Hedging against warmer days: The relationship between local temperature and stock returns

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Abstract

This research aims to find how mood swings regarding climate change affect stocks returns and what strategy could be used to hedge against these changes in perception. Based on prior literature I use local abnormal temperatures as a predictor of changes in the attention given to global warming. I assess the impact abnormal temperatures have on two different long-short portfolios for each of the seven country indices studied; one is based on industries, the other is based on Environmental (E) Scores provided by the London Stock Exchange Group (LSEG, previously Refinitiv). I find that stocks from companies operating in polluting industries as defined by the Intergovernmental Panel on Climate Change (IPCC) tended to underperform those who operate in clean industries in periods of high abnormal temperatures from 2016 to 2022. On a parallel experiment I also find that stocks with low E Scores tend to overperform stocks with high E Scores over the same period. These phenomena are observed essentially in the European Indices. Facing results pointing in opposite directions I study the relationship between E Scores and the industries companies operate in. I find that for the last 22 years, operating in high emissions industries as defined by the IPCC is associated with higher LSEG/Refinitiv E Scores.

Keywords: Climate Change, Environmental Scores, Global Warming, Hedging Strategies, Portfolio Management

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Abstrato

Esta investigação procura descobrir de que forma alterações na opinião dos investidores sobre o aquecimento global, afetam a rentabilidade de ações e que estratégia poderia ser utilizada para cobrir estas alterações. Com base em publicações anteriores, utilizo temperaturas anómalas locais para prever oscilações de perceção de aquecimento global. Avalio o impacto que a temperatura tem em dois portefólios long-short diferentes para cada um dos 7 índices regionais estudados. Verifico que ações de empresas que opera mem indústrias definidas como poluentes pelo Intergovernmental Panel on Climate Change (IPCC) tenderam a apresentar maior rentabilidade que empresas pertencentes a indústrias poco poluentes em períodos de temperaturas extraordinariamente altas entre os anos de 2016 a 2022. Numa experiência paralela verifico também que ações com más pontuações ambientais (E Scores) tendem a apresentar melhor performance que empresas com E Scores altos para o mesmo período de temperaturas altas. Estes fenómenos são observados essencialmente em índices europeus. Por fim verifico que nos últimos 22 anos, operar em indústrias definidas pelo IPCC como poluentes está associado a pontuações ambientais mais altas.

Keywords: Alterações Climáticas, Aquecimento Global, Estratégias de Cobertura, Gestão de Carteira, Pontuações Ambientais

1. Introduction

Global Warming, and sustainable investing in particular, has been a hot topic for the last few years. In 2020, Larry Fink wrote on his annual letter to CEOs that "climate risk is investment risk" (Larry Fink, 2020). The CEO of the largest asset manager in the world showed us that now, even the largest financial institutions were taking climate risk and sustainable investing seriously.

After the COP 21 Paris agreement (December 2015), CO2 emissions have been brought to the spotlight. Several papers have been published, presenting different results regarding the relation between the CO2 emissions produced by a company and its stock returns. Understanding this relationship is crucial, as it reveals how markets may price climate risks.

Bolton and Kacperczyk (2021) find that after controlling for size, book-to-market, momentum, and other factors that predict returns, stocks of firms with higher total CO2 emissions earn higher returns. They portray these higher returns as a *carbon premium* which investors demand for holding stocks more exposed to carbon and technology risks. In an opposite direction, In, Park and Monk (2017) find that a long-short portfolio based on firm-level return-adjusted emissions and other factors such as size and book-to-market, that would be long on carbon efficient stocks and short on inefficient ones, would give positive returns. They find that carbon efficient firms tend to be overall "better" firms in terms of financial performance and governance.

My approach is closer to the one employed by Engle et al. (2020). They find that using Sustainalytics Environmental Scores it is possible to create a portfolio to hedge against climate news. Such findings highlight the potential of using sustainability metrics to mitigate risk in an era of growing climate uncertainty.

With this research, my main aim was to see whether an easy-to-use strategy, only dependent on data publicly available would be able to hedge against investors' mood swings regarding climate change and global warming.

I use local abnormal temperatures as a proxy for the level of care investors have for global warming and test whether those local abnormal temperatures can predict returns on local stocks.

My work depends on a few premises. On the first place, it will be a test on whether investors tend to associate local weather experiences to global warming. This premise is supported by a large body of literature.

Borick and Rabe (2014) and Howe et al. (2013) find that people associate local weather with global warming and research by Choi, Gao and Jiang (2020) and Lang (2014) show that extreme heat increases search activity related to global warming.

Choi, Gao and Jiang (2020) also find that retail investors tend to care more about climate change when the local temperature is abnormally high and that there's a negative correlation between abnormal temperatures and the returns of long-short portfolios long on stocks of companies from high-emission industries and short on all the others.

Another relevant question is whether there is any kind of local influence when trading stocks, meaning: would a stock from a company based in Spain and traded in the Bolsa de Mercados de Madrid be more affected by everyday events in London or in Madrid?

Karolyi and Stulz (2003) mention a local factor which they call home-bias. Their research supports that stocks traded globally are affected by home factors such as interest rates or local politics. Addoum et al. (2023) find that extreme local temperatures may affect companies' earnings both ways and both Hirshleifer and Shumway (2003) and Saunders (1993) show that local sunshine can predict higher returns.

In my work I used country stock indices as the universe from where stocks would be chosen to make up the portfolios. This choice was made for two reasons: I believe it is more relevant as these stocks have a much higher trading volume than smaller stocks that cannot make it into the indices and secondly, because previous papers did not look at indices but at entire stock exchanges. This focus on indices helps to better understand the behaviour of highly liquid stocks, which play a critical role in global markets.

Working with indices instead of stock exchanges will raise questions regarding the impact of institutional investors. Ferreira and Matos (2008) find that institutional investors have a strong appetite for larger stocks. This implies that returns of stocks present in country indices are highly influenced by institutional investors.

Literature also supports the hypothesis that financial institutions are affected by everyday, ordinary events as well as major events heavily publicized in the media. Ben-Raphael, Da and

Israelsen's (2017) research on abnormal institutional investor attention shows that institutional investors react faster to large news events than retail investor. Institutional investors are also affected by weather through mood. Goetzmann et al. (2015) find that cloudier days increase stock selling propensity of institutional investors.

I implemented two different approaches. For the first experiment I studied 7 indices and found that using the IPCC industries definition, my results are consistent to those achieved by Choi, Gao and Jiang (2020) when studying the period from 2016 (Paris Climate Agreement) to 2022. These results are more notable when using a one-month lag. I also check for the period that goes from 2002 to 2022 and find no significant results.

In a second experiment, I intended to find whether Environmental Scores are a good measure of climate risk exposure and how would high and low score stocks react to abnormal temperatures. One hypothesis would be that the E Scores used were highly related to industries and therefore, results would come close to those found using the industry-based portfolios. This would possibly be due to companies with low E Scores being perceived as more sensitive to climate risk and therefore an increase in temperature would cause "Brown" stocks prices to go down or at least perform worse than those of "Green" stocks. Apergis, Poufinas and Antonopoulos (2022) shows that firms with low ESG Scores are considered riskier and face higher borrowing costs. Engle et al. (2020) also find that stocks with high E Scores react better to negative climate news than those with low scores.

Another hypothesis would be that E Scores are not perceived as a good measure for climate risk exposure and therefore portfolios' returns wouldn't be significantly positive nor negative.

One last hypothesis would be that E Scores, in particular those provided by the London Stock Exchange Group (LSEG) (previously Refinitiv), would favour firms operating in high emission industries. This would be the case in which "Green" stocks would show worse reactions to high abnormal temperatures than "Brown" stocks. A justification for these could come from the fact that when adjusting for industries, higher E Scores would be more easily attainable for large companies belonging to high emission industries and harder for large companies operating in low emission industries.

To test for this, I created 2 portfolios for each index. One, the GREEN portfolio, only composed of high E Scores stocks and another one, the BROWN portfolio, made of low E Scores stocks.

The LSEG E Score is a weighted average of scores for Emissions, Innovation and Resource Use, which are made of 68 parameters. These parameters are evaluated and compared against industry peers meaning every Score is industry adjusted.

I find that for a long-short portfolio made of Green stocks on the long leg and Brown stocks on the short leg, results would be significantly and negatively affected by high abnormal temperatures.

I conclude that this significance comes from only 4 of the 7 indices which happen to be the European ones. I also find that both GREEN and BROWN portfolios react negatively to an increase in temperatures only GREEN is more affected and therefore we have a negative impact on a GREEN minus BROWN (GMB) long-short portfolio.

To understand why changing from a portfolio based on industries to a portfolio based on Environmental Scores completely changes results, I check the relationship between the IPCC industries and the E scores and find that companies in high polluting industries have on average higher Environmental Scores.

This could come from the fact that investors demand higher E Scores from highly polluting companies. Zhao et al. (2024) find that ESG Scores have a more significant impact on firm performance in heavy-polluting industries than in non-heavy-polluting industries. This handicap forces companies operating in high emission industries to fight for higher E Scores if they want to make part of a large-companies country index. At the same time, having industry adjusted scores, facilitates attaining these higher E Scores.

2. Methodology

To see whether investors react negatively to warmer temperatures, it is necessary to define abnormal temperatures. I use the same method as used by Choi et al. (2020) but apply it to regional indices instead of Stock Exchanges. $Temperature_{it}$ is the average of daily average temperature through that month *t* in city *i*.

$$Temperature_{it} = Aver\_Temp_{it} + Mon\_Temp_{it} + Ab\_Temp_{it}$$

$Aver\_Temp_{it}$ is the average monthly temperature in city i for the 10 years (120 months) prior to t; Mon_Temp_{it} is the difference between the average temperature in city i of that same calendar month over the 10 years prior to moment t and $Aver\_Temp_{it}$. Ab_Temp_{it} is the remainder and what I am looking for. It will be my explanatory variable as it represents the difference between the norm and what has been observed on that specific month. Abnormal temperature helps measuring deviations and its potential to influence investor sentiment.

As all the portfolios used are based on indices, I first matched each city i to an index. All indices are regional and are matched by the city in which its biggest Stock Exchange is located. As an example, we have the CAC 40 which would be matched with Paris, or the FTSE100 with London. I believe this would make sense as usually, the biggest Stock Exchanges are present in the biggest urban areas. These urban areas tend to be home to the greatest number of investor and decision-makers within a given region, making them particularly relevant for this analysis. The 7 indices and cities are shown in table 1.

Table 1.

For each index, the constituents taken were those belonging to the given index on the 1st of January of 2023. #Emission Stocks represents the number of constituents that are considered by the IPCC to operate in high-emissions industries.

Index	City	Country	Continent	#Constituents	#Emission Stocks
S&P 500	New York City	United States	America	503	125
CAC 40	Paris	France	Europe	40	9
S&P/TSX 60	Toronto	Canada	America	59	18
DAX 40	Frankfurt	Germany	Europe	40	10
FTSE 100	London	United Kingdom	Europe	100	23
Nikkei 225	Tokyo	Japan	Asia	225	61
OMX 30	Stockholm	Sweden	Europe	30	4

The following step would be to decide which criterion would the portfolio construction be based on and to test whether that different criterion would present different results. I built portfolios based on two different stock characteristics: the IPCC polluting industries definitions and Environmental Pillar Scores (E Scores) provided by the Londen Stock Exchange Group. The industries classification might be easier to access by a retail investor and is technically less demanding to use when constructing the portfolios. The E Score, on the other hand, includes more information and is industry-adjusted which should give it some level of independence regarding the industry the company operates in. The E Score includes other factors such as usage of resources and innovation towards eco-friendlier products, enhancing its relevance.

Both portfolios are based on the same idea: a long-short portfolio, long on seemingly cleaner stocks and short on more polluting ones. Table 2 presents the summary statistics for each portfolio.

Table 2.

This table presents the summary statistics for the different portfolios. Full Period goes from 1st of January 2002 to 31st of December 2022, 2016-2022 goes from 1st January 2016 to 31st of December 2022. CME_t and CME_{t+1} represent the CME portfolios' returns in moment t and moment t+1 respectively. The CME portfolios are long-short equal-weighted portfolios, one for each index, long on stocks from companies operating in clean industries as defined by the IPCC and short on stocks from companies operating in highly polluting industries. *GMB_ext* and *GMB_3030* represent the GMB Extremes and the GMB 30-30 portfolios' returns respectively. The GMB Extremes portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 10% companies based on their E Score and short on the 10% worst scored companies. The GMB 30-30 portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 30% companies based on their E Score and short on the 30% worst scored companies.

Variable	Obs	Average	SD
Full Period			
CME_t	1764	0.000593415	0.025604323
CME_{t+1}	1764	0.000667264	0.025571707
GMB_ext_t	1761	-0.00529814	0.044082434
GMB_ext_{t+1}	1761	-0.005137127	0.044074358
GMB_3030_t	1764	-0.002226415	0.029762876
GMB_3030_{t+1}	1764	-0.002208525	0.029737175
2016-2022			
CME_t	588	-0.000187774	0.024095079
CME_{t+1}	588	-0.000234323	0.023976985
GMB_ext_t	588	-0.006739858	0.044475776
GMB_ext_{t+1}	588	-0.00654871	0.044700296
GMB_3030_t	588	-0.002356758	0.026918655
GMB_3030_{t+1}	588	-0.002073446	0.026797328

3. Data

3.1. Weather Data

Daily average temperature data was collected from the Global Surface Summary of the Day database, produced by the National Climatic Data Centre. From this, monthly averages were computed. For each city, data was collected from the closest station to its stock exchange that had available data for the entire time period. The database only has temperature values expressed in degrees Fahrenheit and therefore that measure is the one used.

3.2. Equity Indices Data

Returns data for each constituent in every index was retrieved from LSEG Workspace Datastream. Returns were trimmed at the top and bottom 2.5% at each index in each month. Returns equal to zero or to minus one (-1) were also removed.

3.3. Emissions and Scoring

Two types of data were collected in order to build the GMB and the CME strategies.

For the CME, I collected sub-sector values from Datastream and used the mapping already constructed by Choi et al. (2020) to match Datastream's sub-sectors to IPCC polluting industries. Table 14 presents every industry match.

For the GMB strategy, I used LSEG Workspace scores available on Datastream.

The E score is a component of the ESG Score of each company. It is the average of three other category scores that are then weighted according to the industry the company operates in. These three scores are Emissions, Resource Use and Innovation. Most of the category scores' components are industry adjusted allowing for comparisons between industries. Table 3 shows the themes evaluated by each category score.

Table 3.

This table presents the themes evaluated by each category score of the LSEG Environmental Score. Themes are just a reference. Each theme evaluates several parameters.

Pillar	Category	Theme
Environmental Pillar Score	Emissions Category Score	Emissions
		Waste
		Biodiversity
		Environmental management systems
	Innovation Category Score	Product Innovation
		Green Revenues, Research and Development, Capital Expenditures
	Resource Use Category Score	Water
		Energy
		Sustainable Packaging
		Environmental Supply Chain

Other raters and financial analytics firms such as MSCI and Morningstar Sustainalytics also provide ESG scores but I did not have access to these scores and therefore the ones used are the ones provided by the London Stock Exchange Group (LSEG)

4. Results

4.1. CME

At first, two portfolios were built for each index: an EMISSIONS portfolio with those stocks that operated in the industries defined by the IPCC as polluting ones and a CLEAN portfolio including all the others. Both portfolios were built using equal weights. I then computed the monthly returns for each portfolio and for the long-short with CLEAN on the long side and EMISSIONS on the short leg. . This approach provides a simple way to examine how polluting and non-polluting stocks perform relative to each other in the presence of climate-related variables.

To test whether abnormal temperature has an impact on the CLEAN minus EMISSIONS (CME) long-short portfolio, I used the following regression:

$$CME_{it} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it}$$

in which CME_{it} is the return of the CME portfolio in city/index i and moment t. Ab_Temp_{it} is the abnormal temperature in city/index i in moment t. Month and index fixed effects were included to control for any seasonality and regional variations that could influence returns.

In column 1 of Table 4 we can observe that an increase in the abnormal temperature registered of 1 ºF would lead to an increase of 0.0636 percentage points (t-stat of 1.713) on the returns of the portfolio. This comes in line with the findings described by Choi, Gao and Jiang (2020) but further suggests that institutional investors' views on climate change and risk are also influenced by abnormal temperatures. This is particularly interesting as it expands the evidence from retail investors to institutional players.

In column 2 we find the results for the following regression:

$$CME_{i,t+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it}$$

When lagging Ab_Temp by one period, we can see an increase in the effect abnormal temperature has on $CME_{i,t+1}$. Specifically, a 1 ºF rise in temperature corresponds to a 0.0723 p.p. increase in returns, now significant at the 5% level. This may indicate that the impact of weather on stock returns takes time to materialize, as news or sentiment shifts are reflected over the course of the next month. For instance, a heatwave occurring near the end of a month might delay its effects on returns until the following month.

Table 4.

CME_t and CME_{t+1} represent the CME portfolios' returns in moment t and moment t+1 respectively. The CME portfolios are long-short equal-weighted portfolios, long on stocks from companies operating in clean industries as defined by the IPCC and short on stocks from companies operating in highly polluting industries. These results correspond to time period starting the 1st of January 2016 and ending on the 31st of December 2022

VARIABLES	(1) $CMEt$	(2) $CMEt+1$
Ab_Temp	0.000661*	0.000723**
	(1.808)	(1.989)
Constant	-0.000694	-0.000788
	(-0.673)	(-0.769)
Observations	588	588
Adjusted R-squared	0.003	0.005

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 GMB

To test the effect of abnormal temperatures on returns of stocks with different Environmental Scores, I constructed two distinct long-short portfolios for each index. These portfolios consisted of a long GREEN portfolio and a short BROWN portfolio. On the GMB Extremes long-short portfolio, the GREEN portfolio is made of the top 10% scorers in the index while the BROWN portfolio is composed by the bottom 10% scorers. The second long-short portfolio, the GMB 30-30, follows the same idea but with the top and bottom 30%. All of the portfolios were updated monthly. As shown in table 4, the results are not significant when trying to explain portfolio returns without any kind of lag. However, when using a one-month lag I find significant results. For the GMB Extremes portfolio the regression used was the following:

$$GMB\_ext_{i,t+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it}$$

Where $GMB\_ext_{i,t+1}$ are the monthly equal weighted returns of the GMB Extremes long-short portfolio. Table 5 shows that abnormal temperatures have a negative impact on the portfolios' returns at the 1% significance level. On this portfolio, an increase of 1 ºF in abnormal temperature would imply a decrease in monthly returns of 0.230 p.p. which is a much stronger effect than observed in the CME portfolio (Table 4, Column (1)). We can also observe that its intercept is significantly negative which means that for these two indices, investors have rewarded more low E Score companies than high E Score ones from 2016 to 2022. This may be a demonstration of Bolton's and Kacperczyk's (2021) *carbon premium*.

Table 5.

$GMBext_{t+1}$ and $GMB3030_{t+1}$ represent the GMB Extremes and the GMB 30-30 portfolios' returns on moment t+1 respectively. The GMB Extremes portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 10% companies based on their E Score and short on the 10% worst scored companies. The GMB 30-30 portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 30% companies based on their E Score and short on the 30% worst scored companies. These results correspond to time period starting the 1st of January 2016 and ending on the 31st of December 2022

	(1)	(2)
VARIABLES	$GMBext_{t+1}$	$GMB3030_{t+1}$
Ab_Temp	-0.00230***	-0.00132***
	(-3.477)	(-3.373)
Constant	-0.00479**	-0.00106
	(-2.571)	(-0.965)
Observations	588	588
Adjusted R-squared	0.054	0.079

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the GMB 30-30 portfolio, as in the one seen before, an increase in temperature decreases expected returns. These results are significant at the 99% confidence level (Table 5, Column (2)).

As expected, it is noticeable that this negative effect verified before is more prominent in the Extremes portfolio than in the 30-30. This might indicate that stocks in the bottom and top end are more sensitive to temperature than the ones closer to the median.

Table 6 presents results for the CME portfolio and for both GMB Extremes and GMB 30-30 portfolios for the period that goes from the 1st of January 2002 to the 31st of December 2022. No significant results are found for this extended period, which may indicate that the observed effect has strengthened in recent years, particularly since 2016. This period coincides with growing investor awareness of climate issues and the implementation of the Paris Climate Agreement.

Table 6.

This table presents results for the period that goes from 1st of January 2002 to 31st of December 2022, CME_t and CME_{t+1} represent the CME portfolios' returns in moment t and moment t+1 respectively. The CME portfolios are long-short equal-weighted portfolios, one for each index, long on stocks from companies operating in clean industries as defined by the IPCC and short on stocks from companies operating in highly polluting industries. *GMBext* and *GMB3030* represent the GMB Extremes and the GMB 30-30 portfolios' returns respectively. The GMB Extremes portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 10% companies based on their E Score and short on the 10% worst scored companies. The GMB 30-30 portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 30% companies based on their E Score and short on the 30% worst scored companies.

VARIABLES	(1) CME_t	(2) CME_{t+1}	(3) $GMBext_t$	(4) $GMB3030_t$	(5) $GMBext_{t+1}$	(6) $GMB3030_{t+1}$
Ab_Temp	-0.0000585	0.00000227	-0.000251	4.04e-06	-0.000535	-0.000259
	(-0.295)	(0.0114)	(-0.735)	(0.0176)	(-1.568)	(-1.129)
Constant	0.000616	0.000666	-0.00520***	-0.00223***	-0.00493***	-0.00211***
	(1.003)	(1.086)	(-4.918)	(-3.132)	(-4.663)	(-2.967)
Observations	1,764	1,764	1,761	1,764	1,761	1,764
Adjusted R-squared	0.001	0.000	0.002	0.008	0.003	0.009

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3. Results by country and region

The seven indices chosen, represent seven different countries across three continents. These countries vary significantly in size, demography, and even investment culture. Such differences might influence how investors respond to climate-related variables, particularly abnormal temperatures.

I study the impact of this differences in my results by taking the analysis to the country and regional levels. Specifically, I study the influence of abnormal temperatures on the CME and both GMB strategies from 2016 to 2022 with a period lag. The same regressions from earlier sections are applied here, except the index fixed effects are omitted.

In Table 7, results show almost no significant findings for any of the CME country portfolios. This lack of significance could be attributed to small sample sizes, which limit the statistical power of the analysis.

When testing for the effects of abnormal temperature on the GMB portfolio's returns at the individual index level, notable changes emerge. Now we find significance in all European indices except for France (Table 8, Column (2)). We also see that the US are positively yet insignificantly affected by abnormal temperatures (Table 8, Column (1)).

Interestingly, when excluding the S&P 500, the Nikkei 225 and the S&P/TSX 60 from the analysis, we see the results becoming stronger when compared to the more inclusive take I presented in sections **4.1.** and **4.2.**. Table 9 shows results for the CME portfolios and for both the GMB Extremes and the GMB 30-30 portfolios. All three portfolios gain significance due to an increase in the absolute value of the coefficient when compared to the whole sample.

Choi, Gao, and Jiang (2020) suggest that in larger countries, a CME strategy would be less affected by local temperatures due to the more dispersed population, which exposes investors to varying climate conditions. This observation could explain the less significant results for the US and Canada, as these are the largest countries in the sample. Similarly, Japan, the second most populous country after the US, shows a muted response to temperature variations.

Another explanation could also come from the fact the countries with more significant reactions to abnormal temperature are European countries. A survey from the European Investment Bank that saw its results published in July 2024 concluded that Europeans have a better understanding on the consequences of climate change than Americans (European Investment Bank, 2024).

Moreover, research by Pastor, Robert, and Stambaugh (2023) finds that European institutions tend to tilt their portfolios more heavily toward green investments than their counterparts in other regions.

Additionally, the European Union is also known for regulating sustainability having published in February 2023 the Sustainable Finance Disclosure Regulation (SFDR). The SFDR demands market participants to disclose sustainability-related information allowing for investors to make better and more informed choices.

These two factors—higher climate awareness among Europeans and stricter sustainability regulations in the EU—likely explain the higher sensitivity of stocks to climate change and in this case to changes in temperature in the European countries.

Table 7.

The table shows results for equation (2) for each country separately for the period that goes from the 1st of January 2016 until the 31st of December 2022. CME_{t+1} represents the CME portfolios' returns in moment t+1. The CME portfolios are long-short equal-weighted portfolios, long on stocks from companies operating in clean industries as defined by the IPCC and short on stocks from companies operating in highly polluting industries.

VARIABLES	(1) US_CME_{t+1}	(2) $France\_CME_{t+1}$	(3) $Canada\_CME_{t+1}$	(4) $Germany\_CME_{t+1}$	(5) UK_CME_{t+1}	(6) $Japan\_CME_{t+1}$	(7) $Sweden\_CME_{t+1}$
Ab_Temp	-0.000422	0.00109	-0.000551	0.00187	0.00139*	0.000308	0.000662
	(-0.883)	(1.249)	(-0.582)	(1.584)	(1.801)	(0.524)	(0.573)
Constant	0.00205	0.000524	-0.00188	-0.00434	-0.00108	0.000953	-0.00177
	(1.471)	(0.200)	(-0.667)	(-1.185)	(-0.556)	(0.742)	(-0.445)
Observations	84	84	84	84	84	84	84
Adjusted R-squared	-0.003	0.007	-0.008	0.018	0.026	-0.009	-0.008

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8.

The table shows results for equation (3) for each country separately for the period that goes from the 1st of January 2016 until the 31st of December 2022. *GMBext*$_{t+1}$ represents the GMB Extremes and the portfolios' returns on moment t+1 respectively. The GMB Extremes portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 10% companies based on their E Score and short on the 10% worst scored companies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*US_ext*$_{t+1}$	*France_ext*$_{t+1}$	*Canada_ext*$_{t+1}$	*Germany_ext*$_{t+1}$	*UK_ext*$_{t+1}$	*Japan_ext*$_{t+1}$	*Sweden_ext*$_{t+1}$
Ab_Temp	0.000309	-0.00118	-0.000573	-0.00414*	-0.00583***	-0.0000328	-0.00519**
	(0.388)	(-0.768)	(-0.359)	(-1.961)	(-3.790)	(-0.0232)	(-2.382)
Constant	-0.00754***	-0.00306	-0.0112**	-0.00286	-0.00163	-0.000704	-0.00472
	(-3.251)	(-0.662)	(-2.359)	(-0.436)	(-0.422)	(-0.228)	(-0.629)
Observations	84	84	84	84	84	84	84
Adjusted R-squared	-0.010	-0.005	-0.011	0.033	0.139	-0.012	0.053

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9.

This table presents results for the period that goes from 1st of January 2016 to 31st of December 2022 only for the European indices (FTSE 100, CAC 40, DAX 40, OMX 30).*CME*$_{t+1}$ represents the CME portfolios' returns in moment t+1. The CME portfolios are long-short equal-weighted portfolios, one for each index, long on stocks from companies operating in clean industries as defined by the IPCC and short on stocks from companies operating in highly polluting industries. *GMB_ext* and *GMB_3030* represent the GMB Extremes and the GMB 30-30 portfolios' returns respectively. The GMB Extremes portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 10% companies based on their E Score and short on the 10% worst scored companies. The GMB 30-30 portfolios are long-short portfolios, one for each index, which are long on the stocks from the top 30% companies based on their E Score and short on the 30% worst scored companies.

	(1)	(2)	(3)
VARIABLES	*CME*$_{t+1}$	*GMB_ext*$_{t+1}$	*GMB_3030*$_{t+1}$
Ab_Temp	0.00135**	-0.00387***	-0.00231***
	(2.546)	(-3.892)	(-4.001)
Constant	-0.00174	-0.00327	0.00104
	(-1.121)	(-1.122)	(0.615)
Observations	336	336	336
Adjusted R-squared	0.046	0.055	0.105

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4. GREEN vs BROWN

To better understand the results previously presented, I studied the CLEAN and the EMISSIONS portfolios and compared them to the GREEN and BROWN portfolios. I ran the following regressions:

$$CLEAN_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it},$$

$$EMISSIONS_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it},$$

$$GREEN\_10_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it},$$

$$BROWN\_10_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it},$$

$$GREEN\_30_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it},$$

$$BROWN\_30_{it+1} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t Month_t + \theta_i Ind_i + \epsilon_{it}$$

Where $CLEAN_{it+1}$ represents the returns of the CLEAN portfolio composed by the companies which do not operate in an high-emissions industry as defined by the IPCC from index/city *i* at moment *t+1* and $EMISSIONS_{it+1}$ represents the returns of the EMISSIONS portfolio composed by the companies which operate in an high-emissions industry as defined by the IPCC from index/city *i* at moment *t+1.* $GREEN\_10_{it+1}$ and $GREEN\_30_{it+1}$ are the returns of the GREEN portfolios composed of the 10% and 30% top E scorers in index/city *i* at moment *t+1*, $BROWN\_10_{it+1}$ and $BROWN\_30_{it} + 1$ are the returns of the BROWN portfolios composed of the 10% and 30% bottom E scorers. Ab_Temp_{it} is the abnormal temperature in degrees Fahrenheit in index/city *i* at moment *t+1.* Month and index fixed effects were included to control for any seasonality and regional effects.

Table 10 shows the summary statistics for the studied portfolios.

Table 10.

This table presents the summary statistics for the CLEAN and EMISSIONS portfolios and for the different GREEN and BROWN portfolios from 1st January 2016 to 31st of December 2022. $CLEAN_{t+1}$ represents the results of the CLEAN portfolios. The CLEAN portfolios are composed of those companies that do not operate in high-emissions industries as defined by the IPCC. $EMISSIONS_{t+1}$ represents the results of the EMISSIONS portfolios. The EMISSIONS portfolios includes those companies that operate in high-emissions industries as defined by the IPCC. The CLEAN and the EMISSIONS portfolios are the ones used in the CME long-short portfolios. *GREEN_10* and *BROWN_10* represent the GREEN and BROWN portfolios' returns of those portfolios composed by the 10% best and worst Environmental scorers of each index respectively. These were the portfolios used in the GMB Extremes long-short portfolios. *GREEN_30* and *BROWN_30* represent the GREEN and BROWN portfolios' returns of those portfolios composed by the 30% best and worst Environmental scorers of each index respectively. These were the portfolios used in the GMB 3030 long-short portfolios.

Variable	Obs	Average	SD
2016-2022			
$CLEAN_{t+1}$	588	0.009122	0.0496494
$EMISSIONS_{t+1}$	588	0.0093564	0.0564449
$GREEN\_10_{t+1}$	588	0.006565107	0.060737331
$BROWN\_10_{t+1}$	588	0.013113817	0.056628086
$GREEN\_30_{t+1}$	588	0.008086246	0.055561343
$BROWN\_30_{t+1}$	588	0.010159692	0.050070649

Previous research finds that temperature tends to be negatively correlated with stock returns. Floros (2008) uses a GARCH model to find negative relation between temperature and stock market returns in Austria, Belgium and France and Cao and Wei (2005) had previously found a negative relation between temperature and market returns across a wide a variety of stock markets worldwide.

With this test, my aim is to understand whether this still holds for my data set, as well as to get a better understanding on where are the results regarding the long-short portfolios coming from.

Table 11 shows the results for the first two regressions. It is noticeable that stock returns are negatively correlated to abnormal temperature and that that correlation is, as expected, more prominent in EMISSIONS portfolios. The difference between both coefficients is what drives the CME returns' positive relation with abnormal temperatures.

As hypothesized before, this could come from investors perceiving companies from non-clean industries' returns as more subjective on climate change.

Table 11.

This table presents results for the CLEAN and EMISSIONS portfolios for the period that goes from the 1st of January 2016 to 31st of December 2022. $CLEAN_{t+1}$ represents the results of the CLEAN portfolios. The CLEAN portfolios are composed of those companies that do not operate in high-emissions industries as defined by the IPCC. $EMISSIONS_{t+1}$ represents the results of the EMISSIONS portfolios. The EMISSIONS portfolios includes those companies that operate in high-emissions industries as defined by the IPCC. The CLEAN and the EMISSIONS portfolios are the ones used in the CME long-short portfolios.

	(1)	(2)
VARIABLES	*CLEANt+1*	*EMISSIONSt+1*
Ab_Temp	-0.00358***	-0.00430***
	(-5.000)	(-5.277)
Constant	0.0119***	0.0127***
	(5.877)	(5.504)
Observations	588	588
Adjusted R-squared	0.100	0.097

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12, again, shows negative correlations between temperature and the portfolios returns, which comes in line with findings by other researchers. We can see that the negative correlation between the GMB portfolios and abnormal temperatures comes from the fact that temperature has stronger impact on GREEN portfolios than in the BROWN ones. It is evident that coefficients are higher in models (1) and (3) than in (2) and (4). It is also noticeable that GREEN portfolios have a higher adjusted R-squared meaning that temperature better predicts those portfolios' returns.

Table 12.

This table presents results for the period from 1st January 2016 to 31st of December 2022. *GREEN_10* and *BROWN_10* represent the GREEN and BROWN portfolios' returns of those portfolios composed by the 10% best and worst Environmental scorers of each index respectively. These were the portfolios used in the GMB Extremes long-short portfolios. *GREEN_30* and *BROWN_30* represent the GREEN and BROWN portfolios' returns of those portfolios composed by the 30% best and worst Environmental scorers of each index respectively. These were the portfolios used in the GMB 30-30 long-short portfolios.

VARIABLES	(1) $GREEN\_10_{t+1}$	(2) $BROWN\_10_{t+1}$	(3) $GREEN\_30_{t+1}$	(4) $BROWN\_30_{t+1}$
Ab_Temp	-0.00474***	-0.00245***	-0.00442***	-0.00310***
	(-5.440)	(-2.917)	(-5.583)	(-4.244)
Constant	0.0102***	0.0150***	0.0115***	0.0125***
	(4.147)	(6.333)	(5.141)	(6.087)
Observations	588	588	588	588
Adjusted R-squared	0.107	0.049	0.122	0.079

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As expected, I also find a smaller difference between abnormal temperature's impact on GREEN_30's returns and its impact on BROWN_30's returns than between abnormal temperature's impact on GREEN_10's returns and BROWN_10's returns. I also find that abnormal temperature better explains returns from the more inclusive GREEN_30 and BROWN_30 portfolios.

It is clear that the results previously presented regarding the GMB portfolios are caused by the fact that abnormal temperature has more of a negative impact on the GREEN portfolios than on the BROWN portfolios.

On the next part of this paper, I will try to understand why these results oppose the intuition confirmed by the industries experiment.

4.5. Industries vs Environmental Score

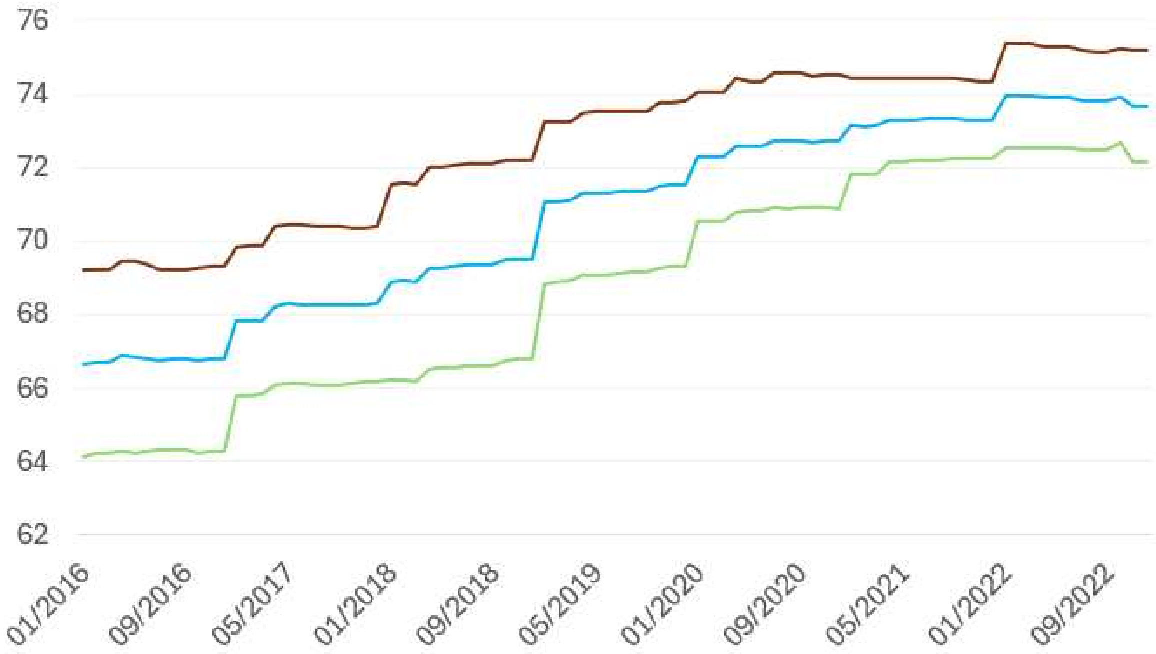
For this time period and this set of indices, the results are unequivocal: abnormally high local temperatures lead to lower returns for a portfolio which is long on stocks with high E Scores and short on stocks with low E Scores. But one should ask what would be the case if these E Scores were not the ones provided by LSEG but by Sustainalytics or by MSCI.

ESG scores and each of its pillar scores can vary quite a lot between raters as Berg, Koelbel and Rigobon (2022) demonstrate. According to them, in 2014, the Sustainalytics and the Refinitiv (currently LSEG) E Scores had a correlation of about 0.64 and the correlation observed between MSCI and Refinitiv E Scores was of only 0.23. This disparity raises concerns about the consistency and comparability of E Scores across different raters, potentially affecting investment strategies and outcomes.

Another pertinent question we should ask is what the relationship between E Scores and Industries is. Figure 1 shows that companies present in the EMISSIONS portfolios have on average a higher E Score than those present in the CLEAN portfolios.

Figure 1. Average E Scores

The green line represents the average E Score of the companies in the CLEAN portfolios, the brown line represents the average E Score of the companies in the EMISSION portfolios and the blue line is for all the stocks. Data presented goes from the 1st of January 2016 until the 31st of December 2022



LSEG Environmental Scores

To better understand this phenomenon, an in-depth research on the LSEG Environmental Scores was done. LSEG provides detailed documentation outlining the methodology used to assign these scores.

For the Environmental Score, 68 metrics are used, divided into 3 categories: Emissions, Resource Use and Innovation. The following table presents the descriptions of each category given by LSEG:

Resource Use	*Resource use category score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management*
Emissions	*Emission category score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes.*
Innovation	*Environmental innovations category score reflects a company's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.*

Source: LSEG Workspace

Interestingly, these definitions appear to favour companies with more room for improvement, as they measure a company's "capacity to reduce" or its "commitment" rather than absolute performance. Moreover, scores are industry-adjusted, meaning that a company's performance is benchmarked against its industry peers rather than all companies globally. At the same time, the score attributed to each category is based on an industry benchmark, meaning the best performers within an industry will have better scores even if they are not the best performers overall.

The CME results support the thesis that the companies in the EMISSIONS portfolios are more sensitive to climate change and climate risk than those on the CLEAN portfolios. At the same time, those portfolios are made from country indices, which means only the largest companies which are also those who receive the most scrutiny among all, are present.

Larger companies also have more meanings to allow themselves to try and innovate and reduce resource waste even if that implies losses in the short term.

It wouldn't be too far-fetched to assume that the EMISSIONS portfolios would be composed of companies that perform significantly better environmentally than their industry peers. This assumption being justified by the fact that those were the ones included in the indices studied. This would support the results found suggesting EMISSIONS portfolios are made of companies with higher Environmental Scores on average.

Concrete Examples

To better understand how different industries are scored I randomly picked a company belonging to the FTSE 100 EMISSIONS Portfolio and one belonging to the FTSE 100 CLEAN Portfolio. These were ANGLO AMERICAN PLC and EXPERIAN PLC.

Anglo American PLC operates in the mining industry. It is one of the world's largest mining companies, with a diverse portfolio of operations that include the extraction and processing of minerals such as Copper, Platinum, Nickel and Coal.

The mining industry has a significant environmental impact being related to acid drainage and heavy metal contamination. Being an energy intensive industry it is also responsible for a large of GHG emissions.

According to Reuters (2024), Chile's environmental regulator has filed four charges for noncompliance with environmental permits against Los Bronces copper mine which is explored by Anglo American. One of these charges was deemed very serious by the regulator and referred to the failure "on resolving acid drainage".

Experian PLC is the largest personal financial information provider. It operates mainly in the UK and the US focusing on credit reporting and having significant relevance in the personal credit market. The industry's environmental impact mainly revolves around the energy consumption from data centres.

Looking at 2022, Anglo American achieved an Environmental Score of 78 while Experian only got a 63. Several factors differentiate these two companies but also the way scores are attributed. On table 13 we can see how weights were attributed.

Table 13
LSEG 2022 Environmental Scores for Anglo American PLC and for Experian PLC. Environmental scores are built based on three categories: Resource Use, Emissions and Environmental Innovation. In the table, the corresponding weight on the overall E Score is shown for each category and for each company. The Resource Use category focus on the "company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management." The Emissions category "measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes" and the Environmental Innovation category score "reflects a company's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products."

	Anglo American PLC		**Experian PLC**	
	Weight	Score	Weight	Score
Resource Use	46.46%	93	38.3%	88
Emissions	44.19%	79	33.19%	87
Environmental Innovation	9.35%	0	28.51%	0
Total E Score	78		63	

Source: LSEG Workspace

In this case, both companies had a score of 0 in Environmental Innovation; this score is explained by the fact that none of the companies reported "on at least one product line or service that is designed to have positive effects on the environment, or which is environmentally labelled and marketed" nor, for the case of Experian, did the company "develop products or technologies for use in the clean, renewable energy".

On Emissions, Experian beat Anglo American as expected. Emissions, as stated before, is the category that "measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes". It is composed by several parameters, different for each of the two companies. Even though Experian presented a better result than Anglo American for this category, it was only by one point yet, when looking at the Emissions each company produced scaled by their revenue we find that Anglo American produced 121.023 tonnes of CO2 equivalent Scope 1 emissions per million euros of revenue while Experian produced only 0.089 tonnes per million euros of revenue (data for Scope 2 and 3 is similar). The fact that the difference between both companies Emissions scores is only of about 10% while Experian is more than a 1000 times more efficient regarding Scope 1 emissions than Anglo American shows how these scores are not really focused on CO2 Emissions but on other factors.

Regarding the Resource Use category, several different parameters are used: 15 for Experian and 17 for Anglo American. As an example, Experian takes a score of 0 on Policy Sustainable Packaging for not having "a policy to improve their sustainable packaging" while Anglo American is not scored on this matter. This once again shows how relatively poorly adjusted are these methodologies to the companies they aim to score as Experian is a “global data and technology company” being evaluated on packaging. On comparable parameters, Experian gets a score of 0 in Targets Water Efficiency and Targets Energy Efficiency for not reporting on any targets set on water or energy efficiency while Anglo American achieves scores of 90 and 94 respectively.

At last, a factor highly influencing these two companies environmental score is weighting. If we reduced Environmental Innovation’s weight to 0, and distributed its weight across the other two scores we would obtain Environmental scores of 86 for Anglo American and 88 for Experian, yet as Environmental Innovation is much more relevant for Experian’s scoring, this category in which both companies are scored with a 0, brings Experian’s Environmental score down to 68 while Anglo American holds at 78.

This example shows that scoring methodology is in some respects flawed, as evidenced by the fact that Experian, an online information services provider, is evaluated on its sustainable packaging efforts while Experian uses no packaging to provide its services. It also shows that methodologies, even in the Emissions category, are not only focused on absolute emissions or even carbon efficiency but also on the efforts made by the company and how it compares to its industry peers and that this, as hypothesized before, might favour companies from high-emission industries.

LSEG, with its Environmental Scores, clearly does not aim at evaluating the absolute environmental impact of a company but how it compares against its peers. There is also a clear focus on rewarding companies for their efforts on tackling climate change and reducing their environmental impact.

Results from this research may be counter intuitive yet they show investors might actually look at them suggesting alternative sustainable investing or hedging strategies could be taken using Environmental Scores.

While E Scores may not fit for a strategy which focuses on investing in the least polluting companies’ stocks, they may be useful when the objective is to keep invested on the “greenest” companies of each industry.

A high Environmental Score may also be a good indicator of the efforts put into the green transition and may help guiding investors.

5. Conclusions

This study finds that low-emission industries tend to be less sensitive to investors' opinion changes regarding global warming. In an opposite direction, I find that stocks with high LSEG E Scores perform worse than those with low E Scores when investors become more aware of climate change. These opposing results raise questions on the methodology and utility of LSEG E Scores and require further research.

While in my work I find that companies from low-emission industries tend to have significantly lower LSEG Environmental Scores, it could be the case that the relationship between industries and other raters' scores is not the same which could change the results found drastically. Therefore, future research could focus on using scores from different providers.

Another important remark to make is one regarding the geographical spread of this research. A more complete analysis could possibly include more Asian, European and American indices so stronger conclusions could be drawn. Why four indices, of the seven chosen, are responsible for all the significance was still left partially unanswered and would be better addressed with more indices to compare.

Even with these limitations, results are strong and point towards a clear direction: a hedge against high (low) abnormal temperatures would be possible by tilting towards (away from) local companies from non-polluting industries and away from (towards) local companies from polluting industries or by investing (divesting) in local companies with low E Scores and divesting (investing) in local companies with high E Scores.

Table 14.

I followed the methodology employed by others such as Choi et al. (2020) and Krey et al. (2014). Updates were done to ICB Subsector names as some have changed slightly.

ICB Subsector Name	IPCC Industry Name
Coal	Mining and Quarrying
Conventional Electricity	Power and Heat Generation
Exploration and Production	Flaring and fugitive emissions from oil and Natural Gas
Gas Distribution	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
Integrated Oil and Gas	Other Energy Industries
Oil Equipment and Services	Other Energy Industries
Airlines	Domestic air transport, International aviation
Marine Transportation	Inland shipping (fossil), International navigation
Railroads	Rail transport
Transport Services	Transport equipment, Road transport (includes evaporation)(fossil)
Trucking	Road transport (includes evaporation) (fossil)
Building Materials and Fixtures	Commercial and public services (fossil), Cement production
Building Materials: Other	Commercial and public services (fossil), Cement production
Heavy Construction	Construction
Home Construction	Residential (fossil)
Aluminum	Non-ferrous metals, Aluminum production (primary)
Automobiles	Transport Equipment
Commercial Vehicles and Parts	Transport Equipment
Commodity Chemicals	Chemicals
Electrical Equipment	Semiconductor Manufacture, Electrical Equipment Manufacture
Electronic Equipment	Semiconductor Manufacture, Electrical Equipment Manufacture
Food Products	Food and Tobacco
General Mining	Mining and Quarrying
Gold Mining	Mining and Quarrying
Machinery: Industrial	Machinery
Iron and Steel	Iron and Steel
Multi-Utilities	Power and Heat Generation, Other industries (stationary) (fossil)
Nonferrous Metals	Non-ferrous metals
Paper	Pulp and paper
Platinum and Precious Metals	Non-ferrous metals production
Semiconductors	Semiconductor Manufacture
Specialty Chemicals	Chemicals
Tobacco	Food and Tobacco
Waste and Disposal Services	Solid waste disposal on land
Farming, Fishing, Ranching and Plantations	Fishing (fossil) , Enteric Fermentation, Manure management, Rice cultivation, Agricultural soils (direct)
Offshore Drilling and Other Services	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
Oil Refining and Marketing	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas

Electronic Equipment: Gauges and Meters	Semiconductor Manufacture, Electrical Equipment Manufacture
Oil: Crude Producers	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
Electronic Equipment: Control and Filter	Semiconductor Manufacture, Electrical Equipment Manufacture
Electronic Equipment: Other	Semiconductor Manufacture, Electrical Equipment Manufacture
Electronic Equipment: Pollution Control	Semiconductor Manufacture, Electrical Equipment Manufacture

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