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Alessandro Ravina

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en Sciences Économiques*

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Alessandro RAVINA

Four essays on Climate Finance

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Abstract

Four essays on Climate Finance

by Alessandro RAVINA

This PhD dissertation explores the repercussions of low-carbon transition risk and climate (physical) risk upon the two most widely traded asset classes: stocks and bonds. Findings show that there are patterns in average stock and bond returns related to carbon pricing and global warming. The results are economically and statistically significant and the methodologies specified are immediately usable by financial practitioners. A carbon stress test and a climate stress test are also put forward in order to give insights to policymakers on the impact of plausible but more severe carbon pricing and global warming upon stock and bond returns. Legislators can leverage results to calibrate a policy response, like carbon pricing, which is in line with their low-carbon transition objectives and with the cost of non-action, i.e. the cost of not addressing global warming.

Keywords: Low-carbon transition risk, climate risk, asset pricing model, stock returns, bond returns, carbon stress test, climate stress test

Cette thèse explore les répercussions du risque de transition bas carbone et du risque climatique (physique) sur les deux classes d'actifs les plus négociées: les actions et les obligations. Les résultats montrent qu'il y a des tendances dans les rendements moyens des actions et des obligations liées à un prix du carbone et au réchauffement climatique. Les résultats sont économiquement et statistiquement significatifs et les méthodologies spécifiées sont immédiatement utilisables par les asset managers. Un stress test carbone et un stress test climat sont également proposés afin de donner aux décideurs un aperçu de l'impact d'un plausible mais plus sévère prix du carbone et réchauffement climatique sur les rendements des actions et des obligations. Les législateurs peuvent tirer parti des résultats pour calibrer une réponse, comme un prix du carbone, qui est en ligne avec leurs objectifs de transition bas-carbone et avec le coût de la non-action, c'est-à-dire le coût de la non-prise en compte du réchauffement climatique.

Mots-clés: Risque de transition bas carbone, risque climatique, model d'évaluation d'actifs, rendement des actions, rendement des obligations, stress-test carbone, stress-test climat

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Introduction française

Réchauffement global: genèse, répercussions et mitigation

Le réchauffement global est défini comme l'augmentation, sur une période de trente ans, des températures moyennes atmosphériques et océaniques. Il est attribué à deux causes différentes: la variabilité climatique naturelle — processus naturels internes — et l'activité humaine qui modifie la composition de l'atmosphère (Intergovernmental Panel on Climate Change, 2014; United Nations, 1992).

Le point de rupture de la contribution humaine au réchauffement global est normalement identifié avec la révolution industrielle étant donné que le développement économique est strictement corrélé à la consommation d'énergie (Energy Information Administration, 2017; Stern, 2007): la combustion de combustibles fossiles a augmenté la concentration de dioxyde de carbone atmosphérique (CO₂), le facteur de forçage plus important, de 280 parties par million (ppm) à l'époque préindustrielle jusqu'à 400 ppm (Wagner & Weitzman, 2016).

Le réchauffement climatique d'origine humaine a atteint approximativement jusqu'à 1°C de plus par rapport à l'époque préindustrielle en 2017, en augmentant de 0.2° chaque décennie (Intergovernmental Panel on Climate Change, 2018). Cependant, il est improbable que les émissions passées, à elles seules, augmentent la température globale moyenne jusqu'à l'objectif fixé à la COP 21 de Paris: 1.5° C au-dessus des niveaux préindustriels (United Nations, 2015). Comme le Intergovernmental Panel on Climate Change (2018) l'a indiqué:

“Si toutes les émissions anthropiques étaient réduites à zéro immédiatement, tout réchauffement au-dessus d'1° C déjà vécu serait probablement inférieur à 0.5°C sur les prochaines deux ou trois décennies (confiance élevée) et probablement inférieur à 0.5°C sur les prochains cent ans (confiance moyenne), grâce aux effets opposés de processus climatiques différents. Un réchauffement climatique supérieur à 1.5° C

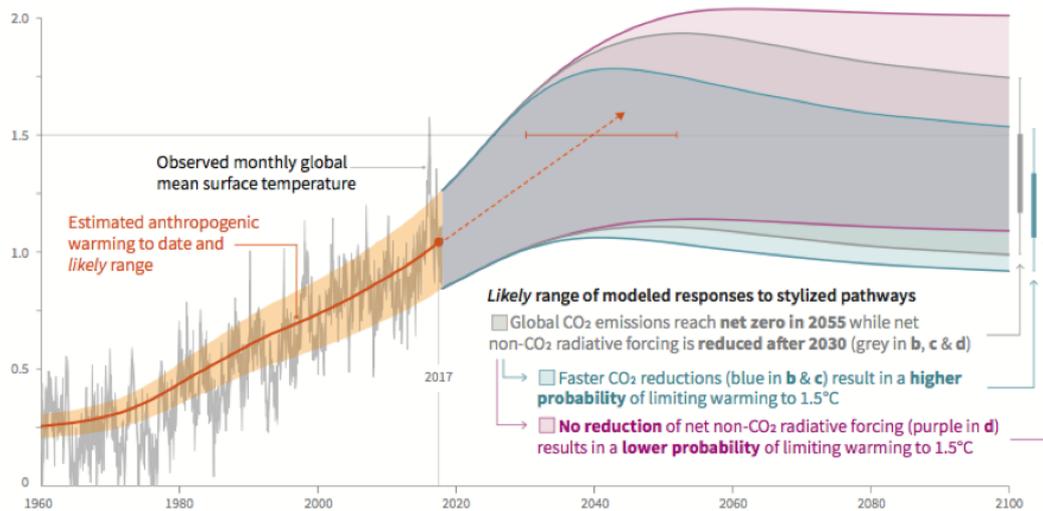


FIGURE 1: Global warming relative to 1850-1900 (IPCC, 2018)

n'est donc pas inévitable: son éventualité dépend des taux futurs de réduction des émissions”.

Les “1.5°C pathways” impliquent la limitation des émissions cumulées de gaz à effet de serre à longue durée de vie: les six gaz à effet de serre couverts par le protocole de Kyoto — dioxyde de carbone (CO₂), méthane (CH₄), protoxyde d'azote (N₂O), hydrofluorocarbures (HFC), perfluorocarbures (PFC), hexafluorure de soufre (SF₆) — et trifluorure d'azote (NF₃). Dans les modèles qui visent à ne pas dépasser l'objectif de 1,5°C, les émissions anthropiques mondiales diminuent d'environ 45% par rapport aux niveaux de 2010 d'ici 2030, pour atteindre zéro vers 2050. Les évaluations suggèrent un budget carbone restant d'environ 420 GtCO₂ pour avoir deux chances sur trois de limiter le réchauffement à 1,5°C, et d'environ 580 GtCO₂ pour une chance sur deux (IPCC, 2018).

Le réchauffement climatique affecte les organismes et les écosystèmes ainsi que les systèmes humains et le bien-être. Le réchauffement induit des augmentations des températures terrestres, de la fréquence des vagues de chaleur, des températures des océans, de la fréquence des vagues de chaleur marines, de la fréquence et de l'intensité des fortes précipitations à l'échelle mondiale et de la fréquence et de l'ampleur des sécheresses. Le réchauffement de la planète augmente le risque de perdre des espèces locales et le risque d'extinction avec un certain nombre d'espèces qui devraient perdre plus de la moitié de leur habitat avec un réchauffement de 1,5°.

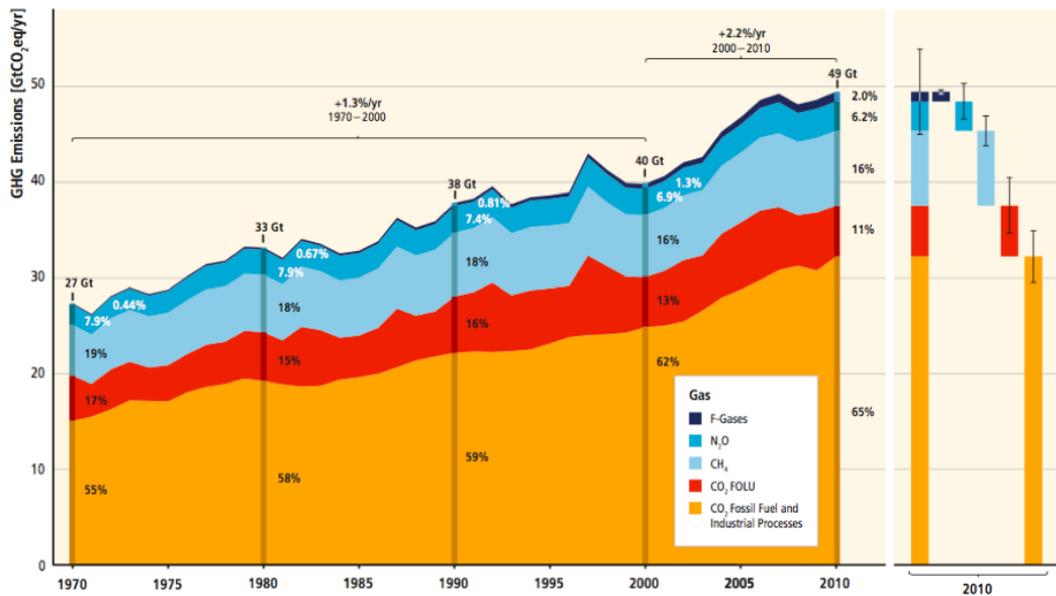


FIGURE 2: Total annual anthropogenic GHG emissions by group of gases 1970-2010 (IPCC, 2014)

En outre, un monde plus chaud augmente les risques liés aux facteurs liés à la biodiversité tels que les incendies de forêt, les événements météorologiques extrêmes et la propagation de parasites et de maladies. La santé humaine est susceptible d'être affectée avec des risques plus élevés de morbidité et de mortalité liés à la chaleur et à l'ozone, de certaines maladies à transmission vectorielle (paludisme et dengue) et de dénutritions (IPCC, 2018). Le réchauffement climatique va sérieusement affecter la croissance économique (Dell, Jones & Olken, 2014; Pycroft, Abrell & Ciscar, 2016), avec des réductions des rendements du maïs, du riz, du blé et d'autres céréales et une perte de 7 à 10% de pâturage, la productivité (Graff Zivin & Neidell, 2014; Hallegatte, Fay, Bangalore, Kane & Bonzanigo, 2015) et les valeurs financières.

Limiter le réchauffement à 1,5°C au-dessus des niveaux préindustriels nécessite un changement systémique en termes de mitigation des gaz à effet de serre et d'adaptation aux niveaux climatiques actuels. La réduction des gaz à effet de serre, à savoir la mitigation, entraîne la décarbonisation de l'approvisionnement énergétique mais aussi la baisse de la consommation d'énergie, la démotorisation et la décarbonisation des transports, l'efficacité énergétique, l'utilisation de technologies de stockage d'énergie et de technologies à usage général. D'autre part, les options pour réduire la vulnérabilité et l'exposition au changement climatique, à savoir

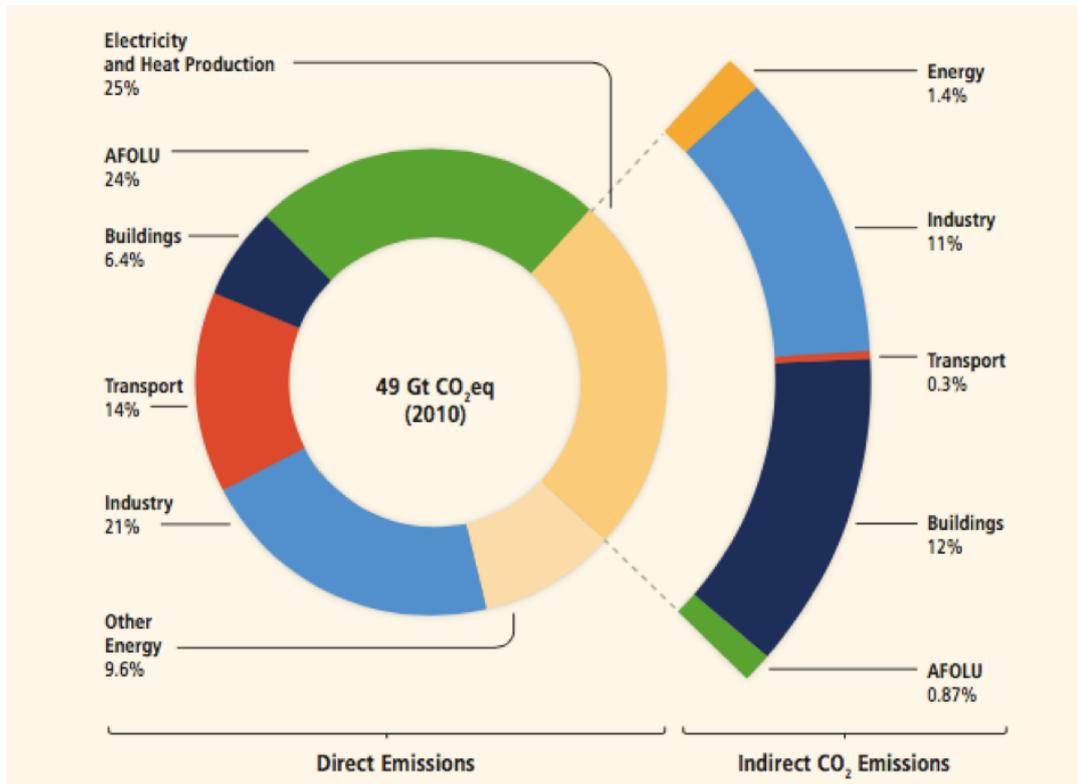


FIGURE 3: Direct and indirect GHG emissions in 2010 (IPCC, 2014)

l'adaptation, comprennent "les infrastructures vertes, services écosystémiques urbains, l'agriculture urbaine et périurbaine, et l'adaptation des bâtiments et de l'utilisation des terres" (IPCC, 2018).

La mitigation et l'adaptation au changement climatique conformément à l'objectif de 1,5° nécessitent une augmentation des flux d'investissements dans les infrastructures et les produits à faibles émissions. Deux outils d'intervention vont dans ce sens: les instruments fondés sur le marché et la "command and control regulation". Les instruments basés sur le marché impliquent un prix du carbone, qui peut être atteint grâce à une taxe sur le carbone ou à un prix des droits d'émissions. La "command and control regulation" vise à induire des changements technologiques et complète généralement la tarification du carbone dans des domaines spécifiques. L'économie de l'environnement suggère souvent que les instruments fondés sur le marché, tels que l'EU-ETS, permettent de réduire les émissions de manière plus rentable et plus flexible que la "command and control regulation", car cette dernière tend à prescrire le même niveau d'activité à tous les entreprises concernées par la réglementation (Demirel et Kesidou, 2011; Engel, Pagiola & Wunder, 2008). La théorie

	Energy Investments	Of which Demand Side	Transport	Other Infra-structures	Total	Ratio to MER GDP
IAM Baseline (mean)	1.96	0.24			1.96	1.8%
IAM NDC (mean)	2.04	0.28			2.04	1.9%
IAM 2°C (mean)	2.19	0.38			2.19	2.1%
IAM 1.5°C (mean)	2.32	0.45			2.32	2.2%
IEA NDC	2.40	0.72			2.40	2.3%
IEA 1.5°C	2.76	1.13			2.76	2.7%
Mean IAM-IEA, 1.5°C	2.38	0.54			2.38	2.53%
Min IAM-IEA, 1.5°C	1.38	0.38			1.38	1.6%
Max IAM-IEA, 1.5°C	3.25	1.13			3.25	4.0%
OECD Baseline					5.74	5.4%
OECD 2°C	2.13	0.40	2.73	1.52	6.38	6.0%

FIGURE 4: Estimated annualized world mitigation investment needed to limit global warming to 2°C or 1.5°C (2015-2035 in trillions of US Dollars at market exchange rates) from different sources. (IPCC, 2018)

économique indique clairement que, pour un niveau donné de réduction des émissions, si le coût marginal de réduction des émissions pour l'entreprise est supérieur au prix du carbone de marché, alors le choix efficace pour l'entreprise est de ne pas réduire mais d'acheter des allocations dans un système "cap and trade". À l'inverse, pour un niveau donné de réduction des émissions, lorsque l'entreprise polluante fait face à un coût marginal de réduction inférieur au prix du carbone de marché, le choix efficace pour l'entreprise est de réduire les émissions et de vendre ses permis dans un système "cap and trade" (Winebrake, Farrell, & Bernstein, 1995).

Les outils d'intervention ci-dessus ainsi que les instruments financiers *ah hoc* (par exemple les obligations vertes) et la réduction des régimes de subvention des combustibles fossiles socialement inefficaces contribuent à réduire la demande de produits et services à forte intensité de carbone et détourner les préférences du marché des technologies basées sur les combustibles fossiles. L'objectif ultime est de promouvoir une réorientation des flux financiers vers des actifs à long terme à faibles émissions. Le financement de la transition écologique devient alors la principale question de recherche de ce qu'on a appelé Finance Climatique.

Besoins financiers de la transition bas carbone et question de recherche du PhD

La figure 4 montre les coûts de l'action pour lutter contre le réchauffement climatique et rester en dessous du seuil de 1,5°. Les investissements annuels nécessaires ont été évalués à environ 2,38 billions USD (valeur moyenne) jusqu'en 2035 uniquement pour le secteur énergétique. Qui fournit actuellement ce financement? Buchner et al. (2013) rapportent qu'en 2012, le financement des mesures de mitigation des gouvernements et des institutions financières publiques était d'environ 255 milliards de dollars américains. D'un autre côté, les institutions financières commerciales, telles que les banques, les fonds de pension, les compagnies d'assurance-vie et d'autres fonds, tout en gérant plus de 71 billions de dollars américains d'actifs, n'ont contribué aux investissements liés au changement climatique qu'avec 22 milliards de dollars américains. À des fins de comparaison, les sociétés énergétiques ont fourni 102 milliards de dollars américains et les sociétés non énergétiques ont fourni 66 milliards. Même les ménages ont contribué plus que les institutions financières avec 33 milliards de dollars américains.

L'image ci-dessus constitue la motivation de cette thèse de doctorat. La principale question de recherche peut être posée comme suit: "Compte tenu des nécessités financières de la transition écologique ou énergétique, comment accroître la contribution des institutions financières à la lutte contre le changement climatique?" Les quatre chapitres qui composent cette thèse de doctorat partent de l'hypothèse que la participation des institutions financières commerciales à la transition bas-carbone est financièrement rationnelle. Au-delà de toute considération éthique concernant l'obtention de la transition écologique que l'auteur approuve sûrement, la prise de participation dans la transition écologique est financièrement rentable. Cette hypothèse devient un argument lorsqu'elle est prouvée empiriquement. Au fil des quatre chapitres que je présente ici, l'objectif est de fournir un fondement scientifique à l'hypothèse de la rentabilité financière de la participation à la transition écologique/énergétique.

En 2019, la valeur du marché obligataire mondiale était d'environ 105,9 billions

de dollars, tandis que la capitalisation boursière mondiale était d'environ 95,0 billions de dollars (SIFMA, 2020). En comparaison, la valeur marchande brute des contrats à terme et des options négociés en bourse était de 9,1 billions de dollars et la valeur marchande brute des dérivés de gré à gré était de 12,1 billions de dollars en 2019 (BRI, 2019). Ces valeurs justifient le choix des instruments financiers analysés dans les quatre chapitres présentés dans cette thèse: actions et obligations. Les dérivés sont laissés pour des recherches supplémentaires.

Risques liés au changement climatique: risque climatique et risque de transition bas carbone

Le réchauffement climatique se connecte à la sphère financière en augmentant le nombre de risques sur le marché. Les académiques ont divisé ce que nous pouvons appeler les risques liés au changement climatique en deux catégories. La première catégorie a été nommée "risque climatique" (Carney, 2015) et fait référence au lien entre le réchauffement climatique et les systèmes naturels et humains. Les phénomènes climatiques extrêmes comme les températures extrêmes, les niveaux extrêmes de la mer et les précipitations extrêmes (Intergovernmental Panel on Climate Change, 2014), sont susceptibles d'affecter gravement la croissance économique et la valeur des actifs financiers. La deuxième catégorie de risques liés au changement climatique a été appelée "risque de transition bas carbone" ou "risque carbone". Le risque de transition bas-carbone fait référence au coût de l'ajustement vers une économie bas-carbone. Ainsi, il inclut tous les facteurs de risque liés à la décarbonation de l'économie: a) les instruments fondés sur le marché comme une taxe carbone ou un prix des droit d'émissions; b) les changements technologiques induits par le "command and control regulation", par exemple les "stranded assets" ou les actifs qui ont souffert de dépréciations, dévaluations ou conversion en passifs imprévus ou prématurés (Caldecott et al., 2016); et c) le risque de marché, c'est-à-dire la demande du marché pour des produits à faible teneur en carbone (Zhou et al., 2016). Les quatre chapitres de cette thèse abordent à la fois le "risque climatique" et le "risque de transition bas carbone" et explorent leurs répercussions sur les deux classes d'actifs les plus négociées: les actions et les obligations.

Dans un article publié en 2016, Cook et al. affirment qu'il existe un large consensus scientifique sur les effets des émissions anthropiques sur le climat: le consensus des climatologues sur le réchauffement climatique anthropique est de l'ordre de 90% à 100%. La question et l'importance du consensus ne concernent pas seulement le réchauffement climatique, mais vont plus loin. Un modèle est une représentation synthétisée de la réalité, qu'elle soit physique ou chimique ou économique ou financière, etc. Le langage utilisé dans une telle représentation est mathématique. Cependant, les modèles s'opposent souvent avec les partisans d'une représentation qui se battent avec les partisans de représentations concurrentes. En d'autres termes, formaliser un ensemble d'énoncés ou d'assertions, c'est-à-dire passer du langage verbal quotidien à un langage formalisé comme les mathématiques, n'augmente pas le consensus. Compte tenu de ces considérations, l'urgence du réchauffement climatique et la nécessité de trouver un accord le plus large possible ont conduit au choix d'employer un modèle largement utilisé à la fois par la communauté scientifique et, en particulier, par les praticiens de la finance. Le modèle factoriel de Fama et French (1993, 2015) peut être apprécié à la fois par les mathématiciens appliqués et les gérants de portefeuille qui ont à faire avec un ensemble de pratiques et de conventions établies et s'appuient davantage sur les analyses quotidiennes de Bloomberg que sur des systèmes complexes d'équations aux dérivées partielles. Le prix Nobel remporté par Eugène Fama en 2013 pour "empirical analysis of asset prices" renforce ce choix.

Les modèles à facteurs classiques ont été modifiés avec deux facteurs supplémentaires. Un facteur, *GMC* (green minus carbon), mesure le green premium ou la prime pour ne pas être affecté par un prix du carbone. Cette analyse, qui vise à quantifier l'effet du risque de transition bas carbone, devait être réalisée dans un lieu où le prix du carbone existe. C'est pour cette raison que l'Europe et son Emission Trading System (ETS) a été préférés aux autres pays du monde. Le facteur *GMC* a été calculé pour les actions européennes (chapitre 1) et les obligations européennes (chapitre 2) avec des données Bloomberg. Mes résultats dans la période 2008-2018 indiquent un rendement hebdomadaire moyen en pourcentage pour *GMC* de 0,17 pour les actions et un rendement en pourcentage hebdomadaire moyen pour *GMC* de 0,02 pour les obligations. Un autre facteur, nommé *LME* (light minus extreme),

mesure la prime pour être moins impacté par le réchauffement climatique, et vise à quantifier l'effet du risque climatique. Cette analyse a été réalisée à l'échelle mondiale: le facteur *LME* a été calculé à la fois pour des actions mondiales (chapitre 3) et des obligations mondiales (chapitre 4) avec des données Reuters. Mes résultats dans la période 2008-2017 donnent un rendement en pourcentage hebdomadaire moyen pour *LME* de 0,08 pour les actions et un rendement en pourcentage hebdomadaire moyen pour *LME* de 0,01 pour les obligations.

Les modèles factoriels ont fait l'objet de critiques. Harvey et al. (2016) soutiennent qu'une statistique *t* supérieure à 2,0 n'est pas suffisante pour accepter un nouveau facteur et proposent un obstacle plus élevé de 3,0. Suivant cette règle, la plupart des facteurs découverts seraient faux. Leurs arguments sont les suivants: a) Le taux de découverte d'un vrai facteur a probablement diminué, b) la quantité de données est limitée et c) le coût de "data mining" a considérablement diminué. Cependant, ils admettent qu'un facteur développé à partir des "first principles" devrait avoir un seuil de statistique *t* plus bas qu'un facteur découvert à partir d'un exercice empirique. Feng et al. (2020) proposent un modèle pour évaluer la contribution de tout nouveau facteur. Lorsqu'on applique le modèle à un ensemble de facteurs récemment découverts, la plupart d'entre eux se révèlent redondants par rapport aux facteurs existants et seuls quelques-uns ont un pouvoir explicatif statistique. L'argument principal est le suivant: un nouveau facteur doit contribuer à la "cross-section" par rapport à l'univers entier des facteurs existants. Le modèle proposé par Feng et al. (2020) vise à devenir un concurrent direct du modèle plus établi de Gibbons, Ross et Shanken (1989) qui est actuellement utilisé par la littérature sur l'évaluation des actifs pour juger de la performance du modèle. Le modèle de Gibbons, Ross et Shanken (1989) valide l'utilisation du facteur *GMC* dans tous les cas. En ce qui concerne le facteur *LME*, son inclusion n'empire jamais la description des rendements moyens des actions ou des obligations; néanmoins, il est intéressant pour les praticiens de la finance et les législateurs d'avoir un aperçu de l'effet du réchauffement climatique sur les rendements des actions et des obligations. Par conséquent, dans l'esprit de Fama et French (2015) j'orthogonalise et garde *LME* exactement comme ils l'ont orthogonalisé et gardé *HML* dans le modèle à cinq facteurs.

Positionnement par rapport à la littérature existante

Si les investisseurs sont réticents à prendre des risques et tentent de minimiser le risque avec les méthodes proposées par la “modern portfolio theory”, alors les marchés financiers seront affectés par la minimisation du risque. Le modèle d'évaluation des actifs (MEDAF) incorpore l'un des principes clés de la théorie moderne du portefeuille, la diversification, et se concentre sur la partie du risque d'un actif qui ne peut être éliminé par la diversification: le risque systématique. Le bêta mesure la sensibilité d'un titre ou d'un portefeuille aux mouvements du marché et fournit une mesure du risque systématique. Suite au MEDAF, de nouveaux types de risques systématiques, par exemple ceux proposés par Fama et French (1993), ont été inclus dans les modèles qui tentent d'expliquer le “cross-section” des rendements boursiers.

Le MEDAF (et les modèles ultérieurs) est construit autour de deux des dogmes de la finance de marché. Le premier stipule que les investisseurs détenant des actifs plus risqués devraient percevoir un rendement attendu plus élevé comme une compensation pour prendre plus de risques: “les cours des actions doivent s'ajuster pour offrir des rendements plus élevés là où plus de risque est perçu pour garantir que toutes les valeurs sont détenues par quelqu'un” (Malkiel, 1982). Dans le cadre du MEDAF, le risque qui est rémunéré par les marchés n'est pas le risque total mais le risque systématique. Le deuxième dogme concerne les marchés efficients sur le plan informationnel: les théoriciens du marché efficients affirment qu'à “tout moment les prix reflètent pleinement toutes les informations disponibles” (Fama, 1970).

Les quatre chapitres présentés dans cette thèse de doctorat fournissent des preuves empiriques contre le premier dogme. Ce n'est pas la première fois que cela se produit. Les tests du MEDAF ont montré que “les actions à faible risque gagnent des rendements plus élevés et les actions à haut risque gagnent des rendements inférieurs à ce que la théorie prédit ... La divergence entre la théorie et l'évidence est encore plus frappante à court terme. Pendant de courtes périodes, il peut arriver que le risque et le rendement soient liés négativement” (Malkiel, 1982). Des études plus récentes (Frazzini et Pedersen, 2013), publiées dans le *Journal of Financial Economics*, confirment également ces résultats pour plusieurs classes d'actifs et pas seulement pour les actions.

L'évidence empiriques montre que le dogme risque élevé = rendement élevé oscille. Il n'est donc pas surprenant que les facteurs de risque systématiques mis en avant dans cette thèse — politique bas carbone (prix du carbone EU-ETS) et réchauffement climatique (événements climatiques extrêmes) — présentent une relation risque-rendement qui est cohérente avec les études empiriques mentionnées ci-dessus. Nous devons donc considérer une hypothèse auxiliaire qui est cohérente avec l'observation selon laquelle, parfois, un risque élevé s'accompagne d'un rendement élevé, mais l'équivalence risque élevé = rendement élevé est loin d'être une loi de la nature. En d'autres termes, cette hypothèse auxiliaire doit être cohérente avec l'énoncé "les rendements des entreprises à petite capitalisation sont en moyenne plus élevés que ceux des entreprises à grande capitalisation", mais aussi avec l'énoncé "les rendements des entreprises vertes (exonérées de l'EU-ETS) sont en moyenne plus élevés que ceux des entreprises carbone (assujettis à l'EU-ETS)" et l'énoncé "les rendements des entreprises peu impactées par les événements climatiques extrêmes sont en moyenne plus élevés que les rendements des entreprises plus impactées par les événements climatiques extrêmes".

Je pense que les anticipations concernant les rendements futurs peuvent jouer ce rôle. Une entreprise à petite capitalisation a plus de marge de croissance qu'une entreprise à grande capitalisation et les anticipations des rendements d'une entreprise à petite capitalisation sont en moyenne plus élevées que les anticipations des rendements d'une entreprise à grande capitalisation. En outre, une entreprise verte (une entreprise qui, dans mon cadre, n'est pas ciblée par la Commission européenne) a plus de marge de croissance qu'une entreprise carbone (une entreprise ciblée) à une époque de changement climatique et de régulation climatique. Là encore, une entreprise peu impactée par les événements climatiques extrêmes, c'est-à-dire une entreprise qui opère dans des pays peu impactés par les événements climatiques extrêmes (les effets du réchauffement climatique ne sont pas également répartis), a plus de marge de croissance qu'une entreprise plus impactée par les événements climatiques extrêmes, c'est-à-dire une entreprise qui opère dans des pays plus impactés par les événements climatiques extrêmes, à une époque de réchauffement climatique progressif.

Les résultats des quatre chapitres sont cohérents avec l'hypothèse selon laquelle

les rendements sont entièrement déterminés par les anticipations des investisseurs. Mes résultats pour la mesure du risque de transition bas-carbone pour les stocks peuvent être liés, quoique avec quelques différences, avec ceux de Garvey, Iyer et Nash (2018) et d'In, Park et Monk (2019). Ces études suggèrent que les portefeuilles avec une position longue sur des actions à faible intensité d'émission et avec une position courte sur des actions à forte intensité d'émission génèrent un "abnormal return" positif. En revanche, Bolton et Kacperczyk (2020a) constatent qu'il existe une prime carbone, et non une prime verte, qui est liée au niveau total des émissions des entreprises et à l'évolution annuelle des émissions des entreprises, mais pas à l'intensité des émissions. Les résultats de Bolton et Kacperczyk (2020a) pour les rendements boursiers américains sont contredits par un article rédigé par les mêmes auteurs: Bolton et Kacperczyk (2020b). De Angelis et al. (2020) rapportent que le "green investing" encourage les entreprises à réduire leurs émissions de gaz à effet serre en augmentant leur coût du capital: le doublement des actifs sous gestion par des investisseurs ayant des préférences environnementales induit une baisse de 5% de l'intensité carbone des entreprises. Ilhan et al. (2020) constatent que le coût de la protection par le biais des options contre le "downside risk" est plus élevé pour les entreprises à forte intensité carbone. Hsu, Li et Tsou (2020) constatent également que les entreprises produisant plus d'émissions sont associées à des rendements plus élevés ; cependant, ils prennent en compte toutes les émissions toxiques, définies comme la somme des émissions de tous les types de produits chimiques des usines des entreprises. En un mot, les preuves sont mitigées.

Ma mesure du risque de transition bas-carbone diffère de la littérature ci-dessus car elle n'aborde pas la relation entre les rendements et les niveaux d'émission ou l'intensité des émissions. Le raisonnement qui sous-tend *GMC* est le suivant: si l'on considère uniquement la part des investissements traditionnels, c'est-à-dire les investissements qui ne sont pas déterminés par les préférences environnementales (les investissements ESG représentent environ un tiers des actifs sous gestion et le E n'est que d'environ 9 per cent du total des actifs sous gestion), alors le niveau des émissions totales (ou l'intensité des émissions ou la variation annuelle des émissions) n'est pas un critère d'évaluation du rendement financier si personne (i.e. un

gouvernement) ne demande de payer ces émissions. En d'autres termes, une entreprise avec un niveau d'émissions égal à Y mais à qui on ne demande pas de payer pour Y, c'est-à-dire qu'elle ne participe pas à l'EU-ETS (dans mon cadre elle s'agit donc d'une entreprise verte), apportera (*ceteris paribus*) une prime par rapport à une entreprise dont le niveau d'émissions est également égal à Y mais qui est appelée à payer pour Y, c'est-à-dire qu'elle participe à l'EU-ETS (dans mon cadre c'est donc une entreprise carbone). Cela est particulièrement vrai lorsque la liste des participants est révisée sur la base de phases (phases EU-ETS).

Je ne nie pas que les clients et les investisseurs (gestionnaires d'actifs) ont des préférences éthiques, comme tout le monde. Néanmoins, les préférences éthiques sur les marchés financiers ont une limite de temps: un client peut demander à son gestionnaire d'actifs d'investir dans des entreprises vertes, mais après une période de mauvais résultats, le client écartera ses préférences éthiques et demandera au gestionnaire d'actifs d'allouer son épargne dans une manière plus traditionnelle. D'autre part, le gestionnaire d'actifs a intérêt à se désengager des actions et des obligations vertes en cas de sous-performance, car le gestionnaire d'actifs ne percevra aucune commission de performance. En un mot, les préférences éthiques doivent être accompagnées d'un rendement financier. C'est pourquoi je mets l'accent sur les rendements plutôt que sur les préférences éthiques, ce que je ne nie pas. Les conclusions du deuxième chapitre suivent la même logique, mais l'objet de l'analyse est les obligations et non les actions. La littérature avec laquelle je peux comparer mes résultats est très rare. Delis et al. (2019) constatent qu'après 2015, les banques ont augmenté les "loan spreads" aux entreprises de combustibles fossiles exposées au risque de politique climatique, augmentant ainsi leur coût de la dette. Si ces résultats semblent contredire les miens, il faut noter que les spreads de crédit n'ont pas augmentés avant 2015 et que les prêts ne sont pas cotés.

Il n'y a pas de littérature disponible avec laquelle je puisse comparer les résultats des chapitres trois et quatre. Cependant, les résultats sont cohérents avec l'hypothèse selon laquelle les rendements sont entièrement déterminés par les anticipations des investisseurs. Étant donné que les effets du réchauffement climatique ne sont pas également répartis dans le monde, il est plausible que les investisseurs vendent des actions d'entreprises qui opèrent dans des pays (ou parties de

pays) qui sont plus exposés aux phénomènes climatiques extrêmes ou qui opèrent dans des pays (ou des parties de pays) qui sont attendus être plus exposés aux phénomènes climatiques extrêmes. En retour, cela affecte les "capital gains" et les rendements. Ainsi, un portefeuille avec une position longue sur des entreprises qui sont en moyenne moins impactées par les événements climatiques extrêmes, et une position courte sur des entreprises qui sont en moyenne plus impactées par les événements climatiques extrêmes, génère des retours positifs. Les données satellitaires peuvent être considérées comme une alternative au calcul que j'ai effectué des pertes liées au réchauffement climatique agrégées au niveau des pays. Néanmoins, ce dernier fournit une approximation de premier niveau qui, dans un monde extrêmement interconnecté et globalisé, peut s'avérer efficace. Par exemple, une entreprise cotée au NYSE avec son siège social et la plupart de ses usines dans l'État de New York peut ne pas être directement touchée par une tempête en Louisiane, mais l'événement météorologique extrême peut avoir un impact sur la même entreprise via sa chaîne d'approvisionnement ou via les dynamiques de demande. Dans cette optique, les résultats pour *LME* représentent une approximation et il y a sûrement de la place pour une amélioration même si les résultats sont économiquement et statistiquement significatifs.

Carbon stress-test et climate stress-test

Une autre innovation méthodologique de la thèse de doctorat amène à la fois sur le développement d'un test de stress carbone et d'un test de stress climatique. Le "carbon stress test" a été conçu pour montrer l'impact d'un prix du carbone plausible mais plus sévère sur les valeurs financières, tandis que le "climate stress test" a été conçu pour montrer l'impact de phénomènes climatiques plausibles mais plus extrêmes sur les rendements des actions et des obligations. Dans l'analyse des risques financiers, un stress-test est caractérisé par quatre caractéristiques essentielles (Borio, Drehmann, & Tsatsaronis, 2014): un ensemble d'expositions au risque, un scénario qui définit les chocs exogènes qui stressent les expositions, un modèle qui met en relation les chocs avec leur répercussions et une mesure de ces répercussions. La littérature récente a proposé les stress-tests comme cadre d'évaluation des risques

liés au changement climatique: la Bank of England Prudential Regulation Authority (2015) suggère une intégration des facteurs de risque du changement climatique dans les techniques de stress-tests standard, Zenghelis et Stern (2016) encouragent les entreprises financières et les entreprises de combustibles fossiles à entreprendre des tests de résistance pour évaluer leur “viabilité future par rapport aux différents prix et réglementations du carbone” (p. 9), Schoenmaker et van Tilburg (2016) appellent à, comme prochaine étape, le développement de “tests de résistance pour avoir une meilleure image de l’exposition du secteur financier”(p. 7), et la Banque mondiale a également pris cette direction (Fay et al., 2015). Au-delà de ce support académique, en France, la récente loi n° 2015-992 (article 173) relative à la transition énergétique pour la croissance verte, promulguée juste avant la COP 21 à Paris, fait référence aux “climate change risk stress tests”.

Le reste de l’introduction présente les quatre chapitres de la thèse.

Chapitre 1. L’impact des politiques bas carbone sur le rendement des actions

L’objectif de ce chapitre est d’étudier l’impact d’une politique bas carbone sur la valeur des actifs financiers, en particulier les rendements actionnaires. Plus précisément, nous cherchons à comprendre et à expliquer l’impact d’une politique européenne particulière, la directive 2003/87/CE sur laquelle repose l’EU-ETS, sur les rendements des actions européennes.

La directive 2003/87 / CE est à l’origine du système d’échange de quotas d’émission de l’Union européenne (EU-ETS). L’EU-ETS est un instrument fondé sur le marché, lancé en tant que projet pilote en 2005, dont l’objectif est de réduire les émissions de gaz à effet de serre (GES) dans tous les pays de l’Union européenne (UE) ainsi qu’en Islande, au Lichtenstein et en Norvège. Le projet pilote de trois ans (2005-2007), phase I, a été suivi d’une phase II de quatre ans (2008-2012) et d’une phase III de sept ans (2013-2020). En 2020, à l’issue de la phase III, les émissions couvertes par l’EU-ETS, environ 45% des GES de l’UE, sont attendues autour de 21%

de moins qu'au début du projet pilote (2005). Depuis le début de la phase III, l'EU-ETS couvre plus de 11000 installations comprenant la production d'électricité et de chaleur, les raffineries de pétrole, l'aviation commerciale et la production d'acier, de fer, d'aluminium, de métaux, de ciment, de chaux, de verre, de céramique, de pâte, papier, carton, acides et produits chimiques organiques en vrac (Commission européenne, 2015).

L'EU-ETS est un système de plafonnement et d'échange: la Commission européenne a plafonné les émissions de GES à l'échelle de l'UE, qui a été progressivement réduite. Lorsqu'une entreprise appartient à l'un des secteurs participants, elle est tenue de couvrir ses émissions avec des quotas d'émission (EUA) qui sont livrés sur le marché primaire, c'est-à-dire qu'ils sont soit mis aux enchères, soit distribués gratuitement. Par la suite, sur le marché secondaire, le commerce des EUA permet aux entreprises qui finissent par manquer de quotas d'acheter des unités supplémentaires.

Ce chapitre utilise un modèle d'asset pricing multifactoriel afin d'étudier l'impact de la politique bas carbone — la directive 2003/87 / CE à l'origine de l'EU-ETS — sur les rendements actionnaires des entreprises européennes. Afin d'accomplir cette tâche, un facteur environnemental, *GMC* (green minus carbon), est ajouté aux facteurs actionnaires classiques introduits par Fama et French (1993, 2015): *SMB* (small minus big), *HML* (high minus low), *RMW* (robust minus weak), *CMA* (conservative minus aggressive). Ce chapitre apporte plusieurs contributions. Tout d'abord, c'est la première fois qu'un facteur, *GMC*, destiné à simuler le facteur de risque lié à la politique bas carbone, la directive 2003/87/CE dans ce cas, est construit. Le facteur *GMC* est obtenu à partir d'un échantillon de 182 entreprises de 19 pays européens opérant dans 35 secteurs: de janvier 2008 à décembre 2018, les rendements pondérés de 91 entreprises réglementées par la directive 2003/87/CE sont soustraits aux rendements pondérés de 91 entreprises exemptées par la directive 2003/87/CE sur laquelle repose l'EU-ETS. Deuxièmement, nous montrons que l'ajout du facteur *GMC* améliore les performances du modèle à 5 facteurs en Europe sur la période 2008-2018: nous montrons que, tout comme il existe des tendances dans les rendements moyens liés à la taille, à la rentabilité et à l'investissement, il existe également

une tendance liée à la participation à l'EU-ETS. Troisièmement, les résultats montrent qu'il y a une prime verte élevée plutôt qu'une prime carbone comme certaines parties de la littérature ont affirmé, et que cette prime verte est très statistiquement significative, c'est-à-dire que les actions vertes surperforment les action carbone sur les 11 ans. De plus, nous suivons la récente vague des stress-tests carbone en proposant un stress-test capable d'indiquer quel est l'impact d'un prix carbone hypothétique sur les rendements des actions: nos résultats montrent les effets d'un plausible mais plus sévère prix moyen de l'EU-ETS sur les entreprises carbone et sur les entreprises vertes pour chaque tranche de capitalisation boursière.

Trois "policy implications" peuvent être tirées de ces contributions. Les deux premières implications intéressent les praticiens financiers et la troisième intéresse les législateurs. Premièrement, la présence d'une prime verte sur le marché actionnaire européen dans les années 2008-2018 est une piste de gestion d'actifs utile pour les praticiens financiers. En d'autres termes, les investissements verts ne peuvent plus être appréhendés uniquement sous l'angle d'une prise de position éthique: de nos jours, comme le montre la prime verte, investir dans des entreprises vertes est un exercice rentable. Deuxièmement, en termes de modèles d'asset pricing, la version augmentée du modèle Fama et French (2015) pour les actions est préférable à l'original, au moins en Europe depuis 2008. Troisièmement, le stress test carbone proposé, en montrant l'impact moyen sur les rendements actionnaires de différents scénarios de carbon pricing, fournit des informations utiles aux législateurs en termes de financement de la transition bas-carbone, i.e. augmenter les entrées de capitaux vers les entreprises vertes et les sorties de capitaux des entreprises carbone. Le scénario à faible choc, par exemple, donnerait un élan supplémentaire à la transition bas-carbone, sans nuire excessivement aux entreprises carbone.

Chapitre 2. Sur les rendements obligataires à une époque de changement climatique

L'impact d'un instrument particulier fondé sur le marché, le système d'échange de quotas d'émission de l'Union européenne (EU-ETS), sur les valeurs financières a déjà été abordé dans la littérature; néanmoins, les efforts portent principalement sur

les actions, laissant le champ des obligations en dehors du tableau. L'objectif de ce chapitre est d'évaluer l'impact de la directive 2003/87/CE, sur laquelle repose l'EU-ETS, sur les rendements des obligations européennes.

Afin de détecter l'impact d'une politique bas carbone — la directive 2003/87/CE qui a initié l'EU-ETS — sur les rendements obligataires des entreprises européennes, le modèle Fama et French (1993), pour la première fois, est utilisé. Aux deux facteurs du marché obligataire proposés par Fama et French (1993), *TERM* et *DEF*, un facteur de participation EU-ETS est ajouté: *GMC*. Ajouter aux facteurs classiques un facteur environnemental a déjà été fait dans des recherches menées sur le marché des actions (Görge et al., 2017; Oestreich et Tsiakas, 2015; Ravina et Kaffel, 2019). Cependant, certaines différences dans la construction du facteur environnemental subsistent. En ce sens, la construction factorielle plus proche de celle présentée ici se trouve dans Ravina et Kaffel (2019). La logique derrière le facteur *GMC* est la suivante: si nous voulons mesurer l'impact de la directive 2003/87/CE avec un facteur, une possibilité est de prendre toutes les entreprises réglementées par la directive, d'effectuer une comptabilité carbone pour chaque entreprise, de construire deux portefeuilles, i.e. un portefeuille haut carbone et un portefeuille bas carbone, puis prendre les différences des rendements pondérés. Malheureusement, cette opération ne nous permettrait pas de découvrir la véritable prime verte (ou carbone) car les entreprises qui participent à l'EU-ETS sont toutes des entreprises très émettrices en carbone. Cela signifie que, lorsque nous construisons les deux portefeuilles, le portefeuille bas carbone contiendrait un ensemble d'entreprises qui ne sont que légèrement moins polluantes que les entreprises de l'autre portefeuille. Le facteur environnemental qui en résulterait serait biaisé, c'est-à-dire négligeable en termes de grandeur. Afin de faire face au fait que l'EU-ETS ne couvre que les secteurs haut carbone, une alternative consiste à construire le facteur environnemental au moyen de deux portefeuilles, un portefeuille composé d'entreprises assujetti à l'EU-ETS (que j'appelle portefeuille "carbone") et un portefeuille composé d'entreprises exonérées de l'EU-ETS (que j'appelle portefeuille "vert"). Dans ce contexte, alors que le facteur *TERM* porte sur le risque commun des rendements obligataires liés aux variations inattendues des taux d'intérêt et le facteur *DEF* porte sur le risque commun des rendements obligataires liés aux changements des conditions économiques qui

modifient la probabilité de défaut des entreprises, *GMC* (Green minus Carbon) vise à simuler le facteur de risque commune des rendements obligataires lié à la politique bas carbone, la directive 2003/87/CE dans ce cas. La nouvelle composante, le facteur *GMC*, est obtenue en soustrayant les rendements pondérés hebdomadaires du portefeuille d'obligations carbone des rendements pondérés hebdomadaires du portefeuille d'obligations vertes depuis le début de la phase II (2008) de l'EU-ETS. Le portefeuille d'obligations carbone est composé de 25 entreprises réglementées par la directive 2003/87/CE et le portefeuille d'obligations vertes est composé de 25 entreprises exemptées par la directive 2003/87/CE sur laquelle repose l'EU-ETS.

Ce chapitre apporte les contributions suivantes. Premièrement, c'est la première fois qu'un modèle factoriel est utilisé pour évaluer la sensibilité des rendements obligataires aux politiques bas carbone. La sensibilité des rendements des portefeuilles obligataires au facteur *GMC* s'est avérée positive dans le cas des portefeuilles verts et négative dans le cas des portefeuilles carbone. Plus important encore, les pentes de *GMC* sont statistiquement très significatives. Deuxièmement, la valeur moyenne de *GMC* elle-même est positive: trouver un *GMC* positif signifie qu'en Europe, sur la période 2008-2018, il n'y a pas de prime carbone comme l'affirme certaines publications, mais plutôt une prime verte. Une telle prime verte confirme que l'EU-ETS a un effet positif sur le financement de la transition bas-carbone: le début de la phase II de l'EU-ETS — la date de début de l'étude — coïncide avec des sorties de capitaux des entreprises réglementées par la directive et des entrées de capitaux vers les entreprises exemptées de l'EU-ETS. Troisièmement, il est prouvé que l'ajout d'un facteur environnemental améliore la performance du modèle à deux facteurs Fama et French pour les obligations, du moins en Europe à partir de 2008. Quatrièmement, depuis que la littérature a récemment proposé des stress tests, une technique développée pour tester la stabilité d'une entité, comme cadre d'évaluation des risques de changement climatique (Bank of England Prudential Regulation Authority, 2015; Fay et al., 2015; Schoenmaker et van Tilburg, 2016; Zenghelis et Stern, 2016), je suis la récente vague et je propose un stress test carbone capable d'indiquer l'impact d'un prix moyen hypothétique de l'EU-ETS sur les rendements obligataires. Les résultats montrent les effets d'un plausible mais plus sévère prix moyen de l'EU-ETS sur les entreprises carbone et les entreprises vertes.

Chapitre 3. Événements climatiques extrêmes et valeurs financières: évidence empirique du marché des actions

Ce chapitre aborde l'impact des événements climatiques extrêmes sur les valeurs financières. Plus précisément, nous nous intéressons à la manière dont les changements dans les phénomènes climatiques extrêmes (températures extrêmes, niveaux de la mer extrêmes et précipitations extrêmes) sont liés aux changements de valeur des actions. Cette question de recherche a, à notre connaissance, à peine été abordée.

Nous répondons à la question de recherche de l'impact des événements climatiques extrêmes sur les rendements actionnaires grâce à une extension climatique du modèle à cinq facteurs Fama et French (2015) pour les actions. C'est la première fois qu'un modèle factoriel est utilisé pour évaluer les implications des changements climatiques sur les rendements actionnaires. Le facteur climatique que nous mettons en avant, *LME* (light minus extreme), répond à la nécessité de capturer le facteur de risque des rendements actionnaires lié au réchauffement climatique associé à des phénomènes climatiques extrêmes comme les températures extrêmes, les niveaux extrêmes de la mer et les précipitations extrêmes (Intergovernmental Panel on Climate Change, 2014). Le facteur climatique est construit à travers deux portefeuilles: le portefeuille à impact climatique extrême (*ECI*) et le portefeuille à impact climatique léger (*LCI*). La procédure de constitution des deux portefeuilles s'appuie sur une analyse des événements climatiques extrêmes mondiaux sur la période 2008-2017. Les rendements hebdomadaires pondérés du portefeuille *ECI* sont ensuite soustraits des rendements hebdomadaires pondérés du portefeuille *LCI*. Les rendements à expliquer dans notre cadre sont des rendements excédentaires pondérés pour six portefeuilles triés en fonction de l'exposition au climat et de la taille (capitalisation boursière) prélevés sur un échantillon de 227 entreprises appartenant à l'indice STOXX 1800 pour lesquelles des données sur la localisation géographique des actifs fixes était disponible.

En fin de compte, nous constatons que les pentes du nouveau facteur de risque proposé augmentent progressivement du portefeuille à impact climatique extrême

au portefeuille à impact climatique léger. De plus, ces résultats sont statistiquement très significatifs. Globalement, nous constatons qu'il y a un effet climatique sur les rendements excédentaires moyens des actions, ce qui confirme notre hypothèse selon laquelle un facteur de risque systématique, le réchauffement climatique en l'occurrence, manquait au cadre classique. Cependant, les résultats montrent que le facteur climatique (*LME*), tout comme le facteur de valeur (*HML*), sont absorbés par les quatre autres facteurs des rendements actionnaire : $RM - RF$ (rendement excédentaire du marché), *SMB* (small minus big, le facteur de taille), *RMW* (robust minus weak, le facteur de rentabilité) et *CMA* (conservative minus aggressive, le facteur d'investissement). Ceci est également observé après le calcul de la statistique GRS, qui montre que l'ajout de *LME* et *HML* aux quatre autres facteurs n'améliore jamais l'efficacité du modèle. Le constat que *HML* devient redondant dans un modèle à cinq facteurs a déjà été fait par Fama et French, et nous pouvons le confirmer. En cohérence avec leur analyse, nous proposons finalement un modèle à six facteurs qui exploite deux facteurs orthogonaux: *LMEO* (orthogonal *LME*) et *HMLO* (orthogonal *HML*). La version orthogonale du modèle CE-FF produit des pentes sur les quatre facteurs non redondants qui sont les mêmes que dans la version à quatre facteurs du modèle, c'est-à-dire un modèle qui n'emploie que comme variables explicatives $RM - RF$, *SMB*, *RMW* et *CMA*, tout en affichant les expositions des rendements excédentaires aux facteurs *HML* et *LME*.

Chapitre 4. Phénomènes climatiques extrêmes et rendements obligataires

Ce chapitre traite du risque climatique et met en évidence l'impact des événements climatiques extrêmes sur les rendements des obligations. En particulier, nous nous intéressons à la manière dont les changements dans les phénomènes climatiques extrêmes (températures extrêmes, niveaux de la mer extrêmes et précipitations extrêmes) sont liés aux changements de valeur des obligations. Cette question de recherche a, à notre connaissance, à peine été abordée.

Nous répondons à la question de recherche de l'impact des événements climatiques extrêmes sur les rendements obligataires au moyen d'une extension climatique du modèle à deux facteurs Fama et French pour les obligations (1993). C'est la première fois qu'un modèle factoriel est utilisé pour évaluer les implications du risque climatique sur les rendements obligataires. Le raisonnement se déroule comme suit: augmenter le modèle à deux facteurs de Fama et French (1993) avec un facteur climatique revient à affirmer qu'il manque un risque systématique dans le cadre. Il y a au moins un autre facteur commun qui affecte les rendements obligataires: le réchauffement climatique. Le facteur climatique, *LME* (light minus extreme), répond à la nécessité de capturer le facteur de risque des rendements obligataires liés au réchauffement climatique représenté ici par des phénomènes climatiques extrêmes comme les températures extrêmes, les niveaux extrêmes de la mer et les précipitations extrêmes (Intergovernmental Panel on Climate Change, 2014). Le facteur climatique est obtenu en construisant deux portefeuilles: le portefeuille à impact climatique extrême et le portefeuille à impact climatique léger. La procédure de constitution des deux portefeuilles s'appuie sur une analyse des événements climatiques extrêmes mondiaux sur la période 2008-2017. Les rendements hebdomadaires pondérés des entreprises qui sont plus touchées par le changement climatique sont ensuite soustraits des rendements hebdomadaires pondérés des entreprises légèrement touchées par le changement climatique. Les rendements à expliquer dans notre cadre sont des rendements excédentaires pondérés pour 27 portefeuilles d'obligations triés en fonction de la notation et de l'échéance, de la notation et du YTM et de l'échéance et du YTM à partir d'un échantillon test de 329 obligations. Globalement, on constate qu'il y a un effet climatique dans les rendements moyens excédentaires des obligations, ce qui confirme notre hypothèse selon laquelle un facteur de risque systématique, le réchauffement climatique dans ce cas, était absent du cadre classique.

Les principales contributions de ce chapitre sont le facteur climatique (*LME*) et le stress test climatique pour les obligations. Les pentes du nouveau facteur climatique se révèlent statistiquement significatives, ce qui implique que le secteur financier (universitaires, praticiens financiers) a maintenant des preuves de l'impact

des événements climatiques extrêmes sur les rendements obligataires. Concrètement, ils sont désormais en mesure de quantifier les implications financières du réchauffement climatique. De plus, le stress test climatique prend ces résultats et les place dans un contexte d'incertitude quant aux trajectoires futures du réchauffement climatique. Ces contributions ont des "policy implications" tant pour les législateurs que pour les praticiens financiers. Un gestionnaire d'actifs peut utiliser les méthodes présentées dans cet article pour évaluer l'impact des phénomènes climatiques sur les obligations et ainsi reconsidérer son allocation d'actifs et ses futures stratégies de portefeuille. En parallèle, il est intéressant pour les décideurs politiques d'avoir un aperçu de l'impact sur les rendements obligataires de phénomènes climatiques extrêmes plausibles mais plus graves, ce que nous avons réalisé avec le stress test climatique. Les législateurs peuvent tirer parti des résultats des stress test pour calibrer une réponse (par exemple, un prix du carbone) en lien avec le coût de la non-action, c'est-à-dire au coût de la non-prise en compte du réchauffement climatique.

Introduction

Global warming: genesis, repercussions and mitigation

Global warming is defined as the increase over a 30-year period of the global average of combined surface air and sea surface temperatures. It is attributed to two different causes: natural climate variability — natural internal processes or external forcings — and human activity that alters the composition of the atmosphere (Intergovernmental Panel on Climate Change, 2014; United Nations, 1992).

The breaking point of human contribution to climate change is usually identified with the industrial revolution since economic development is strictly correlated to energy consumption (Energy Information Administration, 2017; Stern, 2007): the burning of fossil fuels has increased the concentration of atmospheric carbon dioxide (CO₂), the most prominent forcing factor, from 280 parts per million (ppm) in preindustrial times to approximately 400 ppm (Wagner & Weitzman, 2016).

Human induced global warming reached approximately 1°C above pre-industrial levels in 2017, increasing at 0.2° C per decade (Intergovernmental Panel on Climate Change, 2018). However, it is very unlikely that past emissions alone raise the global mean temperature to what is now considered the threshold objective since the COP 21 held in Paris in 2015: 1.5° C above pre-industrial levels (United Nations, 2015). As the Intergovernmental Panel on Climate Change (IPCC, 2018) states it:

“If all anthropogenic emissions (including aerosol-related) were reduced to zero immediately, any further warming beyond the 1°C already experienced would likely be less than 0.5°C over the next two to three decades (high confidence), and likely less than 0.5°C on a century time scale (medium confidence), due to the opposing effects of different climate processes and drivers. A warming greater than 1.5°C is therefore not geophysically unavoidable: whether it will occur depends on future rates of emission reductions”.

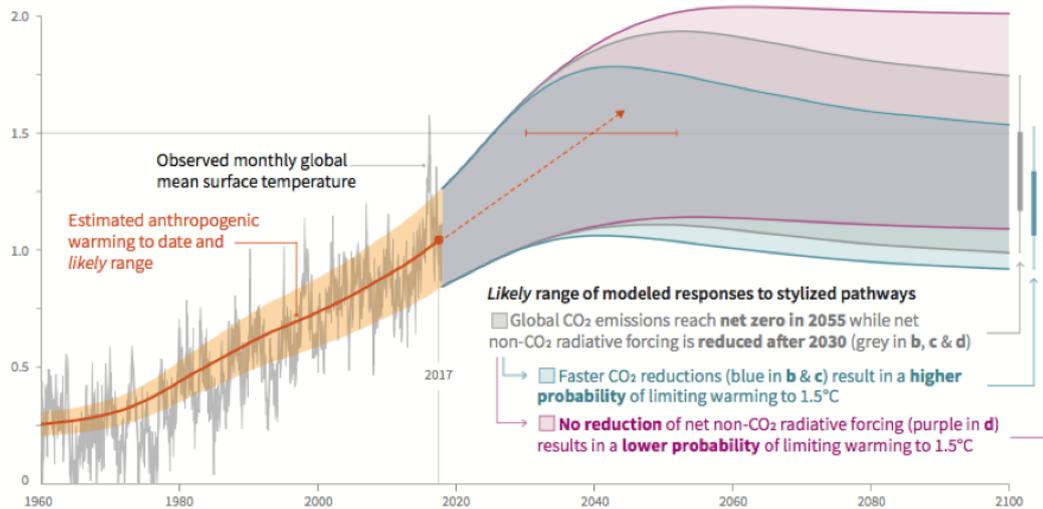


FIGURE 5: Global warming relative to 1850-1900 (IPCC, 2018)

1.5°C pathways involve limiting cumulative emissions of long-lived greenhouse gases: the six greenhouse gases covered by the Kyoto Protocol — carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF₆) — and nitrogen trifluoride (NF₃). In model pathways that aim at no overshoot of the 1.5°C objective, global anthropogenic emissions decline by about 45% from 2010 levels by 2030, reaching net zero in around 2050. Assessments suggest a remaining carbon budget of about 420 GtCO₂ for a two-thirds chance of limiting warming to 1.5°C, and of about 580 GtCO₂ for an even chance (IPCC, 2018).

Global warming affects organisms and ecosystems along with human systems and well-being. It induces raises in land temperatures, in the frequency of heatwaves, in ocean temperatures, in the frequency of marine heatwaves, in the frequency and intensity of heavy precipitations at a global scale and in the frequency and magnitude of droughts. A warmer globe increases the risk of losing local species and the risk of extinction with a number of species projected to lose over half of their climatically determined geographic range at 1.5° warming. Also, a warmer world increases the risks related to biodiversity-related factors like forest fires, extreme weather events, and the spread of invasive species, pests and diseases. Human health is likely to be affected with higher risks for heat-related morbidity and mortality, for ozone-related mortality, for some vector-borne diseases such as malaria and dengue fever and for denutritions (IPCC, 2018). Global warming will seriously

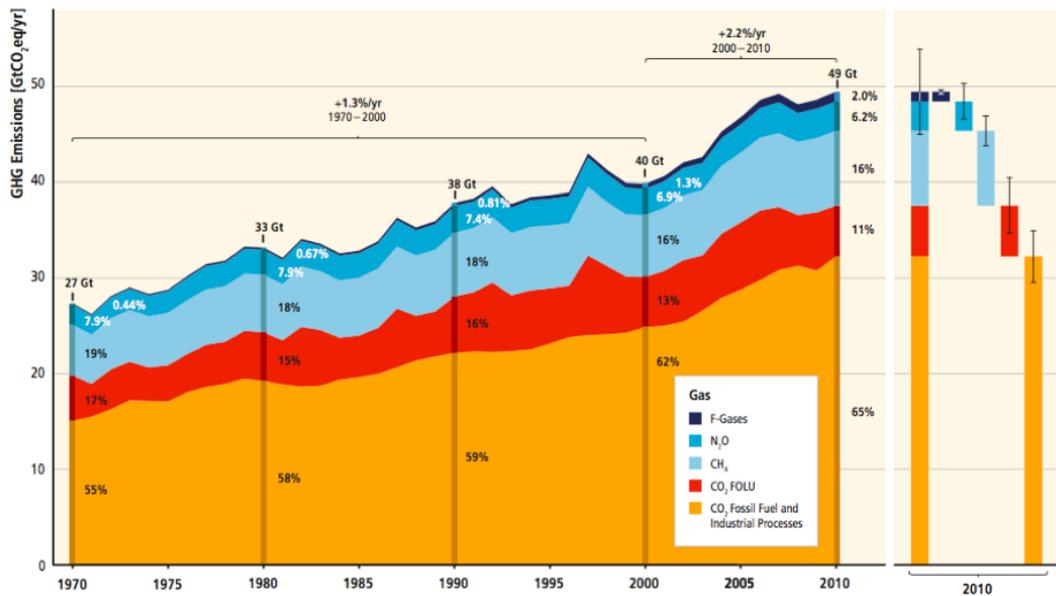


FIGURE 6: Total annual anthropogenic GHG emissions by group of gases 1970-2010 (IPCC, 2014)

affect economic growth (Dell, Jones, & Olken, 2014; Pycroft, Abrell, & Ciscar, 2016), with reductions in yields of maize, rice, wheat and other cereal crops and a loss of 7-10% of rangeland livestock, productivity (Graff Zivin & Neidell, 2014; Hallegatte, Fay, Bangalore, Kane, & Bonzanigo, 2015), and financial values.

Limiting warming to 1.5°C above pre-industrial levels requires a systemic change in terms of both mitigation of greenhouse gases and adaptation to current climate levels. Reducing greenhouse gases, namely mitigation, brings upon the decarbonization of the energy supply but also the lowering of energy use, the demotorization and decarbonization of transport, energy efficiency, use of smart grids, energy storage technologies and general-purpose technologies. On the other hand, options to reduce vulnerability and exposure to climate change, namely adaptation, include “green infrastructure, resilient water and urban ecosystem services, urban and peri-urban agriculture, and adapting buildings and land use through regulation and planning” (IPCC, 2018).

Mitigation and adaptation of climate change in accordance with the 1.5° objective requires increased flows of investments in low-emission infrastructure and products. Two policy instruments move in this direction: market-based instruments and command and control regulation. Market based instruments bring upon carbon pricing,

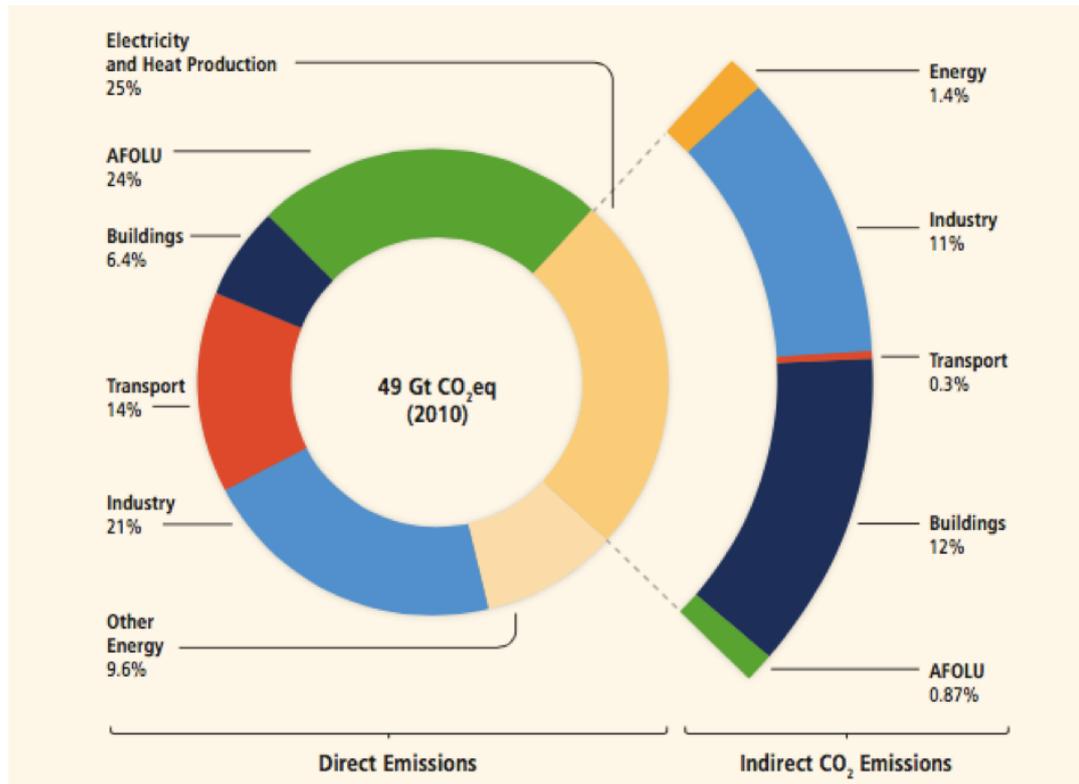


FIGURE 7: Direct and indirect GHG emissions in 2010 (IPCC, 2014)

which can be achieved through a carbon tax or an emission allowance price. Command and control regulation aims at inducing technological shifts or performance standards and usually complements carbon pricing in specific areas. Environmental economics often suggests that market-based instruments, such as the EU-ETS, permit to cut emissions in a more cost efficient and flexible way than command and control regulation, as the latter tends to prescribe the same level of activity to all firms affected by the regulation (Demirel and Kesidou, 2011; Engel, Pagiola, & Wunder, 2008). Economic theory clearly indicates that, for any given level of emission abatement, if the firm's marginal cost of abatement is higher than the market's carbon price, then the efficient choice for the firm is to not abate but purchase allowances in a cap and trade scheme. Conversely, for any given level of emission abatement, when the polluting firm faces a marginal abatement cost lower than the market's carbon price, the efficient choice for the firm is to reduce emissions and sell their permits under a cap and trade scheme (Winebrake, Farrell, & Bernstein, 1995).

Policy instruments along with *ad hoc* financial instruments (e.g. green bonds) and the reduction of socially inefficient fossil fuel subsidy regimes help to reduce

	Energy Investments	Of which Demand Side	Transport	Other Infra-structures	Total	Ratio to MER GDP
IAM Baseline (mean)	1.96	0.24			1.96	1.8%
IAM NDC (mean)	2.04	0.28			2.04	1.9%
IAM 2°C (mean)	2.19	0.38			2.19	2.1%
IAM 1.5°C (mean)	2.32	0.45			2.32	2.2%
IEA NDC	2.40	0.72			2.40	2.3%
IEA 1.5°C	2.76	1.13			2.76	2.7%
Mean IAM-IEA, 1.5°C	2.38	0.54			2.38	2.53%
Min IAM-IEA, 1.5°C	1.38	0.38			1.38	1.6%
Max IAM-IEA, 1.5°C	3.25	1.13			3.25	4.0%
OECD Baseline					5.74	5.4%
OECD 2°C	2.13	0.40	2.73	1.52	6.38	6.0%

FIGURE 8: Estimated annualized world mitigation investment needed to limit global warming to 2°C or 1.5°C (2015-2035 in trillions of US Dollars at market exchange rates) from different sources. (IPCC, 2018)

the demand for carbon-intensive products and services and shift market preferences away from fossil fuel-based technology. The ultimate aim is to promote a redirection of financial flows from potentially stranded assets to long-term low-emission assets. The financing of the ecological transition becomes, then, the main research question of what has been called climate finance.

Financial needs of the low-carbon transition and PhD research question

Figure 4 shows the costs of action to address global warming and stay below the 1.5° threshold. Required yearly investments have been evaluated at around 2.38 trillion USD (mean value) up to 2035 just for the energy sector. Who is currently providing this funding? Buchner et al. (2013) report that, in 2012, funding to mitigation measures of governments and public financial institutions was around 255 billion US dollars. On the other hand, Commercial financial institutions, such as banks, pension funds, life insurance companies, and other funds, while managing over 71 trillion US dollars in assets, contributed to climate change investments only with 22 billion US dollars. For comparison purposes, energy corporations provided 102 billion US dollars and non-energy corporations provided 66 billions. Even households contributed more than financial institutions with 33 billion US dollars.

The above picture constitutes the motivation for this PhD thesis. The main research question can be stated as follows: “Given the financial necessities of the ecological or energetic transition, how can the contribution of the financial institutions to the fight against climate change be increased?” The four chapters that form this PhD thesis start from the hypothesis that the participation of commercial financial institutions to the low-carbon transition is financially rational. Besides any ethical consideration regarding the obtainment of the ecological transition that the author surely endorses, taking a stake in the ecological transition is financially profitable. This hypothesis becomes an argument when it is empirically proven. Throughout the four chapters I present here, the objective is to provide scientific ground to the hypothesis of the financial profitability of taking part to the ecological/energetic transition.

In 2019 the global bond markets outstanding value was about 105.9 trillion dollars while the global equity market capitalisation about 95.0 trillion dollars (SIFMA, 2020). In comparison, the gross market value of exchange traded futures and options was 9.1 trillion dollars and the gross market value of OTC derivatives was 12.1 trillion dollars in 2019 (BIS, 2019). These values provide an argument for the choice of the financial instruments under analysis in the four chapters presented in this PhD thesis: stocks and bonds. Derivatives are left for further research.

Climate change risks: climate risk and low-carbon transition risk

Global warming connects to the financial sphere by increasing the number of risks on the market. Academics have partitioned what we can call 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 and the value of financial assets. 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). The four chapters of this PhD thesis bring upon both "climate risk" and "transition risk" and explore their repercussions on the two most widely traded asset classes: stocks and bonds.

In a paper published in 2016, Cook et al. affirm that there is a wide scientific consensus on the effects of anthropogenic emissions on the climate: publishing climate scientists' consensus on anthropogenic global warming is in the 90%-100% range. The question and the importance of consensus does not only concern global warming but is more far-reaching. A model is a synthesized representation of reality, whether physical or chemical or economic or financial, etc. The language used in such representation is mathematical. However, models often oppose each other with partisans of one representation that battle with partisans of competing representations. In other words, formalizing a set of statements or assertions, i.e. passing from verbal day-to-day language to a formalized language like mathematics, does not increase consensus. Given these considerations, the urgency of global warming and the necessity to find an accord as wide as possible drove the choice to employ a model broadly used by both the scientific community and, especially, financial practitioners. The factor model of Fama and French (1993, 2015) can be appreciated by both applied mathematicians and the portfolio managers who dwell in a set of established practices and conventions and rely more on daily data feedbacks and analysis from Bloomberg than complex systems of partial differential equations. The Nobel prize won by Eugene Fama in 2013 for "empirical analysis of asset prices" reinforces this choice.

The classical factor models have been amended with two additional factors. A factor, *GMC* (green minus carbon), measures the green premium or the premium for not being affected by carbon pricing. This analysis, which is intended to quantify the effect of low-carbon transition risk, needed to be carried out in a place where carbon

pricing exists. This is why Europe and its Exchange Trading System (ETS) has been preferred over other world locations. The *GMC* factor has been calculated for both European stocks (chapter 1) and European bonds (chapter 2) with Bloomberg data. My findings in the 2008-2018 timeframe indicate an average *GMC* weekly percent return of 0.17 for stocks and an average *GMC* weekly percent return of 0.02 for bonds. Another factor, which has been named *LME* (light minus extreme), measures the premium for being impacted by global warming to a lesser extent, and is intended to quantify the effect of climate risk. This analysis has been carried out at a global scale: the *LME* factor has been calculated for both global stocks (chapter 3) and global bonds (chapter 4) with Reuters data. My findings in the 2008-2017 timeframe bring upon an average *LME* weekly percent return of 0.08 for stocks and an average *LME* weekly percent return of 0.01 for bonds.

Factor models have been subject to criticism. Harvey et al. (2016) argue that a t-statistic greater than 2.0 is not enough to accept a newly proposed factor and propose a higher hurdle of 3.0. Following this rule, most of the factors discovered would be false. Their arguments are the following: a) The rate of discovering a true factor has likely decreased, b) there is a limited amount of data and c) the cost of data mining has dramatically decreased. However, they admit that a factor developed from first principles should have a lower threshold t-statistic than a factor discovered from empirical exercise. Feng et al. (2020) propose a model to evaluate the contribution to asset pricing of any new factor. When applying the model to a set of recently discovered factors, most of them are shown to be redundant relative to the existing factors and only a few have statistical explanatory power. The main argument is the following: a new factor must contribute to the cross section relative to the entire universe of existing factors. The model put forward by Feng et al. (2020) aims at becoming a direct competitor of the more established Gibbons, Ross, and Shanken (1989) model that is currently used by the asset pricing literature to judge model performance. The Gibbons, Ross, and Shanken (1989) model validates the use of the *GMC* factor in all cases. Regarding the *LME* factor, its inclusion never worsens the description of average stock or bond returns; nevertheless, it is of interest for financial practitioners and legislators to have insights into the effect of global warming upon stock and bond returns. Therefore, in the spirit of Fama and French (2015) I orthogonalize

and keep *LME* just as they orthogonalized and kept *HML* in the five factor model.

Positioning in relation to existing Literature

If investors are risk adverse and try to minimise risk with the methods put forward by modern portfolio theory, then the financial markets will be affected by risk minimisation. The Capital Asset Pricing Model (CAPM) incorporates one of the key tenets of modern portfolio theory, diversification, and focuses on the part of a security risk which cannot be eliminated by diversification: systematic risk. The beta measures the sensitivity of a security or portfolio to market movements and provides a measure of systematic risk. Following the CAPM, new types of systematic risks, e.g. Fama and French's (1993), have been included in the models that try to explain the cross-section of stock returns.

The CAPM (and later models) is built around two of the dogmas of market finance. The first one states that investors holding riskier assets should perceive a higher expected return as a compensation for taking more risk: "stock prices must adjust to offer higher returns where more risk is perceived to ensure that all securities are held by someone" (Malkiel, 1982). In the CAPM setting the risk which is remunerated by the markets is not the total risk but the systematic risk. The second dogma is informationally efficient markets: efficient market theorists claim that at "any time prices fully reflect all available information" (Fama, 1970).

The four chapters presented in this PhD thesis provide empirical evidence against the first dogma. This is not the first time this happens. 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), published on the Journal of Financial Economics, also confirm these findings for several asset classes and not just stocks.

Empirical evidence shows that the dogma high risk = high return wavers. It should be no surprise, then, that the systematic risk factors put forward in this PhD

thesis — low-carbon policy (EU-ETS carbon price) and global warming (extreme climate events) — display a risk-return relationship which is consistent with the above mentioned empirical studies. We need, then, to consider an auxiliary hypothesis which coheres with the observation that, at times, high risk comes with an high return but the equivalence high risk = high return is far from being a law of nature. In other words, this auxiliary hypothesis must cohere with the statement “small cap firms returns are on average higher than big cap firms returns” but also with the statement “green (EU-ETS exempt) firms returns are on average higher than carbon (EU-ETS liable) firms returns” and the statement “light climatic impact firms returns are on average higher than extreme climatic impact firms returns”.

I believe expectations of future returns can play this role. A small cap firm has more room for growth than a big cap firm and expectations of the returns of a small cap firm are on average higher than the expectations of the returns of a big cap firm. Also, a green firm (a firm which, in my framework, is not targeted by the European Commission) has more room for growth than a carbon firm (a targeted firm) in a time of climate change and climate regulation. Again, a light climatic impact firm, i.e. a firm which operates in light climatic impact countries (global warming effects are not equally distributed), has more room for growth than an extreme climatic impact firm, i.e. a firm which operates in extreme climatic impact countries, in a time of progressive global warming.

Findings of the four chapters are consistent with the hypothesis that returns are completely determined by investors' expectations. My results for the measurement of low-carbon transition risk for stocks can be related, albeit with some differences, with the ones of Garvey, Iyer, and Nash (2018) and of In, Park and Monk (2019). These studies suggest 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. In contrast, Bolton and Kacperczyk (2020a) find that there is a carbon premium, and not a green premium, which is related to the total level of firms' emissions and year by year change in firms' emissions but not to emission intensity. The results of Bolton and Kacperczyk (2020a) for US stock returns are contradicted by a paper written by the same authors: Bolton and Kacperczyk (2020b). De Angelis et al. (2020) report that green investing encourages firms to

reduce their GHG emissions by raising their cost of capital: the doubling of the assets under management by investors with environmental preferences induces a drop of 5% of firms' carbon intensity. Ilhan et al. (2020) find that the cost of option protection against downside risk is larger for carbon intensive firms. Hsu, Li and Tsou (2020) also find that firms producing more emissions are associated with higher returns; however, they account for all toxic emissions, defined as the sum of emissions of all type of chemicals across firms' plants. In a nutshell, evidence is mixed.

My measurement of low-carbon transition risk differs from the above literature since it does not address the relationship between returns and emission levels or emission intensity. The reasoning behind *GMC* is the following: if we just consider the share of traditional investments, i.e. investments that are not determined by environmental preferences (ESG investments account for about a third of assets under management and the E is just about 9 per cent of total assets under management), then the level of total emissions (or emission intensity or the year by year change in emissions) is not an assessment criterion with respect to financial return if nobody (i.e. a government) is asking to pay for such emissions. In other words, a firm with a level of emissions equal to *Y* but which is not asked to pay for *Y*, i.e. in my framework it does not participate in the EU-ETS (it is therefore a green firm), will carry (*ceteris paribus*) a premium with respect to a firm with a level of emissions also equal to *Y* but which is asked to pay for *Y*, i.e. it does participate in the EU-ETS (it is therefore a carbon firm). This holds especially when the list of participants is revised on a phase (EU-ETS phase) basis.

I do not deny that clients and investors (asset managers) have ethical preferences, just like everybody else. Nevertheless, ethical preferences in financial markets have a time limit: a client may ask his asset manager to invest in green firms but after a period of bad results the client will dismiss his ethical preferences and ask the asset manager to allocate his savings in a more traditional way. On the other hand, the asset manager has an interest in divesting from green stocks and bonds if they underperform because the asset manager won't receive any performance fee. In a nutshell, ethical preferences need to be accompanied by financial return. This is why I put emphasis on returns rather than ethical preferences, which I do not deny. Findings of chapter two follow the same logic but the object of analysis is bonds and

not stocks. Literature with which I can compare is very scant. Delis et al. (2019) find that after 2015 banks increased loan spreads to fossil fuel firms that are exposed to climate policy risk, thus increasing their cost of debt. While these results seem to contradict mine, it should be noted that loan spreads have not increased before 2015 and loans are not quoted.

There is no available literature with which I can compare results of chapter three and four. However, findings are consistent with the hypothesis that returns are completely determined by investors' expectations. Given that global warming effects are not equally distributed around the globe, it is plausible that investors sell stocks of 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. In turn, this affects capital gains and returns. Hence, a portfolio with a long position in light climatic impact firms, i.e. firms that on average are less impacted by extreme climate events, and a short position in extreme climatic impact firms, i.e. firms that on average are more impacted by extreme climate events, generates positive returns. Satellite data can be considered an alternative to the calculation I have performed of the aggregated climate related losses at country level. Nevertheless, the latter provides a first level approximation that in an extremely interconnected and globalised world can prove to be efficient. For example, a firm listed on the NYSE with headquarters and most of its plants in the state of New York may not be affected by a storm in Louisiana directly but the extreme weather event can impact the very same firm via its supply chain or via demand dynamics. In this light, *LME* results represent an approximation and there is surely room for improvement even though the results are economically and statistically significant.

Climate and Carbon Stress-tests

Another methodological innovation of the PhD thesis brings upon the development of both a carbon stress test and a climate stress test. The carbon stress test has been designed to show the impact of plausible but more severe carbon pricing upon financial values while the climate stress test has been constructed to show the impact

of plausible but more extreme climate phenomena upon stock and bond returns. In financial risk analysis a stress test is characterized 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 rest of the introduction introduces the four chapters.

Chapter 1. The impact of low-carbon policy on stock returns

The objective of this chapter is to study the impact of low-carbon policy upon the value of financial assets, particularly stock returns. Specifically, we seek to understand and explain the impact of one particular European policy, the 2003/87/CE directive upon which the EU-ETS is based, upon European stock returns.

The 2003/87/CE directive is at the origin of the European Union Emission Trading System (EU-ETS). The EU-ETS is a market based instrument, launched as a pilot project in 2005, whose objective is to reduce greenhouse gases (GHG) emissions in all European Union (EU) countries as well as Iceland, Lichtenstein and Norway. The three-year (2005-2007) pilot project, phase I, has been followed by a four-year (2008-2012) phase II and a seven-year (2013-2020) phase III. In 2020, at the end of phase III, emissions covered by the EU-ETS, around 45% of the EU’s GHG, are expected

to be 21% lower than at the start of the pilot project (2005). From the beginning of phase III, the EU-ETS covers more than 11,000 installations consisting of power and heat generation, oil refineries, commercial aviation, and production of steel, iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals (European Commission, 2015).

The EU-ETS is a cap and trade system: the European Commission has put a cap on EU-wide GHG emissions which has been progressively reduced. When a firm belongs to one of the participating sectors, it is required to cover its emissions with emission allowances (EUAs) which are delivered on the primary market, i.e. they are either auctioned or distributed free of charge. Subsequently, in the secondary-market, EUAs trading enables firms that eventually run short of allowances to purchase additional units.

This chapter uses a multi-factor asset pricing model in order to study the impact of low-carbon policy — the 2003/87/CE directive which originated EU-ETS — upon the stock returns of European firms. In order to accomplish this task an environmental factor, *GMC* (green minus carbon), is added to the classical stock market factors introduced by Fama and French (1993, 2015): *SMB* (small minus big), *HML* (high minus low), *WMR* (weak minus robust), *CMA* (conservative minus aggressive). This chapter makes several contributions. Firstly, it is the first time that a factor, *GMC*, meant to mimic the risk factor in returns related to low-carbon policy, the 2003/87/CE directive in this case, is constructed. The *GMC* factor is obtained by means of a sample of 182 firms from 19 European countries operating in 35 sectors: from January 2008 to December 2018 the value-weight returns of 91 firms regulated by the 2003/87/CE directive are subtracted from the value-weight returns of 91 firms exempted by the 2003/87/CE directive upon which the EU-ETS is based. Secondly, we provide evidence that the addition of the *GMC* factor improves the performance of the 5 factor model in Europe in the 2008-2018 time span: we show that, just as there are patterns in average returns related to size, profitability and investment, there is also a pattern related to EU-ETS compliance. Thirdly, results show that there is a high green premium rather than a carbon premium as it was asserted by parts of the literature, and that this green premium is highly statistically significant, i.e. green stocks outperform on average carbon stocks over the 11-year

span. Additionally, we follow the recent carbon stress test trend by putting forward a stress test able to indicate what is the impact of a hypothetical EU-ETS price upon stock returns: our results show the effects of a plausible but more severe average EU-ETS price on both carbon firms and green firms for each market cap tranche.

Three policy implications can be derived from these contributions. The first two implications are of interest to financial practitioners and the third is of interest to legislators. Firstly, the presence of a green premium in the European stock market in the years 2008-2018 is a useful asset management insight for financial practitioners. In other words, green investments can no longer be understood solely from the point of view of taking an ethical stand: nowadays, as the green premium shows, investing in green firms is a profitable exercise. Secondly, in terms of asset pricing models, the augmented version of the Fama and French (2015) model for stocks is preferable to the original one, at least in Europe since 2008. Thirdly, the low-carbon transition risk stress test put forward, by showing the average impact on stock returns of various scenarios of carbon pricing, provides useful insights to legislators in terms of the financing of low-carbon transition, i.e. increasing capital inflows towards green firms and capital outflows from carbon firms. The low-shock scenario, for example, would provide an additional boost to the low-carbon transition, without harming excessively carbon firms.

Chapter 2. On bond returns in a time of climate change

The impact of a particular market-based instrument, the European Union Emission Trading System (EU-ETS), upon financial values has already been addressed by the literature; nevertheless, efforts pertain primarily to stocks, leaving the bonds field out of the picture. The objective of this chapter is to assess the impact of the 2003/87/CE directive, upon which the EU-ETS is based, on European bond returns.

In order to detect the impact of low-carbon policy — the 2003/87/CE directive which initiated EU-ETS — upon the bond returns of European firms, a Fama and French (1993) framework, for the first time, is employed. Along with the two bond

market factors proposed by Fama and French (1993), *TERM* and *DEF*, an EU-ETS participation factor is added: *GMC*. Supplementing classical factors with an environmental factor has already been done in research carried out on the stock market (Görge et al., 2017; Oestreich and Tsiakas, 2015; Ravina and Kaffel, 2019). However, some differences in the construction of the environmental factor remain. In this sense, the factor construction closer to the one presented here is found in Ravina and Kaffel (2019). The rationale behind the *GMC* factor is the following: if we want to measure the impact of the 2003/87/CE directive with a factor, one possibility is to take all firms regulated by the policy, perform carbon accounting for each firm, construct two portfolios, i.e. a high-carbon portfolio and a low-carbon portfolio, and then take the differences of the value-weight returns. Unfortunately, this operation wouldn't permit us to uncover the real green (or carbon) premium because the firms that take part in the EU-ETS are all high-carbon firms. This means that, when we build the two portfolios, the low-carbon portfolio would contain a set of firms which are only slightly less polluting than firms in the other portfolio. The resulting environmental factor would be biased, i.e. negligible in terms of magnitude. In order to cope with the fact that the EU-ETS covers only high-carbon sectors, an alternative is to construct the environmental factor by means of two portfolios, a portfolio composed of EU-ETS liable firms (which I call "carbon" portfolio) and a portfolio composed of EU-ETS exempt firms (which I call "green" portfolio). In this context, while *TERM* proxies for the common risk in bond returns related to unexpected changes in interest rates and *DEF* mimics the risk factor in returns related to shifts in economic conditions that change the likelihood of default, *GMC* (Green minus Carbon) is meant to mimic the risk factor in returns related to low-carbon policy, the 2003/87/CE directive in this case. The new component, the *GMC* factor, is obtained by subtracting the weekly value-weight carbon bond portfolio returns from the weekly value-weight green bond portfolio returns from the beginning of Phase II (2008) of EU-ETS. The carbon bond portfolio is composed of 25 firms regulated by the 2003/87/CE directive and the green bond portfolio is composed of 25 firms exempted by the 2003/87/CE directive upon which the EU-ETS is based.

This chapter makes the following contributions. Firstly, it is the first time that a factor model is employed to assess the sensitivity of bond returns to low-carbon

policy. The sensitivity of bond portfolio returns to the *GMC* factor has been found to be positive in the case of green portfolios and negative in the case of carbon portfolios. Most importantly, slopes on *GMC* are highly statistically significant. Secondly, the average value of *GMC* itself is positive: finding a positive *GMC* means that in Europe, in the 2008-2018 time-span, there is no carbon premium as some of the literature asserts, but rather a green premium. Such a green premium confirms that the EU-ETS has a positive effect in the financing of the low-carbon transition: the beginning of phase II of EU-ETS — the start date of the study— coincides with both capital outflows from EU-ETS liable firms and capital inflows to EU-ETS exempt firms. Thirdly, evidence is found that the addition of an environmental factor improves the performance of the Fama and French two factor model for bonds, at least in Europe from 2008 onwards. Fourthly, since 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; Schoemaker and van Tilburg, 2016; Zenghelis and Stern, 2016), I follow the recent carbon stress test trend and put forward a stress test that is able to indicate the impact of a hypothetical EU-ETS average price upon bond returns. The results show the effects of a plausible, but more severe, average EU-ETS price on both carbon firms and green firms.

Chapter 3. Extreme climate events and financial values: empirical evidence from the stock market

This chapter 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.

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 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 means of 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 capitalization) 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: $RM - RF$ (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 statistic, 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 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 $RM - RF$

, *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.

Chapter 4. Extreme climate phenomena and bond returns

This chapter addresses climate risk and brings upon the impact of extreme climate events upon bond returns. Particularly, 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 bonds. This research question has, to the best of our knowledge, scarcely being addressed.

We 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 assert 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 our 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, we find that there is a climate effect in average excess

bond returns, which confirms our hypothesis that a systematic risk factor, global warming in this case, was missing from the classical framework.

The main contributions of this chapter are the climatic factor and the bonds climate stress test. The slopes on the novel climatic factor are found to be statistically significant which implies that the financial sector (academics, financial practitioners) has now evidence of the impact of extreme climate events upon bond returns. In practical terms, they are now 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. An asset manager can use the methods presented in this paper to assess the impact of 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 severe extreme climate phenomena, which is something we 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.

Chapter 1

The impact of low-carbon policy on stock returns

1.1 Introduction

Climate change risks can be partitioned in two components: the risk associated with the impacts of global warming on natural and human systems and the risk originating from anthropogenic climate change mitigation. Literature designates the first component with the label “climate risk” (Carney, 2015): changes in extreme climate phenomena — e.g. temperature extremes, high sea levels extremes, precipitation extremes (Intergovernmental Panel on Climate Change, 2014) —, are likely to cause serious damages to agriculture, coastal zones, human health, and affect growth (Dell, Jones, & Olken, 2014; Pycroft, Abrell, & Ciscar, 2016), productivity (Graff Zivin & Neidell, 2014; Hallegatte, Fay, Bangalore, Kane, & Bonzanigo, 2015), the value of financial assets and insurance claims. Addressing climate change implies greenhouse gases (GHG) mitigation: the process of adjustment towards a lower carbon economy carries a cost that the literature refers to as “transition risk” or “carbon risk” (Caldecott & McDaniels, 2014).

Low-carbon transition risk is a multi-faceted concept. It includes all drivers of risk linked to the decarbonisation of the economy: pollution reducing market-based instruments (a carbon price: a carbon tax, an auction price, or a secondary market price); command and control induced technological shifts aimed at a reduction of CO₂ emissions, 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 market risk, i.e. market demands for low carbon products (Zhou et al., 2016). Market based instruments and command and control regulation find their genesis in low-carbon policy. The objective of this paper is to study the impact of low-carbon policy upon the value of financial assets, particularly stock returns. Specifically, we seek to understand and explain the impact of one particular European policy, the 2003/87/CE directive upon which the EU-ETS is based, upon European stock returns.

This research question has been partly addressed by the literature with contradictory results. In the context of the electricity sector Bernardini, Di Giampaolo, Faiella, and Poli (2019) propose a multi-factor model to investigate the effect of carbon risk on the stock returns of 13 European electric utilities finding a low-carbon premium. Zhu, Tang, Peng, and Yu (2018) use a multi-factor market model specification and a panel quantile regression in order to understand the effects of the EU-ETS carbon price on the stock returns of European carbon intensive industries from 2005 to 2017, finding a significant negative impact on the stock market during phases I and III whereas in phase II the impacts are positive. Zhang, Fang, and Wang (2018) assess the influence of carbon prices of different Chinese pilots on the stock value of thermal enterprises finding that carbon prices have a significant negative impact. Oestreich and Tsiakas (2015) investigate the effect of the EU-ETS carbon price on German and UK stock returns finding a carbon premium until march 2009: carbon intensive firms, having a higher exposure to carbon risk, exhibit higher expected returns. Zhang and Gregory-Allen (2018) follow the same methodology proposed by Oestreich and Tsiakas but apply it to the Shenzhen Pilot Emissions Trading Scheme without finding a carbon premium. Gorgen, Jacob, Nerlinger, Riordan, Rohleder and Wilkens (2017) examine carbon risk, intended as a complex of political, technological and regulatory risks, and quantify it via a "Brown-Minus-Green" factor finding that brown firms performed worse than green firms on average during the 2010-2016 sample period. Koch and Bassen (2013) utilize an asset pricing model in order to assess the impact of carbon price risk on firms' cost of capital for a sample of 20 European utility stocks from 2005 to 2010; by means of a discounted cash flow framework employed to simulate carbon-adjusted equity values for three selected

utilities from 2009 to 2020, they find that high-emitting utilities bear carbon risk premiums. Tian, Akimov, Roca, and Wong (2015) study the impact of EU-ETS on the stock returns of electricity companies during phases I and II with OLS, panel data and time-series analysis: stock returns of carbon-intensive companies are negatively affected while the opposite is true for less carbon-intensive producers. Moreno and Pereira da Silva (2016) investigate whether ETS price changes and stock returns of Spanish sectors that participate to the EU-ETS are correlated by employing a multi-factor market model specification and panel data econometric approach and find a statistically significant positive impact of EU-ETS on stock market returns for Phase II and a negative impact for phase III. Brouwers, Schoubben, Van Hulle, and Van Uytbergen (2016) put forward an event study methodology in order to study the impact of European verified emissions publications on the market value of companies participating to the EU-ETS. They find a significant negative relationship between allocation shortfalls and firm value for firms that are more carbon-intensive than sector peers or are less likely to pass through carbon-related costs in their product prices. Nguyen Anh Pham, Ramiah, and Moosa (2019) investigate the impact of environmental regulation on the French stock market by means of an event study methodology: their results show negative returns for chemicals, oil and gas industries whereas other polluters produce positive abnormal returns.

The paper closest to ours is surely Oestreich and Tsiakas' (2015). Nevertheless, there are some substantial differences in terms of: 1) geographical reach, i.e. the data sample is confined to 65 German firms and 83 UK firms whereas we provide a database of 182 firms across 19 European countries, 2) portfolio balance, i.e. the environmental factor in Oestreich and Tsiakas (2015) is built with 24 carbon firms and 41 green firms for Germany and 16 carbon firms and 67 green firms for the UK, whereas our sample includes 91 green stocks and 91 carbon stocks, 3) time-span, i.e. 2003-2012 in Oestreich and Tsiakas (2015) compared to our 2008-2018 sample and 4) model, i.e. Oestreich and Tsiakas (2015) use as a basis Fama and French's (1993) three factor model and Carhart's (1997) four factor model, whereas we use Fama and French's (2015) five-factor model which has been proven more performing by its authors.

Recently, the literature has proposed stress testing, a technique finalized at testing the stability of an entity, as an evaluation framework for climate change risks. In financial risk analysis a stress test is characterized 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 outcome. In this context, 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 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.

On the carbon risk side, these endorsements have been followed up by research on carbon stress test design. Battiston, Mandel, Monasterolo, Schütze, and Visentin (2017) study how climate policy risk may propagate through the financial system by putting forward a second round effect measurement methodology. The Industrial and Commercial Bank of China (2016) evaluates the impact of upcoming environmental protection policies — tightening of emission limits and raise of pollutant discharge fees — for two industries, thermal power and cement, in order to figure out the changes of the firms’ financial indicators and assess their resulting new credit ratings and probabilities of default by using the bank’s rating models. Cambridge Centre for Sustainable Finance (2016) assesses the impacts on oil, gas and utility firms’ profitability of scenarios on environmental regulation and carbon pricing. Both the Industrial and Commercial Bank of China and the Cambridge Centre for Sustainable Finance models are proprietary.

This paper uses a multi-factor asset pricing model in order to study the impact of low-carbon policy —the 2003/87/CE directive which originated EU-ETS— upon

the stock returns of European firms. In order to accomplish this task an environmental factor, GMC (green minus carbon), is added to the classical stock market factors introduced by Fama and French (1993, 2015): SMB (small minus big), HML (high minus low), WMR (weak minus robust), CMA (conservative minus aggressive). This paper makes several contributions. Firstly, it is the first time that a factor, GMC, meant to measure the premium which results from not paying a carbon price is constructed. The GMC factor is obtained by means of a sample of 182 firms from 19 European countries operating in 35 sectors: from January 2008 to December 2018 the value-weight returns of 91 firms regulated by the 2003/87/CE directive are subtracted from the value-weight returns of 91 firms exempted by the 2003/87/CE directive upon which the EU-ETS is based. Secondly, we provide evidence that the addition of the GMC factor improves the performance of the 5 factor model in Europe in the 2008-2018 time span: we show that, just as there are patterns in average returns related to size, profitability and investment, there is also a pattern related to EU-ETS compliance. Thirdly, results show that there is a high green premium rather than a carbon premium as it was asserted by parts of the literature, and that this green premium is highly statistically significant, i.e. green stocks outperform on average carbon stocks over the 11-year span. Additionally, we follow the recent carbon stress test trend by putting forward a stress test able to indicate what is the impact of a hypothetical EU-ETS price upon stock returns: our results show the effects of a plausible but more severe average EU-ETS price on both carbon firms and green firms for each market cap tranche.

The paper is structured in the following way: section 1.2 presents the model; section 1.3 introduces the data; section 1.4 provides the empirical results; section 1.5 explores a PCA-based specification of the model and the consequent results; section 1.6 puts forward the carbon stress test; section 1.7 concludes.

1.2 The model

In order to estimate the impact of the 2003/87/CE directive, which originated EU-ETS, on European firms, we add a factor to Fama and French's (2015) "classical" five

factors. This supplementary factor, GMC (green minus carbon), is obtained by subtracting the monthly value-weight carbon portfolio returns from the monthly value-weight green portfolio returns. Before carrying out the analysis in these terms, the implicit question “is there enough evidence to add a sixth factor?” must be answered. This evidence derives from a comparison of the original 5 factor model with the 5+1 model we put forward. Fama and French’s (2015) original five factor model is based on the following time-series regression:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t} \quad (1.1)$$

In the equation, $R_{i,t}$ is the value weight return for security or portfolio i for period t ; $R_{F,t}$ is the risk free rate; $R_{M,t}$ is the value weight 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.

The environmental factor we put forward, GMC (green minus carbon), is a portfolio meant to mimic the risk factor in returns related to low-carbon policy and it’s calculated as the difference between the returns of the value-weight portfolio of green stocks and the returns of the value-weight portfolio of carbon stocks. Given our research question, we consider firms to be “carbon” if a) they belong to the sectors that take part to the EU-ETS since the beginning of phase II (2008), b) at least one installation of the firm is listed in the EU-ETS transaction log, and c) the firm is listed on a European stock exchange of the countries participating to the EU-ETS,

i.e. the EU countries plus Iceland, Liechtenstein and Norway. We consider firms to be “green” if a) they belong to the sectors which do not take part to the EU-ETS since the beginning of phase II, b) no firm installations are inventoried on the EU-ETS transaction log, and c) the firm is listed on a European stock exchange of the countries participating to the EU-ETS . Participant sectors are the following: power stations and other combustion plants $> 20MW$, oil refineries, coke ovens, iron and steel plants, cement clinker, glass, lime, bricks, ceramics, pulp, paper and board (European Commission, 2015).

Table 1.1 displays the averages of monthly percent returns for the environmental factor, GMC, for each year from 2008 to 2018. We can see that at the very beginning of phase II of EU-ETS (2008), GMC is positive (+2.71%). It is slightly negative in 2009 and then picks up in 2010 (+1.66%), 2011 (+1.45%), 2012 (+0.69%), and 2013 (+0.86%, beginning of phase III), it lowers to almost zero in 2014 (+0.02%) and then picks up again in 2015 (+1.37%). It then drops in 2016 (-1.24%), which singularly is the year after the COP 21 meeting (which took place in Paris in December 2015) and starts to increase slowly from 2017 onwards. There is a clear path in the magnitude of GMC, starting from the beginning of phase II in 2008 and which is only stopped in 2016 by, we suppose, a market negatively perceived COP 21 outcome. Over the 11-year span the average monthly percent return for the GMC factor is 0.73%.

TABLE 1.1: Average monthly GMC percent return from 2008 to 2018

Years	returns
2008	2.71
2009	-0.17
2010	1.66
2011	1.45
2012	0.69
2013	0.86
2014	0.02
2015	1.37
2016	-1.24
2017	0.52
2018	0.24
Average	0.73

Table 1.1 provides an argument to test a 5+1 version of Fama and French’s (2015) five factor model and see if the augmented model outperforms — in Europe in the 2008-2018 time span — the classical one. The 5+1 model specification, which we call

EE-FF (environmentally-extended Fama and French) model is the following:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + g_iGMC_t + e_{i,t} \quad (1.2)$$

1.3 The data

The EE-FF model (1.2) aims at capturing patterns in average returns related to size, value, profitability, investment and EU-ETS compliance. The explanatory variables include the returns on a market portfolio of European stocks, R_M , and mimicking portfolios for the size, SMB , value, HML , profitability, RMW , investment, CMA , and EU-ETS compliance, GMC , factors in returns. The returns to be explained are the value weight returns for subsets of the portfolio of 182 European stocks upon which the GMC factor is based. Such subsets are formed by breaking up the 182 firms into 8 portfolios based on market capitalization and EU-ETS compliance: the 8 stock portfolios are formed from annual (2008-2018) sorts of stocks into 4 size groups (4 quartiles) and two EU-ETS groups — liable firms, which we call carbon, and exempt firms, which we call green —. Liable firms participate to the EU-ETS in the 2008-2018 time frame while exempt firms do not participate. The risk free rate, R_F , is the 1-month Euribor rate.

1.3.1 Explanatory returns

The 5 classical factors — R_M, SMB, HML, RMW, CMA — are taken directly from Fama and French's database of factors for the European market. 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 5 classical factors (2x3) are constructed using 6 value-weight portfolios formed on size and book-to-market, 6 value-weight portfolios formed on size and operating profitability, and 6 value-weight 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 is the return on Europe's value-weight market portfolio.

The environmental factor, GMC (green minus carbon), is constructed using a portfolio of 182 European stocks, out of which 91 participate to the EU-ETS since the beginning of phase II (2008) and 91 do not participate to the EU-ETS since the beginning of phase II. A firm participates to the EU-ETS since the beginning of phase II if it belongs to one of the following sectors: power stations and other combustion plants $> 20\text{MW}$, oil refineries, coke ovens, iron and steel plants, cement clinker, glass, lime, bricks, ceramics, pulp, paper and board (European Commission, 2015). The EU-ETS liable group of firms ("carbon" firms) is formed on the following three criteria: a) belonging to the sectors that take part to the EU-ETS since the beginning of phase II (2008), b) having at least one installation listed in the EU-ETS transaction log, and c) listing on a European stock exchange of the countries participating to the EU-ETS, i.e. the EU countries plus Iceland, Liechtenstein and Norway. We consider firms to be "green", i.e. EU-ETS exempt, if the following three criteria are met: a) belonging to the sectors which do not take part to the EU-ETS since the beginning of phase II, b) no firm installations are inventoried on the EU-ETS transaction log, and c) the firm is listed on a European stock exchange of the countries participating to the EU-ETS.

Two portfolios, comprising in one case stocks of carbon firms and, in the other, stocks of green firms, have been formed from January 2008 to December 2018. The portfolios do not need to be shuffled on a yearly basis since the 182 European firms that are under examination constantly participate (or not) to the EU-ETS in the 2008-2018 time frame. Monthly value-weight stock returns have been calculated for the two portfolios for the 11-year time frame for a total of 24,024 observations. Lastly, GMC is obtained by subtracting the monthly value-weight carbon portfolio return from the monthly value-weight green portfolio return.

1.3.2 Explained returns

In the EE-FF model (1.2), the returns to be explained, R_i , are the value weight returns for subsets of the portfolio of 182 European stocks upon which the GMC factor is based. Descriptive statistics for the 182 European stock portfolio are provided in Table 1.2.

TABLE 1.2: Descriptive statistics for the 182 European stocks: country and sector (ICB) breakdown for Carbon and Green firms

<i>Panel A: Country breakdown</i>			
Green firms		Carbon firms	
EU country	Firms	EU country	Firms
Austria	4	Austria	6
Belgium	4	Belgium	3
Czech Republic	2	Czech Republic	2
Denmark	1	Denmark	2
Finland	6	Finland	6
France	11	France	7
Germany	9	Germany	7
Hungary	1	Hungary	1
Ireland	1	Ireland	1
Italy	6	Italy	13
Lithuania	3	Lithuania	2
Netherlands	3	Netherlands	1
Poland	8	Poland	10
Portugal	1	Portugal	3
Romania	2	Romania	2
Slovenia	1	Slovenia	1
Spain	7	Spain	10
Sweden	6	Sweden	5
UK	15	UK	9
Total	91	Total	91
<i>Panel B: ICB Sector breakdown</i>			
Green firms		Carbon firms	
Sector	Firms	Sector	Firms
Asset managers	2	Alternative Electricity	4
Banks	10	Alternative fuels	2
Broadcasting & Entertainment	4	Building materials and fixtures	13
Broadline retailers	4	Containers and packaging	4
Business support services	9	Conventional electricity	18
Computer hardware	2	Exploration and production	3
Computer services	3	Forestry	1
Distillers & Vintners	1	Gas distribution	3
Durable Household products	1	Integrated Oil & Gas	14
Electronic equipment	3	Iron & Steel	9
Fixed-line telecommunications	4	Multiutilities	7
Full-line insurance	7	Paper	11
Gambling	3	Pipelines	2
Industrial machinery	2		
Media agencies	7		
Publishing	2		
Real-estate holding & development	6		
Recreational services	5		
Software	8		
Specialty finance	3		
Telecommunications equipment	4		
Toys	1		
Total	91	Total	91

Such subsets are formed from annual (2008-2018) sorts of stocks into 4 size groups (4 quartiles) and 2 EU-ETS compliance groups: EU-ETS liability and EU-ETS exemption. Table 1.3 shows the average monthly value-weight excess returns for the 8 portfolios obtained from annual sorts of the 182 European stocks into 4 size groups (4 quartiles) and two EU-ETS compliance groups. Once again, we call the portfolio “carbon” if it includes firms that do participate to the EU-ETS, and we call the portfolio “green” if it includes firms which do not take part to the EU-ETS. Here, average return typically falls from small stocks to big stocks, i.e. there is a clear size effect pattern. Even though the size effect isn’t evident from the second to the third quartile, it clearly shows from the first to the fourth quartile. This holds both in the case of carbon stocks and in the case of green stocks. What matters to us, rather than the size effect, which has been proven elsewhere, is the EU-ETS effect. The latter shows up even more clearly than the size effect: the green portfolio systematically outperforms its carbon counterpart at each size level.

TABLE 1.3: Averages of monthly percent excess returns for 8 value-weight portfolios formed from sorts on size and EU-ETS compliance. January 2008-December 2018.

Size	Green	Carbon
Small	0.03	-0.14
Medium/low	0.46	-0.73
Medium/high	0.20	-0.54
Big	-0.18	-0.55

1.4 Results

The classical Fama and French’s (1.1) five factor model and the EE-FF model (1.2) have been run for each dependent variable for a total of 16 time-series regressions. There is direct evidence that the addition of a sixth factor improves the effectiveness of the classical five factor model, at least in Europe in the 2008-2018 time span. Overall, the slopes and the R^2 values obtained with the EE-FF model are direct evidence of the impact of the EU-ETS (low-carbon policy) upon European stock returns.

Table 1.4 displays the results of the 8 regressions, one for each response variable, that have been run with five explicatory variables — R_M, SMB, HML, RMW, CMA — and of the 8 regressions which have been run with six explicatory variables —

$R_M, SMB, HML, RMW, CMA, GMC$ — . The response variables are the monthly value weight excess returns of the eight portfolios formed from annual sorts of the 182 European stocks into 4 size groups (4 quartiles) and two EU-ETS groups (liable and exempt).

TABLE 1.4: Results of the regressions carried out with the five factor model (FF) and the EE-FF for 8 value-weight portfolios formed on size and EU-ETS participation. January 2008-December 2018.

Portfolio	FF		EE-FF		Portfolio	FF		EE-FF	
	α	$t(\alpha)$	α	$t(\alpha)$		α	$t(\alpha)$	α	$t(\alpha)$
Green/Small	0.01	0.1	-0.01	-0.17	Carbon/Small	0.01	0.40	0.01	1.22
Green/M-l	0.01	2.12	0.01	1.21	Carbon/M-l	-0.01	-1.12	0.01	0.57
Green/M-h	0.01	2.15	0.01	1.41	Carbon/M-h	-0.01	-1.02	0.01	1.02
Green/Big	0.01	0.15	-0.01	-0.41	Carbon/Big	-0.01	-1.51	0.01	0.06
	β	$t(\beta)$	β	$t(\beta)$		β	$t(\beta)$	β	$t(\beta)$
Green/Small	0.49	8.90	0.50	8.93	Carbon/Small	0.42	5.29	0.40	5.12
Green/M-l	0.66	11.28	0.68	11.73	Carbon/M-l	0.51	5.80	0.46	5.87
Green/M-h	0.69	13.06	0.70	13.34	Carbon/M-h	0.79	11.47	0.74	12.57
Green/Big	0.64	10.64	0.65	10.84	Carbon/Big	0.65	11.98	0.62	12.53
	s	$t(s)$	s	$t(s)$		s	$t(s)$	s	$t(s)$
Green/Small	0.58	3.90	0.59	3.95	Carbon/Small	0.16	0.75	0.11	0.53
Green/M-l	0.38	2.39	0.42	2.67	Carbon/M-l	0.84	3.55	0.73	3.41
Green/M-h	0.13	0.91	0.15	1.10	Carbon/M-h	0.45	2.43	0.35	2.20
Green/Big	-0.10	-0.62	-0.07	-0.46	Carbon/Big	-0.22	-1.47	-0.28	-2.05
	h	$t(h)$	h	$t(h)$		h	$t(h)$	h	$t(h)$
Green/Small	0.03	0.16	0.08	0.37	Carbon/Small	-0.20	-0.68	-0.42	-1.37
Green/M-l	-0.38	-1.72	-0.22	-0.99	Carbon/M-l	0.58	1.77	0.12	0.41
Green/M-h	-0.31	-1.56	-0.20	-0.98	Carbon/M-h	0.09	0.36	-0.32	-1.40
Green/Big	0.08	0.34	0.19	0.80	Carbon/Big	0.51	2.49	0.24	1.25
	r	$t(r)$	r	$t(r)$		r	$t(r)$	r	$t(r)$
Green/Small	0.20	0.70	0.23	0.79	Carbon/Small	-0.45	-1.09	-0.58	-1.42
Green/M-l	-0.05	-0.17	0.04	0.14	Carbon/M-l	-0.15	-0.33	-0.42	-1.02
Green/M-h	-0.36	-1.32	-0.30	-1.08	Carbon/M-h	0.18	0.52	-0.06	-0.19
Green/Big	0.15	0.47	0.21	0.68	Carbon/Big	0.55	1.96	0.39	1.52
	c	$t(c)$	c	$t(c)$		c	$t(c)$	c	$t(c)$
Green/Small	-0.08	-0.35	-0.10	-0.42	Carbon/Small	-0.30	-0.90	-0.22	-0.66
Green/M-l	-0.30	-1.20	-0.36	-1.48	Carbon/M-l	-0.73	-2.00	-0.55	-1.67
Green/M-h	-0.49	-2.19	-0.53	-2.40	Carbon/M-h	-0.67	-2.35	-0.51	-2.05
Green/Big	-0.42	-1.68	-0.47	-1.86	Carbon/Big	-0.42	-1.85	-0.32	-1.51
	g	$t(g)$	g	$t(g)$		g	$t(g)$	g	$t(g)$
Green/Small			0.09	0.79	Carbon/Small			-0.44	-2.60
Green/M-l			0.33	2.61	Carbon/M-l			-0.93	-5.44
Green/M-h			0.22	2.00	Carbon/M-h			-0.85	-6.61
Green/Big			0.23	1.73	Carbon/Big			-0.54	-5.02

The adjusted R^2 values for the original Fama and French (FF) model fall in between the 0.31-0.72 range, meaning that the FF model fares quite well in the representation of the variance of the outcome variables, at least in Europe in the 2008-2018 time frame. The 0.31 R^2 value comes from the small cap/carbon portfolio regression, while the second lowest R^2 value is 0.51 (medium-low cap/carbon), which is followed by an R^2 value of 0.54 (small cap/green). All other R^2 values are above 0.64.

We can report that all intercepts of the 8 time-series regressions carried out with the FF model are almost indistinguishable from zero — the lowest being -0.01 and the highest being 0.01 — and 2 intercepts out of 8 are statistically significant at the 0.05 level. Fama and French (2015) suggest two interpretations of the zero-intercept hypothesis: the mean-variance-efficient tangency portfolio combining the explanatory returns and interpreting the factor model as the regression equation of Merton's (1973) model in which unspecified state variables lead to risk premiums that are not captured by the market factor. 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. Under the assumption of the zero-intercept hypothesis, the range of values obtained for the intercepts provide evidence of the accuracy of the FF model to represent the financial reality under analysis.

Table 1.4 also shows coefficients and t -statistics for the five factors. While the market factor is always highly statistically significant, the size factor is significant at the 0.05 level in 4 out of 8 cases (small cap/green, medium-low cap/green, medium-low cap/carbon, medium-high cap/carbon). The value factor is statistically significant at the 0.05 level in one case out of eight (big cap/carbon) and the investment factor —CMA— in three out of eight cases (medium-high cap/green, medium-low cap/carbon, medium-high cap/carbon).

The EE-FF model finds adjusted R^2 values in the 0.34-0.76 range. The regressions carried out with the EE-FF model find adjusted R^2 values which are larger in 6 cases out of 8 than the regressions carried out with the classical FF model. The only R^2 values which do not improve in the *passage* from a five factor model to a six factor model come from the small cap/green regression and the big cap/green regression. In these two cases the adjusted R^2 values are exactly the same for the FF model and

the EE-FF model.

We find highly statistically significant coefficients for the GMC factor in 6 regressions out of 8, the only exception being the small cap/green portfolio (t-statistic=0.79) and the big cap/green portfolio (t-statistic= 1.73). As expected, coefficients are positive when the dependent variable is a green (i.e. does not participate to the EU-ETS) portfolio and negative when the dependent variable is a carbon (i.e. does participate to the EU-ETS) portfolio. GMC's positive coefficients range from 0.09 (small cap/green) to 0.33 (medium-low cap/green), whereas GMC's negative coefficients range from -0.44 (small cap/carbon) to -0.93 (medium-low cap/carbon).

Again, the GMC coefficient for the small cap/green portfolio (0.79) and the big cap/green portfolio (t-statistic= 1.73) are the only two coefficients which are not statistically significant at the 0.05 level. Additionally, the magnitude of the coefficients of the green portfolios are evidently lower than their carbon counterparts, i.e. firms are more penalized for their participation to the EU-ETS rather than rewarded for their exemption from the EU-ETS. We suspect this is due to the fact that there are some sectors which are considered as carbon-intensive by the market but which are not yet included in the EU-ETS participant list. Armed with statistical evidence, we conclude it is legitimate to consider the addition of the GMC factor to the classical Fama and French's five factors in Europe, at least from 2008.

1.5 Redundant factors

The previous section has shown that the inclusion of a sixth factor —GMC— improves the effectiveness of Fama and French's five factor model in Europe from 2008 onwards. Nevertheless, such addition may hinder the explication power of the classical five factors, i.e. the portion of variance in returns explained by a "classical" factor may be partially absorbed by the GMC factor we are putting forward. As such addition may lead to a factor redundancy, we perform a principal component analysis (PCA) on the 5+1 factors in order to figure out how many factors to include in the regression of the returns to be explained, $R_i - R_F$.

Table 1.5 shows the correlations matrix between the 6 factors. Noticeable correlations are shown between R_M , or MkT , and HML (0.49), between RMW and HML

(-0.83) and between RMW and R_M (-0.41).

TABLE 1.5: Correlation Matrix for the market, size, value, profitability, investment and EU-ETS factor

	MkT	SMB	HML	RMW	CMA	GMC
MkT	1.00	-0.02	0.49	-0.41	-0.27	-0.31
SMB	-0.02	1.00	-0.05	-0.08	-0.21	-0.06
HML	0.49	-0.05	1.00	-0.83	0.33	-0.35
RMW	-0.41	-0.08	-0.83	1.00	-0.31	0.24
CMA	-0.27	-0.21	0.33	-0.31	1.00	0.06
GMC	-0.31	-0.06	-0.35	0.24	0.06	1.00

Table 1.6 displays the eigenvalues and the proportion of variances retained by the principal components. If we were to follow Kaiser's rule we would have to retain only two components and thus discard 4 factors out of 6. Given the high correlation between RMW and HML and the relative low contribution of SMB to the two main principal components (figure 1.1), these would be natural candidates to the discarded. Unfortunately, figure 1.1 shows that the contribution of CMA is superior to that of GMC . Ultimately, if we were to follow Kaiser's rule we would just settle for the market factor, R_M (MkT), and the investment factor, CMA . As this choice is not coherent with our research objective, we decide not to follow Kaiser's rule and settle for three components which account for 80% of the total variance: R_M (MkT), CMA and GMC . The reduced version of the EE-FF model, then, becomes:

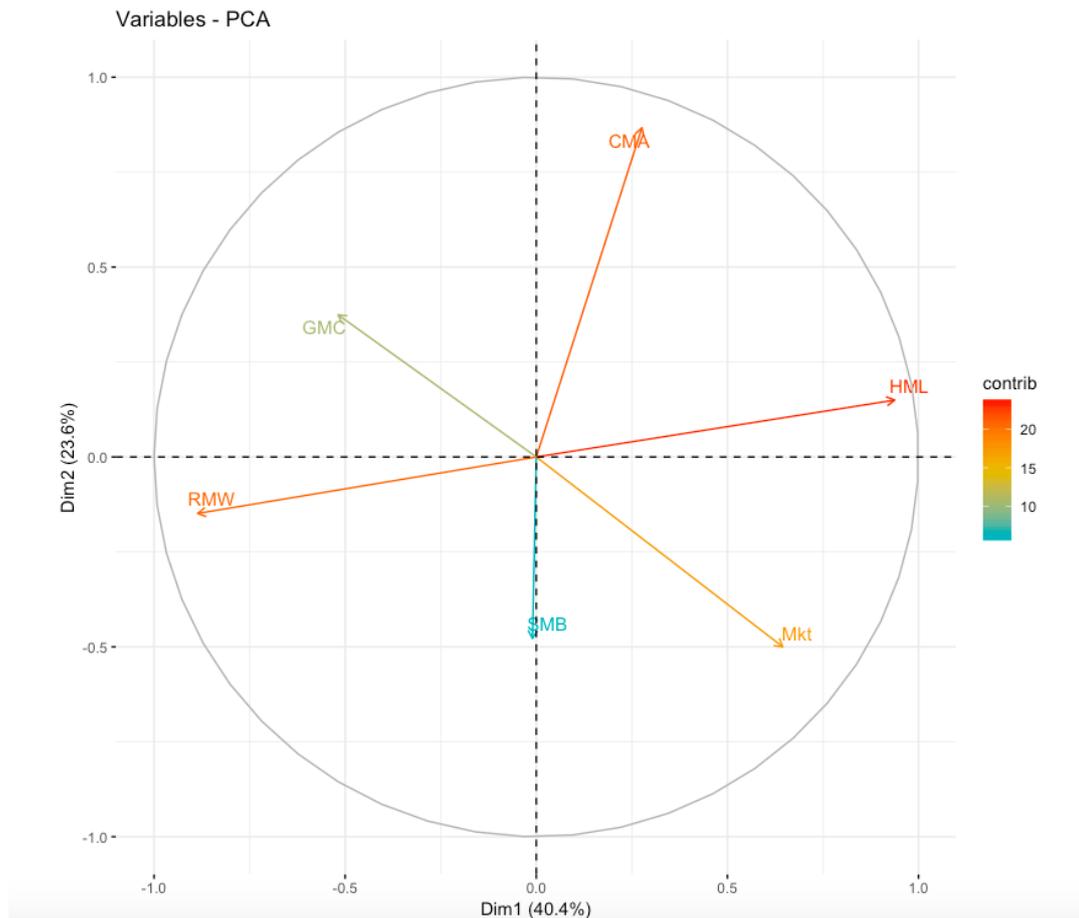
$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + c_i CMA_t + g_i GMC_t + e_{i,t} \quad (1.3)$$

TABLE 1.6: Eigenvalues, variance and cumulative variance for the 6 components

	Eigenvalues	Percent variance	Cum. percent variance
Dimension 1	2.42	40.41	40.41
Dimension 2	1.41	23.57	63.98
Dimension 3	0.97	16.20	80.19
Dimension 4	0.75	12.58	92.77
Dimension 5	0.29	4.88	97.66
Dimension 6	0.14	2.23	100.00

Table 1.7 displays the results of the 8 regressions, one for each response variable, that have been run with three explicatory variables — R_M , CMA , GMC —. The response variables are the monthly value weight excess returns of the eight portfolios

FIGURE 1.1: Contributions of Mkt, SMB, HML, RMW, CMA and GMC variables to the two first dimensions



formed from annual sorts of the 182 European stocks into 4 size groups (4 quartiles) and two EU-ETS groups (liable and exempt).

A comparison of table 1.4 — the EE-FF with 6 factors— and table 1.7 — EE-FF with 3 factors — shows that reducing the number of factors improves t -values for the intercepts in five cases out of eight. On the other hand reducing the number of factors increases the statistical significance of the market coefficient for eight portfolios out of eight and of the investment coefficient for six portfolios out of eight. With regard to the GMC coefficient, moving on from 6 to 3 factors only improves the statistical significance of the coefficient in 4 cases out of 8. The adjusted R^2 values of the EE-FF with 3 factors (table 1.7) only improve over the adjusted R^2 values of the EE-FF with 6 factors (table 1.4) in one case out of eight: the big cap/green portfolio. The adjusted R^2 values for the other portfolios are exactly identical or slightly inferior. Overall, we find that the reduced version of the EE-FF model (3 factors), while

TABLE 1.7: Results of the regressions for 8 value-weight portfolios formed on size and EU-ETS participation carried out with the 3 factor EE-FF model. January 2008-December 2018.

Size	Green	Carbon	Green	Carbon
	α		$t(\alpha)$	
Small	0.01	0.01	0.64	0.85
Medium/low	0.01	0.01	1.70	0.67
Medium/high	0.01	0.01	1.28	1.31
Big	-0.01	0.01	-0.24	0.37
	β		$t(\beta)$	
Small	0.46	0.38	10.04	6.17
Medium/low	0.61	0.52	13.01	7.85
Medium/high	0.69	0.67	16.59	14.01
Big	0.67	0.63	14.12	15.73
	c		$t(c)$	
Small	-0.33	-0.30	-1.73	-1.18
Medium/low	-0.70	-0.44	-3.58	-1.61
Medium/high	-0.59	-0.86	-3.41	-4.31
Big	-0.39	-0.23	-2.01	-1.37
	g		$t(g)$	
Small	0.05	-0.40	0.44	-2.49
Medium/low	0.35	-1.05	2.86	-6.02
Medium/high	0.23	-0.81	2.17	-6.48
Big	0.21	-0.55	1.68	-5.18

leading to some moderate statistical improvements over the EE-FF model with 6 factors, partially loses economic and financial significance by dropping the size, value and profit factor.

1.6 The carbon stress test

The financial stress test literature, following Koliai (2016), can be split in four main categories (table 1.8): 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 realized exercises.

The literature, while portraying stress testing as quintessential to financial risk management (Bensoussan, Guegan, & Tapiero, 2014), describes the technique through dichotomies: top-down and bottom-up approaches, first and second round effects, sensitivity and scenario analysis, historical and hypothetical scenarios, direct and reverse stress tests. In the top-down approaches the empirical relationship between a

TABLE 1.8: Categorisation of stress test literature (Koliai, 2016).

Topic	Selected authors
Conceptual aspects	Berkowitz (2000); Blaschke et al. (2001); Čihák (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 Csiszár (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.

banking variable and an exogenous stressor is assumed at the portfolio level of low granularity, while in the bottom-up approach the empirical relationship is estimated at the highest possible level of granularity of a banking variable. The division refers to the US definitions whereas in Europe top-down refers to stress tests carried out by regulators and bottom-up by banks. First-round effects come from the immediate impact of the shock on the financial system, while second-round effects include “possible domino effects from the institutions that are directly affected by the shock to other intermediaries and, possibly, to market infrastructures and the entire financial system” (Quagliariello, 2009, p.33). Sensitivity testing aims at determining how changes to a single risk factor will impact the institution or the portfolio while scenario analysis studies the effect of a simultaneous move in a group of risk factors. Scenarios have been subjects 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). Direct stress tests set scenarios and derive losses, while “starting from a big loss and working backward to identify how such a loss would occur is commonly referred to among risk management professionals as reverse stress testing” (Breuer, Jandačka, Mencía, & Summer, 2012, p. 332).

The carbon stress test we put forward is based on the GMC factor obtained with the EE-FF model (6 factors). The GMC is a proxy that mimics the risk factor in returns related to the payment of a carbon price and its coefficient—in the EE-FF model—is interpreted as the average effect on stock returns of a one unit increase

in GMC holding all other predictors fixed. It follows that, if GMC increases, the risk factor related to participating to the EU-ETS raises accordingly. Conversely, if GMC decreases, the risk factor related to participating to the EU-ETS diminishes. It is evident that a carbon risk factor increase goes with a higher EU-ETS price, whereas a carbon risk factor decrease goes with a lower EU-ETS price. In order to understand the impact of a hypothetical, but plausible and severe, EU-ETS price upon the stock returns under examination, we stress the average GMC portfolio value by 20% (low shock), 50% (medium shock), and 100% (high shock) and we look at the effect on each of the 8 value-weight portfolios formed from annual sorts of the 182 European stocks into 4 size groups (4 quartiles) and two EU-ETS compliance groups (liable, or carbon, and exempt, or green).

TABLE 1.9: 11-year (2008-2018) average monthly percent excess returns explained by the GMC factor for stressed values of GMC.

Portfolio	Average excess returns		
	Low shock	Medium shock	High shock
Green/Small	0.08	0.10	0.13
Green/M-l	0.29	0.37	0.49
Green/M-h	0.19	0.24	0.32
Green/Big	0.20	0.25	0.34
Carbon/Small	-0.39	-0.49	-0.65
Carbon/M-l	-0.82	-1.03	-1.37
Carbon/M-h	-0.75	-0.94	-1.25
Carbon/Big	-0.48	-0.60	-0.80

Table 1.9 shows the results of the carbon stress test for each of the 8 value-weight portfolios for the three shock scenarios: the second, third and fourth column provide the averages of monthly percent excess returns explained by the GMC factor for stressed values of GMC. Results of the carbon stress test show the magnitude of the increase (decrease) of average excess stock returns for green firms (carbon firms) in case of an average ETS price appreciation of 20% (low shock), 50% (medium shock), and 100% (high shock) for each market cap tranche.

1.7 Conclusions

Changes in extreme climate phenomena such as temperature extremes, high sea levels extremes or precipitation extremes are likely to seriously affect several facets of

natural and human systems. There is scientific evidence that human activity, by altering the composition of the atmosphere, contributes to global warming. Addressing climate change implies greenhouse gases (GHG) mitigation, and, while this can be sometimes autonomous, it is mostly carried out with policy, i.e. low-carbon policy. This leads to the research question of the effect of low-carbon policy upon financial values. In the context of EU-ETS, this question has found contradictory results: some studies find the impact of this low-carbon policy on financial values beneficial, some others find it detrimental.

The objective of this paper is to study the impact of low-carbon policy upon the value of financial assets, particularly stock returns. Specifically, we seek to understand and explain the impact of one particular European policy, the 2003/87/CE directive upon which the EU-ETS is based, upon European stock returns. To answer this question, we selected 182 European firms that fall in two categories: firms that do participate to the EU-ETS (carbon firms) and firms that do not participate to the EU-ETS (green firms) since the beginning of phase II (2008). With 11 years of data (2008-2018) we use a multi-factor model inspired by Fama and French (2015) whose key new component is an EU-ETS compliance factor, GMC (green minus carbon). The GMC portfolio is obtained by subtracting the monthly value-weight carbon portfolio returns from the monthly value-weight green portfolio returns.

Following our analysis, results show that, just as there are patterns in average returns related to size, profitability and investment, which have been proven elsewhere, there is also a pattern related to EU-ETS compliance. Such pattern exists, in Europe, since the implementation of EU-ETS: there is a high green premium, rather than a carbon premium like parts of the literature asserted previously, and this green premium is highly statistically significant, i.e. green stocks outperform on average carbon stocks over the 11-year span. Furthermore, we follow the recent carbon stress test trend by putting forward a stress test able to indicate what is the impact of a hypothetical EU-ETS price upon stock returns: our results show the effects of a plausible but more severe average EU-ETS price on both carbon firms and green firms for each market cap tranche.

These results are also the basis for the policy implications for legislators and

financial practitioners. Our findings show that the 2003/87/CE directive has a positive effect in the financing of the low-carbon transition: the beginning of phase II of EU-ETS — the start date of our study — coincides with both capital outflows from high-carbon firms and capital inflows to low-carbon firms. The carbon stress test we put forward shows by how much an increase of the EU-ETS price would accelerate such process. The low-shock scenario, for example, would provide an additional boost to the low-carbon transition without harming excessively high-carbon firms. From a financial practitioner perspective, our findings show that, in Europe, in the 2008-2018 time span, low-carbon firms have outperformed high-carbon firms and that this outperformance is statistically significant. In other words, low-carbon investments cannot be considered anymore just an ethical stand: nowadays, as the green premium shows, investing in low-carbon firms is a profitable exercise.

Chapter 2

On bond returns in a time of climate change

2.1 Introduction

Climate change is attributed to two different causes: natural climate variability — natural internal processes or external forcings — and human activity that alters the composition of the atmosphere (Intergovernmental Panel on Climate Change, 2014; United Nations, 1992). The consensus of actively publishing climate scientists on anthropogenic global warming is in the 90%-100% range (Cook et al., 2016). The breaking point of human contribution to climate change is usually identified with the industrial revolution since economic development is strictly correlated to energy consumption (Energy Information Administration, 2017; Stern, 2007): the burning of fossil fuels has increased the concentration of atmospheric carbon dioxide (CO₂), the most prominent forcing factor, from 280 parts per million (ppm) in preindustrial times to approximately 400 ppm (Wagner & Weitzman, 2016).

The literature has established a dichotomy of climate change risks. The first category has been labeled “climate risk” (Carney, 2015): changes in extreme climate phenomena — e.g. temperature extremes, high sea levels extremes, precipitation extremes (Intergovernmental Panel on Climate Change, 2014) —, are likely to cause serious damages to agriculture, coastal zones, human health, and affect growth (Dell, Jones, & Olken, 2014; Pycroft, Abrell, & Ciscar, 2016), productivity (Graff Zivin & Neidell, 2014; Hallegatte, Fay, Bangalore, Kane, & Bonzanigo, 2015), the

value of financial assets and insurance claims. The second category, labeled “transition risk” or “carbon risk”, makes reference to the cost of the adjustment towards a low-carbon economy (Caldecott & McDaniels, 2014). Low-carbon transition risk is a multi-faceted concept that includes all drivers of risk linked to the decarbonisation of the economy: a) pollution reducing market-based instruments (a carbon price: a carbon tax, an auction price, or a secondary market price), b) command and control induced technological shifts aimed at a reduction of CO₂ emissions, 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).

The impact of a particular market-based instrument, the European Union Emission Trading System (EU-ETS), upon financial values has already been addressed by the literature; nevertheless, efforts pertain primarily to stocks, leaving the bonds field out of the picture. The objective of this paper is to assess the impact of the 2003/87/CE directive, upon which the EU-ETS is based, on European bond returns.

Literature on the interconnection between carbon pricing and bond values is scant. Mansanet-Bataller and Pardo (2008) look at the effect of including European Union Allowances (EUAs) in diversified portfolios made up of stocks, bonds, and commodities (Brent and Natural Gas) finding that including phase I and phase II EUAs actually improves the investment opportunity set for market practitioners that have initially invested in traditional assets like stocks and bonds. Koch (2014) studies price linkages between EUAs and market fundamentals and how they vary over time. The correlation between EUAs and a set of assets like oil, gas, coal, electricity, but also stocks and bonds, is analysed in order to explain the variations of price linkages; results show that carbon and financial markets are not segmented: high expected market volatility shifts carbon-stock correlation significantly upwards and carbon-bond correlation significantly downwards. Chevallier (2009) examines the relationship between carbon future returns and changes in macroeconomic conditions, finding that macroeconomic variables such as equity dividend yields, the junk bond premium, the U.S. Treasury bill yields, and the excess return on a globally diversified portfolio of commodities are only loosely related to carbon futures returns. While this scarce body of work aims at finding the determinants of a carbon price,

the study of the inverse causal relationship has, to my best knowledge, never been undertaken.

In order to detect the impact of low-carbon policy — the 2003/87/CE directive which initiated EU-ETS — upon the bond returns of European firms, a Fama and French (1993) framework, for the first time, is employed. Along with the two bond market factors proposed by Fama and French (1993), *TERM* and *DEF*, an EU-ETS participation factor is added: *GMC*. Supplementing classical factors with an environmental factor has already been done in research carried out on the stock market (Görge et al., 2017; Oestreich and Tsiakas, 2015; Ravina and Kaffel, 2019). However, some differences in the construction of the environmental factor remain. In this sense, the factor construction closer to the one presented here is found in Ravina and Kaffel (2019). The rationale behind the *GMC* factor is the following: if we want to measure the impact of the 2003/87/CE directive with a factor, one possibility is to take all firms regulated by the policy, perform carbon accounting for each firm, construct two portfolios, i.e. a high-carbon portfolio and a low-carbon portfolio, and then take the differences of the value-weight returns. Unfortunately, this operation wouldn't permit us to uncover the real green (or carbon) premium because the firms that take part in the EU-ETS are all high-carbon firms. This means that, when we build the two portfolios, the low-carbon portfolio would contain a set of firms which are only slightly less polluting than firms in the other portfolio. The resulting environmental factor would be biased, i.e. negligible in terms of magnitude. In order to cope with the fact that the EU-ETS covers only high-carbon sectors, an alternative is to construct the environmental factor by means of two portfolios, a portfolio composed of EU-ETS liable firms (which I call "carbon" portfolio) and a portfolio composed of EU-ETS exempt firms (which I call "green" portfolio). In this context, while *TERM* proxies for the common risk in bond returns related to unexpected changes in interest rates and *DEF* mimics the risk factor in returns related to shifts in economic conditions that change the likelihood of default, *GMC* (Green minus Carbon) is meant to mimic the risk factor in returns related to low-carbon policy, the 2003/87/CE directive in this case. The new component, the *GMC* factor, is obtained by subtracting the weekly value-weight carbon bond portfolio returns from the weekly value-weight green bond portfolio returns from the beginning of Phase

II (2008) of EU-ETS. The carbon bond portfolio is composed of 25 firms regulated by the 2003/87/CE directive and the green bond portfolio is composed of 25 firms exempted by the 2003/87/CE directive upon which the EU-ETS is based.

This paper makes the following contributions. Firstly, it is the first time that a factor model is employed to assess the sensitivity of bond returns to low-carbon policy. The sensitivity of bond portfolio returns to the *GMC* factor has been found to be positive in the case of green portfolios and negative in the case of carbon portfolios. Most importantly, slopes on *GMC* are highly statistically significant. Secondly, the average value of *GMC* itself is positive: finding a positive *GMC* means that in Europe, in the 2008-2018 time-span, there is no carbon premium as some of the literature asserts, but rather a green premium. Such a green premium confirms that the EU-ETS has a positive effect in the financing of the low-carbon transition: the beginning of phase II of EU-ETS — the start date of the study — coincides with both capital outflows from EU-ETS liable firms and capital inflows to EU-ETS exempt firms. Thirdly, evidence is found that the addition of an environmental factor improves the performance of the Fama and French two factor model for bonds, at least in Europe from 2008 onwards. Fourthly, since 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), I follow the recent carbon stress test trend and put forward a stress test that is able to indicate the impact of a hypothetical EU-ETS average price upon bond returns. The results show the effects of a plausible, but more severe, average EU-ETS price on both carbon firms and green firms.

The paper is structured in the following way: Section 2.2 presents the EU-ETS; Section 2.3 introduces the model; Section 2.4 puts forward the data; Section 2.5 provides the empirical results; Section 2.6 presents the diagnostics; Section 2.7 exhibits the carbon stress test; Section 2.8 concludes.

2.2 The 2003/87/CE directive

The 2003/87/CE directive is at the origin of the European Union Emission Trading System (EU-ETS). The EU-ETS is a market based instrument, launched as a pilot project in 2005, whose objective is to reduce greenhouse gases (GHG) emissions in all European Union (EU) countries as well as Iceland, Lichtenstein and Norway. The three-year (2005-2007) pilot project, phase I, has been followed by a four-year (2008-2012) phase II and a seven-year (2013-2020) phase III. In 2020, at the end of phase III, emissions covered by the EU-ETS, around 45% of the EU's GHG, are expected to be 21% lower than at the start of the pilot project (2005). From the beginning of phase III, the EU-ETS covers more than 11,000 installations consisting of power and heat generation, oil refineries, commercial aviation, and production of steel, iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals (European Commission, 2015).

The EU-ETS is a cap and trade system: the European Commission has put a cap on EU-wide GHG emissions which has been progressively reduced. When a firm belongs to one of the participating sectors, it is required to cover its emissions with emission allowances (EUAs) which are delivered on the primary market, i.e they are either auctioned or distributed free of charge. Subsequently, in the secondary-market, EUAs trading enables firms that eventually run short of allowances to purchase additional units. Environmental economics often suggests that market-based instruments, such as the EU-ETS, permit to cut emissions in a more cost efficient and flexible way than command and control regulation, as the latter tends to prescribe the same level of activity to all firms affected by the regulation (Demirel and Kesidou, 2011; Engel, Pagiola, & Wunder, 2008). Economic theory clearly indicates that, for any given level of emission abatement, if the firm's marginal cost of abatement is higher than the market's carbon price, then the efficient choice for the firm is to not abate but purchase allowances in a cap and trade scheme. Conversely, for any given level of emission abatement, when the polluting firm faces a marginal abatement cost lower than the market's carbon price, the efficient choice for the firm is to reduce emissions and sell their permits under a cap and trade scheme (Winebrake, Farrell, & Bernstein, 1995).

One of the identified issues with the EU-ETS has historically been low EUAs prices, which have generally been attributed to an imbalance of supply and demand. While the European commission has tried to address the surplus of EUAs with auction backload in phase III and with the market stability reserve (MSR), which began operations in 2019, research has delivered empirical results on the economic implications of EU-ETS. Some early studies found that the EU-ETS has a negative impact on productivity and profits of firms, while the effect on labour and investment are insignificant (Commins, Lyons, Schiffbauer, & Tol, 2011), while some others found that the EU-ETS effect on firm performance, in terms of profitability, is negligible (Jaraite-Kažukauske and Di Maria, 2016; Zhang and Wei, 2010). Another branch of research found that the EU-ETS positively affected firms' material costs and revenue, at least in the power sector (Chan, Li, & Zhang, 2013) and positively affected turnover, markup, investment intensity and labour productivity (Marin, Marino, & Pellegrin, 2017).

The impact of the EU-ETS upon financial values has also been addressed by the literature. Also in this case, results are contradictory. In the stock market, results can be divided in two categories. A first group of papers finds that the implementation of a carbon price leads to a positive effect on the financing of the low-carbon transition, i.e. capital inflows to low-carbon firms and capital outflows from high-carbon firms (Brouwers, Schoubben, Van Hulle, & Van Uytbergen, 2016; Jong, Couwenberg & Woerdman, 2014; Tian, Akimov, Roca, & Wong, 2015). A second body of work has found that such effect is not straight-forward and it actually depends on the EU-ETS phase (Moreno and Pereira da Silva, 2016; Oestreich and Tsiakas, 2015; Zhu, Tang, Peng, & Yu, 2018). Performing a similar exercise for bonds, which to the best of my knowledge has never been carried out, is the scope of this paper.

2.3 The model

To explain variation in bond returns, it is critical to distinguish systematic risks from specific risks. Systematic risks have a general impact on the returns of most securities, while specific risks influence securities individually and have a negligible effect on diversified portfolios (Litterman and Scheinkman, 1991). Theoretically, a

two-factor model for bond returns can be justified by an Intertemporal Capital Asset Pricing Model (ICAPM) setting: *TERM* and *DEF* are candidate hedging portfolios which proxy for underlying term and default risks in the economy. In such a setting, the factor loadings — the betas — with respect to these two factors can be considered appropriate measures of systematic risk (Gebhardt, Hvidkjaer, & Swaminathan, 2005). The Fama and French (1993) two factor model for bonds is based on the following time-series regression:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + e_{i,t} \quad (2.1)$$

In this equation, $R_{i,t}$ is the value-weight return for bond or bond portfolio i for period t and $R_{F,t}$ is the risk-free rate. $TERM_t$ proxies for the risk factor related to unexpected changes in interest rates. It is calculated as the difference between the returns on a value-weight long-term government bond portfolio and the one-month Treasury bill rate measured at the end of the previous month. In this framework, the T-bill rate is the proxy for the general level of expected returns on bonds, which means that *TERM* indicates what is the difference, due to changes in interest rates, between long-term bond returns and expected returns on bonds. DEF_t is the risk factor in bond returns meant to proxy shifts in economic conditions that change the likelihood of default of a firm. It is calculated as the difference between the returns on a market portfolio of long-term corporate bonds and the returns on a portfolio of long-term government bonds. *DEF* provides the premium for taking a supplementary (default) risk and investing in a corporate bond rather than in a government one. $e_{i,t}$ is a zero-mean residual. If the coefficients of the time-series regression — m_i, d_i — completely capture variation in bonds expected returns, then the intercept, α_i , is indistinguishable from zero.

An environmental extension of equation (2.1) amounts to affirm that a systematic risk is missing from the framework: there is at least another common factor that affects bond returns. This systematic risk, entailed by low-carbon policy, plays a role in the explanation of bonds excess returns. Is it legitimate to think of low-carbon policy as a source of systematic risk? A risk is systematic when it cannot be completely eliminated, but only reduced. As an example, the risk arising from a shift in

interest rates can be reduced with duration hedging or default risk can be reduced by constructing high-rating portfolios. The IPCC Special Report (2018) states that, in order not to exceed a global warming of 1.5°C above pre-industrial levels, global net anthropogenic CO₂ emissions should decline by about 45% from 2010 levels by 2030, reaching carbon neutrality — net zero global CO₂ emissions — by 2050. Carbon neutrality is a global objective that requires a global instrument: low-carbon policy. In other words, low-carbon policy is a systematic risk source because it is the answer to the global warming phenomenon. However, as for every systematic risk, low-carbon policy risk cannot be eliminated but only reduced: it can be reduced by investing in low-carbon emissions firms.

In order to measure the impact of the 2003/87/CE directive, i.e. low-carbon policy, with a factor, one possibility is to take all firms regulated by the policy, perform carbon accounting for each firm, construct two portfolios, i.e. a high-carbon portfolio and a low-carbon portfolio, and then take the differences of the value-weight returns. However, this practice turns out to be problematic in a EU-ETS context: from its inception to the present, the EU-ETS has covered only a fraction of European firms and these happen to be all high-carbon firms, implying that if we were to construct the environmental factor by partitioning current EU-ETS firms into a high-carbon portfolio and a low-carbon portfolio, such a factor would be biased, i.e. negligible in terms of magnitude. In order to cope with the fact that the EU-ETS covers only high-carbon sectors, an alternative is to construct the environmental factor by means of two portfolios, a portfolio composed of EU-ETS liable firms (which I call “carbon” portfolio) and a portfolio composed of EU-ETS exempt firms (which I call “green” portfolio). I call this systematic risk factor *GMC*: green minus carbon. The *GMC* factor is obtained by subtracting the weekly value-weight EU-ETS liable bond portfolio returns (25 firms) from the weekly value-weight EU-ETS exempt bond portfolio returns (25 firms) from the beginning of Phase II (2008) of EU-ETS until 2018.

Is there a EU-ETS participation effect in average bond returns? Table 2.1 shows the summary statistics for the two classical term-structure bond factors and the *GMC* factor (Panel A), correlations between the three factors (Panel B) and the average weekly value-weight excess returns for four bond portfolios formed from sorts on EU-ETS participation and rating (Panel C). Panel C displays a rating effect: average

return falls from low-grade bonds to high-grade bonds. This holds both in the case of carbon bonds and in the case of green bonds. Furthermore, Panel C clearly displays the EU-ETS participation effect: the green portfolio systematically outperforms its carbon counterpart at each rating level.

TABLE 2.1: Summary statistics for weekly dependent and explanatory percent returns; July 2008 to June 2018, 521 weeks.

<i>Panel A: Explanatory returns</i>						
Name	Mean	Std dev.	$t(\text{mean})$	ACF(1)	ACF(2)	ACF(12)
CB	0.14	0.61	5.12	0.00	0.10	-0.04
GP	0.15	0.73	4.57	0.03	0.08	-0.04
CP	0.13	0.53	5.38	-0.04	0.11	-0.04
LTG	0.09	0.55	3.83	-0.08	0.08	0.05
RF	0.01	0.02	8.68	0.98	0.96	0.72
DEF	0.04	0.52	1.87	0.13	0.14	-0.05
TERM	0.08	0.54	3.55	-0.09	0.07	0.05
GMC	0.02	0.35	1.38	0.04	-0.01	-0.05
<i>Panel B: Correlations between factors</i>						
	DEF	TERM	GMC			
DEF	1	-0.31	0.20			
TERM	-0.31	1	0.38			
GMC	0.20	0.38	1			
<i>Panel C: Dependent variables</i>						
Name	Mean	Std dev.	$t(\text{mean})$	ACF(1)	ACF(2)	ACF(12)
Green/HG	0.12	0.69	4.11	0.05	0.09	-0.04
Green/LG	0.15	0.87	3.93	0.05	0.10	-0.03
Carbon/HG	0.11	0.54	4.56	-0.06	0.04	-0.01
Carbon/LG	0.13	0.78	3.71	0.04	0.12	-0.09

CB is the value-weight corporate bond portfolio weekly percent return (50 bonds). *GP* is the value-weight green bond portfolio weekly percent return (25 bonds). *CP* is the value-weight carbon bond portfolio weekly percent return (25 bonds). *LTG* is the value-weight European long-term government bond portfolio weekly percent return (7 bonds). *RF* is the 1-week Euribor rate. *DEF* is $CB - LTG$. *TERM* is $LTG - RF$. *GMC* is $GP - CP$. The four bond portfolios used as dependent variables in the excess return regressions are formed from sorts of the 50 European corporate bonds on EU-ETS participation and rating. The Green/HG portfolio is composed of EU-ETS exempt (green) firms which have a rating higher than or equal to A3 (by Moody's). The Green/LG portfolio is composed of EU-ETS exempt (green) firms which have a rating lower than A3. The Carbon/HG portfolio is composed of EU-ETS liable (carbon) firms which have a rating higher than or equal to A3. The Carbon/LG portfolio is composed of EU-ETS liable (carbon) firms which have a rating lower than A3.

Table 2.1 provides an argument for testing an augmented version of the Fama and French (1993) two factor model for bonds. The environmental extension of equation (2.1) is, then, based on the addition of an EU-ETS participation factor, *GMC*. The augmented specification of the model, which I call environmentally-extended Fama

and French model (EE-FF) is the following:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + g_i GMC_t + e_{i,t} \quad (2.2)$$

2.4 The data

The environmental extension of the Fama and French (1993) two factor model for bonds (EE-FF) aims at capturing patterns in average bond returns related to shifts in interest rates, changes of probability of default and EU-ETS participation. Both the outcome and the explanatory variables are formed by means of a portfolio composition based on a sample of 50 European corporate bonds and 7 European government bonds. The returns to be explained are weekly value-weight excess returns on four bond portfolios formed on sorts on EU-ETS participation (liable or exempt) and rating (provided by Moody's). 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 EU-ETS participation, GMC , factors in returns. All data is from Bloomberg.

2.4.1 Explanatory returns

As Fama and French (1993) pointed out and demonstrated, 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 in the EE-FF model (2.2) by taking the difference between the weekly value-weight returns on a long-term government bond portfolio (LTG) and the one-week Euribor rate (RF) 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 long-term government bond portfolio is formed by 7 European long-term government bonds: issuing countries are Belgium, Italy, the Netherlands, Spain, France, UK and Germany. The value-weight returns of the long-term government bond portfolio have been calculated for each week from July 2008 to June

2018 after adjusting for different coupon frequencies (semi-annual coupon payment frequencies have been converted to annual).

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 portfolio (CB) and the returns of a value-weight long-term government bond portfolio (LTG). 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 portfolio of long-term corporate bonds is formed by 50 European long-term corporate bonds whereas the long-term government bond portfolio is formed by 7 European long-term government bonds (the same government bond portfolio used in the construction of the *TERM* factor).

GMC proxies for the risk factor in bond returns related to EU-ETS participation. *GMC* is constructed using a portfolio of 50 European corporate bonds (the same corporate bond portfolio used in the construction of the *DEF* factor), out of which 25 participate in the EU-ETS since the beginning of phase II (2008) and 25 do not participate in the EU-ETS since the beginning of phase II. A firm participates in the EU-ETS since the beginning of phase II if it belongs to one of the following sectors: power and heat generation, oil refineries, and production of coke, steel, iron, cement, glass, lime, bricks, ceramics, pulp, paper and board (European Commission, 2015). The two portfolios — the “green” portfolio (GP) and the “carbon” portfolio (CP) — have been formed from July 2008 to June 2018. These portfolios do not need to be shuffled on a yearly basis since the 50 European firms that are under examination constantly participate (or not) in the EU-ETS in the 2008-2018 time frame. Weekly value-weight bond returns have been calculated for the two portfolios for the 10-year time frame for a total of 521 weekly observations. Lastly, *GMC* is obtained by subtracting the weekly value-weight carbon portfolio returns from the weekly value-weight green portfolio returns.

Panel A of table 2.1 displays descriptive statistics for the portfolios used as building blocks for the factors (*CB*, *GP*, *CP*, *LTG*), the risk-free rate (RF), along with the three derived risk factors in returns: *TERM*, *DEF* and *GMC*. Correlations between

factors are shown in Panel B. The mean value obtained for the EU-ETS participation factor, 0.02, indicates that the EU-ETS effect is lower than the interest rate effect and the default effect: *TERM* and *DEF* have means of, respectively, 0.08 and 0.04. Nevertheless, the magnitude of the *GMC* factor cannot be ignored. Furthermore, a positive average *GMC* value points to the presence of a green premium in Europe from 2008 onwards; such a green premium confirms that the EU-ETS has a positive effect — intended as capital inflows to green firms and capital outflows from carbon firms — in the financing of the low-carbon transition. In Fama and French (1993) t-statistics for *TERM* and *DEF* are only 0.38 and 0.21. Table 2.1 displays t-statistics for *TERM* of 3.55 and for *DEF* of 1.87. The t-statistic for *GMC* is also above 1, at 1.38. These elements, along with the scarce correlation between *TERM*, *DEF* and *GMC* pave the way for a test of the three factors as independent variables in the environmentally extended version of the Fama and French (1993) model for bonds.

2.4.2 Explained returns

In the augmented model (2.2), 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 2.1. The 4 portfolios are formed from sorts of the 50 European long-term corporate bonds on EU-ETS participation (EU-ETS liability and EU-ETS exemption) and rating (high rating and low rating). Table 2.2 provides descriptive statistics for the 50 European corporate bond sample.

The 25 liable (“carbon”) firms have been selected by applying the following two criteria: a) belonging to the sectors that take part in the EU-ETS since the beginning of phase II (2008), and b) listing of at least one installation in the EU-ETS transaction log. Moreover, bonds issued by firms that fulfil these two criteria need to be comparable: they need to have similar issue dates, similar maturities, and a similar interest payment structure, e.g. the sample cannot contain both fixed-interest rate bonds and callable bonds. These criteria reduced reasonably the number of available bonds for the empirical exercise: around 30 bonds were found. As some of these bonds were missing pricing information, the final amount of bonds available was 25. The number of carbon firms (25) determined the number of exempted (“green”) firms in the

TABLE 2.2: Descriptive statistics for the 50 European corporate bonds;
Country and Sector (ICB) breakdown for Carbon and Green firms

<i>Panel A: Country breakdown</i>			
EU country	Green Firms	EU country	Carbon Firms
Finland	2	Czech Republic	1
France	5	Finland	3
Germany	5	France	4
Italy	4	Germany	4
Netherlands	2	Italy	4
Spain	2	Netherlands	1
UK	5	Portugal	1
		Spain	3
		UK	4
Total	25	Total	25
<i>Panel B: ICB Sector breakdown</i>			
Sector	Green Firms	Sector	Carbon Firms
Banks	5	Alternative Electricity	1
Broadline retailers	1	Building materials and fixtures	2
Diversified industrials	1	Conventional electricity	6
Fixed-line telecommunications	3	Gas distribution	2
Food retailers & wholesalers	3	General mining	1
Life insurance	2	Integrated Oil & Gas	5
Media agencies	2	Multiutilities	5
Mobile telecommunications	2	Paper	3
Mortgage Finance	1		
Non-equity investment services	1		
Publishing	2		
Telecommunications equipment	1		
Water	1		
Total	25	Total	25

Green Firms are EU-ETS exempt firms. Carbon firms are EU-ETS liable firms.

sample: I selected with a random procedure from the Bloomberg database 25 bonds issued by firms that fulfil the following two criteria: a) non belonging to the sectors that take part in the EU-ETS since the beginning of phase II (2008), b) no listing of firm installations in the EU-ETS transaction log. Moreover, bonds need to have, once again, similar issue dates, maturity dates and coupon payment structure. The two rating groups are formed by grouping Moody's rating codes into two categories: the high grade category includes Moody's Aaa, Aa1, Aa2, Aa3, A1, A2 and A3 codes while the low-grade category includes Moody's Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, B1 and B2 codes.

The 50 securities are all "bullets" (non-callable), fixed interest rates bonds with similar issue dates (Q3 2008) and time to maturity (Q2 2018). This set of features, particularly hard to find in a single bond, explain the size of the data set. In order to overcome this relative difficulty, weekly returns have been preferred over monthly

returns. The reason for the choice of the lower bound (2008) is that phase I of EU-ETS (2005-2007) has been a 3-year pilot phase of “learning by doing” to prepare for phase II, when the EU-ETS started to function effectively in order for the EU to meet its Kyoto targets. Furthermore, in Phase I (2005-2007) almost all allowances were given to businesses for free and the cap was largely based on estimates, as there was no reliable emission data available (European Commission, 2015). This resulted in a total amount of allowances issued superior to exceeded emissions that led, in 2007, to the fall of the price of allowances to zero. The upper bound of the time period (2018) is given by the need to compare bonds with similar maturities. As bond maturities are standardised, one of the typical time-to-maturity tranches is 10 years, a 2008 issue date implies a 2018 maturity date.

2.5 Results

The Fama and French (FF) two factor model (2.1) and the environmental extension (EE-FF) of the two factor model (2.2) have been run for each of the four dependent variables — four EU-ETS/Ratings portfolios — for a total of eight time-series regressions. The slopes and the R^2 values are direct evidence that *TERM*, *DEF* and *GMC* proxy for risk factors in bond returns.

2.5.1 Common variation in returns

The results of the four FF regressions and of the four EE-FF regressions are displayed in Table 2.3. If used as explanatory variables in the time-series regressions, *TERM*, *DEF*, and *GMC* capture common variation in bond returns. The four bond portfolios produce slopes on *TERM* in between 17 standard errors from zero (Carbon/LG) and 55 standard errors from zero (Green/HG) when the FF model is run and in between 27 standard errors from zero (Carbon/LG) and 60 standard errors from zero (Green/HG) when the EE-FF model is employed. Slopes on *TERM* are economically significant as well: they are in the 0.81 (Carbon/LG) - 1.38 (Green/LG) range when the FF model is run and in the 0.90 (Green/HG) - 1.20 (Green/LG) range when the EE-FF model is run. Within the two EU-ETS participation subgroups, slopes of

TABLE 2.3: Regressions for 4 value-weight portfolios formed from sorts on EU-ETS participation and Rating; July 2008 - June 2018, 521 weeks.

	Green/HG	Green/LG	CarbonHG	CarbonLG
<i>Panel A: FF model</i>				
α	-0.01	-0.01	0.01	0.01
$t(\alpha)$	-1.32	-1.48	0.36	0.54
m	1.08	1.38	0.82	0.81
$t(m)$	55.76	50.58	42.65	17.70
d	1.07	1.28	0.77	1.07
$t(d)$	48.80	41.27	34.93	20.46
R^2	0.89	0.86	0.82	0.52
<i>Panel B: EE-FF model</i>				
α	-0.01	-0.01	-0.01	-0.01
$t(\alpha)$	-0.36	-0.85	-0.40	-0.41
m	0.90	1.20	0.94	1.15
$t(m)$	60.59	45.16	49.06	27.54
d	0.93	1.13	0.86	1.35
$t(d)$	58.04	39.63	41.94	30.01
GMC	0.48	0.47	-0.32	-0.93
$t(GMC)$	24.85	13.50	-12.78	-17.03
R^2	0.95	0.90	0.86	0.69

At the end of December of each year, bonds are allocated to two EU-ETS participation groups: EU-ETS exempt (Green firms) and EU-ETS liable (Carbon firms). Bonds are then allocated to two rating groups: High-grade (HG) if the bond is rated A3 or higher (notation provided by Moody's) and Low-grade (LG) if the bond is rated lower than A3. The intersections of the two sorts produce 4 EU-ETS/Rating portfolios. The dependent variables in the regressions are the weekly excess returns on the 4 EU-ETS/Rating portfolios. The independent variables in the regressions are the interest rate factor, $TERM$, the default factor, DEF and the EU-ETS participation factor, GMC . Panel A shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the 4 dependent variables on $TERM$ and DEF (FF model). Panel B shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the 4 dependent variables on $TERM$, DEF , and GMC (EE-FF model).

low-grade portfolios are always higher than (or equal) the slopes of high-grade portfolios. The nature of the $TERM$ factor and interest rate expectations explain why the sensitivity of bonds expected returns to the $TERM$ factor drops from low-grade bond portfolios to high-grade bond portfolios, which is a phenomenon found also in Fama and French (1993) or in Lin, Wang, & Wu (2011). $TERM$, calculated as the difference between the weekly long-term government bond return and the one-week Euribor rate measured at the end of the previous week, represents the premium for investing in a bond which is exposed to interest rate fluctuations. Even though duration is on average lower for low-grade bonds than for high-grade bonds when the time to maturity is similar, the higher sensitivity of low-grade bonds to $TERM$ is explained by the ex-ante interest rates: when interest rates are expected to rise, low duration bonds become more attractive than high-duration bonds which are more

affected by interest rate risk.

The slopes on *DEF* are in between 20 standard errors from 0 (Carbon/LG) and 48 standard errors from 0 (Green/HG) when the FF model is run, while they are in between 30 standard errors from 0 (Carbon/LG) and 58 standard errors from 0 (Green/HG) when the EE-FF model is run. The *DEF* slopes are in the 0.77 (Carbon/HG) - 1.28 (Green/LG) range when the FF model is run and in the 0.86 (Carbon/HG) - 1.35 (Carbon/LG) range when the EE-FF model is employed. Again, within the two EU-ETS participation subgroups, slopes of low-grade portfolios are always bigger than slopes of high-grade portfolios, which is consistent with previous literature (Acharya, Amihud, & Bharath, 2013; Gebhardt, Hvidkjaer, & Swaminathan, 2005). *DEF* is the risk factor in bond returns meant to proxy for shifts in economic conditions that change the likelihood of default of a firm. In other terms, it provides the premium for taking a supplementary (default) risk and investing in a corporate bond rather than in a government bond. Declining coefficients from low-grade bonds to high-grade bonds follow this risk-return logic.

GMC slopes are all at least 12 standard errors from zero (Carbon/HG). The second less statistically significant *GMC* slope is 13 standard errors from zero (Green/LG). All other slopes are more than 17 standard errors from 0. In terms of economic significance, one would expect slopes on *GMC* to be positive, i.e. *GMC* positively contributes to bonds excess average returns, when the dependent variable is EU-ETS exempt, and negative, i.e. *GMC* negatively contributes to bonds excess average returns, when the dependent variable is EU-ETS liable. Indeed, this is the case and slopes on *GMC* are positive when the dependent variables are green portfolios and negative when the dependent variables are carbon portfolios: green portfolios have slopes in between 0.47 (Green/LG) and 0.48 (Green/HG) and carbon portfolios have slopes in between -0.32 (Carbon/HG) and -0.93 (Carbon/LG). Slopes on *GMC* are exactly the same when the dependent variable is a green portfolio, which is consistent with the basic intuition that if a firm is EU-ETS exempt then the EU-ETS participation effect is the same for both high-grade firms and low-grade firms. On the other hand, if a firm is EU-ETS liable, slopes on *GMC* vary: low-grade firms have stronger negative exposure to *GMC* to reflect the fact that a firm with weaker fundamentals, i.e. a low-grade firm, is expected to cope less well with a more stringent

low-carbon policy than a firm with stronger fundamentals, i.e. a high-grade firm. It is not surprising, then, to find a higher spread in *GMC* slopes between the Green/LG portfolio and the Carbon/LG portfolio than between the Green/HG portfolio and the Carbon/HG portfolio.

2.5.2 Sub-period analysis

Phase III of EU-ETS (2013-2020) has been described as a considerable step forward with respect to phase II (2008-2012) in terms of environmental goals. For example, a single EU-wide cap on emissions has replaced the previous system of national caps and auctioning has replaced free allocation as the default method for allocating allowances. We can check if the market agrees with the view that Phase III has been more stringent than Phase II by breaking down the time-period of analysis into two sub-periods and verifying if the sensitivity of the left hand-side portfolios to the EU-ETS participation factor varies between the two phases. Table 2.4 displays the results of the regression of the four dependent variables on two (FF model) and three factors (EE-FF model) for the two sub-periods. The phase III sub-period ends, in this exercise, in Q2 2018 with the end of the dataset.

Table 2.4 clearly confirms the results of table 2.3. On the other hand, there is no evidence that phase III of EU-ETS has been perceived as more stringent than phase II by the market: statistical significance is almost unchanged between carbon portfolios, while decreasing for the Green/HG portfolio and increasing for the Green/LG portfolio. Nevertheless, all coefficients on *GMC* are at least 8 standard errors from zero. Also, in terms of economic significance, the differences between the two phases are minimal. The spread between the EU-ETS exempt firms and the EU-ETS liable firms has not increased between phase II and phase III but it is actually slightly smaller (1.12 in phase II and 0.95 in phase III).

2.5.3 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

TABLE 2.4: Regressions for 4 value-weight portfolios formed from sorts on Rating and EU-ETS participation for Phase II of EU-ETS (2008-2012) and Phase III of EU-ETS (2013-2018); July 2008 - June 2018, 521 weeks.

<i>Panel A: FF model</i>								
	Phase II				Phase III			
	Green/HG	Green/LG	Carbon/HG	Carbon/LG	Green/HG	Green/LG	Carbon/HG	Carbon/LG
α	-0.01	-0.01	0.01	0.01	-0.01	-0.01	-0.01	0.01
$t(\alpha)$	-0.03	-1.33	0.74	0.11	-3.07	-0.70	-0.75	3.78
m	1.07	1.38	0.82	0.84	1.11	1.27	0.86	0.73
$t(m)$	38.85	33.81	31.33	12.04	27.24	31.93	17.22	16.09
d	1.08	1.26	0.76	1.15	1.06	1.35	0.80	0.70
$t(d)$	32.52	25.89	24.32	13.75	35.73	46.92	22.02	21.14
R^2	0.89	0.86	0.83	0.51	0.88	0.92	0.74	0.72

<i>Panel B: EE-FF model</i>								
	Phase II				Phase III			
	Green/HG	Green/LG	Carbon/HG	Carbon/LG	Green/HG	Green/LG	Carbon/HG	Carbon/LG
α	0.01	-0.01	0.01	-0.01	-0.01	0.01	-0.01	0.01
$t(\alpha)$	0.90	-1.09	0.41	-0.43	-1.92	2.26	-2.26	2.71
m	0.90	1.22	0.93	1.19	0.95	1.04	1.04	0.94
$t(m)$	45.75	29.91	36.27	18.70	25.72	39.74	21.65	24.30
d	0.94	1.14	0.84	1.41	0.87	1.09	1.01	0.95
$t(d)$	43.30	25.25	29.61	19.94	28.75	50.70	25.83	29.99
GMC	0.50	0.46	-0.31	-0.98	0.40	0.56	-0.43	-0.51
$t(GMC)$	19.11	8.28	-9.01	-11.48	11.20	21.96	-9.21	-13.53
R^2	0.95	0.88	0.87	0.68	0.92	0.97	0.80	0.83

At the end of December of each year, bonds are allocated to two EU-ETS participation groups: EU-ETS exempt (Green firms) and EU-ETS liable (Carbon firms). Bonds are then allocated to two rating groups: High-grade (HG) if the bond is rated A3 or higher (notation provided by Moody's) and Low-grade (LG) if the bond is rated lower than A3. The intersections of the two sorts produce four EU-ETS/Rating portfolios. The dependent variables in the regressions of Panel A and Panel B are the weekly excess returns on the 4 EU-ETS/Rating portfolios for Phase II of EU-ETS (2008-2012) and for Phase III of EU-ETS (2013-2018). The independent variables in the regressions are the interest rate factor, $TERM$, the default factor, DEF and the EU-ETS participation factor, GMC . Panel A shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the 4 dependent variables on $TERM$ and DEF (FF model). Panel B shows the intercepts, coefficients, t-values, and the adjusted R^2 value for the regressions of the 4 dependent variables on $TERM$, DEF , and GMC (EE-FF model).

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 2.3 and 2.4) with the two-factor model (FF) and its environmental extension (EE-FF) are all almost indistinguishable from zero, the lowest being -0.01 and the highest being 0.01, which is of central importance for a well-specified asset pricing model. To test the zero intercept hypothesis for combinations of portfolios and factors, I compute the Gibbons, Ross, and Shanken (1989) GRS statistic for both the FF model and the EE-FF model in the whole sample period and for the two

sub-periods identified as phase II and phase III (Table 2.5). This operation permits us to assess how well the two factor (FF) model and the three factor (EE-FF) model explain average excess bond returns and answer the question of the improvement provided by adding the GMC factor to the two classical bond factors.

TABLE 2.5: GRS statistics for tests of the FF model and the EE-FF model; July 2008 - June 2018, 521 weeks.

<i>Panel A: FF model</i>			
	Phase II (2008-2012)	Phase III (2013-2018)	Phase II & Phase III (2008-2018)
GRS	0.66	4.32	3.31
p-value	0.623	0.002	0.011
<i>Panel B: EE-FF model</i>			
	Phase II (2008-2012)	Phase III (2013-2018)	Phase II & Phase III (2008-2018)
GRS	0.53	2.72	2.82
p-value	0.711	0.030	0.026

The table tests the ability of the two-factor model (FF model) and the three factor model (EE-FF model) to explain weekly excess returns on the 4 EU-ETS/Rating portfolios. Panel A shows the GRS statistic testing whether the expected values of all 4 intercept estimates are zero when the FF model is employed in Phase II of EU-ETS (2008-2012), in Phase III of EU-ETS (2013-2018) and in Phase II and Phase III (2008-2018). Panel B shows the GRS statistic testing whether the expected values of all 4 intercept estimates are zero when the EE-FF model is employed in Phase II of EU-ETS (2008-2012), in Phase III of EU-ETS (2013-2018) and in Phase II and Phase III (2008-2018).

Interestingly, in Phase II, the GRS statistic is 0.66 for the FF model and 0.53 for the EE-FF model with p-values of only, respectively, 0.62 and 0.71. This suggests that the null of zero intercepts cannot be rejected for the 4 left-hand side portfolios when the FF model and the EE-FF model are employed. On the contrary, in Phase III the GRS test rejects the hypothesis that the FF model and the EE-FF model explain the average returns on bonds. However, the GRS statistic of the FF model (4.32) is higher than the GRS statistic of the EE-FF model (2.72). If we take the whole sample period (2008-2018), the GRS test rejects the hypothesis that the FF model and the EE-FF model produce regression intercepts for the 4 bond portfolios that are all equal to zero — the GRS statistic is 3.31 for the FF model and 2.82 for the EE-FF model — but, again, the EE-FF model produces a lower GRS statistic than the FF model. Armed with statistical evidence, I conclude that it is legitimate to consider the addition of the GMC factor to the classical Fama and French bond factors in Europe, at least from 2008.

2.6 Diagnostics

The GRS statistics (Table 2.5) tell us that, in terms of model comparison, the EE-FF model is preferable to the FF model in Phase II, in Phase III and in the full time period 2008-2018. The robustness check for the inference that the EE-FF model explains the cross-section of expected bond returns is based upon two tests. Firstly, correlation among risk factors (Table 2.1) may lead to a concern about the unique information that the newly proposed EU-ETS participation factor carries. To investigate this issue, I first regress the *GMC* factor upon the remaining two factors, *TERM* and *DEF*:

$$GMC_t = \lambda_0 + \lambda_1 TERM_t + \lambda_2 DEF_t + e_t^{GMC} \quad (2.3)$$

Once I generate the residuals from (2.3), I add them to the intercept and label the result as orthogonal *GMC* (*GMCO*). Performing this operation permits us to filter out the common information and retain only the unique information contained in *GMC*. Then, I repeat the 4 time-series regression of the EE-FF model (2.2) for the whole sample period substituting *GMCO* for *GMC*; in this way, *GMCO* — a zero-investment portfolio uncorrelated with *DEF* and *TERM* — captures common variation in bond returns left by *DEF* and *TERM*. Results are reported in Table 2.6.

In the regressions, *GMCO* keeps its significance, both in economic and statistical terms. The slopes on *GMCO* in the EE-FF model (Table 2.6) are identical to the slopes on *GMC* in the EE-FF model (Table 2.3) by construction. Slopes for *TERM* and *DEF* shift up for green portfolios and shift down for carbon portfolios. However, the spreads in the *TERM* and *DEF* slopes for green portfolios (0.29 and 0.21) are almost identical to those of Table 2.3 (0.30 and 0.20), whereas the spreads for carbon portfolios (0.02 and 0.29) are lower than those in Table 2.3 (0.21 and 0.49). In terms of statistical significance, the EE-FF model that uses *GMCO* as explanatory variable produces coefficients for both *TERM* and *DEF* which are more statistically significant than those produced by the EE-FF model that uses *GMC* as explanatory variable. This is the case for six regressions out of eight, the only exception being regressions of Carbon/LG portfolios.

TABLE 2.6: Regressions for four value-weight portfolios formed from sorts on Rating and EU-ETS participation; July 2008 - June 2018, 521 weeks.

	Green/HG	Green/LG	Carbon/HG	Carbon/LG
α	-0.01	-0.01	-0.01	-0.01
$t(\alpha)$	-0.36	-0.86	-0.40	-0.41
m	1.08	1.37	0.83	0.81
$t(m)$	82.52	58.77	48.89	22.09
d	1.07	1.28	0.77	1.06
$t(d)$	72.24	47.96	40.04	25.53
$GMCO$	0.48	0.47	-0.32	-0.93
$t(GMCO)$	24.85	13.50	-12.79	-17.03
R^2	0.94	0.90	0.86	0.69

At the end of December of each year, bonds are allocated to two EU-ETS participation groups: EU-ETS exempt (Green firms) and EU-ETS liable (Carbon firms). Bonds are then allocated to two rating groups: High-grade (HG) if the bond is rated A3 or higher (notation provided by Moody's) and Low-grade (LG) if the bond is rated lower than A3. The intersections of the two sorts produce 4 EU-ETS/Rating portfolios. The dependent variables in the regressions are the weekly excess returns on the 4 EU-ETS/Rating portfolios. The independent variables in the regressions are the interest rate factor, $TERM$, the default factor, DEF and the orthogonal EU-ETS participation factor, $GMCO$. $GMCO$ is the sum of the intercept and the residuals from the regression of GMC on $TERM$ and DEF . The table shows the intercepts, coefficients, t-values, and the adjusted R^2 values for the regressions of the 4 dependent variables on $TERM$, DEF and $GMCO$.

The second robustness test, in the spirit of Fama and French (1993), brings upon the residuals generated from the EE-FF model (2.2) to check that the regressions capture the variation through time in the cross section of expected returns. There is evidence that the default spread, the term spread and short-term interest rates predict bond returns: if the three factors of the EE-FF model actually capture the cross section of expected returns, the predictability of bond returns should be embodied in the explanatory returns and residuals should be unpredictable. This hypothesis is tested with the following regression:

$$e_{i,t+1} = \beta_0 + \beta_1 DFS_t + \beta_2 TS_t + \beta_3 RF_t + \eta_{i,t+1} \quad (2.4)$$

In the equation, $e_{i,t+1}$ are the time series residuals for the four bond portfolios from the EE-FF model (2.2). DFS_t (default spread) is the difference at the end of week t between the yield on a corporate bond portfolio and the long-term government bond yield. TS_t (term spread) is the difference at the end of week t between the long term government bond yield and the 1-week Euribor rate (RF_t). Results clearly

indicate that there is no evidence that the residuals from the EE-FF time series regressions are predictable. R^2 values in the four regressions are, at most, 0.01. Out of the twelve slopes, none are statistically significant at the 0.05 level.

2.7 Stress testing bond returns

Recently, the literature has proposed stress testing, a technique developed for testing the stability of an entity, as an evaluation framework for climate change risks. In financial risk analysis a stress test is characterized 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. In this context, 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 financial stress test literature, following Koliai (2016), can be split in four main categories (table 2.8): 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.

The literature, while portraying stress testing as quintessential to financial risk management (Bensoussan, Guegan, & Tapiero, 2014), describes the technique through dichotomies: top-down and bottom-up approaches, first and second round effects, sensitivity and scenario analysis, historical and hypothetical scenarios, direct and reverse stress tests. In the top-down approaches, the empirical relationship between

TABLE 2.7: Categorisation of stress test literature (Koliai, 2016).

Topic	Selected authors
Conceptual aspects	Berkowitz (2000); Blaschke et al. (2001); Čihák (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 Csiszár (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.

a banking variable and an exogenous stressor is assumed at the portfolio level of low granularity, while in the bottom-up approach the empirical relationship is estimated at the highest possible level of granularity of a banking variable. First-round effects come from the immediate impact of the shock on the financial system, while second-round effects include “possible domino effects from the institutions that are directly affected by the shock to other intermediaries and, possibly, to market infrastructures and the entire financial system” (Quagliariello, 2009, p.33). Sensitivity testing aims at determining how changes to a single risk factor will impact the institution or the portfolio while scenario analysis studies the effect of a simultaneous move in a group of risk factors. 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). Direct stress tests set scenarios and derive losses, while “starting from a big loss and working backward to identify how such a loss would occur is commonly referred to among risk management professionals as reverse stress testing” (Breuer, Jandačka, Mencía, & Summer, 2012, p. 332).

The aim of the carbon stress test is to show the impact of a plausible but more severe average EU-ETS price on European bond returns. How can we get an insight into the effect of more aggressive carbon pricing on bond returns? The carbon stress test put forward leverages the GMC factor as it plays an intermediary role between

carbon pricing and excess bond returns. *GMC* is meant to mimic the risk factor in returns related to low-carbon policy, the 2003/87/CE directive in this case. It follows that the *GMC* factor and the EU-ETS carbon price should be, in theory, positively correlated: when the EU-ETS carbon price increases, *GMC* should rise accordingly. Conversely, if the EU-ETS carbon price decreases, *GMC* should decline as well. The equation for the carbon stress test is, then, based on the sensitivity of the *GMC* factor to the EU-ETS carbon price, which can easily be obtained by multiplying the correlation coefficient between the EU-ETS price and the *GMC* factor (0.48) with the ratio of the standard deviation of the *GMC* factor and the standard deviation of the EU-ETS carbon price:

$$z = \rho_{gmc,ets} \left(\frac{\sigma_{GMC}}{\sigma_{ETS}} \right) \quad (2.5)$$

In equation (2.5), z is the sensitivity of the *GMC* factor to the EU-ETS carbon price (*ETS*) in the 2008-2018 time-span. $\rho_{gmc,ets}$ is the Pearson correlation coefficient between the EU-ETS price and the *GMC* factor, σ_{GMC} is the standard deviation of the *GMC* factor, σ_{ETS} is the standard deviation of the EU-ETS carbon price. Evidently, z is also the slope of the regression of *GMC* on *ETS*. Assuming that such regression is a well-specified model for *GMC*, i.e. intercept is zero, then by simple substitution Equation (2.2) becomes:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + \rho_{gmc,ets} \left(\frac{\sigma_{GMC}}{\sigma_{ETS}} \right) g_i ETS_t + e_{i,t} \quad (2.6)$$

Holding all other variables constant and focusing only on the relation between the left-hand side portfolios and the EU-ETS carbon price, the carbon stress test is based on the following equation:

$$\Delta(R_{i,t} - R_{F,t}) = \rho_{gmc,ets} \left(\frac{\sigma_{GMC}}{\sigma_{ETS}} \right) g_i \Delta ETS_t \quad (2.7)$$

In this equation, $\Delta(R_{i,t} - R_{F,t})$ is the average hypothetical variation in excess bond returns, g_i is the sensitivity of portfolio or bond i to EU-ETS participation, and ΔETS_t is the average hypothetical EU-ETS carbon price variation. In order to

understand the impact of a plausible but more severe EU-ETS average price on the bond returns under examination, the average EU-ETS carbon price (9.46 euros in the July 2008 - June 2018 time span) is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock). The carbon stress test is performed at two levels: bond portfolio level and individual security level. In the first case, the bond returns under examination are the excess returns on the four value-weight bond portfolios formed from sorts on EU-ETS participation and rating. In the second case, the bond returns under examination are the excess returns of the individual bonds of the 50 corporate bond sample.

TABLE 2.8: Carbon stress-test for four value-weight portfolios formed from sorts on EU-ETS participation and Rating and 50 individual corporate bonds; July 2008 - June 2018, 521 weeks.

<i>Panel A: Regressions for four EU-ETS/Rating value-weight portfolios</i>							
	Green/HG	Green/LG	Carbon/HG	Carbon/LG			
Low shock	0.02	0.02	-0.01	-0.03			
Medium shock	0.04	0.04	-0.03	-0.08			
High shock	0.08	0.08	-0.05	-0.16			
<i>Panel B: Individual regressions for green firms</i>							
	Mean	Std	Min	Q1	Q2	Q3	Max
Low shock	0.02	0.02	-0.01	0.00	0.01	0.03	0.06
Medium shock	0.04	0.05	-0.03	0.01	0.03	0.07	0.15
High shock	0.09	0.09	-0.06	0.02	0.07	0.15	0.30
<i>Panel C: Individual regressions for carbon firms</i>							
	Mean	Std	Min	Q1	Q2	Q3	Max
Low shock	-0.02	0.03	-0.09	-0.02	-0.01	-0.01	0.01
Medium shock	-0.04	0.07	-0.23	-0.04	-0.01	-0.01	0.02
High shock	-0.08	0.14	-0.46	-0.08	-0.03	-0.02	0.04

At the end of December of each year, bonds are allocated to two EU-ETS participation groups: EU-ETS exempt (Green firms) and EU-ETS liable (Carbon firms). Bonds are then allocated to two rating groups: High-grade (HG) if the bond is rated A3 or higher (notation provided by Moody's) and Low-grade (LG) if the bond is rated lower than A3. The intersections of the two sorts produce four EU-ETS/Rating portfolios. Panel A shows the results of the Carbon stress-test for the four EU-ETS/Rating bond portfolios. Panel B shows summary statistics of the Carbon stress-test carried out individually for 25 EU-ETS exempt (Green) firms. Panel C shows summary statistics of the Carbon stress-test carried out individually for 25 EU-ETS liable (Carbon) firms. In each stress-test, the average EU-ETS carbon price is stressed by 20% (low shock), 50% (medium shock), and 100% (high shock).

Table 2.8 (Panel A) shows the results of the carbon stress test for each of the four value-weight portfolios under the three shock scenarios: the second, third and fourth rows provide the average variation of weekly percent excess returns under the three EU-ETS carbon price scenarios. The signs of the values in Panel A reflect the signs of the slopes found for GMC in Table 2.3: g_i is positive, i.e. GMC positively contributes to bonds average excess returns, when the portfolio is EU-ETS exempt

and g_i is negative, i.e. *GMC* negatively contributes to bonds average excess returns, when the dependent variable is EU-ETS liable. The average variation of weekly excess returns for the two Green portfolios are identical as the slopes on *GMC* found with the EE-FF model (2.2) are similar: 0.48 (Green/HG) and 0.47 (Green/LG). On the other hand, the average variation of weekly excess returns for the two Carbon portfolios reflects the fact that *GMC* slopes found with the EE-FF model (2.2) are -0.32 (Carbon/HG) and -0.93 (Carbon/LG).

Panel B and Panel C display the results of the carbon stress test carried out at individual bond level. In this case, individual *GMC* slopes have been calculated for each bond; I can report that in the Green category (25 firms) all slopes on *GMC* found by running the EE-FF model (2.2) for each security are positive and statistically significant at the 0.05 level besides three cases (which are negative but not statistically significant at the 0.05 level). Furthermore, all slopes on *GMC* found by running the EE-FF model (2.2) individually for the 25 carbon firms are negative and statistically significant at the 0.05 level with the exception of two cases (which are positive but not statistically significant at the 0.05 level).

2.8 Conclusions

This paper answers the research question of the impact of the 2003/87/CE directive which initiated EU-ETS, i.e. low-carbon policy, upon European bond returns by putting forward a risk factor in bond returns related to EU-ETS participation: *GMC*. The sensitivity of bond portfolio returns to the *GMC* factor has been found to be positive in the case of Green portfolios and negative in the case of Carbon portfolios. Most importantly, slopes on *GMC* are statistically highly significant. Ultimately, the average value of *GMC* itself is positive: finding a positive *GMC* means that in Europe, in the 2008-2018 time-span, there is no carbon premium as some of the literature asserts, but rather a green premium.

The test of the *GMC* factor has been carried out in a Fama and French (1993) framework, where bond returns are explained by means of two risk-factors in returns: *TERM* and *DEF*. It has been found that augmenting the Fama and French (1993) model for bonds with the *GMC* factor improves the effectiveness of the model,

at least with regard to Europe between 2008 and 2018. The description of average bond returns is improved when the *GMC* factor is added: the EE-FF model produces lower GRS statistics than the original FF model. This holds true in the 2008-2018 time-span and in the 2008-2012 (Phase II) and 2013-2018 (Phase III) sub-periods.

The last contribution of this 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 carbon stress test put forward, which leverages the *GMC* factor, is able to indicate the impact of an EU-ETS average price increase upon bond returns: results show the effects of a plausible but more severe EU-ETS average price on bond portfolios formed on EU-ETS participation and rating and on individual bonds.

Three policy implications can be derived from these contributions. The first two implications are of interest to financial practitioners and the third is of interest to legislators. Firstly, the presence of a green premium in the European bond market in the years 2008-2018 is a useful asset management insight for financial practitioners. In other words, low-carbon investments can no longer be understood solely from the point of view of taking an ethical stand: nowadays, as the green premium shows, investing in low-carbon firms is a profitable exercise. Secondly, in terms of asset pricing models, the augmented version of the Fama and French (1993) model for bonds is preferable to the original one, at least in Europe since 2008. Thirdly, the low-carbon transition risk stress test put forward, by showing the average impact on bond returns of various scenarios of carbon pricing, provides useful insights to legislators in terms of the financing of low-carbon transition, i.e. increasing capital inflows towards green firms and capital outflows from carbon firms. The low-shock scenario, for example, would provide an additional boost to the low-carbon transition, without harming excessively high-carbon firms.

Chapter 3

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

3.1 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 3.2 presents the climatic factor, section 3.3 exposes the model, section 3.4 puts forward the data, section 3.5 introduces the results, section 3.6 presents the climate stress test and section 3.7 concludes.

3.2 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:

$$E(Aloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \quad (3.1)$$

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 (3.1) 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:

$$E(GDPloss_{y_1,t}) = E(Aloss_{x_1,y_1,t}) = E(Aloss_{x_2,y_1,t}) = E(Aloss_{x_3,y_1,t}) \quad (3.2)$$

Therefore, if a firm x_1 is active in a set of countries y with $y = 1, 2, \dots, Y$ 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:

$$E(Aloss_{x_1,t}) = \sum_{y=1}^Y E(GDPloss_{y,t}) Assets_{x_1,y,t} \quad (3.3)$$

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 (3.3) 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 (3.3) 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 30th and the 70th 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:

$$LME = (LS + LB)/2 - (ES + EB)/2 \quad (3.4)$$

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.

3.3 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:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t} \quad (3.5)$$

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 (3.5) 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:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + l_iLME_t + e_{i,t} \quad (3.6)$$

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 (3.6) 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 3.1.

In Table 3.1, 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 3.1 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 $R_M - R_F$, RMW , CMA and LME . Among factors, $R_M - R_F$ and LME have the strongest

TABLE 3.1: Summary statistics for weekly dependent and explanatory percent returns; January 2008 to December 2017, 522 weeks.

<i>Panel A: Explanatory returns</i>						
Name	Mean	Std dev.	$t(\text{mean})$	ACF(1)	ACF(2)	ACF(12)
<i>LCI</i>	0.22	3.14	1.60	-0.07	0.03	-0.08
<i>ECI</i>	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
<i>SMB</i>	0.01	0.77	0.39	-0.18	0.07	-0.09
<i>HML</i>	0.01	0.86	0.24	0.05	0.02	-0.04
<i>RMW</i>	0.07	0.56	3.01	0.03	0.02	-0.02
<i>CMA</i>	0.03	0.64	1.14	0.08	0.08	0.02
<i>LME</i>	0.08	2.09	0.91	-0.11	-0.01	-0.04
<i>Panel B: Correlations between factors</i>						
	$R_M - R_F$	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>	<i>LME</i>
$R_M - R_F$	1	-0.38	0.34	-0.38	-0.48	0.05
<i>SMB</i>	-0.38	1	-0.19	0.05	0.07	0.03
<i>HML</i>	0.34	-0.19	1	-0.58	0.23	-0.07
<i>RMW</i>	-0.38	0.05	-0.58	1	-0.03	0.09
<i>CMA</i>	-0.48	0.07	0.23	-0.03	1	-0.23
<i>LME</i>	0.05	0.03	-0.07	0.09	-0.23	1
<i>Panel C: Dependent variables</i>						
Name	Mean	Std dev.	$t(\text{mean})$	ACF(1)	ACF(2)	ACF(12)
<i>L/S</i>	0.31	3.59	1.97	-0.11	0.03	-0.05
<i>L/B</i>	0.11	3.34	0.75	-0.03	-0.02	-0.07
<i>M/S</i>	0.24	3.81	1.43	-0.04	0.01	-0.11
<i>M/B</i>	0.13	4.16	0.73	-0.06	0.01	-0.03
<i>E/S</i>	0.20	3.09	1.48	-0.07	0.09	-0.08
<i>E/B</i>	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 30th and 70th percentiles as breakpoints.

magnitude with average values of 0.09 and 0.08, respectively. Overall, Table 3.1 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.

3.4 The data

The climatic extension (Eq. 3.6) 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, R_F , is the 1-week T-bill rate.

3.4.1 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 (3.3) 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 (3.3) 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 30th and the 70th 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 (3.4).

3.4.2 Explained returns

In the climatic extension of the Fama and French model (CE-FF, eq. 3.6), 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 3.2. 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. (3.3) 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 30th and the 70th 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 3.1. 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 3.2: 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

3.5 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.

3.5.1 Common variation in stock returns

The results of the six regressions carried out with the CE-FF model (Eq. 3.6) are displayed in Table 3.3. 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 impact itself. A loss of assets negatively affects profits which in turn

TABLE 3.3: 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 .

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 (4th column of Table 3.3) 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 3.1) 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.

3.5.2 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 3.3) 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 3.4 displays the GRS statistics for the four factor model (2nd column) which employs only $R_M - R_F$, *SMB*, *RMW*, *CMA* as explanatory variables, for the five

TABLE 3.4: 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 (3rd column), which adds the *HML* factor, and for the six factor model (CE-FF model, 4th 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 3.5: 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 3.5 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.

3.5.3 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:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHMLO_t + r_iRMW_t + c_iCMA_t + l_iLMEO_t + e_{i,t} \quad (3.7)$$

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 3.6 displays the results of the OCE-FF model. The economic and statistical significance of slopes on *LMEO* is unchanged with respect to *LME* (Table 3.3), 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 3.3 in terms of economic significance, while the biggest differences are statistical: the orthogonal version of the CE-FF model (Eq. 3.7) finds coefficients on *SMB* which are more than

TABLE 3.6: 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 $LMEO$.

two standard errors from zero in five cases out of six, rather than four cases out of six when equation (3.6) 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.

3.6 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 3.7): 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 3.7: Categorisation of stress test literature (Koliai, 2016).

Topic	Selected authors
Conceptual aspects	Berkowitz (2000); Blaschke et al. (2001); Čihák (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 Csiszár (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:

$$\Delta(R_{i,t} - R_{F,t}) = l_i \Delta LME_t \quad (3.8)$$

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

	<i>Low shock</i>			<i>Medium shock</i>			<i>High shock</i>		
	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 3.8 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 (3.3). 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.

3.7 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.

Chapter 4

Extreme climate phenomena and bond returns

4.1 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.

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 events upon bond returns. Particularly, 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 bonds. 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) 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 events 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.

We 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 assert 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 our 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, we find that there is a climate effect in average excess bond returns, which confirms our hypothesis that a systematic risk factor, global warming in this case, was missing from the classical framework.

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), Schoemaker 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 climatic factor and the bonds climate stress test. If the novel climatic factor is 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 climatic 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 4.2 presents the climatic factor, section 4.3 exposes the model, section 4.4 puts forward the data, section 4.5 introduces the results, section 4.6 presents the climate stress test and section 4.7 concludes.

4.2 The climatic factor

The climatic factor (LME, light minus extreme) we propose 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 (LMI) and the extreme climate impact portfolio (ECI). The LMI 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. Weekly value-weight returns are calculated for each portfolio and then subtracted from each

other. 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.

Firms (or bonds) in the training set are selected according to data availability on the geographical allocation of firms' fixed assets. These data are necessary 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 we propose 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 we 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 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 firms' fixed assets should be associated with a geographical location, we identified 50 global bonds. These 50 global bonds became our training sample.

The second step of the construction of the *LME* factor is identifying the 50 firms (bonds) 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 50 firms (bonds) 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:

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

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 (4.1) 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:

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

Therefore, if a firm x_1 is active in a set of countries y with $y = 1, 2, \dots, Y$ 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:

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

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 (4.3) 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 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 (4.3) 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 50th percentile as breakpoint and construct two climate-impact portfolios: light climate impact and extreme climate impact. 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.

4.3 The model

We 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 climatic factor, LME . Fama and French's (1993) original two-factor model is based on the following time-series regression:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + e_{i,t} \quad (4.4)$$

In equation (4.4), $R_{i,t}$ 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 climatic 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 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 extension of the Fama and French (1993) model for bonds is, then, the following:

$$R_{i,t} - R_{F,t} = \alpha_i + m_i TERM_t + d_i DEF_t + l_i LME_t + e_{i,t} \quad (4.5)$$

The sensitivity of bonds excess returns, $R_{i,t} - R_{F,t}$, to extreme climate events is represented by coefficient l_i . We have run equation (4.5) for our 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 4.1.

Table 4.1 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 4.1 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.

4.4 The data

Our test of equation (4.5) relies on two distinct set of data. Our 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 (4.3). 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). Our test set consists of 329 global bonds (which do not include the bonds of the training

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

<i>Panel A: Explanatory returns</i>						
Name	Mean	Std.	$t(\text{mean})$	ACF(1)	ACF(2)	ACF(12)
<i>LCI</i>	0.04	1.04	0.82	-0.12	0.11	0.05
<i>ECI</i>	0.03	1.14	0.62	-0.13	0.10	0.08
<i>TERM</i>	0.08	0.93	1.84	-0.09	0.08	0.04
<i>DEF</i>	0.01	0.98	0.14	-0.10	0.07	-0.05
<i>LME</i>	0.01	0.43	0.25	-0.13	0.03	0.01

<i>Panel B: Correlations between factors</i>			
	<i>TERM</i>	<i>DEF</i>	<i>LME</i>
<i>TERM</i>	1	-0.37	-0.16
<i>DEF</i>	-0.37	1	0.24
<i>LME</i>	-0.16	0.24	1

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

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 30th and 70th percentiles as breakpoints.

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 is from Reuters.

4.4.1 Explanatory returns

The climatic extension (Eq. 4.5) 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, 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. We construct the factor that mimics this mechanism, *TERM*, 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. We use equation (4.3) to calculate total expected climate related fixed assets losses for each of the 50 issuing 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 (4.3) 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 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, we obtain the *LME* (light minus extreme) factor, which proxies for the risk factor in bond returns related to extreme climate events, by subtracting the weekly value-weight returns of the ECI portfolio from the weekly value-weight returns of the LCI portfolio.

4.4.2 Explained returns

In the augmented model (equation 4.5), 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 4.1. 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, our 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 the 30th and the 70th 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 the 30th and the 70th 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 4.1, 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.

4.5 Results

The climatic extension of the Fama and French two-factor model for bonds (equation 4.5) 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.

Extreme climate phenomena, at least in our setting, 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 and returns. Results obtained for the *LME* coefficient match our 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 4.1, Panel C) and is poorly diversified with only seven bonds per year on average in the portfolio.

4.5.1 9 Rating/Duration Portfolios

The results of the nine regressions carried out with equation (4.5) on the nine Rating/Duration portfolios are displayed in Table 4.2. 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.

All factors are positive (Table 4.1) 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 our expectations: the higher the coupon rate, the lower the interest rate risk and the lower the premium for changes in interest rate levels. Coherently, we observe slopes on *TERM* of LG bonds to be 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 we observe 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 we expect all slopes on *LME* 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, we would expect climate risk to be higher where issuing firms have weaker fundamentals (LG firms). Therefore, we 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). If we do not consider the LD row, because two *LME* coefficients out of three are not statistically significant at the 0.05 level, we find confirming evidence (especially in the HD row) for this hypothesis. When we control for rating, given that LD bonds have, *ceteris paribus*, a lower grade than HD bonds, we would expect the LD portfolio to carry the greater climate risk which implies a greater risk premium with respect to HD bonds. Once again, our hypothesis is confirmed: the risk premium is higher (closer to zero in this case) for the LD portfolio.

4.5.2 9 Rating/YTM Portfolios

The results of the nine regressions carried out with equation (4.5) on the nine Rating/YTM portfolios are displayed in Table 4.3. 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.

The picture of Table 4.3 looks close to the one of Table 4.2. When bonds are sorted by rating and yield to maturity, slopes on *TERM* are all positive and highly

TABLE 4.2: Regressions for 9 value-weighted portfolios formed from sorts on rating and duration; January 2008 - December 2017, 522 weeks.

	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

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 30th and 70th 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. 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*.

statistically significant. If we control for yield to maturity, we 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 we 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. We explain this phenomenon with 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 4.3 are all positive and statistically significant besides one, the LY/LG portfolio, which is negative. We 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, if we control 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, we expect, just like for the previous sort, that climate risk is higher where issuing firms have weaker fundamentals (LG firms). Coherently with our expectation, slopes on *LME* fall from the LG portfolio to the HG portfolio. On the other hand, when we control for rating, we 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 giving the progressive rising of climate awareness throughout the years. In such a context, bonds with lower YTM depreciate more and, therefore, carry a greater risk premium.

4.5.3 9 YTM/Duration Portfolios

When we sort the test sample by yield to maturity and duration (Table 4.4), 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.

When we look at the effect of interest rate risk on the sorts of Table 4.4, we 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 pays the

TABLE 4.3: Regressions for 9 value-weighted portfolios formed from sorts on rating and yield to maturity; January 2008 - December 2017, 522 weeks.

	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

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 30th and 70th 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. 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*.

highest premium are the one 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 was 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. When we control for duration, following the line of reasoning exposed above for sorts on yield to maturity and rating (table 4.3), we 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 we observe, 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.

TABLE 4.4: Regressions for 9 value-weighted portfolios formed from sorts on yield to maturity and duration; January 2008 - December 2017, 522 weeks.

	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

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 30th and 70th 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. 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*.

4.5.4 Model performance

In this section we 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 we 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 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.

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

	<i>Rating/Duration</i>		<i>Rating/YTM</i>		<i>Duration/YTM</i>	
	<i>TERM, DEF</i>	<i>+LME</i>	<i>TERM, DEF</i>	<i>+LME</i>	<i>TERM, DEF</i>	<i>+LME</i>
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

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.

Table 4.5 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. We 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.

4.6 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 4.6: Categorisation of stress test literature (Koliai, 2016).

Topic	Selected authors
Conceptual aspects	Berkowitz (2000); Blaschke et al. (2001); Čihák (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 Csiszár (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.

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.

According 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 our framework, scenarios are constructed by leveraging on the climatic 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 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.

The ultimate aim of a climate stress test is to show the impact of hypothetically plausible but more severe 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:

$$\Delta(R_{i,t} - R_{F,t}) = l_i \Delta LME_t \quad (4.6)$$

In equation (4.6), $\Delta(R_{i,t} - R_{F,t})$ 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, we 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 4.7 shows the results of the climate stress test for each of the twenty-seven value-weighted portfolios under the three shock scenarios. We quantify the impact

TABLE 4.7: 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.

<i>Panel A: Portfolios formed on Rating and Duration</i>									
	<i>Low shock</i>			<i>Medium shock</i>			<i>High shock</i>		
	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
<i>Panel B: Portfolios formed on Rating and YTM</i>									
	<i>Low shock</i>			<i>Medium shock</i>			<i>High shock</i>		
	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
<i>Panel C: Portfolios formed on YTM and Duration</i>									
	<i>Low shock</i>			<i>Medium shock</i>			<i>High shock</i>		
	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

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 30th and 70th 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 per mille 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).

of extreme climate phenomena at firm level by transposing country level climate related GDP losses into firms fixed assets losses by means of equation (4.3). 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 shown in the previous section and displayed on Table 4.2, Table 4.3 and Table 4.4, 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 4.1) 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 mimics the interpretation of the results of the slopes of the *LME* factor given in the previous section.

4.7 Conclusions

We 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. We have answered the research question 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 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 climatic factor is computed by means of 50 bonds issued by firms for which we have a geographical partition of fixed assets.

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 we used the classical two-factor model as a benchmark, we found that effectiveness is neither lost or gained: adding the climatic 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. For example, an asset manager can use the methods presented in this paper to assess the impact of 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 severe extreme climate phenomena, which is something we 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.

Conclusions

Global warming is defined as the increase over a 30-year period of the global average of combined surface air and sea surface temperatures. It is attributed to two different causes: natural climate variability — natural internal processes or external forcings — and human activity that alters the composition of the atmosphere. The breaking point of human contribution to climate change is usually identified with the industrial revolution since economic development is strictly correlated to energy consumption: the burning of fossil fuels has increased the concentration of atmospheric carbon dioxide (CO₂), the most prominent forcing factor, from 280 parts per million (ppm) in preindustrial times to approximately 400 ppm. Human induced global warming reached approximately 1°C above pre-industrial levels in 2017, increasing at 0.2° C per decade. However, it is very unlikely that past emissions alone raise the global mean temperature to what is now considered the threshold objective since the COP 21 held in Paris in 2015: 1.5° C above pre-industrial levels. A warming greater than 1.5°C is therefore not geophysically unavoidable: whether it will occur depends on future rates of emission reductions

Required yearly investments to address global warming and stay below the 1.5° threshold have been evaluated at around 2.38 trillion US dollars up to 2035 just for the energy sector. However, the yearly contribution of financial institutions such as banks, pension funds, life insurance companies, and other funds, while managing over 71 trillion US dollars in assets, to climate change investments has been evaluated at only 22 billion US dollars. Even households contributed more than financial institutions with 33 billion US dollars.

The main research question of this PhD thesis can be stated as follows: “Given the financial necessities of the ecological or energetic transition, how can the contribution of the financial institutions to the fight against climate change be increased?”

The four chapters that form this PhD thesis start from the hypothesis that the participation of commercial financial institutions to the low-carbon transition is financially rational. Besides any ethical consideration regarding the obtainment of the ecological transition that the author surely endorses, taking a stake in the ecological transition is financially profitable. This hypothesis becomes an argument when it is empirically proven. Throughout the four chapters presented here, the objective is to provide scientific ground to the hypothesis of the financial profitability of taking part to the ecological/energetic transition.

Global warming connects to the financial sphere by increasing the number of risks on the market. Academics have partitioned what we can call climate change risks in two categories. The first category has been labeled “climate risk” 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, are likely to seriously affect economic growth and the value of financial assets. 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; and c) market risk, i.e. market demands for low carbon products. The four chapters of this PhD thesis bring upon both “climate risk” and “transition risk” and explore their repercussions on the two most widely traded asset classes: stocks and bonds. Results show that there are patterns in average stock and bond returns related to carbon pricing and extreme climate phenomena. These results are also the basis for policy implications for legislators and financial practitioners.

Findings show that the 2003/87/CE directive has a positive effect in the financing of the low-carbon transition: the beginning of phase II of EU-ETS—the start date of the study—coincides with both capital outflows from carbon firms and capital inflows to green firms. This holds true for both stocks and bonds. The carbon stress test put forward shows by how much an increase of the EU-ETS price would

accelerate such process. The low-shock scenario, for example, would provide an additional boost to the low-carbon transition without harming excessively carbon firms. From a financial practitioner perspective, findings show that, in Europe, in the 2008-2018 time span, green firms have outperformed carbon firms and that this outperformance is statistically significant. In other words, low-carbon investments cannot be considered anymore just an ethical stand: nowadays, as the green premium shows, investing in green firms is a profitable exercise.

Results also show that extreme climate phenomena, intended as temperatures extremes, high sea levels extremes, and precipitation extremes, do have an impact on returns of stocks and bonds at a global scale. In other words, firms which suffer asset erosion as a result of global warming display lower average returns than firms that do not or suffer asset erosion to a lesser extent. The quantification of the impact of extreme climate events upon stock and bond returns is an undoubted help to both legislators and financial practitioners. An asset manager can use the methods presented in chapter 3 and chapter 4 to assess the impact of extreme climate phenomena upon stocks and bonds and thus reconsider 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 progressive 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.

Appendix A

The stock market factors tested in chapter one and chapter three have been downloaded from the K. French data library available at <http://mba.tuck.dartmouth.edu>. All returns include dividends and capital gains. Information on factor construction for the market factor, *MKT*, the size factor, *SMB*, the value factor, *HML*, the profitability factor, *RMW*, and the investment factor, *CMA*, are available on the above mentioned website.

The newly proposed factor that mimics the risk factor in stock returns related to low-carbon policy, *GMC*, is constructed using two value-weight portfolios formed on EU-ETS participation (i.e. carbon price payment). The green portfolio contains 91 stocks of firms that do not participate in the EU-ETS since the beginning of Phase II of EU-ETS — selected with a random procedure out of the universe of stocks of firms that do not participate in the EU-ETS since the beginning of Phase II of EU-ETS — and the carbon portfolio contains 91 stocks of firms that participate in the EU-ETS since the beginning of Phase II of EU-ETS. All returns include dividends and capital gains. The timeframe is Q1 2008 - Q4 2018. All data are from Bloomberg. *GMC* (green minus carbon) is the average return on the green portfolio minus the average return on the carbon portfolio.

The newly proposed factor that mimics the risk factor in stock returns related to global warming, *LME*, is constructed using two value-weight portfolios formed on climate related fixed assets losses. The light climatic impact portfolio contains 75 global stocks which suffered limited climate related fixed assets losses and the extreme climatic impact portfolio contains 75 global stocks which suffered more relevant climate related fixed assets losses. The procedure used to attribute climate related fixed assets losses to stocks is specified in section 3.2. All returns include dividends and capital gains. The timeframe is Q1 2008 - Q4 2017. All data are from Reuters.

LME (light minus extreme) is the average return on the light climatic impact portfolio minus the average return on the extreme climatic impact portfolio.

Appendix B

The bond market factors tested in chapter two — *TERM* and *DEF* — that mimic, respectively, the risk factors in bond returns related to unexpected changes in interest rates and shifts in economic conditions that change the likelihood of default of a firm have been constructed using a database of 50 European corporate fixed-interest rate bonds, seven European long-term government bonds and the Euribor rate. All returns include accrued interest and capital gains. The timeframe is Q3 2008 - Q2 2018. All data are from Bloomberg.

TERM is the average return of the government bond portfolio minus the Euribor rate.

DEF is the average return of the corporate bond portfolio minus the average return of the government bond portfolio.

The newly proposed factor that mimics the risk factor in bond returns related to low-carbon policy, *GMC*, is constructed using two value-weight portfolios formed on EU-ETS participation (i.e. carbon price payment). The green portfolio contains 25 bonds of firms that do not participate in the EU-ETS since the beginning of Phase II of EU-ETS — selected with a random procedure out of the universe of bonds of firms that do not participate in the EU-ETS since the beginning of Phase II of EU-ETS — and the carbon portfolio contains 25 bonds of firms that participate in the EU-ETS since the beginning of Phase II of EU-ETS. All returns include accrued interest and capital gains. The timeframe is Q3 2008 - Q2 2018. All data are from Bloomberg.

GMC (green minus carbon) is the average return on the green portfolio minus the average return on the carbon portfolio.

The bond market factors tested in chapter four — *TERM* and *DEF* — that mimic, respectively, the risk factors in bond returns related to unexpected changes in interest rates and shifts in economic conditions that change the likelihood of default of a

firm have been constructed using two Exchange traded funds (ETF): one for long-term government bonds (IShares IEF fund) and one for long-term corporate bonds (IShares USIG fund). All returns include accrued interest and capital gains. The timeframe is Q1 2008 - Q4 2017. All data is from Reuters.

TERM is the average return of the IShares IEF fund minus the T-bill rate.

DEF is the average return of the IShares USIG fund minus the average return of the IShares IEF fund.

The newly proposed factor that mimics the risk factor in bond returns related to global warming, *LME*, is constructed using two value-weight portfolios formed on climate related fixed assets losses. The light climatic impact portfolio contains 25 global bonds which suffered limited climate related fixed assets losses and the extreme climatic impact portfolio contains 25 global bonds which suffered more relevant climate related fixed assets losses. The procedure to attribute climate related fixed assets losses to bonds is specified in section 4.2. All returns include accrued interest and capital gains. The timeframe is Q1 2008 - Q4 2017. All data are from Reuters.

LME (light minus extreme) is the average return on the light climatic impact portfolio minus the average return on the extreme climatic impact portfolio.

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