Chapter 4

Extreme climate events and financial values: empirical evidence from the stock market

4.1 Introduction

The literature has partitioned climate change risks in two categories. The first category has been labeled “climate risk" (Carney, 2015) and refers to the link between global warming and natural and human systems. Extreme climate phenomena like temperature extremes, high sea level extremes, and precipitation extremes (Intergovernmental Panel on Climate Change, 2014), are likely to seriously affect economic growth (Dell, Jones, & Olken, 2014; Pycroft, Abrell, & Ciscar, 2016), productivity (Graff Zivin & Neidell, 2014; Hallegatte, Fay, Bangalore, Kane, & Bonzanigo, 2015), and financial values.

The second category of climate change risks has been labeled “low-carbon transition risk" or “carbon risk". Low-carbon transition risk refers to the cost of the adjustment towards a low-carbon economy. Hence, it includes all drivers of risk linked to the decarbonisation of the economy: a) market-based instruments like a carbon tax or an emission allowance price; b) command and control induced technological shifts, e.g. stranded assets or assets that have suffered from unanticipated or premature write-downs, devaluations, or conversion to liabilities (Caldecott et al., 2016); and c) market risk, i.e. market demands for low carbon products (Zhou et al., 2016).

This paper brings upon the impact of extreme climate events upon financial values. Specifically, we are interested in the way changes in extreme climate phenomena (temperatures extremes, high sea levels extremes, and precipitation extremes) are related to changes in the value of stocks. This research question has, to the best of our knowledge, scarcely being addressed.

Literature on the relation between extreme climate events and stock returns is scarce. Anttila-Hughes (2016) finds that new record temperature announcements are associated with negative excess returns for energy firms while ice shelf collapses are associated with positive returns. Balvers, Du & Zhao (2016) find that a significant risk premium exists on a temperature tracking portfolio and its impact on the cost of equity capital has been increasing over time; furthermore, loadings at industry level on the tracking portfolio are generally negative. Bourdeau-Brien and Kryzanowski (2016) find that major natural disasters induce abnormal stock returns and return volatilities and volatility more than doubles following large natural hazards. Hong, Li and Xu (2017) investigate whether the prices of food stocks efficiently discount drought risk finding that high drought exposure is related to poor profit growth and poor stock returns for food companies.

We answer the research question of the impact of extreme climate events upon stock returns by means of a climatic extension of the Fama and French (2015) five-factor model for stocks. This is the first time a factor model is employed for assessing the implications of climate changes upon stock returns. The reasoning proceeds as follows: augmenting the Fama and French (2015) five-factor model with a sixth factor amounts to asserting that a systematic risk is missing from the framework. There is, at least, another common factor that affects stock returns: global warming. The climatic factor we put forward, LME (light minus extreme), responds to the need of capturing the risk factor in stock returns related to global warming which is associated with extreme climate phenomena like temperature extremes, high sea levels extremes, and precipitation extremes (Intergovernmental Panel on Climate Change, 2014). The climatic factor is built by building two portfolios: the extreme climatic impact (ECI) portfolio and the light climatic impact (LCI) portfolio. The procedure to form the two portfolios leverages an analysis of global extreme climate events in the 2008-2017 timeframe. Weekly value-weighted returns of the ECI portfolio are then subtracted from the weekly value-weighted returns of the LCI portfolio. The returns to be explained in our setting are value-weighted excess returns for six portfolios sorted on climate exposure and size (market capitalisation) taken from a sample of 227 firms belonging to the STOXX 1800 index for which data on geographical fixed asset location was available.

In the end, we find that the slopes on the newly proposed risk factor in stock returns gradually increase from the extreme climate impact portfolio to the light climate impact portfolio. Furthermore, these results are statistically highly significant. Overall, we find that there is a climate effect in average excess stock returns, which confirms our hypothesis that a systematic risk factor, global warming in this case, was missing from the classical framework. However, results show that the climate factor (LME), just like the value factor (HML) are absorbed by the remaining four factors in stock returns: $RM - R_F$ (market's excess return), SMB (small minus big, the size factor), RMW (robust minus weak, the profitability factor) and CMA (conservative minus aggressive, the investment factor). This is also observed after computing the GRS statistics, which show that adding LME and HML to the other four factors never improves the effectiveness of the model. The observation that HML becomes redundant in a five-factor model has already been made by Fama and French, and we can confirm it. Coherently with their analysis, we ultimately propose a six-factor model which leverages two orthogonal factors: LMEO (orthogonal LME) and HMLO (orthogonal HML).

The rest of the paper proceeds as follows: section two presents the climatic factor, section three exposes the model, section four puts forward the data, section five introduces the results, section six presents the climate stress test and section seven concludes.

4.2 The climatic factor

The climatic factor we put forward is meant to mimic the risk factor in returns related to global warming. First of all, the sample shall be representative of global stocks, which is why we used as a starting base the STOXX 1800 index. In order to construct the climatic factor, we first need to develop a method to classify a firm according to the degree of impact global warming has on its productive capacities. The method we propose leverages one fundamental evidence: extreme climate events such as temperature extremes, high sea levels extremes, and precipitation extremes impact physical assets. That is, firms' physical assets are damaged by exposure to extreme climate events and we need to establish a method to link such exposure with fixed assets losses. Therefore, the first information needed to construct the climatic factor (LME) is a detailed outline of the geographical allocation of firms' fixed assets. Starting from the 1800 firms of the STOXX 1800 index, and keeping as a rule that at least 80% of the firms' fixed assets should be associated with a geographical location, we identified 227 global stocks. These 227 global stocks became our sample.

The second step of the construction of the LME factor is identifying firms as extremely climate impacted or lightly climate impacted. This is done by leveraging a second fundamental information: country-level climate related GDP losses. We use the Global Climate Risk index developed by Germanwatch to gather data on the GDP losses of countries attributable to extreme climate phenomena such as tropical storms, winter storms, severe weather, hail, tornados, local storms (meteorological events); b) storm surges, river floods, flash floods, landslide mass movement (hydrological events); and c) freezing, wildfires, droughts (climatological events). GDP losses are collected from 2008 to 2017. The lower and upper bound is determined, once again, by the availability of data for countries in the Global Climate Risk index.

In the end, our sample includes 227 firms for which we have a picture of the geographical distribution of fixed assets and operating in countries for which we have climate-related GDP losses from 2008 to 2017. The next step involves creating a link between climate related GDP loss and climate related firm loss, intended as a loss of fixed assets. We do this by building on two assumptions. The first assumption states that the expected climate related fixed assets loss in a given country y_1 at time t can be treated as the expected climate related fixed assets loss of firms operating in country y_1. For example, if we make the hypothesis that in country y_1 only three firms (x_1, x_2, x_3) operate, then the mathematical form of the expression is:

$$E(Aloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \tag{4.1}$$

Firms (x_1, x_2, x_3) operating in country y_1 are exposed to the same climatic events that country y_1 is exposed to. The actual climate related fixed assets loss in a given country y_1 is the sum of the actual fixed assets losses of the individual firms that operate in that country. Also, the expected climate related fixed assets loss in a given country y_1 is the weighted average of the actual fixed assets losses of the individual firms that operate in country y_1. Unfortunately, actual climate related fixed assets losses at firm level are not known. Equation (1) amounts to say that the expected climate related fixed assets losses of the firms operating in country y_1 can be approximated by the expected climate related fixed assets losses of country y_1. Evidently, this holds for a high enough number of firms.

The second assumption states that the expected climate related GDP loss — $E(GDPloss_{y_1,t})$ — of country y_1 at time t is a proxy for the expected climate related fixed assets loss of country y_1 at time t. In other terms, $E(GDPloss_{y_1,t}) = E(Aloss_{y_1,t})$. This amounts to say that a loss of assets induces a GDP loss of the same magnitude. In other words, if we take an open economy, this is equal to affirm that a drop in the productive assets of country y_1 can be regarded as a drop in investments of country y_1 since investments are always expenditures on capital, i.e. assets. This drop of investments induces, *ceteris paribus*, a GDP drop of the same dimension. By substitution, it follows that:

$$E(GDPloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \tag{4.2}$$

Therefore, if a firm x_1 is active in a set of countries y with $y = 1, 2, ..., Y$ and the expected climate related GDP losses at time t in these countries are equal to $E(GDPloss_{y,t})$, then the total expected loss in terms of fixed assets for firm x_1 is given by:

$$E(Aloss_{x_1,t}) = \sum_{y=1}^{Y} E(GDPloss_{y,t}) Assets_{x_1,y,t} \tag{4.3}$$

with $Assets_{x_1,y,t}$ being the value of fixed assets of firm x_1 in country y at time t. We use equation (3) to calculate total expected climate related fixed assets losses for each of the 227 firms of our sample. In order to have comparable figures we calculate asset-weighted climate losses for each firm in year t by dividing the left-hand side and the right-hand side of equation (3) by the value of the firm's total assets, i.e. $\sum_{y=1}^{Y} Assets_{x_1,y,t}$. Once this is done, we take the 30^{th} and the 70^{th} percentile as breakpoints and construct three climate-impact portfolios: light climate impact, moderate climate impact and extreme climate impact. We also assign stocks to two size groups, small and big, using the market cap median as the breakpoint. Weekly value-weighted returns for the six (3x2) portfolios defined by the intersections of the groups are calculated. In the end, we obtain the LME (light minus extreme) factor, which proxies for the risk factor in stock returns related to extreme climate events with the following equation:

$$LME = (LS + LB)/2 - (ES + EB)/2 \tag{4.4}$$

In this equation, LS is the value-weighted return of the Light/Small portfolio, LB is the value-weighted return of the Light/Big portfolio, ES is the value-weighted return of the Extreme/Small portfolio and EB is the value-weighted return of the Extreme/Big portfolio.

4.3 The model

In order to estimate the impact of the extreme climate phenomena identified in section two upon stock returns, we expand the original Fama and French (2015) five factor model with the climatic factor LME. Fama and French's (2015) original five factor model is based on the following time-series regression:

$$\begin{aligned} R_{i,t} - R_{F,t} = &\alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t \\ &+ r_i RMW_t + c_i CMA_t + e_{i,t} \end{aligned} \tag{4.5}$$

In the equation, $R_{i,t}$ is the value-weighted return for security or portfolio i for period t; $R_{F,t}$ is the risk free rate; $R_{M,t}$ is the value-weighted return of the market portfolio; SMB_t is the size factor, i.e. the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks; HML_t is the value factor, i.e. the return on a diversified portfolio of high B/M stocks minus the return on a diversified portfolio of low B/M stocks; RMW_t is the profitability factor, i.e. the difference between the returns on diversified portfolios of stocks with robust and weak profitability; CMA_t is the investment factor, i.e. the difference between the returns on diversified portfolios of the stocks of low and high investment firms; and $e_{i,t}$ is a zero-mean residual. If the coefficients of the time-series regression — $\beta_i, s_i, h_i, r_i, c_i$— completely capture variation in expected returns, then the intercept, α_i, is indistinguishable from zero.

Equation (5) is augmented with the climate factor, LME, which is a systematic factor meant to mimic the risk factor in stock returns related to extreme climate events. The climatic extension (CE-FF) of the Fama and French (2015) model for stocks is, then, the following:

$$\begin{aligned} R_{i,t} - R_{F,t} =& \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t \\ & + r_i RMW_t + c_i CMA_t + l_i LME_t + e_{i,t} \end{aligned} \tag{4.6}$$

The sensitivity of stocks excess returns, $R_{i,t} - R_{F,t}$, to extreme climate events is represented by coefficient l_i. We find LME to be positive; this implies that we expect the l_i coefficient to be decreasing from light climate impacted (LCI) firms to extreme climate impacted (ECI) firms. We run equation (6) for six left-hand side portfolios formed from sorts on climate exposure and size (market capitalisation). Summary statistics for the left-hand side portfolios, the original Fama and French five factors, the LME factor, and correlations are shown in table 1.

In Table 1, all data on classical factors ($R_M - R_F$, SMB, HML, RMW, CMA) are from the Kenneth French database. The most striking information delivered by table 1 is the relative low magnitude of classical factors such as SMB and HML in the January 2008-December 2017 timespan in developed markets. While the statistics displayed make reference to weekly returns, we repeated the exercise with daily returns and the results are the same, if not worse. It seems that, in the developed markets, the only factors having an economic incidence on stock returns are $R_M - R_F$,

TABLE 4.1: Summary statistics for weekly dependent and explanatory percent returns; January 2008 to December 2017, 522 weeks.

Panel A: Explanatory returns						
Name	Mean	Std dev.	*t(mean)*	ACF(1)	ACF(2)	ACF(12)
LCI	0.22	3.14	1.60	-0.07	0.03	-0.08
ECI	0.12	3.03	0.89	-0.06	0.06	-0.06
$R_M - R_F$	0.09	2.56	0.84	-0.02	0.08	-0.08
SMB	0.01	0.77	0.39	-0.18	0.07	-0.09
HML	0.01	0.86	0.24	0.05	0.02	-0.04
RMW	0.07	0.56	3.01	0.03	0.02	-0.02
CMA	0.03	0.64	1.14	0.08	0.08	0.02
LME	0.08	2.09	0.91	-0.11	-0.01	-0.04
Panel B: Correlations between factors						
	$R_M - R_F$	SMB	HML	RMW	CMA	LME
$R_M - R_F$	1	-0.38	0.34	-0.38	-0.48	0.05
SMB	-0.38	1	-0.19	0.05	0.07	0.03
HML	0.34	-0.19	1	-0.58	0.23	-0.07
RMW	-0.38	0.05	-0.58	1	-0.03	0.09
CMA	-0.48	0.07	0.23	-0.03	1	-0.23
LME	0.05	0.03	-0.07	0.09	-0.23	1
Panel C: Dependent variables						
Name	Mean	Std dev.	*t(mean)*	ACF(1)	ACF(2)	ACF(12)
L/S	0.31	3.59	1.97	-0.11	0.03	-0.05
L/B	0.11	3.34	0.75	-0.03	-0.02	-0.07
M/S	0.24	3.81	1.43	-0.04	0.01	-0.11
M/B	0.13	4.16	0.73	-0.06	0.01	-0.03
E/S	0.20	3.09	1.48	-0.07	0.09	-0.08
E/B	0.02	3.40	0.11	-0.03	0.03	-0.03

In panel A, LCI is the value-weighted light climate impact portfolio weekly percent return. ECI is the value-weighted extreme climate impact portfolio weekly percent return. LME is LCI-ECI. $R_M - R_F$ is the value-weighted market portfolio weekly percent return, SMB is the size factor weekly percent return, HML is the value factor weekly percent return, RMW is the profitability factor weekly percent return, CMA is the investment factor weekly percent return. The six stock portfolios (panel C) used as dependent variables in the time-series regressions are formed from sorts of the 227 global stocks retained for the empirical exercise on climate exposure and size (market capitalisation). At the end of December of each year t, stocks are allocated to two size groups (Small and Big) using the sample market cap median as breakpoint. Stocks in each size group are then allocated independently to three climate impact groups (Light, Moderate and Extreme) by running equation (3) for each stock and using the 30^{th} and 70^{th} percentiles as breakpoints.

RMW, CMA and LME. Among factors, $R_M - R_F$ and LME have the strongest magnitude with average values of 0.09 and 0.08, respectively. Overall, Table 1 provides an argument to test an augmented version of the Fama and French (2015) five factor model: an expanded model which is able to capture the climate effect on excess stock returns.

4.4 The data

The climatic extension (Eq. 6) of the Fama and French (2015) model aims at capturing patterns in average returns related to size, value, profitability, investment and extreme climate events. The explanatory variables include the returns on a market portfolio of global stocks, $R_M - R_F$, and mimicking portfolios for the size, SMB, value, HML, profitability, RMW, investment, CMA, and climate impact, LME, factors in returns. The returns to be explained are the value-weighted returns for subsets of the portfolio of 227 global stocks which have been retained for the empirical exercise. Such subsets are formed by breaking up the 227 firms into 6 portfolios based on market capitalisation and climate exposure: the 6 stock portfolios are formed from annual (2008-2017) sorts of stocks into 2 size groups (median) and three climate exposure groups: light, moderate and extreme. The risk-free rate, RF, is the 1-week T-bill rate.

4.4.1 Explanatory returns

The five classical factors ($R_M - R_F$, SMB, HML, RMW, CMA) are taken directly from Kenneth French's database of factors for the developed markets. For a complete description of the construction of the factors we refer the reader to Fama and French (2015): here it suffices to mention that the five classical factors (2x3) are constructed using six value-weighted portfolios formed on size and book-to-market, six value-weighted portfolios formed on size and operating profitability, and six value-weighted portfolios formed on size and investment. All the portfolios are shuffled on a yearly basis. SMB (small minus big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios, HML (high minus low) is the average return on the two value portfolios minus the average return on the two growth portfolios, RMW (robust minus weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA (conservative minus aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, while $R_M - R_F$ is the return on the developed markets' value-weighted market portfolio.

The LME (light minus extreme) factor, which proxies for the risk factor in stock returns related to extreme climate events, is formed by means of a sample of 227 global stocks. These stocks have been selected starting from a bigger sample of firms, the constituents of the STOXX 1800 index, on the basis of available information on the geographical location of firms fixed assets. We use equation (3) to calculate total expected climate related fixed assets losses for each of the 227 firms of our sample. In order to have comparable figures we calculate asset-weighted climate losses for each firm in year t by dividing the left-hand side and the right-hand side of equation (3) by the value of the firm's total assets, i.e. $\sum_{y=1}^{Y} Assets_{x_1,y,t}$. Once this is done, we take the 30^{th} and the 70^{th} percentile as breakpoints and construct three climate-impact portfolios: light climate impact, moderate climate impact and extreme climate impact. We also assign stocks to two size groups, small and big, using the market cap median as the breakpoint. Weekly value weight returns for the six portfolios defined by the intersections of the groups are calculated. In the end, we obtain the LME (light minus extreme) factor, which proxies for the risk factor in stock returns related to extreme climate events by applying equation (4).

4.4.2 Explained returns

In the climatic extension of the Fama and French model (CE-FF, eq. 6), the returns to be explained, R_i, are the value-weighted returns for subsets (six portfolios) of the sample of 227 global stocks which have been selected from the STOXX 1800 index. Descriptive statistics for the sample of 227 firms are shown in Table 2. The procedure for the formation of the six portfolios is the same procedure followed to build the portfolios used in the construction of the LME factor. Once again, the selection of the 227 stocks is based on data availability on geographical location of firms' fixed-assets. Eq. (3) has been run for each of the 227 stocks; this operation permitted us to list the 227 firms from the least impacted to the most impacted. Then, we took the 30^{th} and the 70^{th} percentile of this list as breakpoints and constructed three climate-impact portfolios: light climate impact (LCI), moderate climate impact (MCI) and extreme climate impact (ECI). At the same time, using the market cap median, we split the 227 in two groups: small and big. The intersection of the groups produced six portfolios: light/small (L/S), light/big (L/B), moderate/small (M/S), moderate/big (M/B), extreme/small (E/S) and extreme/big (E/B). Weekly value-weighted returns have been calculated for each portfolio. Successively, the risk-free rate, the 1-week T-bill rate has been subtracted in order to have excess returns.

Average weekly percent value-weighted returns for the six portfolios are shown in Table 1. Here, the size effect clearly shows within each climate exposure group:

average return typically falls from small stocks to big stocks. At the same time there is also an evident climate effect. The three small cap portfolios show declining average returns from the L/S portfolio to the E/S portfolio. This holds true also in the case of big cap portfolios: average return falls from the L/B portfolio to the E/B portfolio.

TABLE 4.2: Descriptive statistics for the 227 Global stocks: Incorporation country and Industry (ICB) breakdown.

Incorporation Country		**ICB Industry**	
Country	Firms	Sector	Firms
Argentina	1	Basic materials	22
Australia	7	Consumer discretionary	30
Bermuda	1	Consumer staples	11
Canada	11	Energy	19
China	1	Financial	14
Denmark	2	Health care	20
Finland	3	Industrials	45
Germany	6	Real estate	9
Hong Kong	9	Technology	40
Ireland	4	Telecommunications	12
Israel	1	Utilities	5
Italy	2		
Japan	5		
The Netherlands	2		
Norway	4		
Singapore	6		
Sweden	7		
Switzerland	10		
Thailand	1		
United Kingdom	15		
United States	129		
Total	227	Total	227

4.5 Results

The climatic extension of the Fama and French five factor model (CE-FF) has been run for each of the six dependent variables: six portfolios sorted on climate exposure and size. The slopes and the R^2 values are direct evidence that $R_M - R_F$, SMB, HML, RMW, CMA and LME proxy for risk factors in stock returns.

4.5.1 Common variation in stock returns

The results of the six regressions carried out with the CE-FF model (Eq. 6) are displayed in Table 3. When used as explanatory variables in the time-series regressions, the factors capture common variation in stock returns. Extreme climate phenomena, at least in our setting, deteriorate physical assets proportionally to the degree of the

TABLE 4.3: Regressions for 6 value-weighted portfolios formed from sorts on climate exposure and size; January 2008 - December 2017, 522 weeks.

	Light	Mod.	Extr.	Light	Mod.	Extr.
		α			$t(\alpha)$	
Small	0.20	0.24	0.18	2.28	2.78	2.60
Big	0.05	0.12	0.06	0.72	1.12	0.90
		β			$t(\beta)$	
Small	0.90	1.07	0.98	18.26	21.85	25.72
Big	1.07	1.15	0.99	27.30	18.95	24.58
		s			$t(s)$	
Small	-0.35	-0.42	-0.14	-2.79	-3.43	-1.48
Big	-0.10	-0.50	-0.30	-1.02	-3.27	-2.94
		h			$t(h)$	
Small	0.34	0.21	-0.18	2.45	1.51	-1.72
Big	-0.63	0.31	-0.12	-5.82	1.81	-1.04
		r			$t(r)$	
Small	0.20	-0.15	-0.03	0.99	-0.77	-0.17
Big	-0.79	0.12	-0.57	-4.96	0.50	-3.48
		c			$t(c)$	
Small	-0.48	-0.92	-0.18	-2.71	-5.20	-1.33
Big	-0.07	-0.65	-0.37	-0.52	-2.99	-2.52
		l			$t(l)$	
Small	0.62	-0.18	-0.45	14.55	-4.37	-13.58
Big	0.38	-0.26	-0.54	11.31	-5.08	-15.70
		R^2			$s(e)$	
Small	0.70	0.74	0.76	1.97	1.95	1.52
Big	0.78	0.66	0.78	1.55	2.41	1.60

At the end of December of each year, stocks are allocated to three climate impact groups: light climate impact (LCI), moderate climate impact (MCI) and extreme climate impact (ECI). Stocks are then allocated to two size groups: Small (S) and Big (B). The intersection of the two sorts produce six Climate impact/Size portfolios. The dependent variables in the regressions are the weekly excess returns on the six Climate impact/Size portfolios. The independent variables in the regressions are the value-weighted market portfolio weekly percent return, $R_M - R_F$, the size factor weekly percent return, SMB, the value factor weekly percent return, HML, the profitability factor weekly percent return, RMW, the investment factor weekly percent return, CMA, and the climate impact factor weekly percent return, LME. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the six dependent variables on $R_M - R_F$, SMB, HML, RMW, CMA, and LME.

impact itself. A loss of assets negatively affects profits which in turn reduces expected stock prices and returns. However, dividend paying firms should be more affected than non-dividend paying firms since a loss of assets does not only reduce expected stock prices but also the dividends that the stock pays. As an example, one would expect that, within the extreme climate impact (4^{th} column of Table 3) category, the returns of the big cap portfolio should be more negatively affected than returns of the small cap portfolio. On the other hand, controlling for size, one would expect returns of the light climate impact portfolio to be higher than the returns of the extreme climate impact portfolio. Results obtained for the coefficients match our expectations.

Keeping in mind that all factors are positive (Table 1) and, therefore, a higher coefficient implies *ceteris paribus* a higher average return, slopes on SMB of small cap portfolios are higher than those of big cap portfolios. Also, SMB slopes of light climate impact (LCI) portfolios are bigger than those of extreme climate impact (ECI) portfolios. Results for SMB are consistent with our expectations: average returns typically fall from small stocks to big stocks, i.e. the size effect, with only one exception which is not statistically significant (L/B portfolio). Also, average returns fall from LCI portfolios to ECI portfolios, i.e. the climate effect, with also one not-statistically significant exception (L/B portfolio).

Small cap stocks have a high BE/ME ratio, while big cap stocks have a low BE/ME ratio. It follows that we can expect high HML slopes for small cap portfolios and low HML slopes for big cap portfolios. Indeed, this is what we obtain: coefficients on HML decline from small portfolios to big portfolios in the LCI column. Slopes in the MCI and ECI columns are close to each other but are not statistically significant. On the other hand, slopes on HML decline from the LCI portfolio to the ECI portfolio in the small cap row but do not in the big cap row. Overall, results for HML slopes lead us to suspect that, as Fama and French (2015) reported for US stocks, the average HML return is absorbed by other factors. We investigate this issue in the next section, but we can anticipate here that it is actually the case.

The interpretation of slopes on RMW and CMA are somehow less evident since the six left-hand side portfolios are built on sorts on size and climate exposure. Both RMW and CMA are related to firms fundamentals. Theoretically, firms which show a higher profit growth than peers are expected to have higher returns regardless of whether a dividend is actually paid. Small cap firms may not commonly offer dividends but reinvest profits to fund growth; conversely, big cap firms do more commonly offer dividends and these are expected to be larger when profits are more important. In both cases, high profit growth firms are expected to have higher returns both in the case of a dividend paying firm and a non-dividend paying firm. On the other hand, firms which invest aggressively are expected to pay less dividends today to fund tomorrow's growth: firms which invest today are expected to have lower returns (today) with respect to a firm that decides not to retain its profits, i.e. that distributes his profits to shareholders. In such a context, we would expect the small cap portfolios, which have higher profit growth, to display higher coefficients on RMW than big cap portfolios and we would expect small cap portfolios, which invest more today in order to finance their growth, to display lower coefficients on CMA than big cap portfolios. We find this to be the case for both slopes on RMW and slopes on CMA. Furthermore, from a climate impact perspective, the intuition that LCI portfolios should outperform ECI portfolios is confirmed where results are statistically significant: slopes on RMW and CMA decline from the LCI portfolio to the ECI portfolio.

Results obtained for the LME coefficient are surprising, both in terms of magnitude and in terms of statistical significance. The intuition that slopes on LME should decline from LCI portfolios to ECI portfolios is confirmed. This holds true for both small cap stocks and for big cap stocks. Also, within each climate impact category, coefficients decline from small cap stocks to big cap stocks, i.e. the size effect. All six coefficients are statistically highly significant. The economic and statistical importance of LME slopes are comparable to that of $R_M - R_F$ slopes: the six left-hand side stock portfolios produce slopes on the market factor, $R_M - R_F$, that are statistically highly significant: slopes are all at least 18 standard errors from zero (Light/S). Coherently with the literature, the slopes on the market factor are both the most economically significant and most statistically significant.

4.5.2 Model performance

As Fama and French (2015) suggest — based on Merton (1973) — the essential indicators of the effectiveness of an asset-pricing model are indistinguishable from zero intercepts: if the coefficients of the time-series regressions completely capture variation in expected returns, then the intercept, α_i, is indistinguishable from zero. The intercepts found (Table 3) with the CE-FF model are all almost indistinguishable from zero, the lowest being 0.05 and the highest being 0.24, which is of central importance for a well-specified asset pricing model. To test the zero intercept hypothesis for combinations of portfolios and factors, we compute the Gibbons, Ross, and Shanken (1989) GRS statistic. This operation permits us to assess how well the CE-FF model explains average excess stock returns and answers the question of the improvement provided by adding the LME factor to the five classical stock factors.

Table 4 displays the GRS statistics for the four factor model (2^{nd} column) which employs only $R_M - R_F$, SMB, RMW, CMA as explanatory variables, for the five

TABLE 4.4: GRS statistics for tests of the four, five and six factor model to explain weekly excess returns; January 2008 - December 2017, 522 weeks.

	$R_M - R_F$, SMB, RMW, CMA	$+HML$	$+HML+LME$
GRS	2.52	2.48	4.56
p-value	0.021	0.023	0.001

The tables tests the ability of the four factor model ($R_M - R_F$, SMB, RMW, CMA), the five factor model ($R_M - R_F$, SMB, RMW, CMA, HML) and the six factor model ($R_M - R_F$, SMB, RMW, CMA, HML, LME) to explain weekly excess returns on the six Climate impact/Size portfolios. The table shows the GRS statistic testing whether the expected values of all six intercept estimates are zero.

factor model (3^{rd} column), which adds the HML factor, and for the six factor model (CE-FF model, 4^{th} column), which adds both HML and LME. Overall, the GRS test rejects the hypothesis that the four, five and six factor models produce regression intercepts for the six stock portfolios that are all equal to zero. Fama and French (2015) suggest that adding HML to the set of explicatory factors worsens, or at best doesn't improve, the description of average returns. We confirm their finding: the GRS statistic is almost identical in the *passage* from a four factor to a five factor model. Furthermore, adding LME to the set of explanatory variables poses the same problem, with the GRS statistic going up to 4.56. The reason for this is the following: both HML and LME average returns are captured by the exposures of HML and LME to the remaining four factors.

TABLE 4.5: Regressions for each of the six factors on the remaining five factors; January 2008 - December 2017, 522 weeks.

	$R_M - R_F$	SMB	HML	RMW	CMA	LME
α	0.29	0.06	0.02	0.08	0.06	0.11
$t(\alpha)$	3.80	2.03	0.60	4.29	2.94	1.19

$R_M - R_F$ is the value-weighted return on the market portfolio minus the risk-free rate; SMB is the size factor; HML is the value factor, RMW is the profitability factor, CMA is the investment factor, LME is the climate impact factor. α is the intercept of the regression of each factor on the remaining five factors.

Table 5 displays regressions of each of the six factors on the other five. In the regressions to explain $R_M - R_F$, SMB, RMW, and CMA, the intercepts have all t-statistics that are at least 2 standard errors from zero. The only intercepts which are not statistically significant at the 0.05 level are those for HML and LME. Ultimately, evidence suggests that adding HML and LME does not improve the effectiveness of the four factor model.

4.5.3 Orthogonal version of the CE-FF

Even though HML and LME are redundant for describing average stock returns, it is of interest for financial practitioners to have insights into value and climate premiums. Therefore, we do not drop HML and LME from the model put forward but rather orthogonalise them. The orthogonal version of the CE-FF model produces slopes on the four non-redundant factors that are the same as in the four factor version of the model, i.e. a model that employs only as explanatory variables $R_M - R_F$, SMB, RMW, and CMA, while, at the same time, showing the exposures of the left-hand side portfolios to the value (HML) and the climate (LME) factor. The orthogonal version of the CE-FF model (OCE-FF model) is:

$$\begin{aligned} R_{i,t} - R_{F,t} = & \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HMLO_t \\ & + r_i RMW_t + c_i CMA_t + l_i LMEO_t + e_{i,t} \end{aligned} \tag{4.7}$$

In the equation, $HMLO$ (orthogonal HML) and $LMEO$ (orthogonal LME) are the sum of the intercept and residual from the regression of HML and LME on the remaining five factors.

Table 6 displays the results of the OCE-FF model. The economic and statistical significance of slopes on $LMEO$ is unchanged with respect to LME (Table 3), while slopes on $HMLO$ range now from -0.56 (L/B) to 0.46 (L/S). We still see declining coefficients from small portfolios to big portfolios in the LCI column while they are close to each other in the MCI column and the ECI column. Furthermore, $HMLO$ slopes decline from the LCI portfolio to the ECI portfolio in the small cap row but still do not in the big cap row. Overall, the statistical significance of slopes on $HMLO$ has increased with regards to the statistical significance of slopes on HML. Slopes on $HMLO$ are in between about one and five standard errors from zero with four slopes out of six which are more than two standard errors from zero. This was the case for only two slopes out of six when HML was used as explanatory variable.

Slopes on SMB, RMW and CMA confirm the results of Table 3 in terms of economic significance, while the biggest differences are statistical: the orthogonal version of the CE-FF model (Eq. 7) finds coefficients on SMB which are more than two

TABLE 4.6: Regressions for 6 value-weighted portfolios formed from sorts on climate exposure and size; January 2008 - December 2017, 522 weeks.

	Light	Mod.	Extr.	Light	Mod.	Extr.
		α			$t(\alpha)$	
Small	0.28	0.23	0.12	3.14	2.60	1.82
Big	0.08	0.09	0.01	1.16	0.91	0.02
		β			$t(\beta)$	
Small	0.92	1.10	0.97	19.62	23.45	26.67
Big	0.99	1.19	0.99	26.58	20.52	25.73
		s			$t(s)$	
Small	-0.31	-0.46	-0.17	-2.54	-3.75	-1.79
Big	-0.01	-0.55	-0.34	-0.06	-3.65	-3.40
		h			$t(h)$	
Small	0.46	0.17	-0.27	3.35	1.24	-2.56
Big	-0.56	0.25	-0.22	-5.14	1.51	-2.01
		r			$t(r)$	
Small	0.13	-0.34	-0.02	0.76	-1.97	-0.15
Big	-0.25	-0.16	-0.63	-1.79	-0.73	-4.42
		c			$t(c)$	
Small	-0.80	-0.67	0.07	-4.98	-4.23	0.60
Big	-0.69	-0.29	0.01	-5.40	-1.49	0.01
		l			$t(l)$	
Small	0.63	-0.18	-0.45	14.73	-4.29	-13.71
Big	0.37	-0.26	-0.55	10.97	-4.97	-15.79
		R^2			$s(e)$	
Small	0.70	0.74	0.76	1.97	1.95	1.52
Big	0.78	0.66	0.78	1.55	2.41	1.60

At the end of December of each year, stocks are allocated to three climate impact categories: light climate impact (LCI), moderate climate impact (MCI) and extreme climate impact (ECI). Stocks are then allocated to two size groups: Small (S) and Big (B). The intersection of the two sorts produce six Climate impact/Size portfolios. The dependent variables in the regressions are the weekly excess returns on the six Climate impact/Size portfolios. The independent variables in the regressions are the value-weighted market portfolio weekly percent excess return, $R_M - R_F$, the size factor weekly percent return, SMB, the orthogonal value factor weekly percent return, $HMLO$, the profitability factor weekly percent return, RMW, the investment factor weekly percent return, CMA, and the orthogonal climate impact factor weekly percent return, $LMEO$. $HMLO$ (orthogonal HML) and $LMEO$ (orthogonal LME) are the sum of the intercept and residual from the regression of HML and LME on the remaining five factors. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the six dependent variables on $R_M - R_F$, SMB, $HMLO$, RMW, CMA, and $LMEO$.

standard errors from zero in five cases out of six, rather than four cases out of six when equation (6) is run. Two slopes on RMW are more than two standard errors from zero (M/S and E/B) when the OCE-FF model is run, which marks no improvement with respect to the CE-FF model. Only three coefficients for CMA are more than two standard errors from zero with the OCE-FF model compared to four out of six when the CE-FF is employed.

Ultimately, the orthogonal version of the CE-FF model performs well. Unexplained average returns are close to zero and, individually, four intercepts out of six are not statistically significant (compared to three out of six when the CE-FF model is run). Intercepts which are not statistically different from zero show that the time-series regressions completely capture variation in expected returns.

4.6 The climate stress test

Stress-testing is a technique developed for testing the stability of an entity. In financial risk analysis, a stress test is characterised by four essential features (Borio, Drehmann, & Tsatsaronis, 2014): a set of risk exposures subjected to stress, a scenario that defines the exogenous shocks that stress the exposures, a model that maps the shocks onto an outcome and a measure of such an outcome. The financial stress test literature, following Koliai (2016), can be split in four main categories (table 7): general presentation of the instrument in the early 2000s, portfolio stress test development, systemic stress test emergence in the wake of the 2007-2009 crisis and diagnosis of the realised exercises.

TABLE 4.7: Categorisation of stress test literature (Koliai, 2016).

Topic	Selected authors
Conceptual aspects	Berkowitz (2000); Blaschke et al. (2001); Čihàk (2007)
Portfolio stress tests	Kupiec (1998); Breuer and Krenn (1999); Bee (2001);Kim and Finger (2001); Aragonés et al. (2001); Breuer et al. (2002); Alexander and Sheedy (2008); McNeil and Smith (2012); Breuer and Csiszàr (2013)
Systemic stress tests	Boss (2008); Alessandri et al. (2009); Aikman et al. (2009); van den End (2010, 2012); Engle et al. (2014); Acharya et al. (2014)
Diagnostics	Haldane (2009); Borio and Drehmann (2009); Hirtle et al. (2009); IMF (2012); Greenlaw et al. (2012); Borio et al. (2012)

The table shows the categorisation of the stress-test literature performed by Koliai (2016) into 4 topics: conceptual aspects, portfolio stress test, systemic stress test and diagnostics.

Stress-testing has been recently proposed by the literature (Bank of England Prudential Regulation Authority, 2015; Schoenmaker and van Tilburg, 2016; Zenghelis and Stern, 2016) as an evaluation framework for climate change risks. The World Bank (Fay et al., 2015) and some national legislations have also taken this direction. In France, for example, the recent law n° 2015-992 (article 173) relative to the energy transition for green growth, which has been promulgated just before the COP 21 in Paris, makes reference to climate change stress tests.

Stress-test scenarios have been subject to requirements by the Basel Committee on Banking Supervision (2009) which demands them to be plausible but severe: historical scenarios rely on a significant market event experienced in the past, whereas a hypothetical scenario is a significant market event that has not yet happened (Committee on the Global Financial System, 2005). The aim of the climate stress test is to show the impact of hypothetically plausible but more severe extreme climate phenomena on stock returns. The climate stress test put forward leverages the LME factor which proxies for the risk factor in stock returns related to extreme climate events. A worsening of adverse climate phenomena, which corresponds to a further deterioration of fixed assets in our framework, is related to the LME factor: higher temperatures, sea levels or heavier rainfalls lead to a larger LME factor since returns of firms which suffer extreme climate impacts are supposed to sink further. Holding all other variables of the orthogonal CE-FF model constant and focusing only on the relation between the left-hand side portfolios and the LME factor, the climate stress test is based on the following equation:

$$\Delta(R_{i,t} - R_{F,t}) = l_i \Delta LME_t \tag{4.8}$$

In this equation, $\Delta(R_{i,t} - R_{F,t})$ is the average hypothetical variation in excess stock returns, l_i is the sensitivity of portfolio or stock i to extreme climate events, and ΔLME_t is the average hypothetical climate variation proxied by the LME factor. In order to understand the impact of a plausible but more severe climate state on the stock returns under examination, the average LME factor is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock).

TABLE 4.8: Climate stress-test for six value-weighted portfolios formed from sorts on climate exposure and size; January 2008 - December 2017, 522 weeks.

	Low shock			*Medium shock*			*High shock*		
	Light	Mod.	Extr.	Light	Mod.	Extr.	Light	Mod.	Extr.
Small	0.06	-0.02	-0.04	0.08	-0.02	-0.06	0.10	-0.03	-0.07
Big	0.04	-0.03	-0.05	0.05	-0.03	-0.07	0.06	-0.04	-0.09

At the end of December of each year, stocks are allocated to three climate impact categories: light climate impact (LCI), moderate climate impact (MCI) and extreme climate impact (ECI). Stocks are then allocated to two size groups: Small (S) and Big (B). The intersection of the two sorts produce six Climate impact/Size portfolios. The table shows the average variation of weekly percent excess returns for the six Climate impact/Size stock portfolios. In each stress-test, the average LME factor is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock).

Table 8 shows the results of the climate stress test for each of the six value-weighted portfolios under the three shock scenarios: the third and fourth rows provide the average variation of weekly percent excess returns under the three climate impact scenarios. We quantify the impact of extreme climate phenomena at firm level by transposing country level climate related GDP losses into firms fixed assets losses by means of equation (3). A loss of fixed assets reduces the firms production capacities and thus the possibility to generate profits, which affects both dividends and expected returns. Consequently, controlling for climate impact, big cap firms experience lower returns than small cap firms and, controlling for size, LCI firms experience higher returns than MCI or ECI firms. The climate stress test exacerbates these empirical results by stressing climate impacts by 20% (low shock), 50% (medium shock), and 100% (high shock).

Weekly percent excess returns of the LCI portfolio tend to increase in presence of a climate shock. This is not the case for the MCI portfolio and the ECI portfolio. In other words, firms in the LCI portfolio manage to profit from a worsening of climate conditions. This is probably due to the fact that they manage to capture market shares from firms which are more severely damaged by a worsening of climate conditions. Statistical evidence leads us to assert that firms in the LCI portfolio are those responsible for driving the growth of about 74% in the STOXX 1800 index observed in between 2008 and 2017. On the other hand, MCI and ECI firms experience negative variations of weekly percent returns under the three climate shock scenarios with return losses which are proportional to the climate impact estimated. A worsening of extreme climate phenomena manages to exacerbate the underperformance of MCI and ECI firms with respect to LCI firms.

4.7 Conclusions

This paper answers the research question of the effect of extreme climate events upon stock returns. The question is answered by means of a model that permits the transposition of country level climate related GDP losses into firms fixed assets losses. Once we have run the model for each of the 227 stocks for which we have a geographical partition of fixed assets (out of the initial 1800 stocks, the initial sample being the STOXX 1800 index), we are able to sort firms into three portfolios: light climate impact (LCI), moderate climate impact (MCI), and extreme climate impact (ECI). Once this operation has been performed, the new factor LME (light minus extreme) has been created and introduced in the original Fama and French (2015) five-factor framework. The sensitivity of the left-hand portfolios to the LME factor is significant both in economic and statistical terms.

We have found that augmenting the original Fama and French (2015) five factor model with the LME factor (CE-FF model) does not improve the effectiveness of the model, measured by the GRS statistic. Furthermore, like the original authors, we have also found that augmenting a four-factor model, i.e. a model which employs only $R_M - R_F$, SMB, RMW, CMA as explanatory variables, with the value factor, HML, doesn't improve the effectiveness of the model. In the end, the best performing factor model for stocks, according to the GRS statistic, is a four-factor model. Nevertheless, it is of interest for financial practitioners to have insights into value and climate premiums. Therefore, we do not drop HML and LME from the model put forward but rather orthogonalize them. The orthogonal version of the CE-FF model produces slopes on the four non-redundant factors that are the same as in the four factor version of the model, i.e. a model that employs only as explanatory variables $R_M - R_F$, SMB, RMW, and CMA, while, at the same time, showing the exposures of the left-hand side portfolios to the value (HML) and the climate (LME) factor.

The last contribution of the paper is inspired by the recent climate change risk stress test trend. The literature has recently proposed stress testing, a technique developed for testing the stability of an entity, as an evaluation framework for climate change risks (Bank of England Prudential Regulation Authority, 2015; Fay et al., 2015; Schoenmaker and van Tilburg, 2016; Zenghelis and Stern, 2016). The climate stress test put forward, which leverages the LME factor, is able to show the impact of plausible but more severe extreme climate phenomena on stock returns.

A couple of policy implications can be deduced from these findings. Firstly, the quantification of the impact of extreme climate events upon stock returns, which to the best of our knowledge occurs for the first time in these terms, is an undoubted help to financial practitioners. An asset manager can use the methods presented in this paper to assess the impact of climate phenomena upon stocks and thus reconsidering his asset allocation and his future portfolio strategies. On the other hand, legislators can leverage the climate stress test to gain insights on the financial losses induced by a continuous global warming and calibrate a policy response, like carbon pricing for example, which is in line with the cost of non-action, i.e. the cost of not addressing global warming.