072	3967388
2011	166	5828297	1.44e+07	109993	4044198
2012	166	5834122	1.53e+07	100140	3681461
2013	166	5659437	1.42e+07	117226	4744431
2014	166	5479751	1.39e+07	117314	4217064
2015	166	5553444	1.42e+07	104734	4173898
2016	166	5304566	1.38e+07	108326	4487749
2017	166	5324252	1.33e+07	106894	4248754
2018	166	5029537	1.24e+07	104111	4091576
2019	166	4454682	1.01e+07	102503	3941068
Total	2490	5829800	1.47e+07	111655	4356134

Source: Carbon Market Data. Authors' calculations.

Overall, despite an increase in CO_2 emissions between 2005 and 2007, we observe a downward trend in average carbon emissions since 2008 from 5915851 to 3907204 tons of CO_2 emitted.

More precisely, we can better appreciate this downward trend by looking at Figure 1. After a slight increase in carbon emissions following the implementation of the first phase of the emissions trading scheme, carbon emissions began to decline considerably over the rest of the period. Indeed, given the cleanup efforts made by companies since the introduction of the ETS, the introduction of an ETS appears to have played a role in reducing carbon emissions, as they have largely declined.

Figure 1: Annual average of verified emissions (2005-2019)



Note: The data presented in Table 1 are plotted.

3.3 Stock returns

Our empirical analysis focuses on the companies which participating in the EU ETS. In this sense, we have financial informations (price and market equity) for 166 companies, and we compute their returns over the observation period from January 2005 to December 2019.

Monthly stock returns are calculated as $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$ where $P_{i,t}$ is the price trade of stock i at time t[4] and all equities price are obtained from *Datastream-Refinitiv Eikon.* We consider the period corresponding to the available carbon emission data. Therefore, the sample period ranges from January 2005 to December 2019.

4 Methodology

4.1 Sorting of the portfolios

We aim to evaluate the impact of verified emissions on stock returns. In a seminar work, Fama and French group stocks into portfolios according to different sorting variables. In the literature at the intersection of finance and climate change, Oestreich and Tsiakas (2015) suggest to define three carbon portfolios

[4]Where P_t is the closing price of the first day of month t.

according to emission allowances. Companies that have received more than one million emission allowances constitute the "dirty" portfolio, those that have received less than one million allowances represent the "medium" portfolio, and those that have not received any allowances are part of the "clean" portfolio.

We depart from Oestreich and Tsiakas (2015) in that we use use our own sorting criteria to define the three carbon portfolios[5]. Looking in detail at the distribution of the emissions variable represented by Table 2, the latter seems to be very spread out on the right with a concentration around 0 suggesting that our sample is very heterogeneous regarding emissions with some very polluting companies (5.65e+07 tons of emissions emitted per year) and others not polluting (0 tons of carbon emissions emitted per year).

Table 2: Details of the distribution of the variable *Emissions*

	Percentiles	Smallest	Obs.	2.490
1%	0	0	Mean	5829800
5%	4766	0	Sd. Dev.	1.47e+07
10%	18385	0	Variance	2.16e+14
25%	111655	0	Skewness	5.545885
			Kurtosis	43.43437
50%	564409.5			
	Percentiles	Largest		
75%	4356134	1.47e+08		
90%	1.77e+07	1.48e+08		
95%	2.73e+07	1.49e+08		
99%	6.96e+07	1.49e+08		

Source: Authors' calculations. The unit is tons of CO_2.

In this sense, we define three carbon portfolios according to the level of emissions. The brown (green) portfolio contains the 25% most (less) polluting firms. The medium portfolio contains the remaining 50% of firms. Since some firms may change groups from year to year, they are assigned to the group in which they remain predominantly. All portfolios are weighted by market capitalization lag.

Table 3 presents the descriptive statistics of the three carbon portfolios. Over the entire observation period, the brown portfolio seems to perform worse than the other ones. Indeed, with the exception of phase 1 of the EU ETS where the average return of the brown portfolio is 0.007%, the only period during which allowances are still allocated for free, the performance of the brown portfolio is lower than that of the other portfolios during the next two phases of the EU ETS. Specifically, the average return of the brown portfolio over the entire observation period is 0.003%, twice the average return of the medium portfolio during the same time period.

[5]Furthermore, their study is restricted to german firms, whereas we analyze all countries in the database.

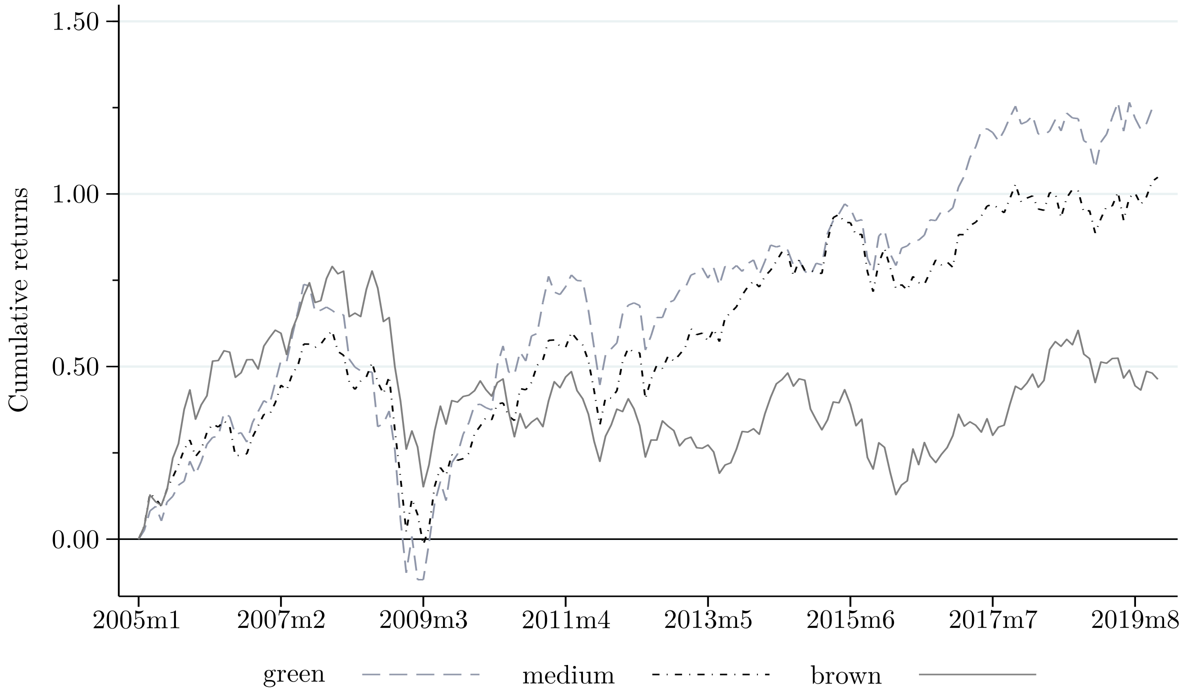
Table 3: Descriptive statistics of the three carbon portfolios

Portfolios	**N**	**Mean**	**Min.**	**Max.**	**Sd.**	**p25**	**p75**
			All observation period: *January 2005 - December 2019*				
Green	179	0.007	-0.205	0.130	0.054	-0.013	0.040
Medium	179	0.006	-0.154	0.121	0.047	-0.016	0.036
Brown	179	0.003	-0.143	0.100	0.050	-0.029	0.039
Total	537	0.005	-0.205	0.130	0.050	-0.018	0.038
			Phase 1: *January 2005 - December 2007*				
Green	35	0.019	-0.075	0.077	0.039	-0.010	0.056
Medium	35	0.016	-0.086	0.095	0.036	-0.009	0.038
Brown	35	0.022	-0.085	0.100	0.047	-0.009	0.057
Total	105	0.019	-0.086	0.100	0.041	-0.009	0.046
			Phase 2: *January 2008 - December 2012*				
Green	60	0.001	-0.205	0.130	0.074	-0.020	0.052
Medium	60	-0.000	-0.154	0.121	0.060	-0.021	0.042
Brown	60	-0.008	-0.143	0.099	0.060	-0.048	0.038
Total	180	-0.002	-0.205	0.130	0.065	-0.031	0.043
			Phase 3: *January 2013 - December 2019*				
Green	84	0.006	-0.112	0.103	0.040	-0.014	0.033
Medium	84	0.006	-0.108	0.095	0.040	-0.016	0.034
Brown	84	0.002	-0.111	0.092	0.041	-0.025	0.027
Total	252	0.005	-0.112	0.103	0.040	-0.017	0.032

Source: Authors' calculations. The phases refer to the three phases of the EU-ETS.

Figure 2 plots the cumulative returns of the carbon portfolios over the entire observation period. In general, we observe an increase in cumulative returns before the financial crisis of 2008 and more particularly for the brown portfolio, suggesting that the most polluting companies may not yet be penalized by the market despite the implementation of the EU-ETS. From 2010 onwards, we observe a decoupling of the cumulative returns of the different portfolios. Indeed, we can see that the brown portfolio underperforms the other two portfolios which follow the same upward trend.

Figure 2: Cumulative returns of the three carbon portfolios on the overall observation period (all EU-ETS phases)

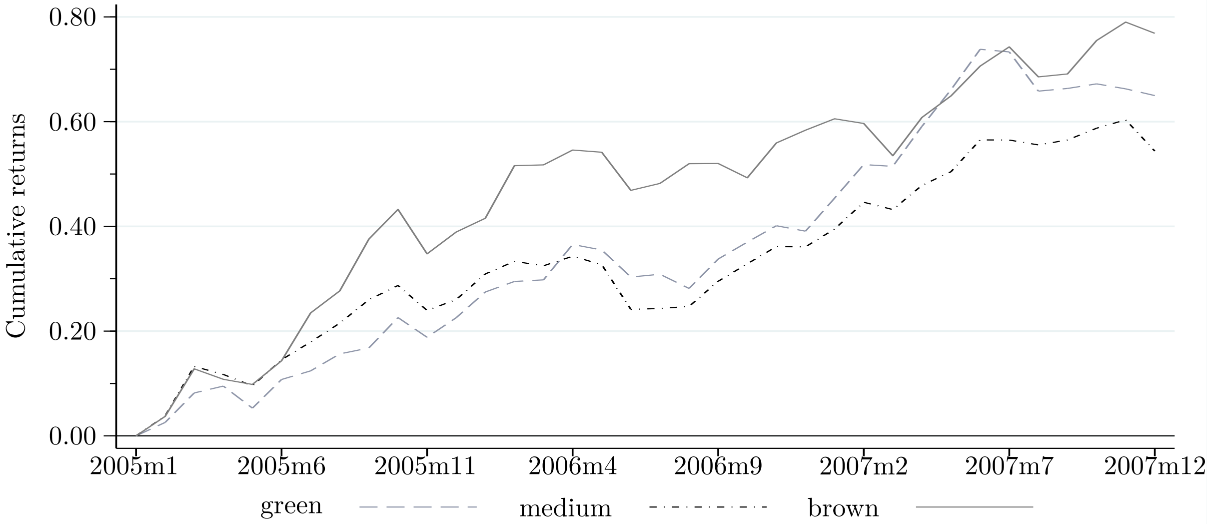


In general, we observe an increase in cumulative returns before the 2008 the financial crisis and especially for the brown portfolio, suggesting that the most polluting companies may not yet be penalized by the market despite the implementation of the EU-ETS. However, all three carbon portfolios are impacted by the 2008 financial crisis by experiencing a downward trend, even reaching negative cumulative returns for the medium and green portfolios. From 2010 onwards, we observe a decoupling of the cumulative returns of the different portfolios. Indeed, we observe that the brown portfolio underperforms the other two portfolios which follow the same upward trend.

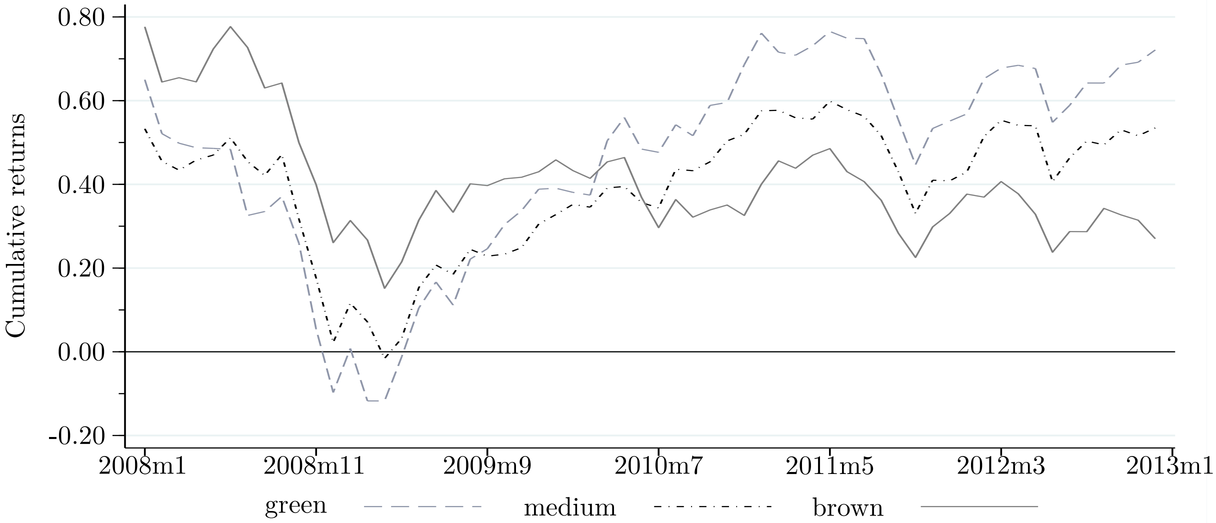
Figure 3 plots the cumulative returns of the three portfolios according to the different phases of the EU-ETS. During the first phase, all three carbon portfolios show an upward trend over the entire period, from January 2005 to December 2007. However, the brown portfolio shows better returns than the other two portfolios. During the second phase, after a common downward trend due to the 2008 crisis, the green portfolio outperforms the other two portfolios during the second part of the phase from 2010 to 2013. During the third phase, the brown portfolio underperforms the other two portfolios during the entire phase.

Figure 3: Cumulative carbon portfolios returns for the three phases of the EU ETS

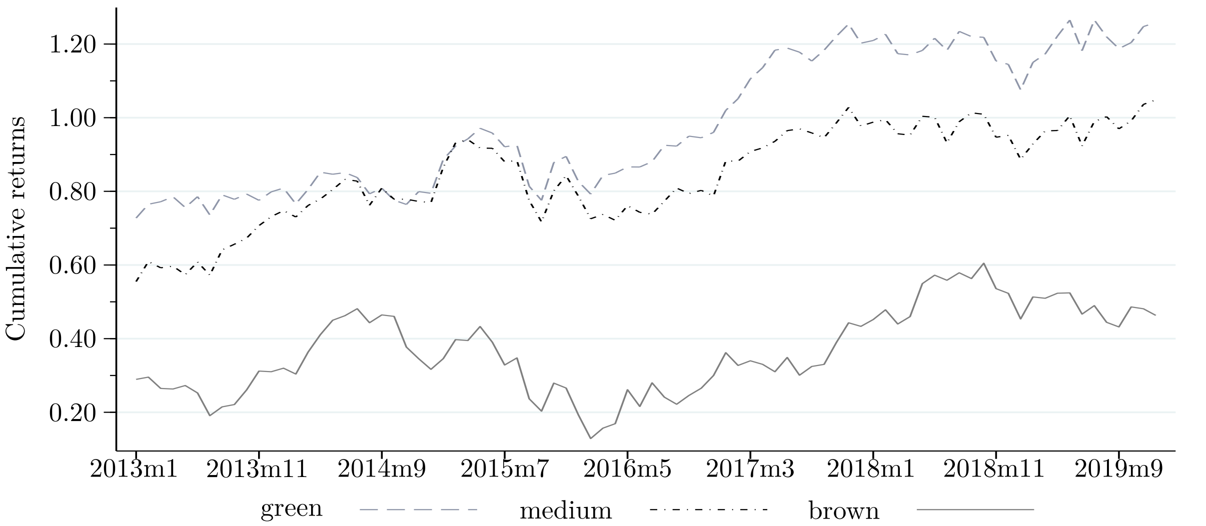
(a) Phase 1: *January 2005 - December 2007*



(b) Phase 2: *January 2008 - December 2012*



(c) Phase 3: *January 2013 - December 2019*



4.2 Factor models approach

Second, our study is based on asset pricing model. The traditional Capital Asset Pricing Model (CAPM) developed by Treynor (1962), Sharpe (1965) and Mossum (1966) highlights the linearity of expected return with volatility (risk) as soon as a risk-free asset is introduced. In its initial form, the model take the following form:

$$r_{i,t} - r_f = \alpha_i + \beta_i(r_{m,t} - r_f) + \epsilon_{i,t} \tag{1}$$

where the excess return over the risk-free rate (the independent variable) is determined by the market risk and $\epsilon_{i,t}$ a normally distributed error term.

Based on this seminal work, Fama and French (1992), Fama and French (1993) have developed a factor model whose objective is to determine the premium resulting from portfolio exposure to these different factors. In other words, the common variation in stock returns is explained by traditional risk factors identified in the literature such as firm size or market. We use this model as:

$$r_{i,t} - r_f = \alpha_i + \beta_i(r_{m,t} - r_f) + \gamma_i SMB_t + \phi_i HML_t + \epsilon_{i,t} \tag{2}$$

where $r_{i,t}$ is the monthly return of portfolio i at time t (where i = brown, medium, green portfolios), r_f the monthly (proxy) free rate[6], α_i is the intercept, $r_{m,t}$ is the return of the market factor[7], SMB denotes the size factor calculated as the difference between the monthly average returns on small and big caps, HML denotes the value factor calculated as the difference between the monthly average returns on "value" stock and "growth" stock.

Besides, we also use an extension of the Fama and French (1993) three factor model, the developed Fama-French-Carhart 4-factor model. Thus, we obtain the following model:

$$r_{i,t} - r_f = \alpha_i + \beta_i(r_{m,t} - r_f) + \gamma_i SMB_t + \phi_i HML_t + \theta_i MOM_t + \epsilon_{i,t} \tag{3}$$

where the momentum is added as an additional risk factor. In fact, MOM denotes the momentum factor calculated as the difference between the monthly average returns on the lowest and the highest performing firms.

We are particularly interested in portfolio performance. In finance, portfolio performance is evaluated by assessing the sign and significance of the constant in the regression equation. More commonly, this constant is called Jensen's alpha. Indeed, it represents the average return attributed to the portfolio's own characteristics, regardless of the traditional risk factors that may influence the portfolio's profitability. In this context, Oestreich and Tsiakas (2015) define this abnormal return as the carbon premium.

[6]We use the 1-month Euribor rate as a risk-free rate.

[7]All factors are directly obtained from the French Kenneth's website for the European market.

Thus, our study amounts to assessing whether portfolios generate more or less alpha, depending on the verified CO_2 emissions of the selected companies. In this sense, we will be able to compare the performance of these different portfolios in order to identify a premium associated with carbon emissions. In other words, we are looking to see if any of the portfolios has a significantly different abnormal return than the others.

In this line, we run a time series regression for each portfolio over the period 2005-2019. To correct for autocorrelation and heteroscedasticity, we use Newey-West standard errors.

5 Results

In this section, we first present the main results, and then present sector and period analysis.

5.1 Main findings

For remind, we examine the performance of portfolios invested in firms for which we have verified emissions. According to our definition of the three carbon portfolios (based on the level of emissions), we study the carbon premium of these portfolios with the four factor model (Fama and French (1993), Carhart (1997)). We first consider both the three and four factor model and the overall observation period (2005-2019) for which the results are presented in Table 4.

We observe a difference between portfolios in abnormal excess returns. In fact, the more the brown portfolio is, the more significant and negative the carbon premium is. It seems that the brown portfolio underperforms the other ones during the observation period. All factors have the expected sign when they are statistically significant.

Besides, as the EU-ETS is splited into three phases, we aim to investigate the behiavour of the alpha of the three carbon portfolios during these phases. For remind, the first phase begins in January 2005 and ends in December 2007, the second phase covers the January 2008 and December 2012 period, and the third phase runs from January 2013 to December 2019. We perform time series regression on each EU-ETS phases period for the three carbon portfolios. Table 6 presents the results from the four factors estimation.

The main significant result is that the brown portfolio underperforms statistically the other portfolios during the second phase of the EU-ETS. This result highlights the existence of a cash flow effect. In fact, during this period, the allocated allowances were not given for free with respect to the first phase. Therefore, this additional cost affects the performance of the highest emitting-firms. In this sense, brown firms are

Table 4: Estimation results for factor models

	FF3			FF4		
Variables	(1) Green	(2) Medium	(3) Brown	(1) Green	(2) Medium	(3) Brown
MKT	0.27832**	0.20589*	0.17759*	0.26785**	0.22487*	0.18549*
	(0.0914)	(0.0872)	(0.0807)	(0.0970)	(0.0877)	(0.0844)
SMB	1.05556***	1.01420***	0.84513***	1.05521***	1.01483***	0.84540***
	(0.2707)	(0.2283)	(0.2198)	(0.2719)	(0.2285)	(0.2207)
HML	0.04779	-0.08012	0.11260	0.00565	-0.00369	0.14439
	(0.2046)	(0.1694)	(0.1837)	(0.2093)	(0.1839)	(0.1983)
MOM				-0.06695	0.12143	0.05050
				(0.1046)	(0.0992)	(0.1205)
Constant	-0.00392	-0.00554	-0.00866*	-0.00347	-0.00636	-0.00900*
	(0.0039)	(0.0035)	(0.0038)	(0.0041)	(0.0037)	(0.0040)
Observations	179	179	179	179	179	179
R^2	0.187	0.178	0.127	0.188	0.183	0.128

Note: This table provides estimated coefficients α, β, γ, ϕ, θ from the time series regression for the three carbon portfolios. The estimated regression models cover the period from 2005 to 2019. Newey-West standard errors are in parentheses. The symbols *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

more penalized than green firms and there is no carbon premium (brown firms earn higher returns). A particularly interesting result is that this effect disappears during the third phase. This suggests that the Jensen's alpha varies over time.

In this line, we perform rolling regressions on the 3 carbon portfolios with three years windows[8], period length of the second phase. Figure 4 plots the alpha of the three carbon portfolios.

[8]Rolling regression over a 3 years window with 90% confidence interval.

Table 5: Estimation results for the four factor model

	Phase 1 (January 2005 - December 2007)			**Phase 2** (January 2008 - December 2012)			**Phase 3** (January 2012 - December 2019)		
	Portfolios								
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variables	Green	Medium	Brown	Green	Medium	Brown	Green	Medium	Brown
MKT	0.1699	0.1721	0.1605	0.2999*	0.2528	0.2140	0.0131	-0.0153	-0.0616
	(0.275)	(0.378)	(0.334)	(0.141)	(0.128)	(0.113)	(0.125)	(0.112)	(0.123)
SMB	1.0549*	0.6259*	0.7761	1.3493*	1.2605**	1.0939**	0.6160*	0.7346**	0.4026
	(0.391)	(0.268)	(0.425)	(0.533)	(0.411)	(0.384)	(0.253)	(0.269)	(0.255)
HML	0.4141	0.3185	0.2793	0.1730	0.0370	0.0388	-0.0018	0.1342	0.2841
	(0.723)	(1.004)	(0.948)	(0.452)	(0.394)	(0.379)	(0.194)	(0.182)	(0.240)
MOM	-0.2731	-0.0115	0.0175	0.0261	0.1368	0.0683	-0.1575	0.2116	-0.1281
	(0.496)	(0.616)	(0.596)	(0.162)	(0.136)	(0.174)	(0.200)	(0.179)	(0.191)
Constant	-0.0093	-0.0154	-0.0094	-0.0101	-0.0131	-0.0217**	0.0074	0.0043	0.0045
	(0.013)	(0.017)	(0.017)	(0.009)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Observations	35	35	35	60	60	60	84	84	84
R^2	0.272	0.159	0.119	0.229	0.238	0.192	0.059	0.102	0.048

Note: This table provides estimated coefficients α, β, γ, ϕ, θ from the time series regression for the three carbon portfolios. The estimated regression models cover the period from 2005 to 2019. Newey-West standard errors are in parentheses. The symbols *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

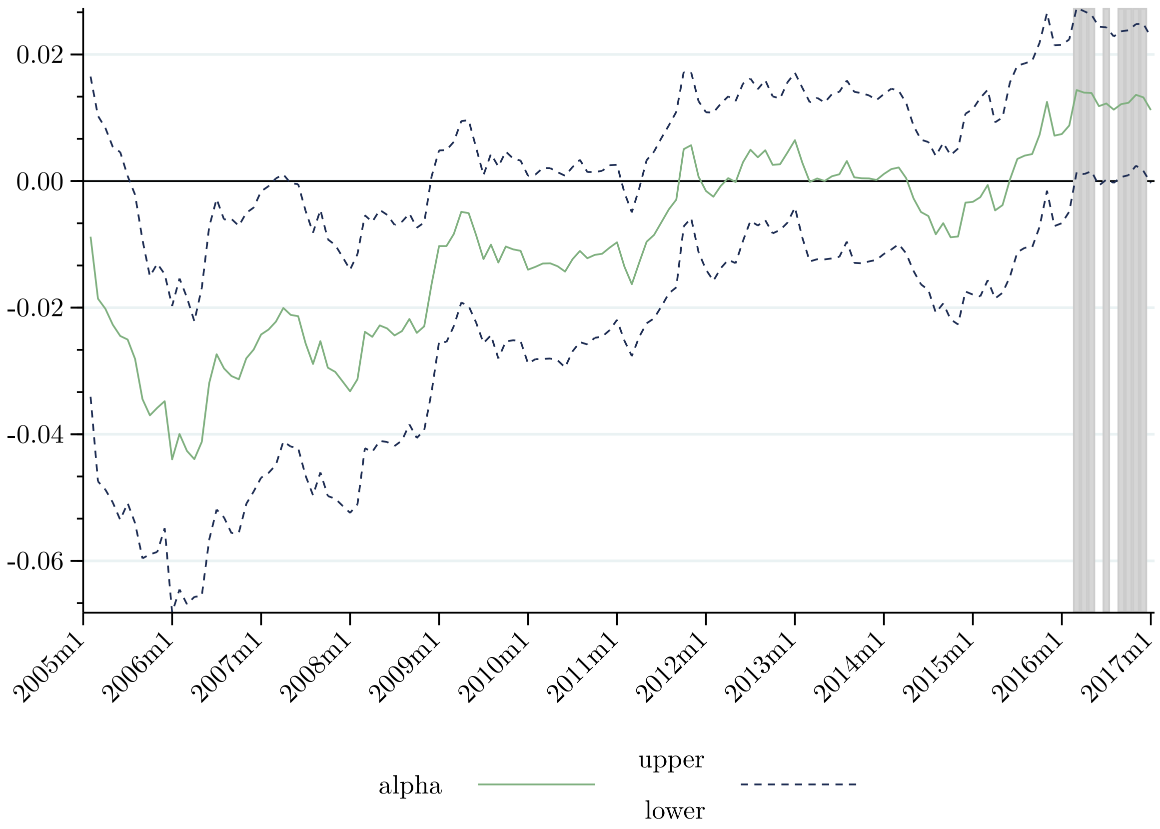
Figure 4: Alpha plot of the three carbon portfolios with a 3-year rolling window

(a) Green portfolio

(b) Medium portfolio

In a global aspect, we have an increasing trend of the alpha for all portfolios excluding the 2007-2011 period. However, we can highlight a difference in the alpha behaviour between the green and brown portfolios. Indeed, we observe that it is constant only for the dirtiest portfolio. This difference can be attributed to an expectation from investors about the second phase of the EU-ETS (whereby the allocated allowances were not given for free). This result is in line with the previous one. A new result is the postive and significant alpha for green portfolio around the 2013-2015 period. At this period, investors' expectations about the Paris Agreement could lead to a green premium which suggests that green firms outperform brown firms.

(c) Brown portfolio



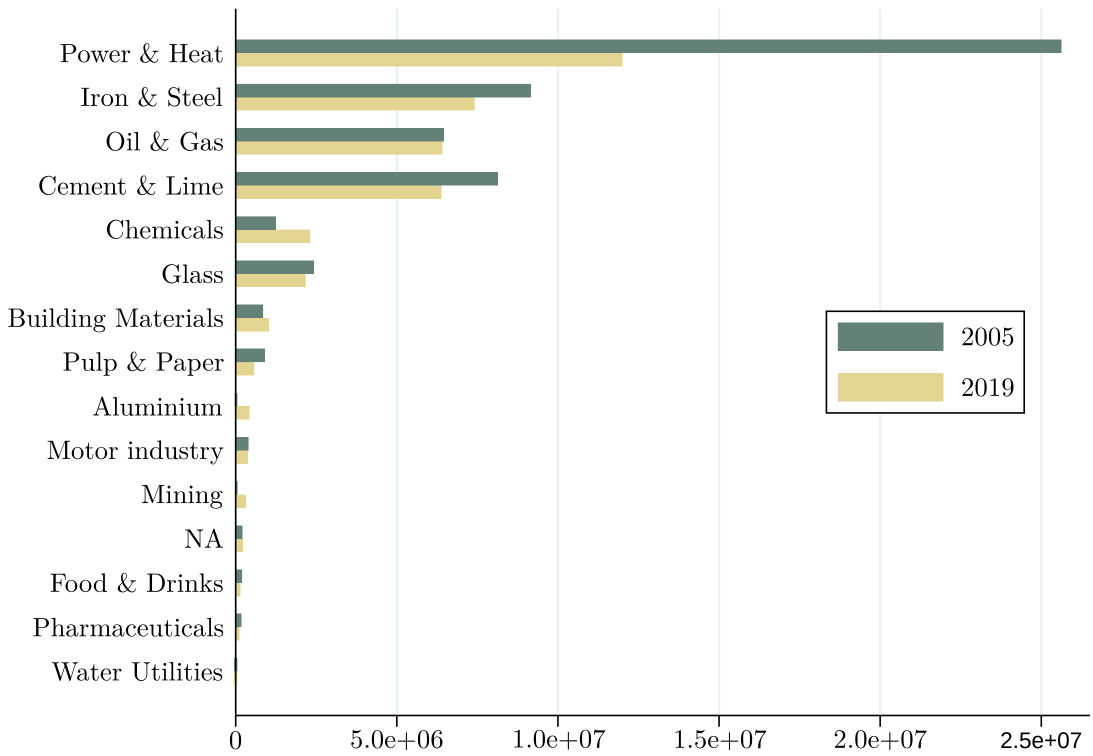
Note: The start of the time window is shown on the abscissa.

5.2 Sector and period analysis

The verified emissions data we use are from EU ETS companies operating mainly in the energy and raw materials sectors. Therefore, we provide in this article a sectoral analysis. Contrary to what is done in the literature, we have decided to define our own criterion for the allocation of assets in the different carbon portfolios. When considering emissions in our selection criterion, it is important to consider the relative emissions of each company to the sector in which it operates. Indeed, the sectoral dimension must be taken into account because of the heterogeneity that can exist in terms of carbon emissions if we consider companies from different sectors.

Figure 5 plots the average emissions of the firms in the different sectors in the sample. We observe the presence of intersectoral heterogeneity that can affect the results presented above.

Figure 5: Annual average of verified emissions by sector



As a result, we use the same methodology as in the previous section, but we modify the construction of the portfolios. Indeed, instead of sorting the portfolios according to the level of emissions, they are now divided according to the distribution of emissions in the sector. The three carbon portfolios are constructed by using the three quartiles of the verified emissions distribution. Thus, the brown (green) portfolio contains the 25% most (least) polluting companies in each sector. The medium portfolio contains the remaining 50% of companies.

As shown in Table 9, we find the underperformance of the brown portfolio during the second phase of the EU ETS. Moreover, the alpha remains negative and significant during the 2011-2014 period for the brown portfolio while it is positive and significant for the green portfolio during the Paris Agreement period (2013-2016).

Table 6: Estimation results for the four factor model

	Phase 1 *(January 2005 - December 2007)*			**Phase 2** *(January 2008 - December 2012)*			**Phase 3** *(January 2012 - December 2019)*		
					Portfolios				
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Variables	Green	Medium	Brown	Green	Medium	Brown	Green	Medium	Brown
MKT	0.2328	0.0616	0.1675	0.3500*	0.2460*	0.2189	0.0401	0.0382	-0.0647
	(0.319)	(0.285)	(0.330)	(0.161)	(0.118)	(0.110)	(0.124)	(0.094)	(0.124)
SMB	1.1939***	0.7147	0.5548	1.2597*	1.4750**	1.1067**	0.6632*	0.5452**	0.4778
	(0.268)	(0.392)	(0.395)	(0.513)	(0.452)	(0.379)	(0.273)	(0.188)	(0.253)
HML	0.0790	0.9275	0.2734	0.0857	0.0625	0.0754	0.2008	-0.1048	0.2252
	(0.909)	(0.761)	(0.911)	(0.514)	(0.400)	(0.356)	(0.193)	(0.162)	(0.222)
MOM	-0.2816	0.1070	0.0380	0.0144	0.1523	0.0928	0.2082	-0.1600	-0.1237
	(0.630)	(0.476)	(0.593)	(0.178)	(0.150)	(0.171)	(0.183)	(0.165)	(0.189)
Constant	-0.0059	-0.0184	-0.0103	-0.0127	-0.0152	-0.0197*	0.0050	0.0086*	0.0046
	(0.018)	(0.013)	(0.016)	(0.010)	(0.008)	(0.008)	(0.005)	(0.004)	(0.005)
Observations	35	35	35	60	60	60	84	84	84
R^2	0.226	0.209	0.104	0.217	0.253	0.208	0.081	0.074	0.050

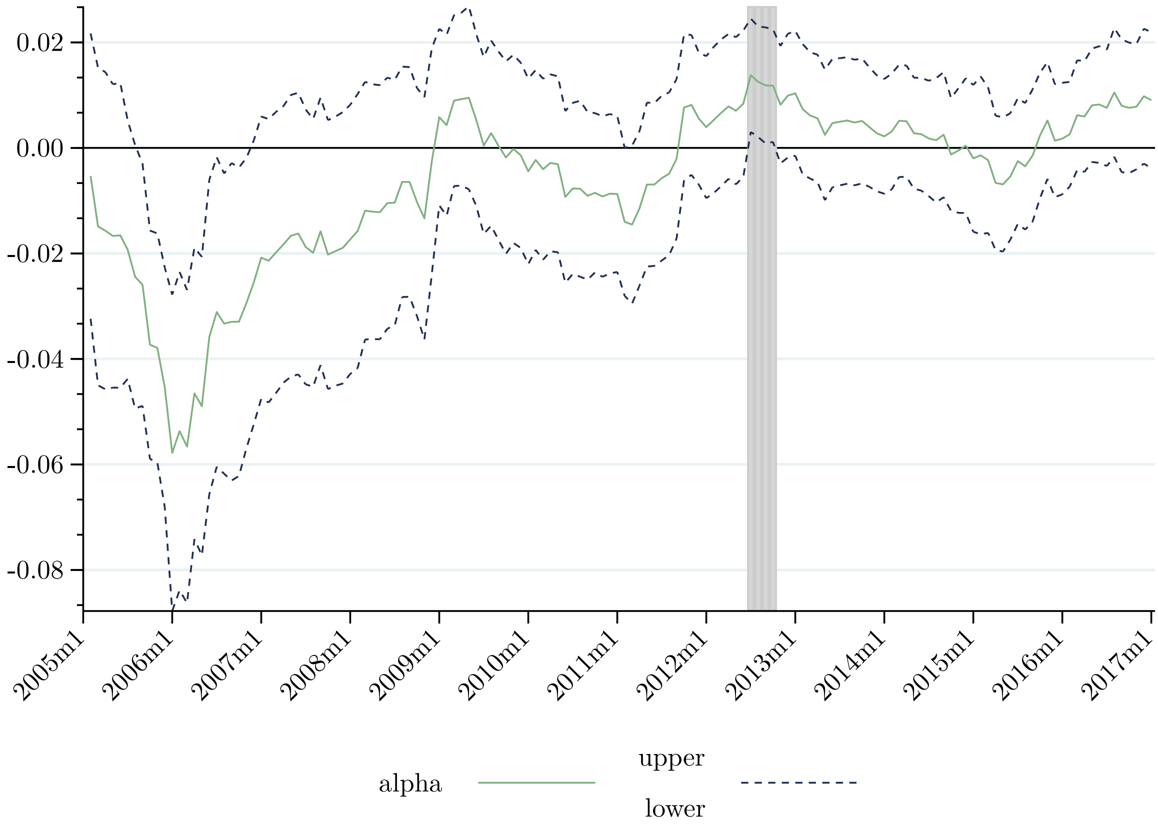
Note: This table provides estimated coefficients α, β, γ, ϕ, θ from the time series regression for the three carbon portfolios. The estimated regression models cover the period from 2005 to 2019. Newey-West standard errors are in parentheses. The symbols *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Figure 6 plots the alpha of the three carbon portfolios estimated from a rolling regression with a 3 years window. Considering the sectors, the pattern of the alpha of the 3 portfolios during the observation period does not seem to be modified. Moreover, the periods during which the alpha is positive and significant seem to correspond suggesting that our results are robust to the method of sorting the portfolios used.

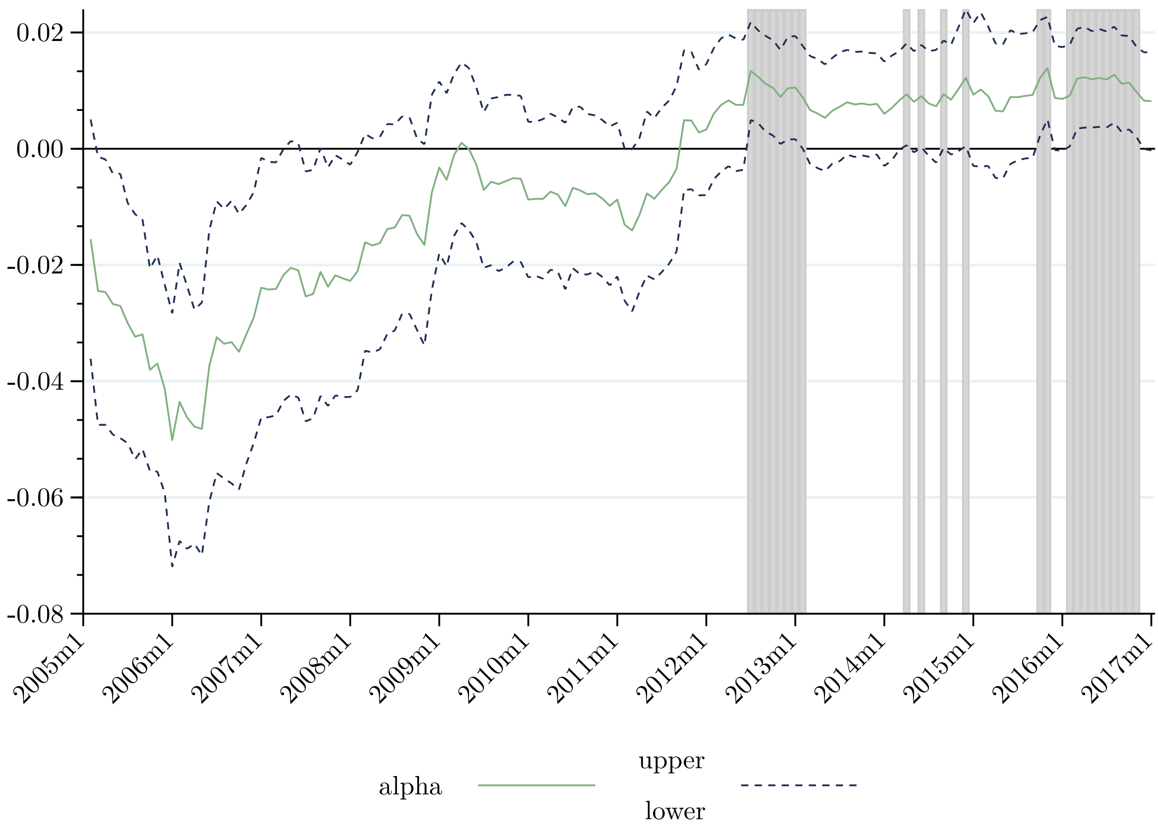
However, we notice that for the medium portfolio, the period during which the alpha is positive and significant increases, especially at the end of the observation period.

Figure 6: Alpha plot of the three carbon portfolios with a 3-year rolling window

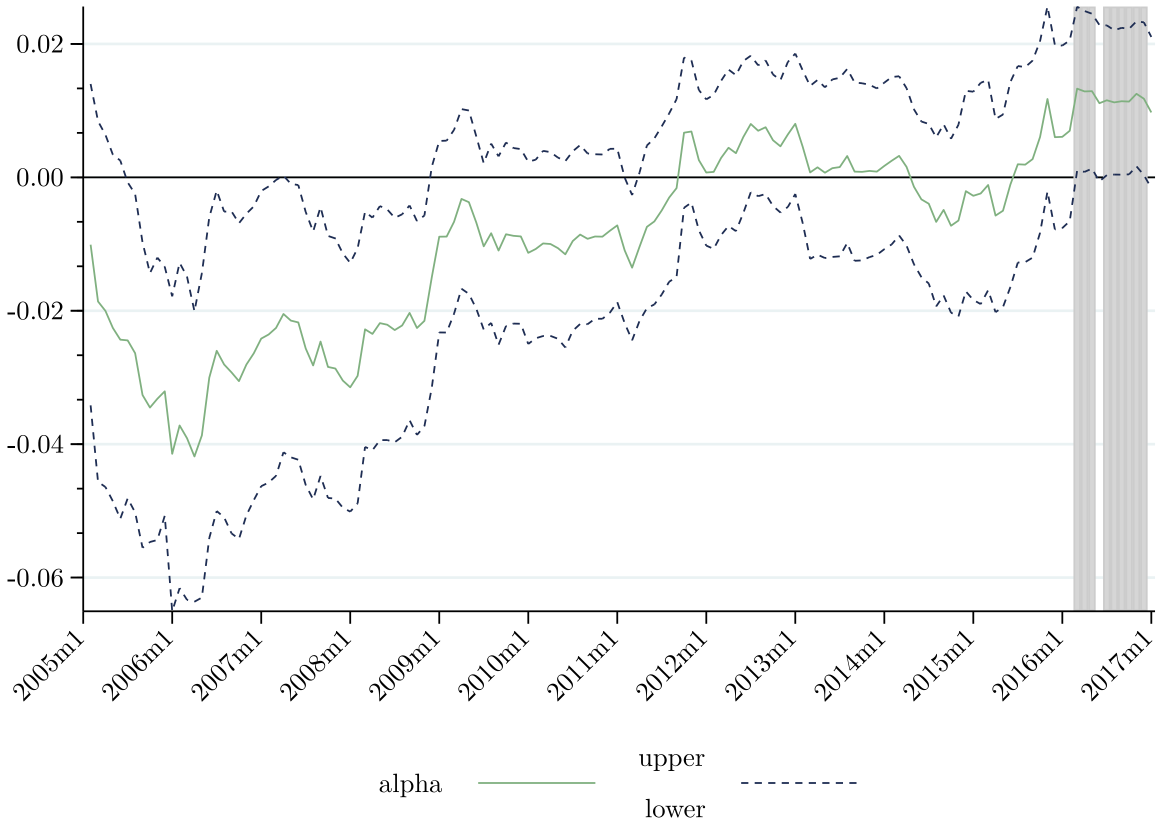
(a) Green portfolio



(b) Medium portfolio



(c) Brown portfolio



6 Conclusions and policy implications

It is now known that the financial system can play a significant role in the fight against climate change. Indeed, finance appears to be a major player in the ecological transition by financing cleanest companies. It is important to identify whether investors take into account the carbon risk in their investment decisions. In this sense, we aim to assess the impact of verified carbon emissions on the performance of firms participating in the EU-ETS.

Our results can be summarized as follow. First, during the 2005-2019 period, the brown portfolio underperform the other ones signficantly. Second, when we split the time period according to the EU ETS phases, the only statistically significant result is that the brown firms portfolio underperforms the other ones. As this period corresponds to the second phase of the EU-ETS, where emission allowances are no longer given for free, the highest emitting firms have had to face an additional cost that has lowered their performance compared to the lowest emitting firms. Interestingly, after performing rolling window we found a significant and positive carbon premium for the green portfolio during the 2014-2017 which corresponds to the Paris Agreement. However, this positive carbon premium disappears until the end of the observation period. The Paris agreement have generated a premium on green firms but not a persistent one. This highlights that the

Paris Agreement were really just a advertising effect for investors. In this sense, the constraints imposed on the most carbon-intensive companies in terms of reducing carbon emissions are not strong enough to sustainably push investments towards the least carbon-intensive companies.

Our results bear some potential implications that could interest decision-makers and policy-makers interested in the energy sector and/or in mitigating climate change with financial tools. As we have shown the impact of the carbon emissions on stock returns, it could be possible to use verified emissions to force funds not to invest in firms which carbon emissions are above a certain threshold. This would channel investments from high CO_2 emitters to low CO_2 emitters. Furthermore, our results call for the systematization of "carbon audits" for all listed firms. There is a need for expanding the profession of CO2-emissions verification and imposing such verification, just as financial audits are mandatory for all firms.

Thus, more subtly, governments, or international organizations, or professional associations, could promote the investment in portfolios that commit to select a minimum fraction of stocks that exhibit a satisfactory level of carbon emissions. Given that our results, compared to others in the literature, it would be interested to build a carbon factor based on verified emissions and assess the firms' sensitivy to this factor. In this sense, it could be useful to build "labels" indicating the percentage of stocks in a portfolio which are satisfactorily reacting to the carbon factor. For the same reasons, those "labels" could be only moderately costly to control. Furthermore, *verified* CO_2 emissions makes sense to ultimate investors, because it could help them allocating their wealth towards portfolios invested in firms which, not only provide higher returns, but also really emit less CO_2 and are not only "greenwashing" their reports or merely "compensating" potentially high levels of CO_2 emissions. As Aglietta and Espagne (2016) explain, financial and climatic stability are related, and it is the interest of financial investors to assess the real CO_2 impact of their investments. Finally, those investors should be warned that higher returns go with higher risks, and regulatory financial institutions would have a key role to play on integrating this aspect into the labelling of such portfolios. Finally, it could be also possible to design tax cuts for capital gains that would be realized with portfolios which receive these labels.

Ultimately our results show that the cost of allowances do have an impact on diminishing the returns on high CO_2 emitters. Then, this constitutes a direct tool by which regulators can influence the channeling of funds from high- to low-emitters.

Though, it is still interesting to measure the extent to which the stock markets are subject to the carbon factor, because these markets are ultimately where large institutional investors, as well as individual investors, are placing their money. Second, future researches could apply our framework to other ETS carbon quotas market throughout the world, and use more sophisticated factor models.

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Appendix A: Details on sample companies, sectors and description of the EU ETS

Company	ISIN	Sector
Rio Tinto Alcan	GB0007188757	Aluminium
Alro	ROALROACNOR0	Aluminium
Rockwool	DK0010219153	Building Materials
Wienerberger	AT0000831706	Building Materials
Creaton	DE0005483036	Building Materials
Cementos Molins	ES0117360117	Cement & Lime
CIMPOR - Cimentos de Portugal	PTCPR0AM0003	Cement & Lime
Italcementi	IT0001465159	Cement & Lime
Holcim	DE0005259006	Cement & Lime
Cementir - Cementerie del Tirreno	IT0003126783	Cement & Lime
LafargeHolcim	FR0000120537	Cement & Lime
Dyckerhoff	DE0005591036	Cement & Lime
HeidelbergCement	DE0006047004	Cement & Lime
Cemmac	CS0009007752	Cement & Lime
Buzzi Unicem	IT0001347308	Cement & Lime
Cementos Portland Valderrivas	ES0117390411	Cement & Lime
TITAN	GRS074083007	Cement & Lime
CRH - Cement Roadstone Holdings	IE0001827041	Cement & Lime
VICAT	FR0000031775	Cement & Lime
Lusical - Companhia Lusitana de Cal	FR0000063653	Cement & Lime
BASF	DE0005151005	Chemicals
Synthos	PLDWORY00019	Chemicals
SKW STAHL-METALLURGIE HOLDING AG	DE000SKWM021	Chemicals
Henkel	DE0006048432	Chemicals
Polimeri Europa	BG11PODEAT11	Chemicals
Lanxess	DE0005470405	Chemicals
Ercros	ES0125140A14	Chemicals
Croda	GB0002335270	Chemicals
ADP Fertilizantes	FR0010340141	Chemicals
Arkema	FR0010313833	Chemicals
Unilever	GB00B10RZP78	Chemicals

Solvay	BE0003470755	Chemicals
Yara International	NO0010208051	Chemicals
SGLCarbon	DE0007235301	Chemicals
Rhodia	FR0010479956	Chemicals
MELAMIN KEMICNA TOVARNA D.D. KOCEVJE	SI0031101304	Chemicals
Air Liquide	FR0000120073	Chemicals
Bayer	DE0005752000	Chemicals
Akzo Nobel	NL0000009132	Chemicals
Diageo	GB0002374006	Food & Drinks
Heineken	NL0000009165	Food & Drinks
InBev	BE0003793107	Food & Drinks
Danisco	DK0010207497	Food & Drinks
Danone	FR0000120644	Food & Drinks
Agrana	AT0000603709	Food & Drinks
Bonduelle	FR0000063935	Food & Drinks
Levické Mliekarne	CS0009008651	Food & Drinks
Eastern Sugar	CS0009006853	Food & Drinks
Pilkington	DE0005588008	Glass
Saint-Gobain	FR0000125007	Glass
KROSNO - Krośnieńskie Huty Szkła	PLKROSN00015	Glass
Sandvik	SE0000667891	Iron & Steel
Acerinox	ES0132105018	Iron & Steel
Grupo Tubos Reunidos	ES0180850416	Iron & Steel
JSC Liepajas metalurgs	LV0000100535	Iron & Steel
Sidenor Industrial	GRS283003002	Iron & Steel
Rába Járműipari Holding Nyrt.	HU0000073457	Iron & Steel
Voestalpine	AT0000937503	Iron & Steel
ArcelorMittal	LU0323134006	Iron & Steel
Outokumpu	FI0009002422	Iron & Steel
SSAB	SE0000171100	Iron & Steel
Salzgitter	DE0006202005	Iron & Steel
Stalprodukt	PLSTLPD00017	Iron & Steel
ThyssenKrupp	DE0007500001	Iron & Steel
Scana	NO0003053308	Iron & Steel
Boliden	SE0000869646	Mining

Michelin	FR0000121261	Motor industry
Fiat Chrysler Automobiles	IT0001976403	Motor industry
BMW	DE0005190003	Motor industry
PSA Peugeot Citroën	FR0000121501	Motor industry
Renault	FR0000131906	Motor industry
Audi	DE0006757008	Motor industry
Ford Motor Company	FR0000064438	Motor industry
Continental	DE0005439004	Motor industry
Pirelli	IT0004623051	Motor industry
Volvo	SE0000115446	Motor industry
Scania	SE0000308280	Motor industry
Faurecia	FR0000121147	Motor industry
Volkswagen	DE0007664005	Motor industry
DS Smith	GB0008220112	NA
British Airways (BA)	GB0001290575	NA
Abengoa	ES0105200416	NA
Alitalia	IT0003918577	NA
DSM	NL0000009827	NA
Umicore	BE0003884047	NA
Colas	FR0000121634	NA
BAE Systems	GB0002634946	NA
IBERIA LINEAS AEREAS DE ESPANA SA	ES0147200036	NA
BT	GB0030913577	NA
Eiffage	FR0000130452	NA
Imerys	FR0000120859	NA
Siemens	DE0007236101	NA
Infineon	DE0006231004	NA
Nyrstar	BE0003876936	NA
SNCF	FR0000032682	NA
Enagás	ES0130960018	Oil & Gas
Grupa Lotos	PLLOTOS00025	Oil & Gas
Slovnaft	CS0009004452	Oil & Gas
Neste Oil	FI0009013296	Oil & Gas
OMV	AT0000743059	Oil & Gas
BG Group	GB0008762899	Oil & Gas

Galp Energia	PTGAL0AM0009	Oil & Gas
Shell	GB00B03MLX29	Oil & Gas
A.P. MOELLER - MAERSK A/S	DK0010244508	Oil & Gas
COMPANIA ESPANOLA DE PETROLEOS SA	ES0132580319	Oil & Gas
ERG	IT0001157020	Oil & Gas
Saras	IT0000433307	Oil & Gas
Statoil	NO0010096985	Oil & Gas
Paramo	CZ0005091355	Oil & Gas
Total	FR0000120271	Oil & Gas
Snam Rete Gas	IT0003153415	Oil & Gas
Rompetrol	ROPESAACNOR0	Oil & Gas
BP	GB0007980591	Oil & Gas
Fluxys	BE0974265945	Oil & Gas
Unipetrol	CZ0009091500	Oil & Gas
Repsol	ES0173516115	Oil & Gas
ConocoPhillips	NL0000009538	Oil & Gas
Eni	IT0003132476	Oil & Gas
MOL	HU0000068952	Oil & Gas
Nafta	LT0000111650	Oil & Gas
ExxonMobil	FR0000031197	Oil & Gas
GlaxoSmithKline	GB0009252882	Pharmaceuticals
AstraZeneca	GB0009895292	Pharmaceuticals
Sanofi-Aventis	FR0000120578	Pharmaceuticals
Merck	DE0006599905	Pharmaceuticals
A2A	IT0001233417	Power & Heat
Lietuvos elektrine	LT0000117681	Power & Heat
Enel	IT0003128367	Power & Heat
Mainova	DE0006553464	Power & Heat
Union Fenosa	ES0181380710	Power & Heat
Veolia	FR0000124141	Power & Heat
RHEIN-RUHR ENERGIE AG	DE000A0HNHE3	Power & Heat
Acea	IT0001207098	Power & Heat
EVN	AT0000741053	Power & Heat
Edison	IT0003152417	Power & Heat
MVV Energie	DE000A0H52F5	Power & Heat

E.ON	DE000ENAG999	Power & Heat
Centrica	GB00B033F229	Power & Heat
Kauno Energija	LT0000123010	Power & Heat
Engie	FR0010208488	Power & Heat
Fortum	FI0009007132	Power & Heat
EDP	PTEDP0AM0009	Power & Heat
Drax Power	GB00B1VNSX38	Power & Heat
EnBW	DE0005220008	Power & Heat
Endesa	ES0130670112	Power & Heat
Iberdrola	ES0144580Y14	Power & Heat
Derwent Cogeneration	DE0007037129	Power & Heat
EDF	FR0010242511	Power & Heat
ČEZ	CZ0005112300	Power & Heat
ASM Voghera	IT0001250932	Power & Heat
Smurfit Kappa Group	IE00B1RR8406	Pulp & Paper
Grupo Empresarial Ence	ES0130625512	Pulp & Paper
Holmen Paper	SE0000109290	Pulp & Paper
Crown Van Gelder (CVG)	NL0000345452	Pulp & Paper
M-real	FI0009000665	Pulp & Paper
Lenzing	AT0000644505	Pulp & Paper
SCA - Svenska Cellulosa Aktiebolaget	DE0006889801	Pulp & Paper
Norske Skog	NO0004135633	Pulp & Paper
Arctic Paper	PLARTPR00012	Pulp & Paper
Kemira	FI0009004824	Pulp & Paper
Ahlstrom	FI0009010391	Pulp & Paper
RenoDeMedici (RDM)	IT0001178299	Pulp & Paper
Mondi	GB00B1CRLC47	Pulp & Paper
Stora Enso	FI0009005961	Pulp & Paper
UPM	FI0009005987	Pulp & Paper
Northumbrian Water	GB0033029744	Water Utilities

Note: Companies are sorted by sector in alphabetical order.

Table 7: Details on sectors

Sectors	Observations	Frequency	Number of companies
Aluminium	30	1.20	2
Building Materials	45	1.81	3
Cement & Lime	225	9.04	15
Chemicals	285	11.45	19
Food & Drinks	135	5.42	9
Glass	45	1.81	3
Iron & Steel	210	8.43	14
Mining	15	0.60	1
Motor industry	195	7.83	13
NA	240	9.64	16
Oil & Gas	390	15.66	26
Pharmaceuticals	60	2.41	4
Power & Heat	375	15.06	25
Pulp & Paper	225	9.04	15
Water Utilities	15	0.60	1

Note: The sectors are defined by the Community Transaction Log. For more detailed information, see the Annex I of the EU ETS directive.

Table 8: Description of the EU ETS

	Phase 1 *(January 2005 - December 2007)*	**Phase 2** *(January 2008 - December 2012)*	**Phase 3** *(January 2012 - December 2019)*
Period	2005-2007	2008-2012	2013-2020
EUAs allocation method	Free[9]	Free and auctioning	Auctioning is the main allocation method[10]
Penalty for non-compliance	40 euros/tCO2	100 euros/tCO2	-
Important timelines	Pilot phase to test the system (law establishing Phase 1 and Phase 2 of EU-ETS)	First commitment period with the Kyoto protocol: significant reduction of the emissions cap (6.5% decrease in the volume of EUAs compared to 2005)	Lowering the emissions cap to 1.74% per year to reduce emissions by 21% in 2020 compared to 2005
	Fixation of EUAs price	Use of other international pollution rights (Kyoto Protocol credits)	Blackloading : postponing the auctioning of 900 million EUAs to the end of the trading period

Note: EUAs' allocation is based on historic emissions called grandfathering. Only companies exposed to "carbon leakage" are allocated their allowances.

Appendix B: Additional results on sorting portfolios according to the level of emissions by sector

Figure 7: Cumulative returns of the three carbon portfolios on the overall observation period (all EU-ETS phases)

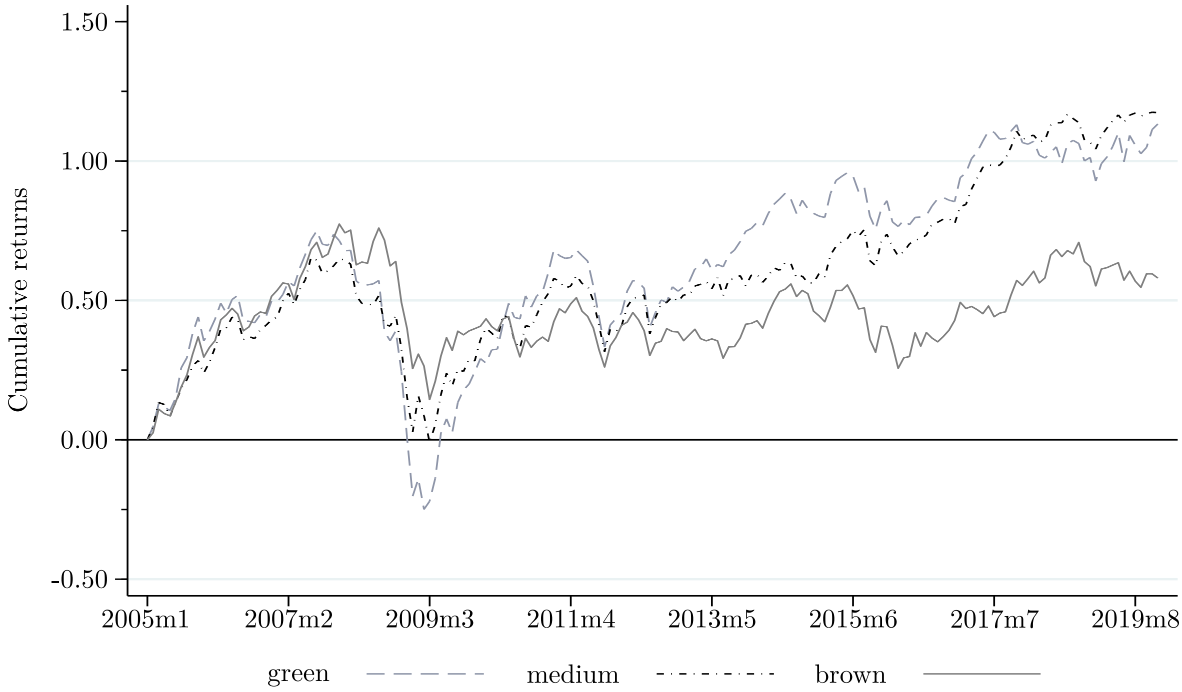
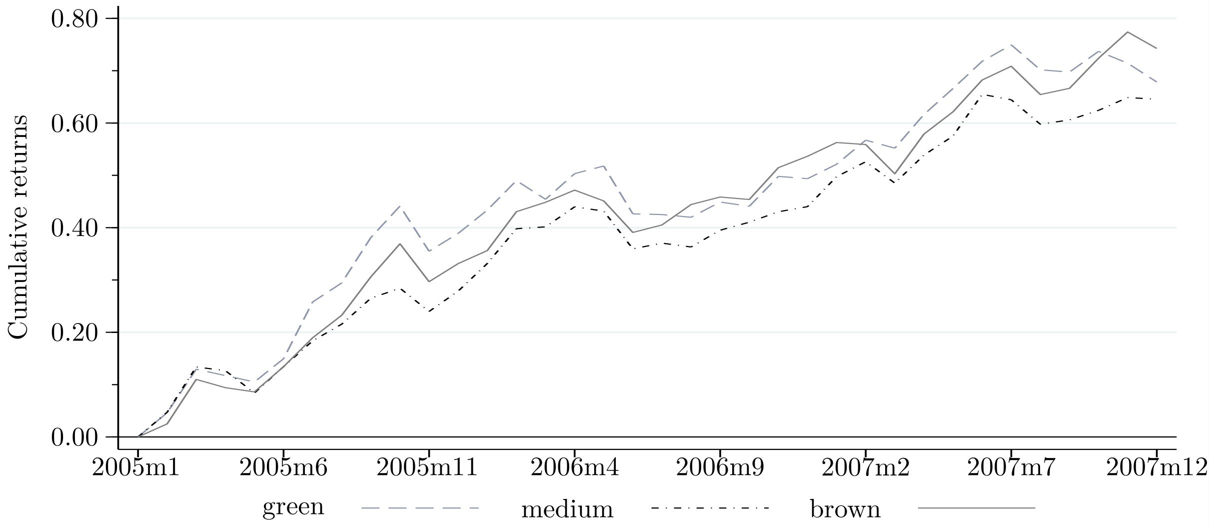
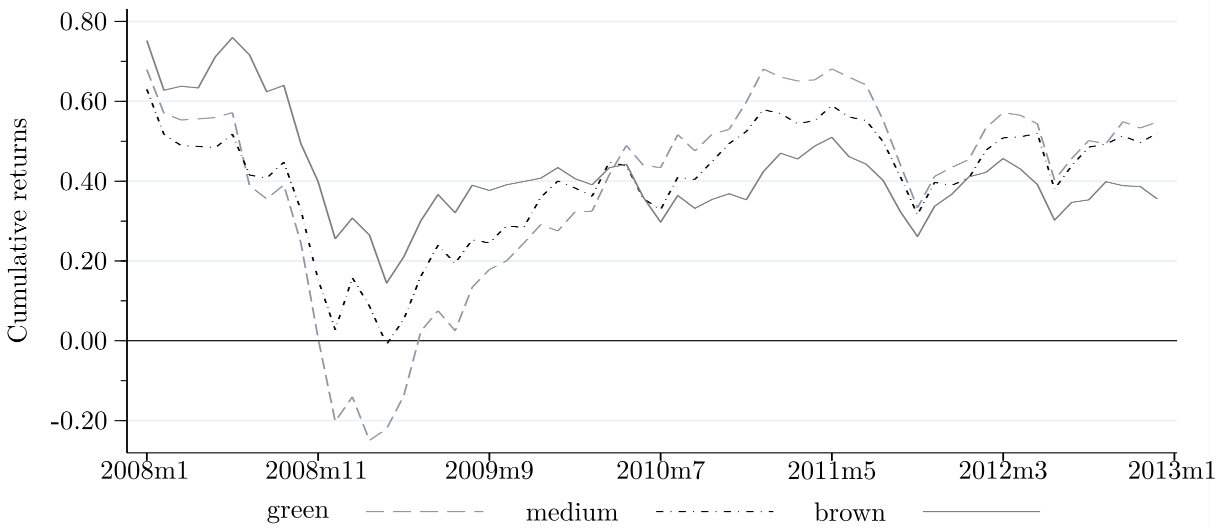


Figure 8: Cumulative carbon portfolios returns for the three phases of the EU ETS

(a) Phase 1: *January 2005 - December 2007*



(b) Phase 2: *January 2008 - December 2012*



(c) Phase 3: *January 2013 - December 2019*

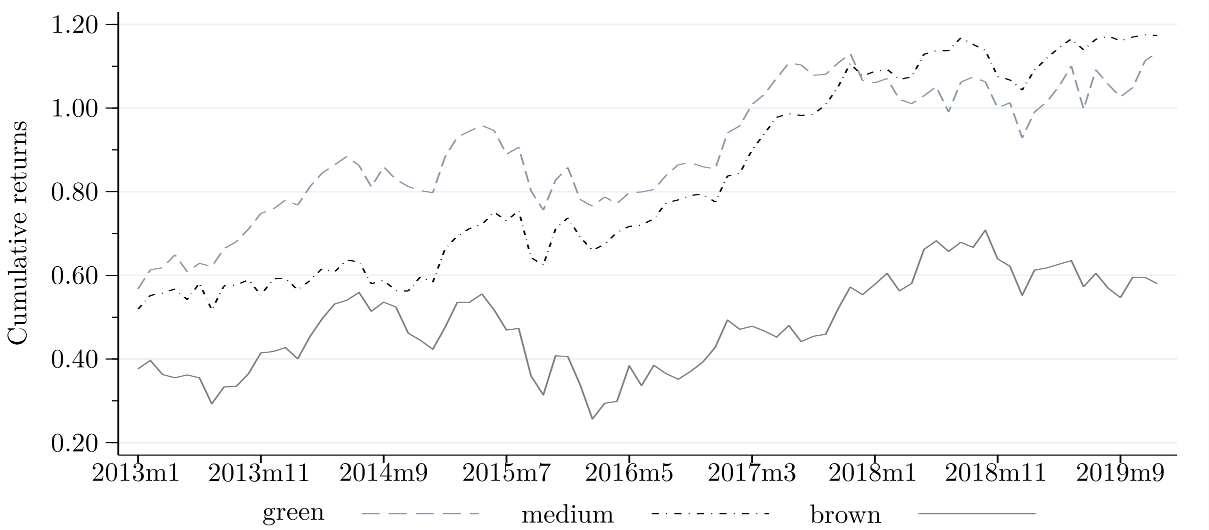


Table 9: Estimation results for factor models

	FF3			FF4		
Variables	(1) Green	(2) Medium	(3) Brown	(1) Green	(2) Medium	(3) Brown
MKT	0.30700**	0.23222**	0.17842*	0.31215**	0.23968**	0.18638*
	(0.1014)	(0.0791)	(0.0802)	(0.1066)	(0.0820)	(0.0836)
SMB	1.07532***	1.04881***	0.83473***	1.07549***	1.04906***	0.83499***
	(0.2664)	(0.2410)	(0.2182)	(0.2670)	(0.2416)	(0.2191)
HML	0.05997	-0.12527	0.08049	0.08068	-0.09520	0.11255
	(0.2118)	(0.1714)	(0.1738)	(0.2272)	(0.1831)	(0.1852)
MOM				0.03291	0.04776	0.05094
				(0.1176)	(0.0997)	(0.1189)
Constant	-0.00448	-0.00477	-0.00801*	-0.00470	-0.00509	-0.00836*
	(0.0042)	(0.0034)	(0.0036)	(0.0045)	(0.0036)	(0.0038)
Observations	179	179	179	179	179	179
R^2	0.185	0.196	0.134	0.185	0.196	0.135

Note: This table provides estimated coefficients α, β, γ, ϕ, θ from the time series regression for the three carbon portfolios. The estimated regression models cover the period from 2005 to 2019. Newey-West standard errors are in parentheses. The symbols *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.