The impact of extreme climate phenomena on bond returns

Abstract

This paper answers the research question of the impact of extreme climate phenomena on bond returns. The question in answered by adding a climate factor, intended to proxy for the risk factor in bond returns related to extreme climate phenomena, to the classical bond market factors. The climate factor is constructed leveraging a novel methodology that permits the transposition of country-level climate related GDP losses into firm-level climate related fixed assets losses. I supplement the analysis with a climate stress test able to show the impact of plausible but more extreme climate phenomena on bond returns.

Keywords: Asset pricing model; climate premium; extreme climate phenomena; climate stress-test

1. Introduction

Time-value of money, risk-return trade-off, diversification are all key tenets of contemporary financial theory. Today, climate change has imposed itself as a supplementary source of risk.

The literature has partitioned climate change risks in two categories. The first category has been labeled "climate risk" (Carney, 2015) and makes reference to the link between global warming and natural and human systems. Extreme climate phenomena like temperature extremes, high sea levels 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 (Choi, Gao, & Jiang, 2020; Krueger, Sautner, & Starks, 2020).

The second category of climate change risks has been labeled "low-carbon transition risk" or "carbon risk". Low-carbon transition risk makes reference 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 article addresses the first category of risk (climate risk) and brings upon the impact of extreme climate phenomena upon bond returns. Particularly, I am 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 bonds. This research question has, to the best of my 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) have found 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 (2019) 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.

Literature on the interconnection between extreme climate phenomena and bond returns is even rarer. Huynh & Xia (2020) show that investors' demand for corporate bonds with high potential to hedge against climate change risk can have an impact on the cross section of corporate bond returns. Goldsmith-Pinkham, Gustafson, Lewis & Schwert (2019) examine how exposure to sea level rise risk is priced in the municipal bond market. Painter (2020) finds that counties more likely to be affected by climate change pay more in underwriting fees and initial yields to issue long-term municipal bonds compared to counties unlikely to be affected by climate change.

I answer the research question of the impact of extreme climate events upon bond returns by means of a climatic extension of the Fama and French two-factor model for bonds (1993). This is the first time a factor model is employed for assessing the implications of climate risk upon bond returns. The reasoning proceeds as follows: augmenting the Fama and French two-factor model (1993) with a climatic factor amounts to make the hypothesis that a systematic risk is missing from the framework. There is, at least, another common factor that affects bond returns: global warming. The climatic factor, LME (light minus extreme), responds to the need of capturing the risk factor in bond returns related to global warming which is represented here by extreme climate phenomena like temperature extremes, high sea levels extremes, and precipitation extremes (Intergovernmental Panel on Climate Change, 2014). The climatic factor is obtained by building two portfolios: the extreme climatic impact portfolio and the light climatic impact portfolio. The procedure to form the two portfolios leverages an analysis of global extreme climate events in the 2008-2017 timeframe. Weekly value weight returns of firms which are extremely impacted by climate change are then subtracted from the weekly value weight returns of firms lightly impacted by climate change. The returns to be explained in my setting are value-weighted excess returns for 27 bond portfolios sorted on rating and duration, rating and yield to maturity and duration and yield to maturity formed from a test sample of 329 bonds. Overall, I find that there is a climate effect in average excess bond returns, but I cannot confirm the hypothesis that a systematic risk factor, global warming in this case, was missing from the classical framework. In fact, classical factors like $TERM$, the factor that mimics unexpected changes in interest rates, and DEF, the factor that mimics changes in economic conditions that change the likelihood of default, absorb the climatic factor, LME. Nevertheless, even though LME is redundant for describing average bond returns (when used together with $TERM$ and DEF), there is a large global warming premium in average bond returns and such premium is of interest to financial practitioners and legislators. Therefore I do not drop LME but rather orthogonalize it: when I run the time-series regressions with $TERM$, DEF and the orthogonal global warming factor ($LMEO$), which has a near zero mean, I get slopes on $TERM$ and DEF that are the same as in a two-factor model that drops LME while producing the same estimate of the global warming tilt of the left-hand side (LHS) portfolios that would be obtained by regressing the same portfolios on $TERM$, DEF and LME.

Another methodological innovation of the article brings upon the development of a climate stress test designed to show the impact of plausible but more extreme climate phenomena upon financial values. 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. Recent literature has proposed stress testing as an evaluation framework for climate change risks: the Bank of England Prudential Regulation Authority (2015) suggests an integration of climate change risk factors in standard stress-testing techniques, Zenghelis and Stern (2016) encourage financial corporations and fossil fuel companies to undertake stress tests to evaluate their "future viability against different carbon prices and regulations" (p. 9), Schoenmaker and van Tilburg (2016) call for, as a next step, the developing of "carbon stress tests to get a better picture of the exposure of the financial sector" (p. 7), and the World Bank has also taken this direction (Fay et al., 2015). Besides these scientific endorsements, in France the recent law n° 2015-992 (article 173) relative to the energy transition for green growth, promulgated just before the COP 21 in Paris, makes reference to climate change stress tests.

The main contributions of the paper are the climate factor and the bonds climate stress test. If the slopes of the novel climate factor are found to be statistically significant, the financial sector (academics, financial practitioners) will have evidence of the impact of extreme climate events upon bond returns and will be able to quantify the financial implications of global warming. Additionally, the climate stress test takes these findings and puts them in a context of uncertainty regarding future pathways of global warming. These contributions carry policy implications for both legislators and financial practitioners. Legislators will have a tool (the climate stress test) that will permit them to assess the impact of a progressive global warming upon the value of investments whereas financial practitioners will have a tool (the climate factor) which will permit them to calibrate asset allocation more profitably in a time of climate change.

In a nutshell, the article explores the interconnections between climate change and bond values and contributes to the novel research field which has been named climate finance. The rest of the paper proceeds as follows: section two presents the climate factor, section three exposes the model, section four puts forward the data, section five introduces the results, section six presents the climate stress test, section seven provides a discussion of the findings and section eight concludes.

2. The climate factor

The climate factor (LME, Light minus Extreme) is intended to mimic the risk factor in bond returns related to global warming. The LME factor is built by means of two portfolios: the Light climate impact portfolio (LCI) and the Extreme climate impact portfolio (ECI). The LCI portfolio includes bonds issued by firms which are lightly impacted by global warming whereas the ECI portfolio includes bonds issued by firms which are more heavily impacted by global warming. The LCI portfolio and the ECI portfolio have exactly the same average characteristics besides one: exposure to extreme climate phenomena (global warming). Weekly value-weight returns are calculated for each portfolio and then the returns of the ECI portfolio are subtracted from the returns of the LCI portfolio. The LME factor is built by means of a training sample of 50 bonds which are not included in the test sample of 329 bonds.

Bonds in the training set are selected according to data availability on the geographical allocation of the issuing firms' fixed assets. These data are necessary in order to feed a novel model whose objective is to classify a firm according to the degree of impact global warming has on its productive capacities. The model proposed leverages a 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. The model put forward responds to the need to establish a way to link climate 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 the issuing firms' fixed assets. Starting from a full database of global bonds quoted between 2008 and 2017, and keeping as a rule that at least 80% of the issuing firms' fixed assets should be associated with a geographical location, we identified 50 global bonds. These 50 global bonds became the training sample.

The second step of the construction of the LME factor is identifying the 50 bond issuing firms as extremely climate impacted or lightly climate impacted. This is done by leveraging a second fundamental information: country-level climate related GDP losses. The Global Climate Risk index developed by Germanwatch is used 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, the training sample includes 50 bond issuing 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. I 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:

$$E(Aloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \tag{1}$$

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:

$$E(GDPloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \tag{2}$$

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:

$$E(Aloss_{x_1,t}) = \sum_{y=1}^{Y} E(GDPloss_{y,t})Assets_{x_1,y,t} \tag{3}$$

with $Assets_{x_1,y,t}$ being the value of fixed assets of firm x_1 in country y at time t. Equation (3) is used to calculate total expected climate related fixed assets losses for each of the 50 bond issuing firms of our sample. In order to have comparable figures I 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, I take the 50^{th} percentile as breakpoint and construct two climate-impact portfolios: light climate impact (LCI) and extreme climate impact (ECI). Weekly value-weighted returns for the two portfolios are calculated and the returns of the ECI portfolio are then subtracted from the returns of the LCI portfolio.

3. The model

I estimate the impact of extreme climate phenomena (temperature extremes, high sea levels extremes, and precipitation extremes) by expanding the Fama and French (1993) two-factor model with the climate factor, LME. Fama and French's (1993) original two-factor model is based on the following time-series regression:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + e_{i,t} \tag{4}$$

In equation (4), $R_{i,t}$ is the value-weighted return for bond or bond portfolio i for period t; $TERM_t$ is the maturity factor, i.e. the difference between the returns of a long-term government bond and the risk-free rate; DEF_t is the default factor, i.e. the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return; and $e_{i,t}$ is a zero-mean residual. If the coefficients of the time-series regression — m_i, d_i— completely capture variation in expected returns, then the intercept, α_i, is indistinguishable from zero.

Augmenting the Fama and French two-factor model (1993) with a climate factor amounts to assert that a systematic risk is missing from the framework. There is, at least, another common factor that affects bond returns: global warming. The climate factor, LME (light minus extreme), responds to the need of capturing the risk factor in bond returns related to global warming which is represented here by extreme climate phenomena like temperature extremes, high sea levels extremes, and precipitation extremes (Intergovernmental Panel on Climate Change, 2014). The climatic extension of the Fama and French (1993) model for bonds is, then, the following:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + l_i LME_t + e_{i,t} \tag{5}$$

The sensitivity of bonds excess returns, $R_{i,t} - R_{F,t}$, to extreme climate events is represented by coefficient l_i. I have run equation (5) for the test sample of 329 international bonds: 27 left-hand side portfolios formed from sorts on rating, duration and yield to maturity (YTM). Summary statistics for the left-hand side portfolios, the original Fama and French two factors, the LME factor, and correlations are shown in table 1.

Table 1: Summary statistics for weekly dependent and explanatory percent returns; January 2008 to December 2017, 522 weeks.[a]

Panel A: Explanatory returns

Name	Mean	Std.	*t(mean)*	ACF(1)	ACF(2)	ACF(12)
LCI	0.04	1.04	0.82	-0.12	0.11	0.05
ECI	0.03	1.14	0.62	-0.13	0.10	0.08
$TERM$	0.08	0.93	1.84	-0.09	0.08	0.04
DEF	0.01	0.98	0.14	-0.10	0.07	-0.05
LME	0.01	0.43	0.25	-0.13	0.03	0.01

Panel B: Correlations between factors

	$TERM$	DEF	LME
$TERM$	1	-0.37	-0.16
DEF	-0.37	1	0.24
LME	-0.16	0.24	1

Panel C: Dependent variables

Name	Mean	Std.	*t(mean)*	Name	Mean	Std.	*t(mean)*	Name	Mean	Std.	*t(mean)*
HG/HD	0.02	1.10	0.41	HG/HY	0.08	1.23	1.53	HY/HD	0.06	1.28	1.07
HG/MD	0.01	0.98	0.29	HG/MY	0.02	1.09	0.43	HY/MD	0.04	0.97	0.95
HG/LD	-0.01	0.84	-0.26	HG/LY	-0.01	0.87	-0.35	HY/LD	0.05	0.85	1.24
MG/HD	0.02	1.05	0.43	MG/HY	0.05	1.10	1.03	MY/HD	0.02	1.13	0.37
MG/MD	0.02	0.97	0.37	MG/MY	0.01	0.99	0.31	MY/MD	0.01	1.01	0.15
MG/LD	-0.01	0.83	-0.11	MG/LY	-0.02	0.82	-0.58	MY/LD	0.01	0.89	0.04
LG/HD	0.01	1.09	0.14	LG/HY	0.04	0.87	1.15	LY/HD	0.01	1.00	0.27
LG/MD	0.02	0.94	0.37	LG/MY	-0.02	0.95	-0.49	LY/MD	-0.01	0.89	-0.27
LG/LD	0.02	0.83	0.43	LG/LY	-0.14	1.65	-1.93	LY/LD	-0.03	0.81	-0.77

[a] 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. $TERM$ is the maturity factor weekly percent return, DEF is the default factor weekly percent return. The twenty-seven bond portfolios (panel C) used as dependent variables in the time-series regressions are formed from sorts of 329 global bonds retained for the empirical exercise on rating, duration and yield to maturity. At the end of December of each year t, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG), three duration groups (High duration, HD, Medium duration, MD and Low duration, LD), and three yield to maturity groups (High yield, HY, Medium yield, MY, and Low yield, LY) using the 30^{th} and 70^{th} percentiles as breakpoints.

Table 1 shows that the most prominent factor in terms of magnitude in the 2008-2017 timespan is $TERM$. The other classical factor, DEF, and LME have both a mean over the 2008-2017 timespan of 0.01. Overall, Table 1 provides an argument to test an augmented version of the Fama and French (1993) two-factor model: an expanded model which is able to capture the climate effect on excess bond returns.

4. The data

The test of equation (5) relies on two distinct set of data. The training set consists of 50 global bonds out of which 25 have been included in the light climate impact (LCI) portfolio and 25 have been included in the extreme climate impact (ECI) portfolio by means of equation (3). The 50 global bonds are used in the estimation of the LME factor. The two classical factors, $TERM$ and DEF have been estimated by means of two Exchange traded funds (ETF): one for long-term government bonds (IShares IEF fund) and one for long-term corporate bonds (IShares USIG fund). The test set consists of 329 global bonds (which do not include the bonds of the training set) quoted between 2008 and 2017 and for which ratings, duration and yield was available. The risk-free rate, RF, is the 1-week T-bill rate. All data are from Reuters.

4.1. Explanatory returns

The climatic extension (Eq. 5) of the Fama and French (1993) model aims at capturing patterns in average bond returns related to maturity, default and extreme climate events. The explanatory variables include the mimicking portfolios for the unexpected changes in interest rates, $TERM$, shifts in economic conditions that change the likelihood of default, DEF, and extreme climate events, LME, factors in returns.

As Fama and French (1993) pointed out and demonstrated, the variation of bond returns are due mainly to two factors. Shifts in interest rates affect both new bond emissions, by means of the coupon, and old emissions, by means of the inverse relationship between bond prices and interest rates. The factor that mimics this mechanism, $TERM$, is constructed by taking the difference between the weekly value-weight returns on a long-term government bond ETF (IShares IEF fund) and the one-week T-bill rate measured at the end of the previous week. In other words, $TERM$ tells us what is the premium for holding a bond that is affected by interest rate risk. The value-weight returns of the $TERM$ factor have been calculated for each week from January 2008 to December 2017.

The second main factor involved in the variation of bond returns is mimicked by DEF. Shifts in economic conditions can change the likelihood of default of a debt-issuing entity: measuring this phenomenon involves taking the difference between the returns of a value-weight long-term corporate bond ETF (IShares USIG fund) and the returns of a value-weight long-term government bond ETF (IShares IEF fund). In the end, DEF provides the premium for investing in a portfolio of long-term corporate bonds that is more likely to be affected by changes in economic conditions than a portfolio of long-term government bonds.

The LME (light minus extreme) factor, which proxies for the risk factor in bond returns related to extreme climate events, is formed by means of a sample of 50 global bonds, issued by 50 different firms. The training sample has been selected starting from a bigger sample of bonds, the complete list of fixed interest rate bonds with a quotation from January 2008 to December 2017 found on Reuters, on the basis of available information on the geographical location of the issuing firms' fixed assets. I use equation (3) to calculate total expected climate related fixed assets losses for each of the 50 issuing firms of the sample. In order to have comparable figures I 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, I take the median as breakpoint and construct two climate-impact portfolios: light climate impact (LCI) and extreme climate impact (ECI). Weekly value weight returns for the two portfolios are then calculated. In the end, the LME (light minus extreme) factor, which proxies for the risk factor in bond returns related to extreme climate events, is obtained by subtracting the weekly value-weight returns of the ECI portfolio from the weekly value-weight returns of the LCI portfolio.

4.2. Explained returns

In the augmented model (eq. 5), the bond returns to be explained, $R_{i,t} - R_{F,t}$, are the average excess returns of portfolios displayed in Panel C of table 1. The 27 portfolios are formed from sorts of 329 global long-term corporate bonds on rating (high rating, medium rating and low rating), duration (high duration, medium duration and low duration) and yield to maturity (high yield, medium yield and low yield).

The 329 global bonds, the test sample which does not include the 50 bonds used in the computation of the LME factor, have been selected by taking all bonds quoted in between January 2008 and December 2017 for which information on rating, duration and yield to maturity (YTM) was available. The bonds in the test sample, just like those in the training sample, are all fixed interest rate bonds. The three rating groups are formed by grouping S&P rating codes into three categories:

the high grade (HG) category includes S&P codes from AAA to A, the medium grade (MG) category includes S&P codes from A- to BBB+, while the low-grade (LG) category includes S&P codes from BBB to CCC+. The three duration groups (high duration, HD, medium duration, MD, low duration, LD) have been formed by taking the 30^{th} and the 70^{th} percentile of the list of bonds sorted out from highest duration to lowest duration. The three yield to maturity groups (high yield, HY, medium yield, MY, low yield, LY) have been formed by taking the 30^{th} and the 70^{th} percentile of the list of bonds sorted out by highest yield to maturity to lowest yield to maturity. The intersection of the 9 groups produced 27 portfolios (Table 1, panel C) which have been named after the initials of their group of origin. 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.

5. Results

The climatic extension of the Fama and French two-factor model for bonds (eq. 5) has been run for each of the 27 dependent variables. The slopes, the t-values, and the R^2 values are direct evidence that $TERM$, DEF and LME proxy for risk factors in bond returns and, when used as explanatory variables in the time-series regressions, capture common variation in bond returns.

Results obtained for the LME coefficients match the expectations: the slopes on LME are constantly negative for the 27 portfolios of the test sample besides in one case, the LG/LY portfolio, which is characterised by an extremely low excess average return (Table 1, Panel C) and is poorly diversified with only seven bonds per year on average in the portfolio.

The reasoning behind negative LME coefficients goes as follows: the LME factor is constructed by means of two portfolios — LCI (Light climatic impact) and ECI (Extreme climatic impact) — and each week the return of the ECI portfolio is subtracted from the return of the LCI portfolio. The LCI portfolio and the ECI portfolio have exactly the same average characteristics besides one: exposure to extreme climate phenomena (global warming).

Global warming induces a reduction of both the returns of the LCI portfolio and of the ECI portfolio but the returns of the ECI portfolio decrease more than the returns of the LCI portfolio.

This explains why the average value of the LME factor is positive over the 2008-2017 time period. LME (i.e. $LCI - ECI$) proxies for the risk factor in bond returns related to extreme climate phenomena and such phenomena deteriorate physical assets proportionally to the degree of the impact itself. A loss of assets negatively affects profits and ratings which in turn reduces bond prices. It is therefore normal that the LME factor lowers the returns of the left-hand side portfolios: given that the LME factor is positive — because the returns of the ECI portfolio decrease more than the returns of the LCI portfolio — its coefficients need to be negative.

5.1. 9 Rating/Duration Portfolios

The results of the nine regressions carried out with equation (5) on the nine Rating/Duration portfolios are displayed in Table 2. Intercepts of the nine portfolios confirm the effectiveness of the model with all slopes being close to zero and with four t-values out of nine above the 0.05 level. R^2 values are all in the 0.43 (LG/LD)-0.77 (HG/MD) range.

Table 2: Regressions for 9 value-weighted portfolios formed from sorts on rating and duration; January 2008 - December 2017, 522 weeks. [a]

	LG	MG	HG	LG	MG	HG
		α			$t(\alpha)$	
LD	-0.03	-0.06	-0.07	-1.18	-2.84	-3.86
MD	-0.04	-0.05	-0.06	-1.25	-2.27	-2.85
HD	-0.06	-0.05	-0.06	-1.81	-1.96	-2.21
		m			$t(m)$	
LD	0.62	0.75	0.81	19.54	30.21	37.90
MD	0.71	0.91	0.95	21.04	34.15	40.20
HD	0.89	0.96	1.03	23.73	31.21	34.75
		d			$t(d)$	
LD	0.24	0.11	0.12	7.98	4.56	5.71
MD	0.11	0.17	0.12	3.30	6.72	5.31
HD	0.17	0.16	0.19	4.76	5.51	6.46
		l			$t(l)$	
LD	-0.15	-0.03	-0.08	-2.23	-0.49	-1.78
MD	-0.30	-0.21	-0.19	-4.25	-3.87	-3.96
HD	-0.20	-0.13	-0.23	-2.57	-2.05	-3.69
		R^2			$s(e)$	
LD	0.43	0.65	0.75	0.62	0.49	0.42
MD	0.49	0.71	0.77	0.67	0.52	0.47
HD	0.54	0.67	0.71	0.74	0.60	0.58

[a] At the end of December of each year, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG) and to three duration groups (High duration, HD,Medium duration, MD and Low duration, LD) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Rating/Duration portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Rating/Duration portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent returns, the default factor DEF weekly percent return and the climatic factor LME weekly percent return. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and LME.

All factors are positive (Table 1) and, therefore, a higher coefficient implies *ceteris paribus* a higher bond average return. Slopes on $TERM$, the mimicking portfolio for the unexpected changes in interest rates all are positive and highly statistically significant. Controlling for duration, the slopes all fall from the HG group to the LG group. These results are consistent with the expectations: the higher the coupon rate, the lower the interest rate risk and the lower the premium for changes in interest rate levels. Coherently, slopes on $TERM$ of LG bonds are lower than slopes on $TERM$ of HG bonds. On the other hand, controlling for rating, slopes on $TERM$ fall from HD portfolios to LD portfolios since the higher the duration, the greater the interest rate risk and the premium for carrying such risk.

Slopes on DEF, the mimicking portfolio for shifts in economic conditions that change the likelihood of default, are all positive and highly statistically significant, even though not as high as those on $TERM$. Controlling for duration, slopes fall from the LG portfolio to the HG portfolio even though this decline is smoother in the HD row. This pattern is consistent with the fallen angel phenomenon which is exposed more clearly in the Rating/YTM sorts. Conversely, controlling for rating, HD bonds take longer to repay investors (higher maturity) and are therefore exposed more to the risk of shifts in economic conditions: HD bonds carry a greater risk premium. This is what is observed with slopes on DEF that tend to fall from the HD portfolio to the LD portfolio.

The climatic factor, LME, proxies for the risk factor in bond returns related to global warming. Extreme climate phenomena deteriorate physical assets lowering profits and ratings of issuing firms which affects negatively bond prices. Consequently, given the global dimension of climate change, all firms in the test sample are affected by climate risk and all slopes on LME are expected to be negative. This is in fact the case. Out of the nine slopes on LME seven are statistically significant at the 0.05 level. Controlling for duration, I would expect climate risk to be higher where issuing firms have weaker fundamentals (LG firms). Therefore, I would expect that the premium for global warming risk is higher for the LG portfolios than the HG portfolios: a low-graded firm (or a firm which issues low-graded bonds) is expected to experience harder times than a counterpart with solid fundamentals (and with a high rating). With the exclusion of the LD row, because two LME coefficients out of three are not statistically significant at the 0.05 level, confirming evidence (especially in the HD row) for this hypothesis is found. Controlling for rating, given that LD bonds have, *ceteris paribus*, a lower grade than HD bonds, I would expect the LD portfolio to carry the greater climate risk which implies a greater risk premium with respect to HD bonds. Once again, the hypothesis is confirmed: the risk premium is higher (closer to zero in this case) for the LD portfolio.

5.2. 9 Rating/YTM Portfolios

The results of the nine regressions carried out with equation (5) on the nine Rating/YTM portfolios are displayed in Table 3. Intercepts of the nine portfolios confirm the effectiveness of the model with all slopes being close to zero and with three t-values out of nine above the 0.05 level. R^2 values are all in the 0.15 (LG/LY)-0.80 (HG/LY) range.

Table 3: Regressions for 9 value-weighted portfolios formed from sorts on rating and yield to maturity; January 2008 - December 2017, 522 weeks. [a]

	LG	MG	HG	LG	MG	HG
		α			$t(\alpha)$	
LY	-0.16	-0.07	-0.07	-2.53	-3.92	-4.49
MY	-0.08	-0.05	-0.05	-2.98	-2.42	-2.24
HY	-0.01	-0.02	0.01	-0.25	-0.72	0.09
		m			$t(m)$	
LY	0.58	0.76	0.85	7.56	32.86	42.81
MY	0.81	0.93	1.03	26.04	34.40	36.01
HY	0.67	0.96	1.05	20.68	27.18	25.93
		d			$t(d)$	
LY	-0.23	0.09	0.07	-3.03	3.86	3.44
MY	0.12	0.16	0.17	3.99	6.01	6.20
HY	0.23	0.23	0.41	7.24	6.71	10.50
		l			$t(l)$	
LY	0.14	-0.06	-0.09	0.90	-1.35	-2.28
MY	-0.22	-0.16	-0.27	-3.38	-2.86	-4.65
HY	-0.21	-0.22	-0.33	-3.12	-3.04	-3.87
		R^2			$s(e)$	
LY	0.15	0.70	0.80	1.52	0.45	0.39
MY	0.59	0.71	0.73	0.61	0.53	0.56
HY	0.46	0.60	0.57	0.64	0.69	0.79

[a] At the end of December of each year, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG) and to three yield to maturity groups (High yield, HY,Medium yield, MY and Low yield, LY) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Rating/Yield to maturity portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Rating/Yield to maturity portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent returns, the default factor DEF weekly percent return and the climatic factor LME weekly percent return. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and LME.

The picture of Table 3 looks close to the one of Table 2. When bonds are sorted by rating and yield to maturity, slopes on $TERM$ are all positive and highly statistically significant. Controlling for yield to maturity, I would expect the premium for interest rate risk to fall from HG bonds to LG bonds since the higher the coupon, the lower the duration and the interest rate risk. This is exactly what I observe: the coefficient on $TERM$ falls from the HG bond portfolio to the LG bond portfolio for each YTM tranche. On the other hand, controlling for rating, interest rate risk decreases from the HY portfolio to the LY portfolio. This phenomenon is explained by the maturity of the portfolios under analysis: the HY portfolio has an higher maturity, and therefore a greater interest rate risk, of the LY portfolio.

Slopes on DEF in Table 3 are all positive and statistically significant besides one, the LY/LG portfolio, which is negative. I do not consider this portfolio to be representative, since it is by far the most poorly diversified with only seven bonds per year on average in the portfolio. Controlling for yield to maturity, the factor mimicking shifts in economic conditions that change the likelihood of default outputs declining coefficients from the HG portfolio to the LG portfolio. This picture is consistent with the fallen angel phenomenon: the period under analysis is characterised by an intensive downgrading and fallen angels, or a corporate bond that has initially an investment grade rating (HG) but is downgraded to high-yield, experience steeper price declines. These depreciations occur in many cases before the downgrading takes place. Conversely, controlling for rating, slopes on DEF decline from the HY portfolio to the LY portfolio, which is consistent with the fact that HY portfolios have longer maturities and are more affected by negative variations of the macroeconomic conditions.

Coefficients on LME are all negative as expected, besides in one case (the poorly diversified LY/LG portfolio). The slopes are all statistically significant in seven cases out of nine, with the two exceptions being the LY/LG and LY/MG portfolios. Controlling for yield to maturity, I expect, just like for the previous sort, that climate risk is higher where issuing firms have weaker fundamentals (LG firms). Coherently with this expectation, slopes on LME fall from the LG portfolio to the HG portfolio. On the other hand, controlling for rating, I would expect LY bonds to carry a greater climate change risk than HY bonds. This is because climate risk induces a depreciation of issued bonds: such depreciation is necessary in order to raise YTM to the level of bonds which discount climate risk, which is the case of more recent bonds given the progressive rising of climate change awareness throughout the years. In such a context, bonds with lower YTM depreciate more and, therefore, carry a greater risk premium.

5.3. 9 YTM/Duration Portfolios

When the test sample is sorted by yield to maturity and duration (Table 4), the three factor model for bonds obtains intercepts which are close to zero, especially for HY portfolios, with three t-values above the 0.05 level (LD/HY, MD/HY, HD/HY). R^2 values are all in the 0.40 (LD/HY) - 0.77 (MD/LY) range.

Table 4: Regressions for 9 value-weighted portfolios formed from sorts on yield to maturity and duration; January 2008 - December 2017, 522 weeks. [a]

	LY	MY	HY	LY	MY	HY
		α			$t(\alpha)$	
LD	-0.08	-0.06	-0.01	-4.97	-2.62	-0.03
MD	-0.07	-0.06	-0.02	-3.97	-2.64	-0.71
HD	-0.05	-0.06	-0.01	-2.23	-2.16	-0.42
		m			$t(m)$	
LD	0.78	0.82	0.61	38.87	30.60	18.37
MD	0.86	0.93	0.81	39.30	34.44	25.02
HD	0.90	1.05	1.02	31.40	32.96	22.40
		d			$t(d)$	
LD	0.06	0.17	0.26	3.20	6.78	8.15
MD	0.07	0.11	0.21	3.40	4.36	6.79
HD	0.08	0.19	0.41	2.85	6.06	9.27
		l			$t(l)$	
LD	-0.05	-0.10	-0.16	-1.17	-1.80	-2.27
MD	-0.07	-0.27	-0.30	-1.55	-4.82	-4.56
HD	-0.07	-0.23	-0.26	-1.21	-3.56	-2.75
		R^2			$s(e)$	
LD	0.76	0.65	0.40	0.39	0.52	0.65
MD	0.77	0.72	0.56	0.43	0.53	0.63
HD	0.68	0.70	0.50	0.56	0.62	0.90

[a] At the end of December of each year, bonds are allocated to three yield to maturity groups (High yield, HY, Medium yield, MY, and Low yield, LY) and to three duration groups (High duration, HD, Medium duration, MD and Low duration, LD) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Yield to maturity/duration portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Yield to maturity/Duration portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent returns, the default factor DEF weekly percent return and the climatic factor LME weekly percent return. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and LME.

When I look at the effect of interest rate risk on the sorts of Table 4, I notice that, controlling for duration, slopes on $TERM$ fall from the HY portfolio to the LY portfolio: the bonds that carry the more interest rate risk and therefore pay the highest premium are the ones with the highest maturity and the lowest grade. On the other hand, controlling for yield to maturity, interest rate risk falls from the HD portfolio to the LD portfolio. All nine slopes are highly statistically significant with the lowest t-value being 18.37 (LD/HY).

All nine slopes on DEF are positive and statistically significant at the 0.05 level. Controlling for duration, slopes on DEF decline from the HY portfolio to the LY portfolio, which is consistent with the fact that low-grade bonds (HY bonds) carry a greater default risk premium. Conversely, controlling for YTM, slopes on DEF fall from the HD portfolio to the LD portfolio. HD bonds take longer to repay investors (higher maturity) and are therefore exposed more to the risk of shifts in economic conditions: HD bonds carry a greater risk premium.

The slopes on LME are consistent with what has been previously found with different sorts of the test sample. The slopes are all negative and five out of nine are statistically significant at the 0.05 level. Controlling for duration, following the line of reasoning exposed above for sorts on yield to maturity and rating (table 3), I expect LY bonds to carry a greater climate risk than HY bonds: bonds with lower YTM depreciate more and, therefore, carry a greater risk premium. Indeed, this is what is observed, with coefficients falling from the LY portfolio to the HY portfolio. Controlling for YTM, slopes fall from the LD portfolio to the HD portfolio. The reason for this is that LD bonds have, *ceteris paribus*, a lower rating than HD bonds and, once again, bonds issued by firms with weaker fundamentals carry a greater climate risk.

5.4. Model performance

In this section I investigate whether the newly proposed three-factor model for bonds performs better than the classical two-factor model for bonds (1993). To accomplish this objective I leverage on what Fama and French (2015), based on Merton (1973), suggest to be the essential indicators of the effectiveness of a well specified asset-pricing model: 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 for different sorts of the test sample with the three factor model for bonds are all almost indistinguishable from zero, which is of central importance for a well-specified asset pricing model. In the sorts of the test sample on rating and duration, intercepts range from -0.07

Table 5: GRS statistics for tests of the two and three factor model to explain weekly excess bond returns; January 2008 - December 2017, 522 weeks. [a]

	Rating/Duration		*Rating/YTM*		*Duration/YTM*	
	$TERM,\ DEF$	$+LME$	$TERM,\ DEF$	$+LME$	$TERM,\ DEF$	$+LME$
GRS	2.43	2.43	5.69	5.72	5.66	5.71
p-value	0.010	0.010	0.001	0.001	0.001	0.001

[a] The tables tests the ability of the two factor model ($TERM$, DEF), and the three factor model ($TERM$, DEF, LME) to explain weekly excess bond returns on the nine rating Rating/Duration portfolios, the nine Rating/Yield to maturity portfolios and the nine Duration/Yield to maturity portfolio. The table shows the GRS statistic testing whether the expected values of all nine intercept estimates for each sort are zero.

and -0.03, with four out of nine intercepts found to be statistically equal to zero. In the sorts on rating and yield to maturity, intercepts range from -0.16 and 0.01, with three intercepts out of nine statistically equal to zero. Lastly, in the sorts on duration and yield to maturity, the lowest intercept found has been -0.08 and the highest -0.01. In this case, three intercepts out of nine have been found to be statistically equal to zero.

Table 6: Regressions for 9 value-weighted portfolios formed from sorts on rating and duration; January 2008 - December 2017, 522 weeks. [a]

	LG	MG	HG	LG	MG	HG
		α			$t(\alpha)$	
LD	-0.03	-0.06	-0.07	-1.18	-2.84	-3.86
MD	-0.04	-0.05	-0.06	-1.25	-2.27	-2.85
HD	-0.06	-0.05	-0.06	-1.81	-1.96	-2.21
		m			$t(m)$	
LD	0.62	0.75	0.82	19.75	30.33	38.13
MD	0.72	0.91	0.96	21.41	34.52	40.59
HD	0.90	0.96	1.04	23.98	31.44	35.11
		d			$t(d)$	
LD	0.23	0.11	0.11	7.69	4.56	5.46
MD	0.08	0.15	0.10	2.49	6.06	4.60
HD	0.15	0.15	0.16	4.33	5.20	5.83
		l			$t(l)$	
LD	-0.15	-0.03	-0.08	-2.23	-0.49	-1.78
MD	-0.30	-0.21	-0.19	-4.25	-3.87	-3.96
HD	-0.20	-0.13	-0.23	-2.57	-2.05	-3.69
		R^2			$s(e)$	
LD	0.43	0.65	0.75	0.62	0.49	0.42
MD	0.49	0.71	0.77	0.67	0.52	0.47
HD	0.54	0.67	0.71	0.74	0.60	0.58

[a] At the end of December of each year, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG) and to three duration groups (High duration, HD,Medium duration, MD and Low duration, LD) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Rating/Duration portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Rating/Duration portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent return, the default factor DEF weekly percent return and the orthogonal climatic factor $LMEO$ weekly percent return. $LMEO$ is the sum of the intercept and residual from the regression of LME on $TERM$ and DEF. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and $LMEO$.

To test the zero intercept hypothesis for combinations of portfolios and factors, the Gibbons, Ross, and Shanken (1989) GRS statistic is computed. This operation permits us to assess how well the three factor model for bonds explains average excess bond returns and answers the question of the improvement provided by adding the LME factor to the two classical bond factors.

Table 5 displays the GRS statistics for the two factor model for bonds, i.e. a model employing only $TERM$ and DEF as explanatory factors, and the three factor model for bonds, i.e. a model employing $TERM$, DEF and LME as explanatory factors. Overall, the GRS test rejects the hypothesis that the two and the three factor models produce regression intercepts for the 27 bond portfolios (9 portfolios sorted on Rating and Duration, 9 portfolios sorted on Rating and YTM and 9 portfolios sorted on Duration and YTM) that are all equal to zero. I find that adding the LME factor never improves the description of average bond returns. However, adding the LME factor to the regression also never worsens the description of average bond returns.

Table 7: Regressions for 9 value-weighted portfolios formed from sorts on rating and yield to maturity; January 2008 - December 2017, 522 weeks. [a]

	LG	MG	HG	LG	MG	HG
		α			$t(\alpha)$	
LY	-0.16	-0.07	-0.07	-2.53	-3.92	-4.49
MY	-0.08	-0.05	-0.05	-2.98	-2.42	-2.24
HY	-0.01	-0.02	0.01	-0.25	-0.72	0.09
		m			$t(m)$	
LY	0.58	0.76	0.85	7.51	33.05	43.09
MY	0.81	0.94	1.04	26.35	34.70	36.44
HY	0.68	0.97	1.06	20.96	27.47	26.28
		d			$t(d)$	
LY	-0.21	0.08	0.06	-2.90	3.66	3.04
MY	0.10	0.14	0.15	3.37	5.55	5.37
HY	0.21	0.21	0.38	6.75	6.22	9.92
		l			$t(l)$	
LY	0.14	-0.06	-0.09	0.90	-1.35	-2.28
MY	-0.22	-0.16	-0.27	-3.38	-2.86	-4.65
HY	-0.21	-0.22	-0.33	-3.12	-3.04	-3.87
		R^2			$s(e)$	
LY	0.15	0.70	0.80	1.52	0.45	0.39
MY	0.59	0.71	0.73	0.61	0.53	0.56
HY	0.46	0.60	0.57	0.64	0.69	0.79

[a] At the end of December of each year, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG) and to three yield to maturity groups (High yield, HY,Medium yield, MY and Low yield, LY) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Rating/Yield to maturity portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Rating/Yield to maturity portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent returns, the default factor DEF weekly percent return and the orthogonal climatic factor $LMEO$ weekly percent return. $LMEO$ is the sum of the intercept and residual from the regression of LME on $TERM$ and DEF. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and $LMEO$.

In the end, I find that there is a climate effect in average excess bond returns, but I cannot confirm the initial hypothesis that a systematic risk factor, global warming in this case, was missing from the classical framework. In fact, classical factors like $TERM$ and DEF absorb the climatic factor, LME. Nevertheless, even though LME is redundant for describing average bond returns, there is a large global warming premium in average bond returns and such premium is of interest to financial practitioners and legislators. Therefore I do not drop LME but rather orthogonalize it: when I run the time-series regressions with $TERM$, DEF and the orthogonal global warming factor, $LMEO$, which has a near zero mean, I get slopes on $TERM$ and DEF that are the same as in a two-factor model that drops LME while producing the same estimate of the global warming tilt of the left-hand side (LHS) portfolios that would be obtained by regressing the same portfolios on $TERM$, DEF and LME (Table 7, Table 8, Table 9).

Table 8: Regressions for 9 value-weighted portfolios formed from sorts on yield to maturity and duration; January 2008 - December 2017, 522 weeks. [a]

	LY	MY	HY	LY	MY	HY
		α			$t(\alpha)$	
LD	-0.08	-0.06	-0.01	-4.97	-2.62	-0.03
MD	-0.07	-0.06	-0.02	-3.97	-2.64	-0.71
HD	-0.05	-0.06	-0.01	-2.23	-2.16	-0.42
		m			$t(m)$	
LD	0.78	0.82	0.62	39.06	30.80	18.58
MD	0.86	0.94	0.82	39.52	34.88	25.42
HD	0.91	1.06	1.03	31.58	33.30	22.66
		d			$t(d)$	
LD	0.06	0.17	0.25	3.03	6.55	7.85
MD	0.06	0.09	0.18	3.14	3.45	5.98
HD	0.07	0.16	0.39	2.66	5.45	8.89
		l			$t(l)$	
LD	-0.05	-0.10	-0.16	-1.17	-1.80	-2.27
MD	-0.07	-0.27	-0.30	-1.55	-4.82	-4.56
HD	-0.07	-0.23	-0.26	-1.21	-3.56	-2.75
		R^2			$s(e)$	
LD	0.76	0.65	0.40	0.39	0.52	0.65
MD	0.77	0.72	0.56	0.43	0.53	0.63
HD	0.68	0.70	0.50	0.56	0.62	0.90

[a] At the end of December of each year, bonds are allocated to three yield to maturity groups (High yield, HY, Medium yield, MY, and Low yield, LY) and to three duration groups (High duration, HD, Medium duration, MD and Low duration, LD) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the two sorts produce nine Yield to maturity/duration portfolios. The dependent variables in the regressions are the weekly excess returns on the nine Yield to maturity/Duration portfolios portfolios. The independent variables in the regressions are the maturity factor $TERM$ weekly percent returns, the default factor DEF weekly percent return and the orthogonal climatic factor $LMEO$ weekly percent return. $LMEO$ is the sum of the intercept and residual from the regression of LME on $TERM$ and DEF. The table shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the nine dependent variables on $TERM$, DEF and $LMEO$.

6. A climate stress test for bonds

Stress-testing is a technique originated in engineering whose purpose is to test the stability of an entity. Such technique was later absorbed by financial risk analysis. From an historical perspective, following Koliai (2016), literature on financial stress testing can be split in four main categories: 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 9: Categorisation of stress test literature (Koliai, 2016). [a]

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)

[a] 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.

Today, stress-testing is 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. Additionally, 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.

Accoring to Borio, Drehmann, & Tsatsaronis, (2014), when applied to financial risk analysis a stress test has four main features: 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 crucial component of a financial stress test is the scenario which is why stress-test scenarios have been subject to requirements by the Basel Committee on Banking Supervision (2009) which demands them to be plausible but severe. In the framework proposed here, scenarios are constructed by leveraging on the climate factor. The LME factor proxies for the risk factor in bond returns related to extreme climate events. A worsening of adverse climate phenomena, which corresponds to a further deterioration of fixed assets, 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.

The ultimate aim of a climate stress test is to show the impact of hypothetically plausible but more extreme climate phenomena on bond returns. Holding all other variables of the three factor model for bonds 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:

$$\Delta(R_{i,t} - R_{F,t}) = l_i \Delta LME_t \tag{6}$$

In equation (6), $\Delta(R_{i,t} - R_{F,t})$ is the average hypothetical variation in excess bond 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 bond returns under examination, I put forward three alternative scenarios in which the average LME factor is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock).

Table 10: Climate stress-test for twenty-seven value-weighted portfolios formed from sorts on rating and duration, rating and YTM and duration and YTM; January 2008 - December 2017, 522 weeks.[a]

Panel A: Portfolios formed on Rating and Duration									
	Low shock			*Medium shock*			*High shock*		
	LG	MG	HG	LG	MG	HG	LG	MG	HG
LD	-0.009	-0.002	-0.005	-0.011	-0.002	-0.006	-0.014	-0.003	-0.008
MD	-0.017	-0.012	-0.011	-0.021	-0.015	-0.014	-0.028	-0.020	-0.018
HD	-0.011	-0.007	-0.013	-0.014	-0.009	-0.016	-0.019	-0.012	-0.022
Panel B: Portfolios formed on Rating and YTM									
	Low shock			*Medium shock*			*High shock*		
	LG	MG	HG	LG	MG	HG	LG	MG	HG
LY	0.008	-0.003	-0.005	0.010	-0.004	-0.006	0.013	-0.006	-0.009
MY	-0.013	-0.009	-0.015	-0.016	-0.011	-0.019	-0.021	-0.015	-0.026
HY	-0.012	-0.013	-0.019	-0.015	-0.016	-0.023	-0.020	-0.021	-0.031
Panel C: Portfolios formed on YTM and Duration									
	Low shock			*Medium shock*			*High shock*		
	LY	MY	HY	LY	MY	HY	LY	MY	HY
LD	-0.003	-0.006	-0.009	-0.004	-0.007	-0.011	-0.005	-0.009	-0.015
MD	-0.004	-0.015	-0.017	-0.005	-0.019	-0.021	-0.007	-0.026	-0.028
HD	-0.004	-0.013	-0.015	-0.005	-0.016	-0.018	-0.007	-0.022	-0.025

[a] At the end of December of each year, bonds are allocated to three rating groups (High grade, HG, Medium grade, MG, and Low grade, LG), three yield to maturity groups (High yield, HY, Medium yield, MY, and Low yield, LY) and to three duration groups (High duration, HD, Medium duration, MD and Low duration, LD) using the 30^{th} and 70^{th} percentiles as breakpoints. The intersection of the three sorts produce nine Rating/Duration portfolios, nine Rating/YTM portfolios and nine YTM/Duration portfolios. The table shows the average variation of weekly permille excess returns for the twenty-seven bond portfolios. In each stress-test, the average LME factor is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock).

Table 10 shows the results of the climate stress test for each of the twenty-seven value-weighted portfolios under the three shock scenarios. I 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 issued bonds ratings and prices. Consequently, given the global dimension of climate change, all firms in the test sample are affected by climate risk and all slopes on LME should be negative as discussed in section 5. As shown in the previous section and displayed on Table 2, Table 3 and Table 4, but also Table 6, Table 7 and Table 8, this is the case for all portfolios besides the poorly diversified LG/LY portfolio.

The climate stress test shows the effects of a plausible but more severe climate state on the bond returns under examination by stressing climate impacts (the LME average, Table 1) by 20% (low shock), 50% (medium shock), and 100% (high shock). By construction bond climate losses tend to increase with the magnitude of the shock and the interpretation of climate losses is identical to the interpretation of the results for the slopes and the sign of the slopes of the LME factor given in the previous section.

7. Discussion

Modern portfolio theory indicates that investors holding riskier assets should perceive a higher expected return as a compensation for taking more risk. This postulate is also implicit in equation (4): the $TERM$ factor is a zero-investment portfolio obtained by buying a risky asset, long-term government bonds, and shorting a risk-free asset, the T-bill; the DEF factor is a zero-investment portfolio obtained by buying riskier corporate bonds and shorting less risky government bonds. Both $TERM$ and DEF have a positive value, which is coherent with the above mentioned theory: prices adjust to offer higher returns where more risk is perceived.

My results contradict this modern portfolio theory postulate. If my results were coherent with the theory, a zero-investment portfolio obtained by buying bonds issued by light climatic impact (LCI) firms and shorting bonds issued by extreme climatic impact (ECI) firms, should have a negative mean value. I find exactly the opposite: buying bonds issued by LCI firms while shorting bonds issued by ECI firms yields a positive return. In the end, I find that the usual risk-return relationship in the bond market holds for interest rate risk and default risk, while it doesn't hold for climate risk.

Finding an inverse risk-return relationship is not new. In other contexts, tests of the CAPM have showed that "low-risk stocks earn higher returns and high-risk stocks earn lower returns than the theory predicts...The divergence of theory from evidence is even more striking in the short run. For some short periods, it may happen that risk and return are negatively related" (Malkiel, 1982). More recent studies (Frazzini and Pedersen, 2013), also confirm these findings for several asset classes and not just stocks. In a climate finance context, Garvey, Iyer, and Nash (2018) and In, Park and Monk (2019) have found that portfolios with a long position in stocks with low emission intensity and with a short position in stocks with a high emission intensity generate a positive abnormal return.

My explanation of the inverse climate risk-return relationship in the bond market between 2008 and 2017 relies on an evidence and an hypothesis. The evidence is that global warming effects are not equally distributed around the globe. The hypothesis, which builds also upon this evidence, is that it is plausible that investors sell bonds issued by firms that operate in countries (or parts of countries) that are more exposed to extreme climate phenomena or operate in countries (or parts of countries) which are expected to be more exposed to extreme climate phenomena. This, in turn, affects capital gains and returns. Hence, a portfolio with a long position in LCI firms, i.e. firms that on average are less impacted by extreme climate events, and a short position in ECI firms, i.e. firms that on average are more impacted by extreme climate events, generates positive returns. My results, which are both economically and statistically significant, seem to corroborate this hypothesis.

8. Conclusions

I have addressed, in this paper, the question of the impact of extreme climate phenomena, identified with temperature extremes, high sea levels extremes, and precipitation extremes (Intergovernmental Panel on Climate Change, 2014) on bond returns. The research question has been answered by putting forward a climatic extension of the Fama and French (1993) two-factor model for bonds. The climatic extension is represented by a factor, LME, which mimics the risk factor in bond returns related to extreme climate phenomena (climate change). The LME factor is the result of a model that permits the transposition of country level climate related GDP losses into firms fixed assets losses. The climate factor is computed by means of 50 bonds issued by firms for which a geographical partition of fixed assets is available.

The newly proposed three factor model has been run for a test set of twenty-seven portfolios which include a total of 329 bonds. This test set does not include the 50 bonds used for the production of the LME factor. The 329 bonds have been split in twenty-seven portfolios by means of three sorts on rating, duration and YTM. Running the three factor model for bonds produces slopes which are significant both in economic and statistical terms.

When the classical two-factor model is used as a benchmark, I have found that effectiveness is neither lost nor gained: adding the climate factor to the set of explanatory variables does not improve or worsens the effectiveness of the two factor model as measured by the GRS statistic. Nevertheless, it is of interest for financial practitioners and legislators to have insights into the effect of global warming upon bond returns. Therefore I do not drop LME but rather orthogonalize it. This operation permits us to expose the large global warming premium in average bond returns while accounting for the fact that LME is absorbed by the two classical factors: $TERM$ and DEF.

Several policy implications can be deduced from the methods and results put forward in this paper. An asset manager can use the methods presented in this paper to assess the impact of extreme climate phenomena upon bonds and thus reconsidering his asset allocation and his future portfolio strategies. In parallel, it is of interest to policy makers to have insights into the impact on bond returns of plausible but more extreme climate phenomena, which is something that has been achieved with the climate stress test. Legislators can leverage stress test results to calibrate a policy response (e.g. carbon pricing) which is in line with the cost of non-action, i.e. the cost of not addressing global warming.

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