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Impact du risque de transition sur les rentabilités boursières

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Genèse du réchauffement climatique

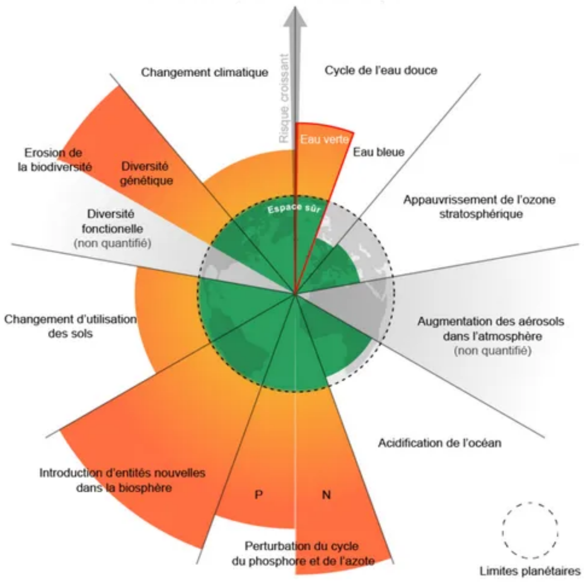
Au cours des dernières décennies, le changement climatique est devenu un enjeu central qui occupe une place prépondérante dans les discours publics et politiques. Que ce soit au sein des nations ou dans le contexte de dialogues et de négociations internationales, le sujet suscite une inquiétude grandissante.

Nous sommes actuellement témoins des effets tangibles du changement climatique sur notre environnement. Ces effets ne sont pas seulement théoriques ou prévisionnels, mais sont bel et bien présents et mesurables dans diverses régions du monde (IPCC, 2018). Ces manifestations concrètes du dérèglement climatique ont conduit de nombreux experts et institutions, dont le Groupe d'experts Intergouvernemental sur l'Evolution du Climat (GIEC) en 2014, à déclarer que nous nous trouvons dans une situation d'urgence climatique (IPCC, 2014), nécessitant une transition rapide vers une économie à faible émission de carbone pour atténuer ses impacts futurs et des conséquences encore plus désastreuses (IPCC, 2022). Les évènements météorologiques extrêmes tendent à se manifester avec plus d'intensité, de fréquence et de durée (Pachauri et al., 2014). Ces phénomènes, déjà dévastateurs pour la biodiversité, perturbent également les moyens de subsistance des populations (OCDE, 2022).

Bien que ces phénomènes soient souvent associés aux effets du changement climatique, ce dernier n'est pas le seul danger pour l'équilibre de l'écosystème mondial (Allen et al., 2018). Pour appréhender et chercher à comprendre la portée de ces défis environnementaux à l'échelle globale, Rockström et al. (2009) ont introduit la notion de "frontières planétaires" ou de "limites" que l'humanité ne devrait pas franchir pour préserver la stabilité de notre système terrestre.

La figure 1 illustre les neuf dimensions cruciales pour la stabilité de notre écosystème, parmi lesquelles figure le changement climatique. Sur ce graphique, le cercle en pointillé symbolise les frontières planétaires, soit les limites à ne pas franchir pour maintenir un écosystème pérenne et sécurisé, tout en évitant des bouleversements drastiques et irréversibles mettant en péril tant la biodiversité que l'humanité. Les zones en orange illustrent le niveau estimé de transgression de ces frontières en 2022, suggérant que, pour ces

FIGURE 1 : Les Limites Planétaires en 2022



Source : Rockström et al. (2009).

dimensions, “la Terre a atteint ses limites”. On observe ainsi que six des neuf limites ont dores et déjà été franchies[1], la dernière en date concernant l'eau verte[2]. Au moment de l'écriture de cette thèse, c'est la frontière de l'eau douce globale qui est outrepassée, marquant ainsi le dépassement officiel de la limite de l'eau bleue.

Il est important de souligner que toutes ces dimensions sont interconnectées[3]. Prenons pour exemple les émissions de gaz à effet de serre (GES), qui constituent la principale source du réchauffement climatique (correspondant à la limite “Changement climatique”). Le rapport spécial du GIEC intitulé “Global warming of 1.5°C” (Masson-Delmotte et al., 2022)[4] souligne que la température globale a augmenté de 1,1 °C depuis l'époque pré-industrielle[5], en augmentant de 0.2°C chaque décennie (Allen et al., 2018). Cette hausse des températures déclenche une série de répercussions sur l'acidification des mers et des océans (correspondant à la limite “l'Acidification de l'océan”), et cet effet domino, se répercute sur la diversité biologique marine, les activités économiques côtières ainsi que la protection des littoraux.

[1]En 2009, trois limites avaient déjà été dépassées : l'altération du cycle de l'azote, le changement climatique et la dégradation de la biodiversité. Paradoxalement, entre 2015 et aujourd'hui, le nombre de limites globales franchies est passé de trois à six. Actuellement, l'acidification des océans, qui représente la 7ème limite, est sur le point d'être dépassée.

[2]Selon l'INRA, l'eau verte est celle qui est “retenue dans le sol et la biomasse, évaporée ou absorbée puis évapotranspirée par les plantes, retournant directement dans l'atmosphère”. L'eau bleue quant à elle correspond à “l'eau présente dans les nappes phréatiques, les lacs et les cours d'eau, et qui s'écoule en surface”. Plus communément, l'eau verte (bleue) est celle destinée aux plantes (humains).

[3]Cette interconnexion entre les différentes limites planétaires a été récemment popularisée sous le terme “Connecting the dots” par Catherine Thibierge, Professeure à l'Université d'Orléans, lors de sa conférence *"Comprendre - Ressentir ce qui nous arrive et Bifurquer"* organisée le 20 juin 2023.

[4]Ce document se penche sur les conséquences d'un réchauffement de 1,5°C par rapport aux niveaux préindustriels, ainsi que sur les trajectoires d'émissions de gaz à effet de serre associées. Il est présenté dans le contexte d'un renforcement de la lutte contre les risques du changement climatique, de la promotion du développement durable et de l'éradication de la pauvreté (SR1.5).

[5]Il prévoit que ce réchauffement atteindra 1,5 °C au début des années 2030.

Selon le scénario à émissions élevées (scénario RCP8.5) du rapport spécial du GIEC dédié à l'océan et la cryosphère (Pörtner et al., 2019), l'acidité marine pourrait connaître une hausse de 100 à 150% d'ici la fin du 21ème siècle. Cela se traduirait notamment par une variation du pH de 0,3 unité, si les émissions persistent à ce rythme, entraînant ainsi des bouleversements significatifs pour les organismes marins[6].

Il est clairement établi que les activités humaines sont identifiées comme la cause majeure des changements climatiques actuels (Stott et al., 2004; Pachauri et al., 2014; Cook et al., 2016; Lynas et al., 2021), à hauteur de 95% (IPCC, 2014). L'accumulation des émissions de gaz à effet de serre (GES) dans l'atmosphère laissant entrer l'énergie solaire tout en bloquant sa sortie, combinée aux changements apportés à la surface de la Terre, - notamment par des activités telles que la déforestation - contribue significativement au réchauffement global.

Il est intéressant de noter que l'idée que l'Homme puisse influencer son environnement n'est pas nouvelle. En réalité, des traces de cette notion remontent jusqu'au XVIIIe siècle[7]. Toutefois, c'est avec la publication du rapport Meadows en 1972[8] par des chercheurs du Massachusetts Institute of Technology (MIT) que la prise de conscience concernant les effets de l'activité humaine sur l'écosystème global a vraiment pris de l'ampleur. En affirmant qu' "*il n'y a pas de croissance infinie dans un monde fini*", une croissance exponentielle de la production et de la population va inéluctablement se heurter aux limites planétaires.

Devant l'impact considérable et les implications profondes des actions humaines sur la Terre, un nouveau terme a émergé pour caractériser cette période géologique marquée par l'empreinte de l'homme : l'Anthropocène. Dérivant du grec ancien "*anthropos*", signifiant "*être humain*", cette dénomination gagne en notoriété depuis les années 1980 grâce au biologiste américain Eugene F. Stoermer et au météorologue et chimiste de l'atmosphère néerlandais Paul J. Crutzen[9]. Ils envisagent l'Anthropocène comme une ère où l'impact humain sur la planète est si puissant qu'il est devenu une force géologique majeure, affectant la géologie, l'environnement, le climat et les écosystèmes de la Terre. D'après ces chercheurs, c'est la révolution industrielle au XVIIIe siècle qui aurait marqué notre transition des 11 700 années d'Halocène, époque géologique d'une remarquable stabilité climatique (+/- 1°) favorisant l'apparition de l'agriculture et la croissance des sociétés humaines, vers l'Anthropocène. Tandis que Richardson et al. (2023)

[6]Dans ce scénario, beaucoup de nos océans, surtout les coraux, sont en danger. Le GIEC estime même que si nous limitons le réchauffement à 1,5°C, comme souhaité par l'Accord de Paris, 70 à 90% des récifs coralliens actuels seraient amenés à disparaître. Avec un réchauffement climatique de 2°C, presque tous les coraux pourraient disparaître. Or ces récifs jouent un rôle crucial dans la fourniture de nourriture, de protection contre les tempêtes et de soutien aux économies locales grâce au tourisme.

[7]En 1778, Buffon faisait remarquer dans son oeuvre "*Les Époques de la Nature*" que la Terre entière portait désormais les marques de l'influence humaine. En 1864, l'écologiste américain George Perkins Marsh a mis en avant cette idée avec son ouvrage "*Man and Nature, Physical Geography as Modified by Human Action*". En 1873, l'abbé Antonio Stoppani, enseignant au Muséum de Milan, a conceptualisé cette influence en proposant une nouvelle ère géologique qu'il a nommée "*Anthropozoïque*".

[8]Voir le rapport intitulé *"Limitis to growth"* (Meadows et al., 1972).

[9]Lauréat du Prix Nobel de chimie en 1995.

plaident en faveur de l'Holocène comme modèle de référence pour définir les frontières d'une Terre stable et résiliente, nous serions, depuis plus de 70 ans, entrés dans une phase de "*Grande Accélération*"[10] caractéristique d'une période de radicalisation de l'Anthropocène. Plus précisément, bien que les graphiques montrant l'évolution historique de l'activité humaine et les modifications physiques impactant le système Terre affichent une croissance modérée depuis 1750, à partir de 1950, ces courbes s'emballent et prennent une allure exponentielle. En effet, alors que nous vivons une mondialisation accrue, accompagnée d'évolutions fulgurantes en science et technologie, et d'une communication toujours plus rapide, les effets des activités humaines sur la géologie, l'environnement, le climat et les écosystèmes ont pris une ampleur sans précédent dans toute l'histoire.

Quelles sont les stratégies pour lutter contre le réchauffement climatique aujourd'hui ?

Confrontés à la crise climatique croissante et à *l'incompatibilité radicale entre notre système économique et la Biosphère*[11], une action décisive pour réduire significativement les émissions anthropiques de GES est devenue essentielle. Bien que les alertes scientifiques concernant le changement climatique induit par l'homme ont vu le jour dès les années 1970-1980, elles étaient alors principalement confinées à la sphère académique et ne s'étaient pas traduites par des mesures politiques concrètes.

L'année 2015 a été un moment déterminant dans la prise de conscience et l'action mondiale contre le changement climatique. Elle a souligné la nécessité impérieuse de s'attaquer directement aux causes principales de ce phénomène, notamment en régulant et réduisant les émissions nettes de GES. Cette stratégie de régulation et de réduction est couramment désignée par le terme "atténuation" ("*mitigation*", en anglais). À ce titre, dans le cadre de la Convention-cadre des Nations unies sur les changements climatiques (CCNUCC)[12], l'Accord de Paris adopté pendant la COP21 a fixé un objectif ambitieux : contenir l'augmentation de la température mondiale bien en deçà de 2°C par rapport aux niveaux préindustriels, tout en s'efforçant de limiter cette hausse à 1,5°C, avec l'objectif de neutralité carbone d'ici 2050. Contrairement au Protocole de Kyoto, l'Accord de Paris implique à la fois les nations industrialisées et celles en développement dans cet effort de réduction des émissions[13].

Afin de quantifier la réduction d'émissions nécessaire à l'atteinte de ces objectifs, il est utile de se

[10] Ce terme a été proposé par Will Steffen, Paul Crutzen et John McNeill en 2005.
[11] Citation de Jean-Marc Jancovici, expert en questions énergétiques et climatiques.
[12] La CCNUCC se donne pour mission de « stabiliser les concentrations atmosphériques de GES à un niveau qui prévienne toute interférence dangereuse d'origine humaine avec le système climatique. »
[13] Signé en 1997, le Protocole de Kyoto était le premier engagement juridique international visant à réduire les émissions de GES. Il fixait des objectifs spécifiques pour les pays industrialisés et est entré en vigueur en 2005.

référer au concept de “budget carbone”. Ce dernier désigne la quantité totale de CO_2 que nous pouvons encore émettre sans dépasser une hausse de température mondiale déterminée, comme 1,5°C ou 2°C par rapport aux niveaux préindustriels. Ainsi, pour maintenir une chance raisonnable (66%) de ne pas dépasser 1,5°C, le budget carbone - à partir de 2018 - est estimé à 420 $GtCO_2$ à l'échelle mondiale. Pour une limite de 2°C, ce budget monte à 1,170 $GtCO_2$. À notre rythme actuel d'émissions, proche de 40 $GtCO_2$ par an, ce budget pourrait être rapidement épuisé, soulignant la nécessité de mesures drastiques et rapides (IPCC, 2022).

Face à cet engagement pour les “1.5° pathways”, les pays signataires ont été incités à mettre en place des politiques climatiques nationales. Ces politiques servent de cadre pour définir les objectifs et les directions stratégiques en matière de lutte contre le changement climatique. À ce jour, près de 1,800 législations liées au climat ont été adoptées à l'échelle mondiale, dont 1,092 visent spécifiquement à l'atténuation des émissions de GES[14]. Eskander et Fankhauser (2020) indiquent qu'en 2016, grâce à ces politiques, une baisse des émissions mondiales de CO_2 de 5,9 $GtCO_2$ a été enregistrée, surpassant les émissions de CO_2 des États-Unis cette année-là. De 1999 à 2016, la réduction totale des émissions de CO_2 s'établissait à 38 $GtCO_2$, équivalante aux émissions mondiales sur une année.

Cependant, ces politiques, bien que cruciales, nécessitent des outils précis pour être mises en oeuvre efficacement. Ces instruments de politiques climatiques ont pris différentes formes pour inciter les acteurs économiques à privilégier les énergies renouvelables et les technologies à faible empreinte carbone plutôt que celles émettant des GES. Ils reposent à la fois sur des mécanismes basés sur le marché et des mécanismes non basés sur le marché. Les mécanismes de marché consistent en l'attribution d'un coût économique à l'émission d'une tonne de CO_2. L'idée sous-jacente est que, si émettre du carbone a un coût, les entreprises et les consommateurs auront des incitations financières à réduire leurs émissions (Marshall, 1890; Coase, 1960). De ce fait, plusieurs régions du monde comme l'Europe, les États-Unis et la Chine ont mis en place des Systèmes d'Échange de Quotas d'Émission (SEQE), suivant le principe du « pollueur-payeur ». Ce mécanisme fixe un plafond maximal d'émissions de GES, qui diminue de manière linéaire chaque année. Les entreprises intégrées à ce dispositif peuvent acquérir des droits d'émission supplémentaires (1 quota est égal à 1 tonne de CO_2 émise) si elles dépassent ce seuil, ou les céder si elles n'utilisent pas la totalité des quotas qui leur ont été attribués[15]. En parallèle, en 2019, 53% des revenus du carbone sont engendrés par des taxes (principalement sur les carburants), soit quasiment 26 milliards de dollars (MTE, 2021). La fixation du “prix du carbone” pour évaluer le coût du changement climatique a fait l'objet de plusieurs études économiques. Etablir un prix qui reflète le mieux les dommages futurs

[14]Ces chiffres sur les lois climatiques sont issus de la base de données publiquement accessible “*Climate Change Laws around the World*” (CCLW) et disponible sur le lien suivant : `https://climate-laws.org/`

[15]Par exemple, L'union Européenne a lancé en 2005 le premier système d'échange de quotas d'émissions contribuant directement à son ambition d'atteindre la neutralité carbone d'ici 2050 en offrant un mécanisme basé sur le marché pour réduire les émissions de manière efficace et rentable.

causés par le changement climatique soulève un problème d'arbitrage temporel, illustré par la Tragédie des Horizons (Carney, 2015*a*) où l'actualisation des coûts futurs liés aux changements climatiques se contraste avec les bénéfices de court terme liés la poursuite de l'utilisation d'énergies fossiles par exemple. Les mécanismes non basés sur le marché sont liés à la fois aux régulations environnementales, aux subventions ainsi qu'aux engagements volontaires pris par les gouvernements et les entreprises en faveur de la transition vers une économie "bas carbone" (Venturini, 2022).

Toutefois, en raison de la persistance des effets du changement climatique et de la longévité des gaz à effet de serre présents dans l'atmosphère, une hausse des températures d'ici la fin du siècle est inéluctable, touchant toutes les régions du globe (estimée à plus de 1,5° d'ici 2040, même en cas de très fortes réductions d'émissions de GES selon le dernier rapport du GIEC (IPCC, 2022)). Face à cette réalité et aux conséquences déjà perceptibles comme l'accentuation des canicules, la recrudescence des inondations ou la persistance des sécheresses, il est essentiel d'adopter une démarche d'*adaptation*. Notre futur climatique dépendra non seulement de nos efforts en matière de réduction des émissions (par le biais des politiques d'atténuation), mais aussi de notre aptitude à nous ajuster aux changements inévitables. Cette adaptation indispensable nécessite une transformation profonde des pratiques économiques orientant ainsi nos sociétés vers une économie sobre en carbone. Elle a, en outre, pour objectif de prévoir et limiter les dommages du changement climatique, notamment en ciblant des facteurs aggravants comme l'urbanisation des zones à risques, tout en élaborant des solutions adaptées à différents horizons temporels. A ce titre, la lutte contre le changement climatique s'inscrit désormais dans une perspective de développement durable, embrassant à la fois les défis climatiques, écologiques et sociaux. Sur les dix-sept Objectifs de Développement Durable (ODD) formulés par les Nations Unies en 2015, deux ont une relation directe avec le climat, dont l'ODD 13 qui se consacre aux initiatives contre le changement climatique. À ce titre, le rapport spécial du GIEC sur le 1.5°C (IPCC, 2018) met particulièrement l'accent, dans son cinquième chapitre, sur la synergie entre développement durable et la maîtrise du réchauffement climatique à 1,5°C par rapport à l'époque préindustrielle.

Les politiques climatiques, mentionnées antérieurement, ciblent en priorité la diminution de la demande de produits à forte empreinte carbone. Néanmoins, l'urgence de réduire considérablement les émissions de GES et la nécessité d'une transition rapide vers une économie bas carbone, exigent une harmonisation entre les objectifs climatiques à long terme et les préférences du marché à court terme. De manière générale, les mesures politiques conçues pour réaffecter les capitaux afin de lutter contre le changement climatique ne seront réellement efficaces que si elles entraînent une hausse du coût du capital pour les entreprises émettrices importantes de CO_2 en comparaison à celles adoptant des pratiques plus respectueuses de l'environnement. C'est pourquoi cette thèse se concentre sur les émissions de carbone comme principale contribution des entreprises au changement climatique. Cet intérêt est motivé par l'impact considérable que peuvent avoir les mesures réglementaires des pouvoirs publics sur ces émissions, dans le but de respecter les engagements pris dans le cadre de l'Accord de Paris, tout en reconnaissant que ces émissions sont le facteur dominant dans l'évolution du réchauffement de la planète.

Dans cette perspective, le secteur financier joue un rôle essentiel en allouant du capital vers les acteurs économiques appropriés. La transition vers une économie plus verte requiert, en effet, une réorientation des investissements incitant les acteurs économiques à privilégier des alternatives à faible consommation énergétique au détriment des solutions fondées sur les énergies fossiles.

Le rôle du secteur financier dans la transition vers une économie bas carbone

Face à l'urgence du changement climatique, il est essentiel que les stratégies d'atténuation et d'adaptation soient soutenues par des mécanismes de financement adaptés pour plus d'efficacité. Les besoins mondiaux en investissements pour le climat sont estimés à environ 5 000 milliards de dollars par an d'ici 2030 (IEA, 2021). Concernant le secteur de l'énergie uniquement, un investissement annuel de près de 2,4 milliards de dollars serait requis entre 2016 et 2035 pour rester sur une trajectoire compatible avec l'Accord de Paris en contenant la hausse des températures à 1,5°C (IEA, 2023)[16]. Il est donc essentiel de combler l'écart entre les besoins en financement et les flux d'investissements actuels, s'élevant à environ 1,75 milliards de dollars (IEA, 2018; IPCC, 2018) pour assurer la transition vers une économie à faibles émissions de carbone. Pour y parvenir, des mesures incitatives sont requises, ainsi qu'une prise en compte renforcée des risques climatiques dans les choix d'investissement et une collaboration plus étroite entre les secteurs public et privé.

Dans ce contexte, le secteur financier [17] se positionne au coeur du processus (Hammett et Mixter, 2017). Il a le pouvoir et la responsabilité d'accélérer cette transition. En effet, la réorientation des flux financiers vers des projets durables répondant à des critères environnementaux et sociaux stricts est une étape essentielle pour assurer la pérennité de notre économie face aux défis climatiques. D'une part, les marchés financiers fournissent des plateformes pour mobiliser des capitaux pour des projets respectueux de l'environnement, tels que les énergies renouvelables, l'efficacité énergétique, les transports propres,

[16] Selon le Global Financial Stability Report (GFSR) du Fonds Monétaire International (FMI) paru en octobre 2023, les pays émergents et en développement (EMDEs) devraient voir leurs besoins d'investissement en matière d'atténuation climatique grimper à 2 milliards de dollars à l'horizon 2030, constituant ainsi près de 40% des exigences financières mondiales pour contrer les effets du changement climatique. Cette somme représenterait près de 12% de l'ensemble des investissements prévus dans les EMDEs pour cette année-là, marquant une multiplication par quatre comparé à la proportion actuelle qui est d'environ 3%.

[17] Nous faisons référence aux institutions financières et aux marchés financiers.

entre autres. Ces derniers manifestent leur rôle dans l'atténuation du risque climatique à travers des innovations telles que les "obligations vertes" et la montée en puissance des fonds communs de placement affichant une sensibilisation accrue aux enjeux environnementaux dans les stratégies d'investissement. En outre, les marchés financiers peuvent offrir des moyens pour couvrir le risque climatique, comme par exemple, donner aux investisseurs la possibilité de diversifier leurs portefeuilles à travers des investissements dans des indices boursiers axés sur la durabilité, qui sont mieux positionnés pour tirer profit de la transition vers une économie respectueuse de l'environnement. D'autre part, les institutions financières, comme les banques centrales ou commerciales, les fonds d'investissement et les compagnies d'assurance, facilitent le financement de ces projets en fournissant des prêts, des investissements directs ou en émettant des instruments financiers verts. De ce fait, grâce à sa capacité d'allouer du capital aux différents agents économiques ou à développer de nouveaux instruments financiers mieux alignés sur les objectifs de transition écologique, le secteur financier peut induire une refonte majeure des pratiques économiques à l'échelle globale. Toutefois, bien que ces innovations soient souvent mises en avant comme des outils pour l'atténuation du risque climatique, il est important de reconnaître que la classification "verte" peut s'étendre à une grande variété d'actifs, notamment les obligations ou les fonds ESG (Environnementaux, Sociaux et de Gouvernance) ce qui demande une évaluation plus approfondie de leur efficacité. En effet, l'impact réel de ces démarches sur la durabilité environnementale reste un sujet de débat académique, soulignant une divergence entre les intentions affichées et les résultats tangibles.

Dans cette lignée, plusieurs banques centrales ont déjà manifesté leur intérêt et leur implication dans l'atténuation du changement climatique. La création du Network for Greening the Financial System (NGFS) (ou Réseau pour la verdurisation du système financier) en décembre 2017 lors du sommet "One Planet" à Paris à l'initiative de la la Banque de France, aux côtés de sept autres banques centrales et autorités de supervision, matérialise leur volonté d'intégrer les risques liés au changement climatique dans leurs décisions économiques et définit comment ces derniers peuvent être intégrés dans la supervision financière et la gestion des risques des institutions financières. Son objectif principal est d'aider le secteur financier à aborder les défis posés par le changement climatique et de promouvoir une réponse financière systémique au changement climatique[18]. A ce titre, Christine Lagarde, actuelle présidente de la Banque Centrale Européenne (BCE), disait :

> "*[..] Toute institution doit véritablement placer les risques liés au changement climatique et la protection de l'environnement au cœur de la compréhension de sa mission.*"

au regard du plan d'action sur le changement climatique visant à intégrer les considérations relatives au climat dans son cadre politique présenté par la BCE. De plus, Campiglio (2016) souligne l'importance

[18]A l'heure actuelle, le NGFS compte 83 institutions financières.

du rôle que jouent les banques centrales *via* la politique monétaire et les régulations macroprudentielles. Ces auteurs suggèrent que la tarification du carbone, du moins en tant que signal, n'est pas suffisante pour atteindre les objectifs de faibles émissions. En ajustant les incitations et les restrictions que les banques commerciales rencontrent lors de la définition de leur politique de prêt, comme en adaptant les exigences de réserves en fonction de la finalité du prêt, l'orientation de la politique monétaire pourrait stimuler de manière significative l'attribution de crédits aux secteurs favorisant une faible empreinte carbone.

Toutefois, les risques associés au changement climatique ne sont plus une simple préoccupation théorique mais une réalité tangible nécessitant leur évaluation et leur prise en compte dans la gestion des risques du fait de leur potentiel impact sur la stabilité financière (Battiston et al., 2017; FSB, 2020). En effet, au delà de son rôle actif dans le financement de la transition écologique, le secteur financier est confronté à la nécessité de gérer une nouvelle catégorie de risques financiers exogènes, ceux engendrés par le changement climatique. Ces risques découlent à la fois i) des effets directs et tangibles du changement climatique lui-même, comme les événements climatiques extrêmes, et ii) des mesures prises pour en réduire l'impact dans le cadre de la transition vers une économie faible en carbone. Afin de développer des stratégies de gestion et d'atténuation efficaces face à ces risques climatiques, l'intérêt de cette thèse porte donc sur la réalisation d'une évaluation détaillée de ces risques, spécifiquement sur le second risque, ainsi que des mécanismes par lesquels ils impactent les marchés financiers.

Les nouveaux risques financiers induits par le changement climatique

Bien que cette thèse se focalise sur le risque résultant des initiatives adoptées pour atténuer les effets du changement climatique en transitionnant vers une économie bas carbone - le risque de transition -, il est essentiel de comprendre qu'il existe en réalité plusieurs catégories de risques induits par le changement climatique pouvant impacter la stabilité financière (Battiston et al., 2017; Allen et al., 2018; FSB, 2020; Svartzman et al., 2021). C'est en 2015 que Mark Carney, alors gouverneur de la Banque d'Angleterre, a été le précurseur parmi les banquiers centraux à souligner cette vulnérabilité du système financier face aux risques climatiques, tout en proposant une définition formelle de ces risques.

Le risque physique

Le "risque physique" est celui qui émane directement des conséquences palpables du changement climatique, comme les catastrophes naturelles d'origine climatique[19]. L'impact des catastrophes naturelles sur

[19]Le Groupe de travail sur les divulgations financières liées au climat (Task Force on Climate-related Financial Disclosures, en anglais) fournit une définition plus granulaire du risque physique en distinguant i) les risques physiques aigus, qui font référence à ceux qui sont déclenchés par des événements spécifiques, tels que l'intensification des phénomènes météorologiques

le système financier s'exprime à travers plusieurs canaux. La littérature académique montre comment des événements climatiques extrêmes, comme la montée des eaux qui menace les infrastructures côtières, peuvent provoquer des pertes matérielles, entraînant une dévaluation des actifs immobiliers (Barnett et Adger, 2003; Hammett et Mixter, 2017). Ces pertes se traduisent souvent par des conséquences en cascade sur le secteur financier. Par exemple, face à de tels risques, les primes d'assurance peuvent augmenter (Hallegatte et al., 2013; Kunreuther et al., 2013), et il pourrait devenir plus difficile d'assurer des actifs situés dans des zones considérées comme "à haut risque" (Von Peter et al., 2012). Cette situation pourrait alors impacter la capacité des ménages concernés à accéder au crédit ou à honorer leurs obligations financières (Batten et al., 2016). L'augmentation subséquente des prêts non performants à la suite de catastrophes naturelles (Klomp, 2014) met en péril la stabilité et la résilience des institutions financières à travers l'exacerbation de ce risque de crédit (Avril et al., 2023) et, par extension, la croissance économique globale (Noy, 2009; Hsiang et Jina, 2014).

Bien que les risques physiques liés au changement climatique soient indéniablement un enjeu majeur pour les marchés financiers (Gourio, 2012; Dafermos et al., 2018), nous mettons l'accent dans cette thèse sur le risque de transition, compte tenu de la focalisation majeure des politiques climatiques actuelle sur la gestion de ce dernier.

Le risque de transition

Le "risque de transition" est celui qui, paradoxalement, découle des efforts d'atténuation entrepris pour limiter l'impact du changement climatique. Il ne résulte pas des effets physiques liés au changement climatique, mais de la réponse aux risques climatiques physiques. La transition écologique induit principalement une modification des prévisions des flux de trésorerie futurs des entreprises. On identifie principalement quatre sources du risque de transition (TFCD, 2017), généralement imbriquées, pouvant affecter ces flux. *Les risques politiques et légaux* renvoient aux changements dans les réglementations et les politiques climatiques. Par exemple, l'instauration d'une taxe carbone (précédemment évoquée dans la section précédente comme une politique d'atténuation visant à limiter les émissions de GES) engendrerait des coûts additionnels pour les entreprises qui s'appuient majoritairement sur l'utilisation d'energies fossiles dans leur processus de production. Les entreprises qui possèdent d'importantes réserves de combustibles fossiles pourraient voir la valeur de ces réserves diminuer ou devenir "échoués" ("*stranded*" en anglais, inexploitables économiquement) si la demande pour ces énergies diminue à cause de l'instauration de la taxe ou si leur extraction devient non rentable (Caldecott, 2017). Cette dépréciation d'actifs peut déclencher un effet domino pouvant se matérialiser par un *risque de marché*. En effet, ces actifs "bruns",

extrêmes comme les cyclones, ouragans ou inondations et ii) les risques physiques chroniques, désignant les variations à long terme des tendances climatiques, par exemple, des températures plus élevées sur la durée pouvant entraîner une montée du niveau de la mer ou des vagues de chaleur persistantes.

qui se déprécient en réponse à la transition vers une économie plus verte, ne représentent pas seulement des pertes financières potentielles pour les entreprises directement engagées dans des activités liées aux combustibles fossiles. En effet, les institutions financières ayant intégré ces actifs à leurs portefeuilles pourraient elles aussi faire face à d'importantes pertes, telles que les banques qui financent ces entreprises, les compagnies d'assurance (Scott et al., 2017), ainsi que d'autres acteurs financiers tels que les fonds de pension et investisseurs institutionnels (Weyzig et al., 2014). Ainsi, du fait de l'étroite interdépendance des marchés financiers au niveau global, une dévalorisation des actifs liés aux entreprises exploitant les énergies fossiles pourrait déclencher des répercussions qui s'étendraient bien au-delà de ces seules entreprises, entraînant une contagion potentielle à travers l'ensemble du système financier (Battiston et al., 2017). A titre illustratif, en 2020, les actifs gérés par les institutions financières, incluant les banques, les compagnies d'assurance et les fonds d'investissement, étaient estimés à près de 103 mille milliards de dollars. *Le risque technologique* émane du developpement de nouvelles technologies compatibles avec la transition vers une économie bas carbone. Il peut se traduire par des dépenses supplémentaires en recherche et développement (R&D) et en capital pour investir dans des énergies propres (énergies renouvelables, stockage d'énergie ou du carbone, amélioration de l'efficacité énergétique) pouvant modifier la structure du capital des entreprises en générant des coûts additionnels de mises en oeuvre. *Le risque de réputation* découle de la façon dont l'engagement environnemental d'une entreprise est perçu par les acteurs du marché, ce qui peut entraîner une réduction des investissements dans les entreprises perçues comme ayant une faible responsabilité environnementale. De ce fait, les avancées technologiques et les évolutions des habitudes de consommation peuvent affecter la demande et l'offre de certains produits (en réduisant la demande pour les produits des entreprises polluantes et augmentant celle pour les entreprises éco-responsables), conduisant à exarcerber le risque de marché précédemment évoqué.

Bien que ces différents risques ne se concrétisent souvent pas simultanément (Giglio et al., 2021), la matérialisation de ces deux risques extra-financiers représentent des sources de risque systémique, notamment à travers leur effet en cascade sur le système financier et l'économie réelle (Battiston et al., 2017; Dafermos et al., 2018; Bolton et al., 2020; FSB, 2020). De plus, l'hétérogénéité de ces risques climatiques, l'imprévisibilité de leur portée et de leur chronologie, ainsi que la complexité d'évaluer leur impact sur les acteurs économiques peuvent amener les agents économiques et les marchés à sous-estimer ou mal interpréter l'enjeu du risque (NGFS, 2022). C'est précisément ce que cette thèse ambitionne d'explorer et d'éclaircir en se penchant sur l'impact du risque de transition sur les rendements boursiers.

Motivations

C'est dans ce contexte que s'inscrit l'écriture de cette thèse. En effet, la crise financière de 2007-2008 a été un important rappel des lourdes conséquences qu'une gouvernance d'entreprise inappropriée et des pratiques de gestion des risques insuffisantes peuvent avoir sur la valeur des actifs amenant à la mise en place de nouvelles mesures réglementaires, notamment Bâle III, visant à renforcer la régulation et la gestion des risques dans le secteur bancaire (TFCD, 2017).

À la lumière des éléments présentés dans la section précédente, le risque de transition et ses conséquences représentent un enjeu majeur pour le secteur financier. Dans un environnement où l'asymétrie d'information relative à l'intégration du risque de transition peut engendrer d'importantes pertes financières exposant l'ensemble du système financier à un risque systémique (Battiston et al., 2017), il est crucial d'élaborer des recommandations pour une communication financière transparente et pertinente. Cela permettrait aux acteurs de marché d'être en mesure d'évaluer ce risque climatique dans leurs opérations et leurs décisions d'investissement (TFCD, 2017).

Dans cette perspective, il est primordial de comprendre l'efficacité des marchés financiers. En partant du postulat que ces marchés sont efficients[20](Fama, 1970), ils devraient alors être capables d'appréhender et d'intégrer de manière appropriée les risques financiers liés au climat dans leurs décisions d'investissement. Ainsi, une telle compréhension éviterait une réévaluation abrupte des prix des actifs financiers (Battiston et al., 2017; Carney, 2015*a*), limitant ainsi le risque de marché et la potentielle contagion à l'économie réelle, comme exposé précédemment. Le cas échéant, l'inefficience des marchés financiers à intégrer ces risques peut signifier qu'il existe des opportunités d'arbitrage pouvant avoir des implications pour les stratégies d'investissement, la réglementation financière, et la politique climatique (Charles et al., 2013; Hong et al., 2019). Par conséquent, examiner comment les marchés financiers tiennent compte du risque climatique dans la valorisation des actions constitue une voie de recherche pertinente pour établir si ces marchés encouragent ou entravent la transition vers une économie à faible émission de carbone. Nous nous focalisons sur le risque de transition car il est au centre de l'attention des acteurs de marchés. En effet, il est perçu comme plus susceptible d'impacter les portefeuilles d'investissement à moyen terme, en particulier dans la perspective du renforcement des politiques de transition (Eskander et Fankhauser, 2020; Fankhauser et al., 2022). De plus, sa matérialisation dans le système financier s'opère dans un horizon temporel beaucoup plus court que celui du risque physique (Stroebel et Wurgler, 2021; Krueger et al., 2020*a*). Selon ces auteurs, les risques de transition pourraient se concrétiser dans les cinq années à

[20]Nous faisons référence à l'efficience au sens informationnel faible, *i.e.* que le prix d'un actif reflète l'intégralité de l'information publique disponible à un instant donné.

venir, alors que les risques physiques pourraient poser un danger majeur pour le système financier dans les trente années à venir.

La compréhension de la relation empirique entre le risque de transition et les prix des actions offre l'avantage de nous fournir des indications concrètes sur la manière d'utiliser les marchés financiers pour couvrir ce risque (Giglio et al., 2021). Depuis environ une décennie, une nouvelle littérature académique, la "Finance Climatique", s'est davantage penchée sur l'analyse de l'intégration des risques climatiques dans la valorisation des prix des actifs par les marchés financiers[21]. Cependant, le risque de transition a fait l'objet d'une sous-estimation, voire d'une négligence, entraînant un manque de stratégies politiques adéquates pour une gestion appropriée. Parallèlement, le développement d'études académiques sur l'évaluation, l'impact et l'intégration subséquente du risque de transition dans les décisions d'investissements des acteurs financiers reste toutefois récent et limité (Giglio et al., 2021; Stroebel et Wurgler, 2021). Il est essentiel de reconnaître l'effet du risque de transition sur le système financier afin de renforcer la résilience et la pérennité des systèmes économiques. Dans cette optique, on s'attend à ce que la recherche académique s'attache à développer des études qui orienteront les politiques publiques dans la réalisation des objectifs au regard de la transition vers une économie bas carbone. Le but de cette thèse doctorale est donc de répondre à ce besoin.

Cadres théoriques

Selon la théorie financière, les fondements des modèles d'évaluation d'actifs reposent sur la manière dont les investisseurs perçoivent les informations favorables relatives aux perspectives de bénéfices futurs de certaines entreprises. Par conséquent, les investisseurs ajustent leurs attentes concernant les flux de bénéfices ou de dividendes futurs à la hausse. Dans ce contexte, toutes choses étant égales par ailleurs, des bénéfices attendus plus élevés impliquent un rendement attendu plus élevé (et réciproquement). De plus, les investisseurs peuvent considérer que le risque associé à certaines entreprises est supérieur à d'autres pour diverses raisons. Selon la logique de maximisation des rendements sous contrainte de minimisation des risques (Markowitz, 1952), "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, 1981). Autrement dit, les investisseurs riscophobes ne consentiraient à assumer ce risque élevé que s'ils s'attendent à un rendement supérieur correspondant en guise de compensation. Ainsi, à l'équilibre, les entreprises jugées plus risquées sont censées offrir de meilleurs rendements.

[21]Les premières explorations académiques examinant les interactions entre le changement climatique et l'économie réelle trouvent leurs racines dans les travaux avant-gardistes de Nordhaus en 1977 (Nordhaus, 1977). Bien que basés sur des modèles macro-financiers prenant en compte le changement climatique, les études ultérieures utilisant cette approche ne traitaient pas directement des conséquences du changement climatique sur la valorisation des actifs et les primes de risque.

Dans le cadre de cette thèse, il n'y aurait, a priori, aucune raison théorique pour qu'une entreprise fortement polluante ait nécessairement des rendements moyens à long terme supérieurs à une entreprise faiblement émettrice de GES, ou inversement. En effet, la théorie n'est pas explicite sur les facteurs déterminants des rendements attendus (Fama et French, 2018). Selon Bolton et Kacperczyk (2021*a*,*b*), les entreprises brunes pourraient offrir des rendements supérieurs à travers deux principaux canaux de transmission : la prime carbone et le désinvestissement. Premièrement, les entreprises brunes pourraient offrir des rendements supérieurs parce qu'elles sont plus exposées au risque de transition du fait que les stratégie d'atténuation aux changements climatiques pourraient les pénaliser dans le futur (*via* une taxe ou des réglementations visant à limiter l'émissions de GES, etc...) (Zakeri et al., 2022; Semieniuk et al., 2022). Par conséquent, les investisseurs demanderaient une compensation pour couvrir ce risque, la prime carbone. Deuxièment, d'après l'hypothèse de désinvestissement, les entreprises à haute empreinte carbone sont assimilées à des "actions du péché" (Hong et Kacperczyk, 2009). A mesure que les investisseurs institutionnels soucieux de responsabilité sociale se retirent des titres fortement intensifs en carbone, leur prix diminue. En conséquence, pour un niveau de bénéfice constant, le rendement de ces actions tend à s'accroître. A l'inverse, les entreprises vertes pourraient surperformer du fait de la préférence des investisseurs et des consommateurs pour des entreprises plus vertueuses augmentant ainsi leurs ventes et parts de marché (Barbu et al., 2022), ou à cause d'un risque perçu élevé pour ces entreprises du fait de l'incertitude des technologies qui vont prévaloir dans le cadre de la transition vers une économie bas carbone (Harris, 2015).

La section suivante présente une synthèse des études empiriques menées autour du débat cherchant à savoir si les entreprises fortement émettrices ont des rendements boursiers plus élevés, ou inversement.

Positionnement par rapport à la littérature

En se focalisant sur les actions[22], un pan de la littérature empirique trouve que les entreprises les plus émettrices offrent de meilleurs rendements. Görgen et al. (2020) ont défini un facteur "brun moins vert" (*brown minus green*, en anglais) en calculant la différence de rentabilité entre les entreprises à fortes et à faibles empreintes carbone sur la base d'un score de carbone. En incluant ce facteur de risque *commun* dans un modèle multi-factoriel d'évaluation d'actifs, leur étude n'a pas mis en évidence de "prime carbone" significative globalement sur la période 2010-2017, suggérant que les entreprises les plus polluantes n'offrent pas forcément de meilleurs rendements. En suivant une démarche analogue, Oestreich et Tsiakas (2015) ont élaboré un portefeuille "sale" moins "propre" basé sur les quotas d'émissions attribués aux entreprises allemandes participant au Système d'Échange de Quotas d'Émission de l'UE (EU ETS) durant

[22]Pour voir une revue de la littérature sur l'impact du risque de transition sur une plus large classe d'actifs financiers, voir Giglio et al. (2021).

2003-2009. Leurs résultats indiquent que les entreprises recevant plus de 1 million de quotas d'émissions — c'est-à-dire les plus gros émetteurs inclus dans le portefeuille "sale" — surperforment systématiquement celles qui en reçoivent moins, incluses dans le portefeuille "propre". L'étude de Witkowski et al. (2021) confirme cette tendance pour les entreprises à forte intensité énergétique de l'EU ETS, mais prolonge la période d'étude jusqu'en 2012. En utilisant spécifiquement les émissions toxiques comme critère d'évaluation de la "verdure" (*greenness*, en anglais) pour représenter de manière plus large l'impact environnemental d'une entreprise, Hsu et al. (2023) trouve qu'une stratégie d'investissement privilégiant les entreprises à fortes émissions pouvait aboutir à un rendement annuel moyen de 4,42%, qualifié de "prime de pollution". Par ailleurs, en utilisant directement les émissions de carbone comme mesure du risque de transition et variable explicative dans un modèle de régression en panel, Bolton et Kacperczyk (2021*b*) a identifié une prime carbone mondiale significative, soulignant que tant le niveau que les variations des émissions de carbone ont un impact positif et notable sur les rendements boursiers. L'étude menée par Bolton et Kacperczyk (2021*a*) sur le marché boursier américain a mis en évidence que les entreprises avec de fortes émissions de carbone tendent à afficher des rendements réalisés plus élevés car les investisseurs exigent une compensation (une prime de risque supérieure) pour se couvrir contre ce risque carbone.

À l'inverse, un second pan de la littérature trouve que les entreprises eco-responsables ont tendance à avoir des rendements réalisés supérieurs. Harris (2015) élabore un facteur "efficace moins intensif" (EMI) et démontre que les entreprises à faible émission réalisent des rendements supérieurs en raison du risque plus élevé associé à l'investissement dans des processus et des technologies à faible émission de carbone. Cependant, le facteur n'est pas significativement différent de zéro. En se focalisant sur les services électriques européens, Bernardini et al. (2021) ont constaté qu'une stratégie d'investissement dans des entreprises à faibles émissions de carbone produit des rendements réalisés plus élevés au cours de la période post-2012, au cours de laquelle le processus de décarbonisation s'est accéléré. Alessi et al. (2021) corroborent ce résultat en mettant en évidence une prime carbone négative pour les rendements individuels des actions européennes. En utilisant une métrique novatrice pour évaluer l'exposition des entreprises aux risques associés au carbone — intégrant les émissions de carbone et la qualité des informations environnementales divulguées — leur étude souligne que les investisseurs acceptent des rendements inférieurs pour détenir des actions plus écologiques et transparentes. Les récentes contributions de Bauer et al. (2022); Aswani et al. (2023) ont souligné que, lorsqu'on évalue la "verdure" des entreprises en fonction de leurs émissions de carbone déclarées, les actions vertes ont surpassé les actions brunes dans les pays du G7 au cours des dix dernières années. Dans le même esprit, In et al. (2017); Garvey et al. (2018) trouve qu'une faible intensité d'émissions de carbone est associée à des rendements boursiers plus élevés.

Les résultats des études empiriques sur le sens de la prime carbone ne semble pas faire consensus. Une explication possible serait que cet effet pourrait être compensé par des dynamiques de marché telles qu'une demande accrue de la part des investisseurs pour des titres issus d'entreprises eco-responsables, influençant positivement leur rendement. En ce sens, l'étude récente réalisée par Pástor et al. (2021*a*) fournit un éclaircissement quant aux divergences observées dans les résultats des études précédentes. Ces auteurs ont proposé un cadre théorique dans lequel des rendements réalisés plus faibles et des rendements attendus plus élevés pour les entreprises à forte empreinte carbone pourraient se manifester simultanément si les prix des actions vertes ont grimpé récemment en raison d'une évolution des préférences des investisseurs. En réponse à cela, plusieurs études empiriques se sont attachées à tester cette prédiction. Bolton et Kacperczyk (2021*b*) suggèrent que la prime carbone qu'ils ont identifiée peut être attribuée, au moins en partie, au filtrage sélectif effectué par les investisseurs institutionnels. Ce filtrage est réalisé pour limiter le risque carbone dans leurs portefeuilles d'investissement. A partir d'un indicateur de nouvelles climatiques basé sur une analyse textuelle de grands journaux américains visant à mesurer les préférences des investisseurs influencées par le changement climatique, Pástor et al. (2022); Ardia et al. (2022) ont constaté que les actions vertes surperforment les brunes lors des jours marqués par une augmentation inattendue des préoccupations liées au changement climatique. Dans le même esprit, Engle et al. (2020) démontrent que les actions d'entreprises avec des scores environnementaux élevés – reflètant une moindre exposition aux risques climatiques réglementaires – enregistrent de meilleurs rendements lors de périodes marquées par des nouvelles négatives concernant l'évolution future du changement climatique.

Tandis que cette thèse examine directement la relation entre les émissions de carbone et les rendements des actions, il est important de noter qu'un champs de cette littéraure relativement récent s'est attaché à mettre en lumière le mécanisme par lequel les émissions devraient influer sur les rendements des actions. En d'autres termes, ces études évaluent si la relation entre les émissions de carbone et les rendements boursiers est exacerbée par le risque réglementaire. Dans cette perspective, Hengge et al. (2023) souligne les actions réglementaires qui entraînent des surprises positives en matière de politique carbone (c'est-à-dire, des prix du carbone plus élevés[23]) conduisent à des rendements anormaux négatifs qui s'accentuent avec l'augmentation des émissions de carbone. Dans le même esprit, Bolton et al. (2023); Millischer et al. (2023) soulignent qu'un durcissement de la politique environnementale conduit à augmenter le coût du capital des entreprises fortement émettrices et par conséquent à une réduction de leurs rendements. Les résultats empiriques de Sautner et al. (2023)[24] indiquent qu'une exposition accrue aux actions réglementaires entraîne une dévaluation des actions en bourse. Faccini et al. (2023) ont segmenté les risques climatiques

[23] Les surprises de politiques en matière de carbone sont définis en utilisant des événements réglementaires relatifs à l'allocation des permis d'émission européens (EUAs). Plus précisément, elles sont déterminées par la variation en pourcentage des prix futurs des EUAs lors des journées marquées par des interventions réglementaires.

[24] Sautner et al. (2023) ont développé un nouvel indicateur pour mesurer l'exposition des entreprises aux risques liés au climat basé sur l'analyse du discours sur le changement climatique lors des réunions sur les résultats financiers. Cette étude s'appuie sur une base de données large, incluant plus de 10 000 entreprises de 34 pays entre 2002 et 2020, disponible sur `https://osf.io/fd6jq/#!`.

en quatre groupes distincts : les catastrophes naturelles, le réchauffement climatique, les conférences internationales, et la politique climatique américaine. Leurs résultats suggèrent que depuis 2012, les prix des actions américaines n'intègrent que le risque climatique associé aux mesures gouvernementales, et que l'exposition d'une entreprise à des perturbations réglementaires est corrélée négativement à l'évaluation boursière de ses actions.

Contributions des chapitres de la thèse

L'objectif de cette thèse est d'enrichir la littérature existante en apportant de nouvelles contributions sur l'impact du risque de transition sur les rentabilités boursières, une question primordiale dans le cadre actuel de la lutte contre le changement climatique. Le risque de transition, inhérent au passage vers une économie sobre en carbone, présente des défis et opportunités significatifs pour les marchés financiers comme souligné dans les sections précédentes. Cette thèse vise à quantifier et à analyser l'influence de ce risque - mesurée principalement par les émissions de carbone[25] - sur les rendements boursiers, en tenant compte des évolutions réglementaires, technologiques et des préférences des consommateurs et investisseurs.

La principale contribution de cette thèse repose sur une analyse approfondie de l'impact du risque de transition sur les marchés financiers. Prenant part dans un premier temps au débat sur la mesure la plus adéquate pour approximer la contribution des entreprises au risque de transition (Bauer et al., 2022; Aswani et al., 2023), nous proposons dans le chapitre 1 une nouvelle métrique de cette contribution - les émissions de carbone vérifiées - pour évaluer l'impact du risque de transition sur les entreprises participant à l'EU ETS. Ensuite, conscient du rôle pivot des banques centrales dans la transition vers une économie sobre en carbone, le chapitre 2 propose une évaluation de l'empreinte environnementale de la politique monétaire des États-Unis vis-à-vis du risque de transition. La principale conclusion de non-neutralité de la politique monétaire américaine, favorisant les entreprises polluantes, mènent au troisième chapitre. Celui-ci, portant sur les Etats-Unis également, explore la manière dont le risque de transition est pris en compte dans la valorisation du marché et comment la réglementation climatique peut influer sur cette intégration.

En effet, ces chapitres ont pour but de permettre une meilleure intégration du risque de transition dans l'évaluation des actions par les investisseurs qui habiliterait les autorités réglementaires et les acteurs du marché financier à élaborer des politiques plus adéquates et à instaurer des dispositifs préventifs face

[25] Étant donné l'impératif de diminution significative des émissions de carbone conformément aux objectifs des "1.5 pathways" soutenu par les politiques d'atténuation clés visant à réaliser cette objectif pour lutter contre le réchauffement climatique, nous avons choisi cette indicateur comme principale métrique de l'exposition des entreprises au risque de transition.

à ce risque. Cela peut se traduire par des investissements plus stratégiques dans la transition vers une économie respectueuse de l'environnement et mieux alignées avec les objectifs de long terme au regard de la transition vers une économie bas carbone.

Chapitre 1 : Émissions de carbone vérifiées et rentabilités boursières dans le cadre du Système d'échange de quotas d'émission de l'UE

Dans ce chapitre, nous étudions les rentabilités boursières des entreprises participant au Système d'échange de quotas d'émission de l'Union Européenne (EU ETS)[26], qui sont en grande majorité des émetteurs importants de GES issus du secteur de l'énergie ou de secteurs industriels à forte consommation énergétique. Ce système de "plafonnement et d'échange" implique que les gros émetteurs (les entreprises "brunes") doivent acheter des droits d'émission aux émetteurs plus faibles (les entreprises "vertes"). La question centrale que nous cherchons à élucider est de savoir si, au sein d'un système d'échange de quotas d'émission, les entreprises aux faibles émissions de carbone vérifiées génèrent des rendements supérieurs par rapport à leurs homologues à fortes émissions.

Ce chapitre offre deux principales contributions. Premièrement, l'analyse de la relation entre les rendements des actions et les émissions de carbone, visant à quantifier l'effet du risque de transition vers une économie bas carbone, nécessite idéalement d'être conduite dans un environnement où un prix du carbone est établi. Cette exigence s'explique principalement par la nécessité de mesurer de manière précise l'impact financier des émissions de carbone sur les entreprises. Dans un tel cadre, il devient plus facile d'évaluer comment les coûts associés au carbone influencent directement la performance financière des entreprises, et par conséquent, leurs rentabilités boursières. Deuxièmement, notre étude repose sur l'utilisation d'émissions de carbone vérifiées comme principale mesure de contribution des entreprises au risque de transition. En se focalisant sur les entreprises participant à l'EU ETS, les autorités exigent que les émissions équivalentes en CO_2 soient vérifiées par des auditeurs indépendants spécialisés dans le carbone. Par conséquent, nos données sont moins susceptibles d'être biaisées par l'écoblanchiment, contrairement à la littérature qui utilise des émissions déclarées par les entreprises ou estimées par les fournisseurs de données.

En utilisant un modèle de régression en panel, nos résultats suggèrent qu'il existe une relation négative

[26] Une analyse visant à mesurer l'impact du risque de transition sur les rentabilités boursières devrait se faire dans un environnement où il est possible de mesurer plus directement l'impact de ce coût sur les entreprises et leurs actions. En effet, les entreprises qui émettent moins de carbone ou qui sont mieux adaptées à un monde avec des prix du carbone plus élevés pourraient être récompensées par les marchés par des rendements plus élevés, ou elles pourraient éviter des pertes qui affecteraient les entreprises plus intensives en carbone. Cela permet d'évaluer de manière plus exacte la manière dont le risque de transition est reflété dans la valorisation des entreprises.

entre les rendements boursiers et les niveaux d'émissions, tandis qu'aucun lien significatif n'est constaté entre les rendements et l'intensité des émissions (émissions par rapport au chiffre d'affaires). Cela suggère que, sur la période 2006-2021 et en prenant en compte divers prédicteurs de rentabilité communément idenfiés dans la littérature, les entreprises ayant des niveaux d'émissions vérifiées élevés enregistrent des rendements inférieurs, ce qui signifie que les entreprises vertes surpassent les entreprises brunes. De plus, nos résultats corroborent ceux de Bauer et al. (2022) en utilisant une variable indicatrice pour mesurer la "*greenneess*" d'une entreprise. Par la suite, nous avons constitué un portefeuille "brun moins vert" (BMV) à partir des émissions vérifiées des entreprises et analysé son rendement ajusté au risque en utilisant des modèles multifactoriels (Fama et French, 1993*b*, 1995). Notre analyse confirme la surperformance des entreprises vertes, qui affichent systématiquement des rendements supérieurs. Plus précisément, nos résultats suggèrent un rendement annuel excédentaire entre 6,6% et 7,9% selon les différentes variantes, et avec un risque légèrement plus élevé pour ces entreprises.

En conclusion, nos résultats montrent donc que le système d'échange de quotas modifie le profil risque-rendement des actions, ce qui peut fournir une incitation financière à prendre en compte les émissions dans les décisions d'investissement. Pour favoriser la transition écologique, les décideurs politiques pourraient alors généraliser les systèmes d'échange de quotas et les audits indépendants des émissions, et augmenter le coût des droits d'émission.

Chapitre 2 : Surprises de politiques monétaires et rendements boursiers : les émissions de carbone comptent

Ce chapitre étudie l'impact de la politique monétaire sur la rentabilité des entreprises en fonction de leurs niveaux d'émissions de CO_2. Intuitivement, on peut s'attendre à trouver une corrélation positive entre les émissions de carbone et l'influence de la politique monétaire (PM). A titre illustratif, les entreprises polluantes sont généralement sujettes à un risque de transition plus important, et il est établi que les primes de risque sont influencées par la rigueur de la PM, surtout lorsque les investisseurs recherchent du rendement dans un environnement de taux d'intérêt faibles (Bernanke et Kuttner, 2005). De plus, les actions d'entreprises vertes peuvent être moins sensibles aux nouvelles fondamentales car la performance financière est moins cruciale pour les investisseurs qui les détiennent. Cependant, selon la théorie classique de la valorisation des actions (comme exposé dans la section "Cadres théoriques"), une variation du taux d'actualisation devrait affecter de manière plus importante les entreprises dont on prévoit une augmentation des dividendes futurs, ce qui suggère que les sociétés vertes pourraient être plus affectées par les décisions de PM. Nous formalisons cette idée à l'aide d'un modèle théorique[27] selon lequel les entreprises vertes sont moins sensibles aux chocs de la politique monétaire que les entreprises brunes, en raison de leur moindre exposition au risque de transition et parce qu'elles procurent une utilité non pécuniaire aux investisseurs.

La principale contribution de ce chapitre est qu'en testant les hypothèses du modèle théorique, notre analyse fournit une évaluation empirique de l'impact environnemental de la politique monétaire, un sujet avec des répercussions politiques majeures qui font l'objet de discussions approfondies.

Nous testons cette prédiction en utilisant une approche de régression d'étude d'événement en panel sur 857 entreprises américaines entre 2010 et 2019. Nos résultats montrent que les entreprises à forte intensité carbone sont significativement plus affectées par les surprises de PM. La prime de sensibilité des entreprises brunes reste significative lorsqu'on contrôle les sources classiques d'hétérogénéité de la PM, persistante dans le temps, et s'accroît lorsque les préoccupations autour du changement climatique sont élevées.

Nos résultats suggèrent que le principe de neutralité du marché qui guide la mise en oeuvre de la PM pourrait induire un biais en faveur des entreprises brunes. En d'autres termes, nos conclusions indiquent qu'une banque centrale qui décide de baisser les taux d'intérêt subventionne indirectement les entreprises polluantes. Ce fait stylisé peut intéresser les banquiers centraux qui réfléchissent actuellement à leur rôle dans la promotion d'un système financier plus vert.

Chapitre 3 : Risque de transition carbone et lois climatiques aux États-Unis

Avec les préoccupations croissantes concernant les risques climatiques et leur importance dans la prise de décision, une question importante se pose : comment les investisseurs sur les marchés boursiers réagissent-ils aux actions environnementales gouvernementales, en particulier à l'introduction de réglementations environnementales ?

Dans ce chapitre, nous cherchons à répondre à cette question en déterminant si, d'une part, le marché boursier américain intègre le risque de transition dans ses prix. D'autre part, nous cherchons également à évaluer l'effet des émissions de carbone sur les rendements boursiers lorsqu'une loi climatique est promulguée. L'impact combiné de ces variables nous permet de déterminer si le marché ajuste le prix

[27]Le modèle théorique proposé est celui dans lequel un investisseur représentatif répartit son patrimoine entre une action verte, une action brune et un actif sans risque. L'investisseur réajuste son portefeuille suite à une modification inattendue des taux d'intérêt pour conserver un rendement cible. Dans le modèle, le risque de transition rend l'action brune plus risquée que son homologue verte, et l'investisseur tire une utilité non pécuniaire de la détention d'actions qui respectent ses principes. Ce modèle aboutit à deux hypothèses empiriquement testables : (i) les actions brunes réagissent davantage aux surprises de taux de la PM, et (ii) cette plus grande réactivité résulte d'un mélange de facteurs d'offre liés aux fondamentaux et de facteurs de demande associés aux préférences des investisseurs.

du risque de transition en réponse aux initiatives américaines visant à réduire les émissions de carbone. Intuitivement, nous nous attendons à ce que cet impact soit négatif. Cela implique qu'après la mise en oeuvre des lois climatiques, l'influence des émissions de carbone sur les rendements boursiers est susceptible d'être négative.

Empiriquement, nous examinons l'effet de la législation climatique des États-Unis sur la relation entre les émissions de carbone des entreprises du S&P 500 et leurs rendements boursiers entre 2010 et 2019. Contrairement à la méthodologie d'études d'événement communément utilisée dans la littérature, qui capture essentiellement les réactions immédiates du marché dans de courtes périodes entourant un événement, nous adoptons dans ce chapitre une approche plus globale. Dans un modèle Two-Way Fixed Effects (TWFE), nous utilisons les émissions totales de carbone déclarées comme principal indicateur du risque de transition. Pour approfondir les implications à long terme, nous introduisons un indicateur de lois climatiques constuit à partir d'une base de données publique récente recensant les lois climatiques. Ce dernier est une variable indicatrice prenant la valeur de un pour la durée spécifique pendant laquelle nous cherchons à observer l'impact[28]. Cette stratégie d'identification nous permet d'examiner à la fois les effets immédiats et prolongés sur les prix des actions. Le but n'est pas seulement de mesurer les répercussions immédiates d'une loi climatique spécifique, mais de comprendre les implications plus larges et soutenues de la réglementation américaine sur le risque de transition et son évaluation par le marché sur une période prolongée.

Nos résultats empiriques initiaux révèlent une prime apparente liée aux ajustements de prix avant la mise en oeuvre de la législation climatique, suggérant que les entreprises vertes pourraient surpasser celles moins respectueuses de l'environnement lorsque les préoccupations climatiques augmentent. Plus précisément, une augmentation d'un écart-type dans les émissions totales signalées est associée à une diminution moyenne de 2,8% des rendements boursiers. Avec l'introduction de la législation climatique, il semble que les investisseurs adoptent une approche attentiste, mais aussi qu'ils pénalisent les entreprises avec des empreintes carbone plus importantes. Les effets sont particulièrement visibles dans les mois suivant la mise en œuvre de ces lois, mais moins lorsqu'on examine leur impact à long terme. L'accent est mis sur les émissions totales de carbone puisqu'elles offrent une vision plus transparente de l'empreinte environnementale d'une entreprise, exposant potentiellement les entreprises à fortes émissions à un risque accru de réglementation climatique. De plus, en utilisant l'indicateur temporel de sensibilisation au climat de Engle et al. (2020), obtenu à partir de la couverture médiatique sur le changement climatique, des investigations supplémentaires suggèrent que pendant les périodes de forte sensibilisation au climat, l'impact négatif des émissions de carbone sur les rendements boursiers devient plus marqué deux mois

[28]Par exemple, si nous visons à examiner les effets un mois après la promulgation de la loi, la variable est définie par la valeur 1 pour ce mois. Nous étendons cette logique pour saisir les effets pour des durées allant jusqu'à 12 mois.

après l'introduction d'une loi climatique, se poursuivant pendant près d'un an. Cependant, 12 mois après la législation, cet effet diminue, ce qui indique que des impacts législatifs persistants pourraient nécessiter un renforcement continu.

En conclusion, notre analyse met en évidence des implications notables pour l'élaboration des politiques environnementales. Elle révèle comment les risques climatiques sont intégrés dans la valorisation du marché et le rôle régulateur des lois climatiques dans ce processus. L'impact à long terme des lois américaines sur la corrélation entre émissions de carbone et rendements boursiers nécessite un renforcement pour assurer sa pérennité. Actuellement, les mesures législatives ont un effet plus marqué à moyen terme, mais leur durabilité reste incertaine. Pour encourager un changement environnemental durable, il est crucial que les marchés financiers valorisent de manière constante et progressive les pratiques d'entreprises respectueuses de l'environnement. Les décideurs doivent donc affiner et renforcer les réglementations existantes pour qu'elles ne se limitent pas à des solutions immédiates mais qu'elles établissent également des bases solides pour des ajustements de marché à long terme vers une économie à faibles émissions de carbone.

General Introduction

Genesis of Global Warming

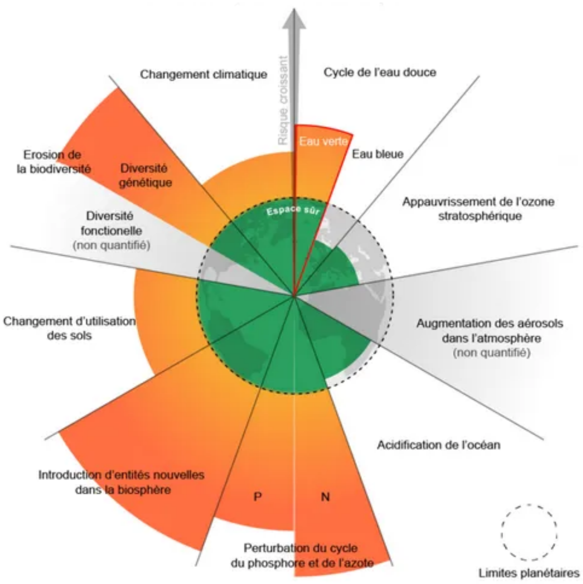
Over the past few decades, climate change has become a central issue, occupying a prominent place in public and political discourse. Whether within nations or in the context of international dialogues and negotiations, the topic is generating increasing concern.

We are currently witnessing the tangible effects of climate change on our environment. These effects are not merely theoretical or predictive, but are indeed present and measurable in various regions of the world (IPCC, 2018). These concrete manifestations of climate disruption have led many experts and institutions, including the Intergovernmental Panel on Climate Change (IPCC) in 2014, to declare that we are in a state of climate emergency (IPCC, 2014), necessitating a rapid transition to a low-carbon economy to mitigate its future impacts and even more disastrous consequences (IPCC, 2022). Extreme weather events are tending to occur with greater intensity, frequency, and duration (Pachauri et al., 2014). These phenomena, already devastating for biodiversity, are also disrupting the livelihoods of populations (OCDE, 2022).

Although these phenomena are often associated with the effects of climate change, it is not the only threat to the balance of the global ecosystem (Allen et al., 2018). To grasp and seek to understand the extent of these environmental challenges on a global scale, Rockström et al. (2009) introduced the concept of "planetary boundaries" or "limits" that humanity should not cross in order to preserve the stability of our Earth system.

The figure 1 illustrates the nine crucial dimensions for the stability of our ecosystem, among which is climate change. In this graphic, the dotted circle symbolizes the planetary boundaries, the limits that should not be crossed to maintain a sustainable and secure ecosystem, while avoiding drastic and irreversible upheavals that endanger both biodiversity and humanity. The orange areas represent the estimated level of transgression of these boundaries in 2022, suggesting that, for these dimensions, "the

Figure 2 : The Planetary Boundaries in 2022



Source : Rockström et al. (2009).

Earth has reached its limits". It is observed that six out of the nine limits have already been breached[29], the most recent concerning green water[30]. At the time of writing this thesis, the global freshwater boundary has been surpassed, thus marking the official breach of the blue water limit.

It is important to underline that all these dimensions are interconnected[31]. Take, for example, greenhouse gas emissions (GHGs), which are the main source of climate warming (corresponding to the 'Climate Change' limit). The IPCC's special report titled "Global warming of 1.5°C" (Masson-Delmotte et al., 2022)[32] highlights that the global temperature has increased by 1.1°C since the pre-industrial era[33], increasing by 0.2°C each decade (Allen et al., 2018). This rise in temperatures triggers a series of repercussions on ocean acidification (corresponding to the 'Ocean Acidification' limit), impacting marine biodiversity, coastal economic activities, and shoreline protection.

According to the high-emission scenario (RCP8.5 scenario) of the IPCC's special report dedicated to the ocean and cryosphere (Pörtner et al., 2019), marine acidity could increase by 100 to 150% by the end

[29]In 2009, three limits had already been exceeded : the alteration of the nitrogen cycle, climate change, and biodiversity degradation. Paradoxically, between 2015 and today, the number of global limits breached has increased from three to six. Currently, ocean acidification, which represents the 7th limit, is about to be exceeded.

[30]According to INRA, green water is "retained in the soil and biomass, evaporated or absorbed and then transpired by plants, returning directly to the atmosphere". Blue water, on the other hand, corresponds to "water present in groundwater, lakes, and rivers, and which flows on the surface". More commonly, green water (blue) is intended for plants (humans).

[31]This interconnection between the different planetary limits has been recently popularized under the term "Connecting the dots" by Catherine Thibierge, Professor at the University of Orleans, during her conference "Comprendre - Ressentir ce qui nous arrive et Bifurquer" organized on June 20, 2023.

[32]This document focuses on the consequences of warming of 1.5°C compared to pre-industrial levels, as well as on the associated greenhouse gas emission trajectories. It is presented in the context of strengthening the fight against climate change risks, promoting sustainable development, and eradicating poverty (SR1.5).

[33]It predicts that this warming will reach 1.5°C in the early 2030s.

of the 21st century. This would result in a pH variation of 0.3 units if emissions continue at this rate, causing significant disruptions for marine organisms[34].

It is clearly established that human activities are identified as the major cause of the current climate changes (Stott et al., 2004; Pachauri et al., 2014; Cook et al., 2016; Lynas et al., 2021), accounting for 95% (IPCC, 2014). The accumulation of greenhouse gases (GHGs) in the atmosphere, which allows solar energy to enter while blocking its exit, combined with changes to the Earth's surface - notably through activities such as deforestation - significantly contributes to global warming.

It is interesting to note that the idea of humans influencing their environment is not new. In fact, traces of this notion date back to the 18th century[35]. However, it was with the publication of the Meadows report in 1972[36] by researchers at the Massachusetts Institute of Technology (MIT) that awareness of the effects of human activity on the global ecosystem really took hold. By asserting that "there is no infinite growth in a finite world," exponential growth in production and population will inevitably collide with planetary boundaries.

Faced with the considerable impact and profound implications of human actions on Earth, a new term has emerged to characterize this geological period marked by the human footprint : the Anthropocene. Derived from the ancient Greek "anthropos," meaning "human being," this term has been gaining notoriety since the 1980s thanks to American biologist Eugene F. Stoermer and Dutch atmospheric chemist and meteorologist Paul J. Crutzen[37]. They envision the Anthropocene as an era where human impact on the planet is so powerful that it has become a major geological force, affecting Earth's geology, environment, climate, and ecosystems. According to these researchers, it was the Industrial Revolution in the 18th century that marked our transition from the 11,700 years of the Holocene, a geological epoch of remarkable climate stability (+/- 1°) favoring the emergence of agriculture and the growth of human societies, to the Anthropocene. While Richardson et al. (2023) argue in favor of the Holocene as a reference model to define the boundaries of a stable and resilient Earth, we have been, for more than 70 years, in a phase of "Great Acceleration"[38] characteristic of a period of radicalization of the Anthropocene. More specifically, although graphs showing the historical evolution of human activity and physical changes impacting the Earth system show moderate growth since 1750, from 1950 onwards, these curves skyrocket and take an

[34] In this scenario, many of our oceans, especially the corals, are in danger. The IPCC even estimates that if we limit warming to 1.5°C, as desired by the Paris Agreement, 70 to 90% of current coral reefs would be likely to disappear. With a 2°C global warming, almost all corals could vanish. Yet these reefs play a crucial role in providing food, protection against storms, and support to local economies through tourism.

[35] In 1778, Buffon noted in his work "Les Époques de la Nature" that the entire Earth now bore the marks of human influence. In 1864, American ecologist George Perkins Marsh emphasized this idea with his work "Man and Nature, Physical Geography as Modified by Human Action". In 1873, Abbot Antonio Stoppani, a teacher at the Museum of Milan, conceptualized this influence by proposing a new geological era he called "Anthropozoic".

[36] See the report titled "Limits to Growth" (Meadows et al., 1972).

[37] Nobel Prize in Chemistry laureate in 1995.

[38] This term was proposed by Will Steffen, Paul Crutzen, and John McNeill in 2005.

exponential turn. Indeed, as we experience increased globalization, accompanied by rapid advancements in science and technology, and ever-faster communication, the effects of human activities on geology, environment, climate, and ecosystems have reached an unprecedented scale in history.

What are the strategies to address global warming today ?

Faced with the escalating climate crisis and the radical incompatibility between our economic system and the Biosphere[39], decisive action to significantly reduce anthropogenic GHG emissions has become essential. Although scientific alerts about human-induced climate change emerged in the 1970s-1980s, they were mainly confined to the academic sphere and had not translated into concrete political measures.

The year 2015 was a pivotal moment in the awareness and global action against climate change. It underscored the urgent need to directly address the main causes of this phenomenon, particularly by regulating and reducing net GHG emissions. This strategy of regulation and reduction is commonly referred to as "mitigation". Within the framework of the United Nations Framework Convention on Climate Change (UNFCCC), the Paris Agreement adopted during COP21 set an ambitious goal : to keep the global temperature increase well below 2°C compared to pre-industrial levels, while striving to limit this increase to 1.5°C, aiming for carbon neutrality by 2050. Unlike the Kyoto Protocol, the Paris Agreement involves both industrialized and developing nations in this emission reduction effort.

To quantify the emission reduction necessary to achieve these objectives, the concept of "carbon budget" is useful. This refers to the total amount of CO_2 that can still be emitted without exceeding a determined global temperature increase, such as 1.5°C or 2°C compared to pre-industrial levels. For example, to maintain a reasonable chance (66%) of not exceeding 1.5°C, the global carbon budget from 2018 is estimated at 420 $GtCO_2$. For a 2°C limit, this budget increases to 1,170 $GtCO_2$. At our current emission rate of about 40 $GtCO_2$ per year, this budget could be quickly exhausted, highlighting the need for drastic and rapid measures.

In response to the commitment to the "1.5° pathways," signatory countries have been encouraged to implement national climate policies. These policies serve as frameworks for defining goals and strategic directions in combating climate change. To date, nearly 1,800 climate-related legislations have been adopted globally, with 1,092 specifically targeting GHG emission mitigation. These policies led to a decrease in global CO_2 emissions of 5.9 $GtCO_2$ in 2016, surpassing the CO_2 emissions of the United States that year. From 1999 to 2016, the total reduction in CO_2 emissions amounted to 38 $GtCO_2$, equivalent to global emissions over a year.

However, these policies, though crucial, require precise tools for effective implementation. Climate

[39] Quote by Jean-Marc Jancovici, expert in energy and climate issues.

policy instruments have taken various forms to encourage economic actors to favor renewable energies and low-carbon technologies over GHG-emitting ones. They rely on both market-based and non-market-based mechanisms. Market mechanisms involve assigning an economic cost to the emission of a ton of CO_2, incentivizing businesses and consumers to reduce emissions. As a result, regions like Europe, the United States, and China have implemented Emission Trading Systems (ETS), following the "polluter pays" principle. This mechanism sets a maximum GHG emission cap, decreasing linearly each year. Companies can purchase additional emission allowances or sell unused quotas. In parallel, in 2019, 53% of carbon revenues were generated by taxes, amounting to nearly 26 billion dollars. Setting a "carbon price" to assess the cost of climate change has been the subject of several economic studies. Establishing a price that best reflects the future damages caused by climate change raises a temporal arbitrage issue, exemplified by the Tragedy of the Horizons, where the discounting of future climate change costs contrasts with the short-term benefits of continuing to use fossil fuels, for example. Non-market mechanisms are related to environmental regulations, subsidies, and voluntary commitments by governments and companies towards a low-carbon economy transition.

Due to the persistence of climate change effects and the longevity of GHGs in the atmosphere, a temperature increase by the end of the century is inevitable, affecting all regions of the globe (estimated to exceed 1.5° by 2040, even with significant GES emission reductions). Faced with this reality and the already perceptible consequences such as intensified heatwaves, increasing floods, and persistent droughts, adopting an adaptation approach is essential. Our future climate will depend not only on our emission reduction efforts but also on our ability to adjust to inevitable changes. This adaptation requires a profound transformation of economic practices, steering our societies towards a low-carbon economy. It aims to foresee and limit climate change damages, targeting aggravating factors like urbanization in risk areas, while developing solutions adapted to different time horizons. In this context, combating climate change is now part of a sustainable development perspective, embracing climate, ecological, and social challenges. Of the seventeen Sustainable Development Goals (SDGs) formulated by the United Nations in 2015, two have a direct relationship with climate, including SDG 13, which is dedicated to initiatives against climate change. In this regard, the IPCC's special report on 1.5°C (IPCC, 2018) particularly emphasizes, in its fifth chapter, the synergy between sustainable development and controlling global warming to 1.5°C compared to the pre-industrial era.

The climate policies previously mentioned primarily target the reduction of demand for high-carbon footprint products. However, the urgency to significantly reduce GHG emissions and the need for a rapid transition to a low-carbon economy require harmonization between long-term climate objectives and short-term market preferences. Generally, political measures designed to reallocate capital to combat climate change will only be truly effective if they lead to an increase in capital cost for major CO_2

emitting companies compared to those adopting more environmentally friendly practices. That's why this thesis primarily focuses on carbon emissions as a measure of companies' exposure to climate change. This interest is motivated by the considerable impact that public regulatory measures can have on these emissions, in order to comply with the commitments made under the Paris Agreement, while recognizing that these emissions are the dominant factor in the evolution of global warming.

From this perspective, the financial sector plays an essential role in allocating capital to the appropriate economic actors. The transition to a greener economy indeed requires a reorientation of investments, encouraging economic actors to favor low-energy consumption alternatives over fossil fuel-based solutions.

The Role of the Financial Sector in the Transition to a Low-Carbon Economy

Faced with the urgency of climate change, it is essential that mitigation and adaptation strategies are supported by suitable financing mechanisms to be effective. The global investment needs for climate are estimated at around $5 trillion per year by 2030 (IEA, 2021). Specifically for the energy sector, an annual investment of nearly $2.4 trillion would be required between 2016 and 2035 to stay on a path compatible with the Paris Agreement, aiming to contain the temperature rise to 1.5°C (IEA, 2023)[40]. Therefore, it is crucial to bridge the gap between the financing needs and the current investment flows, estimated at about $1.75 trillion (IEA, 2018; IPCC, 2018), to ensure the transition to a low-carbon economy. To achieve this, incentives are required, as well as a stronger consideration of climate risks in investment choices and closer collaboration between the public and private sectors.

In this context, the financial sector[41] is positioned at the heart of the process (Hammett et Mixter, 2017). It has the power and responsibility to accelerate this transition. Indeed, redirecting financial flows towards sustainable projects that meet strict environmental and social criteria is an essential step to ensure the sustainability of our economy in the face of climate challenges. Financial markets provide platforms for mobilizing capital for environmentally friendly projects, such as renewable energies, energy efficiency, clean transport, among others. They play a role in mitigating climate risk through innovations such as green bonds and the rise of mutual funds sensitive to environmental issues in their investment strategies. Additionally, financial markets can offer means to cover climate risk, such as enabling investors to diversify their portfolios through investments in sustainability-focused stock indices, which are better

[40] According to the Global Financial Stability Report (GFSR) of the International Monetary Fund (IMF) published in October 2023, emerging and developing countries (EMDEs) should see their climate mitigation investment needs rise to $2 trillion by 2030, thus constituting about 40% of the global financial requirements to counter the effects of climate change. This sum would represent nearly 12% of all investments planned in EMDEs for that year, marking a fourfold increase compared to the current proportion of about 3%.

[41] Referring to financial institutions and financial markets.

positioned to benefit from the transition to an environmentally friendly economy. Financial institutions, like central and commercial banks, investment funds, and insurance companies, facilitate the financing of these projects by providing loans, direct investments, or issuing green financial instruments. Therefore, with its ability to allocate capital to different economic agents or develop new financial instruments better aligned with ecological transition objectives, the financial sector can induce a major overhaul of global economic practices. However, while these innovations are often highlighted as tools for mitigating climate risk, it is important to recognize that the "green" classification can extend to a wide variety of assets, including bonds or ESG (Environmental, Social, and Governance) funds, which necessitates a more thorough evaluation of their effectiveness. Indeed, the actual impact of these approaches on environmental sustainability remains a subject of academic debate, highlighting a divergence between stated intentions and tangible results.

In line with this, several central banks have already shown their interest and involvement in mitigating climate change. The creation of the Network for Greening the Financial System (NGFS) in December 2017 at the "One Planet" summit in Paris, initiated by the Bank of France alongside eight other central banks and supervisory authorities, materializes their desire to integrate climate change risks into their economic decisions and defines how these can be incorporated into financial supervision and risk management of financial institutions. Its main goal is to help the financial sector address the challenges posed by climate change and promote a systemic financial response to climate change[42]. Christine Lagarde, current President of the European Central Bank (ECB), stated :

> "*[..] any institution has to actually have climate-change risks and protection of the environment at the core of the understanding of its mission*".

In light of the action plan on climate change aiming to integrate climate considerations into its policy framework presented by the ECB, the importance of the role played by central banks through monetary policy and macroprudential regulations is emphasized. Campiglio (2016) highlights that carbon pricing, at least as a signal, is not sufficient to achieve low-emission objectives. By adjusting the incentives and restrictions that commercial banks encounter in defining their lending policies, such as adapting reserve requirements based on the purpose of the loan, the orientation of monetary policy could significantly stimulate the allocation of credit to sectors promoting a low carbon footprint.

However, the risks associated with climate change are no longer merely a theoretical concern but a tangible reality that requires their assessment and consideration in risk management due to their potential impact on financial stability (Battiston et al., 2017; FSB, 2020). Indeed, beyond its active role in financing the ecological transition, the financial sector is faced with the need to manage a new category of exogenous

[42] Currently, the NGFS has 83 financial institutions.

financial risks generated by climate change. These risks arise both from i) the direct and tangible effects of climate change itself, such as extreme weather events, and ii) the measures taken to reduce its impact in the context of the transition to a low-carbon economy. To develop effective management and mitigation strategies against these climate risks, the interest of this thesis is therefore focused on conducting a detailed assessment of these risks, specifically on the latter risk, as well as the mechanisms by which they impact financial markets.

The New Financial Risks induced by Climate Change

Although this thesis focuses on the risk resulting from initiatives adopted to mitigate the effects of climate change by transitioning to a low-carbon economy - the transition risk -, it is essential to understand that there are actually several categories of risks induced by climate change that can impact financial stability (Battiston et al., 2017; Allen et al., 2018; FSB, 2020; Svartzman et al., 2021). In 2015, Mark Carney, then Governor of the Bank of England, was a pioneer among central bankers in highlighting this vulnerability of the financial system to climate risks, while proposing a formal definition of these risks.

Physical risk

The "physical risk" arises directly from the tangible consequences of climate change, such as climate-induced natural disasters[43]. The impact of natural disasters on the financial system is expressed through several channels. Academic literature shows how extreme climate events, like rising sea levels threatening coastal infrastructure, can cause material losses, leading to a devaluation of real estate assets (Barnett et Adger, 2003; Hammett et Mixter, 2017). These losses often translate into cascading consequences on the financial sector. For example, in the face of such risks, insurance premiums can increase (Hallegatte et al., 2013; Kunreuther et al., 2013), and it might become more difficult to insure assets located in areas considered "high risk" (Von Peter et al., 2012). This situation could then impact the ability of affected households to access credit or meet their financial obligations (Batten et al., 2016). The subsequent increase in non-performing loans following natural disasters (Klomp, 2014) jeopardizes the stability and resilience of financial institutions through the exacerbation of credit risk (Avril et al., 2023) and, by extension, overall economic growth (Noy, 2009; Hsiang et Jina, 2014).

Although physical risks associated with climate change are undoubtedly a major issue for financial markets (Gourio, 2012; Dafermos et al., 2018), this thesis emphasizes the transition risk, considering the current major focus of climate policies on managing this particular risk.

[43]The Task Force on Climate-related Financial Disclosures provides a more granular definition of physical risk by distinguishing i) acute physical risks, which refer to those triggered by specific events, such as the intensification of extreme weather phenomena like cyclones, hurricanes, or floods, and ii) chronic physical risks, designating long-term variations in climate trends, for example, higher temperatures over time leading to rising sea levels or persistent heatwaves.

Transition risk

The "transition risk" paradoxically stems from mitigation efforts undertaken to limit the impact of climate change, transitioning towards a low-carbon economy. It does not arise from the physical effects related to climate change, but rather from the response to physical climate risks. The ecological transition primarily leads to a change in future cash flow forecasts for companies. Four main sources of transition risk are generally identified (TFCD, 2017), often intertwined, that can affect these flows. "Political and legal risks" refer to changes in regulations and climate policies. For example, the introduction of a carbon tax (previously discussed in the previous section as a mitigation policy aimed at limiting GHG emissions) would entail additional costs for companies that rely primarily on the use of fossil fuels in their production process. Companies with significant fossil fuel reserves could see the value of these reserves decrease or become "stranded" if the demand for these energies decreases due to the tax implementation or if their extraction becomes unprofitable (Caldecott, 2017). This asset depreciation can trigger a domino effect that may materialize as a "market risk". Indeed, these 'brown' assets, which depreciate in response to the transition towards a greener economy, represent not only potential financial losses for companies directly engaged in fossil fuel-related activities. Consequently, financial institutions that have integrated these assets into their portfolios could all face significant losses, such as banks financing these companies, insurance companies (Scott et al., 2017), as well as other financial actors such as pension funds and institutional investors (Weyzig et al., 2014). Thus, due to the close interdependence of financial markets globally, a devaluation of assets related to companies exploiting fossil fuels could trigger repercussions that extend far beyond these companies alone, potentially causing contagion throughout the entire financial system (Battiston et al., 2017). For example, in 2020, assets managed by financial institutions, including banks, insurance companies, and investment funds, were estimated at nearly $103 trillion. "Technological risk" arises from the development of new technologies compatible with the transition to a low-carbon economy. It can translate into additional expenditures in research and development (R&D) and capital to invest in clean energies (renewable energies, energy or carbon storage, improvement of energy efficiency) which can change the capital structure of companies by generating additional implementation costs. "Reputation risk" stems from how a company's environmental commitment is perceived by market actors, which can lead to a reduction in investments in companies perceived as having low environmental responsibility. Hence, technological advancements and changes in consumption habits can affect the demand and supply of certain products (by reducing the demand for products from polluting companies and increasing it for eco-responsible companies), leading to exacerbate the previously mentioned market risk.

Although these different risks often do not materialize simultaneously (Giglio et al., 2021), the realization of these two extra-financial risks represents sources of systemic risk, particularly through their cascading effect on the financial system and the real economy (Battiston et al., 2017; Dafermos et al., 2018; Bolton et al., 2020; FSB, 2020). Moreover, the heterogeneity of these climate risks, the unpredictability of their scope and timeline, and the complexity of assessing their impact on economic actors can lead economic agents and markets to underestimate or misinterpret the issue of risk (NGFS, 2022). This is precisely what this thesis aims to explore and clarify by focusing on the impact of transition risk on stock returns.

Motivations

It is in this context that the writing of this thesis is situated. Indeed, the 2007-2008 financial crisis served as a major reminder of the severe consequences that improper corporate governance and insufficient risk management practices can have on asset values, leading to the implementation of new regulatory measures, notably Basel III, aimed at strengthening regulation and risk management in the banking sector (TFCD, 2017).

In light of the elements presented in the previous section, the transition risk and its consequences represent a major issue for the financial sector. In an environment where information asymmetry regarding the integration of transition risk can lead to significant financial losses, exposing the entire financial system to systemic risk (Battiston et al., 2017), it is crucial to develop recommendations for transparent and relevant financial communication. This would enable market players to assess this climate risk in their operations and investment decisions (TFCD, 2017).

From this perspective, understanding the efficiency of financial markets is paramount. Assuming that these markets are efficient[44](Fama, 1970), they should then be able to apprehend and integrate financial risks related to climate in their investment decisions. Such understanding would prevent an abrupt revaluation of financial asset prices (Battiston et al., 2017; Carney, 2015*a*), thus limiting market risk and potential contagion to the real economy, as previously outlined. Conversely, the inefficiency of financial markets in integrating these risks may indicate the existence of arbitrage opportunities with implications for investment strategies, financial regulation, and climate policy (Charles et al., 2013; Hong et al., 2019). Consequently, examining how financial markets account for climate risk in stock valuations is a relevant research avenue to establish whether these markets encourage or hinder the transition to a low-carbon economy. Furthermore, we focus on transition risk as it is at the center of market actors' attention and is perceived as more likely to impact investment portfolios in the medium term, especially in light of strengthening transition policies (Eskander et Fankhauser, 2020; Fankhauser et al., 2022). Its manifestation in the financial system occurs within a much shorter time horizon than that of physical

[44]Referring to efficiency in the weak informational sense, i.e., that the price of an asset reflects all publicly available information at a given moment.

risk (Stroebel et Wurgler, 2021; Krueger et al., 2020*a*). According to these authors, transition risks could materialize in the next five years, while physical risks could pose a major threat to the financial system over the next thirty years.

Understanding the empirical relationship between transition risk and stock prices offers the advantage of providing concrete indications on how to use financial markets to hedge this risk (Giglio et al., 2021). For about a decade, a new academic literature, "Climate Finance," has increasingly focused on analyzing the integration of climate risks into asset price valuations by financial markets[45]. However, transition risk has been underestimated or neglected, leading to a lack of adequate political strategies for proper management. Concurrently, the development of academic studies on the evaluation, impact, and subsequent integration of transition risk into the investment decisions of financial actors remains recent and limited (Giglio et al., 2021; Stroebel et Wurgler, 2021). Recognizing the effect of transition risk on the financial system is essential to strengthen the resilience and sustainability of economic systems. In this view, academic research is expected to develop studies that will guide public policies in achieving objectives related to the transition to a low-carbon economy. The purpose of this doctoral thesis is thus to meet this need.

Theoretical Frameworks

According to financial theory, the foundations of asset valuation models are based on how investors perceive favorable information regarding the future profit prospects of certain companies. Consequently, investors adjust their expectations of future profit or dividend flows upwards. In this context, all other things being equal, higher expected profits imply a higher expected return (and vice versa). Additionally, investors may consider the risk associated with some companies to be higher than others for various reasons. According to the logic of maximizing returns under the constraint of minimizing risks (Markowitz, 1952), "stock prices must adjust to offer higher returns where more risk is perceived to ensure that all values are held by someone" (Malkiel, 1981). In other words, risk-averse investors would only be willing to take on this high risk if they expect a corresponding higher return as compensation. Thus, at equilibrium, companies perceived as riskier are supposed to offer better returns.

In the context of this thesis, there would, a priori, be no theoretical reason for a heavily polluting company to necessarily have higher long-term average returns than a company with low GHG emissions, or vice versa. Indeed, the theory is not explicit about the factors determining expected returns (Fama et French, 2018). According to Bolton et Kacperczyk (2021*a*,*b*), brown companies could offer higher

[45] The first academic explorations examining the interactions between climate change and the real economy find their roots in the pioneering work of Nordhaus in 1977 (Nordhaus, 1977). Although based on macro-financial models taking into account climate change, subsequent studies using this approach did not directly address the consequences of climate change on asset valuation and risk premiums.

returns through two main transmission channels : the carbon premium and divestment. Firstly, brown companies could offer higher returns because they are more exposed to transition risk, as climate change mitigation strategies could penalize them in the future (*via* a tax or regulations aimed at limiting GHG emissions, etc...) (Zakeri et al., 2022; Semieniuk et al., 2022). Consequently, investors would demand compensation to cover this risk, the carbon premium. Secondly, according to the divestment hypothesis, high carbon footprint companies are assimilated to "sin stocks" (Hong et Kacperczyk, 2009). As socially responsible institutional investors withdraw from heavily carbon-intensive securities, their price decreases. Consequently, for a constant profit level, the return on these shares tends to increase. Conversely, green companies might outperform due to investors' and consumers' preference for more virtuous companies, thus increasing their sales and market share (Barbu et al., 2022), or because of the perceived high risk for these companies due to the uncertainty of the technologies that will prevail in the transition to a low-carbon economy (Harris, 2015).

The following section presents a synthesis of empirical studies conducted around the debate seeking to determine whether heavily emitting companies have higher stock returns, or vice versa.

Positioning in Relation to Existing Literature

In focusing on stocks[46], a segment of empirical literature finds that the most emitting companies offer better returns. Görgen et al. (2020) defined a "brown minus green" factor by calculating the profitability difference between high and low carbon footprint companies based on a carbon score. Including this common risk factor in a multifactorial asset valuation model, their study did not reveal a significant overall "carbon premium" for the period 2010-2017, suggesting that the most polluting companies do not necessarily offer better returns. Following a similar approach, Oestreich et Tsiakas (2015) developed a "dirty minus clean" portfolio based on emission quotas allocated to German companies participating in the EU Emission Trading System (EU ETS) during 2003-2009. Their results indicate that companies receiving more than 1 million emission quotas — the largest emitters in the "dirty" portfolio — systematically outperform those receiving less, included in the "clean" portfolio. The study by Witkowski et al. (2021) confirms this trend for high energy-intensive companies in the EU ETS, extending the study period until 2012. Using toxic emissions as a criterion to assess a company's "greenness" to more broadly represent a company's environmental impact, Hsu et al. (2023) found that an investment strategy favoring high-emission companies could yield an average annual return of 4.42%, described as a "pollution premium". Additionally, using carbon emissions directly as a measure of transition risk and explanatory variable in a panel regression model, Bolton et Kacperczyk (2021*b*) identified a significant global carbon premium,

[46] For a review of the literature on the impact of transition risk on a broader class of financial assets, see Giglio et al. (2021).

highlighting that both the level and variations in carbon emissions have a positive and notable impact on stock returns. The study conducted by Bolton et Kacperczyk (2021*a*) on the US stock market showed that companies with high carbon emissions tend to display higher realized returns as investors demand compensation (a higher risk premium) to cover this carbon risk.

Conversely, another segment of the literature suggests that companies with lower carbon emissions tend to realize higher returns. Harris (2015) developed an "Efficient Minus Intensive" (EMI) factor and demonstrated that low-emission companies achieve higher returns due to the higher risk associated with investing in low-carbon processes and technologies. However, the factor is not significantly different from zero. Focusing on European electrical services, Bernardini et al. (2021) found that an investment strategy in low-carbon emission companies yields higher realized returns during the post-2012 period, during which the decarbonization process accelerated. Alessi et al. (2021) corroborate this result by highlighting a negative carbon premium for individual returns of European stocks. Using an innovative metric to evaluate companies' exposure to carbon-related risks — incorporating carbon emissions and the quality of disclosed environmental information — their study underlines that investors accept lower returns to hold greener and more transparent stocks. Recent contributions from Bauer et al. (2022); Aswani et al. (2023) have emphasized that, when assessing companies' "greenness" based on their declared carbon emissions, green stocks have outperformed brown stocks in G7 countries over the past decade. Similarly, In et al. (2017); Garvey et al. (2018) found that low carbon emission intensity is associated with higher stock returns.

The results of empirical studies on the direction of the carbon premium do not seem to reach a consensus. A possible explanation is that this effect could be offset by market dynamics such as increased demand from investors for securities from eco-responsible companies, positively influencing their return. In this regard, the recent study conducted by Pástor et al. (2021*a*) provides clarification on the divergences observed in previous studies' results. These authors proposed a theoretical framework in which lower realized returns and higher expected returns for high carbon footprint companies could occur simultaneously if the prices of green stocks have recently risen due to a shift in investor preferences. In response to this, several empirical studies have sought to test this prediction. Bolton et Kacperczyk (2021*b*) suggest that the carbon premium they identified could be attributed, at least in part, to selective filtering by institutional investors to limit carbon risk in their investment portfolios. Using a climate news indicator based on a textual analysis of major US newspapers to measure investor preferences influenced by climate change, Pástor et al. (2022); Ardia et al. (2022) found that green stocks outperform brown stocks on days marked by an unexpected increase in climate change concerns. Similarly, Engle et al. (2020) demonstrate that stocks of companies with high environmental scores – reflecting less exposure to regulatory climate risks – record better returns during periods marked by negative news about the future evolution of climate change.

While this thesis directly examines the relationship between carbon emissions and stock returns, it is important to note that a relatively recent field of literature has focused on shedding light on the mechanism through which emissions should influence stock returns. In other words, these studies assess whether the relationship between carbon emissions and stock returns is exacerbated by regulatory risk. In this perspective, Hengge et al. (2023) highlights regulatory actions that lead to positive surprises in carbon policy (i.e., higher carbon prices[47]) resulting in negative abnormal returns that increase with rising carbon emissions. Similarly, Bolton et al. (2023); Millischer et al. (2023) emphasize that stricter environmental policies lead to an increase in the cost of capital for highly emitting companies and, consequently, a reduction in their returns. The empirical results of Sautner et al. (2023)[48] indicate that increased exposure to regulatory actions leads to a devaluation of stocks in the stock market. Faccini et al. (2023) segmented climate risks into four distinct groups : natural disasters, global warming, international conferences, and US climate policy. Their results suggest that since 2012, US stock prices only incorporate climate risk associated with government measures, and a company's exposure to regulatory disruptions is negatively correlated with the stock valuation of its shares.

Contributions of the thesis chapters

The objective of this thesis is to enrich the existing literature by providing new contributions on the impact of transition risk on stock returns, a crucial question in the current context of combating climate change. Transition risk, inherent in the shift towards a low-carbon economy, presents significant challenges and opportunities for financial markets, as highlighted in the previous sections. This thesis aims to quantify and analyze the influence of this risk - primarily measured by carbon emissions[49] - on stock returns, taking into account regulatory, technological, and consumer and investor preference developments.

The main contribution of this thesis is based on a thorough analysis of the impact of transition risk on financial markets. First, by participating in the debate on the most appropriate measure to approximate companies' exposure to transition risk (Bauer et al., 2022; Aswani et al., 2023), we propose in Chapter 1 a new metric of this exposure - verified carbon emissions - to assess the impact of transition risk

[47]Carbon policy surprises are defined using regulatory events related to the allocation of European Union Emission Allowances (EUAs). Specifically, they are determined by the percentage variation in future EUA prices on days marked by regulatory interventions.

[48]Sautner et al. (2023) developed a new indicator to measure companies' exposure to climate-related risks based on the analysis of discourse on climate change during earnings conference calls. This study is based on a large database, including over 10,000 companies from 34 countries between 2002 and 2020, available at `https://osf.io/fd6jq/#!`.

[49]Given the imperative need to significantly reduce carbon emissions in line with the "1.5 pathways" objectives supported by key mitigation policies to address climate change, we have chosen this indicator as the primary metric for a company's exposure to transition risk.

on companies participating in the EU ETS. Next, recognizing the pivotal role of central banks in the transition to a low-carbon economy, Chapter 2 provides an assessment of the environmental footprint of U.S. monetary policy concerning transition risk. The main conclusion of the non-neutrality of U.S. monetary policy, favoring polluting companies, leads to the third chapter. This chapter, also focusing on the United States, explores how transition risk is taken into account in market valuation and how climate regulation can influence this integration.

Indeed, the purpose of these chapters is to enable better integration of transition risk into the evaluation of stocks by investors, empowering regulatory authorities and financial market participants to develop more appropriate policies and preventive measures in response to this risk. This can translate into more strategic investments in the transition to an environmentally friendly economy and better alignment with long-term goals regarding the transition to a low-carbon economy.

Chapter 1 : Verified carbon emissions and stock returns in the EU Emissions Trading Scheme

In this chapter, we examine the stock returns of companies participating in the European Union Emissions Trading System (EU ETS), which are predominantly major greenhouse gas emitters from the energy sector or energy-intensive industrial sectors. This 'cap and trade' system entails that large emitters (the "brown" companies) must purchase emission allowances from lower emitters (the "green" companies). The central question we seek to address is whether, within an emissions trading system, companies with low verified carbon emissions generate superior returns compared to their high-emitting counterparts.

This chapter offers two main contributions. First, the analysis of the relationship between stock returns and carbon emissions, aimed at quantifying the effect of the transition risk to a low-carbon economy, ideally needs to be conducted in an environment where a carbon price is established. This requirement is primarily due to the need to precisely measure the financial impact of carbon emissions on companies. In such a framework, it becomes easier to assess how carbon-related costs directly influence the financial performance of companies and, consequently, their stock returns. Second, our study relies on the use of verified carbon emissions as the primary measure of a company's contribution to transition risk. By focusing on companies participating in the EU ETS, authorities require that CO_2 equivalent emissions be verified by independent auditors specialized in carbon. Therefore, our data is less likely to be biased by greenwashing, unlike the literature that uses emissions self-reported by companies or estimated by data providers.

Using a panel regression model, our results suggest a negative relationship between stock returns and emission levels, while no significant link is observed between returns and emission intensity (emissions relative to revenue). This suggests that, over the period 2006-2021 and accounting for various profitability predictors commonly identified in the literature, companies with high verified emissions levels record lower returns, indicating that green companies outperform brown companies. Furthermore, our results corroborate those of Bauer et al. (2022) by using an indicator variable to measure a company's "greenness". Subsequently, we constructed a "Brown Minus Green" (BMG) portfolio based on verified emissions of companies and analyzed its risk-adjusted return using multifactor models (Fama et French, 1993*b*, 1995). Our analysis confirms the outperformance of green companies, which consistently exhibit higher returns. Specifically, our results suggest an annual excess return between 6.6% and 7.9% depending on the different variants, with slightly higher risk for these companies.

In conclusion, our findings show that the emissions trading system alters the risk-return profile of stocks, which can provide a financial incentive to consider emissions in investment decisions. To promote ecological transition, policymakers could then generalize emissions trading systems and independent emissions audits, and increase the cost of emission allowances.

Chapter 2 : Monetary Policy Surprises and Stock Returns : Carbon Emissions Matter

This chapter examines the impact of monetary policy on the stock returns of companies based on their levels of CO_2 emissions. Intuitively, one might expect to find a positive correlation between carbon emissions and the influence of monetary policy (MP). For instance, polluting companies are generally more susceptible to transition risk, and it is established that risk premiums are influenced by the severity of MP, especially when investors seek returns in a low-interest-rate environment (Bernanke et Kuttner, 2005). Furthermore, shares of green companies may be less sensitive to new fundamentals because financial performance is less critical for the investors who hold them. However, according to classical stock valuation theory (as outlined in the "Theoretical Frameworks" section), a change in the discount rate should have a more significant impact on companies expected to see an increase in future dividends, suggesting that green companies might be more affected by MP decisions. We formalize this idea using a theoretical model[50] in which green companies are less sensitive to monetary policy shocks than brown companies due to their lower exposure to transition risk and because they provide non-pecuniary utility to investors.

The main contribution of this chapter is that by testing the hypotheses of the theoretical model, our

[50]The proposed theoretical model is one in which a representative investor allocates their wealth among a green stock, a brown stock, and a risk-free asset. The investor adjusts their portfolio following an unexpected change in interest rates to maintain a target return. In the model, transition risk makes the brown stock riskier than its green counterpart, and the investor derives non-pecuniary utility from holding stocks that align with their principles. This model leads to two empirically testable hypotheses : (i) brown stocks react more to MP rate surprises, and (ii) this higher responsiveness results from a mixture of supply-side fundamentals and demand-side factors related to investor preferences.

analysis provides an empirical evaluation of the environmental impact of monetary policy, a subject with major policy implications that is the subject of extensive discussions.

We test this prediction using a panel event study regression approach on 857 US firms between 2010 and 2019. Our results show that carbon-intensive companies are significantly more affected by MP surprises. The sensitivity premium of brown companies remains significant when controlling for classical sources of MP heterogeneity, is persistent over time, and increases when concerns about climate change are high.

Our findings suggest that the principle of market neutrality that guides the implementation of MP could lead to a bias in favor of brown companies. In other words, our conclusions indicate that a central bank that decides to lower interest rates indirectly subsidizes polluting companies. This stylized fact may be of interest to central bankers who are currently considering their role in promoting a greener financial system.

Chapter 3 : Carbon Transition Risk and Climate Laws in the United States

With the growing concerns about climate risks and their significance in decision-making, an important question arises : how do stock market investors react to government environmental actions, especially the introduction of environmental regulations ?

In this chapter, we seek to answer this question by determining whether, on the one hand, the U.S. stock market incorporates transition risk into its prices. On the other hand, we also aim to assess the effect of carbon emissions on stock returns when climate legislation is enacted. The combined impact of these variables allows us to determine whether the market adjusts the price of transition risk in response to U.S. initiatives to reduce carbon emissions. Intuitively, we expect this impact to be negative. This implies that after the implementation of climate laws, the influence of carbon emissions on stock returns is likely to be negative.

Empirically, we examine the effect of U.S. climate legislation on the relationship between carbon emissions of S&P 500 companies and their stock returns between 2010 and 2019. Unlike the commonly used event study methodology in the literature, which essentially captures immediate market reactions in short periods surrounding an event, we adopt a more comprehensive approach in this chapter. In a Two-Way Fixed Effects (TWFE) model, we use total reported carbon emissions as the main indicator of transition risk. To delve into long-term implications, we introduce a climate legislation indicator constructed from a database of climate laws. This indicator is a binary variable that takes the value of one for the specific duration during which we aim to observe the impact[51]. This identification strategy allows us to examine both immediate and sustained effects on stock prices. The goal is not only to measure the immediate repercussions of specific climate legislation but also to understand the broader and sustained implications of American regulation on transition risk and its market valuation over an extended period.

Our initial empirical results reveal an apparent premium related to price adjustments before the implementation of climate legislation, suggesting that green companies may outperform less environmentally friendly ones when climate concerns increase. Specifically, an increase of one standard deviation in total reported emissions is associated with an average decrease of 2.8% in stock returns. With the introduction of climate legislation, it appears that investors adopt a wait-and-see approach, but they also penalize companies with larger carbon footprints. The effects are particularly pronounced in the months following the enactment of these laws but less so when examining their long-term impact. Emphasis is placed on total carbon emissions as they offer a more transparent view of a company's environmental footprint, potentially exposing high-emission companies to increased climate regulation risk. Furthermore, using the climate awareness time series indicator from Engle et al. (2020), derived from media coverage of climate change, additional investigations suggest that during periods of heightened climate awareness, the negative impact of carbon emissions on stock returns becomes more pronounced two months after the introduction of a climate law, continuing for nearly a year. However, 12 months after the legislation, this effect diminishes, indicating that persistent legislative impacts may require ongoing reinforcement.

In conclusion, our analysis highlights significant implications for environmental policy development. It reveals how climate risks are integrated into market valuation and the regulatory role of climate laws in this process. The long-term impact of U.S. laws on the relationship between carbon emissions and stock returns needs strengthening to ensure its sustainability. Currently, legislative measures have a more pronounced effect in the medium term, but their sustainability remains uncertain. To encourage lasting environmental change, it is crucial for financial markets to consistently and progressively value environmentally friendly practices. Therefore, policymakers must refine and strengthen existing regulations to not only provide immediate solutions but also establish a solid foundation for long-term market adjustments towards a low-carbon economy.

[51] For example, if we aim to examine the effects one month after the enactment of the law, the variable is defined as 1 for that month. We extend this logic to capture effects for durations of up to 12 months.

Chapitre 1

Chapter 1

Verified Carbon Emissions and Stock Returns in the EU Emissions Trading Scheme

Co-written with Sébastien Galanti.

1.1 Introduction

Draining savings and orienting investment toward firms that emit less carbon will be among the greatest challenges in the financial world in the coming decades (OECD, 2016) and is now unanimously acknowledged as a crucial element of the success of climate policies (Campiglio et al., 2018; NGFS, 2019).

As a consequence, the academic literature examines the return from investing in firms with low carbon emissions (referred to as "green" firms) compared to those with high carbon emissions (referred to as "brown" firms). To conduct this investigation, researchers have three primary methodological options: (1) employing panel or factor models, (2) focusing on the level or intensity of carbon emissions, and (3) selecting the appropriate data source for carbon emissions.

First, panel ordinary least square (OLS) fixed effects regression generally find a positive correlation between emission levels and stock returns, indicating a "carbon premium" where brown firms tend to yield higher returns than green firms (Bolton and Kacperczyk, 2021*a*). Alternatively, factor models can be employed, in which case the models account for the returns of a specific portfolio using risk factors. In this line of research, Görgen et al. (2019) and Bauer et al. (2022) demonstrate that green firms typically achieve higher returns. The literature offers various explanations to reconcile these seemingly contradictory findings. For example, periods of negative climate concerns are associated with higher returns for green firms (Pástor et al., 2022; Ardia et al., 2022), or, the recent 2022 energy crisis is associated with brown stocks outperforming green stocks (Bauer et al., 2022).

Second, returns can be associated with the absolute level of carbon emissions or with carbon intensity i.e., carbon emissions scaled by a variable related to firm size. Pástor et al. (2022) uses emission levels and finds that when accounting for climate concern shocks, brown stocks slightly outperform green stocks. Huij et al. (2022) uses emissions intensity and finds that green firms earn higher returns[1]. Bauer et al. (2022) indicates a significant impact of the level of carbon emissions, but the relationship becomes insignificant and inversely proportional when instead considering emissions intensity.

Third, the data on carbon emissions can be: self-reported by firms (as gathered in, for example, Refinitiv), vendor-provided estimated data (such as Truecost and Refinitiv when reported data are not available), or verified emissions. Bauer et al. (2022) show that both reported and estimated emissions support green outperformance for emissions intensity, but not when using estimated data from Refinitiv for emissions level, whereas Huij et al. (2022) find green outperformance using estimated data from Truecost. As highlighted by Aswani et al. (2023), the presence of a carbon premium in earlier studies is primarily attributed to the utilization of unscaled and vendor-estimated emissions data. In contrast, verified emissions are measured by an independent third party. Just as independent auditors control the financial statement of a firm, carbon audits exist and are mandatory for firms involved in the European Union Exchange Trading Scheme (hereafter EU ETS). Oestreich and Tsiakas (2015) use such data and report outperformance for brown firms, but their study restricts the sample to German firms and for a period (2003-2012) in which climate concerns where less acute than in subsequent years.

In this analysis, we use verified carbon emissions data from the EU ETS, for which the risk of greenwashing is reduced[2]. The core question we seek to address is whether, within an emission trading scheme, companies with verified low carbon emissions generate significantly different returns than their high-emission counterparts. In pursuit of this goal, we employ various methodologies previously mentioned: panel and factor models, as well as the examination of emission levels and intensities. Note that firms participating in the EU ETS do not represent the entire stock market, as they primarily belong to sectors known for their high pollution levels, such as Oil and Gas, Power and Heat, Building Materials, Pharmaceuticals, and so forth. Consequently, our study is not susceptible to the "sector bias" identified by Pástor et al. (2022). They report

[1]There are other measures of a firms' contribution to climate change, which also lead to contradictory results, see Pástor et al. (2022); Bolton and Kacperczyk (2020, 2021*a*).

[2]Greenwashing refers to a practice where companies exaggerate or misrepresent their environmental efforts, including their actual emissions levels, to create a more eco-friendly public image.

that industry-level brownness, as opposed to within-industry brownness, largely accounts for the superior performance of green stocks. By focusing on companies within the EU ETS, we can better isolate the impact of verified carbon emissions on stock returns.

Our findings reveal that stock returns are negatively associated with emission levels, while no significant association is observed between returns and emission intensity (emissions per sales). This implies that, over the 2006-2021 period and while accounting for various profitability variables, firms with higher verified emission levels exhibit lower returns, meaning that green firms outperform brown firms. Additionally, we employ a dummy variable to indicate a firm's "brownness", following the approach of Bauer et al. (2022), which confirms these results.

Subsequently, we construct a "brown-minus-green" (hereafter BMG) portfolio and analyze its risk-adjusted return using a Fama-French three-factor and four-factor model. Our analysis confirms the outperformance of green firms, as they consistently exhibit higher returns across all specifications. However, we note that 5 out of the 8 specifications are not significant, which is likely due to the high exposure of firms within the EU ETS market to the Fama-French "value" factor. The strongest significant association is observed in equal-weighted portfolios based on emission intensity. In that case, green firms earn an excess monthly risk-adjusted return in a range between 0.53% and 0.64% (i.e., an annual excess return between 6.6% and 7.9%) over brown firms. Green firms are also slightly riskier (annual standard deviation of 23.24 vs. 22.03 for brown).

This article contributes to the existing literature by using verified emissions to examine the returns from firms that are subject to the polluter pays principle of the EU ETS. Unlike prior studies[3], we reconcile the panel and factor approaches, which both indicate the higher performance of green firms. Therefore, selecting green stocks from firms participating in an emission trading scheme can: 1) make a tangible difference in mitigating climate change (as emissions are verified rather than merely reported or estimated) and 2) yield higher returns for investors. For information, buying the right to emit 1 ton of CO_2 cost 25 euros in 2006, then plummeted to less than 10 euros in 2011-2017, but rose to near 25 euros during 2020 and 70 euros late 2021. Our results thus hold despite this relatively harmless average cost to pollute for brown firms. However, this price exceeded 100 euros in early 2023, and recent regulatory changes [4] will likely reinforce this trend. In that context, investors will expect higher costs for brown firms, thus modifying portfolios in a way that further widens the difference in returns between brown and green firms.

The remainder of the article is structured as follows. Section 1.2 presents the related literature, Section 1.3 describes the data, Section 1.4 outlines our identification strategy, empirical hypotheses

[3]Except Bauer et al. (2022).

[4]In April, 2023, the European Council (2023) voted the end of free allowances in the EU ETS (which were temporarily authorized for air transport), the mandatory Cross-Border Adjustment Mechanism (CBAM), which will require foreign products to meet the climate standards imposed in the EU, and the addition of new sectors in the EU ETS market, such as maritime transport, road transport, buildings and small industries.

and results, and Section 1.5 presents the robustness checks. Section 1.6 concludes the paper.

1.2 Literature and context

It is now acknowledged that climate change influences finance (Aglietta and Espagne, 2016; Campiglio et al., 2018; ECB, 2019; NGFS, 2019; Krueger et al., 2020*b*) and that finance should support the energy transition (Carney, 2015*b*; Millar et al., 2018), subject to the constraint that no prosperity can arise in an economy with costly energy supplies. The subsequent question is how to provide incentives to finance green projects. Studying returns with respect to carbon emissions is an important path in that direction.

The theoretical grounds suggest determining why a certain category of stocks would yield, on average in the long run, higher returns than another category. We describe two plausible theoretical channels.

First, we follow Fama and French (e.g., in Fama and French (2015, 2018)) who base the theoretical grounds of their factor models on valuation models, like the dividend discount model. When favorable information about future earnings prospects of certain firms is available, investors update their expectations about future earnings or dividend streams upward. In that context, all else equal, higher expected earnings imply a higher expected return (and reciprocally).

Second, investors may perceive the risk associated with certain companies to be higher than others for various reasons. Within the risk-return framework, as proposed by Markowitz (1952); Merton (1972), risk-averse investors would only agree to shoulder this elevated risk if they expect a correspondingly higher return as compensation. Thus, in equilibrium, riskier firms are anticipated to yield higher returns.

However, the theory "says nothing about what determines expected returns" (Fama and French, 2018, p.236). We follow these authors on that point, and we posit that for the brown vs. green debate, there is, *a priori*, no theoretical reason for one to necessarily have greater long-term average returns than the other [5]. This is not satisfactory because one could ex-post justify any result. For example, brown firms could outperform because fossil fuels or energy prices increase, due to a steady global demand, or because governments are still supporting the fossil fuel industry and attempting to open new fossil fuel routes (Zakeri et al., 2022), or because of a higher risk due to assets being "stranded" (Semieniuk et al., 2022). Or, green firms could outperform because the appetite of consumers for "green" goods and services could increase steadily, and green firms should then increase their sales and market shares (Barbu et al., 2022), or because of high perceived risk for green firms, as the the conditions to a transition to a fully renewable energy system in 2050

[5] For example in the theoretical model of Pástor et al. (2021*b*), green firms only temporarily outperform when there are, for example, concerns about climate change

are quite restrictive in terms of lifestyle and country cooperation (Holechek et al., 2022).

What are the facts? The empirical literature can be presented in three groups. Some studies show no pricing of carbon risk, others show "brown outperformance" (higher returns for brown firms), and others show "green outperformance" (higher returns for green firms).

First, in a review of the empirical literature, Campiglio et al. (2019) identify some studies in which carbon risk does not seem to be fully priced, is only priced in very recent years, or is only priced for some industries. Monasterolo and De Angelis (2020) show that stock markets react to low-carbon firms after the 2015 Paris Agreement but do not seem to penalize high-emitters' assets. Similarly, Delis et al. (2019) study the loan rate that banks charge to fossil-fuel firms, and compare it to that charged to non-fossil-fuel firms. They confirm a "carbon bubble" before 2015 (banks neglected the fact that fossil fuel reserves would become "stranded", i.e., lose value) but not after 2015. Interestingly, in 2015, Harris (2015) builds a carbon factor (the efficient-minus-intensive (EMI) factor) and shows that green firms earn higher returns (because of the higher risk associated with investment in carbon-efficient processes and technologies); however, the factor is not significantly different from zero ($t = 1.14$).

Second, Görgen et al. (2019) showed that the difference between the returns on high- and low-carbon-scoring firms (equal to -0.25%) is not significant ($t = 1.17$); however, when regressing this factor, the above authors find that the coefficient indicates that firms with high (low) carbon scores are more (less) exposed to carbon risk. In the same vein, but without explicitly building a carbon factor, Bolton and Kacperczyk (2020) and Bolton and Kacperczyk (2021*a*) demonstrate the existence of a "carbon premium", i.e., brown firms exhibit higher returns.

Third, in contrast, Ardia et al. (2022) and Huij et al. (2022) find that greener firms earn higher returns. Ardia et al. (2022) explain that in a period of an unexpected increase in climate change concerns, green firms outperform their brown counterparts. In this line, Bauer et al. (2022) also confirm this fact, however the authors also observe that the results are influenced by the method utilized, as evoked in the introduction. This will be discussed in greater detail Section 1.3.

The current literature suffers from two main limitations. The first one pertains to the measure of CO_2 emissions. Most empirical studies rely on self-reported or vendor-reported data. These data, by definition, are not verified by an independent and impartial third party, which could lead to companies distorting their data or engaging in "greenwashing" (Wu et al., 2020). Moreover, data providers do not cover the same time period, geographical location, or even the type of carbon emissions considered. This creates mixed conclusions about the impact of carbon emissions on stock returns. As an alternative, we propose using verified carbon emissions data from the EU ETS. The second limitation comes from the difficulty to justify why green and brown stocks return should differ. In contrast, an ETS provides a direct explanation. Because the EU ETS was designed to "internalize externalities" from carbon emissions, the “cap and trade” scheme implies that high emitters must buy allowances for emission from low emitters. As a consequence, green firms should experience higher expected earnings, and in turn, higher returns[6]. To our knowledge, the only other study using this data is by Oestreich and Tsiakas (2015), who found that companies with high carbon emissions have higher expected returns. However, their study is limited to German firms (2003-2012) and focuses on carbon allowances as a company’s brownness indicator. Giglio et al. (2021) emphasize the fact that data on carbon emissions is relatively recent, limiting the observation period of analyses using this data. In contrast, we use data from all available countries over the 2006-2021 period.

1.3 Data

In this section, we outline the data employed to assess the influence of verified CO_2 emissions on the stock returns of companies in our sample. Our final dataset is derived from the combination of two distinct databases. The first database comprises carbon emissions data sourced from the *Carbon Market Data* platform, while the second contains accounting and price data obtained from *Datastream-Refinitiv Eikon*. To merge these two databases, we utilize the ISIN code as the primary identifier.

1.3.1 Verified CO_2 emissions

Our analysis is based on the Carbon Market Data database which gathers verified emissions data for the firms participating to the EU ETS.

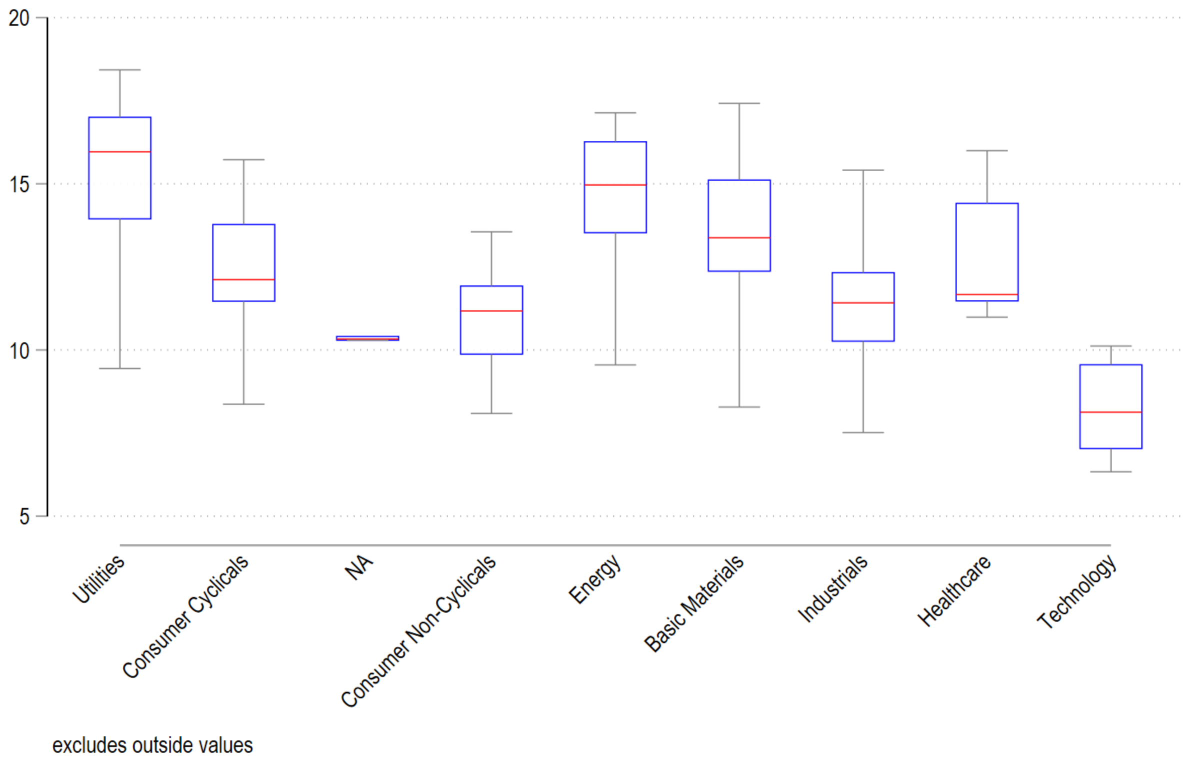
To date, several proxies have been used to measure the carbon footprint of companies. The standard for measuring a company’s carbon footprint refers to the emissions it releases. The Greenhouse Gas Protocol[7] classifies carbon emissions into three categories corresponding to the company’s emissions scope (Scope 1, 2 and 3). Our data corresponds to Scope 1 (direct carbon emissions emitted from sources that are owned or controlled by the company).

The EU ETS company database displays verified carbon emissions by EU accredited carbon verifiers such as DNV, SGS, Bureau Veritas or TÜV. Thus, the verified emissions correspond to the amount of emissions actually emitted by a facility. The emissions of each facility are monitored and verified by independent third parties in accordance with the monitoring and reporting guidelines published by each member state. Despite that this significantly reduces our sample size, relative to using reported or declared emissions, it allows us to improve the reliability of our results.

[6]The question of the optimal price for carbon is out of our scope, see (Daniel et al., 2016) for a theoretical model.
[7]see https://ghgprotocol.org/.

Currently, self-reported data produced on a voluntary basis are common when investigating a company's greenhouse gas emissions. Since these data are provided on a voluntary basis and are not subject to a clear legal framework, their accuracy and reliability remain an issue. As evoked earlier, Bauer et al. (2022) note that the lack of consensus in the literature is mainly due to the methodology and/or data used. We consider both the emissions level (as a standard measure) and intensity. The second measure allows us to control for the effect of company size. Obviously, a larger company has higher emissions, but it is relevant to to compare their emissions emitted per unit of production. We scale carbon emissions by firms' sales to obtain a measure of carbon intensity. The two measures of a company's brownness are then normalized using the natural log to facilitate the interpretation of the results.

Figure 1.1: Emissions level (sector)



Note: The figure graphically shows the box plot of the distribution of emissions level reported in natural logarithm scale across sector over the period 2005-2021. Note that outside values have been excluded to clarity.

Figure 1.1 provides a visual representation of the distribution of verified emissions by sector[8][9].

[8]We use the TR1N sector classification which is the Economic Sector name from The Refinitiv Business Classification system. TRBC is the most comprehensive, detailed, and up-to-date sector and industry classification available. TRBC consists of five levels of hierarchical structure. Each company is allocated an Activity that falls under an Industry, then an Industry group, then Business Sector, which is then part of an overall Economic Sector. The "NA" sector refers to the one company operating in the aviation sector and not referred in the TR1N classification. For further details on the TRBC classification system, see https://my.refinitiv.com/content/mytr/en/product/thomson-reuters-businessclassification.html. We would like to clarify that both the Consumer Cyclical and Consumer Non-Cyclical sectors include high-emitting companies that participate in the EU ETS.

[9]Table 1.7 in subsection 1.7.1 provides further descriptive statistics on emissions intensity.

This allows for an initial overview of the emissions in the sample, revealing a significant level of heterogeneity across sectors. Notably, the Utilities, Basic Materials, and Energy sectors exhibit the highest levels of pollution, while the Technology sector is the least polluting. Furthermore, there is also significant variability within sectors, as evidenced by the range of box plots for all sectors except for the "NA" sector, which refers to the single company operating in the aviation sector and not classified in the TR1N classification.

Our research is focused on a firm-level analysis. To conduct our investigation, we must construct a sample consisting of companies listed on stock exchanges. Consequently, we initially gather 169 companies with an ISIN code from the Carbon Market Data database[10]. Within this sample, 10% of the companies have either been delisted or acquired. Ultimately, our sample consists of 146 publicly traded companies. We obtain carbon emissions data for these companies at an annual frequency covering the 2005-2021 period, which serves as the basis for our time span sample. We will use a one-year lag for the emission variable, as in Ilhan et al. (2021), since carbon emissions are not published instantaneously, and stock investors can only react with a delay.

1.3.2 Dependent variable

We retrieve stock prices for 146 primary quote companies listed on European stock index. We compute monthly stock returns as the first logarithm difference according to the following formula: $r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1})$ where $P_{i,t}$ is the price of stock i at time t[11]. We apply several filters consistent with the literature to limit the impact of outliers[12]. Equity prices and all accounting and financial variables at the firm level are obtained from *Datastream-Refinitiv Eikon*[13][14].

1.4 Hypotheses and empirical strategy

This section is dedicated to outlining the design of our empirical strategy in detail. The primary question we seek to answer is as follows: Are higher realized stock returns associated with higher carbon emissions? We address this query through an empirical analysis utilizing two distinct methodologies. We first present the following research hypotheses corresponding to each methodology we employ.

[10]The other companies in the database do not have an ISIN code and are not publicly traded and therefore cannot be included in the analysis.

[11]Here, P_t is the closing price on the first day of month t.

[12]We delete zero returns and returns exceeding 100%, winsorize returns at the 1% level and only include primary quotes are included in the analysis.

[13]Our sample brings together companies listed on various European stock exchanges with various currencies. Therefore, we convert the companies' returns and all accounting and financial variables into dollars to allow comparison with Fama French factors and avoid trading frictions (Ang et al., 2009).

[14]Since we use two different methodologies in the subsequent empirical analysis, specific information regarding the control variables can be found in their corresponding sections.

1.4.1 Hypotheses

First, we start the empirical investigation with a panel fixed-effects regression (Section 1.4.2). This method enables us to control for unobserved time-invariant factors that may influence the relationship between stock returns and carbon emissions. Within this framework, the null hypothesis states that there is no difference in returns between companies with low carbon emissions (green firms) and those with high carbon emissions (brown firms). As a consequence, we can consider two alternative hypotheses:

H1. *Carbon Premium*: High-emitting firms generate higher returns than low-emitting firms.

H2. *Green Premium*: Low-emitting firms generate higher returns than high-emitting firms.

Following that, we adopt a portfolio-based approach to explore the impact of carbon emissions on stock returns from an investor's standpoint (Section 1.4.3). This method allows us to analyze how a portfolio constructed based on the companies' carbon emissions performance might generate different returns from other investment strategies.

Rejecting the null hypothesis (and not rejecting one of the alternative hypotheses) implies that there is a premium associated with verified carbon emissions. Subsequently, a "carbon portfolio" can be created by investing in the group with higher emissions and short-selling the group with lower emissions. We call it the "brown minus green" (BMG) portfolio. We will then evaluate whether this portfolio demonstrates positive risk-adjusted returns, or a positive intercept when analyzed using the standard factor model. In this context, the null hypothesis posits that the risk-adjusted returns of a BMG portfolio are not significantly different from zero. We can consider two alternative hypotheses:

H3. *Positive BMG Portfolio*: A "brown-minus-green" portfolio displays significantly positive risk-adjusted returns.

H4. *Negative BMG Portfolio*: A "brown-minus-green" portfolio exhibits significantly negative risk-adjusted returns.

Hypotheses H3 and H4 are mutually exclusive. If H3 is not rejected (and H4 is rejected), this indicates that brown firms outperform green firms. Conversely, if H4 is not rejected (and H3 is rejected), green firms outperform brown firms.

The overarching goals of this empirical strategy are: (i) to obtain an extensive understanding of the effect of verified CO_2 emissions on the returns of companies participating in the EU ETS, and (ii) to ensure the reliability of our findings, regardless of the methodology employed. By employing both methodologies, we attempt to provide robust evidence to support our conclusions.

1.4.2 Panel setting framework

We employ a panel fixed-effects model to estimate the sensitivity of individual stock returns to verified carbon emissions. We will use the emissions level and intensity (See section 1.4.2) as our primary specification, and a brownness indicator variable (See Section 1.4.2) as a key variable to explain the variation in stock returns.

Verified CO_2 emissions as the main variable of interest

We follow the methodology initiated by Bolton and Kacperczyk (2020) to assess the impact of carbon emissions on stock returns. To this end, this specification takes the following form:

$$r_{i,t} = \alpha + \beta_1 Emissions_{i,t-1} + \beta_2 \mathbf{X}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{1.1}$$

where $r_{i,t}$ denotes the stock returns of firm i in month t. $Emissions_{i,t-1}$ refers to the emissions level and intensity from the previous year. Our coefficient of interest is β_1. It represents the expected change in stock returns for a one-ton increase in the emissions. For instance, if β_1 is positive and statistically significant, this means that brown companies generate higher returns than green companies. $\mathbf{X}$ denotes the vector of control variables widely used in the literature and contains the following variables: Size of a company operationalized as the natural logarithm of the market capitalization; Book-to-market is computed as the inverse of the market-to-book; return on equity (ROE); Leverage is calculated as the ratio of total debt to total assets; Sales growth is operationalized as the one-year net sales growth; Investment-to-assets is calculated as the change in total assets divided by lagged total assets; Volatility is calculated as the standard deviation over the past twelve months of returns; and Momentum is the cumulative returns from $t-12$ to $t-2$ and the returns from the previous month[15]. γ_i and δ_t denote sector and time fixed effects, respectively. $\varepsilon_{i,t}$ denotes the normally distributed error term.

We make an important contribution to the literature by adding sector-time fixed effects. Our sample consists solely of companies participating in the EU ETS. As a result, they are subject to the regulations of the various phases of the EU ETS[16]. It is even more important in our specification to control for sector fixed effects, and especially sector-time fixed effects. This allows us to capture the specific effects of each sector that evolve differently over time. Besides, we cluster standard errors at the firm level to account for the serial correlation within firms, and we account for the emissions publication lag in our specification as discussed in subsection 1.3.1.

Finally, we estimate Equation 1.1 by OLS. Table 1.1 presents the estimation results for the

[15] All control variables are lagged by one period except the sales growth and investment-to-assets variables. Consistent with the existing literature and in order to reduce the influence of outliers, we have winsorized the stock returns at 1%. Similarly, metrics such as ROE, Leverage, Book-to-market, and Investment-to-assets are winsorized at 2.5%. For Momentum and Volatility, the winsorization is done at 0.5% level.

[16] Table 1.5 in subsection 1.7.1 provides details on the four phases of the EU ETS.

panel regression with emissions level (columns 1–4) and intensity (5–8) as the main variables of interest in explaining monthly stock returns. We begin our analysis by estimating the specification without any controls or fixed effects (columns 1 and 5). Then, we include time and sector fixed effects (2–4 and 6–8).

Table 1.1: Estimation results for the panel regression with emissions level and intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emissions level	-0.022	-0.078**	-0.128***	-0.118***				
	(-1.06)	(-2.43)	(-3.34)	(-3.20)				
Emissions intensity					-0.085***	0.002	0.018	0.010
					(-3.86)	(0.08)	(0.43)	(0.23)
Size		0.352***	0.406***	0.380***		0.314***	0.329***	0.305***
		(7.32)	(6.31)	(5.98)		(6.52)	(6.44)	(6.03)
Book-to-market		1.107***	1.134***	1.078***		1.050***	1.057***	1.007***
		(6.32)	(6.16)	(5.91)		(6.30)	(6.09)	(5.84)
Momentum		-0.001	-0.001	-0.003		-0.001	-0.002	-0.004
		(-0.41)	(-0.49)	(-1.15)		(-0.46)	(-0.55)	(-1.19)
Leverage		-0.048	-0.099	-0.096		-0.038	-0.055	-0.058
		(-0.36)	(-0.70)	(-0.68)		(-0.30)	(-0.42)	(-0.45)
ROE		0.055***	0.054***	0.059***		0.058***	0.057***	0.062***
		(7.58)	(7.42)	(7.80)		(8.02)	(7.91)	(8.25)
Investments-to-assets		0.000	0.000	-0.001		0.000	0.000	-0.001
		(0.00)	(0.01)	(-0.03)		(0.01)	(0.00)	(-0.03)
Sales growth		0.436	0.394	0.348		0.398	0.392	0.344
		(1.32)	(1.25)	(1.14)		(1.23)	(1.21)	(1.09)
Volatility		0.055***	0.056***	0.046**		0.056***	0.054***	0.044**
		(2.97)	(2.87)	(2.22)		(2.98)	(2.77)	(2.10)
r_{t-1}		-0.025**	-0.025**	-0.035***		-0.025**	-0.025**	-0.035***
		(-2.09)	(-2.11)	(-2.66)		(-2.10)	(-2.11)	(-2.66)
Constant	0.317	-6.604***	-6.874***	-6.471***	-0.175**	-7.024***	-7.236***	-6.784***
	(1.03)	(-7.94)	(-7.17)	(-6.96)	(-1.99)	(-8.33)	(-7.87)	(-7.55)
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Sector FE	No	No	Yes	No	No	No	Yes	No
Time × Sector FE	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.000	0.428	0.428	0.490	0.000	0.428	0.428	0.489
Observations	23346	20209	20209	20069	23020	20209	20209	20069

Note: The table presents estimation results for the panel regression with the emissions level (Columns 1-4) and intensity (Columns 5-8) as the main variables of interest. The dependent variable is monthly stock returns. There are eight different model specifications (Columns 1-8) with different combinations of fixed effects (time, sector, and time × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and presented in parentheses. The significance levels are denoted * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

In Table 1.1, presents the estimation results for the panel regression with emissions level and intensity as the main variables of interest in explaining monthly stock returns. The coefficients for the emissions level are negative and significant in Columns 2–4. For instance, this suggests that an increase in the emissions level by one ton of CO_2 is associated with a decrease in monthly stock returns by 7.8 basis points in Column 2. Similarly, in Columns 3 and 4, the coefficients are -0.128 and -0.118, respectively, suggesting that higher emissions levels lead to lower stock returns. Interestingly, the specification in Column 4 has the highest adjusted R^2 (almost 49 %), highlighting the relevance of accounting for the specificities of each sector over time. Regarding emissions intensity, our findings reveal contrasting results. The coefficient β_1 is significant at the 1% level in the baseline specification (Column 5) without any controls or fixed effects. However, in Columns 6 to 8, the coefficients' signs reverse, and they no longer exhibit a significant impact on stock returns. These outcomes align with the existing literature, such as Bolton and Kacperczyk (2020); Bauer et al. (2022), which report a reversed sign when emissions intensity is employed as an indicator of a company's environmental performance.

However, our significant results challenge those of Bolton and Kacperczyk (2020). We found that higher carbon emissions are associated with lower returns suggesting that firms with higher emissions may face lower expected earnings from investors. With regard to the hypothesis outlined in subsection 1.4.1, we reject the null hypothesis and **H1**, and we do not reject hypothesis **H2**, which suggests the existence of a green premium.

Brownness indicator as the main variable of interest

To reconcile the results on the impact of carbon emissions on stock returns given the methodologies used, we now follow the methodology initiated by Bauer et al. (2022). Carbon emissions can vary considerably across companies, which can lead to significant weighting effects in the regression. Using a dummy variable can avoid these weighting effects and simplify the analysis. Furthermore, assigning a value of 1, -1, or 0 for each year to indicate whether the company is brown, green, or neither, respectively, allows for a direct comparison with the asset pricing approach in the following Section 1.4.3.

We denote by $\mathbf{B}_{i,t}$ the indicator variable taking value 1 if the firm is brown, -1 if the firm is green and 0 otherwise at time t based on a quintile sort on emissions. To avoid the emissions publication lag discussed in subsection 1.3.1, the indicator variable is based on the emissions from the previous year. For instance, a company with a value of 1 in 2006 is part of the highest emission quintile based on 2005 emissions. Alternatively, if the value of the indicator variable is equal to -1 in 2006, it is part of the group corresponding to the lowest 2005 emissions quintile. The specification takes the following form:

$$r_{i,t} = \alpha + \beta_1 \mathbf{B}_{i,t} + \beta_2 \mathbf{X}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{1.2}$$

where $r_{i,t}$ denotes the stock returns of firm i in month t, $\mathbf{B}_{i,t}$ refers to the brownness indicator taking the value 1, -1 if firm i is brown or green, respectively and 0 otherwise at time t. We include the same control variables and fixed effects as Equation 1.2, and $\varepsilon_{i,t}$ denotes the normally distributed error term.

We estimate Equation 1.2 by OLS. We are particularly interested in the coefficient associated with the indicator variable β_1, representing the difference in average returns between brown and green companies[17].

[17] As explained in Bauer et al. (2022): "In a cross-sectional regression of stock returns in month t, the coefficient on $\mathbf{B}_{i,t}$ ($\mathbf{D}_{i,t}$ in their paper) would yield the spread return in that month, and the time-series average of the regression coefficients would reproduce the mean spread table from Table 1.3 (Table 2 in their analysis)".

Table 1.2: Estimation results for the panel regression with a brownness indicator variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Brownness indicator (level)	-0.096	-0.373***	-0.474***	-0.395***				
	(-1.18)	(-3.53)	(-3.57)	(-3.05)				
Brownness indicator (intensity)					-0.332***	-0.128	-0.111	-0.084
					(-3.46)	(-1.19)	(-0.79)	(-0.59)
Size		0.334***	0.370***	0.339***		0.281***	0.295***	0.277***
		(7.12)	(6.22)	(6.05)		(6.20)	(5.93)	(5.75)
Book-to-market		1.178***	1.207***	1.116***		1.098***	1.116***	1.040***
		(6.53)	(6.43)	(6.14)		(6.33)	(6.21)	(5.93)
Momentum		-0.001	-0.001	-0.002		-0.001	-0.001	-0.003
		(-0.22)	(-0.22)	(-0.83)		(-0.25)	(-0.27)	(-0.88)
Leverage		-0.032	-0.070	-0.080		-0.032	-0.057	-0.069
		(-0.24)	(-0.52)	(-0.59)		(-0.25)	(-0.43)	(-0.52)
ROE		0.054***	0.054***	0.059***		0.056***	0.056***	0.060***
		(7.35)	(7.18)	(7.59)		(7.75)	(7.49)	(7.86)
Investment-to-assets		0.001	0.001	-0.001		0.001	0.001	-0.001
		(0.07)	(0.06)	(-0.07)		(0.07)	(0.07)	(-0.07)
Sales growth		0.449	0.424	0.370		0.424	0.426	0.365
		(1.35)	(1.31)	(1.21)		(1.27)	(1.26)	(1.15)
Volatility		0.048***	0.048**	0.042**		0.049***	0.048**	0.042**
		(2.63)	(2.54)	(2.12)		(2.67)	(2.52)	(2.10)
r_{t-1}		-0.025**	-0.025**	-0.033**		-0.025**	-0.025**	-0.033***
		(-2.08)	(-2.07)	(-2.61)		(-2.09)	(-2.09)	(-2.62)
Constant	0.095	-7.311***	-7.936***	-7.374***	0.092	-6.442***	-6.701***	-6.341***
	(1.63)	(-8.92)	(-7.76)	(-7.73)	(1.61)	(-8.01)	(-7.59)	(-7.57)
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Sector FE	No	No	Yes	No	No	No	Yes	No
Time × Sector FE	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.000	0.423	0.423	0.484	0.000	0.423	0.423	0.484
Observations	25361	20648	20648	20562	25361	20648	20648	20562

Note: The table presents estimation results for the panel regression with a brownness indicator variable based on emissions level (Columns 1-4) and intensity (Columns 5-8). The dependent variable is monthly stock returns. There are eight different model specifications (Columns 1-8) with different combinations of fixed effects (time, sector, and time × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and presented in parentheses. The significant levels are denoted * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Table 1.2 summarizes the estimation results for Equation 1.2. The coefficient is negative and significant at the 1% level in Columns 2-4, suggesting a negative relationship between the emissions level and monthly stock returns. It becomes larger in absolute value and significant when we include control variables and time fixed effects in the regression. Note that the adjusted R^2 has significantly improved from Column 1 to Column 2.

More interestingly, the coefficient associated with carbon emissions becomes even larger in absolute value after adding sector fixed effects, meaning that the impact of carbon emissions on the stock returns of EU ETS firms is even more significant and robust. In other words, this indicates that, when accounting for the specificities of each sector, the effect of carbon emissions on firm performance is more pronounced.

In Column 4, the mean spread returns between brown and green firms is approximately -0.395% compared to -0.373% in Column 2 (with only time fixed effects). This indicates that the average impact of carbon emissions on stock returns is even larger when accounting for the temporal variations in the specificities of each sector.

The coefficient on emissions intensity is negative and only significant at the 1% level in Column 5, suggesting that higher emissions intensity is associated with lower monthly stock returns in the simplest specification. However, the coefficient is not significant in Columns 6-8. This result is not surprising given the findings in the literature on the impact of carbon emissions intensity and are in line with those of Table 1.1. Hence, our results are in line with Bauer et al. (2022), highlighting the outperformance of green companies with respect to brown companies for our sample period. These results remain significant even after considering the broader set of variables in the model influencing monthly stock returns.

In line with the findings from Section 1.4.2, we reject the null hypothesis that carbon emissions have no effect on stock returns. Consequently, we confirm the secondary alternative hypothesis **H2** suggesting that firms with higher carbon emissions are associated with lower stock returns. Consistent with our empirical approach, we extend the analysis by examining the relationship between carbon emissions and stock returns within the context of an asset pricing model.

1.4.3 Empirical asset pricing

The current approach of "factor models" in the empirical asset pricing literature is to group stocks into portfolios according to firm characteristics to assess their performance. In a seminal work, Fama and French group stocks into portfolios according to size and book-to-market. At the intersection of the finance and climate risk literature, Oestreich and Tsiakas (2015) define three carbon portfolios according to emission allowances. Companies that have received more than one million emission allowances constitute the "dirty" portfolio, those that have received less than one million allowances represent the "medium" portfolio, and those that have not received any allowances are part of the "clean" portfolio. More closer in spirit than our study, Huij et al. (2022); Bauer et al. (2022) rely on estimated/reported emissions as a main sort variable to define the carbon portfolio whereas Engle et al. (2020) and Görgen et al. (2019) use E-scores and carbon scores, respectively.

In this line, we seek to to test Hypotheses **H3** and **H4** by assessing the performance of portfolios based on verified carbon emissions. Carbon emissions are verified in April in the year after they are reported. To avoid the publication lag evoked earlier, green and brown portfolios are built based on the previous year's emissions. Portfolios returns are calculated every mid-year (in June), over the 12 consecutive months until the next sorting. Hence, portfolios are rebalanced each year on a lagged emissions basis. For example, the monthly performance of portfolios calculated from July to June of the following year is based on the verified emissions from the previous year.

An important issue remains to define "green" and "brown" portfolios. We use quintile sort based on emissions level and intensity to group stocks and returns are calculated for each quintile portfolio. We compute both equal and value weighted returns of the resulting 10 portfolios. Therefore, for each emissions category (level and intensity), we define two brown-minus-green portfolios as the spread returns between the most and least carbon-intensive portfolios. From an investor's perspective, this portfolio corresponds to taking a long position on the most carbon-intensive companies and a short position on the least carbon-intensive companies. Such a portfolio difference more accurately controls for common market trends and thus allows us to study any potential impacts related to the sorting criterion, in this case emissions.

Prima facie evidence

This subsection reports some prima facie evidence regarding the empirical relationship between verified CO_2 emissions and stock returns using the portfolio method[18].

To facilitate the comparison and to be closely aligned with the brownness indicator presented in 1.4.2, we examine in detail the average returns of the equal-weighted BMG portfolios. Since the panel regression method assigns equal weight to observations, this serves as our starting point, as suggested by Bauer et al. (2022).

Table 1.3 provides estimates from a mean-comparison test of the average monthly returns for different portfolios based on emissions level and intensity. The table is organized into two main sections, with the first three columns under the "Emissions level" heading and the next three columns under the "Emissions intensity" heading. The brown, green, and BMG portfolios are compared. The brown portfolio represents companies with high carbon emissions, while the green portfolio comprises companies with low carbon emissions based on the same quintile sort as employed previously. The BMG portfolio calculates the difference between the returns of the brown and green portfolios. This table highlights the differences in average monthly returns between high and low carbon-emitting companies, with green portfolios consistently outperforming brown portfolios based on both emissions level and emissions intensity. Consistently, BMG portfolios have a negative sign and are highly significant for emissions intensity with a t-statistic equal to -2.74 at the 90% significance level (Cheema-Fox et al., 2021).

After the initial evidence suggested that green stocks may be outperforming, we delve deeper into this trend using an empirical asset pricing framework.

[18] As we use one-year lagged emissions to sort portfolios, our sample period runs from July 2006 to December 2021 at monthly frequency.

Table 1.3: Average monthly returns

	Emissions level			Emissions intensity		
Portfolios	Brown	Green	BMG	Brown	Green	BMG
	-0.09	0.07	-0.15	-0.21	0.42	-0.63
	(-0.17)	(0.15)	(-0.76)	(-0.45)	(0.85)	(-2.74)

Note: t-statistics (in parentheses) are based on robust standard errors.

Factor model approach

In line with our empirical design, we use factor models to assess the performance of the BMG portfolio. Within this framework, factor models serve as a popular method in empirical finance to account for the differences in stock returns across various stocks. We use the three-factor model (Fama and French, 1993*a*) (hereafter FF3F) and the four-factor model (Carhart, 1997) (hereafter FF4F), both of which expand upon the traditional capital asset pricing model (CAPM). The three-factor model incorporates size and value factors, while the four-factor model adds momentum as an additional common factor to explain stock returns. We denote the monthly returns of the BMG portfolio as $r_{i,t}$. This portfolio signifies an investor's stance when holding a long position in brown companies and a short position in green companies. Hence, the FF3F model takes the following form:

$$r_{i,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t} \tag{1.3}$$

and the FF4F model is as follows:

$$r_{i,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{i,t} \tag{1.4}$$

where MKT denotes the market factor, which is the excess return of the market over the risk-free rate. The size factor, denoted SMB, is computed by finding the difference between the monthly average returns on small-cap and large-cap stocks. The value factor, represented by HML, is determined by calculating the difference between the monthly average returns on "value" and "growth" stocks. The momentum factor, referred to as MOM, represents the excess return of past winners over past losers, capturing the momentum effect[19].

We estimate the FF3F and FF4F models using time series regression over the 2006-2021 period at a monthly frequency accounting for 186 observations per regression. We use robust standard errors to account for heteroskedasticity, serial correlation, cross-sectional dependence, and potential model misspecification. Our main focus is on the intercept term α, which represents the risk-adjusted performance of the BMG portfolio. By construction, it reflects the difference in average

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

Table 1.4: Brown-minus-green portfolio analysis

	Three-factor model (FF3F)				Four-factor model (FF4F)			
	Emissions level		Emissions intensity		Emissions level		Emissions intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolios	VW	EW	VW	EW	VW	EW	VW	EW
Constant	-0.393	-0.159	-0.160	-0.534**	-0.501*	-0.264	-0.264	-0.639***
	(0.270)	(0.207)	(0.244)	(0.225)	(0.289)	(0.206)	(0.258)	(0.234)
MktRF	-0.027	0.034	-0.012	-0.163***	0.001	0.062	0.015	-0.135***
	(0.069)	(0.048)	(0.051)	(0.046)	(0.070)	(0.052)	(0.055)	(0.052)
SMB	-0.095	-0.006	0.286**	0.224*	-0.083	0.006	0.297**	0.236*
	(0.169)	(0.143)	(0.143)	(0.127)	(0.165)	(0.141)	(0.140)	(0.125)
HML	0.422***	0.070	0.344***	0.194**	0.531***	0.177	0.451***	0.301***
	(0.144)	(0.118)	(0.116)	(0.094)	(0.149)	(0.137)	(0.123)	(0.108)
WML					0.157	0.154**	0.153	0.155*
					(0.127)	(0.075)	(0.115)	(0.086)
Observations	186	186	186	186	186	186	186	186

Note: Robust standard errors are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

returns between brown and green stocks.

Table 1.4 presents the BMG portfolio analysis, where the BMG portfolio takes a long position in brown stocks and a short position in green stocks. The table analyzes the performance of these portfolios using two different risk models: the three-factor model (FF3F) and the four-factor model (FF4F). The results are reported separately for value-weighted (VW) and equal-weighted (EW) portfolios based on both emissions level and emissions intensity.

In terms of the estimates derived from the FF3F model, all portfolios generate a negative intercept, which is significant for the equal-weighted portfolio based on emissions intensity highlighting the outperformance of green firms. This suggests that investors going long on firms with high carbon emissions and short in firms with low carbon emissions generate higher realized returns. Specifically, if we consider specification 4, the BMG portfolio generates a monthly return loss of 0.534%. Based on our findings using the portfolio method, the consistently negative intercept allows us to reject the null hypothesis, which posits that the risk-adjusted returns of the BMG portfolio are not significant.

The outperformance of green stocks is even more pronounced when we consider the estimates from the FF4F model. Specification 4 (8), which corresponds to the value-weighted (equal-weighted) BMG portfolio based on emissions level (intensity), indicates a significant negative risk-adjusted return at the 10% (1%) level. We observe that portfolios based on emissions level (intensity) are negatively (positively) exposed to the SMB factor. Significantly, portfolios based on emissions intensity contain small carbon intensive companies. In line with the estimation results from Bauer et al. (2022), we observe a significant positive exposure to the HML factor in 3 out of

4 regressions. This reflects that green firms tend to be growth stocks and brown companies tend to be value stocks. We also employed a percentile sort (30/70) categorize companies as low and high carbon emitters. The estimation results with the FF3F model can be found in Table 1.16 in subsection 1.7.3. The findings are fairly consistent, with higher coefficients observed for value-weighted portfolios in the percentile sort than in the quintile sort. This is due to the inclusion of more carbon-intensive firms in the brown portfolios and fewer carbon-intensive firms in the green portfolios. Consistent with the literature, the portfolio-based approach leads us not to reject **H4** and confirm a negative greenium, i.e., higher returns for green firms (Alessi et al., 2021).

1.5 Robustness check

We conduct a series of robustness checks to confirm the reliability of our results for both implemented methodologies. Initially, we focus on our primary specification derived from Equation 1.1. Table 1.8 summarizes the estimation results with no emissions publication lag (Bolton and Kacperczyk, 2020)[20]. The impact of emissions level is still significantly negative on stock returns, but remains non-significant when considering emissions intensity.

Moreover, to ensure the robustness of our findings, we also test the sensitivity of our estimates to a possible non-linear effect. Given that the variable "emissions" displays a pronounced right-skewness, it's plausible that the highest emitting firms could be influencing the results. In this context, we are seeking to answer the following question: Is the relationship between verified CO_2 emissions and the performance of companies within the EU ETS non linear? To evaluate this potential non-linearity, we estimate equations 1.1 by considering two sets of observations using both percentile and quintile sorting methods (with the same publication lag as before). Table 1.11 presents the results from the panel regression analysis that examines the impact of emission levels on monthly stock returns. All coefficients are again negative and statistically significant, reinforcing the finding that higher emissions correlate with lower stock returns. The magnitude of these coefficients increases with each quintile, indicating a stronger negative effect for firms with higher emissions.

Furthermore, we estimated Equations 1.1 and 1.2 using an alternative fixed effects combination. Although our analysis is conducted at the firm level, our sample of companies covers 24 European countries[21]. As a result, we reestimated Equations 1.1 and 1.2 by adding country fixed effects to control for all time-invariant characteristics specific to each country. The baseline specification considers both time and country effects. Then, we add sector fixed effects, and finally the inter-

[20]This implies that the emissions accounted for in the regression align with the stock returns of the corresponding year. For example, the stock returns from 2006 are paired with the emissions data from the same year, 2006. The results are quite similar, suggesting an outperformance of green companies than brown companies.

[21]Table 1.6 in subsection 1.7.1 provides the list of countries in our sample.

action between date, country, and sector. Estimation results are presented in subsection 1.7.2 and remain robust to all alternative specifications. Consequently, these robustness checks support the hypothesis **H2** which posits that over the sample period, green stocks tend to outperform brown stocks.

Concerning the empirical asset pricing framework,we perform a placebo test using the Five-factor (FF5F) model proposed by Fama and French (2015). This model is employed to evaluate the performance of the BMG portfolio and considering both the percentile and quintile sort. It includes the following factors: MktRF (market risk factor), SMB (size factor), HML (value factor), CMA (investment factor), and RMW (profitability factor). Table 1.17 in subsection 1.7.3 showcases the results of the BMG portfolios analysis conducted using the Five-factor (FF5F) model. The findings demonstrate strong similarity among the results, with three out of the eight specifications showing a significant and negative intercept. These consistent results lend support to hypothesis **H4**, which suggests that green stocks generate higher risk-adjusted returns than brown stocks.

1.6 Conclusions and policy implications

We evaluate the influence of carbon emissions on the stock returns of companies participating in the EU ETS. Our methodology aligns with current academic trends, employing both panel fixed effects regression and the factor model approach, and both emission levels and emissions intensity. We employ verified (not reported or estimated) carbon emissions. Furthermore, studying firms within an ETS provides a *rationale* for the returns of brown and green firms to differ.

Our findings emphasize the outperformance of green stocks across all methodologies considered during the 2006-2021 sample period. Our panel estimates suggest that higher levels of carbon emissions are significantly associated with lower stock returns. The result is robust to using brownness indicator as the variable of interest, however, emissions intensity does not have a significant impact. The factor model approach estimates reveal that green portfolios outperform brown ones in all specifications, with statistical significance in three cases out of eight –especially with equal-weight portfolios based on emissions intensity.

These results remain consistent and reliable across various panel specifications and factor model alternatives. Further investigations reveal a non-linear pattern between carbon intensity and stock returns: categorizing emissions intensity into percentile and quintile categories indicates a significant negative relationship (firms with higher carbon intensity tend to have lower stock returns).

Our results bear some potential implications that could interest decision-makers and policy-makers engaged in the energy sector and/or in mitigating climate change with financial tools.

First, because we use verified CO_2 emissions, our results call for the systematization of “carbon audits" for all listed firms. There is a need to expand the profession of CO_2 emissions verification and impose such verification, just as financial audits are mandatory for all firms.

Second, it illustrates the effectiveness of the "polluter pays" principle implemented in the EU ETS. It is important to underline that, in the period under study (2006-2021), the price for carbon allowances was relatively low. Buying the right to emit 1 ton of CO_2 cost 25 euros in early 2006, then plummeted to less than 10 euros in 2011-2017, then rose to near 25 euros again during 2020, with a sharp increase to 70 euros in late 2021. Some sectors were even attributed free allowances. On the one hand, this is a weakness of our study, because it probably contributes to numerous non-significant results. On the other hand, it is in support of ETS markets, because despite this relatively harmless cost to pollute, we are able to detect higher returns for green firms. We conjecture that the recent rise in carbon price (above 100 euros in early 2023) will be sustained by the regulatory evolution impulsed by the European Commission and the objective to reduce by 55% the emissions level by 2030. In that case, this should further straighten the results we observe for the EU ETS market and modify the risk-return profile of stocks, providing investors with a reason to choose green firms.

Of course our article has several caveats and limitations. Our firm sample is small and results should be interpreted with caution. Besides, it implies that we cannot reliably split the sample in short sub-periods, whereas it could be interesting to study the role of allowances price. Sectors in the EU ETS are specific, and our results may not extend to other sectors. Future studies could thus apply our framework to other ETS carbon quota markets around the world and use more sophisticated factor models.

1.7 Appendix

1.7.1 Details on the EU ETS, emissions and sample

Since 2005, the European Union has adopted an emissions trading scheme to reduce greenhouse gas emissions. It is the largest emissions trading scheme in the world with the objective of reducing emissions by 20% in 2020 and by at least 30% by 2030 (objective updated by Law No. 2019-1147 of November 8, 2019, on energy and climate). The system covers approximately 1000 firms (approximately 12 industrial installations) from 31 European countries representing 45% of the European Union's greenhouse gases.

The functioning of the EU ETS is based on the "polluter pays" principle. First, allowances are allocated free of charge by auction. Then, they can be traded (bought or sold) according to the quantity of emissions emitted by the installation. Each year, the European states determine the number of quotas to which the companies involved the carbon market are entitled. This allocation is made according to the company's sector of activity and the quantity of greenhouse gases emitted by the greenest players in the sector. Some installations may benefit from free allowances, essentially for two reasons: to avoid weakening their competitiveness, and to avoid carbon leakage (i.e., the relocation of greenhouse gas emitting activities to countries where regulations are more flexible). Thus, each year, companies participating in the system must surrender several allowances corresponding to the amount of carbon emissions they have emitted (1 European Union Allowance (EUA) = 1 ton of CO_2). If an installation emits more than it has received in allowances, it can either pay a fine (see Table 1.5 below for details of fines) or buy additional allowances from companies that have not exceeded the cap. Therefore, we can consider two cases:

- The company's emissions are lower than the allowances allocated to it, and the company will be able to sell its additional allowances on the carbon market (cash flow effect[22] underlined by Oestreich and Tsiakas (2015)).
- If the company's emissions are higher than the allowances allocated to it, the company must buy additional allowances on the carbon market. Allowances can be purchased in dedicated marketplaces (European Energy Exchange) or traded directly between companies or over the counter.

Since the amount of emissions is fixed each year for companies participating in the EU ETS, it can be more or less costly for a company to reduce its greenhouse gas emissions. Therefore, if the cost of reducing emissions is higher than the price of the allowance, it is more appealing

[22]First, firms face a higher marginal cost that is reflected in the selling price, generating higher revenues for the firm. Second, the decrease in output resulting from the higher marginal cost may lead to the sale of unused allowances, which are allocated for free, and increase the revenue of the firms.

for a company to buy additional allowances. In this case, the number of buyers is greater than the number of sellers, which will cause the price of the allowance to fall according to the law of supply and demand. Conversely, if the cost of reducing emissions is lower than the price of the allowance, the company will have an incentive to effectively reduce its emissions so that it can sell its additional allowances to higher emitting companies. Thus, the price of the allowance can influence the clean-up effort of companies.

The EU ETS is divided into 4 phases. The first covers the period 2005–2007, the second covers that from 2008 to 2012, the third that from 2013 to 2020 and the fourth phase started in 2021 and ends in 2030. Each phase is characterized by different actions designed to optimize the trading system and achieve the set objectives as shown in the table above.

Table 1.5: Description of the EU ETS

	Phase 1 *(January 2005 - December 2007)*	**Phase 2** *(January 2008 - December 2012)*	**Phase 3** *(January 2012 - December 2019)*
Period	2005-2007	2008-2012	2013-2020
EUA allocation method	Free[23]	Free and auctioning	Auctioning is the main allocation method[24]
Penalty for noncompliance	40 euros/tCO2	100 euros/tCO2	-
Important timelines	Pilot phase to test the system (law establishing Phase 1 and Phase 2 of EU-ETS)	First commitment period with the Kyoto protocol: significant reduction of the emissions cap (6.5% decrease in the volume of EUAs compared to 2005)	Lowering the emissions cap to 1.74% per year to reduce emissions by 21% in 2020 compared to 2005
	Fixation of EUA price	Use of other international pollution rights (Kyoto Protocol credits)	Blackloading : postponing the auctioning of 900 million EUAs to the end of the trading period

Note: Details about the fourth period are not available at this time because the system is presently in this phase, so all specifics cannot be provided. EUA allocation is based on historic emissions called grandfathering. Only companies exposed to "carbon leakage" are allocated their allowances.

Table 1.6 provides a comprehensive overview of the countries where firms are participating in the European Union Emission Trading Scheme (EU ETS). It includes countries from all over Europe, ranging from Austria and Belgium to the United Kingdom and Sweden. This diversity highlights the widespread adoption of the EU ETS across the continent.

Table 1.6: Country list

Austria	Latvia
Belgium	Lithuania
Bulgaria	Netherlands
Czech Republic	Norway
Denmark	Poland
Finland	Portugal
France	Romania
Germany	Slovakia
Greece	Slovenia
Hungary	Spain
Ireland	Sweden
Italy	United Kingdom

Table 1.7 presents the carbon emissions intensity, which is calculated as emissions (in tons of CO_2) divided by companies' net sales by sector for firms participating in the EU ETS over the 2005-2021 period. This table provides an overview of emissions intensity across various sectors. Each sector's emissions intensity is represented using key statistical measures such as mean, standard deviation, minimum, maximum , and the first (p25), second (p50), and third quartiles (p75).

It is clear from the table that the Energy sector presents the highest mean emissions intensity, registering at 3.08, significantly surpassing other sectors. Additionally, the Energy sector also records the maximum emissions intensity, at an outstanding 149.64, the topmost value observed in the entire table. However, the standard deviation for this sector is also high (14.27), indicating a wide spread in the data, with some companies having considerably higher emissions intensities than others. The Basic Materials and Utilities sectors also show relatively high mean emissions intensity values (1.09 and 1.03 respectively), although not as high as the Energy sector. Note that the Basic Materials sector also has a wide data spread, with a standard deviation of 4.80 and a maximum value reaching 105.01. On the other hand, the Technology sector appears to be the least polluting, with zero emissions intensity across all measures, indicating that companies in this sector have effectively managed their carbon footprint. The sectors including Consumer Cyclicals, Consumer Non-Cyclicals, Healthcare, Industrials, and NA exhibit relatively low mean emissions intensity values that span from 0.00 to 0.84. This implies that these sectors are typically less carbon-intensive.

Overall, the table presents a stark contrast in emissions intensity across sectors, highlighting the significant role of the Energy sector and to a lesser extent, the Basic Materials and Utilities sectors in carbon emissions.

Table 1.7: Descriptive statistics on emissions intensity (sector)

Sector	Mean	Sd.	Min.	Max.	p25	p50	p75
Basic Materials	1.09	4.80	0.00	105.01	0.10	0.25	0.82
Consumer Cyclicals	0.27	0.66	0.00	3.34	0.00	0.01	0.13
Consumer Non-Cyclicals	0.02	0.06	0.00	0.71	0.00	0.01	0.02
Energy	3.08	14.27	0.01	149.64	0.13	0.21	0.37
Healthcare	0.07	0.12	0.00	0.43	0.00	0.01	0.05
Industrials	0.84	3.66	0.00	31.82	0.00	0.01	0.01
NA	0.01	0.00	0.00	0.01	0.01	0.01	0.01
Technology	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Utilities	1.03	1.63	0.00	9.80	0.17	0.46	0.90

1.7.2 Additional tables for the panel regression

No emissions publication lag

Table 1.8: Estimation results for the panel regression with no emissions publication lag

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emissions level	-0.015	-0.078**	-0.122***	-0.118***				
	(-0.73)	(-2.36)	(-3.22)	(-3.20)				
Emissions intensity					-0.069***	-0.000	0.019	0.006
					(-3.30)	(-0.01)	(0.44)	(0.14)
Size		0.347***	0.396***	0.374***		0.307***	0.322***	0.299***
		(7.09)	(6.11)	(5.92)		(6.22)	(6.23)	(5.93)
Book-to-market		1.146***	1.171***	1.111***		1.090***	1.097***	1.041***
		(6.26)	(6.11)	(5.94)		(6.26)	(6.06)	(5.88)
Momentum		-0.000	-0.001	-0.003		-0.000	-0.001	-0.003
		(-0.14)	(-0.22)	(-0.97)		(-0.17)	(-0.26)	(-1.00)
Leverage		-0.050	-0.101	-0.101		-0.039	-0.058	-0.065
		(-0.37)	(-0.71)	(-0.71)		(-0.30)	(-0.44)	(-0.49)
Leverage		0.054***	0.053***	0.058***		0.056***	0.056***	0.061***
		(7.25)	(7.01)	(7.43)		(7.66)	(7.44)	(7.85)
Investments-to-assets		0.000	0.000	0.000		0.001	0.000	0.000
		(0.02)	(0.03)	(0.01)		(0.03)	(0.02)	(0.01)
Sales growth		0.429	0.394	0.352		0.387	0.392	0.344
		(1.32)	(1.26)	(1.16)		(1.23)	(1.23)	(1.11)
Volatility		0.049**	0.051**	0.041**		0.049**	0.049**	0.039*
		(2.59)	(2.57)	(2.01)		(2.57)	(2.49)	(1.90)
r_{t-1}		-0.023*	-0.023*	-0.033**		-0.023*	-0.023*	-0.033**
		(-1.92)	(-1.94)	(-2.52)		(-1.92)	(-1.94)	(-2.52)
Constant	0.272	-6.475***	-6.755***	-6.364***	-0.049	-6.875***	-7.107***	-6.672***
	(0.95)	(-7.63)	(-6.98)	(-6.91)	(-0.62)	(-7.98)	(-7.66)	(-7.49)
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Sector FE	No	No	Yes	No	No	No	Yes	No
Time × Sector FE	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.000	0.428	0.428	0.490	0.000	0.428	0.428	0.490
Observations	24738	20155	20155	20023	24165	20155	20155	20023

Note: The table presents estimation results for the panel regression with the emissions level (Columns 1-4) and intensity (Columns 5-8) as the main interest variables. The dependent variable is monthly stock returns. There are eight different model specifications (Columns 1-8) with different combinations of fixed effects (time, sector, and time × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and presented in parentheses. The significance levels are denoted * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Alternative combination of fixed effects

Table 1.9 and Table 1.10 present the estimation results with emissions and the brownness indicator as the main variables of interest, respectively with an alternative combination of fixed effects. The results are quite similar to those of Table 1.1 and Table 1.2 from Section 1.4.2. In general, the results indicate that higher carbon emissions (both level and intensity) have a negative impact on stock returns. In Table 1.9, the emissions level is significant in Columns 2-4, with the most negative coefficient (-0.189) in Column 3, which includes time, country, and sector fixed effects. The emissions intensity is significant only in Column 5, with a coefficient of -0.085. This suggests that, overall, firms with higher emissions levels or intensities tend to experience lower stock returns. The control variables, such as size, book-to-market, ROE, and volatility, show consistent results across different specifications. For example, larger firms, firms with higher book-to-market ratios, and firms with higher ROE generally experience higher stock returns. Additionally, higher volatility is associated with higher stock returns in some specifications, but not all. The adjusted R-squared values range from 0.000 to 0.657, indicating that the models with time × country × sector fixed effects (Columns 4 and 8) perform better in terms of explanatory power. With higher coefficients due to the use of an indicator variable for a company's carbon footprint, the results of Table 1.10 remain stable and in line with those previously presented. Interestingly, the specifications with the interaction between fixed effects (Columns 4 and 8) yield higher R^2 values.

Table 1.9: Estimation results for the panel regression with emissions level and intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emissions level	-0.022	-0.103***	-0.189***	-0.145***				
	(-1.06)	(-3.02)	(-4.77)	(-3.01)				
Emissions intensity					-0.085***	-0.004	-0.019	-0.034
					(-3.86)	(-0.11)	(-0.47)	(-0.67)
Size		0.361***	0.446***	0.340***		0.299***	0.316***	0.235***
		(6.72)	(6.38)	(3.80)		(6.32)	(5.99)	(3.23)
Book-to-market		1.302***	1.394***	1.084***		1.228***	1.282***	0.963***
		(7.07)	(7.66)	(5.80)		(7.41)	(7.67)	(5.64)
Momentum		-0.002	-0.002	-0.007*		-0.002	-0.002	-0.007*
		(-0.70)	(-0.67)	(-1.81)		(-0.71)	(-0.63)	(-1.86)
Leverage		-0.186	-0.238	-0.082		-0.144	-0.180	-0.033
		(-1.21)	(-1.52)	(-0.43)		(-1.02)	(-1.25)	(-0.18)
ROE		0.059***	0.059***	0.060***		0.062***	0.061***	0.062***
		(8.17)	(7.93)	(5.02)		(8.52)	(8.23)	(5.25)
Investment-to-assets		-0.001	-0.001	-0.010		-0.001	-0.001	-0.010
		(-0.04)	(-0.04)	(-0.36)		(-0.03)	(-0.04)	(-0.36)
Sales growth		0.432	0.398	1.336*		0.399	0.399	1.372*
		(1.27)	(1.23)	(1.88)		(1.19)	(1.20)	(1.94)
Volatility		0.065***	0.072***	0.020		0.064***	0.067***	0.015
		(3.49)	(3.63)	(0.64)		(3.39)	(3.32)	(0.48)
r_{t-1}		-0.026**	-0.026**	-0.038		-0.026**	-0.026**	-0.038
		(-2.19)	(-2.20)	(-1.61)		(-2.20)	(-2.17)	(-1.62)
Constant	0.317	-6.896***	-7.280***	-5.234***	-0.175**	-7.236***	-7.644***	-5.443***
	(1.03)	(-8.04)	(-7.39)	(-3.98)	(-1.99)	(-8.48)	(-8.18)	(-4.28)
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Country FE	No	Yes	Yes	No	No	Yes	Yes	No
Sector FE	No	No	Yes	No	No	No	Yes	Yes
Time × Country × Sector FE	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.000	0.430	0.430	0.657	0.000	0.429	0.430	0.657
Observations	23346	20209	20209	14062	23020	20209	20209	14062

Note: The table presents estimation results for the panel regression with the emissions level (Columns 1-4) and intensity (Columns 5-8) as the main interest variables. The dependent variable is monthly stock returns. There are eight different model specifications (Columns 1-8) with different combinations of fixed effects (time, sector, country and time × country × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and are in parentheses. The significance level are denoted * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

In summary, the results from this regression table suggest that carbon emissions, in both level and intensity, have a negative impact on the stock returns of firms participating in the EU ETS. This is consistent across various specifications, providing robust evidence for the relationship between carbon emissions and stock returns. Our results suggest a negative effect of emission levels on EU ETS companies' stock returns. The coefficient associated with emission levels is significantly different from 0. Consequently, the initial null hypothesis presented in subsection 1.4.1 is not supported by the results. This leads us to consider the alternative hypotheses. A negative relationship between returns and emissions is evident, which indicates the rejection of **H1**. Consequently, the presence of a green premium in our sample leads us to confirm the **H2** Hypothesis. In other words, this means that green firms generate higher returns than brown firms even with the emissions measures used as a key variable in the regression. This is consistent with our baseline analysis in subsection 1.4.2.

Table 1.10: Estimation results for the panel regression with a brownness indicator variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Brownness indicator (level)	-0.096	-0.448***	-0.666***	-0.585***				
	(-1.18)	(-4.41)	(-4.92)	(-3.38)				
Brownness indicator (intensity)					-0.332***	-0.129	-0.174	-0.189
					(-3.46)	(-1.07)	(-1.22)	(-1.13)
Size		0.359***	0.420***	0.322***		0.290***	0.311***	0.231***
		(7.17)	(6.44)	(3.88)		(6.17)	(5.93)	(3.23)
Book-to-market		1.337***	1.430***	1.060***		1.239***	1.298***	0.916***
		(7.59)	(8.22)	(5.53)		(7.42)	(7.77)	(5.03)
Momentum		-0.001	-0.001	-0.007*		-0.001	-0.001	-0.007*
		(-0.54)	(-0.42)	(-1.85)		(-0.54)	(-0.43)	(-1.92)
Leverage		-0.126	-0.156	-0.042		-0.119	-0.159	-0.027
		(-0.87)	(-1.10)	(-0.25)		(-0.82)	(-1.10)	(-0.16)
ROE		0.058***	0.058***	0.060***		0.060***	0.059***	0.060***
		(7.86)	(7.54)	(4.99)		(8.12)	(7.66)	(5.14)
Investment-to-assets		0.001	0.001	-0.010		0.001	0.001	-0.010
		(0.03)	(0.03)	(-0.39)		(0.04)	(0.03)	(-0.39)
Sales growth		0.437	0.414	1.336*		0.407	0.410	1.361*
		(1.31)	(1.29)	(1.92)		(1.21)	(1.21)	(1.94)
Volatility		0.062***	0.067***	0.019		0.062***	0.064***	0.014
		(3.30)	(3.43)	(0.63)		(3.25)	(3.25)	(0.47)
r_{t-1}		-0.026**	-0.026**	-0.039		-0.026**	-0.026**	-0.039*
		(-2.19)	(-2.17)	(-1.65)		(-2.20)	(-2.17)	(-1.67)
Constant	0.095	-8.129***	-9.244***	-6.817***	0.092	-6.991***	-7.445***	-5.230***
	(1.63)	(-8.66)	(-7.97)	(-4.61)	(1.61)	(-7.99)	(-7.89)	(-4.17)
Time FE	No	Yes	Yes	No	No	Yes	Yes	No
Country FE	No	Yes	Yes	No	No	Yes	Yes	No
Sector FE	No	No	Yes	No	No	No	Yes	Yes
Time × Country × Sector FE	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.000	0.425	0.425	0.656	0.000	0.424	0.424	0.656
Observations	25361	20648	20648	14233	25361	20648	20648	14233

Note: The table presents estimation results for the panel regression with the emissions level (Columns 1-4) and intensity (Columns 5-8) as the main interest variables. The dependent variable is monthly stock returns. There are eight different model specifications (Columns 1-8) with different combinations of fixed effects (time, sector, country and time × country × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and are in parentheses. The significance levels are denoted * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Investigation of non linear effects

In Table 1.11 and Table 1.12, the coefficients of the emissions categories are negative and statistically significant across all models, implying that firms with higher emissions intensity tend to have lower stock returns. The categorical analysis contrasts with previous findings in Table 1.1 and Table 1.2 that showed no significant effect of emissions intensity on stock returns when emissions were treated as a continuous variable. The statistical significance observed here suggests that the impact of emissions intensity on stock returns may be non-linear or influenced by extreme values in the emissions data. By categorizing emissions intensity, we mitigate these effects and reveal a significant relationship between emissions intensity and stock returns. The findings presented here can be surprising in light of previous studies such as (Bolton and Kacperczyk, 2020; Huij et al., 2022; Bauer et al., 2022). Indeed, in the context of emission intensity, it may be crucial to acknowledge the non linear relationship between carbon intensity and stock returns. By doing so, we could capture the relationship between emissions and stock returns more accurately.

Table 1.11: Non linear effects (Emissions level)

	(1)	(2)	(3)	(4)	(5)	(6)
Low Emissions	-1.122***	-1.266**	-1.768***			
	(0.426)	(0.493)	(0.524)			
Mid Emissions	-1.152***	-1.411***	-1.769***			
	(0.397)	(0.445)	(0.473)			
High Emissions	-1.712***	-2.072***	-2.461***			
	(0.400)	(0.472)	(0.512)			
Q1 Emissions				-1.232**	-1.452**	-1.902***
				(0.516)	(0.574)	(0.607)
Q2 Emissions				-1.567***	-1.817***	-2.151***
				(0.493)	(0.519)	(0.542)
Q3 Emissions				-1.144**	-1.549***	-1.845***
				(0.483)	(0.531)	(0.550)
Q4 Emissions				-1.499***	-1.882***	-2.218***
				(0.469)	(0.504)	(0.533)
Q5 Emissions				-2.023***	-2.596***	-2.879***
				(0.486)	(0.557)	(0.595)
Constant	-6.493***	-7.003***	-6.366***	-7.207***	-8.056***	-7.204***
	(0.850)	(1.062)	(1.008)	(1.063)	(1.370)	(1.280)
Firms' controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Sector FE	No	Yes	No	No	Yes	No
Time × Sector FE	No	No	Yes	No	No	Yes
Adj. R^2	0.423	0.423	0.486	0.408	0.409	0.469
Observations	20648	20648	20583	20648	20648	20583

Note: The table presents estimation results for the panel regression with the emissions level as the main variable of interest. The dependent variable is monthly stock returns. In the first three columns, the emissions are categorized as Low (observations below the 25th percentile), Mid (observations between the 25th and 75th percentiles), and High (observations above the 75th percentile). In the next three columns (4-6), emissions are divided into quintiles (Q1-Q5). We use the same control variables than subsection 1.4.2: Size of a company considered as the natural logarithm of the market capitalisation; Book-to-market computed as the inverse of the market-to-book, return on equity (ROE), Leverage calculated as the ratio of total debt to total assets, Sales growth considered as the one-year net sales growth, Investment-to-assets calculated as the change in total assets divided by lagged total assets, Volatility as the standard deviation over the twelve month past returns, Momentum as the cumulative returns from $t-12$ to $t-2$ and the one month past returns. There are six different model specifications (Columns 1-6) with different combinations of fixed effects (time, sector, country and time × country × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and presented in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.12: Non linear effects (Emissions intensity)

	(1)	(2)	(3)	(4)	(5)	(6)
Low Emissions	-1.210***	-1.433***	-1.915***			
	(0.431)	(0.518)	(0.556)			
Mid Emissions	-1.059***	-1.056**	-1.453***			
	(0.385)	(0.437)	(0.464)			
High Emissions	-1.381***	-1.419***	-1.854***			
	(0.398)	(0.453)	(0.475)			
Q1 Emissions				-1.487***	-1.752***	-2.238***
				(0.523)	(0.602)	(0.628)
Q2 Emissions				-1.425***	-1.525***	-1.956***
				(0.496)	(0.536)	(0.557)
Q3 Emissions				-1.059**	-0.988*	-1.373***
				(0.470)	(0.505)	(0.514)
Q4 Emissions				-1.263***	-1.268**	-1.644***
				(0.467)	(0.501)	(0.517)
Q5 Emissions				-1.588***	-1.654***	-2.059***
				(0.485)	(0.528)	(0.538)
Constant	-5.788***	-6.205***	-5.648***	-6.372***	-6.954***	-6.242***
	(0.792)	(0.823)	(0.799)	(0.996)	(1.086)	(1.040)
Firms' controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Sector FE	No	Yes	No	No	Yes	No
Time × Sector FE	No	No	Yes	No	No	Yes
Adj. R^2	0.423	0.423	0.485	0.408	0.408	0.469
Observations	20648	20648	20583	20648	20648	20583

Note: The table presents estimation results for the panel regression with the emissions intensity as the main variable of interest. The dependent variable is monthly stock returns. In the first three columns, the emissions are categorized as Low (observations below the 25th percentile), Mid (observations between the 25th and 75th percentiles), and High (observations above the 75th percentile). In the next three columns (4-6), emissions are divided into quintiles (Q1-Q5). We use the same control variables than subsection 1.4.2: Size of a company considered as the natural logarithm of the market capitalisation; Book-to-market computed as the inverse of the market-to-book, return on equity (ROE), Leverage calculated as the ratio of total debt to total assets, Sales growth considered as the one-year net sales growth, Investment-to-assets calculated as the change in total assets divided by lagged total assets, Volatility as the standard deviation over the twelve month past returns, Momentum as the cumulative returns from $t-12$ to $t-2$ and the one month past returns. There are six different model specifications (Columns 1-6) with different combinations of fixed effects (time, sector, country and time × country × sector FEs) and control variables. One-way cluster-robust standard errors at the firm level are used and presented in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

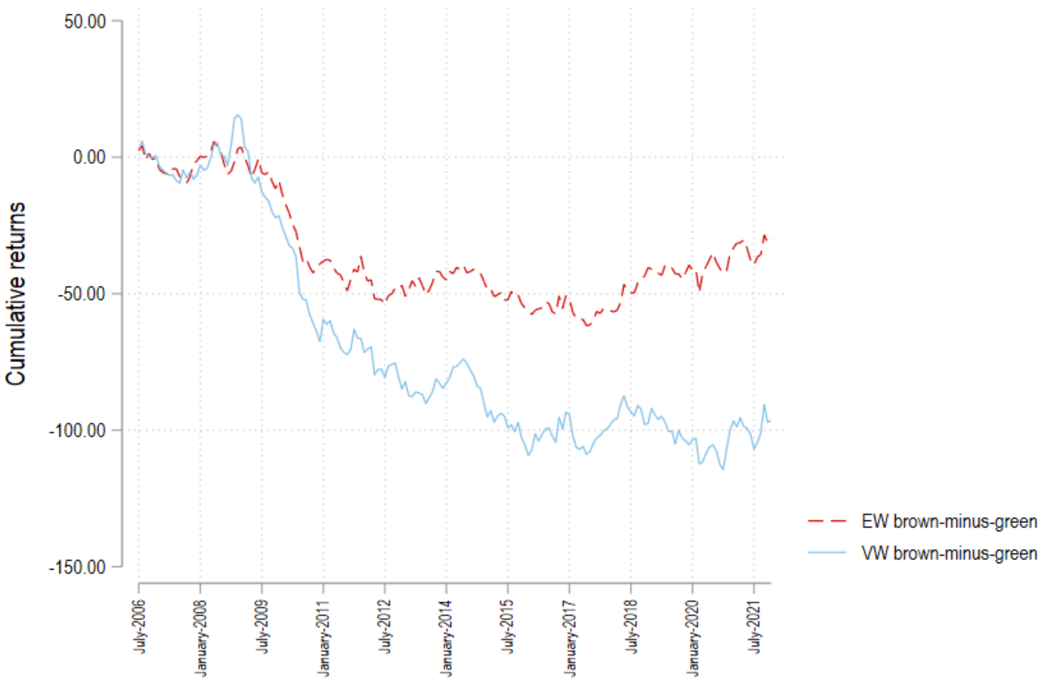
1.7.3 Additional details on carbon portfolios

Figure 1.2 plots the cumulative log returns for the BMG portfolios based on the emissions level. We observe the outperformance of green stocks since 2009 for both equal- and value-weighted brown-minus-green portfolios, which is further pronounced in the value-weighted portfolio after November 2010. The average cumulative returns over the sample period for the value-weighted portfolio are approximately -69% and half that size for the equal-weighted portfolios (-35%). By definition, this means that large green firms tends to have higher returns than large brown firms. Since early 2017, we observe a reversal pattern between the two brown-minus-green portfolios. While the value-weighted spread is still decreasing until reaching -114%, the equal-weighted spread increases until the end of 2021. This path divergence between the two portfolios reflects the difference in performance between small and large companies. From 2017, small brown companies tend to generate higher returns than small green companies. In contrast, large green firms tends to outperform their brown firms counterparts.

Figure 1.3 plots the cumulative log returns for the BMG portfolios considering emissions intensity. We also note that green firms outperform brown firms since 2009. In contrast to the portfolios sorted on emissions in levels, the equal-weighted spread performs better than the value-weighted spread since January 2011. More interestingly, we observe that since 2015, the cumulative returns for small green firms are even larger than those of brown firms, while the value-weighted portfolio fluctuates around -50%. Specifically, the average cumulative returns for the equal-weighted portfolios is approximately -68% with a minimum of 121% over the period.

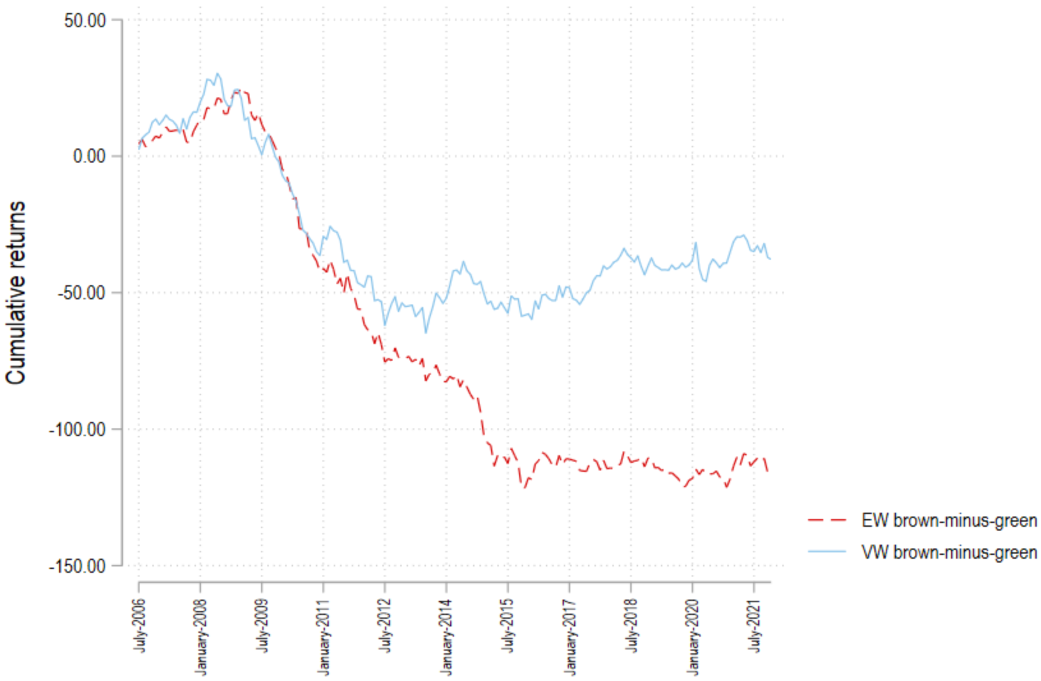
In addition to the brown-minus-green portfolio, we graph the green and brown portfolio over the 2006-2021 observation period. Figure 1.4, Figure 1.5, Figure 1.6 and Figure 1.7 plot the cumulative returns for each portfolio based on emissions level and intensity.

Figure 1.2: Brown-minus-green cumulative returns based on emissions level



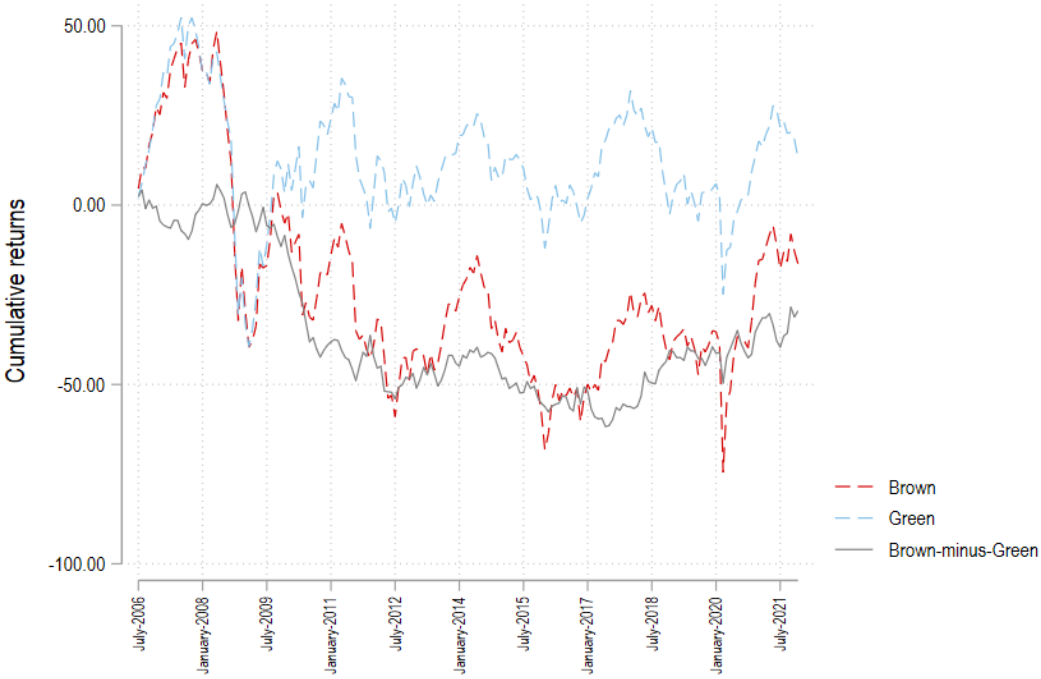
Note: The figure graphically shows the cumulative log returns for the equal-weighted brown-minus-green portfolios based on the emissions level over the observation period 2006-2021.

Figure 1.3: Brown-minus-green cumulative returns based on emissions intensity



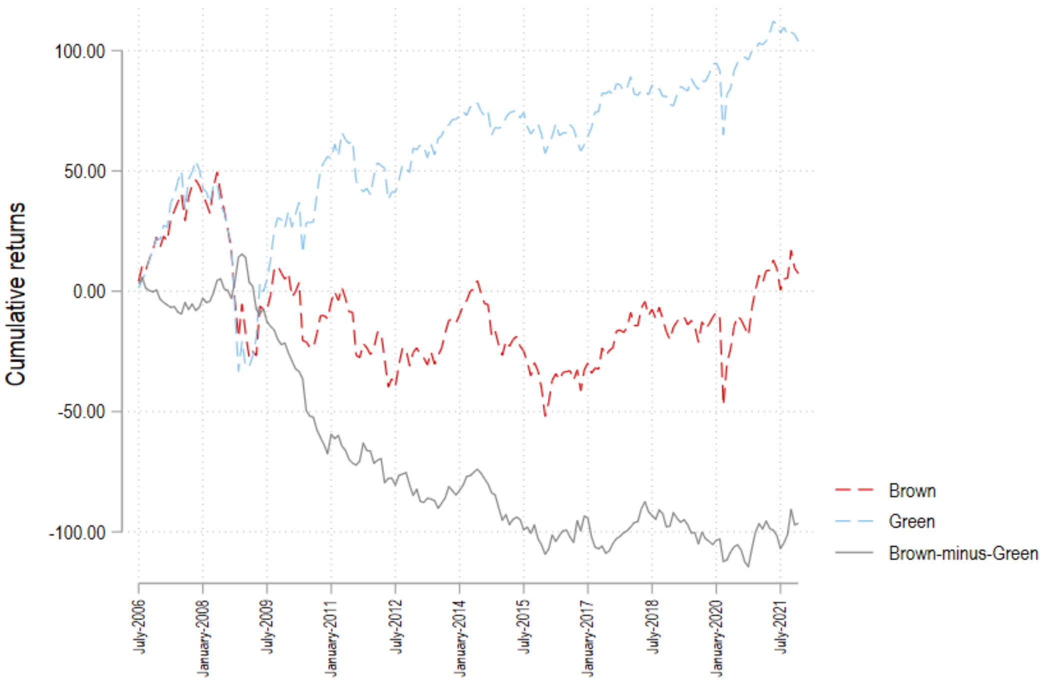
Note: The figure graphically shows the cumulative log returns for the value-weighted brown-minus-green portfolios based on the emissions intensity over the observation period 2006-2021.

Figure 1.4: Cumulative returns based on emissions level - EW portfolios



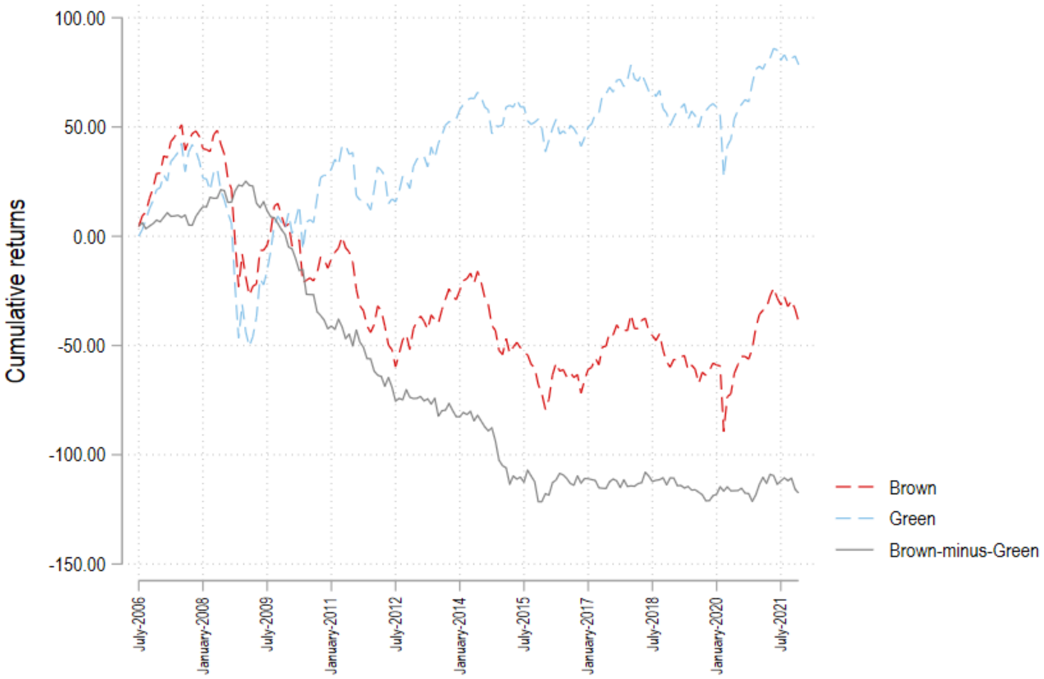
Note: The figure graphically shows the cumulative log returns for the equal-weighted green, brown and brow-minus-green portfolios based on the emissions level over the observation period 2006-2021.

Figure 1.5: Cumulative returns based on emissions level - VW portfolios



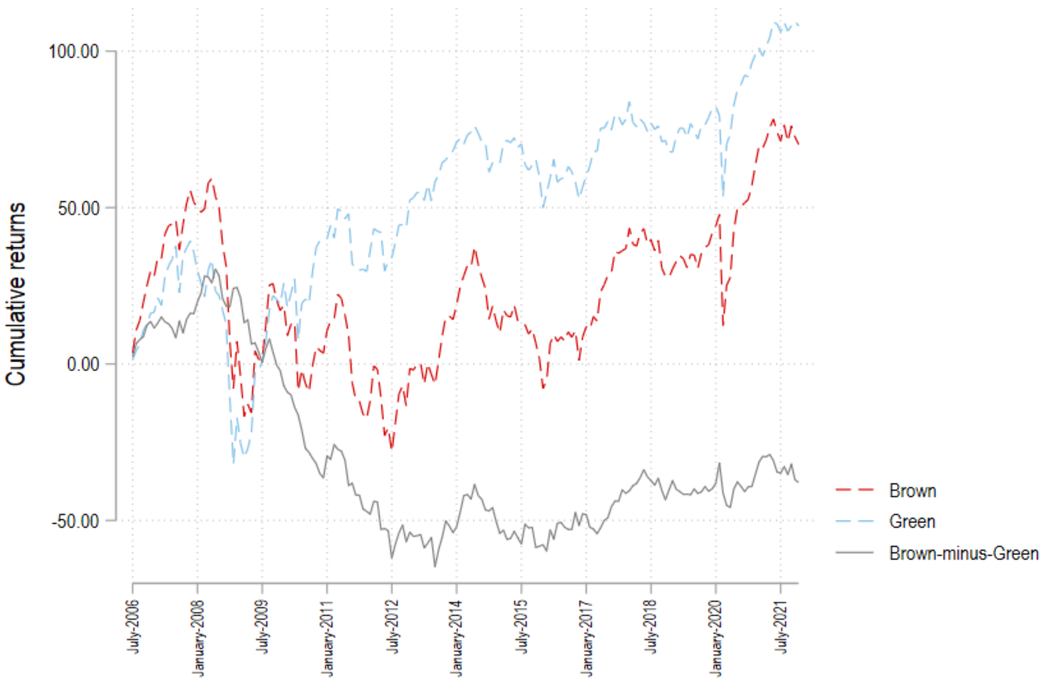
Note: The figure graphically shows the cumulative log returns for the value-weighted green, brown and brow-minus-green portfolios based on the emissions level over the observation period 2006-2021.

Figure 1.6: Cumulative returns based on emissions intensity - EW portfolios



Note: The figure graphically shows the cumulative log returns for the equal-weighted green, brown and brow-minus-green portfolios based on emissions intensity over the observation period 2006-2021.

Figure 1.7: Brown-minus-green cumulative returns based on emissions intensity - VW portfolios



Note: The figure graphically shows the cumulative log returns for the value-weighted green, brown and brow-minus-green portfolios based on emissions intensity over the observation period 2006-2021.

Additional tables

Table 1.13 provides further statistics on portfolios sorted by emissions in level and intensity. The average return of the green portfolio is consistently higher than that of the brown portfolio for each proxy for carbon footprint considered. As a result, the return of the BMG portfolio is always negative. This difference in performance between the brown and green portfolios can also be highlighted through the Sharpe ratio. Although the brown portfolio is slightly more volatile than the green portfolio, the latter still performs better with a higher Sharpe ratio for both level and intensity of emissions. We note that the average return of the brown portfolio is positive only when considering value-weighted returns. By reducing the weight of large companies, the equal-weighted brown portfolio performs worse. In this sense, the equal-weighted BMG portfolio has an average return of approximately -16% for emissions level and 5 times less if we consider emission intensity.

Table 1.13: Portfolio descriptive statistics based on verified emissions

Portfolios	**Mean**	**Std.Dev.**	**Min.**	**Max.**	**p25**	**p50**	**p75**	**Sharpe ratio**	**N**
Panel A: Emissions level									
Equal-weighted									
Brown	-0.09	6.94	-35.86	19.54	-3.74	0.67	4.46	-0.01	186
Green	0.07	6.36	-27.28	14.26	-3.43	0.61	4.24	0.01	186
Brown-minus-Green	-0.16	2.84	-8.59	7.26	-2.18	-0.13	1.80	-0.06	186
Value-weighted									
Brown	0.04	6.89	-36.14	20.59	-3.44	0.36	4.38	0.01	186
Green	0.56	6.46	-27.97	22.41	-1.77	0.92	3.84	0.09	186
Brown-minus-Green	-0.52	3.74	-13.13	10.46	-2.97	-0.82	1.80	-0.14	186
Panel B: Emissions intensity									
Equal-weighted									
Brown	-0.21	6.36	-30.08	15.96	-3.80	0.47	3.93	-0.03	186
Green	0.42	6.71	-28.73	17.53	-2.77	1.13	4.17	0.06	186
Brown-minus-Green	-0.63	3.15	-11.38	7.31	-2.58	-0.38	1.29	-0.20	186
Value-weighted									
Brown	0.38	6.82	-35.50	19.83	-3.19	0.83	4.24	0.06	186
Green	0.58	5.99	-25.97	19.47	-1.80	1.14	3.57	0.10	186
Brown-minus-Green	-0.20	3.38	-9.53	6.99	-2.05	-0.26	1.94	-0.06	186

Note: Author's calculations.

Additional estimation results

Table 1.14 presents the results of the brown and green portfolio analysis using two different models: the three-factor model (FF3F) and the four-factor model (FF4F). The table is divided into two panels: Panel A: Emissions level and Panel B: Emissions intensity. Each panel contains the results of the regression analysis for the two portfolios and weighting methods (value-weighted (VW) and equal-weighted (EW)).

The intercept in each model signifies the average portfolio return after considering the effects of the market, size, value, and momentum factors. The intercept coefficients in this analysis reveal that the relationships between emissions level and intensity are not consistent across different portfolio types (brown vs. green) and weighting methods (value-weighted (VW) vs. equal-weighted (EW)).

In Panel A (emissions level), brown portfolios' intercepts are predominantly negative, ranging from -0.358 (-0.540) to -0.550 (-0.704) in the FF3F (FF4F) model, implying that these portfolios have lower average returns after accounting for the market, size, and value factors. However, except for Column 6, the coefficients are not statistically significant, as p-values exceed 0.10. Conversely, green portfolios exhibit mixed intercept results, with some positive and some negative values. Regarding emissions intensity (Panel B), both brown and green portfolios display mixed intercepts, with brown portfolios generally having negative values and green portfolios having positive values. However, only one coefficient for brown portfolios is significant (brown EW in the three-factor model (FF3F) with a p-value < 0.10), while none of the green portfolio intercepts are significant. The other factors also provide insights into the portfolios' performance concerning the market risk, size, value, and momentum factors. Most of these factors exhibit statistical significance across models and weighting schemes, signifying their role in explaining the portfolios' returns. For example, MKT consistently presents positive and significant coefficients at the 1% level. This suggests a positive correlation between portfolio returns and overall market returns, indicating that the portfolios tend to perform well when the market thrives.

In Table 1.15, the analysis incorporates two distinct sorting methods: percentile sort and quintile sort, for both brown and green portfolios. The aim of this approach is to provide a more comprehensive understanding of the relationship between carbon emissions and stock returns by examining the results under different sorting methodologies. Note that only the three-factor model is considered in this analysis. This model accounts for the market risk, size, and value factors, which are essential in explaining stock return variations. The estimation results are presented similarly to those found in above table.

Table 1.16 presents the estimation results for the BMG portfolio using the Fama-French three-

Table 1.14: Brown and Green portfolio analysis

	Three-factor model (FF3F)				Four-factor model (FF4F)			
Portfolios	(1) Brown VW	(2) Brown EW	(3) Green VW	(4) Green EW	(5) Brown VW	(6) Brown EW	(7) Green VW	(8) Green EW
Panel A: Emissions level								
Constant	-0.358	-0.550	0.035	-0.390	-0.540	-0.704*	-0.039	-0.439
	(0.359)	(0.350)	(0.353)	(0.311)	(0.389)	(0.367)	(0.379)	(0.328)
MktRF	0.784***	0.799***	0.810***	0.765***	0.831***	0.839***	0.829***	0.778***
	(0.086)	(0.082)	(0.093)	(0.075)	(0.093)	(0.090)	(0.096)	(0.079)
SMB	0.421	0.766***	0.516**	0.772***	0.442*	0.783***	0.524**	0.778***
	(0.255)	(0.246)	(0.249)	(0.202)	(0.250)	(0.242)	(0.249)	(0.201)
HML	0.356*	0.337*	-0.066	0.267*	0.541**	0.493**	0.010	0.316**
	(0.216)	(0.199)	(0.182)	(0.150)	(0.247)	(0.220)	(0.210)	(0.160)
WML					0.266	0.226*	0.109	0.072
					(0.170)	(0.135)	(0.115)	(0.105)
Observations	186	186	186	186	186	186	186	186
Panel B: Emissions intensity								
Constant	-0.058	-0.627*	0.102	-0.093	-0.248	-0.790**	0.016	-0.150
	(0.369)	(0.325)	(0.322)	(0.338)	(0.404)	(0.344)	(0.347)	(0.358)
MktRF	0.746***	0.678***	0.758***	0.841***	0.795***	0.721***	0.780***	0.856***
	(0.087)	(0.076)	(0.082)	(0.083)	(0.093)	(0.081)	(0.087)	(0.089)
SMB	0.727***	0.935***	0.441*	0.711***	0.748***	0.953***	0.451**	0.717***
	(0.249)	(0.208)	(0.226)	(0.207)	(0.244)	(0.204)	(0.226)	(0.206)
HML	0.302	0.359**	-0.043	0.165	0.494**	0.525***	0.044	0.223
	(0.220)	(0.171)	(0.171)	(0.157)	(0.238)	(0.177)	(0.196)	(0.179)
WML					0.278	0.238*	0.125	0.083
					(0.181)	(0.138)	(0.111)	(0.110)
Observations	186	186	186	186	186	186	186	186

Note: The table is divided into two panels: Panel A: Emissions level and Panel B: Emissions intensity. Each panel contains the results of the regression analysis for the two portfolios and weighting methods (value-weighted (VW) and equal-weighted (EW)). The dependant variable is the monthly stock returns of each brown and grenn portfolio. Robust standard errors are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Factor (FF3F) model. Similar to the previous analysis, this examination incorporates both percentile and quintile sorting methods. This approach provides a more comprehensive understanding of the relationship between carbon emissions and stock returns, allowing for a more robust assessment of the results. By considering these different sorting methods in the analysis, we can better understand the potential implications of carbon emissions for stock returns for the BMG portfolio. We remark that the results are quite similar with respect to the sorting method.

Table 1.15: Brown and Green portfolio analysis (Percentile & Quintile sort)

	(1)-(4) Emissions level				(5)-(8) Emissions intensity			
	Percentile sort		Quintile sort		Percentile sort		Quintile sort	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Green	Brown	Green	Brown	Green	Brown	Green	Brown
Constant	0.137	-0.483	0.035	-0.550	0.001	-0.610*	0.102	-0.627*
	(0.314)	(0.339)	(0.353)	(0.350)	(0.310)	(0.310)	(0.322)	(0.325)
MktRF	0.737***	0.789***	0.810***	0.799***	0.752***	0.695***	0.758***	0.678***
	(0.080)	(0.079)	(0.093)	(0.082)	(0.080)	(0.074)	(0.082)	(0.076)
SMB	0.399*	0.829***	0.516**	0.766***	0.447**	0.969***	0.441*	0.935***
	(0.223)	(0.227)	(0.249)	(0.246)	(0.225)	(0.202)	(0.226)	(0.208)
HML	-0.033	0.390**	-0.066	0.337*	0.037	0.384**	-0.043	0.359**
	(0.167)	(0.190)	(0.182)	(0.199)	(0.176)	(0.170)	(0.171)	(0.171)
Observations	186	186	186	186	186	186	186	186

Note: Robust standard errors at firm-level are used and are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.16: BMG portfolio analysis (Percentile & Quintile sort)

	(1)-(4) Emissions level				(5)-(8) Emissions intensity			
	Percentile sort		Quintile sort		Percentile sort		Quintile sort	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	VW	EW	VW	EW	VW	EW	VW	EW
Constant	-0.417*	-0.107	-0.393	-0.159	-0.219	-0.318*	-0.160	-0.534**
	(0.214)	(0.170)	(0.270)	(0.207)	(0.228)	(0.168)	(0.244)	(0.225)
MktRF	0.027	0.010	-0.027	0.034	-0.014	-0.119***	-0.012	-0.163***
	(0.049)	(0.037)	(0.069)	(0.048)	(0.051)	(0.036)	(0.051)	(0.046)
SMB	0.048	0.070	-0.095	-0.006	0.248*	0.229**	0.286**	0.224*
	(0.114)	(0.109)	(0.169)	(0.143)	(0.140)	(0.100)	(0.143)	(0.127)
HML	0.359***	0.157*	0.422***	0.070	0.336***	0.143**	0.344***	0.194**
	(0.109)	(0.087)	(0.144)	(0.118)	(0.102)	(0.070)	(0.116)	(0.094)
Observations	186	186	186	186	186	186	186	186

Note: Robust standard errors at the firm level are used and presented in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.17: BMG portfolios analysis with the Five-factor model

	(1)-(4) Emissions level				(5)-(8) Emissions intensity			
	Percentile sort		Quintile sort		Percentile sort		Quintile sort	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.470**	-0.131	-0.482*	-0.185	-0.109	-0.238	-0.104	-0.543**
	(0.231)	(0.193)	(0.286)	(0.242)	(0.246)	(0.179)	(0.262)	(0.239)
MktRF	0.050	0.040	0.044	0.065	0.008	-0.124***	0.039	-0.153***
	(0.054)	(0.044)	(0.069)	(0.054)	(0.062)	(0.042)	(0.062)	(0.056)
SMB	0.083	0.105	-0.005	0.030	0.246	0.207**	0.324**	0.236*
	(0.117)	(0.115)	(0.172)	(0.151)	(0.150)	(0.104)	(0.154)	(0.130)
HML	0.339	0.073	0.265	-0.016	0.103	0.055	0.071	0.166
	(0.213)	(0.148)	(0.266)	(0.194)	(0.178)	(0.129)	(0.219)	(0.198)
CMA	0.176	0.216	0.517	0.222	0.129	-0.052	0.346	0.075
	(0.274)	(0.172)	(0.336)	(0.213)	(0.245)	(0.162)	(0.278)	(0.241)
RMW	0.107	0.005	0.105	0.006	-0.381	-0.229	-0.283	0.004
	(0.239)	(0.196)	(0.312)	(0.264)	(0.239)	(0.189)	(0.259)	(0.260)
Observations	186	186	186	186	186	186	186	186

Note: Robust standard errors at firm-level are used and are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Chapitre 2

Chapter 2

Monetary Policy Surprises and Stock Returns : Carbon Emissions Matter

Co-written with Aurélien Leroy & Louis Raffestin.

> *[..] any institution has to actually have climate-change risks and protection of the environment at the core of the understanding of its mission.*
>
> C. Lagarde.

2.1 Introduction

Global warming confronts central banks (CBs) with a dilemma. On the one hand, carbon emissions are, at first glance, outside the scope of CBs' mandate. On the other hand, monetary policy (MP) can be a powerful tool for incentivizing agents to invest in projects enabling a reduction in carbon emissions. This ambivalence has recently translated into a disagreement between CBs over the need to take active measures to combat climate change. In January 2023, J. Powell declared that "We are not, and will not be, a climate policymaker" (RiskBank conference, 1/10/2023). By contrast, ECB President Christine Lagarde expressed her willingness to see the ECB take a more active role (see quote). Other CBs have gone as far as to implement climate-oriented policies. In 2016, the bank of England notably launched a corporate bond purchase program tilted toward companies that satisfy certain climate-related criteria.

In the discussion over the need to "green" MP, a useful first step is to characterize how "brown" classical – non-climate-targeted – MP is. There are reasons to expect CO_2 emissions to be positively associated with MP exposure. For instance, brown firms face more transition risk, all else being equal, and risk premia are known to depend on MP tightness, as investors search for yield when risk-free rates are low (Bernanke and Kuttner, 2005). Green assets may also be less sensitive to fundamental news because financial performance is less important for the investors who hold them. On the other hand, some theoretical channels run in the opposite direction. Standard stock pricing theory for instance suggests that a change in the discount rate should have a relatively larger impact on firms whose future dividends are expected to rise over time, implying that green firms should be more sensitive to MP announcements.

This paper examines these issues by testing whether MP has a neutral impact on firms across CO_2 emission levels and by investigating the reasons for this nonneutrality if applicable. The paper starts with a theoretical model in which a representative investor allocates her wealth between a green stock, a brown stock and a risk-free asset. The investor rebalances her portfolio following a surprise rate change to maintain a target return for her portfolio. In the model, transition risk leads the brown stock to be more risky than its green counterpart, and the investor draws nonpecuniary utility from holding stocks that conform to her principles. Two testable hypotheses emerge: (i) brown stocks are more responsive to MP rate surprises, and (ii) this higher responsiveness comes from a mixture of supply factors linked to fundamentals and demand factors linked to investor preferences.

We test both hypotheses by estimating the heterogeneity of the stock price reaction of U.S. firms with varying levels of CO_2 emission intensities to Fed surprise rate changes between 2010 and 2019. Our baseline empirical model regresses the price return of a firm on an MP surprise indicator and on the interaction of this indicator with the firm's CO_2 intensity. Our hypothesis is that the coefficients on the policy surprise indicator and on the interaction term are both negative. Negativity of the first coefficient implies that an unexpected increase (decrease) in rates leads to a decrease (increase) in stock prices. Negativity of the second coefficient implies that the relationship between rate surprises and stock prices becomes increasingly negative as CO_2 intensity rises, meaning that brown stocks are more sensitive to MP shocks.

Our empirical design requires reliable measures of exogenous policy changes and firms' brownness. Exogenous MP shocks are obtained by using high-frequency changes in interest rates around the Federal Reserve's Federal Open Market Committee (FOMC) announcements. This approach is viewed in the literature as an efficient tool to rule out reverse causality and other endogeneity problems (Kuttner, 2001; Rigobon and Sack, 2004; Gürkaynak et al., 2005; Bernanke and Kuttner, 2005).[1] The brownness of each firm by its reported total CO_2 emissions (Scope 1 + Scope 2)

[1]Recent developments in this field question whether the identified surprises (from change in Federal funds or Eurodollars futures prices around FOMC announcements) are really exogenous monetary policy shocks. On the one hand, surprises could convey information about the central bank's assessment of the economic outlook as documented by the "Fed information effect" studies (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Andrade and

per unit of sales. Measuring brownness with reported emissions intensity avoids issues with third-party estimated emissions or scores as well as any mechanical correlation with firm size induced by unscaled carbon emissions (Bauer et al., 2022; Aswani et al., 2023).

Our empirical findings are in line with expectations. The variable "Emissions $\times$ MP surprise" is negative and highly significant, with a coefficient estimate of -0.052. A firm that is one standard deviation more carbon intensive than the sample average should expect a stock return of +0.504% following a one-standard-deviation decrease in monetary surprise, against +0.452% for the average stock in our sample. Importantly, the sensitivity premium of brown firms remains significant when controlling for classic sources of MP heterogeneity such as size or market beta. Brown firms react more because they are brown, not because their brownness correlates with other factors. MP heterogeneity across brownness is also not driven by a pure industry effect. The differential in carbon intensity within a given industry matters. The results are robust in terms of (i) outliers, (ii) the consideration of abnormal returns from the Fama-French 5-factor model, and (iii) alternative ways to measure the carbon footprint and MP surprises.

We provide further analysis on two points. First, we investigate the dynamics behind CO_2 nonneutrality. Based on our theoretical model, we test two hypotheses: i) the impact of CO_2 intensity on the relationship between MP and stock returns increases in absolute value with the overall level of climate awareness; (ii) the impact of CO_2 intensity on the relationship between MP and stock returns increases in absolute value with CO_2 intensity itself. To test (i), we use the climate awareness indicator of Engle et al. (2020), who rely the Crimson Hexagon proprietary sentiment measure to capture negative reports relating to climate change in a large set of news items. As expected, brown firms become even more relatively exposed to monetary policy when climate is salient in the news. To test (ii), we run estimations that allow CO_2 intensity to enter nonlinearly. As expected, MP nonneutrality is a growing and convex function of CO_2 intensity.

The second issue on which we provide further analysis is the level of persistence of the difference between green and brown stock returns following an MP surprise. We estimate impulse response functions from local projections (Jordà, 2005) to check that the price movements during FOMC meeting days are not counterbalanced by an opposite effect over the following days. We find that the heterogeneous impact of MP surprises across carbon footprint sizes is permanent. This suggests that the initial return responses reflect an efficient incorporation of relevant information, rather than short-term frictions.

Our paper is at the intersection of two literatures. The first investigates MP nonneutrality. A long line of research that has shown that firms with varying characteristics experience varying

Ferroni, 2021). On the other hand, a few recent papers call into question the assumption that MP shocks are unpredictable (Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023). We account for these points in our paper.

exposure to MP shocks (Gorodnichenko and Weber, 2016; English et al., 2018; Ozdagli and Velikov, 2020). Ehrmann and Fratzscher (2004) find that financially constrained and cyclical firms are more sensitive to interest rate surprises. Ammer et al. (2010) highlight that the response of foreign firms to U.S. monetary shocks is comparable to that of U.S. firms on average, but cyclical foreign firms' responses are more marked, in contrast to equally cyclical U.S. firms. Price reactions to MP innovations are also stronger among firms that are subject to greater information frictions (Ozdagli, 2018), do not hedge their loans against rate changes Ippolito et al. (2018), or have had low stock returns in past months (Kontonikas and Kostakis, 2013; Haitsma et al., 2016). Other studies concentrate on how monetary policy affects firms' investment decisions. They find that financial frictions amplify the real effects of monetary policy (Ottonello and Winberry, 2020; Durante et al., 2022; Cloyne et al., 2023). Our results complement this literature by showing that carbon intensity constitutes a new vector of nonneutrality.

The second literature connected to this paper relates to the pricing of transition risk. Textbook financial theory states that investors should demand compensation for holding the riskier brown stocks, implying that the return on green assets is lower in equilibrium. Several studies have attempted to test this idea using realized returns. Bolton and Kacperczyk (2021*b*) and Hsu et al. (2022) find higher realized returns for brown firms using, as we do, panel regressions of realized equity returns on CO_2 emissions. In contrast, Bauer et al. (2022) find that the realized returns on green assets exceed those of brown assets after controlling for fundamentals. These results may not as opposed as it appears. Indeed, as noted by Pástor et al. (2021*a*), lower realized returns and higher expected returns for brown firms may coexist if the price of green assets has increased in recent years because of a change in investors' tastes. Ardia et al. (2021) and Pástor et al. (2022) provide empirical support for this possibility. Our results complement this literature by showing that some of the risk differential between green and brown stocks comes from differences in MP exposure and that climate awareness plays a role in driving realized returns around MP announcements.

The main contribution of this paper is that it provides an empirical estimation of the ecological footprint of monetary policy, an issue that bears significant policy implications that are being actively considered. To the best of our knowledge, the scarce literature relating monetary policy to carbon emissions consists exclusively of theoretical or descriptive contributions. Schoenmaker (2021) estimates the change in asset holdings that a movement toward a carbon-neutral QE would imply for the ECB in 2020. Papoutsi et al. (2021) compute the carbon footprint of QE by feeding data on ECB asset purchases between 2016 and 2018 into a multisector general equilibrium model. They conclude that the ECB private bond portfolio is biased toward high-emission firms. Our study differs from these papers in many respects, but the results share a common idea: the market neutrality principle benchmark used by central banks induces a carbon bias, which in turn may prevent an efficient allocation of resources in the transition toward a low-carbon economy.

The paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the data. Section 4 presents our empirical approach to test for heterogeneity in MP responsiveness across carbon emission levels. Section 5 presents our baseline empirical results. Section 6 presents the robustness tests. Section 7 provides further analysis on CO_2 nonneutrality. Section 8 concludes.

2.2 Theoretical model

This section formally presents some channels through which CO_2 emissions can lead to heterogeneity in the transmission of MP. We emphasize that the model is built to convey intuition as concisely as possible and thus features some simplifying assumptions.

2.2.1 Framework

Basics

Consider an investor who allocates a share w_g of her wealth to a green stock, a share w_b to a brown stock, and a share $w_c = (1 - w_g - w_b)$ to a riskless bond. The investor follows a simple buy-and-hold strategy. The wealth she is willing to invest at every period is constant and denoted by W.

Let $d_{g,t}$ and $d_{b,t}$ be the dividend rate on the green and brown asset, respectively, between t and $t+1$, a timespan referred to as period t. In contrast, the riskless bond pays a certain coupon rate of c_t. The investor can secure c_t at t, but the rate c_{t+1} that can be secured in the following period may change. The total monetary amount received during period t is $W\left(w_{g,t}d_{g,t} + w_{b,t}d_{b,t} + w_{c,t}c_t\right)$, which can be reexpressed as :

$$\Pi_t = Wc_t + W\left(w_{g,t}(d_{g,t} - c_t) + w_{b,t}(d_{b,t} - c_t)\right)$$

$d_{g,t}$ and $d_{b,t}$ are two normally distributed random variables, with expected values of $\mu_{g,t}$ and $\mu_{b,t}$, respectively, and variances of $\sigma^2_{g,t}$ and $\sigma^2_{b,t}$, respectively. For conciseness and without loss of generality, both assets are assumed to be independent.

The investor has classic mean-variance preferences regarding the financial performance of her portfolio :

$$MV = E(\frac{\Pi_t}{W}) - \frac{1}{2\tau}V(\frac{\Pi_t}{W}) = c_t + w_{g,t}(\mu_{g,t} - c_t) + w_{b,t}(\mu_{b,t} - c_t) - \frac{1}{2\tau}\left((w_{g,t})^2\sigma^2_{g,t} + (w_{b,t})^2\sigma^2_{b,t}\right) \quad (2.1)$$

with $E(\frac{\Pi_t}{W})$ and $V(\frac{\Pi_t}{W})$ being the expected value and variance of the total portfolio return and $\frac{1}{2\tau}$ being the coefficient of risk aversion.

Green utility and search for yield

Two key elements are added to the investor's problem. First, the investor draws nonfinancial utility from holding stocks that match her principles. Formally, holding one monetary unit of the green asset provides the investor with a utility of $u_g \times (\mu_{g,t} - c_t)$, where u_g is the utilitarian gain of holding a green asset relative to its financial gain. We decompose this utility gain as $u_g = \phi \triangle CO2$ where $\phi > 0$ is the nonpecuniary utility provided by a one-unit decrease in the total emissions in the portfolio, and $\triangle CO2 = CO2_b - CO2_g > 0$ is the number of units of C02 saved by investing in the green asset instead of the brown asset.

The second addition to the investor's problem is that she is set to have a target return of $E(\frac{\Pi_t}{W}) = G > c_t$. This constraint is a crude way of capturing search-for-yield dynamics. To maintain her expected return at G following a decrease in c_t the investor must rebalance her portfolio toward risky assets.

Accounting for nonfinancial utility and the search for yield, the maximization problem of the investor is:

$$\begin{aligned} Max \;\; U = c_t + w_{g,t}(\mu_{g,t} - c_t)(1 + \phi \triangle CO2) + w_{b,t}(\mu_{b,t} - c_t) - \tfrac{1}{2\tau}((w_{g,t})^2\sigma^2_{g,t} + (w_{b,t})^2\sigma^2_{b,t}) \\ s/c \quad w_{g,t}(\mu_{g,t} - c_t) + w_{b,t}(\mu_{b,t} - c_t) = G - c_t \end{aligned} \tag{2.2}$$

Asset moments

We turn to the modeling of the relationship between the brown asset and the green asset in terms of expected return and variance. First, we set the variance of the brown stock higher than the variance of the green stock. Theoretically, this comes from the fact that, holding all other risk factors constant, brown firms' assets are more exposed to transition risk. Formally:

$$\sigma^2_{b,t} = (1 + \psi \triangle CO2)\sigma^2_{g,t} \tag{2.3}$$

where $\psi > 0$ is the relative increase in asset risk spurred by an additional unit of CO2 and $\triangle CO2$ is the number of units of C02 saved by investing in the green asset instead of the brown asset.

Although the idea that brown stocks are more exposed to transition risk is not controversial, a complex question relates to the way this risk translates into expected returns. As discussed the introduction, standard theory predicts that investors should demand compensation for holding the riskier brown stocks, and several empirical studies have confirmed this assertion. However it is unclear "how much" returns should rise to compensate for transition risk. Because we have no prior on this issue, and because it eases presentation, we set the relative difference in expected returns to exactly match the relative difference in variances. Formally:

$$\mu_{b,t} - c = (1 + \psi \triangle CO2)(\mu_{g,t} - c)$$

This implies that both assets have the same Sharpe ratio S:

$$S = \frac{(\mu_{g,t} - c_t)}{\sigma^2_{g,t}} = \frac{(\mu_{d,t} - c_t)}{\sigma^2_{d,t}} \tag{2.4}$$

2.2.2 Equilibrium

Quantities and prices

Maximizing yields:

$$w_{b,t} = \tau(1 - \lambda_t)S \tag{2.5}$$

$$w_{g,t} = \tau(1 + \phi \triangle CO2 - \lambda_t)S \tag{2.6}$$

where λ_t is the Lagrange multiplier and is equal to:

$$\lambda_t = 1 + \frac{1}{2 + \psi \triangle CO2} \left(\phi \triangle CO2 - \frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}} \right) \tag{2.7}$$

The market for equities clears when the monetary demand for an asset is equal to its market value. Assuming that the number q of shares is fixed in the short run, the market equilibrium condition for any asset $k = (b, g)$ is:

$$w_{k,t} W = p_{k,t} q \tag{2.8}$$

Plugging Equations (2.5) and (2.7) into (2.8) yields:

$$p_{b,t} = \frac{W}{q} \tau S \left(\frac{1}{2 + \psi \triangle CO2} \right) \left(\frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}} - \phi \triangle CO2 \right) \tag{2.9}$$

$$p_{g,t} = \frac{W}{q} \tau S \left(\frac{1}{2 + \psi \triangle CO2} \right) \left(\frac{(G - c_t)}{\tau S^2 \sigma^2_{g,t}} + \phi \triangle CO2 (1 + \psi \triangle CO2) \right) \tag{2.10}$$

Note that $p_{b,t} < 0$ if $\frac{(G-c_t)}{\tau S^2 \sigma^2_{g,t}} < \phi \triangle CO2$. This means that it is theoretically possible that investors are so climate sensitive – and/or the brown asset is so brown – that investors require payment to hold the brown stock. Of course this is an extreme case, and in what follows, we focus on parameter sets for which $p_{b,t} > 0$.

Equations (2.9) and (2.10) directly yield the first result on MP responsiveness.

Lemma 1: Both green and brown stock returns respond negatively to a shock to the interest rate.

Proof: $\frac{d\,p_{g,t}}{d\,c_t} < 0$ and $\frac{d\,p_{b,t}}{d\,c_t} < 0$ are immediate from (2.9) and (2.10); thus, $\frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} < 0$ and $\frac{d\,p_{b,t}/d\,c_t}{p_{b,t}} < 0$ for any $p_{g,t} > 0$ and $p_{b,t} > 0$

Price reaction to changes in the riskless rate

We can now compare the brown price return reaction $\frac{d\,p_{b,t}/d\,c_t}{p_{b,t}}$ to a change in the interest rate to the green price return reaction $\frac{d\,p_{g,t}/d\,c_t}{p_{g,t}}$ to the same change in the interest rate.

Using Equations (2.9) and (2.10), the price ratio $\frac{p_{g,t}}{p_{b,t}}$ can be expressed as:

$$\frac{p_{g,t}}{p_{b,t}} = 1 + \frac{\phi \triangle CO2(2 + \psi \triangle CO2)}{\left(\frac{(G-c_t)}{\tau S^2 \sigma^2_{g,t}} - \phi \triangle CO2\right)} \tag{2.11}$$

Let NN, which stands for nonneutrality, be defined by the difference in MP responsiveness between the green and the brown asset, i.e., $NN = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} - \frac{d\,p_{b,t}/d\,c_t}{p_{b,t}}$. Appendix A-1 shows that deriving both sides of Equation (2.11) with respect to c_t yields:

$$NN = \frac{p_{b,t}}{p_{g,t}} \left(\frac{\phi \triangle CO2(2 + \psi \triangle CO2)}{(\frac{(G-c_t)}{\tau S^2 \sigma^2_{g,t}} - \phi \triangle CO2)^2} \right) \left(\frac{1}{\tau S^2 \sigma^2_{g,t}} \right) \tag{2.12}$$

This expression spurs the main proposition of the model.

Proposition 1: Brown asset returns respond more negatively than green asset returns to an innovation in the risk-free rate.

Proof: $NN = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} - \frac{d\,p_{b,t}/d\,c_t}{p_{b,t}} > 0$.

As a final step, we investigate how the impact $\frac{d\,NN}{d\,\triangle CO2}$ of CO_2 on nonneutrality changes with CO2 itself, with the green preference ϕ, and with the brown risk channel ψ. This leads to Lemmas 2 and 3.

Lemma 2: CO_2 has a growing and convex impact on nonneutrality, i.e., $\frac{d\,NN}{d\,\triangle CO2} > 0$ and $\frac{d^2\,NN}{d^2\,\triangle CO2} > 0$.

Proof: See Appendix A-2.

Lemma 3: The impact of CO_2 on nonneutrality rises with the investors' preference for green asset ϕ and the relative increase in risk ψ involved in holding the brown asset, i.e., $\frac{d^2\,NN}{d\,\triangle CO2\ d\,\psi} > 0$ and $\frac{d^2\,NN}{d\,\triangle CO2\ d\,\phi} > 0$.

Proof: See Appendix A-2.

2.2.3 Comments

In the model above, brown assets respond relatively more to monetary policy shocks for two reasons. First, they provide higher returns in compensation for their higher risk. This makes them the best adjustment variable for portfolio managers with an increased (decreased) need for finding yield following a fall (rise) in the interest rate. This is the search-for-yield channel. Second, green assets provide nonfinancial returns, which makes investor demand less elastic to a change in excess returns. This is the nonfinancial utility channel.

The model generates testable implications. Consider estimating the following linear regression, for any firm i:

$$r_{i,t} = \alpha_i + \beta_1 c_t + \beta_2 \left(c_t \times CO2_{i,t}\right) + \varepsilon_{i,t}$$

$$\Rightarrow \frac{d\,r_{i,t}}{d\,c_t} = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}} = \beta_1 + \beta_2 \times CO2_{i,t}$$

If all stock returns are negatively linked to rate innovations for any positive level of CO_2 emissions as posited by Lemma 1, we should have $\beta_1 < 0$. If the reaction of high-emissions stocks is more negative than that of low-emissions stocks as posited by Proposition 1, we should have $\beta_2 < 0$. Lemma 1 and Proposition 1 are jointly tested in Section 5 and checked for robustness in Section 6.

Furthermore, if the MP response of stock returns in absolute value is a growing convex function of CO_2, as posited by Lemma 2, we should have $\frac{d\,\beta_2}{d\,CO_2} < 0$. Similarly if the impact of CO_2 on the MP response of stock returns in absolute value increases with ϕ and ψ, as posited by Lemma 3, we should have $\frac{d\,\beta_2}{d\,\phi} < 0$ and $\frac{d\,\beta_2}{d\,\psi} < 0$. These possibilities is investigated in Section 7, which is dedicated to further analyzing the dynamics of CO_2 nonneutrality.

2.3 Empirical framework

2.3.1 Econometric specification

Our estimation strategy relies on an event-study approach: we consider the stock price response to monetary policy innovations on the day of FOMC announcements only. This approach has become the standard in the literature on the transmission of MP to asset prices since the pioneering work of Cook and Hahn (1989) and Kuttner (2001) (see, for example, Bernanke and Kuttner (2005); Gürkaynak et al. (2005); Hanson and Stein (2015); Nakamura and Steinsson (2018)). It can be easily amended to panel data and to assess the heterogeneity of the transmission. Our baseline regression takes the following form:

$$r_{i,t} = \beta_1 MP_t + \beta_2 MP_t \times CO2_{i,t} + \beta_3 CO2_{i,t} + \sum_{k=4}^{K} \beta_k \mathbf{X}_{k,i,t} + \alpha_i + \varepsilon_{i,t} \quad (2.13)$$

where t indexes the days on which an FOMC announcement occurs, $r_{i,t}$ represents the daily returns of firm i on day t, MP_t refers to the change in MP on day t, $CO2_{i,t}$ represents the firm's carbon intensity at time t, $\mathbf{X}_{k,i,t}$ is a set of control variables, α_i refers to firm fixed effects, and $\varepsilon_{i,t}$ is the error term.[2] The interaction term, $MP_t \times CO2_{i,t}$, is our main variable of interest. As stated in the theoretical model, we expect $\beta_1 < 0$ and $\beta_2 < 0$, meaning that a monetary tightening (loosening) leads to a drop (rise) in stock prices and that this negative relationship is stronger for polluting firms. We estimate our regressions using ordinary least squares (OLS) and report two-way cluster-robust standard errors to account for correlation within firms and within FOMC meetings.

The dependent variable is constructed using stock price data obtained from Thomson Reuters. We take all common shares listed on US major stock exchanges, excluding financial companies, from January 1, 2010, through December 31, 2019. Daily returns are computed as the logarithm of the first difference in prices:

$$r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \quad (2.14)$$

where $P_{i,t}$ is the price of stock i on trading day t. To mitigate the impact of outliers, returns are winsorized at the 1% level in the baseline estimation. Other levels are considered in robustness checks.

[2]The vector $\mathbf{X}_{k,i,t}$ comprises firm-level and macro-level variables. Further details are provided below.

2.3.2 Monetary policy data

Our baseline indicator of MP surprises is taken from Bauer and Swanson (2022).[3] These authors measure policy announcement surprises using changes in the first four quarterly Eurodollar futures contracts (ED1, ED2, ED3 and ED4) in a 30 minute window around the time of the FOMC's press release. The price movements on the four contracts are turned into a single indicator through a first principal component analysis. The Bauer and Swanson (2022) indicator thus provides a broad measure of the overall MP stance that incorporates both the change in the federal funds rate target as well as the change in forward guidance.

Generally, the identification of causal effects from monetary policy to stock prices must satisfy three conditions. First, there is no reverse causation, i.e., MP actions do not react to asset price changes. Second, there are no omitted variables that jointly and contemporaneously impact $r_{i,t}$ and MP_t. Third, the impact of MP on prices is observable on the day of the meeting, meaning that movement in prices and/or in the monetary policy indicator cannot be predicted – and thus priced in – ex ante. The use of daily returns on FOMC days at the firm level ensures that the causality runs from MP to stocks. Condition 1 is likely filled. Using daily returns also ensures that there are no macroeconomic shocks systematically biasing the results. Nevertheless two problems may arise regarding conditions 2 and 3.

The first problem is that high-frequency interest rate surprises could reveal information not just about policy but also about the central bank's assessment of the economic outlook that does not identify a purely exogenous MP shock (Hubert et al., 2021; Jarociński and Karadi, 2020; Andrade and Ferroni, 2021). Reassuringly, in their paper, Bauer and Swanson (2022) find that the effects of MP on financial markets are largely unchanged when bias-adjusted indicators are considered. They argue that Fed communication influences only the relationship between MP and the economic outlook, not the relationship between MP and daily stock prices. Nevertheless to address any concerns, we provide estimations using the indicator of MP surprises of Jarociński and Karadi (2020) in robustness checks. These authors decompose the standard measure of MP surprises into "pure monetary" shocks and "central bank information" shocks based on the observation of the comovement of interest rates and stock prices around policy announcements. Negative comovement identifies "pure monetary" shocks, while positive comovement identifies "central bank information" shocks. The indicator is downloaded from Martin Jarocinski's personal site.[4] We also estimate the model using the "central bank information" surprise indicator instead of the "pure monetary" surprise indicator, as a placebo test.

The second problem is that policy rate surprise may in fact be predictable using information available prior to the FOMC announcements, which violates the third condition (Cieslak, 2018;

[3]The data are obtained from Michael Bauer's personal site: https://www.michaeldbauer.com/research/.
[4]`https://marekjarocinski.github.io/`.

Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023, 2022). To ensure that we identify pure surprises, we include in the baseline regression the set of macroeconomic and financial variables that have been identified as potential predictors of MP surprises by Bauer and Swanson (2022): nonfarm payroll releases, employment growth over the last year, the log change in the S&P500 from 3 months before to the day before the FOMC announcement, the change in the yield curve slope over the same period, the log change in a commodity price index over the same period, and the option-implied skewness of the 10-year Treasury yield. The data are obtained from Michael Bauer's personal site.[5] The Bauer-Swanson controls are included in the baseline regressions as control variables. Following Bauer and Swanson (2021, 2022), we also provide a robustness test in which the monetary policy surprise indicator is orthogonalized with respect to the Bauer-Swanson controls. Note that all monetary surprises will be standardized to ease the interpretation of the results.

2.3.3 Emission data

Data on CO_2 emissions at the firm level – measured in tons of CO_2 per year – are obtained from Thomson Reuters. According to the Greenhouse Gas Protocol nomenclature[6] established in 2001, a company's greenhouse gas emissions are categorized into three scopes (or levels) that represent its emissions perimeter. Scope 1 encompasses direct carbon emissions originating from sources owned or controlled by the company. Scope 2 comprises indirect carbon emissions resulting from the consumption of purchased energy due to the company's activities. The combination of Scope 1 and Scope 2 emissions constitutes Total emissions. Scope 3 encompasses carbon emissions produced by the production units within the company's value chain. We concentrate on Total emissions calculated as the sum of Scope 1 and Scope 2, primarily because Scope 3 data are scarcer and more difficult to measure.[7] Specifications using Scope 1 or 2 emissions separately are provided for robustness.

Another choice involved in defining CO_2 emissions is whether to use reported emissions or estimated emissions. While the number of companies disclosing their carbon emissions (either mandatorily or voluntarily) has grown over the years, a significant portion of companies still do not report their carbon footprint. Using reported emissions then reduces the size of the sample. However, as argued by Aswani et al. (2023); Bauer et al. (2022), there are significant discrepancies between estimated and reported emissions, which casts doubt on the reliability of estimated emissions. With this in mind, reported emissions are used in the baseline estimations. Nonetheless, carbon emissions as estimated by Thomson Reuters are considered in robustness tests.

[5] https://www.michaeldbauer.com/research/.

[6] see https://ghgprotocol.org/.

[7] Busch et al. (2022) show that the consistency of CO_2 emission intensities (disclosed by firms or estimated by third parties) between third-party providers is very high although decreasing from Scope 2 to Scope 3.

The last step in defining our CO_2 indicator is to divide the emissions of a firm by its sales, obtained from Thomson Reuters. This carbon intensity approach is standard in the literature. It prevents CO_2 from measuring the size of a firm rather than its ecological footprint. We consider in robustness checks alternative measures such as carbon emissions per unit of equity value to account for the fact that exposure to climate risk may be relatively higher for firms with low market value (Ilhan et al., 2021). The carbon intensity measure is standardized to ease the interpretation of the results.

2.3.4 Control variables

To account for variation in returns that stems from non-CO_2 related factors, we add six firm-level variables to the set of controls (vector $\mathbf{X}$ of Equation 2.13), in addition to the macro-level predictors from Bauer and Swanson (2022) discussed previously. These variables include size, debt, cash flows, market beta, price-to-earnings ratio, and return on equity. Size is proxied by the natural logarithm of market capitalization. Debt is expressed as the proportion of both short- and long-term debt to total assets. Cash flow is expressed as a percentage of total sales. Market beta is estimated by running a CAPM model on each stock over a one-year window. The price-to-earnings ratio is computed by dividing operating income by market value. Return on equity is obtained by dividing net profit by book value. All relevant firm-level data are obtained from Thomson Reuters.

In the baseline regression (Section subsection 2.5.1) the firm-level controls are included on their own, but in Section subsection 2.5.2, they enter both directly and in interaction with MP. Interacting the controls means allowing variables other than CO_2 intensity to influence the relationship between stock returns and MP surprises, which allows us to pin down the pure effect of CO_2 on nonneutrality. The intuition is as follows: Section subsection 2.5.1 seeks to measure whether there is a difference in MP exposure between brown stocks and green stocks, regardless of its source. Section subsection 2.5.2 investigates whether brownness is relevant in itself, as suggested by the theoretical model, or simply correlates with other factors that cause MP heterogeneity.

We sort our variables into 4 vectors of MP heterogeneity identified by Ozdagli and Velikov (2020): financial constraints, cash flow duration, cash flow cyclicality and operating profitability. Financially constrained firms are expected to be more affected by MP shocks through the credit channel (Gertler and Gilchrist, 1994; Perez-Quiros and Timmermann, 2000). We use a firm's size, debt, and cash flows as (inverse) proxies for financial constraints. Duration leads to heterogeneity in MP responses because cash flows that are far in the future are relatively more discounted (Ozdagli, 2018). We measure this channel through the price-to-earnings ratio. Cyclical stocks typically rely on external financing more often, which increases their sensitivity to the cost of external financing. We measure a firm's cyclicality through its market beta. Finally, firms that generate profits should be less sensitive to variation in the cost of external financing. Profitability is estimated through the return on equity (ROE).

2.4 Preliminary evidence

2.4.1 Summary statistics

Merging the financial database with the reported CO_2 emissions data leads to an unbalanced sample of 857 companies in our baseline estimation[8]. In the time dimension, our sample contains a total of 81 FOMC meeting days. Overall the total number of observations is 315,157.

Table 2.1 summarizes all firm-level variables in the sample. The average firm in our sample is large but not necessarily profitable. Its Scope 1 emissions represent the bulk of its Total emissions.

Table 2.2 shows the correlation between our preferred CO_2 intensity measure and reported emissions in absolute value. As expected, the relationship is positive and significant, but far from 1, which shows that total emissions partly reflect size.

Figure 2.1 plots the MP indicator over our sample period. Table 2.3 displays its correlation with the orthogonalized indicator of Bauer and Swanson (2022) and the "pure monetary" and "central bank information" surprises indicators of Jarociński and Karadi (2020). As expected, correlations are high among all indicators except the "central bank information" surprise indicator.

2.4.2 Prima-facie evidence

This section examines the correlation between stock returns and MP surprises. Figure 2.2 plots the average returns of stocks on FOMC meeting days against the average policy surprise. As expected, the relationship is negative: a loosening (tightening) MP surprise has a positive (negative) impact on stock returns on average.

We next search for preliminary evidence on the impact of CO_2 emissions on the relationship between returns and MP. Each stock return of a firm i is regressed on the MP indicator throughout the sample period to obtain an estimate of the firm's sensitivity to MP shocks. We then connect the estimated coefficient to the average carbon intensity of the firm. Figure 2.3 shows the results across all firms. Consistent with our prior, the effect of an MP shock on stock returns becomes increasingly negative as carbon emission intensity increases.

[8]The sample with estimated emissions covers 2325 companies.

Table 2.1: Summary statistics

	Mean	**Std.Dev.**	**Min.**	**Max.**
Dependent variable				
Returns (%)	0.051	2.000	-8.34	8.60
Emissions measures				
Total emission intensity (std.)	0	1	-0.412	5.297
Scope 1 intensity (std.)	0	1	-0.371	5.472
Scope 2 intensity (std.)	0	1	-0.479	6.111
Estimated total emission intensity (std.)	0	1	-0.345	6.505
Total emissions by equity value	0	1	-0.352	6.572
MP surprises				
Baseline surprises (std.)	0	1	-3.042	2.898
Pure monetary surprises (std.)	0	1	-3.031	2.241
Central bank information surprises (std.)	0	1	-3.194	2.435
Orthogonalized surprises (std.)	0	1	-3.363	2.553
Firms' controls				
ROE	16.663	32.036	-407.98	138.50
Size	14.293	2.296	0.691	21.973
Cash flows	-0.001	0.014	-0.168	0.000
Debt	0.269	0.258	0.00	1.388
PER	0.19	1.25	-11.87	53.74
Beta	1.021	0.268	-0.098	1.885
Macroeconomic controls				
Nonfarm payrolls surprise	-7.447	67.398	-160	136
Employment growth	1.421	0.793	-3.817	2.243
S&P 500	0.025	0.049	-0.176	0.111
Yield curve slope	-0.084	0.368	-1.118	1.276
Commodity prices	0.001	0.061	-0.143	0.166
Treasury skewness	-0.028	0.377	-0.77	0.78

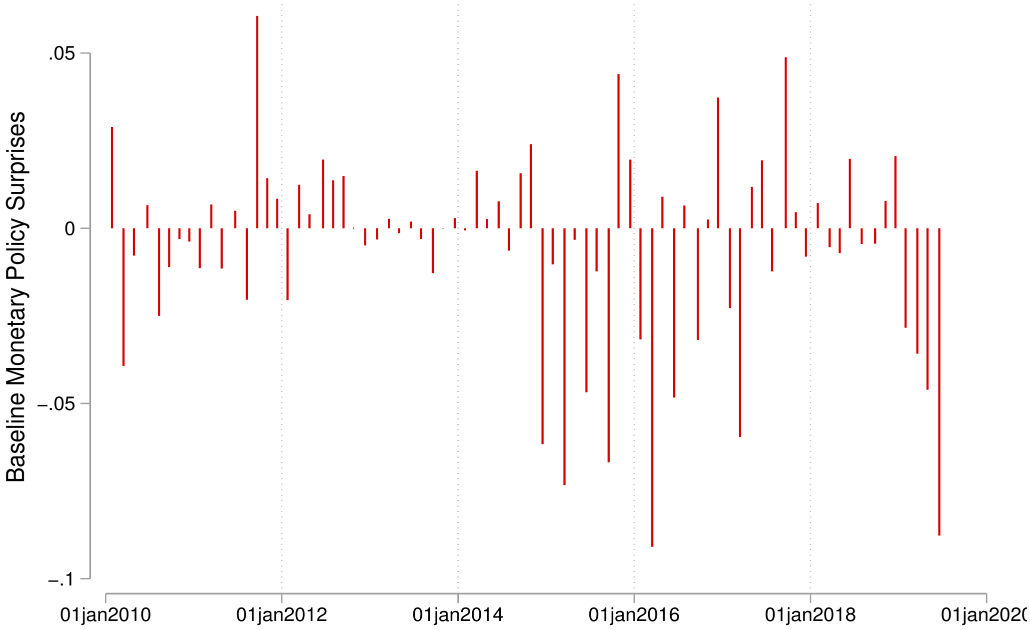
Note: The table represents the summary statistics of variables used in our estimation during the sample period 2010-2019.

Table 2.2: Cross-correlation between environmental variables

	Total emissions	Total emissions intensity	Scope 1 emissions	Scope 1 emissions intensity
Total emissions	1			
Total emissions intensity	0.744***	1		
Scope 1 emissions	0.902***	0.757***	1	
Scope 1 emissions intensity	0.683***	0.890***	0.872***	1

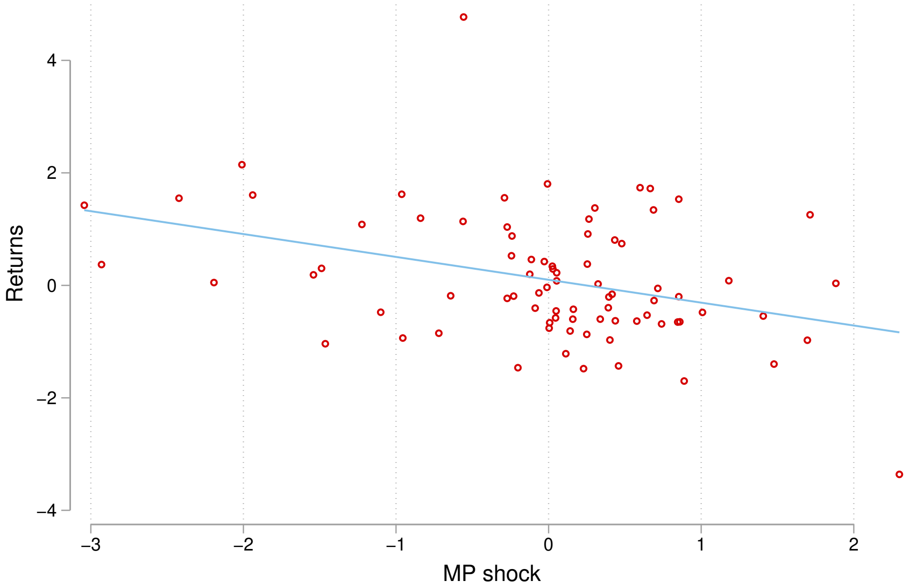
Note: This table provides the correlation between all environmental variables that we used as our firm brownness indicators.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2.1: Monetary policy surprises



Note: The figures plots our baseline indicator of MP surprises over the period 2010-2019.

Figure 2.2: Relationship between stock price returns and monetary policy shock



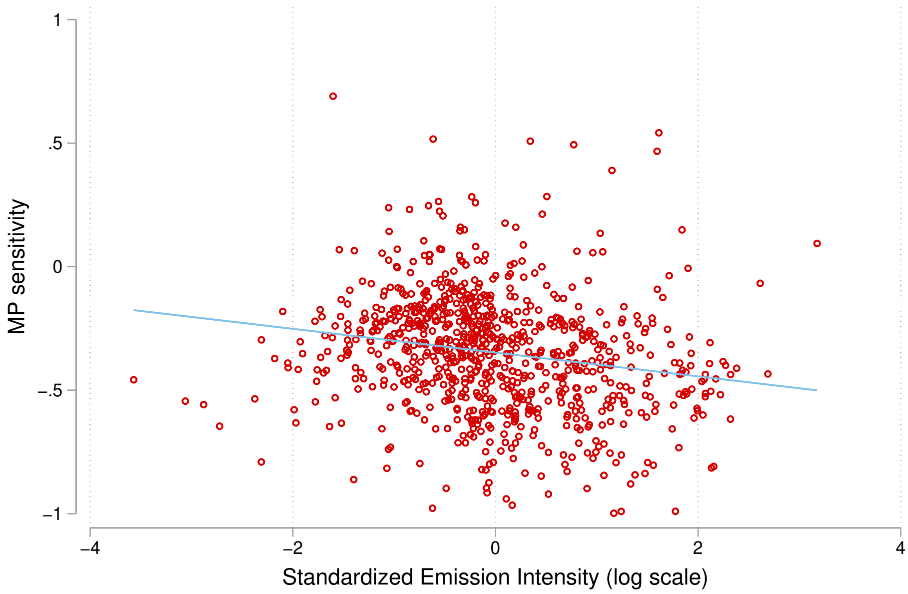
Note: The figure shows the relationship between the average returns of stocks and the estimated monetary policy surprise over the observation period 2010-2019.

Table 2.3: Correlation of the monetary policy surprises

	Baseline	Orth.	PM	CBI
Baseline	1			
Orth.	0.927	1		
PM	0.857	0.791	1	
CBI	0.305	0.233	-0.036	1

Note: This table presents the correlation between baseline, orthogonalized (Orth.), Pure Monetary (PM) and Central Bank Information (CBI) surprises.

Figure 2.3: MP sensitivity & CO_2 emissions intensity



Note: The figure displays the relationship between the sensitivity of firm returns to an MP surprise (estimated coefficient per firm) and the carbon footprint quantified by Scope 1 emissions intensity (calculated as the ratio of total emissions (Scope 1 + Scope 2) to company sales).

2.5 Baseline results

2.5.1 The carbon effect on MP transmission

section 2.5 reports the results from estimating different specifications of Equation 2.13.[9]

Column 1 shows our baseline estimation that features Bauer-Swanson controls, financial controls, and firm/year fixed effects. As expected, the variables " MP surprise" and "Emissions × MP surprise" are both negative and highly significant. Specifically, a one-standard-deviation of "MP surprise" induces an immediate average contraction of 0.452% for U.S. individual stock returns. This is closely in line with the macro-estimates provided by Jarociński and Karadi (2020). "Emissions × MP surprise" has a coefficient estimate of -0.052, which means that a firm that is one standard deviation more carbon intensive than the sample average should expect a stock return of

[9]Throughout, the estimates are based on a sample including only the days of the FOMC meetings. We also note that MP surprises as well as emissions indicators are standardized to make the estimates easily interpretable.

Table 2.4: Heterogeneous responses of stock returns to monetary policy: baseline estimation

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.451***		-0.429***	-0.450***	-0.395***	-0.375***
	(0.109)		(0.103)	(0.110)	(0.109)	(0.135)
Emissions × MP surprise	-0.052***	-0.051***	-0.057***	-0.052***	-0.054***	-0.047***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.014)
Emissions	0.013	0.010	-0.006	-0.018	0.037	0.003
	(0.067)	(0.071)	(0.070)	(0.015)	(0.037)	(0.066)
Control variables	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.124	0.288	0.103	0.105	0.104	0.127
Observations	28062	28062	35157	28065	28062	28062
Nb. of Firms	771	771	857	771	771	771

Note: This table represents our baseline estimation results of Equation 2.13. Only the days of FOMC meetings during the sample period 2010-2019 are considered. The independent variable represents the daily stock return. The columns correspond to 6 different specifications which are differentiated by the inclusion or not of certain variables, controls or fixed effects. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

+0.504% following a one-standard-deviation decrease in monetary surprise, against +0.452% for the average stock in our sample.

Column 2 removes the MP surprise variable and controls for FOMC time fixed effects. This implies that the parameter estimates are based on the within-firm-meeting variation and ensure that the results are not driven by an omitted variable bias or a fixed meeting component. The estimates displayed are very similar to the baseline. Column 3 removes all the controls to maximize the sample size, which has little impact on our estimates. Columns 4, 5 and 6 correspond to different ways of capturing the industry effect of MP. Column 4 replaces the firm fixed effects with industry fixed effects. Column 5 adds an industry × year fixed effect to our baseline specification to account for time-varying industry shocks. Both specifications have limited impact on the estimates. Column 6 exploits the variation in the data that is orthogonal to the industry average effect of MP surprises. This means that we examine whether the differential in carbon footprints inside a given industry explains the heterogeneity of the asset price transmission of the MP. This specification is useful to break down the overall effect in our baseline specification into an industry component and a firm-residual component. This contributes to an understanding whether financial markets look at carbon emissions at the firm-level or whether they do not look beyond industry categories. We find that the point estimate of the "Emissions × MP surprise" is slightly lower than in our baseline estimate but still significant. This implies that our findings are not driven by systematic different sectoral responses to MP surprises: intra-industry variation in CO_2 intensity also matters.

The general message of Table 2.4 is that the variables " MP surprise" and "Emissions × MP surprise" are both negative and highly significant in all specifications. Brown stocks are relatively more impacted by MP surprises. From a policy standpoint, this result implies that a central bank that takes an accommodative stance indirectly subsidizes firms with a high carbon footprint. Another interesting implication of our results is that, since brown stocks are more likely to experience large fluctuations on FOMC meeting days, investors should demand compensation for this risk. However we do not observe this: firms with higher carbon emissions do not earn higher return across FOMC meetings days.[10]

2.5.2 A new channel of MP transmission?

This section turns to the issue of whether CO_2 is relevant in itself or simply correlates with other sources of MP heterogeneity. We interact our MP indicator with the set of firm-level control variables described in subsection 2.3.4.[11] Table 2.5 presents the results.

Specification (1) is a reminder of the baseline results of Table 2.4. In specifications (2) to (7), interacted controls are introduced individually. The coefficients on all interacted control are of the expected sign but are only significant for the indicators of cyclicality (Beta) and profitability (ROE). Our indicators of financial constraint (size, debt, and cash flows) and duration (PER) are nonsignificant. For conciseness, we do not seek to explain these results or discuss how they contribute to the literature on the heterogeneity of monetary transmission. We focus on the way the interacted controls impact the effects of CO_2 intensity on transmission.

Unsurprisingly, the effect of CO_2 intensity is not impacted by the introduction of the nonsignificant financial constraint and duration indicators. In contrast, the coefficient on "Emissions × MP surprise" becomes more negative when "Beta × MP surprise" is included. This result implies that the coefficient of "Emissions × MP surprise" in the baseline regression was driven up by the fact that emissions are negatively correlated with cyclicality, which itself negatively impacts the relationship between returns and MP. The coefficient of correlation of -0.1686 between CO_2 intensity and market beta in our sample supports this view. Conversely, the coefficient on "Emissions × MP surprise" becomes less negative when "Beta × ROE" is included. This result implies that the coefficient of "Emissions × MP surprise" in the baseline regression was driven down by the fact that emissions are negatively correlated with profitability, which itself positively impacts the

[10]This result is in contrast with basic economic logic and with the general message of Bolton and Kacperczyk (2021*a*). However, these authors also find insignificant climate premia when using carbon intensity, as we do, rather than the total emissions.

[11]In fact, we have already partially controlled for this potential bias by including in our baseline table (Table 2.4) a specification in which we have sector dummies in interaction with the MP surprise. This specification controls for heterogeneity in stocks responses related to unobservable sector heterogeneity. In this section, the aim is to go a step further by controlling for observable firm characteristics that can identity a particular MP transmission mechanism.

Table 2.5: Heterogeneous responses of stock returns to monetary policy: Controlling for alternative heterogeneity sources

Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP surprise	-0.452***	-0.518***	-0.469***	-0.449***	-0.192***	-0.552***	-0.481***	-0.383**
	(0.109)	(0.130)	(0.113)	(0.109)	(0.043)	(0.126)	(0.112)	(0.146)
Emissions × MP surprise	-0.052***	-0.052***	-0.053***	-0.052***	-0.052***	-0.072***	-0.047***	-0.067***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.011)	(0.017)	(0.019)
Size × MP surprise		0.004						0.004
		(0.004)						(0.004)
Debt × MP surprise			0.046					0.040
			(0.043)					(0.050)
Cash flows × MP surprise				1.357				1.270
				(1.317)				(1.333)
PER × MP surprise					-0.000			-0.000
					(0.000)			(0.000)
Beta × MP surprise						-0.260***		-0.249*
						(0.037)		(0.126)
ROE × MP surprise							0.002***	0.001***
							(0.001)	(0.000)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	Yes	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	No	No	Yes
R-squared	0.124	0.124	0.124	0.124	0.124	0.128	0.125	0.129
Observations	28062	28062	28062	28062	28062	27627	28062	27627
Nb.of Firms	771	771	771	771	771	771	771	771

Note: This table represents the estimation results of Equation 2.13 when controls are interacted with our MP indicator. Column (1) is a reminder of the baseline results of Table 2.4. In columns (2) to (7) the controls (size, debt, cash flows, PER, Beta, and ROE) are introduced individually. In column (8) they are included jointly. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

relationship between returns and MP. The coefficient of correlation between CO_2 intensity and ROE in our sample is -0.1083.

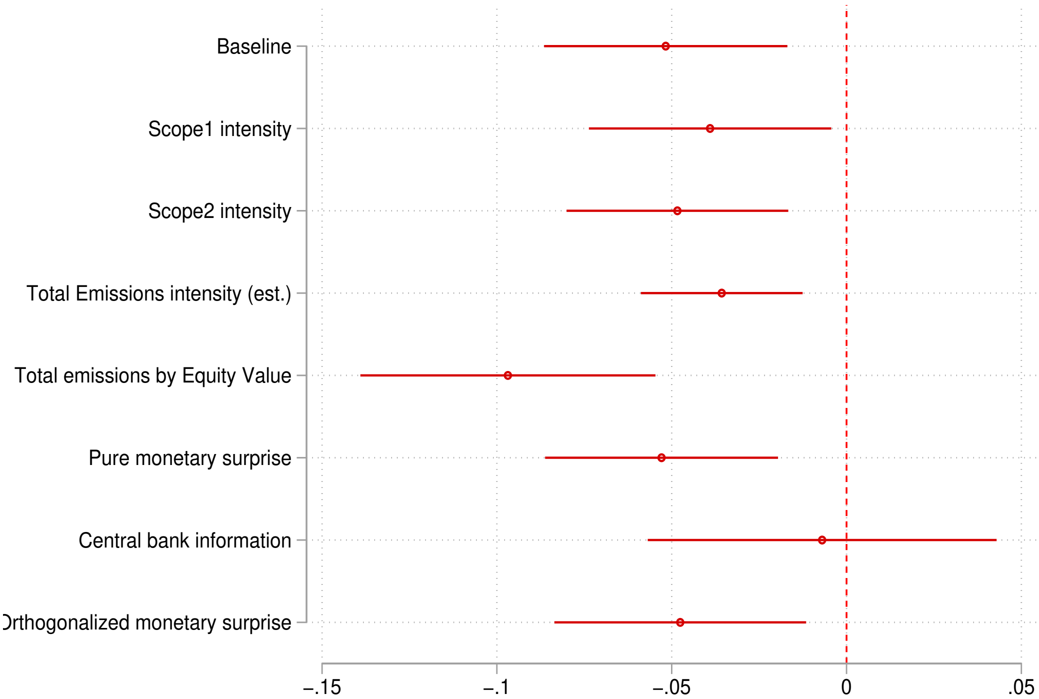
The general message of Table 2.5 is that CO_2 emissions remain a significant driver of MP heterogeneity even after including known drivers of MP heterogeneity in the estimations. Column 8 confirms this by showing that the channel does not disappear and remains statistically and financially significant when we include all channels together.

2.6 Robustness checks

2.6.1 Alternative explanatory variables

We explore the sensitivity of our results to changes in the definition of our variables. We first consider alternative measures of emissions intensity: using Scope 1 or Scope 2 emissions instead of their sum, using estimated emissions instead of reported emissions, and using total emissions per unit of equity value instead of sales. We then consider the alternative measures of MP surprises defined in subsection 2.3.2: the "pure monetary" surprise indicator of Jarociński and Karadi (2020), the "central bank information" indicator of Jarociński and Karadi (2020) and the orthogonalized Bauer and Swanson (2022) indicator. Figure 2.4 compares the coefficient on our main variable "Emissions × MP surprise" in these alternative specifications to the baseline estimates.

Figure 2.4: Responses of stock returns to alternative indicators



Note: This figure plots the "Emissions × MP surprise" coefficient estimates from Equation 2.13 considering alternative indicators for both the emissions and MP surprise measures. For the emissions variable, we consider the decomposition of Total emission intensity into Scope 1 intensity and Scope 2 intensity (emissions scaled by firms' revenues), the total estimated emissions intensity and total emissions scaled by equity value. In terms of MP surprises, we use Orthogonalized MP, Pure MP and Central bank information surprise. Bars represent 95 percent confidence intervals, and standard errors are clustered at firm and time level.

The results are robust to alternative definitions of CO_2 emissions. The "pure monetary" surprise indicator of Jarociński and Karadi (2020) produces estimates that are very similar to our baseline results, suggesting that movement in rates stemming from communication does not drive our result. As expected, the placebo test using the "central bank communication" indicator makes the nonneutral impact of CO_2 intensity disappear. The orthogonalized indicator of Bauer and Swanson (2022) yields point estimates that are almost identical to our baseline.

2.6.2 Abnormal returns

This section considers an alternative version of the model in which abnormal returns are used instead of returns. The goal is to verify that the stock return variation captured by the baseline estimation does not stem from differences in exposure to global factors. We rely on the classic

Fama-French 5 factor model to estimate abnormal returns.[12] The data are obtained from Kenneth French's website for the US market. In Column (1) the factors are included as controls, and the dependent variable is the return of firm i on day t. In all subsequent specifications, the dependent variable is the abnormal returns of firm i on day t, as estimated by the residual of the regressions of returns of i on the five factors. Table 2.6 presents the results.

Table 2.6: Heterogeneous responses of stock returns to monetary policy: adding Fama and French factors

	Returns	Abnormal returns					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP surprise	-0.102***	-0.097***		-0.100***	-0.097***	-0.106***	-0.157*
	(0.023)	(0.021)		(0.022)	(0.021)	(0.024)	(0.088)
Emissions × MP surprise	-0.051***	-0.075***	-0.073***	-0.075***	-0.075***	-0.076***	-0.043***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
Emissions	0.016	0.047	0.045	0.026	-0.007	0.037	-0.006
	(0.073)	(0.070)	(0.070)	(0.068)	(0.014)	(0.058)	(0.013)
Control variables	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	No	Yes	No	No	No	No
Year & month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	No	Yes
R-squared	0.287	0.042	0.050	0.037	0.014	0.046	0.018
Observations	27691	27691	27691	35157	27692	27691	27692
Nb. of Firms	771	771	857	771	771	771	771

Note: This table represents the estimation results of Equation 2.13 when factors from the Fama and French five factors model are included in the regressions. In column (1) the factors are included as controls. Columns (2) to (7) reproduces the specification of Equation 2.13 using abnormal returns (estimated by the residual of the regressions of returns of i on the five factors) instead of returns. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

In all specifications, the average effect of MP surprise decreases significantly. This is not surprising: the effects of MP surprise on firm returns are largely channeled by the impact of MP on the global factors. By rendering MP surprises orthogonal to the factors, we close several transmission channels of MP (which is in fact the reason why the factors were not included in the baseline estimation). Most important from our perspective, the coefficient on "Emissions × MP surprise" remains negative and significant in these specifications. Stocks with a higher carbon footprint react more to an MP shock. From a quantitative viewpoint, the point estimates for the interaction term are slightly higher in absolute value than the baseline estimate of -0.052. Carbon intensity induces more heterogeneity in the response of MP when we consider abnormal stock price returns. This further supports the idea that CO_2 intensity per se is a vector of nonneutrality.

2.6.3 Sensitivity to outliers

This section explores the sensitivity of our results to outliers. First, we winsorize returns at the 2.5% level, instead of 1%. Second, we conduct a new regression restricted to observations for which the standardized residuals are less than 1.96 in absolute value in the baseline regression. Third,

[12]The five factors are the Small Minus Big (SMB) factor, the High Minus Low (HML) factor, the Conservative Minus Aggressive (CMA) factor, the Robust Minus Weak (RMW) factor and the excess return on the market.

we restrict the sample to observations for which Cook's distance is less than $4/n$, with n being the number of observations used in computing the estimates. Fourth, we perform a robust regression à la Huber. Finally, Column (5) implements a placebo test that lags the policy surprises by one week. Table 2.7 plots the results.

Table 2.7: Heterogeneous responses of stock returns to monetary policy: Sensitivity to outliers

Returns	(1)	(2)	(3)	(4)	(5)
MP surprise	-0.438***	-0.399***	-0.395***	-0.378***	0.074
	(0.106)	(0.086)	(0.086)	(0.011)	(0.093)
Emissions × MP surprise	-0.050***	-0.043***	-0.047***	-0.043***	0.002
	(0.017)	(0.016)	(0.016)	(0.008)	(0.020)
Emissions	0.011	-0.048	-0.079	-0.039	0.022
	(0.063)	(0.044)	(0.049)	(0.038)	(0.050)
Control variables	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.134	0.174	0.167	0.154	0.098
Observations	27691	26125	26182	27692	27691
Nb. of Firms	771	771	771	771	771

Note: This table represents the estimation results of Equation 2.13, using alternative sample selection rules and/or variable lags. The 5 columns correspond to the 5 different specifications described in the body of the text. Controls and fixed effects are the same as in Column (1) of Table 2.4. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

In all cases, the estimates remain similar to our baseline, except for the placebo MP surprise test in which the interaction term has no significant impact on stock returns, as expected.

More robustness checks can be found in Appendix B. Table 2.10 reports estimates based on a sample including all business days, not only FOMC meeting days. Table 2.11 reproduces Table 2.4 with estimated emissions instead of reported emissions.

2.7 Further investigation

2.7.1 Is the impact of CO_2 on MP responsiveness nonlinear?

In the theoretical model in Section 2, the impact of CO_2 on nonneutrality was positive and convex. If this assertion is correct, the coefficient on "Emissions × MP surprise" should become increasingly negative as CO_2 rises.

To explore this possible nonlinearity, we decompose our variable of interest "Emissions × MP surprise" into different variables according the CO_2 intensity of companies. In the baseline form, we create three dummies that indicate whether an observation is below the 25th percentile of firm emissions, between the 25th percentile and the 75th percentile of firm emissions, or above the 75th percentile of firm emissions. We then interact the dummies with "Emissions × MP surprise" to capture the impact of CO_2 intensity on MP responsiveness for low, medium, and high CO_2 intensity firms. For robustness, we also create dummies based on quintiles (Columns 2 and 3). The difference between Columns 2 and 3 is that in Column 3, we exclude the top 5% of observations in the fifth quintile. Table 2.8 presents the results.

Table 2.8: Nonlinear effects

Returns	(1)	(2)	(3)
Low emissions × MP	-0.387***		
	(0.114)		
Medium emissions × MP	-0.414***		
	(0.111)		
High emissions × MP	-0.595***		
	(0.123)		
Q1 emissions × MP		-0.404***	-0.381***
		(0.114)	(0.110)
Q2 emissions × MP		-0.368***	-0.346***
		(0.114)	(0.109)
Q3 emissions × MP		-0.407***	-0.385***
		(0.110)	(0.105)
Q4 emissions × MP		-0.520***	-0.498***
		(0.123)	(0.120)
Q5 emissions × MP		-0.560***	
		(0.118)	
Q5 (without top 5%) × MP			-0.541***
			(0.125)
Control variables	Yes	Yes	Yes
Firm FE	Yes	Yes	
Year & month FE	Yes	Yes	Yes
R-squared	0.140	0.142	0.127
Observations	27691	27691	27691
Nb. of Firms	771	771	771

Note: This table represents the estimation results of Equation 2.13 when the MP surprise indicator is interacted with dummies that sort each observation according to its place in the distribution of CO_2 intensity across firms and days. In column (1) three groups are defined. In column (2) five groups are defined. In column (3) five groups are defined, and the top 5% of observations are removed from the fifth quintile

As expected from the model, we find that the marginal impact of CO_2 intensity on MP responsiveness typically increases with CO_2 intensity. The increase is remarkably monotonic in Column (1). The stock price of a company with high emissions decreases by 0.595% on average after a standard monetary surprise, against 0.414% when the emissions are moderate and 0.387% only when the emissions are relatively low. In Columns (2) and (3) the relationship is not perfectly monotonic since the stock return effect is lower – in absolute terms – for the second quintile than it is for the first quintile. However, the estimates for the other quintiles confirm that the more carbon intensive a firm is, the more its equity prices react to a MP shock.

2.7.2 Do climate change concerns matter?

In the theoretical model in Section 2.2, the relationship between CO_2 and MP responsiveness was strengthened by two factors: the nonpecuniary utility ϕ involved in holding green assets and the relative increase in risk ψ involved in holding brown assets that carry transition risk. This section tests these predictions by introducing into the model a variable that should be positively correlated with both green utility and transition risk: climate awareness. We expect CO_2 intensity to have an increasingly negative impact on MP responsiveness as climate concerns increase.

Our measure of climate awareness is based on newspaper coverage of climate change related events. The underlying idea is that newspapers may lead investors to update both their subjective probabilities of climate risk and their feeling of doing good by owning shares in green firms. To proxy for newspaper coverage of climate change, we use two different time-series indicators drawn from textual analysis of news sources. The first indicator is from Engle et al. (2020) and relies on the Crimson Hexagon proprietary sentiment measure to capture negative reports relating to climate change from a large corpus of over one trillion news articles. We also use the Media Climate Change Concerns (MCCC) indicator from Ardia et al. (2021), which uses a different algorithm and corpus to extract a climate change news series.[13]

Our estimation strategy is based on decomposing our variable of interest "Emissions $\times$ MP surprise" into three variables according the level of climate concerns, as done for CO_2 intensity in the previous section. We consider "Emissions $\times$ MP surprise" when climate concerns are low (all observations inferior to the 33rd percentile), moderate (all observations between the 33rd percentile and the 66th percentile) and high (all observations superior to the 66th percentile). Table 2.9 presents the results.

As expected, MP responsiveness is higher during periods of high estimated climate concerns, using either Crimson Hexagon's negative sentiment climate change news index (Column 1) or the MCCC indicator (Column 2). The coefficient estimate in Column (1) is 2.6 times higher during periods of high climate concerns than across periods (-0.135 vs. -0.052). The MCCC indicator generates a coefficient on "Emissions $\times$ MP surprise" that is more negative when climate concerns are moderate than when climate concerns are low, but this does not hold for the Crimson index. Overall, these empirical results align with our theoretical expectations: the higher (lower) the increase in climate change concerns, the more (less) brown stocks react to a MP surprise.

[13] Crimson Hexagon's negative sentiment climate change news index is obtained from Stefano Giglio's website (`https://sites.google.com/view/stefanogiglio/data-code`), while the CCC indicator is available at `https://sentometrics-research.com`.

Table 2.9: Climate awareness

Returns	(1)	(2)
Low climate concerns - Emissions × MP	-0.060***	-0.048*
	(0.021)	(0.027)
Moderate climate concerns - Emissions × MP	-0.024	-0.063**
	(0.063)	(0.032)
High climate concerns - Emissions × MP	-0.135***	-0.097***
	(0.034)	(0.036)
Control variables	Yes	Yes
Firm FE	Yes	Yes
Year & month FE	Yes	Yes
R-squared	0.140	0.142
Observations	27691	27691
Nb. of Firms	771	771

Note: This table represents the estimation results of Equation 2.13 when the MP surprise indicator is interacted with dummies that sort each observation into one of three groups according to its place in the distribution of climate concern across days. Column (1) uses the Crimson Hexagon's negative sentiment climate change. Column (2) uses the MCCC indicator of Ardia et al. (2021). Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

2.7.3 Is the nonneutral impact of CO_2 persistent?

This section assesses the persistence of the differential in MP responsiveness between green stocks and brown stocks. We estimate impulse response functions (IRFs) using the local projection (LP) procedure of Jordà (2005), which is a standard approach to capture the dynamic effect of MP shocks on stock returns. LPs are based on using simple regression methods to predict cumulative returns at different time horizons. They are well suited to our event-study framework with possible nonlinear effects. Formally, the dynamic response of cumulative stock returns to an MP shock for different horizons (h = 0,...,10) takes the following form:

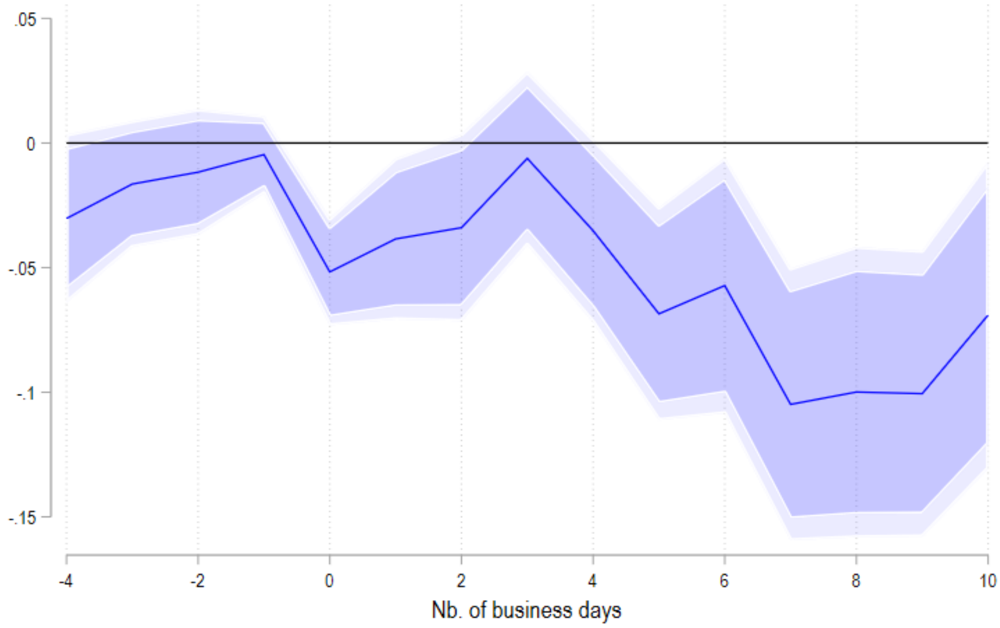
$$r_{i,t+h} = \alpha_i^h + \beta^h MP_t + \phi^h CO2_{i,t} + \psi^h MP_t \times CO2_{i,t} + \theta^h \mathbf{Z}_{i,t} + \varepsilon_{i,t}^h \tag{2.15}$$

where h is the time horizon and $r_{i,t+h}$ is the cumulative stock return between $t-1$ and $t+h$. ψ^h represents the difference in MP response between the average firm and a firm that is one standard deviation more carbon-intensive than the average firm at horizon h. Our estimation uses the same explanatory variables as those used in the Equation 2.13 and considers returns within a window of 4 days before each FOMC meeting up until 10 days after. Figure 2.5 displays the estimated ψ^h.

The figure shows that the differential impact of a monetary policy surprise on cumulative returns is not significant before the event but begins to be statistically significant on the day of the FOMC meeting (h=0).[14] A positive monetary policy surprise leads to a more immediate and

[14]This pattern suggests that our panel estimates do not violate the parallel trends assumption.

Figure 2.5: Response of US stock returns to MP shock (baseline)



Note: This figure shows the difference in the response of stock returns to an MP shock (solid line) between a firm that is one standard deviation more carbon intensive than the sample average and the average firm. It depicts the sequence of estimates of ψ from Equation 2.15 over horizons from -4 to 10 business days. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with standard errors clustered at the firm and time level.

pronounced contraction in stock returns for brown firms, as expected. This supports the notion that the monetary policy shock is exogenous with respect to other macroeconomic factors as well as the communication component of MP on FOMC meeting days.

The heterogeneous impact of a monetary policy shock on returns across different carbon footprints appears to be permanent: there is no reversion to the mean in the business days following the shock. The effect remains statistically significant up to the 10 business days considered (except for the third day). This finding has interesting implications. From a market efficiency perspective, it suggests that the market successfully prices in long-term information on FOMC days, as opposed to being driven by short-term frictions. From an ecological policy standpoint, the long-lived heterogeneity between brown and green firms implies that the ecological footprint of MP is not negligible.

More information on impulse response functions can be found in Appendix C. Figure 2.6 estimates LPs for each of the specifications considered in Table 2.4. It displays similar results than our baseline local projection estimates. Figure 2.10, Figure 2.11 and Figure 2.7, Figure 2.8, Figure 2.9 break down the local projection into 3 groups according to their carbon intensity. The results show that the impact of a positive policy surprise leads to a larger negative response in cumulative returns for the highest carbon-emitting firms' category, confirming our previous results.

2.8 Conclusion

This paper tests the theoretically plausible hypothesis than brown firms are more affected by monetary policy than green firms. We find strong evidence that this is the case. A one-standard-deviation MP surprise results in an immediate 0.452% drop in returns on average, but this decline is 0.052 higher for a firm that is one standard deviation more carbon intensive than average. The nonneutral impact of CO_2 intensity remains robust to several alternative specifications. In particular, it is not solely driven by sectoral factors, as is often the case in the literature.

Investigating the mechanisms behind CO_2 nonneutrality, we uncover that CO_2 intensity remains significant when we allow classic sources of MP heterogeneity to influence the relationship between rate surprises and stock prices. We also provide theoretical and empirical elements suggesting that the impact of CO_2 on MP responsiveness grows with climate awareness and with CO_2 intensity itself. Finally, the difference in stock price reactions to MP shocks across CO_2 intensity does not revert over the days that follow a given FOMC meeting, indicating that the initial price reaction reflects relevant information, not short-term frictions.

Our results imply that a central bank that decides to lower interest rates indirectly subsidizes polluting firms. This stylized fact can be of interest to central bankers who are currently reflecting on their role in promoting a greener financial system. A possible policy path for central banks is to attempt to neutralize the differentiated effects of their announcement across CO_2 intensity, through either communication and/or asset purchases. Nevertheless the benefit of such a policy should be weighed against the cost in terms of credibility associated with taking such active measures on issues that are only distantly related to inflation.

2.9 Appendix

2.9.1 Appendix A

A-1

Using Equations (2.9) and (2.10):

$$\frac{p_{g,t}}{p_{b,t}} = \frac{\frac{W}{q}\tau S\left(\frac{1}{2+\psi\triangle CO2}\right)\left(\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}+\phi(1+\psi\triangle CO2)(\triangle CO2)\right)}{\frac{W}{q}\tau S\left(\frac{1}{2+\psi\triangle CO2}\right)\left(\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2\right)}$$

$$\frac{p_{g,t}}{p_{b,t}} = \frac{\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2+\phi\triangle CO2+\phi\triangle CO2(1+\psi\triangle CO2)}{\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2}$$

$$\Rightarrow \frac{p_{g,t}}{p_{b,t}} = 1+\frac{\phi\triangle CO2(2+\psi\triangle CO2)}{\left(\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2\right)}$$

Let us define $f=\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2$ to ease notation. Deriving both sides of the equation above with respect to c_t leads to:

$$\frac{d\,(p_{g,t}P_{b,t})}{d\,c_t} = (\phi\triangle CO2(2+\psi\triangle CO2))\,\frac{d\,\frac{1}{f}}{d\,f}\frac{d\,f}{d\,c_t}$$

$$\Rightarrow \frac{\frac{d\,p_{g,t}}{d\,c_t}p_{b,t}-\frac{d\,p_{b,t}}{d\,c_t}p_{g,t}}{(p_{b,t})^2} = -\left(\phi\triangle CO2(2+\psi\triangle CO2)\right)\frac{1}{f^2}\left(-\frac{1}{\tau S^2\sigma^2_{g,t}}\right)$$

$$\Rightarrow \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}}-\frac{d\,p_{b,t}/d\,c_t}{p_{b,t}} = \frac{(p_{b,t})^2}{p_{g,t}p_{b,t}}\left(\phi\triangle CO2(2+\psi\triangle CO2)\right)\frac{1}{f^2}\left(\frac{1}{\tau S^2\sigma^2_{g,t}}\right)$$

$$NN = \frac{d\,p_{g,t}/d\,c_t}{p_{g,t}}-\frac{d\,p_{b,t}/d\,c_t}{p_{b,t}} = \frac{p_{b,t}}{p_{g,t}}\left(\frac{1}{\tau S^2\sigma^2_{g,t}}\right)\left(\frac{\phi\triangle CO2(2+\psi\triangle CO2)}{(\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2)^2}\right)>0$$

A-2

Let $C=\frac{p_{b,t}}{p_{g,t}}\left(\frac{1}{\tau S^2\sigma^2_{g,t}}\right)>0$, $u=\phi\triangle CO2(2+\psi\triangle CO2)>0$, and $v=\frac{1}{(\frac{(G-c_t)}{\tau S^2\sigma^2_{g,t}}-\phi\triangle CO2)^2}=\frac{1}{f^2}>0$

$$\frac{d\,u}{d\,\triangle CO2} = \phi(2+2\psi\triangle CO2)>0$$

$$\frac{d\,v}{d\,\triangle CO2} = \frac{d\,v}{d\,f}\frac{d\,f}{d\,\triangle CO2} = \left(-\frac{2}{f^3}\right)(-\phi) = \frac{2\phi}{f^3}>0$$

Using the expressions for C, u and v, NN in Equation (2.12) can be reexpressed as $NN = C\times u\times v$. It follows that

$$\frac{d\,NN}{d\,\triangle CO2} = C\left(\frac{d\,u}{d\,\triangle CO2}v+\frac{d\,v}{d\,\triangle CO2}u\right)$$

which is positive since all terms involved are positive, which proves Lemma 2.

Let us now take the derivative of $\frac{d\,NN}{d\,\triangle CO2}$ with respect to $\triangle CO2$

$$\frac{d^2\,u}{d^2\,\triangle CO2} = \frac{d\,(d\,u/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\,\phi(2+2\psi\triangle CO2)}{d\,\triangle CO2} = 2\psi\phi>0$$

$$\frac{d^2\,v}{d^2\,\triangle CO2} = \frac{d\,(d\,v/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\left(2\phi/f^3\right)}{d\,\triangle CO2} = 2\phi\frac{d\left(1/f^3\right)}{d\,f}\frac{d\,f}{d\,\triangle CO2} = 2\phi\left(\frac{-3}{f^4}\right)(-\phi) = \frac{6\phi^2}{f^4}>0$$

The second derivative of NN with respect to $\triangle CO2$ is thus:

$$\frac{d^2\,NN}{d^2\,\triangle CO2} = \frac{d\left(C\left(\frac{d\,u}{d\,\triangle CO2}v + \frac{d\,v}{d\,\triangle CO2}u\right)\right)}{d\,\triangle CO2}$$

$$\frac{d^2\,NN}{d^2\,\triangle CO2} = C\left(\left(\frac{d^2\,u}{d^2\,\triangle CO2}v + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\triangle CO2}\right) + \left(\frac{d^2\,v}{d^2\,\triangle CO2}u + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\triangle CO2}\right)\right)$$

$\frac{d^2\,NN}{d^2\,\triangle CO2} > 0$ since all the terms are positive, which proves Lemma 2.

Let us now take the derivative of $\frac{d\,NN}{d\,\triangle CO2}$ with respect to ϕ. First note that:

$\frac{d\,u}{d\,\phi} = \frac{d\,\phi\triangle CO2(2+\psi\triangle CO2)}{d\,\phi} = \triangle CO2(2+\psi\triangle CO2) > 0$

$\frac{d\,v}{d\,\phi} = \frac{d\,v}{d\,f}\frac{d\,f}{d\,\phi} = \left(-\frac{2}{f^3}\right)(-\triangle CO2) = \frac{2\triangle CO2}{f^3} > 0$

$\frac{d^2\,u}{d\,\triangle CO2\;\;d\,\phi} = \frac{d\,(d\,u/d\,\triangle CO2)}{d\,\triangle\phi} = \frac{d\,\phi(2+2\psi\triangle CO2)}{d\,\phi} = (2+2\psi\triangle CO2) > 0$

$\frac{d^2\,v}{d\,\triangle CO2\;\;d\,\phi} = \frac{d\,(d\,v/d\,\triangle CO2)}{d\,\triangle CO2} = \frac{d\left(2\phi/f^3\right)}{d\,\triangle CO2} = \frac{2}{f^3} > 0$

The cross derivative of NN with respect to $\triangle CO2$ and ϕ is:

$$\frac{d^2\,NN}{d\,\triangle CO2\;\;d\,\phi} = \frac{d\,(d\,NN/d\,\triangle CO2)}{d\,\phi} = \frac{d\left(C\left(\frac{d\,u}{d\,\triangle CO2}v + \frac{d\,v}{d\,\triangle CO2}u\right)\right)}{d\,\phi}$$

$$\frac{d^2\,NN}{d\,\triangle CO2\;\;d\,\phi} = C\left(\left(\frac{d^2\,u}{d\,\triangle CO2\;\;d\,\phi}v + \frac{d\,u}{d\,\triangle CO2}\frac{d\,v}{d\,\phi}\right) + \left(\frac{d^2\,v}{d\,\triangle CO2\;\;d\,\phi}u + \frac{d\,v}{d\,\triangle CO2}\frac{d\,u}{d\,\phi}\right)\right)$$

$\frac{d^2\,NN}{d\,\triangle CO2\;\;d\,\phi} > 0$ since all the terms are positive. Taking the derivative of $\frac{d^2\,NN}{d\,\triangle CO2\;\;d\,\psi}$ with respect to ψ involves the same steps and leads to the same outcome $\frac{d^2\,NN}{d\,\triangle CO2\;\;d\,\psi} > 0$, which proves Lemma 3.

2.9.2 Appendix B

Table 2.10: Heterogeneous responses of stock returns to monetary policy: All days

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.327***		-0.347***	-0.327***	-0.327***	-0.281**
	(0.103)		(0.108)	(0.103)	(0.105)	(0.110)
Emissions × MP surprise	-0.057***	-0.051***	-0.058***	-0.057***	-0.057***	-0.046***
	(0.018)	(0.019)	(0.017)	(0.018)	(0.018)	(0.017)
Emissions	0.001	0.001	-0.003	0.001	-0.003	0.001
	(0.012)	(0.012)	(0.010)	(0.003)	(0.009)	(0.012)
Controls	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.05	0.284	0.04	0.04	0.04	0.06
Observations	848373	848373	1079943	848373	848373	848373
Nb. of Firms	771	771	857	771	771	771

Note: This table represents the estimation results of Equation 2.13 considering all the business days (not only the days of FOMC meetings). The columns correspond to the 6 different specifications estimated in Table 2.4. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

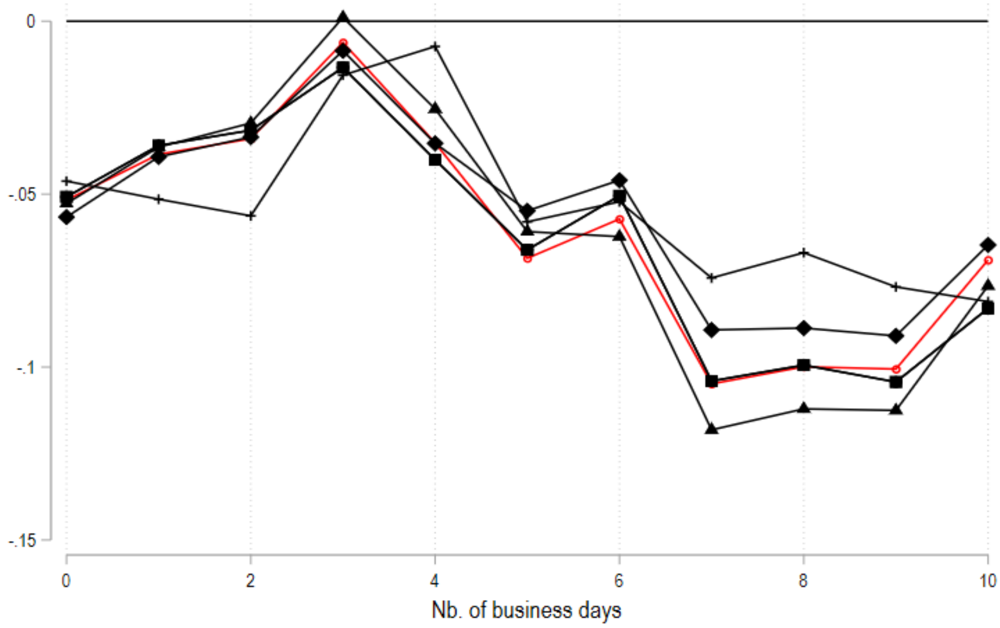
Table 2.11: Estimated total emissions

Returns	(1)	(2)	(3)	(4)	(5)	(6)
MP surprise	-0.392***		-0.402***	-0.390***	-0.392***	-0.442***
	(0.131)		(0.135)	(0.131)	(0.131)	(0.136)
Emissions × MP surprise	-0.076***	-0.072***	-0.084***	-0.073***	-0.079***	-0.031**
	(0.024)	(0.024)	(0.027)	(0.025)	(0.023)	(0.015)
Emissions	-0.044	-0.058*	-0.084**	-0.042***	-0.042	-0.030
	(0.030)	(0.033)	(0.036)	(0.015)	(0.029)	(0.027)
Controls	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes
Date FE	No	Yes	No	No	No	No
Year & Month FE	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	No
Industry × MP FE	No	No	No	No	No	Yes
R-squared	0.079	0.245	0.073	0.048	0.083	0.081
Observations	67500	67500	89657	67508	67500	67500
Nb. of Firms	2041	2041	2325	2041	2041	2041

Note: This table represents the estimation results of Equation 2.13 using estimated emissions instead of reported emissions. The columns correspond to the 6 different specifications estimated in Table 2.4. Standard errors are clustered at the firm and time level and reported below the coefficient estimates. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

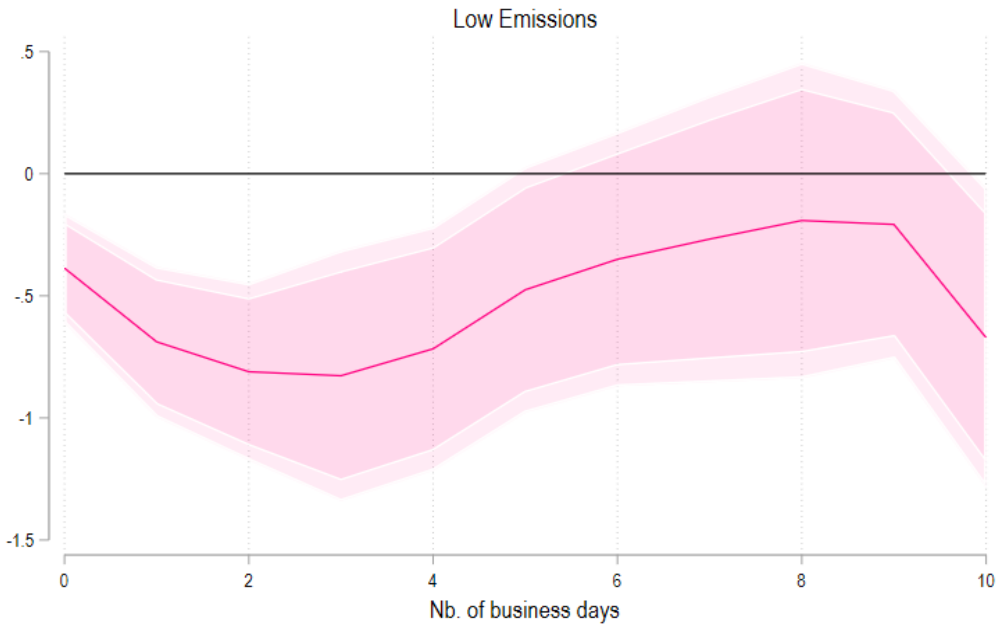
2.9.3 Appendix C

Figure 2.6: Response of US stock returns to MP shock from local projections, across specifications)



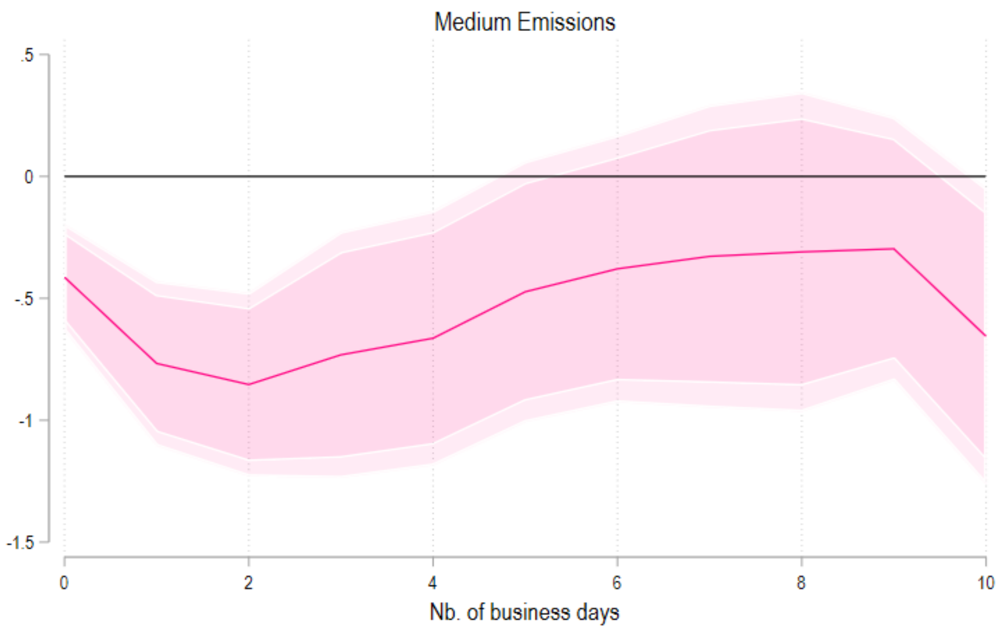
Note: This figure shows the coefficient on the variable 'Emissions × MP surprise" as estimated by local projections, for all specification considered in Table 2.4. The x-axis represents the horizon at which the cumulative return is estimated. The y-axis represents the value of the point estimate. Each different marker corresponds to a given specification ("circle" = specification of column 2; "diamond" = specification of column 3; "triangle" = specification of column 4; "square" = specification of column 5; "plus" = specification of column 6). The red line corresponds to the baseline LP estimates.

Figure 2.7: Impulse response function - Low emissions



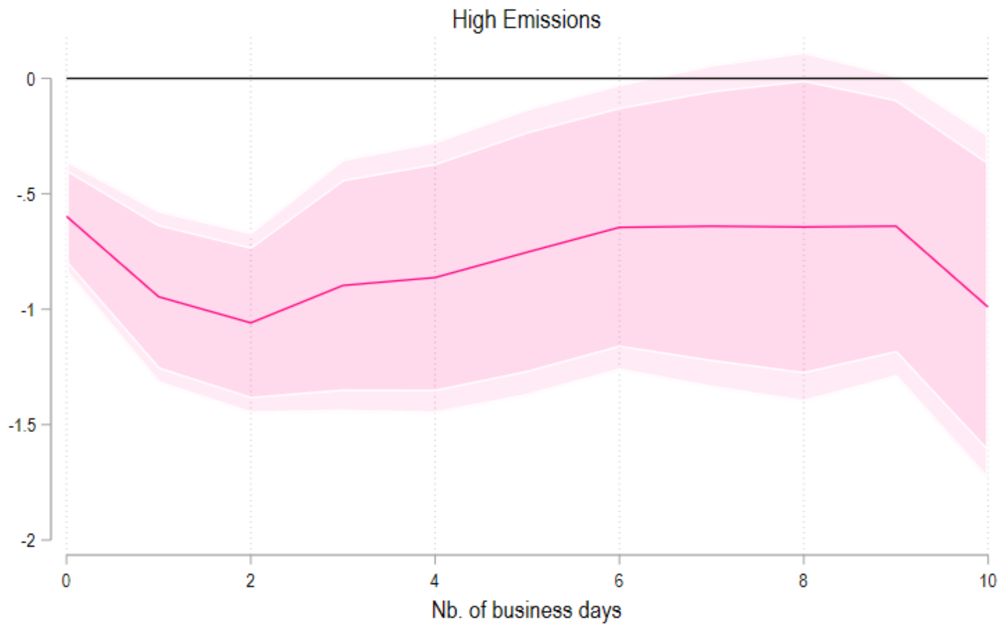
Note: This figure shows the response of cumulative stock returns over horizons from 0 to 10 (business days) to a one-standard-deviation monetary policy shock for the "low" group defines observations below the 25^{th} percentile, sorted by Total emissions intensity. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with robust standard errors.

Figure 2.8: Impulse response function - Medium emissions



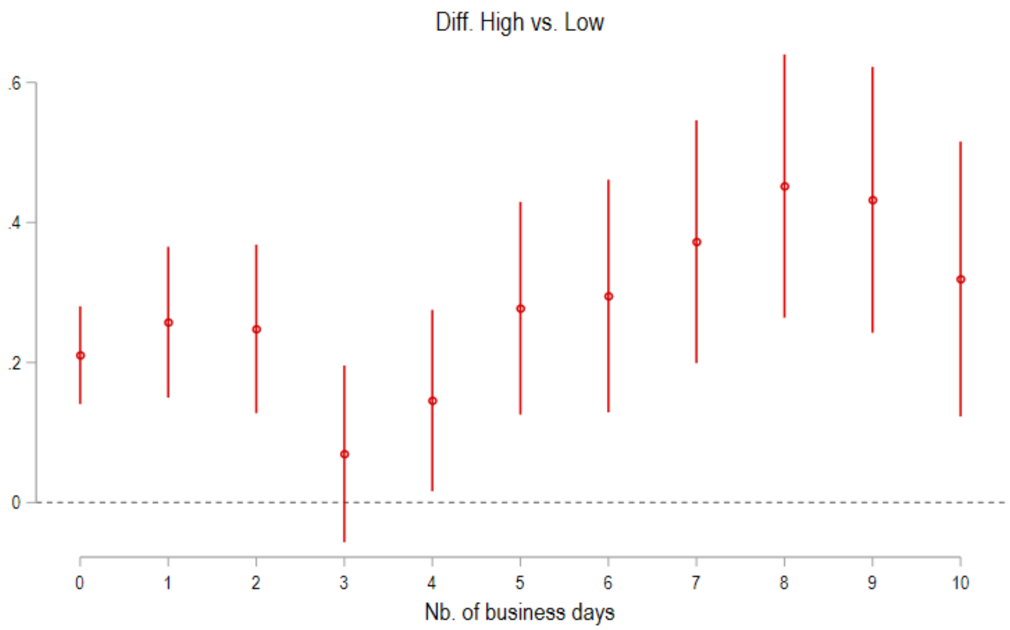
Note: This figure shows the response of cumulative stock returns over horizons from 0 to 10 (business days) to a one-standard-deviation monetary policy shock for the "medium" group includes observations between the 25^{th} and 75^{th} percentile, sorted by Total emissions intensity. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with robust standard errors.

Figure 2.9: Impulse response function - High emissions



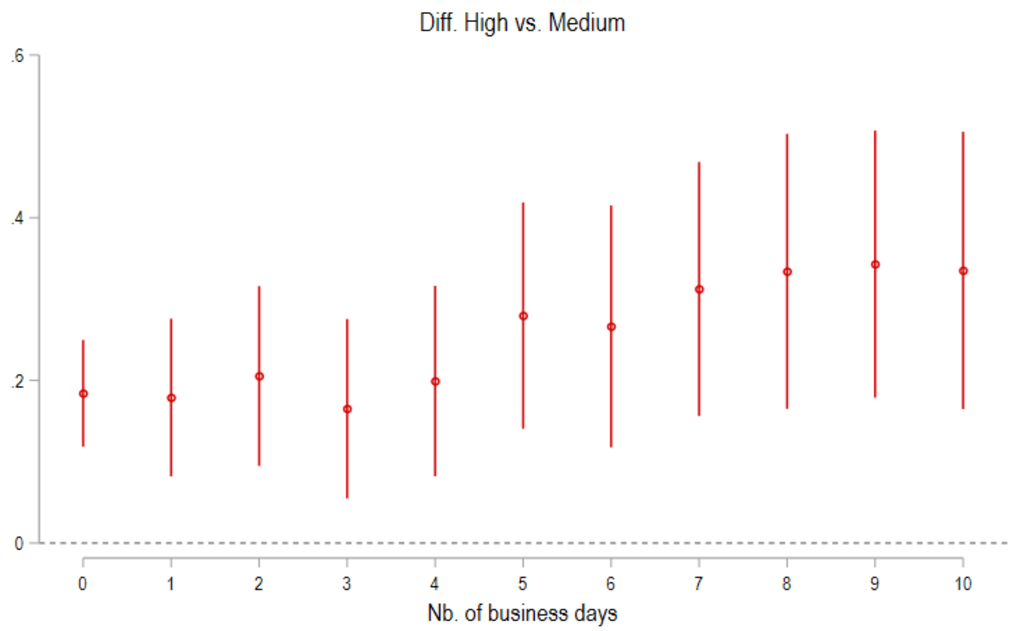
Note: This figure shows the response of cumulative stock returns over horizons from 0 to 10 (business days) to a one-standard-deviation monetary policy shock for the "high" group represents observations above the $75^t h$ percentile, sorted by Total emissions intensity. The shaded areas correspond to the 90% (darkest) and 95% (lightest) confidence intervals computed with robust standard errors.

Figure 2.10: Response of US stock returns to MP shock (High vs Low emissions)



Note: This figure depicts the difference in estimated coefficients β^h between the different CO_2 groups the "high" group represents observations above the $75^t h$ percentile and the "low" group defines observations below the 25^{th} percentile at each h time horizon and the associated 90% confidence intervals.

Figure 2.11: Response of US stock returns to MP shock (High vs Medium emissions)



Note: This figure depicts the difference in estimated coefficients β^h between the different CO_2 groups the "high" group represents observations above the $75^t h$ percentile and the "medium" group includes observations between the 25^{th} and 75^{th} percentile at each h time horizon and the associated 90% confidence intervals.

Chapitre 3

Chapter 3

Carbon Transition Risk and Climate Laws in United States

[..] Climate change is happening now and to all of us. Every week brings a new example of climate-related devastation. No country or community is immune.

A. Guterres, United Nations Secretary General.

3.1 Introduction

Climate change stands out as one of the most pressing challenges of our era. The rising global temperatures have amplified awareness because of the diverse threats they pose to all aspects of society. The increasing frequency of natural disasters, combined with the evident consequences of climate change, heightens public attention to environmental issues and concern about climate-related risks (El Ouadghiri et al., 2021; Ardia et al., 2022; Guo et al., 2020). Consequently, countries across the globe are faced with the challenging endeavor of implementing policies to limit the temperature rise. Recognizing this undeniable reality, it becomes imperative for policymakers to adopt swift measures to mitigate the climate emergency. For instance, when the Paris Agreement was ratified in 2015, all 196 participating countries pledged to deliver their nationally determined contributions (NDCs). These commitments primarily detail their strategies for curbing greenhouse gas emissions (GHGs) to meet the objectives set by the Paris Agreement. More recently, the U.S. House of Representatives has approved the Inflation Reduction Act of 2022, allocating roughly $370 billion towards clean energy and climate measures in the upcoming decade. This act is set to cut the country's carbon emissions by around 40% by 2030, fulfilling the U.S.'s international commitments. Upon its enactment, this law will signify the leading global carbon emitter's dedicated effort to tackle the climate challenge head-on.

With the rising concerns over climate risks and their importance in decision-making, an important question emerges: how do stock market investors respond to governmental environmental actions, particularly the introduction of environmental regulations? For instance, Monasterolo and De Angelis (2020) reveal that investors demanded higher returns for holding carbon-intensive assets, but this was notably evident only post the Paris Agreement. In a similar vein, a recent study by Bolton and Kacperczyk (2023) highlights a significant shift in the carbon premium before and after the enactment of the Paris Agreement, noting a considerable and statistically significant premium following the agreement. More related to our study, Bolton and Kacperczyk (2021*b*) find that domestic policy tightening is a driver of the relationship between stock returns and firm-level carbon emissions.

In this study, we aim to investigate how the U.S climate legislation influences the relationship between stock returns and S&P500 companies' carbon emissions during the period from 2010 to 2019. To achieve this, we first design a climate law indicator. This indicator draws its data from the publicly accessible "Climate Change Laws around the World" database, which is a comprehensive collection of national laws specifically aimed at reducing greenhouse gas emissions. To represent the exposure to carbon transition risk, we use companies' carbon emissions as a primary measure of their environmental stance. In our baseline analysis, we place emphasis on the reported carbon emissions of the more carbon-intensive or "brown" companies, specifically their total CO_2 emissions (Scope 1 + Scope 2). We also consider carbon emissions intensity (total reported carbon emissions normalized by sales) to avoid the potential bias associated with firm size that might result from unscaled carbon emissions, as highlighted by studies such as (Bolton and Kacperczyk, 2021*b*; Bauer et al., 2022; Aswani et al., 2023). Using a generalized panel Two-Way Fixed Effects (TWFE) model, our analysis involves regressing the monthly stock returns of S&P500 companies on our climate law indicator, the reported carbon emissions, and most importantly, the interaction term of these two factors.

Our baseline empirical results indicate an apparent premium linked to price adjustments prior to climate law implementation, suggesting green companies might outperform less eco-friendly ones when climate concerns rise. Investors have shifted their focus, valuing total emissions over just emissions intensity, indicating a change in the perception of environmental risks in the market. Specifically, an increase of one standard deviation in reported total emissions is associated with a decrease of 2.8% in stock returns, on average. Upon the introduction of climate legislation, there's evidence that investors may adopt a wait-and-see approach, but also penalize companies with larger carbon footprints. The effects are notably visible in the months after these laws come into play, but less so when looking at their long-term impact. The focus is on total carbon emissions since they offer a more transparent view of a company's environmental footprint, potentially putting high-emitting companies at greater risk of climate regulation.

Furthermore, using the climate awareness time-series indicator from Engle et al. (2020) derived from media coverage on climate change, further investigations suggest that during periods of high climate awareness, the negative impact of carbon emissions on stock returns becomes more pronounced two months after the introduction of a climate law, continuing for nearly a year. However, 12 months post-legislation, this effect diminishes, indicating that persistent legislation impacts might require continuous reinforcement.

Our study intersects two distinct areas of focus within the climate finance literature. The first of these is concerned with how climate risks affect asset price valuations, specifically investigating whether carbon emissions are incorporated into stock prices. While empirical research on this subject has been gaining ground only recently (Campiglio et al., 2019), the existing studies show varied conclusions based on the proxies used for assessing climate risk and the methodologies applied, such as asset pricing or panel regression frameworks (Bauer et al., 2022; Aswani et al., 2023), or the kind of financial assets considered (Giglio et al., 2021)[1].

Focusing on the cross-section of stock returns, most of empirical studies develop a "carbon portfolio" taking a long or short position on a firm-level climate risk exposure and investigate whether it is priced on the market. A seminal work in this area is by Görgen et al. (2020), who define a "brown" minus "green" (BMG) factor by calculating the returns between companies with higher and lower carbon scores. Their work did not reveal a significant global carbon premium during the 2010-2017 period, meaning that companies with higher carbon footprint levels do not necessarily earn higher returns. Oestreich and Tsiakas (2015) designed a "dirty" minus "clean" portfolio based on emission allowances allocated to German companies participating in the EU Emissions Trading System (ETS) during the 2003-2009 period. Their findings indicate that companies granted more than 1 million emission allowances—essentially the highest emitters included in the "dirty" portfolio—consistently outperformed those that received fewer allowances, which were included in the "clean" portfolio. Similarly, research by Witkowski et al. (2021) corroborated this trend for energy-intensive companies in the EU ETS, but extended the study period to 2003-2012. On the contrary, focusing on European electric utilities, Bernardini et al. (2021) report that an investment strategy on low-carbon companies delivers higher realized returns during post-2012 period, during the years in which the decarbonization process accelerated. In a same vein, Alessi et al. (2021) found a negative carbon premium –lower emitting companies exhibit higher realized returns– for European individual stock returns. Using an innovative metric to gauge firm-level exposure to carbon-associated risks — incorporating both carbon emissions and the quality of environmental disclosures — they found that investors accept lower returns to hold greener and more

[1] The author provides a comprehensive and general literature review on climate finance.

transparent stocks. Closer in spirit, Hsu et al. (2023) study focused on the broader environmental impact, specifically analyzing toxic emissions. By using these emissions as a metric for assessing a company's greenness, they found that an investment strategy favoring companies with high toxic emissions could result in average annual return of 4.42%, termed as a "pollution premium". Besides, a study by Bolton and Kacperczyk (2021*b*) found a significant carbon premium, particularly indicating that both the level and changes in carbon emissions have a positive, significant impact on stock returns. One key difference with the previous studies lies in the sample size, the direct use of carbon emissions as a proxy for transition risk by Bolton and Kacperczyk (2021*b*) instead of carbon scores and the panel regression framework to assess the impact of carbon emissions on stock returns. The study conducted by Bolton and Kacperczyk (2021*a*) on the US stock market highlighted that companies that have higher carbon emissions tend to have increased realized returns because investors demand compensation (higher risk premia) to hedge this carbon risk. Conversely, Bauer et al. (2022) found that, when assessing companies greenness based on reported carbon emissions, green stocks have outperformed brown stocks in G7 countries over the past ten years. One key difference between these two studies

Nevertheless, given the divergent findings in prior research, a growing subset of the literature on green finance is placing more emphasis on how investors and the general public perceive the impact of climate risk on stock market valuations. Theoretically, Pástor et al. (2022) demonstrate that green companies could outperform their brown counterparts when concerns about climate change increase unexpectedly. This suggests that while brown firms might experience lower realized returns, they could simultaneously exhibit higher expected returns. Such a scenario might arise if the valuation of green assets has seen a spike in recent years due to a shift in investor preferences. For instance, Bolton and Kacperczyk (2021*b*) suggests that the carbon premium they identified can be attributed, at least in part, to the selective screening undertaken by institutional investors. This screening is performed to curtail the carbon risk within their investment portfolios. Based on textual analysis of major US newspapers, Ardia et al. (2022)[2] develop a climate news indicator aiming to gauge the environmentally-driven preferences of investors stemming from climate change and found that green stocks outperform brown ones during the days with an unexpected increased in climate change concerns. Choi et al. (2020) found that unexpected local temperature spikes cause investors to reconsider their perceptions of global warming captured by the Google Search Index (GSI). Their result indicates that high carbon-emitting companies tend to face reduced returns during these unusual temperature increases. In the same line, Guo et al. (2020) suggest that environmental concerns play a major role in the response of stock market to environmental policies. Another relevant paper that touches upon the regulatory impacts, especially

[2]In the same line, Engle et al. (2020) introduced a climate news index derived from US newspapers, formulating a portfolio strategy explicitly designed to hedge climate-related risks.

in the European context is the one from Busch et al. (2016). Their study explores the evolving understanding of sustainable development within financial markets. The authors delve into how stricter environmental regulations, coupled with increased investor and consumer awareness, can affect company valuations and stock performance. However, in a study conducted with institutional investors, Krueger et al. (2020*a*) determined that while these investors are concerned about climate and regulatory risks, such risks aren't entirely reflected in equity valuations.

Our study builds on a line of research examining the impact of climate legislation on stock returns. Many studies in this field use the event study methodology, focusing on the stock market's reactions to unexpected climate events, often measured through cumulative abnormal returns as dependant variable. For example, Hengge et al. (2023) explored the EU ETS's effect on stock returns and found that unexpected rises in carbon prices led to negative returns. Similarly, Guo et al. (2020) noted that stocks of major Chinese polluters reacted more strongly to new environmental policy announcements, highlighting that stricter environmental laws induce more significant stock market reactions. Borghesi et al. (2022) analyzed reactions to green-policy announcements by major European governments in 2020, finding positive returns for both green and brown portfolios, but a stronger positive effect for the green one. Sautner et al. (2023) introduces an innovative metric to evaluate firm-level exposure to climate-related risks deriving from an analysis of the discourse pertaining to climate change among participants in earnings calls[3]. They found that exposure to regulatory events have a negative impact on stock valuations. Along these lines, Faccini et al. (2023) broke down climate risks into four categories: natural disasters, global warming, international summits, and US climate policy. They document that, notably after 2012, only the climate risk tied to government interventions is reflected in US stock prices and that a firm's exposure to regulatory shocks is negatively associated with stock valuation.

Our study contributes to the existing literature through two main ways. Firstly, we employ a publicly accessible climate laws database to measure U.S. climate legislation. Secondly, in light of the ongoing debate on transition risk pricing in stock markets, our research brings a nuanced perspective. Besides, we explore the extended effects on stock returns following the introduction of climate laws during the 2010-2019 timeframe instead of focusing solely on notable climate events or environmental news. In doing so, our work not only bridges these two domains of research but also investigates the implications of transition risk pricing in the stock market, specifically in response to U.S. climate actions—a facet that remains underexplored in previous studies.

The remainder of the paper is organized as follow. Section 3.2 presents our data and especially how we construct the US' climate law indicator. Section 3.3 describes our empirical strategy to assess how US climate legislation affects the relationship between stock returns and company-level

[3]The dataset spans a considerable breadth, encompassing over 10,000 firms across 34 countries within the time frame of 2002 to 2020 and available at: `https://osf.io/fd6jq/#!`.

carbon emissions. Section 3.4 presents our baseline empirical results. Section 3.5 provides further investigations on our analysis and Section 3.6 concludes.

3.2 Data

This section presents the data used in our empirical study. We outline how we constructed our indicator for US climate initiative laws and the exposure of S&P500 companies to transition risk.

Our final dataset is assembled by combining two primary databases. The climate law database discussed in subsection 3.2.1 is publicly accessible, while the databases covered in subsection 3.2.3, subsection 3.2.4, subsection 3.2.5 are sourced from Thomson Reuters. In the case of the latter, we employ ISIN as the principal identifier to merge the data. Ultimately, we integrate the CCLW and Thomson Reuters databases, using the monthly date as the key identifier. The database ultimately compiles 17,791 observations spanning the years 2005-2018.

3.2.1 Climate Change Laws of the World database

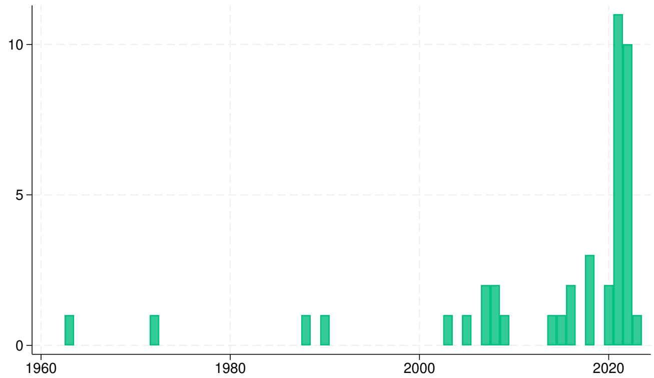
The *Climate Change Laws of the World* (CCLW) is issued from the collaboration between The Sabin Center and the Grantham Research Institute on Climate Change and the environment. The database is publicly available that encompasses roughly 2,000 climate policies and laws from 200 countries globally. To date, it stands as one of the most expansive and accessible free resources on climate policy available for download. The database incorporates laws and policies that detail a government's approach to addressing climate change or are part of its climate strategy. This encompasses overarching climate change laws, as well as laws tailored to specific sectors or issues, and those promoting decarbonization and/or climate resilience. More specifically, it includes laws directly targeting climate change and dedicated climate measures as well as those that inadvertently affect it. It addresses all pertinent measures geared towards diminishing greenhouse gas emissions, including foundational regulations. Only laws and policies of national significance are included[4]. The database adopts a fairly broad definition of climate legislation. This can be divided between legislative acts (those passed by the government), accounting for about 40%, and executive orders (issued by the government), making up roughly 60%. To simplify the analysis, we refer to all these measures as ''laws" (Eskander and Fankhauser, 2020).

Our analysis focuses on the United States, and we're constrained by the accessible data on CO_2 emissions. Originally, we identified 53 climate laws spanning from 1963 to 2023. However, some laws have undergone amendments or are part of the same legislative family. To prevent double-counting of a single law, we've excluded these overlapping entries to maintain a unique identifier

[4]https://www.lse.ac.uk/granthaminstitute/climate-change-laws-of-the-world-database/

for each distinct legislative event. As a result, Figure Figure 3.1 shows the initial count of climate laws included in the database.

Figure 3.1: Number of US Climate Laws (1963-2023)



Note: The figure represents the number of environmental laws passed in the United States, as recorded in the CCLW database, over the period 1963-2023.

subsection 3.2.2 illustrates the annual enactment of climate laws in United States. The former climate law was the Clean Air Act, ratified on December 17, 1963. The figure reveals that a mere four climate laws were instituted before the turn of the millennium. Post-1999, there's a notable uptick in the enactment of climate laws. We observe an increasing trend from 2007, with legislative activity peaking between 2021 and 2023. Over 11 new laws came into effect just since 2021.

3.2.2 Climate law indicator

This subsection is dedicated to detailing the construction of the US' climate law indicator.

We aim to investigate the pricing of transition risk in the US stock market following the enactment of climate laws. Initially, we introduce an indicator variable named "Law_Event". This variable is assigned a value of 1 for every time a climate law is enacted during our study period and 0 otherwise, designing to an event study approach. Formally, we denote the following dummy variable as follows:

$$LAW_t = \begin{cases} 1, & \text{the date the climate legislation was enacted} \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

Furthermore, our aim is to analyze the reaction of S&P 500 companies post the introduction of these climate laws. To delve deeper into the long-term implications, we establish a dummy variable that assumes a value of one for the specific duration in which we seek to observe the impact. For instance, if we aim to examine the effects one month post-law enactment, the variable is set to "1" for that month. We extend this logic to capture effects for durations of up to 12 months. For clarity and simplicity, consider the following example detailing the construction of our climate law index. Suppose a climate law was enacted in January 2013, marking it as the Law Event. We then structure the climate law index as outlined in Table 3.1:

Table 3.1: Climate Law Index

t	0M	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
01/2013	1	1	1	1	1	1	1	1	1	1	1	1	1
02/2013	0	1	1	1	1	1	1	1	1	1	1	1	1
03/2013	0	0	1	1	1	1	1	1	1	1	1	1	1
04/2013	0	0	0	1	1	1	1	1	1	1	1	1	1
05/2013	0	0	0	0	1	1	1	1	1	1	1	1	1
06/2013	0	0	0	0	0	1	1	1	1	1	1	1	1
07/2013	0	0	0	0	0	0	1	1	1	1	1	1	1
08/2013	0	0	0	0	0	0	0	1	1	1	1	1	1
09/2013	0	0	0	0	0	0	0	0	1	1	1	1	1
10/2013	0	0	0	0	0	0	0	0	0	1	1	1	1
11/2013	0	0	0	0	0	0	0	0	0	0	1	1	1
12/2013	0	0	0	0	0	0	0	0	0	0	0	1	1
01/2014	0	0	0	0	0	0	0	0	0	0	0	0	1

Note: This table provides an example of the construction of the climate law indicator. Source: Author's computation.

The primary objective of our study is to understand the response of S&P 500 companies to the introduction of climate laws. Rather than using the traditional event study methodology, which primarily captures immediate market reactions within short windows surrounding an event, we employ a more encompassing approach. We introduce a dummy variable in our baseline specification, where this binary variable is triggered for a specified duration to observe the impact. This approach, unlike the narrow focus of traditional event studies, allows us to delve into both immediate and prolonged effects on stock prices. The aim is not just to measure the immediate repercussions of a specific climate law but to understand the broader, sustained implications of the U.S.'s climate change regulation on stock market valuations over an extended timeframe. This methodology provides depth, minimizes short-term market noise, and captures evolving long-term market sentiments, offering a comprehensive view of the market's adjustment to climate regulations.

3.2.3 Measure of CO_2 indicator

To assess companies' exposure to transition risk, we rely on their carbon emissions, quantified in tons of CO_2 annually. Such a metric has become a standard method in empirical research to proxy a company's carbon footprint (Bolton and Kacperczyk, 2021*b*,*a*).

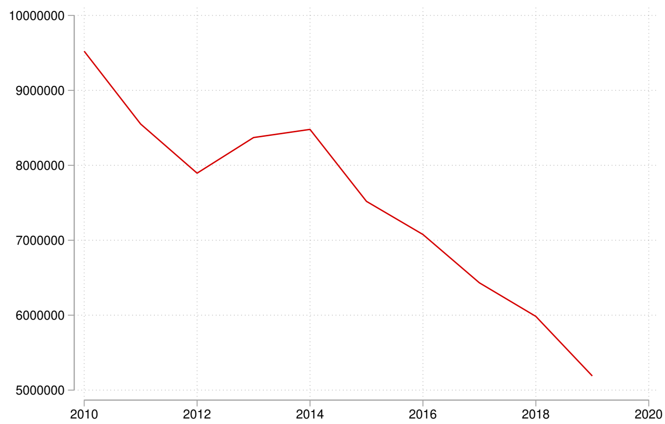
However, employing this indicator necessitates a multi-step process. Initially, carbon emissions are classified according to the categories delineated by the Greenhouse Gas Protocol nomenclature[5], formulated in 2001. Essentially, a company's greenhouse gas emissions fall into three distinct scopes that define its emission boundaries. Scope 1 covers the company's direct carbon emissions from

[5]For more details, see https://ghgprotocol.org/.

its owned or controlled sources. Scope 2 encompasses the indirect emissions arising from the company's purchased energy consumption. The sum of Scope 1 and Scope 2 forms the Total emissions, while Scope 3 captures emissions from the production units within a company's supply chain. Our analysis primarily hones in on Total emissions—derived from the sum of Scope 1 and Scope 2—given the challenges and scarcity of data surrounding Scope 3.[6] We also provide robustness checks using just Scope 1 or 2 emissions.

The Figure 3.2 displays the average carbon emissions over our sample period ranging from 2010 to 2019. We observe a general decline during the overall observation period, with emissions dropping to less than half of what they were at the start of the observation period[7].

Figure 3.2: Average reported total carbon emissions (in tons)



Note: This figure represents the average carbon emissions measured in tons of CO_2 over the our observation period 2010-2019.

Furthermore, a potential bias emerges when using carbon emissions related to the company's scale. Companies emitting identical carbon amounts but varying in size might have distinct carbon footprints. (Ilhan et al., 2021) advocate for the carbon intensity approach, which involves dividing a company's emissions by its sales, as a main metric for assessing carbon emissions' impact on stock returns. This method of evaluating carbon intensity is a prevalent standard in the field, helping sidestep any size-related biases in our CO_2 measurements.

Lastly, a pertinent concern while using carbon emissions is choosing between reported and estimated emissions. The former restricts the sample size, while the latter could introduce bias. Notably, Aswani et al. (2023); Bauer et al. (2022) highlight significant variations between these two, questioning the dependability of estimated emissions. While more companies are now either mandatorily or voluntarily disclosing their emissions, many still remain non-transparent about

[6]Busch et al. (2022) demonstrate that the CO_2 emission intensity consistency (either self-reported by firms or estimated by third parties) among various third-party entities diminishes from Scope 2 to Scope 3.

[7]For our empirical analysis, we express carbon emissions using their natural logarithm. Besides, we winsorize carbon emissions variables at 1% level following (Bolton and Kacperczyk, 2021*b*,*a*). Estimation results are provided in subsection 3.7.4 when we release the winsorization at 2.5% level.

their carbon footprint.

Consequently, our main analyses primarily focus on using reported emissions, turning to estimated emissions only for the purpose of conducting robustness tests. Concerning the aforementioned challenges related to using carbon emissions as the primary metric for carbon emissions indicators, our sample selection is restricted. As previously mentioned, there are still companies that do not report their carbon emissions data. To enhance the reliability of our findings and optimize our sample size, we focus on companies listed in the US S&P 500 index. This approach provides us with a strongly-balanced dataset, featuring 437 companies after dropping firms operating in the financial sector and covering the period from January 2010 to December 2019 on a monthly basis. All the carbon emissions data are standardized to ensure clarity in our empirical estimation.

3.2.4 Dependent variable

Our analysis focuses on US S&P 500 companies listed on the primary US stock exchanges, NYSE and NASDAQ. We limit our consideration to active and primary quotations, excluding companies within the financial sector. Monthly stock returns are calculated using the logarithmic difference of the adjusted closing price:

$$r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \tag{3.2}$$

where $P_{i,t}$ is the price of stock i at time t[8]. We have expressed the monthly returns in percentage to simplify interpretation. To mitigate the influence of outliers, we winsorize the returns at the 1% level[9].

3.2.5 Control variables

In this subsection, we provide details on the control variables specific to each company within our dataset. These individual characteristics have been conventionally adopted in academic literature to adjust for potential trends or cross-sectional variations that are likely to explain our dependent variable, individual stock returns. Specifically, we consider the following variables: Size; Return on Equity (ROE); Tobin Q; Debt; Book-to-market; Property, Plant, and Equipment; Research and Development expenditures; Sales growth; Momentum; and Investment.

To integrate these variables into our empirical framework, we undertook several transformations. Size is defined as the logarithm of market capitalization.[10]. Tobin Q is represented by the

[8]Here, P_t is the closing price on the first day of month t.
[9]Table 3.2 in subsection 3.7.1 provides descriptive statistics of the dependant variable.
[10]In robustness checks, we utilize the logarithm of total assets as an alternate measure of company size.

logarithm of the market-to-book value ratio. Book-to-market is calculated as the inverse of the lagged market-to-book value. Property, Plant, and Equipment (PPE) variable is the ratio of PPE to total assets. Research and Development expenditures is normalized by dividing the expenditure by total assets. Investment is initially computed as the ratio of total assets to its lagged value; we then determine its difference and represent it in percentage terms. Sales growth is derived from the annual growth rate of net sales. Momentum is captured using a rolling window of monthly stock returns from $t-12$ to $t-2$. Through these transformations, we aim to ensure compatibility and consistency in our empirical analysis. Table 3.3 in subsection 3.7.1 provides descriptive statistics of the control variables[11].

3.3 Empirical methodology

In this section, we describe our identification strategy to assess the impact of carbon emissions on stock returns, conditional upon climate change litigation in the US. Initially, we seek to determine whether this climate risk is priced in following the enactment of climate laws. Following that, we intend to evaluate if carbon emissions influence stock prices, regardless of the climate regulatory landscape.

Given that context, we adopt an empirical approach grounded in a traditional panel framework. Using a generalized Two-way Fixed Effect model (TWFE), we assess the effect of carbon emissions on S&P500 companies conditionally to US's climate initiatives.

This method is commonly utilized in research to estimate a causal effect from panel data. To enhance our model's accuracy, we factor in unit and time-based adjustments to account for any unobserved consistent characteristics that could affect the dependent variable. Specifically, we include a variable to balance out any average discrepancies across our sample, ensuring a more accurate representation of the data.

In its former specification, the model takes the following form:

$$r_{i,t} = \beta_0 + \theta_i + \gamma_t + \beta_1 CO2_{i,t-1} + \beta_2 CO2_{i,t-1} \times LAW_t + \sum_{k=3}^{K} \beta_k X_{k,i,t-1} + \varepsilon_{i,t} \qquad (3.3)$$

The dependant variable $r_{i,t}$ represents the monthly stock returns of US S&P500 companies. $CO2_{i,t}$ indicates the total carbon emissions reported by each company at a specific time, t. In this baseline specification, we consider carbon emissions as a continuous variable. As detailed in subsection 3.2.3, reported total emissions is used as our main measure of carbon emissions indicator. To mitigate potential endogeneity concerns, we refrain from regressing stock returns on

[11]Tobin Q, Debt, Book-to-market, Sales growth, Momentum, Investment and ROE are winsorized at 1% level to limit the impact of outliers.

carbon emissions for the same year. Following the approach of Bauer et al. (2022), we lagged the carbon emissions data by one period (equivalent to one year, given that carbon emissions data is available annually). As we focus on reported carbon emissions, it is inferred that companies experience a reporting lag in disclosing their carbon emissions data, implying that such data might not be instantly reflected in stock prices[12]. LAW_t refers to climate law indicators discussed in subsection 3.2.2.

Lastly, $X_{k,i,t}$ is a set of control factors specific to each company, which we detail in the subsection 3.2.5. In line with established financial literature, we also lagged the control variables by one period. This approach helps prevent look-ahead bias and guarantees that the information was accessible to investors during the relevant stock return period[13].

Both γ_i and θ_t denote firm-specific and time fixed effects, respectively. These are fundamental features of a TWFE model as explained above, which controls for unobserved characteristics and patterns that vary across units and over time. $\varepsilon_{i,t}$ refer to a normally distributed error term.

We estimate Equation 3.3 using Ordinary Least Squares (OLS) and report one-way cluster-robust standard errors to account for correlation within firms.

Our interest in estimating this relationship is twofold. Firstly, we aim to discern if the US stock market prices the risk associated with climate change. This is represented by the coefficient β_1 in the Equation 3.3. More precisely, this coefficient illustrates the average impact of carbon emissions on stock returns when no climate law has been enacted during the observation period, while adjusting for all confounding variables that might affect stock returns. For instance, a positive and significant coefficient implies that, on average, companies with higher emissions in our sample earn higher returns.

More crucially, our focus is directed towards the coefficient of the interaction term between carbon emissions and our climate law indicators β_2. This coefficient signifies the effect of carbon emissions on stock returns when a climate law is enacted. The combined impact of these variables sheds light on whether the market adjusts the pricing of transition risk in response to US initiatives aimed at carbon emission reductions. In this way, we expect that β_2 is negative. This implies that after the implementation of climate laws, the influence of carbon emissions on stock returns is likely to be negative.

Given its design, our model might introduce multicollinearity challenges due to the concurrent inclusion of time-invariant dummy variables and time fixed effects. Although the coefficient for the dummy variable isn't a focal point of our analysis[14], we carry out econometric tests to confirm

[12]We provide in subsection 3.7.3 estimation results with no emissions publication lag as Bolton and Kacperczyk (2021*a*).

[13]All control variables are lagged by one period, except for the sales growth and investment-to-assets variables.

[14]We've chosen to exclude the coefficient related to this variable to prevent potential issues with overlapping data effects. At this point, we're keen on understanding how carbon emissions influence stock returns after a climate law is implemented, rather than how a climate law affects stock returns when the average emissions of our observed

the robustness and appropriateness of our model for the empirical study. Specifically, we aim to determine whether adding our climate law indicator significantly improves the model's ability to explain the relationship between carbon emissions and stock returns. To achieve this, we use the Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978), which are widely recognized in academic research for model selection. We first compare the coefficients from the initial model, which doesn't include climate law indicators, to the coefficients of subsequent models. While there's a contradiction between the two information criteria, the AIC criterion suggests that in 90% of the specifications, incorporating our climate laws indicator results in a better fit to the data. This lends further support to the validity of the model we've chosen for our study.

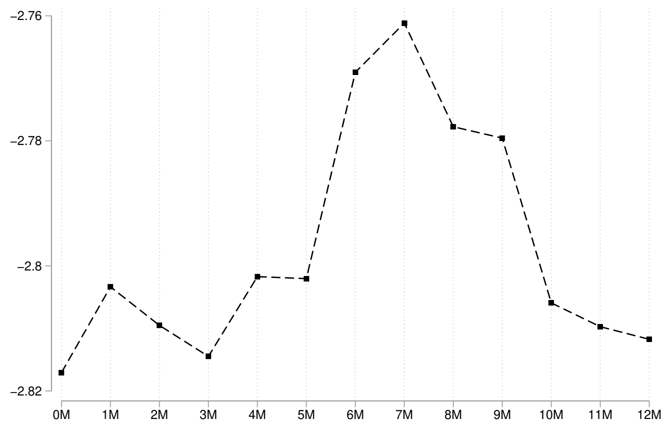
3.4 Baseline results

In this section, we set forth our principal empirical findings from Equation 3.3. To begin our discussion, we'll highlight the debate on whether the transition risk is incorporated in stock prices in subsection 3.4.1.[15]. Following that, in subsection 3.4.2 we explore the potential causal effects of US climate legislation on the relationship between carbon emissions and stock returns.

3.4.1 Are carbon emissions reflected in stock prices?

In the context of discussing whether transition risk is reflected into stock valuation, Figure 3.3 presents the coefficient related to our carbon emissions indicator, β_1.

Figure 3.3: Carbon premium (Emissions Level)



Note: The figure represents the estimated coefficient of β_1 from our baseline Equation 3.3 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

companies are zero.

[15]Corresponding tables are provided in subsection 3.7.2.

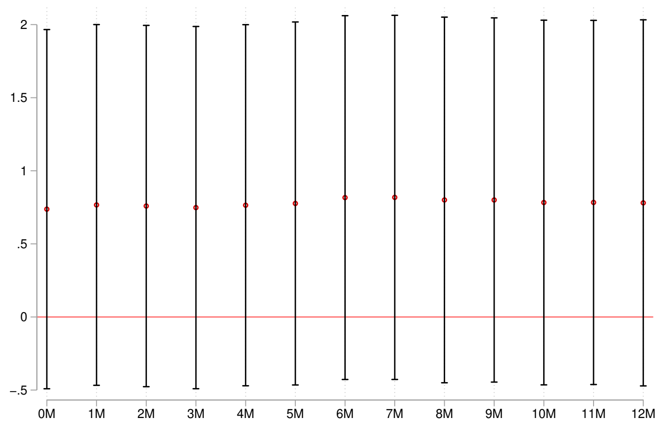
To be more precise, according to the formulation of our baseline Equation 3.3, the coefficients in this graph represent the main effect of reported total emissions on stock returns without the climate law[16].

Our analyses consistently show that carbon emissions have a negative impact on stock returns across different specifications. The coefficient is notably negative, statistically significant, and tends to hover around -2.8. This suggests that investors are pricing in the carbon transition risk at the company level. More specifically, this means that in the absence of the climate law (or before its implementation), an increase of one standard deviation in the reported total emissions is associated with a decrease of 2.8% in stock returns, on average. This is particularly true when we use emission levels as the main measure for carbon emissions, although the findings contrast with those reported in Bolton and Kacperczyk (2021*a*). They found that brown companies exhibit higher realized returns than green ones because investors demand a compensation to carry this carbon transition risk. At this time, a crucial distinction between our study and theirs is the scope. First, their observation period ranging from 2005 to 2017 differs from ours. Then, their study encompasses a broader set of companies due to different sources for carbon emissions data: they use Trucost, while we draw from Thomson Reuters. As detailed in section subsection 3.2.3, our sample is constrained by the number of companies disclosing their carbon emissions data, leading to a smaller sample size. Furthermore, they argue that incorporating industry fixed effects can significantly alter results. We did not include industry fixed effects in our baseline estimation since we used a TWFE model, focusing specifically on US S&P 500 companies. In conclusion, our results are in line with recent studies, suggesting that green stocks may outperform their brown counterparts during times of heightened climate change concerns (Bauer et al., 2022; Aswani et al., 2023).

Figure 3.4 illustrates the fluctuations of the coefficient tied to emissions intensity across various specifications. We observe that although the coefficient hints at a positive sign, it doesn't show any statistical significance across all specifications in capturing a carbon premium based on emissions intensity. This trend is in line with the findings from Bolton and Kacperczyk (2021*b*,*a*, 2023). Bolton and Kacperczyk (2023) suggest that emissions intensity isn't a factor for investors when evaluating carbon risk premia. Such a perspective arises from the metric's inherent limitations. Even Garvey et al. (2018) emphasizes that an investor who takes a long position on low carbon intensity stocks outperforms another who opts for a short position on stocks with high emissions intensity, Bolton and Kacperczyk (2023) argue that large companies can appear disproportionately eco-friendly. A large company can decrease its emissions intensity while simultaneously increasing

[16] Note that carbon emissions indicators in both level and intensity are transformed into logarithms and standardized to facilitate interpretation.

Figure 3.4: Carbon premium (Emissions Intensity)



Note: The figure represents the estimated coefficient of β_1 from our baseline Equation 3.3 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

its overall emissions in the same year.

3.4.2 US Climate legislation and Pricing of the transition risk

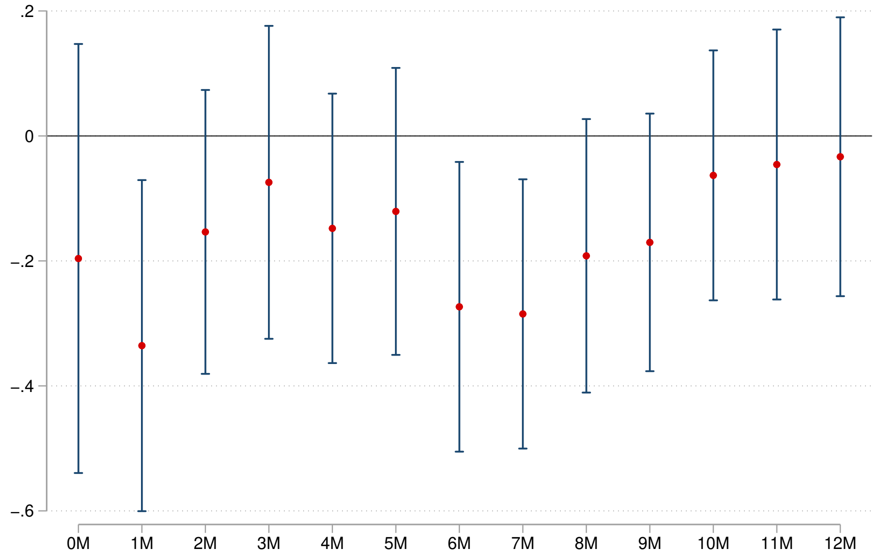
Figure 3.5 illustrates the coefficient of the interaction term β_2 [17]. The results provided displays the effect of reported total emissions after the enactment of climate laws on the stock returns of US S&P500 companies. We investigate the immediate and delayed effects of these laws for up to 12 months after the laws' enactment. Specifically, each point on the graph corresponds to the coefficient resulting from the interaction between carbon emissions and a dummy variable: this dummy takes on the value of 1 in the month the law is enacted (0M), 1 month afterwards (1M), and so on. We initially focus on total reported emissions as our indicator for carbon emissions.

First and foremost, we've observed a consistent negative sign for the interaction term between carbon emissions and our climate law indicator throughout various specifications. This aligns with our initial predictions. We anticipated that after the introduction of a climate law, "brown" or environmentally-unfriendly companies would face heightened penalties from the market due to climate regulations. This reasoning stems from the primary goal of many climate regulations, which is to reduce global greenhouse gas emissions. As such, companies with a larger carbon footprint, or "brown" companies, may be viewed as more vulnerable to these regulations and subsequently face steeper penalties.

To shed more light, when combining the coefficient related to carbon emissions with the interaction term's coefficient, the negative impact of carbon emissions on stock returns becomes even more pronounced post-climate law enactment than when considering just the carbon emissions

[17]Confidence intervals have been computed at 90% level. The same chart, featuring both 95% and 99% confidence intervals, is provided in the subsection 3.7.4.

Figure 3.5: Stock returns' response to US climate legislation (Emissions Level)



Note: The figure represents the estimated coefficient of β_2 from our baseline Equation 3.3 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

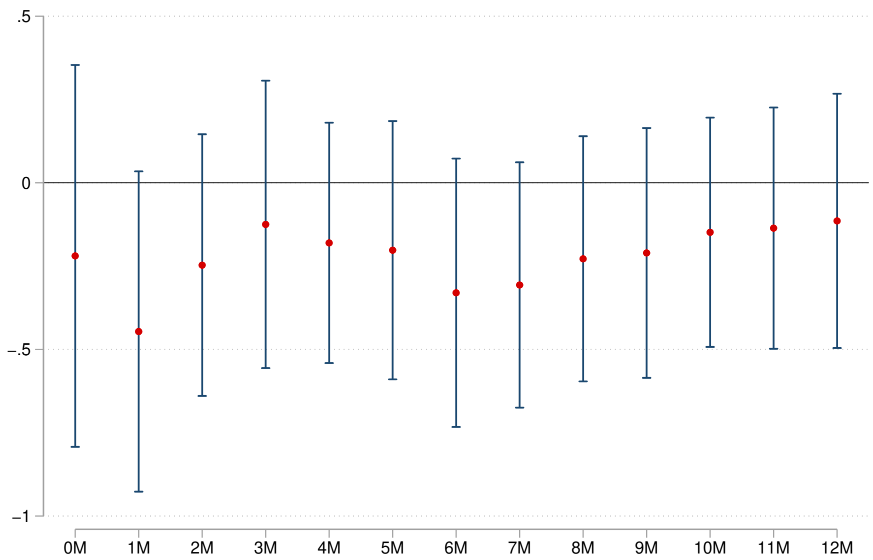
alone.

However, when viewed from an investment standpoint, this trend is less straightforward. A distinct change becomes evident from the second month after the enactment of the climate law. Initially, the interaction term's coefficient shows statistical significance at the 1% level. For instance, given the interaction coefficient is estimated to be -0.336, after the implementation of the climate law (after the first month), a firm should expect a stock return of -3.139% against -2.803% without any climate law enactment or before its implementation. This estimation result suggests that 1 month subsequent to the introduction of new climate legislation, companies with high levels of carbon emissions tend to experience a consequent decline in their returns. But this level of significance decreases over the following months, fading by the sixth month post-enactment. This initial significance might be pointing to a short-lived "signal effect" following the climate law's introduction. During this phase, investors may not be overly concerned about the real-world implications of the climate law, resulting in no additional discernible impact on the relationship between carbon emissions and stock returns.

However, a noticeable downturn is observed during the 6th and 7th months post-enactment, indicating a heightened negative impact. This suggests that during this medium-term phase, stock valuations may be influenced by carbon emission levels. This shift could be attributed to either the tangible effects of the climate law or merely investor perceptions in the half-year following the law's introduction. Yet, this significant coefficient declines as we extend our observation, indicating that long-term investors might not factor in climate regulations when assessing carbon transition risks in the stock market.

In Figure 3.6, we present results that shift our focus from carbon emissions level to emissions intensity. Emissions intensity is calculated by dividing carbon emissions by sales. This provides an adjusted view, essentially offering insights into how much carbon emission is produced for every unit of sales.

Figure 3.6: Stock returns' response to US climate legislation (Emissions Intensity)



Note: The figure represents the estimated coefficient of β_2 from our baseline Equation 3.3 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Turning our focus to the graph or table indicated by Figure 3.6, it's evident that the insights derived from it don't significantly deviate from what we observed regarding the carbon emissions level. More specifically, the coefficient of the interaction term aligns with our anticipated results. It holds a negative value, reaffirming the notion that once climate laws come into play, carbon emissions adversely affect stock returns.

However, we discern that the coefficient's value, regardless of which model specification we're evaluating, is so proximate to 0 that it's virtually indistinguishable from it. Such an observation is in line with our prior discussions. Given that we employ emissions intensity as the main indicator to measure a company's susceptibility to the risks linked with transitioning away from carbon, these findings are expected. It signifies that during times when climate laws are enacted, investors appear to place greater emphasis on the total volume of a company's carbon emissions rather than its emissions intensity. Given the overarching goal of climate regulations—restricting the global temperature increase to a threshold of 1.5° degrees—it's understandable that investors prioritize the absolute carbon emissions of a company over its emissions intensity when assessing stock valuations.

3.4.3 General discussion

So, what does this translate to in terms of investor behavior? It suggests a nuanced perspective. In contrast with Bolton and Kacperczyk (2021*a*), we found an apparent premium linked to price adjustments without or before the climate law implementation. This is line with Pástor et al. (2022) supporting the idea that while brown firms might experience lower realized returns, they could simultaneously exhibit higher expected returns. Such a scenario might arise if the valuation of green assets has seen a spike in recent years due to a shift in investor preferences. Furthermore, investors appear to be weighing emissions level with more consideration when factoring in the risks that arise from climate change. In simpler terms, they're more focused on emissions level rather than just the raw emissions intensity, indicating a shift in how environmental risks are priced and perceived in the market.

Figure 3.5 gives insights on how carbon transition risk can be perceived given the U.S. climate legislation. This pattern suggests that given the uncertainty that often surrounds new legislation, many investors adopt a wait-and-see approach. They might wait to observe how companies adjust and what the actual financial ramifications are before making significant portfolio adjustments. Companies themselves might take a few months to communicate their strategic responses to the new laws. Investors might be waiting for clearer signals from company management about their mitigation strategies and potential impacts.

Furthermore, our data suggests that investors place a higher emphasis on carbon transition risk in the first month, as well as during the 6th and 7th months, following the enactment of climate laws. This implies that the financial market continues to penalize companies with notable carbon footprints, as defined by their emissions level. The coefficient of the interaction term is even more pronouncedly negative. A possible reason could be the market's adaptation to the new legislative context, with investors having gauged the law's ramifications and realigned their forecasts. Besides, following the implementation of climate legislation, companies that are seen to be compliant or proactive in their approach might be viewed as environmental friendly. From an investor perspective, these companies may be perceived as forward-looking and better prepared for future regulatory shifts, leading to increased investor confidence. If legislation is seen as the first step toward a broader trend of increasing climate regulations, companies that adapt quickly are seen as better prepared for the future, making them more attractive investments.

Finally, the interaction term is significant exclusively for levels of carbon emissions in the baseline estimation. Particularly, regulations often target absolute emissions levels rather than intensity. Companies with high emissions may be more exposed to regulatory risks, carbon taxes, and other policy measures. This may offer insights into how investors view climate-related risks. One possible explanation is that investors might consider companies with high emission levels as being more vulnerable to climate-related legislation, and as a result, they might be more inclined to penalize such high-emitting firms. Besides, as discussed in Section 3.1, while emissions intensity can show efficiency or improvements in environmental performance, it does not provide a direct measure of a company's total impact on the environment Bolton and Kacperczyk (2021*a*). Investors concerned with the broader environmental impact might prioritize total emissions over intensity because a very large company could still have significant total emissions even if it has a low emissions intensity.

3.5 Further investigations

Our empirical results necessitate further exploration. Specifically, the estimation outcomes from Figure 3.5 urge us to delve deeper into understanding the underlying factors that influence investor behavior. We're particularly interested in how they price carbon transition risks in the context of U.S. climate regulations during the timeframe of our empirical observations.

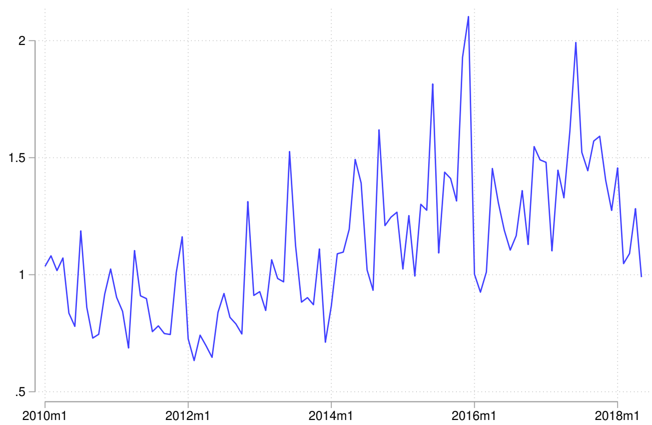
As discussed in the Section 3.1, some empirical studies emphasis the the link between climate awareness, regulatory changes, and their impacts on companies (Busch et al., 2016; Choi et al., 2020; Guo et al., 2020; Bolton and Kacperczyk, 2021*a*). What are the reasons a priory to expect that the impact of climate law on the relationship between carbon emissions and stock returns increases with climate awareness?

Firstly, as climate awareness rises, investors might become more selective, often shunning companies not aligned with environmental goals due to potential regulatory risks and future liabilities. This can depress stock prices for high-emission firms. Additionally, growing environmental consciousness may sway investor preferences towards sustainable stocks. Concurrently, stricter climate regulations may impose fines or necessitate costly changes for high-emitting companies, impacting their financial performance. Thus, as these companies are perceived as riskier, investors seek higher returns for holding their stocks, leading to lower stock prices and subsequently, a stronger negative relationship between carbon emissions and stock returns (Pástor et al., 2022; Ardia et al., 2022).

In this section, we focus on how heightened climate consciousness impacts the relationship between U.S. climate legislation, carbon emissions, and stock returns. To do this, we introduce a variable that we believe correlates with both carbon transition risk exposure and U.S. climate legislation. We postulate that a rise in climate awareness typically parallels tighter climate regulations. As a result, high carbon-emitting companies could encounter regulatory penalties, face operational challenges, or be compelled to undertake expensive modifications — factors that could dampen their financial health and, consequently, depress their stock returns. Consequently, we anticipate that as concerns about climate change increase, the negative effect of carbon emissions on stock returns becomes more pronounced.

Our measure for climate awareness stems from the coverage newspapers give to events related to climate change. The key idea is that media coverage can lead investors to reassess their views on climate risks and derive a renewed sense of ethical fulfillment from investing in eco-friendly companies. To represent the newspaper coverage surrounding climate change, we employ a time-series indicator taken from Engle et al. (2020). This indicator is derived from a textual examination of news sources, utilizing the proprietary sentiment measure from Crimson Hexagon. It specifically hones in on negative coverage concerning climate change, sourced from an extensive collection of over one trillion news articles[18]. Their indicator ends in May 2018. After merging it with our main database, the observation timeframe for this section extends from January 2010 to May 2018, resulting in 14,105 observations.

Figure 3.7: Climate Awareness Time-Series Indicator



Source: Engle et al. (2020).

The graph in Figure 3.7 showcases the climate change concerns time-series indicator from Engle et al. (2020), recorded monthly over our sample observation period. A higher value in this indicator suggests heightened awareness and concerns about the impact of climate change.

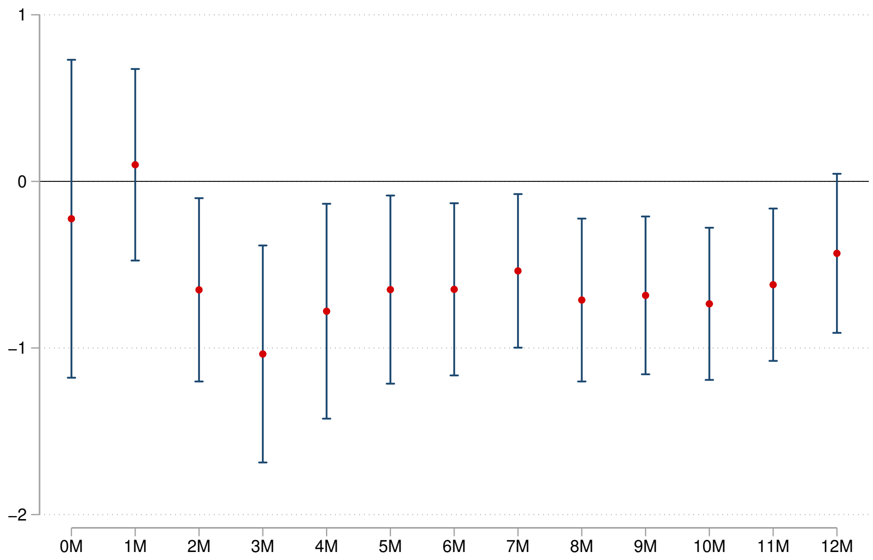
The trajectory of the indicator reveals a general upward trend over time, with peaks indicating periods of heightened climate change apprehension. Notably, the indicator peaks around early 2016, coinciding with the Paris Agreement. Given that the indicator incorporates sentiment analysis, it might not only capture concerns related to extreme weather events or the prevalence of climate-related discussions but also their intensity or sentiment. A surge in the indicator might indicate the media's usage of more dire or urgent language regarding climate change.

Our approach to estimation involves breaking down our primary variable of interest, "Emissions × Law", based on the levels of climate concerns. We segment this variable into four distinct

[18]Results obtained using the climate awareness metric from Ardia et al. (2022) are available upon request.

variables, each corresponding to a specific degree of climate concern. For the forthcoming results, we focus on "Emissions × Law" during periods of high climate concerns, specifically selecting observations that exceed the threshold of the fourth quartile[19].

Figure 3.8: Stock returns' response to US climate legislation - High Climate Change Concerns (Emissions Level)



Note: The figure represents the estimated coefficient of β_2 from our baseline Equation 3.3 when considering both emissions level and high climate change concerns periods. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.8 illustrates the coefficient of the interaction term (identical to the baseline estimation) for periods of heightened climate change concerns. These findings align well with our initial hypotheses. Interestingly, while the coefficient isn't statistically significant at the 0M mark (the month when the law came into effect) and a month later, its significance grows from the second month post climate law enactment, continuing up to the 11th month. This implies that in periods of heightened climate awareness, the negative effect of carbon emissions on stock returns begins to manifest two months post the implementation of a climate law and remains notable for nearly a year. During periods of heightened climate change awareness, investors appear to place greater weight on the risks associated with climate change, leading to more significant penalization of companies with high carbon emissions. This heightened awareness seems to magnify the perceived stringency of climate regulations, making investors more vigilant in how they price in carbon transition risks into their stock valuations. Essentially, intensified climate concerns amplify the effects of U.S. climate legislation on the relationship between carbon emissions and stock returns, underlying a trend where investors are integrating climate risks more strongly into their assets evaluations. Especially, high-emission companies are viewed as increasingly riskier, particularly when climate awareness are pronounced and in the wake of new climate-related legal frameworks.

[19]Results for periods with medium and low levels of climate change concerns can be found in the Appendix.

Besides, the discernable lag – the pronounced negative relationship between carbon emissions and stock returns emerging two months after the introduction of climate laws – indicates that investors don't react immediately. Instead, they seem to adopt a more measured approach, taking the time to understand, interpret, and respond to the nuances of the new regulations. This suggests a contemplative assessment of the legislation's medium to long-term ramifications for businesses.

However, the significant negative impact of carbon emissions on stock returns disappears 12 months after the introduction of a climate law. This indicates that, over the long run, even the period of high climate awareness, the U.S. climate legislation doesn't further influence the relationship between carbon emissions and stock returns. This could be interpreted as investors, over time, perceiving the climate laws as either insufficiently stringent or not effectively implemented to perpetually influence their stock valuation decisions in light of the existing climate regulations. In essence, while climate awareness and legislation can have a pronounced impact on stock returns, especially for high carbon-emitting firms, these effects might not be persistent in the long run without continuous reinforcement.

3.6 Conclusion

In this paper, we empirically investigate how the U.S. climate legislation influence the relationship between carbon emissions and stock returns over the 2010-2019 period. Specifically, our research objectives are twofold.

Firstly, our study aims to answer the question of whether carbon emissions are reflected in stock prices. Our primary indicator for measuring the carbon transition risk is the reported total carbon emissions. Among the ongoing debate surrounding the pricing of transition risk on stock market, our findings indicate a discernible investor attention to carbon risks. Our estimates reveals a noteworthy pattern: companies with lower carbon emissions generate higher realized returns. However, when focusing on emissions intensity, discern any apparent premium linked to market shifts when using emissions intensity as a main indicator for a company's greenness (Bolton and Kacperczyk, 2021*a*).

Secondly, our analysis extends to understanding how U.S. climate legislation influences the dynamics between carbon emissions and stock returns. Using a publicly available database on national climate laws, we construct a climate law index. Our analysis suggests a 2.8% decrease in stock returns following the enactment of a climate law, on average. Our findings indicate a intricate relationship between investors' valuation of carbon transition risk and the enactment of climate laws. Notably, we observed a marked effect of carbon emissions on stock returns within a month following the introduction of the climate law and continuing into the medium term. This raises concerns about the regulation's ability to ensure sustained long-term outcomes. Besides, it seems that investors account for carbon transition primarily based on carbon emission levels and to a larger degree once climate laws come into play. This reinforces the notion that investors continue to penalize high-emission companies in the face of climate legislation. Given that climate policies frequently aim at company emission levels to meet global greenhouse gas reduction targets, the context of these regulations might be influenced by how companies communicate their efforts to reduce emissions or internalize associated costs. However, when assessing the pricing of carbon transition risks on U.S. S&P 500 companies, our results suggest that climate regulations might not be considered by long-term investors.

Then, using a climate awareness indicator derived from major U.S. newspapers, further investigations reveal that during times of high concerns about climate change, the negative effect of carbon emissions on stock returns is amplified following U.S. climate legislation.

Our paper calls for several extensions. On one hand, it would be relevant to assess the relationship between carbon emissions and stock returns, primarily considering the location of the company's headquarters. Indeed, certain states may be subject to specific regulations while others are not. On the other hand, it could also be of interest to examine whether the state in which the company operates is Republican or Democrat. The political segmentation in the United States leads to different directions in terms of combating climate change, leading to empirical results that could completely diverge.

In conclusion, our empirical findings bear significant implications for environmental policy-making. Specifically, our research sheds light on the market's approach to pricing climate risk and how climate regulations play a role in influencing this pricing mechanism. The long-term implications of U.S. legislation on the relationship between carbon emissions and stock returns warrant reinforcement. Current legislative measures appear to have a more pronounced influence in the medium term, However the sustainability and longevity of these impacts remain uncertain. Ensuring that financial markets consistently and progressively reward eco-friendly corporate behavior is key to driving long-lasting environmental change. To achieve this, policymakers should consider refining and bolstering the existing regulations, ensuring they not only respond to immediate concerns but also lay a solid foundation for long-term market adjustments in favor of a lower-carbon economy.

3.7 Appendix

3.7.1 Descriptive statistics

Table 3.2: Descriptive statistics of the dependent variable

Variable	Mean	Std. Dev.	Min.	Max.	N
Returns	0.866	7.506	-28.252	24.951	27191

Source: Author's computation.

Table 3.3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Size	17.14	1.157	14.128	20.989	17180
Tobin Q	1.324	0.784	-0.446	4.089	17180
Debt	0.279	0.142	0	0.708	17180
Book-to-market	0.344	0.241	-0.123	1.538	17180
PPE	0.222	0.187	0.018	0.932	17180
R&D	0.043	0.051	0	0.399	17180
Sales growth	0.063	0.155	-0.402	1.109	17180
Momentum	11.157	23.168	-84.016	81.626	17180
Investment-to-assets	-3.571	0.729	-7.436	-1.531	17180
ROE	25.575	33.81	-68.430	237.94	17180

Source: Author's computation.

3.7.2 Corresponding tables to estimation results from baseline Equation 3.3

Table 3.4 refers to Figure 3.3 and Figure 3.5 in Section 3.4. Table 3.5 corresponds to Figure 3.4 and Figure 3.6 in the same section.

Table 3.4: Responses of stock returns to Climate laws (Emissions Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	-2.817***	-2.803***	-2.810***	-2.814***	-2.802***	-2.802***	-2.769***	-2.761***	-2.778***	-2.780***	-2.806***	-2.810***	-2.812***
	(0.825)	(0.827)	(0.827)	(0.828)	(0.827)	(0.828)	(0.829)	(0.830)	(0.831)	(0.831)	(0.829)	(0.828)	(0.828)
Law Event × Emissions	-0.196												
	(0.208)												
1M Dummy × Emissions		-0.336**											
		(0.160)											
2M Dummy × Emissions			-0.154										
			(0.138)										
3M Dummy × Emissions				-0.074									
				(0.152)									
4M Dummy × Emissions					-0.148								
					(0.131)								
5M Dummy × Emissions						-0.121							
						(0.139)							
6M Dummy × Emissions							-0.273*						
							(0.140)						
7M Dummy × Emissions								-0.285**					
								(0.130)					
8M Dummy × Emissions									-0.192				
									(0.132)				
9M Dummy × Emissions										-0.170			
										(0.125)			
10M Dummy × Emissions											-0.063		
											(0.121)		
11M Dummy × Emissions												-0.046	
												(0.131)	
12M Dummy × Emissions													-0.033
													(0.135)
Size	3.731***	3.714***	3.721***	3.726***	3.712***	3.713***	3.676***	3.669***	3.688***	3.691***	3.719***	3.723***	3.726***
	(0.275)	(0.274)	(0.275)	(0.276)	(0.275)	(0.276)	(0.275)	(0.276)	(0.278)	(0.278)	(0.279)	(0.278)	(0.278)
Tobin Q	-1.775***	-1.779***	-1.778***	-1.777***	-1.780***	-1.780***	-1.791***	-1.795***	-1.791***	-1.791***	-1.782***	-1.780***	-1.779***
	(0.364)	(0.364)	(0.364)	(0.364)	(0.365)	(0.364)	(0.365)	(0.366)	(0.365)	(0.365)	(0.364)	(0.363)	(0.364)
Debt	3.974***	3.947***	3.962***	3.972***	3.948***	3.951***	3.894***	3.886***	3.917***	3.921***	3.962***	3.968***	3.972***
	(1.259)	(1.255)	(1.258)	(1.261)	(1.258)	(1.260)	(1.255)	(1.255)	(1.259)	(1.258)	(1.263)	(1.264)	(1.264)
Book-to-market	2.176*	2.172*	2.170*	2.174*	2.168*	2.166*	2.144*	2.130*	2.141*	2.140*	2.160*	2.164*	2.166*
	(1.129)	(1.128)	(1.128)	(1.128)	(1.129)	(1.129)	(1.131)	(1.133)	(1.133)	(1.133)	(1.130)	(1.129)	(1.129)
PPE	3.864	3.887	3.878	3.869	3.887	3.884	3.930	3.949	3.929	3.929	3.885	3.878	3.870
	(2.701)	(2.697)	(2.700)	(2.703)	(2.696)	(2.699)	(2.692)	(2.693)	(2.703)	(2.699)	(2.705)	(2.701)	(2.701)
R&D	27.127***	26.978***	27.082***	27.140***	27.055***	27.069***	26.884***	26.867***	26.980***	27.020***	27.151***	27.171***	27.183***
	(7.844)	(7.859)	(7.858)	(7.851)	(7.873)	(7.861)	(7.900)	(7.919)	(7.898)	(7.901)	(7.856)	(7.853)	(7.848)
Sales growth	-0.300	-0.289	-0.293	-0.296	-0.290	-0.293	-0.284	-0.289	-0.298	-0.302	-0.305	-0.305	-0.304
	(0.538)	(0.537)	(0.537)	(0.537)	(0.535)	(0.536)	(0.533)	(0.533)	(0.534)	(0.535)	(0.537)	(0.537)	(0.537)
Momentum	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.353	-0.350	-0.352	-0.353	-0.352	-0.352	-0.351	-0.352	-0.353	-0.354	-0.355	-0.355	-0.355
	(0.267)	(0.266)	(0.267)	(0.267)	(0.267)	(0.267)	(0.267)	(0.268)	(0.268)	(0.269)	(0.268)	(0.268)	(0.268)
ROE	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364
Observations	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.5: Responses of stock returns to Climate laws (Emissions Intensity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	0.738	0.766	0.759	0.748	0.764	0.776	0.817	0.818	0.801	0.800	0.783	0.783	0.781
	(0.747)	(0.750)	(0.751)	(0.753)	(0.751)	(0.755)	(0.756)	(0.757)	(0.760)	(0.757)	(0.758)	(0.757)	(0.761)
Law Event × Emissions	-0.219												
	(0.291)												
1M Dummy × Emissions		-0.446*											
		(0.244)											
2M Dummy × Emissions			-0.247										
			(0.199)										
3M Dummy × Emissions				-0.125									
				(0.219)									
4M Dummy × Emissions					-0.180								
					(0.183)								
5M Dummy × Emissions						-0.202							
						(0.197)							
6M Dummy × Emissions							-0.330						
							(0.204)						
7M Dummy × Emissions								-0.307					
								(0.187)					
8M Dummy × Emissions									-0.228				
									(0.187)				
9M Dummy × Emissions										-0.210			
										(0.190)			
10M Dummy × Emissions											-0.148		
											(0.175)		
11M Dummy × Emissions												-0.136	
												(0.184)	
12M Dummy × Emissions													-0.114
													(0.194)
Size	3.366***	3.353***	3.356***	3.361***	3.354***	3.348***	3.331***	3.331***	3.339***	3.340***	3.348***	3.348***	3.351***
	(0.285)	(0.284)	(0.285)	(0.284)	(0.284)	(0.283)	(0.282)	(0.282)	(0.283)	(0.284)	(0.284)	(0.284)	(0.284)
Tobin Q	-1.576***	-1.584***	-1.583***	-1.580***	-1.584***	-1.588***	-1.598***	-1.600***	-1.595***	-1.595***	-1.591***	-1.590***	-1.589***
	(0.375)	(0.375)	(0.375)	(0.375)	(0.376)	(0.375)	(0.376)	(0.376)	(0.376)	(0.376)	(0.376)	(0.375)	(0.375)
Debt	3.061**	3.032**	3.038**	3.049**	3.033**	3.022**	2.985**	2.987**	3.006**	3.006**	3.022**	3.022**	3.026**
	(1.313)	(1.307)	(1.310)	(1.313)	(1.309)	(1.308)	(1.302)	(1.303)	(1.307)	(1.307)	(1.310)	(1.313)	(1.314)
Book-to-market	2.000*	1.985*	1.983*	1.991*	1.980*	1.970*	1.936	1.929	1.943	1.941	1.953	1.953	1.959*
	(1.179)	(1.178)	(1.178)	(1.178)	(1.180)	(1.179)	(1.182)	(1.183)	(1.185)	(1.188)	(1.184)	(1.183)	(1.184)
PPE	1.461	1.451	1.452	1.454	1.447	1.441	1.426	1.433	1.443	1.446	1.449	1.446	1.442
	(3.037)	(3.032)	(3.030)	(3.029)	(3.028)	(3.025)	(3.023)	(3.026)	(3.029)	(3.033)	(3.033)	(3.034)	(3.033)
R&D	27.233***	27.118***	27.167***	27.212***	27.174***	27.148***	27.066***	27.079***	27.129***	27.154***	27.207***	27.220***	27.234***
	(6.889)	(6.876)	(6.889)	(6.890)	(6.889)	(6.886)	(6.877)	(6.882)	(6.891)	(6.895)	(6.891)	(6.893)	(6.895)
Sales growth	-0.097	-0.093	-0.092	-0.094	-0.093	-0.094	-0.096	-0.099	-0.101	-0.103	-0.103	-0.102	-0.101
	(0.604)	(0.603)	(0.603)	(0.603)	(0.603)	(0.603)	(0.602)	(0.602)	(0.603)	(0.604)	(0.605)	(0.605)	(0.605)
Momentum	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.363	-0.365	-0.364	-0.363	-0.365	-0.367	-0.373	-0.373	-0.371	-0.371	-0.369	-0.369	-0.368
	(0.268)	(0.268)	(0.269)	(0.269)	(0.269)	(0.269)	(0.270)	(0.271)	(0.272)	(0.271)	(0.271)	(0.271)	(0.271)
ROE	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362
Observations	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

3.7.3 Additional tables and figures

In Figure 3.9, Figure 3.10, Figure 3.11 and Figure 3.12, we present the estimation results without lagging the carbon emissions indicator by one period for both intensity and level measures. This approach aligns with the methodology initiated by Bolton and Kacperczyk (2021*b*), wherein monthly stock returns are regressed on carbon emissions from the same year.

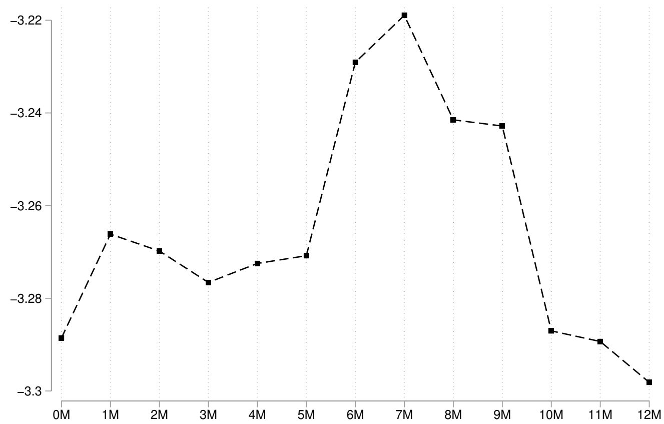
Therefore, we estimate the following model:

$$r_{i,t} = \beta_0 + \theta_i + \gamma_t + \beta_1 CO2_{i,t} + \beta_2 CO2_{i,t} \times LAW_t + \sum_{k=3}^{K} \beta_k X_{k,i,t-1} + \varepsilon_{i,t} \tag{3.4}$$

Table 3.6 and Table 3.7 refer to the corresponding estimation tables.

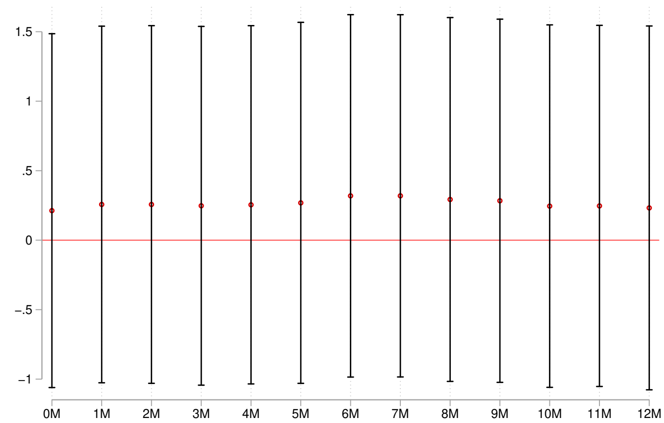
Table 3.8 and Table 3.9 refer to estimation results provided in Section 3.5.

Figure 3.9: Carbon premium with no emissions lag (Emissions Level)



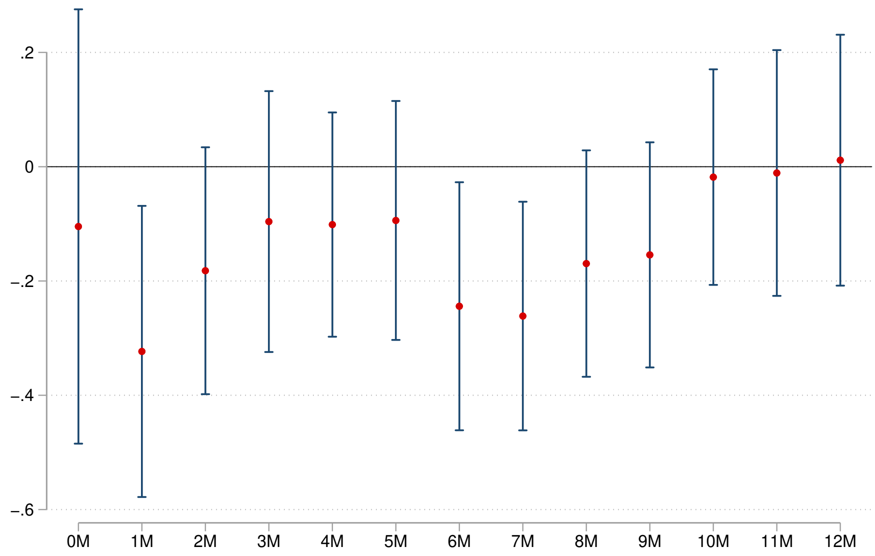
Note: The figure represents the estimated coefficient of β_1 from Equation 3.4 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.10: Carbon premium with no emissions lag (Emissions Intensity)



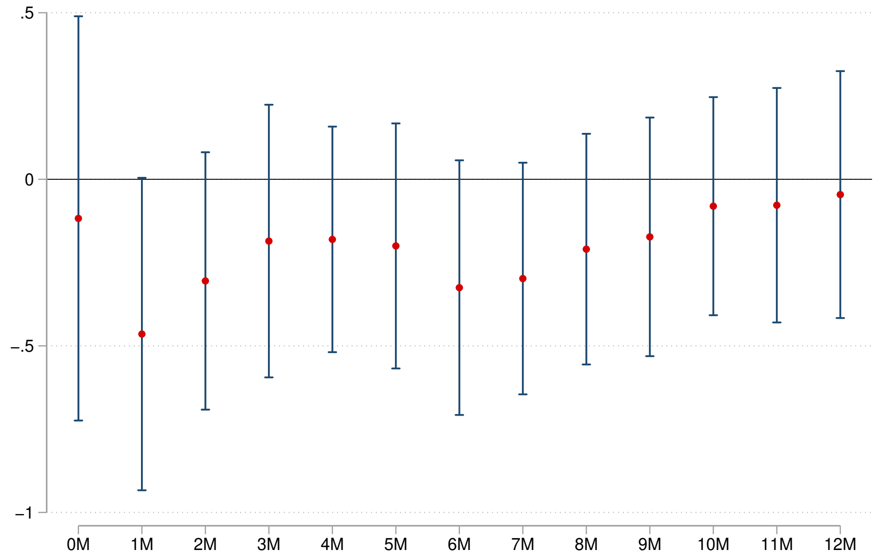
Note: The figure represents the estimated coefficient of β_1 from Equation 3.4 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.11: Stock returns' response to US climate legislation with no emissions lag (Emissions Level)



Note: The figure represents the estimated coefficient of β_2 from Equation 3.4 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.12: Stock returns' response to US climate legislation with no emissions lag (Emissions Intensity)



Note: The figure represents the estimated coefficient of β_2 from Equation 3.4 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Table 3.6: Responses of stock returns to Climate laws with no emissions publication lag (Emissions Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	-3.289***	-3.266***	-3.270***	-3.277***	-3.272***	-3.271***	-3.229***	-3.219***	-3.241***	-3.243***	-3.287***	-3.289***	-3.298***
	(0.845)	(0.848)	(0.848)	(0.849)	(0.849)	(0.849)	(0.851)	(0.851)	(0.851)	(0.851)	(0.848)	(0.845)	(0.847)
Law Event × Emissions	-0.105												
	(0.230)												
1M Dummy × Emissions		-0.323**											
		(0.154)											
2M Dummy × Emissions			-0.182										
			(0.131)										
3M Dummy × Emissions				-0.096									
				(0.138)									
4M Dummy × Emissions					-0.101								
					(0.119)								
5M Dummy × Emissions						-0.094							
						(0.127)							
6M Dummy × Emissions							-0.244*						
							(0.131)						
7M Dummy × Emissions								-0.261**					
								(0.121)					
8M Dummy × Emissions									-0.170				
									(0.120)				
9M Dummy × Emissions										-0.154			
										(0.119)			
10M Dummy × Emissions											-0.018		
											(0.114)		
11M Dummy × Emissions												-0.011	
												(0.130)	
12M Dummy × Emissions													0.011
													(0.133)
Size	3.854***	3.837***	3.839***	3.844***	3.841***	3.839***	3.806***	3.798***	3.816***	3.818***	3.852***	3.854***	3.860***
	(0.287)	(0.287)	(0.287)	(0.289)	(0.288)	(0.288)	(0.287)	(0.286)	(0.287)	(0.288)	(0.289)	(0.287)	(0.288)
TobinQ	-1.996***	-2.001***	-2.000***	-1.999***	-2.000***	-2.000***	-2.011***	-2.016***	-2.010***	-2.011***	-1.997***	-1.997***	-1.994***
	(0.361)	(0.362)	(0.361)	(0.361)	(0.362)	(0.362)	(0.363)	(0.363)	(0.363)	(0.362)	(0.361)	(0.361)	(0.361)
Debt	4.432***	4.414***	4.416***	4.421***	4.417***	4.414***	4.373***	4.363***	4.385***	4.385***	4.429***	4.431***	4.440***
	(1.196)	(1.193)	(1.194)	(1.194)	(1.194)	(1.195)	(1.191)	(1.190)	(1.193)	(1.193)	(1.199)	(1.201)	(1.201)
Book-to-market	2.102**	2.095**	2.094**	2.098**	2.096**	2.094**	2.070**	2.058*	2.071**	2.069**	2.099**	2.100**	2.106**
	(1.042)	(1.041)	(1.041)	(1.042)	(1.042)	(1.042)	(1.044)	(1.045)	(1.046)	(1.047)	(1.044)	(1.043)	(1.043)
PPE	5.152**	5.194**	5.182**	5.168**	5.174**	5.176**	5.241**	5.268**	5.236**	5.238**	5.156**	5.151**	5.137**
	(2.352)	(2.344)	(2.346)	(2.349)	(2.346)	(2.348)	(2.332)	(2.330)	(2.343)	(2.338)	(2.354)	(2.353)	(2.353)
R&D	27.866***	27.666***	27.738***	27.804***	27.795***	27.792***	27.601***	27.567***	27.677***	27.702***	27.884***	27.893***	27.916***
	(8.469)	(8.475)	(8.482)	(8.478)	(8.485)	(8.473)	(8.499)	(8.518)	(8.503)	(8.513)	(8.467)	(8.461)	(8.459)
Sales growth	-0.481	-0.468	-0.468	-0.472	-0.472	-0.473	-0.463	-0.466	-0.475	-0.479	-0.483	-0.483	-0.483
	(0.483)	(0.482)	(0.482)	(0.483)	(0.482)	(0.482)	(0.480)	(0.479)	(0.480)	(0.482)	(0.482)	(0.482)	(0.482)
Momentum	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.313	-0.309	-0.310	-0.311	-0.311	-0.311	-0.309	-0.310	-0.312	-0.313	-0.314	-0.314	-0.314
	(0.258)	(0.257)	(0.257)	(0.258)	(0.258)	(0.258)	(0.258)	(0.258)	(0.259)	(0.259)	(0.258)	(0.258)	(0.258)
ROE	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368	0.368
Observations	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.7: Responses of stock returns to Climate laws with no emissions publication lag (Emissions Intensity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	0.213	0.257	0.257	0.247	0.254	0.269	0.319	0.319	0.293	0.284	0.245	0.247	0.232
	(0.774)	(0.780)	(0.782)	(0.785)	(0.784)	(0.790)	(0.793)	(0.792)	(0.796)	(0.794)	(0.793)	(0.790)	(0.796)
Law Event × Emissions	-0.117												
	(0.308)												
1M Dummy × Emissions		-0.465*											
		(0.238)											
2M Dummy × Emissions			-0.305										
			(0.196)										
3M Dummy × Emissions				-0.185									
				(0.208)									
4M Dummy × Emissions					-0.180								
					(0.172)								
5M Dummy × Emissions						-0.200							
						(0.187)							
6M Dummy × Emissions							-0.325*						
							(0.194)						
7M Dummy × Emissions								-0.298*					
								(0.176)					
8M Dummy × Emissions									-0.210				
									(0.176)				
9M Dummy × Emissions										-0.173			
										(0.182)			
10M Dummy × Emissions											-0.081		
											(0.166)		
11M Dummy × Emissions												-0.078	
												(0.179)	
12M Dummy × Emissions													-0.046
													(0.188)
Size	3.334***	3.321***	3.321***	3.323***	3.322***	3.317***	3.302***	3.302***	3.310***	3.313***	3.325***	3.325***	3.329***
	(0.278)	(0.277)	(0.277)	(0.277)	(0.277)	(0.276)	(0.275)	(0.275)	(0.275)	(0.276)	(0.276)	(0.277)	(0.278)
Tobin Q	-1.764***	-1.774***	-1.775***	-1.772***	-1.773***	-1.776***	-1.787***	-1.787***	-1.781***	-1.779***	-1.771***	-1.771***	-1.768***
	(0.374)	(0.374)	(0.374)	(0.375)	(0.375)	(0.375)	(0.376)	(0.376)	(0.376)	(0.375)	(0.374)	(0.374)	(0.374)
Debt	3.604***	3.581***	3.578***	3.582***	3.577***	3.567***	3.534***	3.534***	3.552***	3.556***	3.581***	3.580***	3.590***
	(1.264)	(1.258)	(1.258)	(1.259)	(1.258)	(1.257)	(1.251)	(1.252)	(1.255)	(1.257)	(1.263)	(1.266)	(1.268)
Book-to-market	1.875*	1.852*	1.848*	1.856*	1.852*	1.842*	1.807	1.803	1.821*	1.826*	1.851*	1.851*	1.862*
	(1.093)	(1.092)	(1.093)	(1.093)	(1.094)	(1.094)	(1.098)	(1.100)	(1.101)	(1.102)	(1.097)	(1.096)	(1.097)
PPE	2.389	2.386	2.381	2.378	2.377	2.372	2.364	2.373	2.381	2.385	2.387	2.384	2.384
	(2.732)	(2.725)	(2.723)	(2.723)	(2.722)	(2.719)	(2.713)	(2.715)	(2.720)	(2.723)	(2.728)	(2.728)	(2.730)
R&D	27.890***	27.712***	27.749***	27.799***	27.799***	27.771***	27.673***	27.678***	27.734***	27.769***	27.853***	27.861***	27.887***
	(7.252)	(7.228)	(7.241)	(7.243)	(7.245)	(7.238)	(7.224)	(7.231)	(7.242)	(7.251)	(7.253)	(7.255)	(7.261)
Sales growth	-0.322	-0.318	-0.315	-0.315	-0.316	-0.316	-0.316	-0.319	-0.321	-0.322	-0.323	-0.323	-0.322
	(0.498)	(0.499)	(0.498)	(0.497)	(0.497)	(0.498)	(0.498)	(0.498)	(0.498)	(0.499)	(0.498)	(0.498)	(0.498)
Momentum	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.321	-0.322	-0.322	-0.321	-0.323	-0.324	-0.329	-0.330	-0.328	-0.328	-0.324	-0.324	-0.323
	(0.267)	(0.266)	(0.266)	(0.267)	(0.267)	(0.267)	(0.268)	(0.269)	(0.269)	(0.269)	(0.268)	(0.269)	(0.268)
ROE	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.365	0.366	0.365	0.365	0.365	0.365	0.366	0.366	0.365	0.365	0.365	0.365	0.365
Observations	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727	17727

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.8: Responses of stock returns to Climate laws - High period of Climate Awareness (Emissions Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	-2.196**	-2.188**	-2.218**	-2.251***	-2.233**	-2.233**	-2.217**	-2.211**	-2.233**	-2.233**	-2.244**	-2.228**	-2.217**
	(0.865)	(0.866)	(0.867)	(0.865)	(0.865)	(0.864)	(0.866)	(0.867)	(0.867)	(0.867)	(0.867)	(0.866)	(0.865)
High Concerns - Law Event × Emissions	-0.224												
	(0.578)												
High Concerns - 1M Dummy × Emissions		0.100											
		(0.348)											
High Concerns - 2M Dummy × Emissions			-0.651*										
			(0.333)										
High Concerns - 3M Dummy × Emissions				-1.036***									
				(0.394)									
High Concerns - 4M Dummy × Emissions					-0.779**								
					(0.390)								
High Concerns - 5M Dummy × Emissions						-0.650*							
						(0.342)							
High Concerns - 6M Dummy × Emissions							-0.648**						
							(0.313)						
High Concerns - 7M Dummy × Emissions								-0.537*					
								(0.279)					
High Concerns - 8M Dummy × Emissions									-0.712**				
									(0.296)				
High Concerns - 9M Dummy × Emissions										-0.684**			
										(0.287)			
High Concerns - 10M Dummy × Emissions											-0.735***		
											(0.276)		
High Concerns - 11M Dummy × Emissions												-0.620**	
												(0.277)	
High Concerns - 12M Dummy × Emissions													-0.432
													(0.289)
Size	4.099***	4.087***	4.114***	4.157***	4.122***	4.131***	4.085***	4.078***	4.106***	4.104***	4.114***	4.096***	4.106***
	(0.352)	(0.351)	(0.354)	(0.355)	(0.352)	(0.354)	(0.351)	(0.352)	(0.354)	(0.354)	(0.356)	(0.356)	(0.356)
TobinQ	-1.732***	-1.732***	-1.732***	-1.730***	-1.738***	-1.731***	-1.742***	-1.744***	-1.736***	-1.735***	-1.730***	-1.737***	-1.733***
	(0.409)	(0.409)	(0.409)	(0.410)	(0.411)	(0.409)	(0.411)	(0.411)	(0.409)	(0.409)	(0.409)	(0.408)	(0.409)
Debt	4.021***	4.006***	4.025***	4.076***	4.021***	4.052***	3.966***	3.965***	4.001***	3.998***	4.013***	3.992***	4.018***
	(1.385)	(1.383)	(1.391)	(1.402)	(1.393)	(1.398)	(1.385)	(1.386)	(1.394)	(1.392)	(1.395)	(1.393)	(1.395)
Book-to-market	3.103**	3.102**	3.101**	3.099**	3.091**	3.107**	3.077**	3.069**	3.092**	3.096**	3.115**	3.095**	3.105**
	(1.407)	(1.406)	(1.408)	(1.409)	(1.410)	(1.407)	(1.409)	(1.410)	(1.409)	(1.411)	(1.408)	(1.407)	(1.408)
PPE	3.689	3.703	3.691	3.650	3.710	3.661	3.766	3.770	3.699	3.697	3.658	3.707	3.660
	(2.963)	(2.967)	(2.970)	(2.970)	(2.968)	(2.960)	(2.977)	(2.973)	(2.960)	(2.950)	(2.940)	(2.938)	(2.934)
R&D	22.914**	22.866**	22.920**	23.079**	22.946**	22.978**	22.734**	22.724**	22.830**	22.831**	22.874**	22.816**	22.899**
	(8.983)	(9.007)	(8.978)	(8.915)	(8.980)	(8.946)	(9.029)	(9.030)	(8.978)	(8.985)	(8.961)	(9.013)	(8.997)
Sales growth	-0.710	-0.703	-0.722	-0.744	-0.730	-0.727	-0.731	-0.731	-0.723	-0.718	-0.708	-0.718	-0.709
	(0.565)	(0.564)	(0.564)	(0.564)	(0.563)	(0.564)	(0.562)	(0.563)	(0.565)	(0.565)	(0.566)	(0.566)	(0.566)
Momentum	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Investment	-0.451*	-0.450*	-0.452*	-0.456*	-0.454*	-0.454*	-0.454*	-0.454*	-0.454*	-0.453*	-0.451*	-0.452*	-0.449*
	(0.266)	(0.265)	(0.265)	(0.265)	(0.265)	(0.265)	(0.265)	(0.265)	(0.264)	(0.264)	(0.263)	(0.264)	(0.264)
ROE	0.008*	0.008*	0.008*	0.008*	0.009*	0.009*	0.008*	0.008*	0.009*	0.009*	0.009*	0.009*	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355	0.355
Observations	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.9: Responses of stock returns to Climate laws - High period of Climate Awareness (Emissions Intensity)

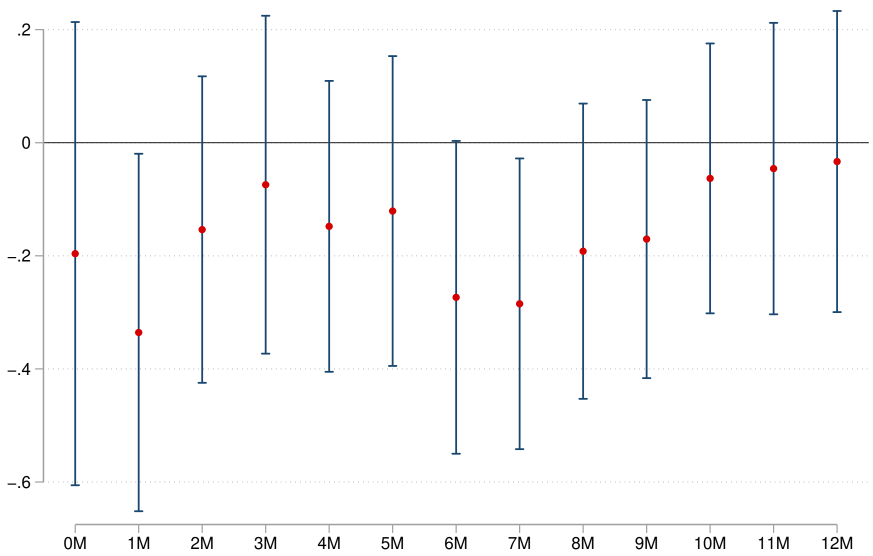
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	1.493**	1.500**	1.451**	1.403**	1.431**	1.433**	1.470**	1.468**	1.429**	1.428**	1.431**	1.449**	1.432**
	(0.700)	(0.702)	(0.702)	(0.702)	(0.700)	(0.702)	(0.701)	(0.703)	(0.709)	(0.705)	(0.708)	(0.704)	(0.709)
High Concerns - Law Event × Emissions	0.159												
	(0.692)												
High Concerns - 1M Dummy × Emissions		0.149											
		(0.484)											
High Concerns - 2M Dummy × Emissions			-0.757*										
			(0.449)										
High Concerns - 3M Dummy × Emissions				-1.142**									
				(0.508)									
High Concerns - 4M Dummy × Emissions					-0.884*								
					(0.533)								
High Concerns - 5M Dummy × Emissions						-0.650							
						(0.462)							
High Concerns - 6M Dummy × Emissions							-0.519						
							(0.427)						
High Concerns - 7M Dummy × Emissions								-0.440					
								(0.357)					
High Concerns - 8M Dummy × Emissions									-0.631				
									(0.386)				
High Concerns - 9M Dummy × Emissions										-0.608			
										(0.378)			
High Concerns - 10M Dummy × Emissions											-0.567		
											(0.357)		
High Concerns - 11M Dummy × Emissions												-0.474	
												(0.361)	
High Concerns - 12M Dummy × Emissions													-0.498
													(0.368)
Size	3.897***	3.892***	3.909***	3.929***	3.914***	3.915***	3.893***	3.896***	3.912***	3.912***	3.910***	3.903***	3.914***
	(0.341)	(0.340)	(0.341)	(0.340)	(0.340)	(0.340)	(0.339)	(0.340)	(0.340)	(0.342)	(0.341)	(0.342)	(0.343)
TobinQ	-1.560***	-1.562***	-1.552***	-1.544***	-1.554***	-1.551***	-1.562***	-1.560***	-1.551***	-1.551***	-1.551***	-1.556***	-1.553***
	(0.421)	(0.420)	(0.421)	(0.421)	(0.422)	(0.420)	(0.420)	(0.420)	(0.420)	(0.420)	(0.419)	(0.419)	(0.419)
Debt	3.189**	3.178**	3.222**	3.272**	3.234**	3.238**	3.183**	3.189**	3.218**	3.217**	3.212**	3.199**	3.218**
	(1.390)	(1.391)	(1.398)	(1.404)	(1.400)	(1.400)	(1.395)	(1.397)	(1.403)	(1.402)	(1.401)	(1.400)	(1.401)
Book-to-market	3.091**	3.086**	3.107**	3.126**	3.106**	3.118**	3.081**	3.085**	3.124**	3.128**	3.129**	3.109**	3.128**
	(1.419)	(1.419)	(1.420)	(1.419)	(1.420)	(1.419)	(1.422)	(1.424)	(1.425)	(1.429)	(1.422)	(1.421)	(1.420)
PPE	1.259	1.257	1.284	1.309	1.306	1.290	1.298	1.292	1.282	1.277	1.274	1.277	1.260
	(3.266)	(3.267)	(3.253)	(3.239)	(3.248)	(3.242)	(3.267)	(3.259)	(3.231)	(3.226)	(3.228)	(3.240)	(3.225)
R&D	25.138***	25.115***	25.209***	25.332***	25.282***	25.250***	25.146***	25.147***	25.206***	25.207***	25.195***	25.179***	25.199***
	(8.054)	(8.062)	(8.059)	(8.051)	(8.059)	(8.055)	(8.073)	(8.065)	(8.054)	(8.053)	(8.051)	(8.065)	(8.054)
Sales growth	-0.731	-0.731	-0.735	-0.738	-0.739	-0.734	-0.744	-0.741	-0.727	-0.724	-0.724	-0.733	-0.728
	(0.615)	(0.615)	(0.615)	(0.614)	(0.615)	(0.617)	(0.616)	(0.617)	(0.619)	(0.619)	(0.621)	(0.620)	(0.620)
Momentum	-0.008*	-0.008*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Investment	-0.447	-0.448	-0.443	-0.437	-0.443	-0.441	-0.450	-0.449	-0.441	-0.440	-0.440	-0.444	-0.438
	(0.275)	(0.276)	(0.275)	(0.274)	(0.274)	(0.274)	(0.276)	(0.276)	(0.274)	(0.273)	(0.272)	(0.273)	(0.272)
ROE	0.007	0.007	0.007	0.008	0.008	0.008	0.007	0.007	0.008	0.008	0.008	0.008	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354	0.354
Observations	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105	14105

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

3.7.4 Robustness check

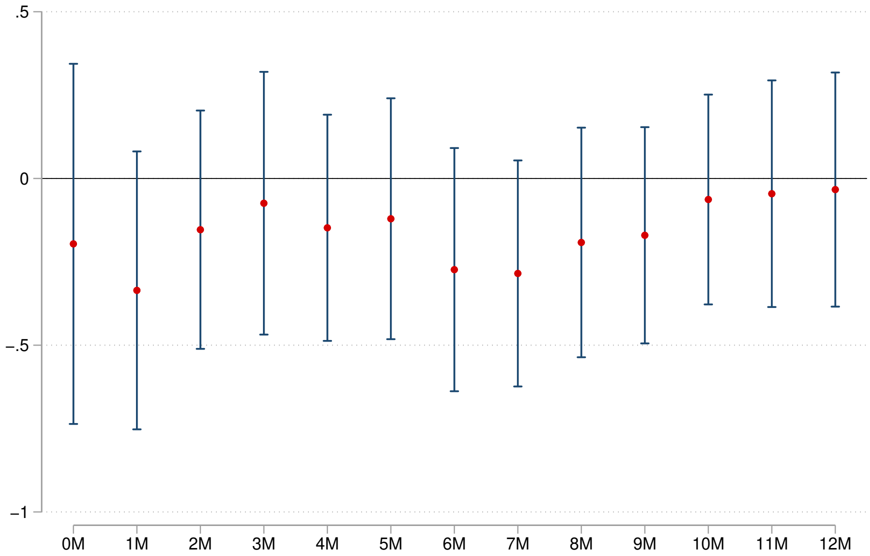
We consider emissions level (intensity) in Figure 3.13 and Figure 3.14 (Figure 3.15 and Figure 3.16) corresponding to estimation results from our baseline equation in subsection 3.4.2 in Section 3.4. More specifically, we graphically represent the estimated coefficient β_2 with both 95% and 99% confidence intervals. The estimation results when we remove the winsorization of our carbon emissions indicators (both in level and intensity) at 2.5% can be found in Table 3.10 and Table 3.11.

Figure 3.13: 95% Confidence interval (Emissions Level)



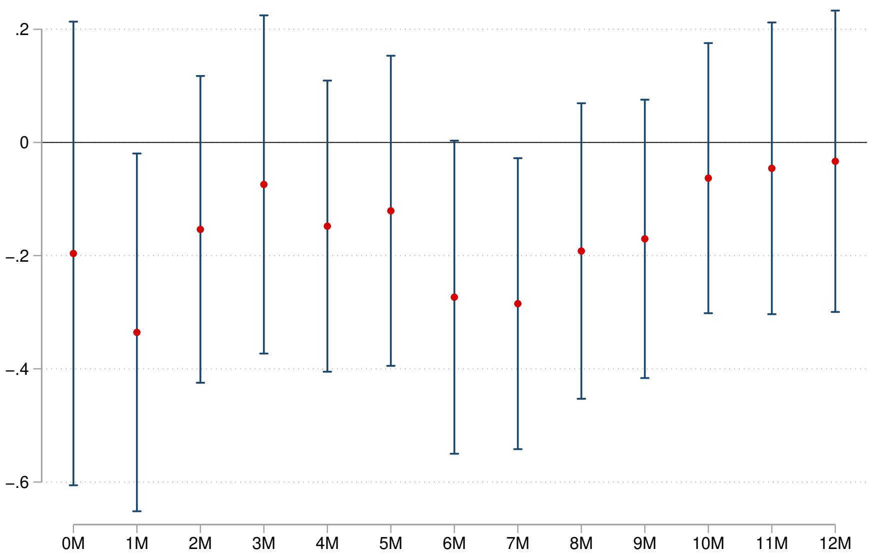
Note: The figure represents the estimated coefficient of β_2 with a 95% confidence interval from Equation 3.3 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.14: 99% Confidence interval (Emissions Level)



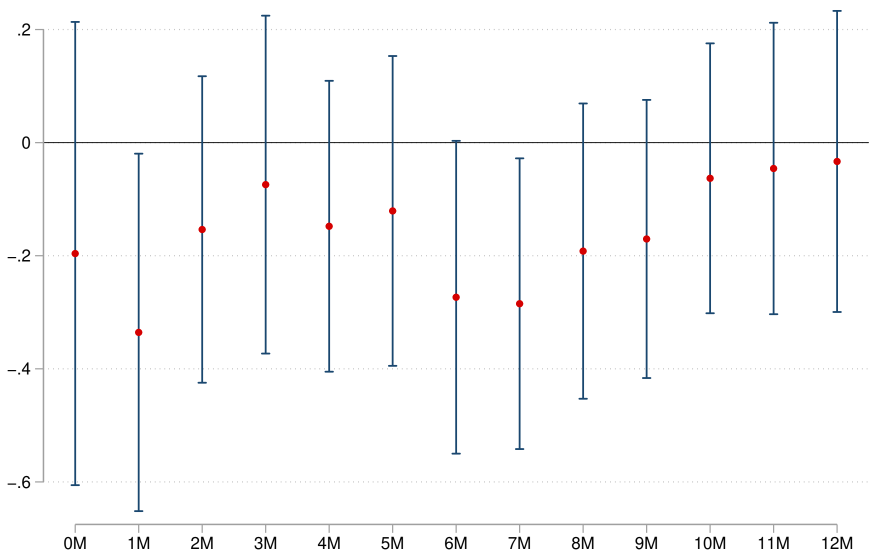
Note: The figure represents the estimated coefficient of β_2 with a 99% confidence interval from Equation 3.3 when considering emissions level. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.15: 95% Confidence interval (Emissions Intensity)



Note: The figure represents the estimated coefficient of β_2 with a 95% confidence interval from Equation 3.3 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Figure 3.16: 99% Confidence interval (Emissions Intensity)



Note: The figure represents the estimated coefficient of β_2 with a 99% confidence interval from Equation 3.3 when considering emissions intensity. Note that each point in the figure represents the estimated coefficient corresponding to different specifications distinguished by the value of the considered climate law indicator on the x-axis.

Table 3.10: Responses of stock returns to Climate laws with winsorization at 2.5% (Emissions Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	-2.834***	-2.821***	-2.827***	-2.832***	-2.819***	-2.820***	-2.788***	-2.780***	-2.797***	-2.798***	-2.823***	-2.825***	-2.827***
	(0.828)	(0.829)	(0.829)	(0.830)	(0.830)	(0.831)	(0.831)	(0.832)	(0.833)	(0.833)	(0.832)	(0.831)	(0.832)
Law Event × Emissions	-0.204												
	(0.207)												
1M Dummy × Emissions		-0.329**											
		(0.161)											
2M Dummy × Emissions			-0.152										
			(0.138)										
3M Dummy × Emissions				-0.070									
				(0.150)									
4M Dummy × Emissions					-0.146								
					(0.128)								
5M Dummy × Emissions						-0.119							
						(0.137)							
6M Dummy × Emissions							-0.270*						
							(0.140)						
7M Dummy × Emissions								-0.281**					
								(0.129)					
8M Dummy × Emissions									-0.186				
									(0.129)				
9M Dummy × Emissions										-0.170			
										(0.124)			
10M Dummy × Emissions											-0.064		
											(0.119)		
11M Dummy × Emissions												-0.052	
												(0.128)	
12M Dummy × Emissions													-0.039
													(0.132)
Size	3.745***	3.730***	3.735***	3.741***	3.727***	3.728***	3.692***	3.685***	3.704***	3.706***	3.734***	3.736***	3.739***
	(0.276)	(0.276)	(0.276)	(0.277)	(0.276)	(0.278)	(0.276)	(0.277)	(0.279)	(0.280)	(0.281)	(0.280)	(0.280)
Tobin Q	-1.774***	-1.777***	-1.777***	-1.775***	-1.778***	-1.779***	-1.789***	-1.794***	-1.789***	-1.790***	-1.780***	-1.779***	-1.778***
	(0.364)	(0.364)	(0.364)	(0.364)	(0.365)	(0.364)	(0.365)	(0.365)	(0.365)	(0.364)	(0.364)	(0.363)	(0.363)
Debt	3.965***	3.939***	3.953***	3.964***	3.939***	3.942***	3.886***	3.878***	3.910***	3.912***	3.953***	3.956***	3.961***
	(1.259)	(1.256)	(1.258)	(1.261)	(1.258)	(1.260)	(1.255)	(1.254)	(1.259)	(1.257)	(1.262)	(1.264)	(1.263)
Book-to-market	2.220**	2.215**	2.214**	2.217**	2.212**	2.210**	2.188*	2.175*	2.186*	2.184*	2.203*	2.205*	2.208*
	(1.121)	(1.120)	(1.120)	(1.121)	(1.121)	(1.121)	(1.123)	(1.124)	(1.124)	(1.125)	(1.123)	(1.122)	(1.123)
PPE	3.819	3.842	3.833	3.823	3.841	3.838	3.883	3.901	3.880	3.882	3.839	3.834	3.827
	(2.698)	(2.694)	(2.697)	(2.700)	(2.694)	(2.696)	(2.689)	(2.690)	(2.699)	(2.696)	(2.701)	(2.697)	(2.697)
R&D	27.399***	27.262***	27.361***	27.420***	27.335***	27.349***	27.168***	27.149***	27.263***	27.294***	27.424***	27.439***	27.451***
	(7.868)	(7.884)	(7.882)	(7.874)	(7.897)	(7.887)	(7.926)	(7.945)	(7.922)	(7.927)	(7.882)	(7.880)	(7.876)
Sales growth	-0.316	-0.305	-0.309	-0.313	-0.306	-0.309	-0.300	-0.304	-0.313	-0.317	-0.320	-0.320	-0.320
	(0.537)	(0.536)	(0.536)	(0.537)	(0.535)	(0.536)	(0.533)	(0.532)	(0.534)	(0.535)	(0.536)	(0.536)	(0.536)
Momentum	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.350	-0.348	-0.350	-0.350	-0.349	-0.350	-0.348	-0.349	-0.350	-0.351	-0.352	-0.352	-0.352
	(0.266)	(0.265)	(0.265)	(0.266)	(0.266)	(0.266)	(0.266)	(0.267)	(0.267)	(0.268)	(0.267)	(0.267)	(0.267)
ROE	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364
Observations	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.11: Responses of stock returns to Climate laws with winsorization at 2.5% (Emissions Intensity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Emissions	0.748	0.777	0.769	0.759	0.776	0.788	0.828	0.830	0.812	0.812	0.795	0.796	0.794
	(0.739)	(0.742)	(0.744)	(0.746)	(0.743)	(0.747)	(0.749)	(0.750)	(0.753)	(0.750)	(0.751)	(0.750)	(0.753)
Law Event × Emissions	-0.217												
	(0.289)												
1M Dummy × Emissions		-0.445*											
		(0.242)											
2M Dummy × Emissions			-0.247										
			(0.198)										
3M Dummy × Emissions				-0.128									
				(0.216)									
4M Dummy × Emissions					-0.183								
					(0.181)								
5M Dummy × Emissions						-0.203							
						(0.195)							
6M Dummy × Emissions							-0.329						
							(0.203)						
7M Dummy × Emissions								-0.306					
								(0.186)					
8M Dummy × Emissions									-0.229				
									(0.185)				
9M Dummy × Emissions										-0.212			
										(0.189)			
10M Dummy × Emissions											-0.151		
											(0.173)		
11M Dummy × Emissions												-0.140	
												(0.181)	
12M Dummy × Emissions													-0.119
													(0.190)
Size	3.366***	3.354***	3.356***	3.361***	3.354***	3.349***	3.332***	3.332***	3.340***	3.340***	3.348***	3.348***	3.350***
	(0.285)	(0.284)	(0.285)	(0.284)	(0.284)	(0.284)	(0.282)	(0.282)	(0.283)	(0.284)	(0.284)	(0.284)	(0.284)
Tobin Q	-1.575***	-1.583***	-1.583***	-1.580***	-1.584***	-1.587***	-1.598***	-1.599***	-1.594***	-1.594***	-1.590***	-1.590***	-1.589***
	(0.375)	(0.375)	(0.375)	(0.375)	(0.376)	(0.375)	(0.376)	(0.376)	(0.376)	(0.376)	(0.376)	(0.375)	(0.376)
Debt	3.055**	3.026**	3.031**	3.042**	3.026**	3.015**	2.978**	2.980**	2.999**	2.999**	3.014**	3.014**	3.018**
	(1.314)	(1.307)	(1.310)	(1.313)	(1.309)	(1.308)	(1.302)	(1.303)	(1.307)	(1.307)	(1.310)	(1.313)	(1.314)
Book-to-market	2.002*	1.987*	1.985*	1.993*	1.983*	1.972*	1.939	1.933	1.946	1.944	1.955	1.955*	1.960*
	(1.180)	(1.178)	(1.178)	(1.179)	(1.180)	(1.179)	(1.182)	(1.183)	(1.185)	(1.188)	(1.184)	(1.183)	(1.184)
PPE	1.448	1.436	1.437	1.440	1.432	1.425	1.409	1.417	1.427	1.430	1.433	1.430	1.426
	(3.039)	(3.033)	(3.031)	(3.031)	(3.030)	(3.026)	(3.025)	(3.028)	(3.030)	(3.034)	(3.035)	(3.035)	(3.035)
R&D	27.240***	27.124***	27.173***	27.216***	27.179***	27.153***	27.072***	27.084***	27.134***	27.159***	27.213***	27.225***	27.239***
	(6.886)	(6.873)	(6.885)	(6.887)	(6.886)	(6.883)	(6.873)	(6.879)	(6.888)	(6.892)	(6.888)	(6.890)	(6.892)
Sales growth	-0.102	-0.097	-0.097	-0.098	-0.098	-0.099	-0.101	-0.103	-0.106	-0.107	-0.108	-0.107	-0.106
	(0.605)	(0.604)	(0.604)	(0.604)	(0.604)	(0.603)	(0.602)	(0.603)	(0.604)	(0.605)	(0.606)	(0.606)	(0.606)
Momentum	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Investment	-0.362	-0.364	-0.364	-0.363	-0.365	-0.366	-0.372	-0.372	-0.370	-0.370	-0.369	-0.369	-0.368
	(0.268)	(0.268)	(0.269)	(0.269)	(0.269)	(0.269)	(0.270)	(0.271)	(0.272)	(0.271)	(0.271)	(0.271)	(0.271)
ROE	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firms FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362	0.362
Observations	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079	17079

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Conclusion Générale

Conclusion Générale

L'urgence climatique est aujourd'hui une réalité tangible à prendre en compte afin de maintenir un écosystème pérenne et sécurisé (IPCC, 2018, 2022). Face aux effets délétères et persistants du réchauffement climatique, largement attribuables aux activités humaines, une refonte profonde de nos systèmes économiques est impérative pour réduire notre empreinte sur la planète et éviter des bouleversements drastiques et irréversibles mettant en péril tant la biodiversité que l'humanité. Cette transformation vise principalement à réduire de façon draconienne les émissions de GES - la principale source du réchauffement climatique - et à engager une transition rapide vers une économie à faible émission de carbone.

Dans ce contexte, le système financier apparaît alors comme un protaganiste clé dans l'atténuation et l'adaptation des sociétés face au changement climatique. En effet, en allouant du capital aux différents agents économiques, ce dernier est en mesure d'orienter les flux de capitaux vers des projets durables compatibles avec l'objectif de contenir le réchauffement climatique à 1,5°C par rapport à l'époque préindustrielle. Toutefois, en dépit de son rôle actif dans le financement de cette transition, le secteur financier est lui même confronté aux risques émanant du changement climatique. D'une part, le risque phyisque est celui qui émane directement des conséquences palpables du changement climatique, comme des catastophes naturelles plus fréquentes et plus fortes (Pachauri et al., 2014; Masson-Delmotte et al., 2022). La fréquence des températures extrêmes et précipitations, et la montée du niveau de la mer sont susceptibles d'affecter sérieusement la croissance économique et la valeur des actifs financiers (Noy, 2009; Gourio, 2012; Dafermos et al., 2018). D'autre part, le risque de transition représente un double défi pour le secteur financier car il ne résulte pas des effets physiques liés au changement climatique, mais des stratégies d'atténuation et d'adapation pour en limiter les effets. D'une manière générale, ce dernier se réfère au coût de l'ajustement vers une économie bas carbone. Il se manifeste principalement par une modification des prévisions des flux de trésorerie futurs des entreprises à la suite de l'instauration de politiques ou régulations environnementales, d'innovations technologiques, de l'évolution de la préférence des agents économiques en faveur de produits moins intensifs en carbone. La modification de la valorisation des actifs financiers, résultant de ces facteurs de risque associés à la décarbonisation de l'économie, constitue un risque de marché qui peut affecter la stabilité financière (Carney, 2015*a*).

La matérialisation de ces deux risques extra-financiers, notamment à travers leurs effets en cascade, représente une source potentielle de risque systémique pouvant mener à une crise financière semblable à celle de 2007 (Battiston et al., 2017). Cette dernière a été un important rappel des lourdes conséquences qu'une gouvernance d'entreprise inappropriée et des pratiques de gestion des risques insuffisantes peuvent avoir sur la valeur des actifs. Il devient alors crucial d'analyser comment les marchés financiers intègrent les risques climatiques pour formuler des recommandations en faveur d'une communication financière claire et adaptée. Cela permettrait aux acteurs du marché de mesurer adéquatement le risque climatique dans leurs opérations et choix d'investissement. Toutefois, bien que les risques physiques soient indéniablement un enjeu majeur pour les marchés financiers (Gourio, 2012; Dafermos et al., 2018), son impact sur le système financier se manifeste sur un horizon temporel bien plus long que le risque transition (Stroebel et Wurgler, 2021). De surcroît, ce dernier est plus susceptible d'impacter les portefeuilles d'investissement à moyen terme, en particulier dans la perspective du renforcement des politiques de transition (Eskander et Fankhauser, 2020; Fankhauser et al., 2022). C'est la raison pour laquelle cette thèse se focalise sur l'analyse de l'intégration du risque de transition par les marchés financiers.

L'analyse de l'impact et de l'intégration du risque de transition dans les stratégies d'investissement des acteurs financiers est un sujet qui a récemment émergé dans la littérature spécialisée en "Finance climatique[20]". Cependant, le volume d'études empiriques demeurant restreint, le risque de transition a fait l'objet d'une sous-estimation, voire d'une négligence, entraînant un manque de stratégies politiques adéquates pour une gestion appropriée (Giglio et al., 2021).

Cette thèse contribue donc à cette littérature en se penchant sur l'impact du risque de transition sur les rentabilités boursières. Elle est constituée de trois chapitres s'articulant autour de la problématique générale suivante : est-ce que les marchés encouragent ou entravent la transition vers une économie à faibles émissions de carbone ? Dans cette perspective, si les marchés financiers n'évaluent pas correctement ce risque, ils freinent la transition en retardant le réaffectation des investissements et en augmentant les coûts politiques et financiers de cette transition. Cependant, si prendre part à la transition écologique peut s'avérer financièrement profitable, cela peut ainsi encourager la transition en harmonisant les objectifs climatiques à long terme avec les tendances et préférences du marché à court terme.

Les chapitres de cette thèse ambitionnent donc de fournir une analyse approfondie de la relation empirique entre le risque de transition et les prix des actions afin de fournir des indications

[20]Cette littérature s'attache à évaluer l'intégration des risques climatiques dans la valorisation des prix des actifs par les marchés financiers.

concrètes sur la manière d'utiliser les marchés financiers pour couvrir ce risque. Cette compréhension est cruciale pour évaluer les risques et opportunités liés aux politiques environnementales, qui influençent les décisions d'investissement et la valorisation des actifs. Indépendamment des aspects éthiques liés à la transition écologique, l'objectif principal de cette thèse est d'établir un fondement scientifique à l'hypothèse selon laquelle participer à la transition écologique et énergétique est financièrement rentable et d'expliciter les conditions dans lesquelles cette hypothèse est vérifiée.

Le premier chapitre de cette thèse évalue l'impact du risque de transition sur la rentabilité des entreprises participant à l'EU ETS. La question centrale que nous cherchons à élucider est de savoir si, au sein d'un système d'échange de quotas d'émission, les entreprises aux faibles émissions de carbone vérifiées engendrent des rendements supérieurs par rapport à leurs homologues à fortes émissions. Dans ce chapitre, nous utilisons une nouvelle métrique pour quantifier l'exposition des entreprises au risque de transition, les émissions de carbone vérifiées. En utilisant dans un premier temps un modèle de régression en panel, nos résultats suggèrent sur la période 2006-2021, et en prenant en compte divers prédicteurs de rentabilité communément idenfiés dans la littérature, que les entreprises ayant des niveaux d'émissions vérifiées élevés enregistrent des rendements inférieurs, soulignant la superformance des entreprises vertes. Par la suite, après avoir constitué un portefeuille "brun moins vert" (BMV) à partir des émissions vérifiées des entreprises et analysé son rendement ajusté au risque en utilisant des modèles multifactoriels (Fama et French, 1993*b*, 1995). Notre analyse confirme la surperformance des entreprises vertes, avec un rendement annuel excédentaire entre 6,6% et 7,9% selon les différentes variantes considérées.

Ensuite, conscient du rôle pivot des banques centrales dans la transition vers une économie sobre en carbone, le chapitre 2 propose une évaluation de l'empreinte environnementale de la politique monétaire des États-Unis vis-à-vis du risque de transition. Plus précisément, il propose dans un premier temps un cadre théorique permettant de mesurer l'impact de la politique monétaire américaine sur la rentabilité des entreprises en fonction de leurs niveaux d'émissions de CO_2. Ce modèle aboutit à deux hypothèses où (i) les actions "brunes" sont plus réactives aux surprises des taux de politique monétaire (PM), et (ii) cette plus grande réactivité résulte d'un mélange de facteurs d'offre liés aux fondamentaux et de facteurs de demande liés aux préférences des investisseurs.

Nous testons ces hypothèses en estimant l'hétérogénéité de la réaction des prix des actions des entreprises américaines avec différents niveaux d'intensité d'émissions de CO_2 aux changements inattendus des taux de la Réserve Fédérale entre 2010 et 2019. Dans un premier temps, nos résultats montrent que les entreprises à forte intensité carbone sont significativement plus affectées par les surprises de PM. Par le suite, même en contrôlant par les sources classiques d'hétérogénéité de la PM, la surréaction des entreprises “brunes” reste significative, persistante dans le temps, et s'intensifie en période de fortes préoccupations liées au changement climatique.

Toutefois, la principale conclusion de non-neutralité de la politique monétaire américaine, favorisant les entreprises polluantes, mène au troisième chapitre. Celui-ci, portant sur les Etats-Unis également, explore la manière dont le risque de transition est pris en compte dans la valorisation du marché et comment la réglementation climatique peut influer sur cette intégration. Dans ce chapitre, nous cherchons principalement à savoir si le marché boursier américain intègre le risque de transition dans ses prix. De plus, nous cherchons également à évaluer l'effet des émissions de carbone sur les rendements boursiers lorsqu'une loi climatique est promulguée. L'impact combiné de ces variables nous permet de déterminer si le marché ajuste le prix du risque de transition en réponse aux initiatives américaines visant à réduire les émissions de carbone.

Empiriquement, nous examinons l'effet de la législation climatique américaine sur la relation entre les émissions de carbone des entreprises du S&P 500 et leurs rendements boursiers entre 2010 et 2019. Contrairement à la méthodologie d'études d'événement communément utilisée dans la littérature, qui capture essentiellement les réactions immédiates du marché dans de courtes périodes entourant un événement, nous adoptons dans ce chapitre une approche plus globale. Dans un modèle Two-Way Fixed Effects (TWFE), nous introduisons un indicateur de lois climatiques constuit à partir d'une base de données recensant les lois climatiques. Ce dernier est une variable indicatrice prenant la valeur de un pour la durée spécifique pendant laquelle nous cherchons à observer l'impact[21]. Cette stratégie d'identification nous permet d'examiner à la fois les effets immédiats et prolongés sur les prix des actions. Le but n'est pas seulement de mesurer les répercussions immédiates d'une loi climatique spécifique, mais de comprendre les implications plus larges et soutenues de la réglementation américaine sur le risque de transition et son évaluation par le marché et ceci sur une période prolongée.

Nos résultats initiaux révèlent une prime apparente liée aux ajustements de prix avant la mise en oeuvre de la législation climatique, suggérant que les entreprises vertes pourraient surpasser celles moins respectueuses de l'environnement lorsque les préoccupations climatiques augmentent. Avec l'introduction de la législation climatique, il semble que les investisseurs adoptent une approche attentiste, mais aussi qu'ils pénalisent les entreprises avec des empreintes carbone plus importantes. Les effets sont particulièrement visibles dans les mois suivant la mise en oeuvre de ces lois, mais moins lorsqu'on examine leur impact à long terme. De plus, des investigations supplémentaires suggèrent que pendant les périodes de forte sensibilisation au climat, l'impact négatif des émissions de carbone sur les rendements boursiers devient plus marqué deux mois après l'introduction

[21] Par exemple, si nous visons à examiner les effets un mois après la promulgation de la loi, la variable est définie par la valeur 1 pour ce mois. Nous étendons cette logique pour saisir les effets pour des durées allant jusqu'à 12 mois.

d'une loi climatique, se poursuivant pendant près d'un an. Cependant, 12 mois après la législation, cet effet diminue, ce qui indique que des impacts législatifs persistants pourraient nécessiter un renforcement continu.

En termes de recommandations politiques, les résultats du chapitre 1 indiquent que le système d'échange de quotas influence le profil risque-rendement des actions, offrant ainsi une motivation financière pour intégrer les émissions vérifiées dans les décisions d'investissement. Pour favoriser la transition écologique, les décideurs politiques pourraient alors généraliser les systèmes d'échange de quotas et les audits indépendants des émissions, et augmenter le coût des droits d'émission. Par la suite, le second chapitre de cette thèse suggère que le principe de neutralité du marché qui guide la mise en oeuvre de la PM pourrait induire un biais en faveur des entreprises brunes. En d'autres termes, cela indique qu'une banque centrale qui décide de baisser les taux d'intérêt subventionne indirectement les entreprises polluantes. Ce fait stylisé peut intéresser les banquiers centraux qui réfléchissent actuellement à leur rôle dans la promotion d'un système financier plus vert. Finalement, le dernier chapirre de cette thèse souligne que l'impact à long terme des lois américaines sur la corrélation entre émissions de carbone et rendements boursiers nécessite un renforcement pour assurer sa pérennité. Actuellement, les mesures législatives ont un effet plus marqué à moyen terme, mais leur durabilité reste incertaine. Pour encourager un changement environnemental durable, il est crucial que les marchés financiers valorisent de manière constante et progressive les pratiques d'entreprises respectueuses de l'environnement. Les décideurs doivent donc affiner et renforcer les réglementations existantes pour qu'elles ne se limitent pas à des solutions immédiates mais qu'elles établissent également des bases solides pour des ajustements de marché à long terme vers une économie à faibles émissions de carbone. Ces chapitres ont donc pour but de permettre une meilleure intégration du risque de transition dans l'évaluation des actions par les investisseurs qui habiliterait les autorités réglementaires et les acteurs du marché financier à élaborer des politiques plus adéquates et à instaurer des dispositifs préventifs face à ce risque.

Toutefois, compte tenu du développement récent de la littérature en Finance climatique, il est clair que les recherches menées dans cette thèse sont susceptibles de connaître de nombreuses extensions futures. Par exemple, le premier chapitre de cette thèse peut être complémenté par la méthode des doubles différences (*Differences-in-Differences*, en anglais). L'objectif est de réaliser une analyse comparative entre les entreprises participant à l'EU ETS et celles n'y participant pas. En effet, cela peut générer des différences significatives dans l'étude des rentabilités boursières de ces entreprises. De plus, plusieurs études empiriques se sont attachées à examiner le mécanisme sous-jacent par lequel les émissions de carbone influencent la rentabilité des entreprises, notamment à travers la variation du prix du carbone (Hengge et al., 2023; Millischer et al., 2023; Bolton et al., 2023). Il serait alors pertinent d'agrémenter cette littérature en utilisant les émissions vérifiées comme principale mesure d'exposition des entreprises au risque de transition. Enfin, une comparaison avec des systèmes similaires dans d'autres régions du monde offrirait une perspective internationale et permettrait de comprendre comment différents contextes réglementaires influencent les marchés boursiers. En effet, le rapport de l'International Carbon Action Partnership (ICAP) paru en 2022[22] souligne que les ETS sont bien adaptés pour réaliser l'ambition d'atteindre zéro émission nette d'ici le milieu du siècle, en fournissant des assurances sur les niveaux d'émissions et des signaux de marché à long terme nécessaires pour stimuler les investissements indispensables à la transition bas carbone[23]. A ce stade, il est également important de souligner que la question du changement climatique représente un enjeu clé de la future politique monétaire. Bien que J. Powell ait déclaré en janvier 2023 "*Nous ne sommes pas et ne serons pas un décideur en matière de politique climatique*", les banques centrales ne peuvent plus rester en marge de la lutte contre le réchauffement climatique (NGFS, 2022). En effet, elles sont confrontées à des défis spécifiques, comme l'impact du changement climatique sur la transmission de leurs mesures de politique monétaire, l'effet sur le taux d'intérêt réel d'équilibre et l'influence directe du changement climatique et de ses politiques d'atténuation sur la dynamique de l'inflation. Dans ce contexte, le chapitre 2 appelle à l'ouverture d'une voie politique possible pour les banques centrales qui chercheraient à neutraliser les effets différenciés de leurs annonces en fonction de l'intensité des émissions de CO_2, par le biais de la communication et/ou des achats d'actifs. Une extension naturelle serait donc d'examiner le coût potentiel en terme de crédibilité de telles actions pour les banques centrales, qui doivent équilibrer leur rôle traditionnel de maintien de la stabilité des prix avec les nouvelles exigences liées au changement climatique. Enfin, il serait pertinent pour le dernier chapitre d'explorer l'impact du clivage politique aux États-Unis sur l'intégration du risque de transition par le marché. Cette perspective permettrait d'examiner comment les changements de gouvernance et les politiques divergentes entre administrations démocrates et républicaines influencent la réaction du marché à la législation climatique. Par exemple, analyser les différences dans les réactions du marché boursier aux initiatives climatiques sous différentes présidences pourrait mettre en lumière le rôle de la politique dans la valorisation du risque climatique par les marchés financiers. A ce titre, les États dirigés par des républicains ou des démocrates peuvent appliquer différemment les directives fédérales sur le climat, influençant ainsi la manière dont les entreprises situées dans ces États intègrent le risque de transition. Cette dynamique interétatique pourrait avoir un impact

[22]Voir (Mehling, 2022).

[23]Ce rapport précise que les systèmes d'échange d'émissions continuent de gagner en importance, devenant un outil clé pour atteindre les objectifs de décarbonisation à long terme. Environ 90% des émissions mondiales sont désormais soumises à un objectif de zéro net, et plus d'un tiers des émissions de GES dans les juridictions visant le zéro net sont couvertes par un ETS. En début 2022, 25 systèmes d'échange d'émissions étaient opérationnels dans le monde, représentant 55% du PIB mondial et couvrant 17% des émissions mondiales.

significatif sur les marchés boursiers, reflétant la diversité des politiques environnementales et leur acceptation à travers le pays.

De manière plus générale, comme soulevé précédemment, le risque de transition représente une source potentielle de risque systémique (Battiston et al., 2017). Compte tenu de l'exposition croissante des institutions financières au risque de transition et de l'interconnexion mondiale des marchés financiers (NGFS, 2022), l'usage de mesures de risques systémiques pour quantifier cette contagion potentielle induite par le risque de transition à travers l'ensemble du système financier devient crucial (Hui-Min et al., 2021; Jourde et Moreau, 2022). Parmi ces mesures, l'Expected Shortfall (ES) offre une évaluation de la perte moyenne attendue dans des scénarios extrêmes, permettant d'anticiper les conséquences d'événements tels que l'adoption rapide de réglementations strictes sur les émissions de carbone. La Marginal Expected Shortfall (MES), quant à elle, mesure la contribution d'entités individuelles au risque global, identifiant ainsi les entreprises ou secteurs dont la défaillance aurait un impact significatif sur le système financier. Enfin, la Systemic Expected Shortfall (SES) élargit cette perspective en évaluant le risque qu'une institution financière pose pour la stabilité du système financier dans son ensemble. Ces outils analytiques avancés sont indispensables pour les régulateurs et les institutions financières qui cherchent à comprendre et à atténuer les risques systémiques liés à la transition écologique, assurant ainsi une meilleure résilience et gestion des défis financiers futurs.

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Inessa BENCHORA

Impact du risque de transition sur les rentabilités boursières

Résumé :

Le risque de transition, inhérent au passage vers une économie sobre en carbone, présente des défis et opportunités significatifs pour les marchés financiers. Cette thèse vise à quantifier et à analyser l'influence de ce risque sur les rentabilités boursières, en tenant compte des évolutions réglementaires, technologiques et des préférences des consommateurs et investisseurs. Prenant part dans un premier temps au débat sur la mesure la plus adéquate pour approximer la contribution des entreprises au risque de transition, nous proposons dans le chapitre 1 d'utiliser les émissions de carbone vérifiées pour évaluer l'impact du risque de transition sur les entreprises participant à l'EU ETS. Nos résultats montrent que le système d'échange de quotas modifie le profil risque-rendement des actions, ce qui peut fournir une incitation financière à prendre en compte les émissions dans les décisions d'investissement. Ensuite, conscient du rôle pivot des banques centrales dans la transition vers une économie sobre en carbone, le chapitre 2 propose une évaluation de l'empreinte environnementale de la politique monétaire des États-Unis vis-à-vis du risque de transition. La principale conclusion de non-neutralité de la politique monétaire américaine, favorisant les entreprises polluantes, mène au troisième chapitre. Celui-ci, portant sur les Etats-Unis également, explore la manière dont le risque de transition est pris en compte dans la valorisation du marché et comment la réglementation climatique peut influer sur cette intégration. Nos résultats suggèrent que l'impact à long terme des lois américaines sur la relation entre émissions de carbone et rendements boursiers nécessite un renforcement pour assurer sa pérennité. Actuellement, les mesures législatives ont un effet plus marqué à moyen terme, mais leur durabilité reste incertaine. En conclusion, ces chapitres ont pour but de permettre une meilleure intégration du risque de transition dans l'évaluation des actions par les investisseurs qui habiliterait les autorités réglementaires et les acteurs du marché financier à élaborer des politiques plus adéquates et à instaurer des dispositifs préventifs face à ce risque.

Mots clés : Changement climatique, Risque de transition, Finance verte, Evaluation d'actifs, Rentabilités boursières, Marché des quotas, Politique monétaire, Lois climatiques, Économétrie des données de panel, Projections locales, Modèle théorique.

Impact of Transition Risk on Stock Returns

Transition risk, inherent in the shift to a low-carbon economy, presents significant challenges and opportunities for financial markets. This thesis aims to quantify and analyze the influence of this risk on stock returns, taking into account regulatory, technological, and consumer and investor preference developments. Taking part initially in the debate on the most appropriate measure to approximate a company's contribution to transition risk, in Chapter 1, we propose the use of verified carbon emissions to assess the impact of transition risk on companies participating in the EU ETS. Our results show that the emissions trading system alters the risk-return profile of stocks, which can provide a financial incentive to consider emissions in investment decisions. Next, recognizing the pivotal role of central banks in the transition to a low-carbon economy, Chapter 2 provides an evaluation of the environmental footprint of U.S. monetary policy concerning transition risk. The main conclusion of non-neutrality in U.S. monetary policy, favoring polluting companies, leads to the third chapter. This chapter, also focused on the United States, explores how transition risk is taken into account in market valuation and how climate regulation can influence this integration. Our results suggest that the long-term impact of U.S. laws on the relationship between carbon emissions and stock returns needs strengthening to ensure its sustainability. Currently, legislative measures have a more pronounced effect in the medium term, but their sustainability remains uncertain. In conclusion, these chapters aim to enable a better integration of transition risk into stock evaluation by investors, which would empower regulatory authorities and financial market participants to develop more suitable policies and preventive measures against this risk.

Keywords : Climate change, Transition risk, Green finance, Asset valuation, Stock returns, Emissions trading market, Monetary policy, Climate laws, Panel data econometrics, Local projections, Theoretical model.

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