



UNIVERSITÉ PARIS I PANTHÉON-SORBONNE

École doctorale ED 465

Centre d'Économie de la Sorbonne

Thèse

pour obtenir le grade de

DOCTEUR DE L'UNIVERSITÉ PARIS I PANTHÉON-SORBONNE

Spécialité : Sciences Économiques

**AN ASSET PRICING APPROACH TO MEASURING CLIMATE
TRANSITION RISK AND ASSESSING LOW-CARBON ALIGNMENT**

Présentée et soutenue par

JEANNE MANSOUX (GOHIER)

Jeudi 16 janvier 2025

Sous la direction de:

MARC-ARTHUR DIAYE Professeur, Université Paris I

PATRICIA CRIFO Professeur, Ecole polytechnique

JURY

ANNA CRET	Professeur, Université Paris-Dauphine	Rapporteur
ANTOINE MANDEL	Professeur, Université Paris I	Président
SOPHIE MOINAS	Professeur, Université Toulouse Capitole	Rapporteur
THIBAUT SOLER	Directeur de la recherche, Fideas Capital	Examineur
OLIVIER-DAVID ZERBIB	Assistant-Professor, ENSAE	Examineur

REMERCIEMENTS

Je remercie en premier lieu Marc-Arthur Diaye, Patricia Crifo et Thibault Soler, qui m'ont fait l'honneur de m'encadrer pendant cette thèse. Je les remercie pour leurs conseils précieux. Leur expertise a été une source d'inspiration et a considérablement enrichi ce travail. Je remercie tout particulièrement Thibault Soler pour sa grande disponibilité, son soutien constant et le temps qu'il a consacré à l'accompagnement de mes travaux de recherche.

Je souhaite également remercier les membres du jury pour le temps qu'ils ont consacré à l'évaluation de mon travail. Je remercie tout particulièrement Anna Creti et Sophie Moinas, qui m'ont fait l'honneur de rapporter mon travail de thèse. Un grand merci à Antoine Mandel et Olivier-David Zerbib pour leurs remarques précieuses, qui ont contribué à améliorer la qualité de cette thèse.

Je remercie toute l'équipe de Fideas Capital, particulièrement Pierre Filippi et Alexis Merville, pour leur confiance et pour m'avoir offert cette belle opportunité d'effectuer ces travaux de recherche en partenariat avec une société de gestion. Les échanges entre l'équipe de recherche et l'équipe de gestion ont grandement enrichi mes travaux.

Mes pensées les plus affectueuses vont à mes parents et à mes sœurs. Merci pour votre soutien infaillible toutes ces années. Cette thèse est l'aboutissement d'études longues et exigeantes ; vos encouragements ont été une véritable force pour aller jusqu'au bout. Merci à mes parents de m'avoir inculqué la persévérance et le goût du travail. Merci également à ma belle-famille pour leur soutien.

Enfin, je remercie mon mari, Jean-Baptiste. Je mesure l'ampleur des sacrifices consentis durant cette thèse et je le remercie pour son soutien, sa patience et ses encouragements immuables. Je lui dédie cette thèse avec toute ma gratitude et tout mon cœur. L'avenir nous réserve le meilleur.

À mon mari et à notre fille à naître, avec tout mon amour.

Jeanne Mansoux

CONTENTS

Contents	vi
Abstract	vii
Résumé en français	ix
List of abbreviations	xi
Notations	xiii
1 Introduction	1
1.1 Motivations	2
1.1.1 Climate scenarios and carbon budget	3
1.1.2 Involvement of the financial sector	5
1.2 Literature Review	7
1.2.1 Investors and climate change	7
1.2.2 Measuring climate risks and performance metrics	10
1.2.3 Impact of climate finance on financial performance	17
1.2.4 Main limitations	19
1.3 PhD objectives	21
1.4 Main contributions	22
1.4.1 Chapter 2: identification of a brown-minus-green factor	22
1.4.2 Chapter 3: climate scenarios and alignment strategies of companies	27
1.4.3 Chapter 4: drivers and successes of low-carbon strategies	32
1.5 Outline of the thesis	35
2 A price signal approach to measure climate transition risk and improve asset pricing	37
2.1 Introduction	40
2.2 Literature review	44
2.3 Theoretical identification of a climate market trend and isolation of green and brown assets	47
2.3.1 Theoretical identification of a climate market trend	47
2.3.2 Covariance matrix estimation of ecological indexes	48
2.3.3 Determination of the climate market trend	48
2.3.4 Construction of the Brown-minus-Green factor from the sensitivity to the climate market trend	49

2.4	Empirical construction of Brown-minus-Green factors	51
2.4.1	Empirical identification of a trend from ecological indexes	51
2.4.2	Isolation of green and brown assets using the climate market trend	57
2.5	Relevance of the Brown-minus-Green factor	61
2.5.1	Relevance for asset pricing models	61
2.5.2	Relevance within previous literature	67
2.5.3	Dynamic analysis of sensitivities to the BMG factor	74
2.6	Application: measuring the climate transition risk of enabler stocks	80
2.7	Discussion and conclusion	83
2.8	Appendix	85
2.8.1	Benchmark regulation - Sensitive sectors	85
2.8.2	Tyler-M estimator recursive algorithm	85
2.8.3	Huber loss function	86
2.8.4	List of green and brown companies	86
2.8.5	Sensitivity of Green/Brown portfolios to the Paris Agreement	86

3 Climate scenarios and low-carbon targets of companies: A theoretical approach on alignment strategies and market equilibrium **89**

3.1	Introduction	92
3.2	Model set-up	96
3.2.1	General set-up	96
3.2.2	Evaluation phase: choosing a low-carbon pathway	98
3.2.3	Decision of investors: allocation of the portfolios	101
3.3	Market equilibrium	104
3.3.1	“Lemon market” structure: only one type of company within the economy	104
3.3.2	Economy with type B and type N companies	106
3.3.3	Model with three assets	109
3.3.4	General market equilibrium	112
3.4	Empirical illustration: identifying a climate risk premium from low-carbon target alignment strategies	114
3.4.1	Identification of a target announcement risk premium	114
3.4.2	Identification of a risk premium associated with the alignment performance of a company	119
3.5	Discussion	122
3.5.1	Alignment strategies of firms	122
3.5.2	Market equilibrium	126
3.6	Conclusion	128

3.7	Appendix	129
3.7.1	Low-carbon pathways	129
3.7.2	Variables and parameters	131
3.7.3	Ability threshold	132
3.7.4	Demand for stocks	133
3.7.5	Market equilibrium with type B and type N stocks	134
3.7.6	Market equilibrium with type H, type B, and type N stocks	135
3.7.7	Portfolio allocation under a decarbonization constraint	136
3.7.8	General market equilibrium	137
3.7.9	Empirical identification of alignment risk premia	138
4	Financial and climate performance drivers for low-carbon strategies	141
4.1	Introduction	144
4.2	Low-carbon target metrics	149
4.2.1	Low-carbon target metrics	149
4.2.2	Financial and environmental metrics	153
4.2.3	Dataset description	155
4.3	Drivers behind the ambition of targets	157
4.3.1	Ex-ante approach: identifying drivers for setting a target	157
4.3.2	Net-zero ambition of targets: binary approach	163
4.3.3	Predicting the ambition of a company	169
4.4	Drivers behind the credibility of target	172
4.4.1	Achieving a target: industry breakdown	172
4.4.2	Credibility of targets: binary approach	175
4.4.3	Predicting the success of targets	179
4.4.4	Comparative analysis: does ambition signify success?	181
4.5	Net-Zero portfolio construction	183
4.6	Discussion and conclusion	189
4.7	Appendix	192
4.7.1	CDP target breakdown by GICS Industry Group and country	192
4.7.2	Addition and merging of targets	193
4.7.3	IEA Net Zero emissions abatement	193
4.7.4	IEA sector match	193
4.7.5	High Climate Impact Sectors (HCIS)	194
4.7.6	Support Vector Machine model	194
5	Conclusion	197

List of figures	202
List of tables	204
Bibliographie	221
Synthèse en français	223
5.1 Motivations	223
5.1.1 Scénarios climatiques et budget carbone	224
5.1.2 Implication du secteur financier	226
5.2 Objectifs de la thèse	228
5.3 Contributions principales	229
5.3.1 Chapitre 2 : identification d'un facteur brown-minus-green	229
5.3.2 Chapitre 3 : scénarios climatiques et stratégies d'alignement des entreprises	234
5.3.3 Chapitre 4 : moteurs et succès des stratégies bas-carbone	239
5.4 Conclusion	241

ABSTRACT

This thesis explores measuring climate transition risk and evaluating the low-carbon targets of companies through an asset pricing framework, addressing a pressing concern for investors: safeguarding their portfolios from climate-related risks.

Several challenges arise when assessing climate transition risks using fundamental carbon data such as greenhouse gas emissions, mostly through inconsistencies in the data and a lack of clarity regarding the impact of climate performance on financial performance. The implications of low-carbon strategies on both climate risk and asset pricing remain ambiguous, posing significant concerns for investors in a rapidly evolving policy landscape. Furthermore, the theoretical foundation for companies' commitments to low-carbon targets is underdeveloped. Additionally, there is limited literature on evaluating low-carbon targets, and uncovering the financial and climate performance factors influencing the strategies of firms.

To begin, I enhance the measurement of climate transition risk by isolating market signals from leading firms in transition risk mitigation to create a brown-minus-green factor. This factor, which focuses on the sensitivity of asset prices without relying on fundamental climate data, enables a more accurate assessment of risk exposure for a specific class of assets: enabler stocks. The brown-minus-green factor substantially improves asset pricing models.

In the second part, I tackle the concept of low-carbon targets from a theoretical perspective to improve the evaluation of future climate transition risk exposure. The model comprises two phases, where companies decide whether to commit to emission reduction targets. Investors adjust their portfolio allocation based on these company announcements. I demonstrate that there is a cost to announcing a low-carbon target for companies with lower abilities. My theoretical and empirical findings highlight a climate risk premium influenced by investors' climate preferences, which significantly affect the likelihood of companies setting low-carbon targets.

Lastly, I adopt an empirical approach to aggregate and assess the low-carbon targets set by companies, providing insights into their ambition and credibility. Through this analysis, I identify key financial and climate performance indicators that drive common characteristics among successful companies: findings indicate that profitability, investment levels, and greenhouse gas emissions metrics are significant indicators.

Keywords: Climate transition risk, Climate scenario, Enabling activities, Price signals, Climate risk premium, Brown-minus-Green factor, Asset pricing, Net-zero Alignment, Low-carbon target.



RÉSUMÉ

Cette thèse examine la mesure du risque de transition climatique et les stratégies bas-carbone des entreprises en utilisant de nouveaux modèles d'évaluation du prix des actifs, répondant ainsi à une préoccupation des investisseurs : la protection de leurs portefeuilles contre les risques liés au climat.

L'évaluation des risques de transition, souvent établie via des données fondamentales telles que les émissions de gaz à effet de serre, pose plusieurs problèmes, principalement en raison des incohérences dans les données et du manque de clarté concernant l'impact de la performance climatique sur la performance financière. L'impact des stratégies bas-carbone sur le risque de transition et sur le prix des actifs reste ambigu, ce qui pose des problèmes importants pour les investisseurs dans un monde où les politiques publiques évoluent rapidement. En outre, les fondements théoriques des stratégies d'alignement des entreprises sont peu développés, et l'influence des investisseurs dans sur leurs choix n'est pas bien comprise. La littérature reste limitée sur la notation des objectifs de réduction d'émissions et sur la mise en évidence des facteurs de performance financière et climatique qui influencent ces objectifs.

Pour commencer, j'améliore la mesure du risque de transition en isolant des signaux de marché liés aux entreprises les plus avancées dans la transition, afin de créer un facteur Brown-minus-Green. Ce facteur, qui s'appuie sur la sensibilité des prix des actifs sans avoir recours à des données fondamentales, permet une évaluation plus précise de l'exposition au risque pour une catégorie spécifique d'actifs : les entreprises habitantes. Le facteur Brown-minus-Green améliore sensiblement les modèles d'évaluation des actifs.

Dans la deuxième partie, j'aborde le concept des stratégies bas-carbone d'un point de vue théorique afin d'améliorer l'évaluation de l'exposition future aux risques de transition. Le modèle comprend deux phases, au cours desquelles les entreprises décident de s'engager ou non à atteindre des objectifs de réduction des émissions. Les investisseurs ajustent l'allocation de leur portefeuille en fonction des annonces faites par les entreprises. Je démontre que les entreprises les plus compétentes ont toujours la possibilité d'annoncer un objectif, tandis que l'établissement d'un objectif a un coût pour les autres. Mes résultats théoriques et empiriques mettent en évidence une prime de risque climatique influencée par les préférences des investisseurs en matière de climat. Les investisseurs ont aussi une incidence significative sur les stratégies des entreprises.

Enfin, j'adopte une approche empirique pour agréger et évaluer les objectifs bas-carbone fixés par les entreprises, ce qui permet de mieux comprendre leur ambition et leur crédibilité. Grâce à cette analyse, j'identifie les principaux indicateurs de performance financière et

climatique qui déterminent l'ambition et la crédibilité des objectifs, en mettant en évidence les caractéristiques communes aux entreprises performantes : la rentabilité, les niveaux d'investissement et les émissions de gaz à effet de serre sont des indicateurs significatifs de réussite.

Mots clés: risque de transition, scénario climatique, entreprises habilitantes, signaux de prix, prime de risque climatique, facteur Brown-minus-Green, évaluation du prix des actifs, alignement net-zéro.

LIST OF ABBREVIATIONS

BMG Brown-minus-Green.

CAPM Capital Asset Pricing Model.

CARA Constance Absolute Risk Aversion.

CB carbon budget.

CO₂ carbon dioxide, dioxyde de carbone.

COP Conference of the Parties.

ESG environmental, social and governance.

GES gaz à effet de serre.

GFANZ Glasgow Financial Alliance for Net Zero.

GHG greenhouse gas emissions.

GIEC Groupe d'experts intergouvernemental sur l'évolution du climat.

IEA International Energy Agency.

IPCC Intergovernmental Panel on Climate Change.

MP Marčenko-Pastur.

N₂O nitrous oxide, protoxyde d'azote.

NGFS Network for Greening the Financial System.

NLP Natural Language Processing.

NZE Net-Zero Emissions.

OECD Organisation for Economic Co-operation and Development.

RCPs Representative Concentration Pathways.

RMT Random Matrix Theory.

SBTi Science-Based Targets initiative.

SCM Sample Covariance Matrix.

SSPs Shared Socio-economic Pathways.

TCFD Task Force on Climate-related Financial Disclosures.

TPI Transition Pathway Initiative.

UNPRI Principles for Responsible Investments.

VaR Value-at-Risk.

NOTATIONS

\mathbf{v} Column vectors (bold lowercase letters)

v_j The element j of \mathbf{v}

\mathbf{A} Matrices (bold capital letters)

$v_{i,j}$ The element i, j of \mathbf{A}

$\hat{\mathbf{A}}$ Any estimate of matrix \mathbf{A}

\mathbf{I}_m The $m \times m$ identity matrix

\mathbf{A}' The transpose of \mathbf{A}

\mathbb{E} Expected value

$U(x)$ Utility function

$\mathcal{N}(\mu, \sigma^2)$ Gaussian distribution

$\|A\|_F$ The Frobenius norm $\|A\|_F = \sqrt{\sum_{i,j} |a_{i,j}|^2}$



INTRODUCTION

1.1	Motivations	2
1.1.1	Climate scenarios and carbon budget	3
1.1.2	Involvement of the financial sector	5
1.2	Literature Review	7
1.2.1	Investors and climate change	7
1.2.2	Measuring climate risks and performance metrics	10
1.2.3	Impact of climate finance on financial performance	17
1.2.4	Main limitations	19
1.3	PhD objectives	21
1.4	Main contributions	22
1.4.1	Chapter 2: identification of a brown-minus-green factor	22
1.4.2	Chapter 3: climate scenarios and alignment strategies of companies	27
1.4.3	Chapter 4: drivers and successes of low-carbon strategies	32
1.5	Outline of the thesis	35

This introduction is organized as follows: first, I outline the motivations for this work, emphasizing the urgency of climate change in the 21st century and the critical role of the financial sector in addressing this issue. Next, I review the climate finance literature, focusing on how investors assess climate change and integrate climate-related risks into their investment strategies. After detailing the research objectives of this PhD, I will present the contributions of the three subsequent chapters.

1.1 Motivations

In 1958, Charles David Keeling started measuring atmospheric carbon dioxide (CO_2) daily from the Mauna Loa observatory; aside from identifying a seasonal variability to atmospheric CO_2 , he observed that the concentration was rising and that this was due to human activities. In 1969, during a symposium on atmospheric pollution (Keeling, 1970), he presented his findings and ended his talk with the following warning:

“If the human race survives into the twenty-first century with the vast population increase that now seems inevitable, the people living then, along with their other troubles, may also face the threat of climatic change brought about by an uncontrolled increase in atmospheric CO_2 from fossil fuels.”

Sixty years later, there is a scientific consensus that climate change is primarily driven by human activities. Although Charles D. Keeling predicted that most people would not witness the consequences of climate change during his lifetime, we have since identified significant impacts that are becoming more severe and frequent. There is now an urgent need to accelerate efforts in adapting to and mitigating climate change. In the latest assessment report from the Intergovernmental Panel on Climate Change (IPCC), several potential impacts threaten the economy in the medium to long term (Lee and Romero, 2023). For instance, crop yields may decrease by up to 20% by 2050, and between 1 and 3 billion people could face severe heat each year if the average surface temperature rises by 2°C.

Addressing climate change through adaptation and mitigation requires significant transformations in the global economy. The primary goal is to drastically reduce fossil fuel consumption, which currently accounts for 75% of the global energy mix. This transition to a low-carbon economy necessitates a rethinking of business models and production systems. The intensity and speed of this transition will play a crucial role in determining the risks and opportunities that companies encounter. In this context, climate scenarios serve as valuable tools, linking socio-economic factors to greenhouse gas (GHG) emissions and, subsequently, to the extent of global warming.

1.1.1 Climate scenarios and carbon budget

Climate scenarios are essential tools that help policymakers project possible futures based on their economic decisions. Since the early 21st century, researchers have developed advanced models to project the evolution of the climate system following a set of parameters. In the case of the IPCC, a dual approach is used: first, the Representative Concentration Pathways (RCPs, Pachauri and Meyer (2014)) utilize global climate models to forecast climate data (change in surface temperature, precipitation patterns, etc.) from radiative forcing¹, which itself originates from an increase in GHG emissions. The Shared Socio-economic Pathways (SSPs) provide a complementary approach by projecting how socio-economic parameters, such as population, economic growth, international trade, conflicts, technological innovation etc., may evolve throughout the 21st century and thus determine the level of GHG emissions. When merged, the RCPs and SSPs determine the evolution of the climate system according to the social, economic, and political choices we make.

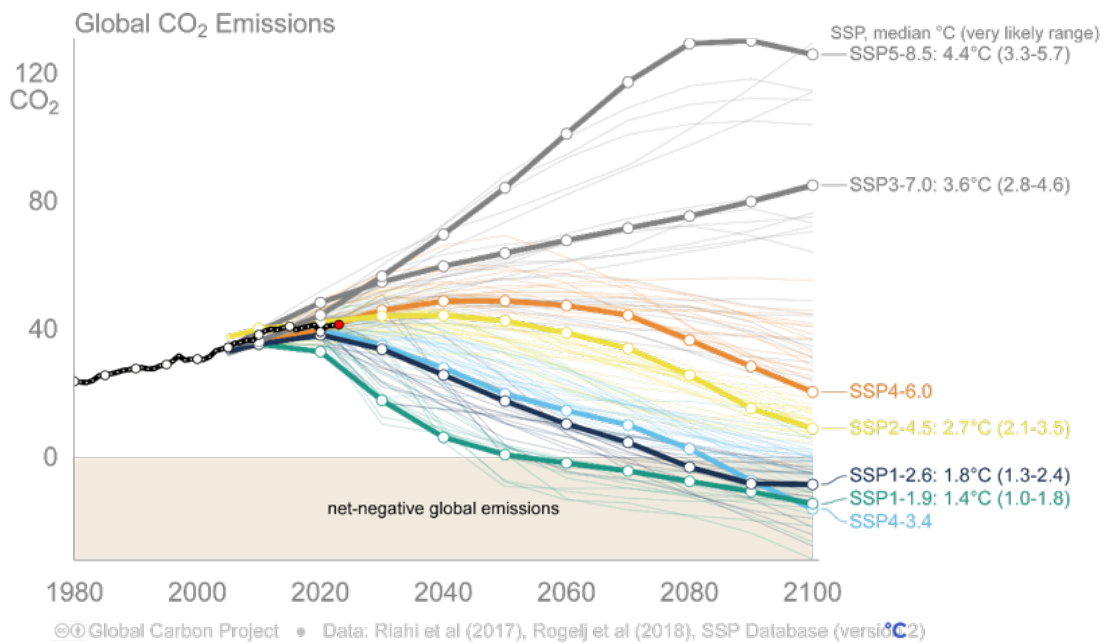


Figure 1.1: Global CO_2 emissions from the Shared Socio-economic Pathways database.

Source: Global Carbon Project

Figure 1.1 shows a range of possible futures from different combinations of SSPs and

¹Radiative forcing is defined as the change in radiative flux (in $W.m^2$) due to a change in an external driver of climate change, such as a change in the concentration of carbon dioxide (CO_2), the concentration of volcanic aerosols or in the output of the Sun (see the IPCC definition in the glossary).

RCPs. Some SSPs, such as the SSPs 5 or the ‘Fossil Fuel Development’ scenario lead to a heavy increase of global GHG emissions and a global warming of 3°C to 5°C by 2100, depending on the RCPs. Other scenarios, such as the SSP 1 with corresponding RCPs of 2.6 W.m² or 1.9 W.m², lead to a large decline of GHG emissions from 2020 onwards, with net-negative emissions by 2080 or earlier. The business-as-usual scenario is the SSPs 2-4.5 where emissions follow the past trend, likely leading to a global warming of 4°C by the end of the 21st century.

Since the second half of the 20th century, scientists have been alerting on the impacts of climate change and the need for both mitigation and adaptation initiatives. However, International coalitions began to tackle the topic at the very end of the 20th century, with the creation of the IPCC and the Conference of the Parties (COP). In 2015, the Paris Agreement or COP21 was a landmark in the fight against climate change: 295 countries committed to limiting global warming well below 2°C by the end of the 21st century. This implied continuous and important efforts to lower emissions from greenhouse gases covered by the Kyoto Protocol: carbon dioxide, methane, nitrous oxide (*N₂O*), hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride. In the aftermath of the Paris Agreement, the notion of a CB emerged and was made popular by institutions such as the Global Carbon Project or the Mercator Research Institute on Global Commons and Climate Change. The CB is useful for setting a low-carbon transition pathway that limits global warming to less than 2°C. The term ‘carbon budget’ refers to two concepts in the literature [Lee and Romero \(2023\)](#):

- *The global carbon budget*: sum of all carbon cycle sources and sinks on a global level. Fossil fuel burning and land-use change are the two main sources of carbon, while the oceans and vegetation are the two natural carbon sinks. When there is an imbalance between carbon sources and carbon sinks, the atmospheric concentration of *CO₂* rises: this is called the budget imbalance. The Global Carbon Project assesses the global CB every year.
- *The remaining carbon budget*: from a specified date, the remaining cumulative amount of net global anthropogenic *CO₂* emissions limiting global warming to a given level with a given probability. In other terms, the remaining CB is the remaining amount that human activities can emit in the future while limiting global warming to a certain temperature. For the remainder of this thesis, when mentioning the term ‘carbon budget’, we refer to this second concept: the remaining carbon budget.

The Global Carbon Project [Friedlingstein et al. \(2023\)](#) assessed that from 2024, “the remaining carbon budget to limit global warming to 1.5°C , 1.7°C and 2°C is 275 GtCO₂,

625 GtCO₂, and 1150 GtCO₂ respectively, equivalent to 7, 15 and 28 years from 2024”. This leaves a short window and requires the involvement of both the public and private sectors to accelerate the low-carbon transition.

1.1.2 Involvement of the financial sector

The transition to a low-carbon economy is crucial for mitigating the impacts of climate change and requires significant efforts from the private sector. This transition affects the financial sector through a concept known as double materiality [Baumüller and Sopp \(2022\)](#):

- the financial system faces risks both from the impacts of climate change and from the transformation of the economy through the low-carbon transition ([Battiston et al. \(2017\)](#); [Mercure et al. \(2018\)](#), see section 1.2.2);
- it also has an impact on the climate system through the destination of its cash flows.

As a result, investors face a double fiduciary duty: they must limit their exposure to climate-related risks; they can also be inclined to direct their investments towards companies that have a low impact on the climate system, or firms that are transitioning towards low-impact economic activities ([Campiglio and van der Ploeg, 2022](#)). In other words, investors should be aware that firms are exposed to climate risks and that these risks permeate financial portfolios; at the same time, many of them have started to develop preferences or tastes for low-carbon or green stocks and favor sectors such as clean energy, low-carbon technologies, and energy-saving solutions. This double mechanism encapsulates the climate finance field.

Companies make their business strategies under this double pressure: by mitigating their exposure to climate risk they become more attractive to risk-aware investors, and all activities they pursue or develop in favour of the low-carbon transition can make them more attractive to investors with strong climate preferences. In both cases, their decisions are crucial factors for investors when allocating capital.

The financial sector has been increasingly adapting to the low-carbon transition following the Paris Agreement of 2015, which emphasized the need to direct financial flows towards reducing GHG emissions. There has been significant progress in climate finance: monetary flows have increased towards sectors with lower climate impact, and the channels through which the investments originate have expanded ([Lee and Romero, 2023](#)). According to the International Energy Agency (IEA), investments in clean energy amounted to 1.74 trillion USD in 2023, while investments in fossil fuels have slowly been decreasing since 2015, although they remain very high at 1.05 trillion USD. Most of the investments

focus on mitigating climate change. The investment gap between clean energy and fossil fuels is steadfastly increasing, due to a sharp decrease in clean energy costs between 2014 and 2020. The private finance sector plays an important role in funding the transition (625 billion USD in 2023); however, cash flows are very geographically concentrated (East Asia, North America, and Europe) and insufficient to withhold the transition towards a well-below 2°C scenario (Buchner et al., 2023).

It is essential for regulators to guide investors toward low-carbon solutions while gradually phasing out high-emission economic activities. At the same time, maintaining the stability of the financial system is critical. The destabilization of the financial system can occur from not making enough progress and unanticipated climate-related shocks, or, on the contrary, from imposing too harsh adjustments that disrupt the economy. If economic agents do not mitigate and adapt to climate change impacts, the risks of financial losses are massive (Battiston et al., 2017). However, if regulators force investors to brutally reorient their investments, this creates stranded assets² (Semieniuk et al., 2022) and threatens global financial and economic stability.

Since 2015, several organizations have been created to help investors align their investments with the low-carbon transition: first, a coalition of central banks created the Network for Greening the Financial System (NGFS) in 2017 which publishes frequent reports that highlight the impact of climate risk on the stability of the financial system (for *Greening the Financial System*, 2024). The Task Force on Climate-related Financial Disclosures (TCFD) was created by the Financial Stability Board in 2015, with the aim of providing standardized metrics on the reporting of climate-related data for financial institutions. The TCFD has since merged with the International Sustainability Standards Board, aiming to bring the reporting of sustainability-related metrics to the same level as traditional financial reporting. The private sector has also mobilized resources to orient investments towards the low-carbon transition: the Glasgow Financial Alliance for Net Zero (GFANZ), created in 2023, is a coalition of CEOs from the financial sector that share best practices and technological knowledge to accelerate the transition. Indeed, some of the main challenges for investors are identifying and measuring climate risk, its impacts on financial portfolios, and measuring the extent of companies' responses to climate mitigation and adaptation. The investors' climate preferences are also an important factor when allocating capital. The academic literature has therefore heavily increased its focus on these topics in the past ten years. We review the main contributions of this branch of literature in the following paragraph.

²Stranded assets are resources and infrastructures that, in the future, could be no longer used and may end up as a liability before the end of their anticipated economic lifetime (Welsby et al., 2021).

1.2 Literature Review

1.2.1 Investors and climate change

Climate finance is a branch of sustainable finance that focuses both on mitigating climate risk within portfolios and on promoting the investment in green stocks via climate preference or taste.

In traditional finance, the main objective of an investor is how to allocate her assets in order to maximize her return while minimizing the risk of her portfolio. The mean-variance framework of Markowitz (Markowitz, 1952, 1956) has served as a basis for allocation strategies and supports the idea that investors only care about the risk-return profile of their portfolio. The minimization of risk also includes accounting for climate-related risks to which firms are exposed. This is why there is empirical evidence that investors aim to reduce their exposure to climate-related risks (Ceccarelli et al., 2024) and anticipate future regulation (Ramelli et al., 2021; Krueger et al., 2020). However, the paradigm has shifted in recent years, with growing empirical evidence that investors also have preferences for socially responsible investments (Pástor and Vorsatz, 2020), which are defined as investments that mitigate negative environmental, social, and governance (ESG) impacts. Studies have shown that they are willing to sacrifice returns to invest in socially responsible investments (Crifo and Sami, 2019; Hartzmark and Sussman, 2021; Barber et al., 2021). There is empirical evidence that investors develop preferences related to responsible investment (especially around the climate theme): they do so for product differentiation purposes (Rankin, 2021), to cater to customer demand (Amel-Zadeh and Serafeim, 2018; Nilsson, 2008), or because of moral values (Garg et al., 2024).

Third-party verification organizations, such as the Principles for Responsible Investments (UNPRI) play a role in encouraging investors to mitigate risk by providing resources to protect their investments: for example, they enable them to decrease the GHG emissions of their portfolio (Humphrey and Yong, 2021), a common metric for measuring climate-related risk.

There are different climate investment strategies (Busch et al., 2022c) that are very often employed both for risk-mitigation purposes and to cater to preference:

- *Exclusions*: investors exclude certain economic activities, companies, or countries from their portfolios due to their negative environmental impact. Although this practice started with “sin stocks” (alcohol, biotech, defense, gaming, tobacco, and adult entertainment), outside of any environmental consideration, it has since extended to

industries such as coal production and use (in the utilities sector for example), oil & gas exploration and production, or pesticides (Dimson et al., 2020).

- *Negative norm-based screening*: investors select or reject stocks according to their compliance with international norms and business standards: the United Nations Global Compact Compact (2022), OECD Guidelines OECD (2011) are among the most popular standards that investors use, and include several environmental criteria, such as the precautionary principle.
- *Integration of climate performance and risk*: this strategy includes the systematic analysis of the climate performance and risk of a stock and its subsequent integration in the overall rating by the investor: the climate risk exposure of the stock, as well as its positive environmental contribution, are included in the standard financial analysis, therefore the climate performance becomes an asset allocation factor along the traditional financial performance of the stock.
- *Best-in-universe/best-in-class selection*: this is a slightly different approach to the former strategy, in that the selection of assets according to their climate performance is separated from the selection process using financial performance. This strategy consists of selecting the best-performing assets within the entire investment universe (best-in-universe) or within their industry (best-in-class).
- *Positive contribution/thematic funds*: contrary to the negative norm-based screening strategy, assets are selected according to their positive impact on a specific environmental theme: clean energy, eco-efficiency, climate adaptation solutions, or green buildings for example. This creates concentrated thematic portfolios or indices with little diversification that are useful if the investor seeks to have a positive impact on climate change mitigation and adaptation.

These strategies are useful when the investor makes her portfolio allocation. Other post-investment strategies exist: engagement and voting, which are a form of shareholder activism (Dimson et al., 2015; Barko et al., 2022). Engagement practices consist of approaching investee companies on certain environmental themes, such as climate change, environmental management, or ecosystem services under various formats: letters, emails, meetings, etc. There are also coordinated practices, where coalitions of long-term investors seek a higher impact on a firm's climate performance by collaborating (Dimson et al., 2018).

Climate investment strategies can be modeled by incorporating a climate risk premium and the climate preferences of an investor within an allocation model (Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022). Let us consider a portfolio of N companies,

$n = 1, \dots, M$ at time $t \geq 0$. There is a risk-free asset in the economy, with return r_f which is constant over time. We assume that the return of stock n is normally distributed:

$$r_n(t) = r_f + \mu_n(t) + \rho_n(t) + \epsilon_n(t)$$

$\mu_n(t)$ and $\rho_n(t)$ form the expected excess return of the stock: $\mu_n(t)$ is the expected excess return associated to traditional factors (Markowitz, 1952; Fama and French, 1995, 2005) and $\rho_n(t)$ is a climate risk premium. The volatility of the stock price at time t is $\epsilon_n \sim \mathcal{N}(0, \sigma_n^2(t))$ and it follows a normal distribution of mean 0 and variance $\sigma_n^2(t)$.

Each stock also has a climate rating that depends on the company's performance in terms of climate change mitigation and adaptation, labeled $g_n(t)$ for company n .

There is a continuum of investors in the economy, we consider investor i who makes her portfolio allocation in the N stocks as well as in the risk-free asset. The investor has an initial wealth $W_{0,i}$ at time $t = 0$. Let $\mathbf{x}_i(t)$ be a $N \times 1$ vector in which the n -th element is the stock's weight within the portfolio. At time $t \geq 1$, the investor's wealth will be:

$$W_{t,i} = W_{t-1,i} [1 + r_f + \mathbf{x}_i(t)' \cdot \mathbf{r}(t)]$$

where $\mathbf{r}(t)$ is the $N \times 1$ vector of returns from the risky assets. The investor seeks to minimize the risk of her portfolio and has a certain risk aversion, modeled using a risk aversion coefficient. At the same time, she has climate preferences reflected through a coefficient that quantifies her taste for high climate-performing ("green") stocks. The investor's preference is modeled using a Constant Absolute Risk Aversion (CARA) utility function (Pratt, 1964; Arrow, 1971):

$$U(W_{t,i}) = -e^{-A_i W_{t,i} - d_i \mathbf{g}(t)' \mathbf{x}_i(t)}$$

A_i is the investor's absolute risk aversion and d_i is her climate preference (it can also be interpreted as an aversion for climate risk), while $\mathbf{g}(t)$ is the $N \times 1$ vector which n th element is the stock's climate performance metric. The additional term reflects the idea that investors may derive benefit from holding green assets: in this case, their climate preference is positive: $d_i > 0$.

The investor's objective is to maximize her utility, the first-order condition suggests that the optimal portfolio with climate preferences is:

$$\mathbf{x}_i(\mathbf{t}) = \frac{1}{a_i} \boldsymbol{\Sigma}^{-1}(t) \left(\boldsymbol{\mu}(\mathbf{t}) + \boldsymbol{\rho}(\mathbf{t}) + \frac{d_i}{a_i} \mathbf{g}(\mathbf{t}) \right) \quad (1.1)$$

where $a_i = A_i W_{0,i}$ is the relative risk aversion of investor i . When $d_i > 0$, investors will tend to overweight stocks that have a high climate performance in their portfolio allocation, and under-weight or even exclude assets that have a poor climate rating. If $d_i = 0$ then the investors have no climate preferences and seek only to maximize the return of their portfolio, which is the same (according to [Markowitz \(1952\)](#)) as minimizing the risk.

The decisions of investors (both the mitigation of climate risk and the shift in preferences) have had an impact on financial markets, which has been documented in several empirical studies. There is for example evidence that investors trade according to climate-related news ([Chen et al., 2020](#); [Goldstein et al., 2022](#); [Antoniuk and Leirvik, 2024](#)) both to improve performance and to cater to their tastes. There is also evidence that investors expect higher returns on stocks that are heavily exposed to climate risks ([Chava, 2014](#); [Bolton et al., 2020](#)). To accommodate their allocation according to their climate taste, investors are willing to sacrifice financial return in order to gain non-pecuniary benefits ([Martin and Moser, 2016](#); [Riedl and Smeets, 2017](#); [Li et al., 2023](#)).

1.2.2 Measuring climate risks and performance metrics

Physical, transition, and liability risks

One of the objectives of academic research in climate finance is to appropriately identify and measure climate risks. These fall into three categories: physical risks, transition risks, and liability risks ([Carney, 2015](#)). Physical risks arise as extreme climate events (heatwaves, droughts, floods, cyclones, hurricanes, etc.) are expected to increase in frequency and severity. These events have an impact on the capital of a company, and can also disrupt operations, which leads to financial loss. Transition risks appear from a shift of an economy with unlimited GHG emissions to a low-carbon economy, with a lack of anticipation from companies that can cause unexpected costs. Finally, liability risks appear when companies do not mitigate physical or transition risks and face legal or financial obligations. Transition risks are the most studied in the academic literature and are also the main point of focus for investors for several reasons:

- they are more immediately tied to asset values and investment decisions because they directly influence business operations and cash flows. Physical risks, on the other hand, manifest over longer time horizons, making them more difficult to apprehend ([Dietz et al., 2016](#));

-
- transition risks often arise due to climate policies, they are therefore easier to identify and monitor;
 - finally, they are easier to quantify, as there is more available data (Battiston et al., 2017).

There is therefore a stronger market response to transition risk rather than physical risk, as policy announcements and technological shifts are more visible and immediate (Monasterolo and Raberto, 2018).

There are several challenges to modeling and measuring climate risks. The main challenge is the existence of uncertainty around the long-term impacts of climate change (Daniel et al., 2018), especially for physical risks. This means that there is uncertainty in the future cash flows that arise with climate change and mitigation policies (Weitzman, 2011; Gollier, 2013; Bolton et al., 2020). To be more precise, physical risks can be unpredictable because of the uncertainty in climate models used to project future climate and economic impacts (Barnett et al., 2021); transition risks can be unpredictable due to uncertainty on the extent and the pace of the low-carbon transition: this depends on the policy choices, consumer behavior, business models of companies and the orientation of cash flows (Semieniuk et al., 2021; Campiglio et al., 2023; Ceccarelli and Ramelli, 2024). Another challenge is the identification, access, and commensurability between variables that can be used as direct metrics or proxies for measuring climate risks.

As previously mentioned, investors focus less on physical risks and this reflects in the academic literature. It is less extensive and more difficult as it requires a multidisciplinary approach: climate modeling is used for predicting the probability of extreme-weather events (Pérez-Zanón et al., 2022), economic models that quantify the expected losses (Mandel et al., 2021; Jongman et al., 2012), and the geolocalisation of assets and infrastructure (Bressan et al., 2024). The main objective is to translate the vulnerability and the exposure to climate change impacts of physical assets into economic and financial losses (Ranger et al., 2022). Several studies studied the financial impacts of certain extreme weather events, such as cyclones, droughts, or floods. In many studies, the financial losses are underestimated or not even priced in financial markets. Several papers also study the impact of weather events on sovereign default risk and show that climate change already has an impact on sovereign bond spreads.

Transition risks arise from the low-carbon transition, a major shift in the economy that is going from a state of dependence on fossil fuels as the main source of energy, to a state where low-carbon energy sources such as solar power, wind power, hydroelectricity, and

nuclear energy become the main sources of energy in all industrial sectors, and where the resort to fossil fuels is marginal (Bouckaert et al., 2021). This major economic change has started to be implemented through public policies, and consumer behavior has also been shifting (Niamir et al., 2018). This creates a risk for companies that do not adapt to the transition: financial losses can occur from a lack of anticipation in the regulation or a loss of market share. An important objective for investors is to integrate the potential economic and financial losses into risk metrics, which is why the measure of transition risk as a financial risk occupies an important branch of climate finance literature.

Measuring transition risks

There are several metrics for measuring transition risks. Firstly, the exposure to transition risk can be translated into financial losses that are measured using climate and macroeconomic scenarios, for example the Integrated Assessment Models (Nordhaus, 1992, 2018). These models compute possible futures that are obtained using several projections of macroeconomic and climate variables and produce metrics that can be used to estimate financial losses from a lack of adaptation to a low-carbon economy. The most commonly used metric is the social cost of carbon that determines the price that should be applied to GHG emissions in order to maximize present and future welfare. In other words, the social cost of carbon represents the price that companies and investors should anticipate so that the current price of emissions balances any future cost from damages that will occur if nothing is done to abate GHG emissions. Public policies have introduced a carbon price using two mechanisms: either through a tax on GHG emissions of goods and services or through a market of emission permits. The financial sector is indirectly exposed to this social cost of carbon by investing in companies that are subjected either to a carbon tax or to carbon permits. One of the most popular ways to measure the exposure of investments to transition risks is to induce shocks to the carbon price via stress tests (Battiston et al., 2017; Vermeulen et al., 2021; Reinders et al., 2023). The climate Value-At-Risk (VaR) is therefore a commonly used metric for computing the exposure of financial portfolios to climate risks (Dietz et al., 2016; Monasterolo, 2020).

The cost of carbon is not the only metric to assess the transition risk exposure of stocks. Stranded assets are also a liability for companies, and their value is measured through the financial statements of firms (Caldecott et al., 2016; Caldecott, 2017). These stranded assets can be a threat to the financing capacities of firms (Sen and von Schickfus, 2020).

Several studies have also assessed transition risk using market measures. Under the

efficient market hypothesis, the pricing of transition risk reflects the exact value of future cash flows. Therefore any change in the anticipation of climate risks should have a proportionate impact on the asset price. The literature on the market response to climate transition risk is extensive: the market measure is often captured using the sensitivity of stock prices to a transition risk factor. This factor is often referred to as a brown-minus-green factor: it is a portfolio that is long of “brown” stocks, which have a high exposure to transition risks, and short of “green” stocks, which have a low exposure to transition risks. The difference in returns reflects a transition risk premium that is either positive or negative. The transition risk measure of a stock is therefore the sensitivity of the stock price to the factor return. The most common methodologies for identifying brown and green stocks include using the GHG emissions of firms (Gorgen et al., 2020; Bolton et al., 2020; Roncalli et al., 2020, 2021; Enders et al., 2024; Cassola et al., 2024).

The sensitivity of stock prices is modeled using a multi-factor approach, by adding an additional factor to models such as the Fama-French 3-factor and 5-factor models (Fama, 1965; Fama and French, 1995) or the Carhart model (Carhart, 1997):

$$r_n(t) = r_f + \alpha_n(t) + \sum_{p=1}^F \beta_{n,p} r_p(t) + \beta_{n,BMG} r_{BMG}(t) + \epsilon_n(t)$$

where $r_n(t)$ is the stock return of asset n at time t , r_f is the return of the risk-free asset, $\alpha_n(t)$ is the idiosyncratic risk that can include a firm-specific climate risk, $r_p(t)$ is the return of factor $p \in [1, F]$, $\beta_{n,p}$ is the sensitivity to factor p , $r_{BMG}(t)$ is the return of the Brown-minus-Green (BMG) factor, and $\beta_{n,BMG}$ is the sensitivity of the stock to the BMG factor, or the market measure of transition risk. It is therefore the climate systematic risk of the stock. Factors of the Fama-French models or the Carhart model include the market, size, value, momentum, profitability, and investment factors.

Studies have shown that adding the BMG factor in asset pricing models significantly improves the estimation of the expected returns of stocks (Gorgen et al., 2020; Roncalli et al., 2020), which indicates that investors trade on the transition risk exposure of stocks.

The market measure of transition risk may be however be imperfect if the efficient market hypothesis is not verified: the sensitivity of a stock price to a brown-minus-green factor may only partially reflect the full exposure to transition risk as it may reflect other information related to the carbon performance of a firm. A growing literature in behavioral finance highlights the existence of abnormal returns due to irrational reactions to climate change-related news in the market: important but non-informative climate events can cause

initial overreaction in financial markets, followed by a correction as investors process the implications more rationally [Akin and Akin \(2024\)](#). There is also evidence that investor sentiment, driven by psychological factors, increases the negative effect of climate change risk on the performance of newly listed firms when investors are pessimistic ([Kashefi Pour, 2024](#)). Building an emissions-minus-clean portfolio based on investor sentiment (not preference), [Santi \(2023\)](#) shows evidence for abnormal positive returns of green stocks when climate sentiment is strong.

Forward-looking measures of transition risks

In order to improve and complete the measure of transition risk, a recent literature has also focused on assessing the mitigation strategies to integrate the future exposure to transition risk into the asset price. This strand of literature focuses on forward-looking metrics using the alignment of companies to low-carbon scenarios.

The concept of “alignment” has become a useful tool for companies and investors since the 2015 Paris Agreement ([Cochran et al., 2019](#)). Companies align their strategy to a certain climate scenario, which means that their objective is to contribute to reaching a global level of emissions compatible with the climate scenario. For example, a company can align its strategy to the IEA Net-Zero Emissions (NZE) scenario, this means that it commits to maintain its emissions on a trajectory that is compatible with reaching net-zero emissions by 2050 on a global scale.

There are various methodologies for measuring the alignment of a company. First, the choice of scenarios is crucial in order to define the benchmark for companies to follow. A low-carbon scenario usually provides a decarbonization pathway, which is a trajectory of global emissions in the future that is compatible with a certain temperature rise. Then, the trajectory of emissions needs to be distributed between industries and eventually to companies themselves. The Alignment Cookbook ([Raynaud et al., 2020](#)) considers two approaches, illustrated in Figure 1.2: a contraction-based approach, where a common decarbonization rate is applied to the industry (either to absolute GHG emissions or to GHG emissions intensity), and a convergence-based approach, where companies must reduce their carbon intensity to a common value. In many cases, the contraction-based approach determines a single sector-agnostic rate, irrespective of the geography, sector, or initial amount of emissions from companies. The convergence-based approach is used in certain specific sectors and takes into account the initial level of GHG emissions of companies. However, deriving a convergence-based approach from a global decarbonization scenario is difficult, as the objective of firms is to reduce their carbon intensity and not their absolute emissions:

the reconciliation between global decarbonization objectives and the reduction in a carbon intensity metric can lead to uncertainties about the overall achievement of the scenario.

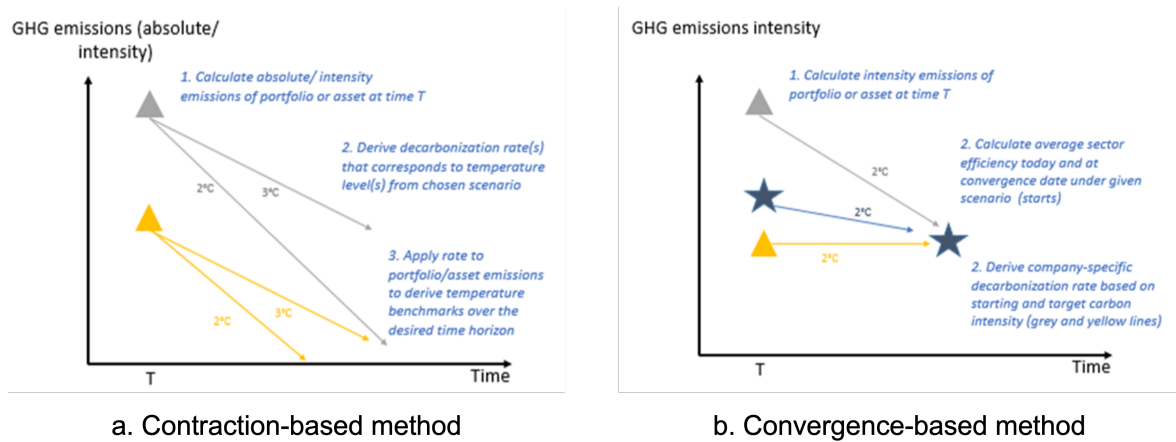


Figure 1.2: Contraction-based and convergence-based methodologies for aligning the company to a low-carbon scenario

Announcing an alignment to a low-carbon scenario is a way for a company to communicate to investors how it intends to manage its transition risk (Fernandez-Feijoo et al., 2014; Haleem et al., 2022). This information is a long-term indicator of the firm’s transition risk exposure for the investor. There are other objectives behind committing to a low-carbon target: to lessen the impact of climate change, to increase customer demand, and to attract investors (Flammer, 2012; Chen et al., 2019; Bolton and Kacperczyk, 2021b). The notion of alignment extends to financial portfolios, with ratings such as the Implied Temperature Ratings (Raynaud et al., 2020) and is used to measure the portfolio’s future exposure to climate risk (Giese et al., 2021). Multi-stakeholder initiatives such as the CDP, the Science-Based Targets initiative (SBTi), or the Transition Pathway Initiative (TPI) play an important role in accelerating the commitment of firms to low-carbon targets (de Bakker et al., 2019; Nikolaeva et al., 2023). These initiatives provide methodologies for companies to set low-carbon targets and align themselves to low-carbon scenarios, but they also certify that these targets are compatible with global scenarios. Finally, they often provide ratings to investors on the ambition of firms, which improves the measure of future exposure to climate transition risk.

Carbon performance metrics and investor preferences

Investors may use other types of metrics to measure the carbon performance of firms when they have a preference for green stocks. Even though they are commonly used metrics to assess the transition risk exposure of a company, GHG emissions are also used to assess the climate performance of firms. They are distributed in three categories (Protocol, 2005):

-
- *Scope 1* emissions correspond to the direct emissions of a firm that occur from sources that are owned or controlled by the company: boilers, furnaces, vehicles for internal operations, etc.
 - *Scope 2* emissions account for GHG emissions from the generation of purchased electricity and heat consumed by the company.
 - *Scope 3* emissions are all other indirect emissions. They are often split into two sub-categories: upstream emissions in the value chain (emissions from purchased goods, business travel, etc.) and downstream emissions in the value chain (use of sold products, emissions generated by waste from the products, investments, etc.).

GHG emissions, or carbon emissions, are purveyed by data providers (MSCI, Sustainalytics, Trucost S&P Global, etc.) and can also be reported by companies on platforms such as the CDP. Investors often correct for the market capitalization or size of companies by using the GHG intensity emissions: they divide emissions by the revenue or the earnings before interests and taxes. Yet there are several issues when using carbon data to evaluate the performance or “greenness” of a firm. Firstly, there is a lack of historical climate data, especially for small companies: this size bias is due to the fact that the biggest firms are the most polluting and investors believe that putting pressure on companies to report their carbon emissions will also make them mitigate said emissions (Matisoff, 2013). Secondly, there are inconsistencies in the reporting methodology between firms, both in terms of what they report on (scopes) and what methodology they use (Stanny, 2018; Busch et al., 2022b). The lack of consistency also exists between GHG emissions reported by companies and third-party providers, especially for indirect emissions; in that regard, mandatory reporting does not improve data consistency enough (Busch et al., 2022b). The lack of consistency and commensurability impacts portfolio performance (Gibson et al., 2021; Avramov et al., 2022) by generating a negative relationship between data consistency and financial performance, as investors consider that there is a risk premium when holding an asset with more uncertainty on its carbon performance. Finally, carbon performance metrics such as GHG emissions are often reported with an important delay, often close to two years: therefore the stock return does not reflect the current climate mitigation strategy of the company, but its past strategy, thereby falsifying the firm’s true exposure to transition risk (Chatterji et al., 2009; Zhang, 2024).

Like transition risk, carbon performance can also be detected using market measures. This is often done by capturing the response to the market climate preference for green stocks using natural language processing algorithms (NLP) that detect positive and negative climate change related news (Hsu and Wang, 2013; Engle et al., 2020; Ardia et al., 2023;

Sautner et al., 2023). This has the advantage of overcoming the lack of standardization in the reporting of climate performance metrics, as the market aggregates the information.

1.2.3 Impact of climate finance on financial performance

We now turn to the question of the impact of climate finance on the financial performance of firms. This question has been extensively studied in the literature as the existence of an opportunity cost could discourage investors from investing in firms that mitigate their climate risk. The low-carbon transition depends on investor decisions (both their willingness to mitigate transition risk and their climate preferences) and cannot be achieved without a massive reorientation of capital towards low-carbon solutions.

There are several mechanisms that explain how the financial performance of a firm may be impacted (Campiglio et al., 2022):

- if a climate-related event, such as an extreme weather event or a sudden change in policies destroys assets or make their use unprofitable: this creates a massive climate risk shock;
- if investments are required to adapt to new policies: this increases the exposure of portfolios to transition risk;
- if investors shift in their preference for climate risks, which could imply a devaluation for brown stocks as investments are reoriented.

Several studies have focused on the measuring the effect of climate risks and investor preference on stock returns. A strand of literature studies how climate risks impact the fundamentals (financial and extra-financial metrics) of a company, and whether this in turn impacts its market valuation (Hong et al., 2019).

From a theoretical standpoint, having climate preferences means that investors should be ready to accept lower financial returns for stocks that have higher climate performances. We illustrate this drawing from the theoretical contribution of Pástor et al. (2021). We consider a group of investors that have heterogeneous climate preferences: using the same notations as in section 1.2.1, we consider that the relative aversion to risk of investor i is a_i and her climate preference is labeled d_i . Equation 1.1 showed her optimal portfolio:

$$\mathbf{x}_i(\mathbf{t}) = \frac{1}{a_i} \Sigma^{-1}(\mathbf{t}) \left(\boldsymbol{\mu}(\mathbf{t}) + \boldsymbol{\rho}(\mathbf{t}) + \frac{d_i}{a_i} \mathbf{g}(\mathbf{t}) \right)$$

The market-clearing condition where the $N \times 1$ market portfolio weight vector \mathbf{X} satisfies:

$$\mathbf{X}(t) = \int_i w_i(t) \mathbf{x}_i(t) di$$

where $w_i(t)$ is the relative wealth of investor i at time t . Considering that the relative risk aversion of investors is unique: $a_i = a$ and the weighted average mean of climate preferences is labeled $\bar{d} = \int_i w_i d_i di$, the average mean of stock returns has an additional component related to the climate performance:

$$\boldsymbol{\mu}(t) + \boldsymbol{\rho}(t) = a \boldsymbol{\Sigma}(t) \mathbf{X}(t) - \frac{\bar{d}}{a} \mathbf{g}(t)$$

If $\bar{d} = 0$, then the market holds a neutral average climate preference and therefore the expected returns of stocks do not differ from their value in traditional asset pricing models, such as the CAPM or the Fama-French 3-factor model, to which a climate risk premium can be added. However, if investors have preferences for stocks with lower exposure to climate risk, i.e. $\bar{d} > 0$, then the expected return is lower for stocks with a high climate performance: this means that investors are willing to sacrifice returns in order to hold more assets with lower climate risk. This result is confirmed in other theoretical studies (Pedersen et al., 2021; Avramov et al., 2022).

Furthermore, climate preferences are not the only motivation for expecting higher returns from brown stocks from a theoretical point of view. According to the risk/return framework of Markowitz (1952), investors should be rewarded for stocks that hold a higher climate risk, therefore brown stocks (Hsu et al., 2023). There is also empirical evidence to support this claim, with the existence of a positive carbon premium on stock returns (Chava, 2014; Bolton et al., 2020; Bolton and Kacperczyk, 2021a; Alessi et al., 2021; Busch et al., 2022a). There are more mixed results that show that brown firms bear more transition risk than green firms but that they do not necessarily outperform them (Broccardo et al., 2024).

However, the theoretical contribution of Pástor et al. (2021) also states that green firms can outperform brown firms during transitional periods where climate finance leads to higher demand and therefore drives asset prices up. Empirical evidence supports this claim when there are unanticipated concerns around climate change (Pástor et al., 2022; Lioui and Tarelli, 2022), or, on the contrary, following positive climate change news (Noailly et al., 2021). The increase in demand for green stocks can occur when investors have increased

their climate preferences. This leads to a lower financial performance for stocks that are within a cap-and-trade system (Ravina and Hentati-Kaffel, 2020), and a higher financial performance for stocks that exhibit lower emissions (Soh et al., 2017; Cheema-Fox et al., 2019; Bernardini et al., 2021; Monasterolo and de Angelis, 2020) or stocks within the renewable energy and cleantech industry (Kempa et al., 2021; Noailly et al., 2021). Other empirical contributions support the evidence that green firms outperform brown firms while a transition to a “carbon-aware equilibrium” is happening (In et al., 2017; Garvey et al., 2018; Duan et al., 2023; Zhang, 2024; Cassola et al., 2024). However, it is expected that once this transition has been made, a positive carbon premium (outperformance of brown firms) should prevail (Enders et al., 2024).

Beyond the impact on stock returns, climate risks can also affect other financial metrics. The valuation of a company may be negatively impacted if it does not mitigate its exposure to climate risk (Hong and Kacperczyk, 2009; De Villiers et al., 2023). There is also evidence that firms that make more reporting efforts on their climate risks disclosure pay more dividends (De Villiers et al., 2023). The climate performance of firms also has a negative impact on their operational performance, measured using the return-on-assets (Alareeni and Hamdan, 2020). The cost of equity is impacted as well, with a negative correlation between the cost and the reporting efforts of companies (Matsumara et al., 2022).

1.2.4 Main limitations

Although the literature on climate finance has extensively grown in the last ten years, there are still several issues with the assessment of climate risks and the market mechanisms at play.

Brown-minus-green factors are useful tools for capturing the impact of climate preference on asset prices or measuring the transition risk of stocks (although they can only capture systematic risk). However, these brown-minus-green factors are mostly built using fundamental carbon data, such as greenhouse gas emissions, or with ratings that rely on fundamental climate data. There are several issues with resorting to fundamental carbon data: the methodologies for computing the GHG emissions of companies may differ between companies, with additional inconsistencies between companies and third-party providers, especially for scope 3 emissions. Another issue is the absence of a relation between GHG emissions and future stock performance, due to the fact that GHG emissions are divulged many months after they have been emitted. GHG emissions are also updated only annually, making BMG factors passive instruments that do not necessarily capture the contemporary transition risk exposure of stocks. There is also a longer timeline than for

fundamental financial metrics to collect carbon emissions from companies, which creates a forward-looking bias in studies using emissions [Zhang \(2024\)](#). Furthermore, past environmental performances do not reflect future environmental behavior and strategies, ([Chatterji et al., 2009](#)), making it hard for investors to anticipate future performance (both financial and extra-financial) with fundamental climate data and invest according to their preference.

The exposure to carbon risk remains an important issue, as investors will seek to protect their assets from fast-changing policies and the potential loss of capital from firms that do not mitigate these risks. There is a nascent literature on low-carbon targets, which reflect a firm's climate ambitions and provide information on its future exposure to transition risk. While announcing low-carbon targets has become a standard practice in the private sector, there is uncertainty in the probability of achieving said targets. This can be a risk for investors: if a firm fails to achieve its target, it faces an increased exposure to climate risk ([Carney, 2015](#)) through two channels: investor rejection can brutally revise its financial value, and decreased customer demand can lead to a loss of capital.

Furthermore, to date, the choice of a company to commit to a low-carbon target has not been approached theoretically, and the financial return of committing to a target remains uncertain. Existing theoretical models on the relationship between climate risk and financial performance have not modeled the impact of committing to a low-carbon target, as they do not consider the exposure to future climate risk, especially the reputational risk of a firm. The role of investors in encouraging firms to commit to low-carbon targets also remains unclear, as they do not only seek to mitigate transition risk but also have climate preferences.

From an empirical point of view, the rating of low-carbon targets has not been extensively approached in the literature, even though the ambition (compatibility of a target with a macroeconomic low-carbon scenario) and credibility (realizable nature of the target) of targets are indicators of future risk for the investor. Several problems arise when a firm announces multiple low-carbon targets: they can overlap in scopes: two targets can be announced, one for scope 1 emissions and another for scope 1 and scope 2 emissions. Targets can also evolve and be updated, but are difficult to benchmark against macro climate scenarios, thus giving the investor unclear information as to their overall compatibility with an efficient climate change mitigation policy. Finally, although the target announcement of a firm can be interpreted as a signal of its future exposure to climate risk, there is no guarantee that the target will be achieved; the investor ignores the scale of necessary financial and operational changes the company should make in order to be successful. Investors would

expect that several financial performance indicators should change after committing to a low-carbon target, yet this remains unclear in the literature.

1.3 PhD objectives

In this thesis, we aim to improve the measure of climate transition risk using both theoretical and empirical approaches. We also seek to understand the impact of climate preferences on low-carbon strategies adopted by companies.

The first objective is to improve the market measure of transition risk by building a Brown-minus-Green factor that relies on the contemporary analyses of investors within the market, which by nature will be more dynamic than a factor built using fundamental climate data. The creation of this BMG factor will allow the construction of a portfolio that is hedged against transition risks.

The second objective is to contribute to an improvement of asset pricing models by incorporating climate risk components and empirically verifying the existence of both idiosyncratic and systematic climate transition risks within stock prices.

The third objective is to focus on the notion of low-carbon targets from both theoretical and empirical standpoints. The question of firms' climate ambitions must be approached from a theoretical point of view, and the role of investors in encouraging companies to mitigate their future risks should be clarified. Furthermore, ratings that measure the quality, ambition, and credibility of low-carbon targets should also be developed, and their relation with the fundamental financial and climate performance indicators of a company (before and after a target is announced) must be explored. This may give investors an indication of the actual mitigation strategy of companies and help them identify companies that will achieve ambitious low-carbon targets from others.

Our last objective is to help investors build portfolios that are hedged against transition risk: using the different methodologies to measure climate transition risk, we aim at building both diversified and thematic portfolios that focus on the best-adapted firms to the low-carbon transition.

1.4 Main contributions

1.4.1 Chapter 2: identification of a brown-minus-green factor

In this chapter, we aim to improve the measure of systematic transition risk by building a brown-minus-green factor using market signals from leaders in the low-carbon transition. We isolate price signals from indexes that track these transition leaders. Using statistical multi-factor models (Rosenberg, 1974), we create a climate risk mitigation trend from the covariance matrix of these indexes using the Random Matrix Theory (RMT) (Wigner, 1955). The Brown-minus-Green factor is built from the sensitivities of stock prices against this climate market trend.

Identification of a climate market trend

We consider a number m of ecological indexes composed of companies with the lowest exposure to climate change. Let us consider $\mathbf{r}_t = (r_t(1), r_t(2), \dots, r_t(m))'$ the m -dimensional daily return vector of the m ecological indexes. We also suppose that \mathbf{r}_t admits a K factors structure, where the $K < m$ common factors are unknown, but one of them is a “climate market” trend. The assumed model for \mathbf{r}_t is as follows:

$$\mathbf{r}_t = \mathbf{B}_t \mathbf{f}_t + \boldsymbol{\epsilon}_t \quad (1.2)$$

where \mathbf{r}_t is the m -vector of returns at time t , \mathbf{B}_t is the $m \times K$ -matrix of index sensitivities to each factor at time t , \mathbf{f}_t is the K -vector of factor values at t supposed to be common to all indexes, and $\boldsymbol{\epsilon}_t$ is a m -vector of Gaussian white noises with variances σ^2 uncorrelated to the factors.

Given Equation (2.1), the covariance matrix at time t is expressed as:

$$\mathbf{C}_t = \mathbf{B}_t \mathbf{C}_t^f \mathbf{B}_t' + \boldsymbol{\Omega}_t$$

where $\mathbf{C}_t^f = \mathbb{E}[\mathbf{f}_t \mathbf{f}_t']$ is the factor-related term and $\boldsymbol{\Omega}_t$ is the covariance matrix of $\boldsymbol{\epsilon}_t$. In the case where the factors are known *a priori*, we deal only with the estimation of \mathbf{B}_t and $\boldsymbol{\epsilon}_t$. In our case, however, the factors are unobservable and have to be determined from the m ecological indexes.

We use two covariance matrix estimators: the Sample Covariance Matrix (SCM), which

is the optimal estimator in the case of multivariate Gaussian samples. However, in financial modeling, the returns are non-Gaussian as they are asymmetric, have fat tails, and tail-dependence (Mandelbrot, 1963; Fama, 1965; Cont, 2001). Therefore, we also use a robust covariance matrix estimator, the Tyler-M estimator (Tyler, 1987):

$$\hat{\mathbf{C}}_{tyl} = \frac{m}{T} \sum_{t=1}^T \frac{\mathbf{r}_t \mathbf{r}_t'}{\mathbf{r}_t' \hat{\mathbf{C}}_{tyl}^{-1} \mathbf{r}_t}$$

where $Tr(\hat{\mathbf{C}}_{tyl}) = m$.

Using Random Matrix Theory (RMT) (Wigner, 1955), we identify the K highest eigenvalues of $\hat{\mathbf{C}}_{tyl}$ expected to represent the K factors. We use the eigenvalues that are above the Marčenko-Pastur (MP) threshold (Marčenko and Pastur, 1967) to isolate factors of interest.

We empirically test the existence of a climate market trend by selecting thematic indexes that focus on ecological topics with a particular emphasis on the low-carbon transition: clean energy, water management, and compliance with low-carbon transition policies. For both estimations of the covariance matrix from the returns of these indexes (SCM and Tyler-M), we isolate the first eigenvalue as the only one above the MP threshold. We then seek to confirm that the associated eigenvector, or factor, is actually a climate market trend. We observe that the trend holds a very high correlation to the indexes with which it was built and has a much lower correlation to the market factor. This points out the fact that the first factors yield a specific trend, different from the market, which, given the transition focus of indexes, reflects what we call a “climate market” trend. Moreover, the first factors from the SCM and the Tyler-M covariance matrix show a correlation of over 99% at all periods, which suggests that the first two factors capture quite similar information. We select the factor built using the Tyler-M covariance matrix to build a BMG factor. The climate market trend covers the September 2010-September 2022 period.

Construction of Brown-minus-Green factors

We then move on to build a BMG factor by measuring the sensitivity of stock prices to the climate market trend. We use the following regression model to separate green stocks from brown stocks:

$$r_i(t) = \alpha_i + \beta_{m,i}r_m(t) + \beta_{g,i}r_g(t) + \beta_{ind,i}r_{ind}(t) + \epsilon_i(t)$$

where $r_i(t)$ is the daily return of stock i at date t , $r_m(t)$ the market return, $r_g(t)$ the climate market trend return, and $r_{ind}(t)$ is the industry³ return. The sensitivities to the market factor, climate market trend, and industry factor are β_m and β_g , and β_{ind} . $\epsilon_i(t)$ is the error term. The regressions are conducted using the Huber loss function (Huber, 1964; Rousseeuw and Leroy, 1987) to estimate the BMG factor with a robust regression so as to account for the non-Gaussian characteristic of stock returns.

We perform 47 quarterly regressions (March 2011 to September 2022) with a window of 130 past daily returns for stocks within the MSCI[®] World Index that are in sectors that are the most exposed to the low-carbon transition (High Climate Impact Sectors). At each quarter, using coefficients from the regression, we create a green portfolio and a brown portfolio that are defined as follows:

- The green quarterly portfolio holds stocks that have a strictly positive sensitivity to the climate market trend returns at the 5% confidence interval; when there is a high number of stocks for which it is the case, we select the top 30% of stocks with the highest sensitivity.
- The brown quarterly portfolio holds stocks that have a strictly negative sensitivity to the climate market trend returns at the 5% confidence interval; when there is a high number of stocks for which it is the case, we select the bottom 30% of stocks with the lowest sensitivity.

The performance of the BMG factor is shown in Graph 1.3.

³We use the first level of the Global Industry Classification Standard (GICS[®] Sectors).

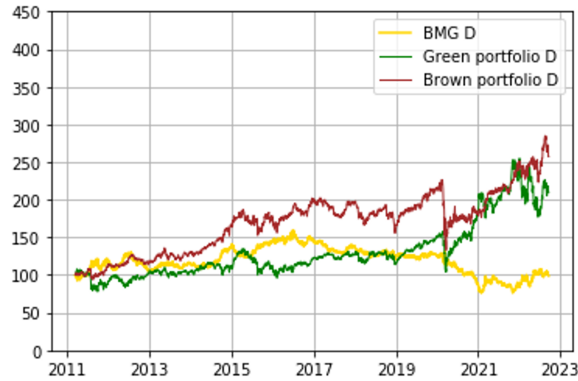


Figure 1.3: Cumulative performance of the BMG factor, brown and green portfolios.

The performances are shown for daily prices between March 2011 and September 2022.

Relevance of the Brown-minus-Green factor

To test the relevance of the BMG factor, we introduce the different BMG factors in asset pricing models and observe the adjusted R^2 of the regressions. The results show that the BMG factor significantly enhances the explanatory power of factor models: there is an increase of 3.77 percentage points between the CAPM (Markowitz, 1956) and the CAPM + BMG model. The result holds for the Fama-French 3-factor model (Fama and French, 1995) and the Carhart model (Carhart, 1997), with the BMG factor improving the average adjusted R^2 by 2.79 and 2.36 percentage points respectively.

We also observe the correlation between the BMG factor and other factors from the Carhart model: the market (Mkt), size (SMB), value (HML), and momentum (WML) factors. We find that the BMG factor is almost uncorrelated to the market factor, which can be very helpful for diversification purposes. The BMG correlation to the size and momentum factors is relatively low: there is, on average between the BMG factors, a 20% correlation for the size factor, which is lower than what was previously observed in other papers on BMG factors (Gorgen et al., 2020; Roncalli et al., 2020). The highest effect we find is for the value factor, which can be partially explained by the construction methodology of the BMG factor which focuses on high climate impact sectors.

We go on to compare our BMG factor to others built previously in the literature. We observe a low correlation with BMG factors built using GHG emissions performance (Roncalli et al., 2020) or climate ratings from data providers (Gorgen et al., 2020). Overall the performance and volatility profile of our factor fluctuates following different dynamics in the perception of market transition risk and preference of investors for green stocks (Broc-

cardo et al., 2024): this result is more consistent with theoretical predictions (Pástor et al., 2021; Pedersen et al., 2021), which state that brown stocks tend to outperform green stocks as they hold a higher exposure to transition risk. For example, it appears that during the 2017-2021 period, and especially in the aftermath of the Covid crisis, green stocks started to overperform brown stocks, consistent with the prediction of theoretical models that green stocks outperform brown stocks when there is a positive climate shock (Pástor et al., 2021). In this case, we find a similar result to Cassola et al. (2024) and observe positive returns following events such as the launch of the EU Green Deal. The outperformance of green firms during this period could therefore be explained by the increase in the demand for green stocks, which increases the asset prices and therefore the returns of stocks. However, after the start of the Ukraine war, the dynamic inverts itself and brown stocks outperform green stocks, in line with Bauer et al. (2022); there is uncertainty as to whether this is linked to a transition risk premium for brown stocks, or, as Zhang (2024) states, to a pure financial outperformance that does not integrate climate-related risk. We also show that, overall, our BMG factor improves the asset pricing model better than the other BMG factors. We also verify that our BMG factor improves the capture of transition risk and not simply the shift in investors' preferences using a climate-related news index (Ardia et al., 2023).

We end by computing a new measure of the climate transition risk of stocks, by using the sensitivity of prices to the BMG factor, which we call the climate beta β_C . A stock that has a negative climate beta can be considered as having a low climate transition risk exposure. We find that the climate beta is significant in sectors that are usually hard to rate due to a lack of fundamental data: the Capital Goods, Materials, Energy, or Utilities sectors. We also analyze the dynamics of the climate betas within industrial sectors and find that despite the low volatility of industries' climate beta, we can detect certain events that could be the source of an increase or a decrease in transition risk exposure. Our climate beta could therefore be useful for rating companies more dynamically than with fundamental data, or capturing information on stocks that are hard to rate. This is especially the case for enabler stocks which, through their activities, allow other companies or consumers to make a positive contribution to environmental objectives, such as the lowering of GHG emissions. We find that most enabler stocks have a negative sensitivity to the BMG factor, which means that a majority of enabler stocks can be considered green stocks. Unlike other BMG factors found in the literature, our BMG factor has the most explanatory power. Enabler stocks are thus more exposed to climate transition risk than what has been previously observed.

By building a BMG factor from a climate market trend, we are therefore able to capture the global market consensus of price-makers on the climate transition risk exposure of a

stock. Furthermore, we can provide a more dynamic measure of the exposure of a stock to climate transition risk. This is very useful in the context of extra-financial performance data, which is not up-to-date. The new measure of climate risk, the climate beta, is accessible for any stock and easily comparable to other market factors such as size or value. The climate beta should be considered as a complementary metric to capture additional information to fundamental climate data, especially regarding dynamic trends.

Policymakers should still consider improving the standardization in the reporting on climate transition risk: for this purpose, firms should give more information on their potential stranded assets, their avoided emissions, and other standardized metrics. Another possibility could be to encourage firms (especially in the financial sector) to conduct transition stress tests on their activities and to share the information with investors, so that the transition risk is reflected in stock prices. This could help the interpretation of BMG factor performance, often the product of two driving forces: the premium associated to transition risk and the climate preference of investors, which can deviate asset prices.

1.4.2 Chapter 3: climate scenarios and alignment strategies of companies

In this chapter, we contribute to the nascent literature on climate scenario alignment. We focus on two issues: first, the underlying mechanism in a company deciding to set a target, and the potential influence of investors behind this strategic decision; second, whether the financial risk of a company decreases (lower risk premium) when setting a target. We start by defining low-carbon targets for companies through a decarbonization rate associated with a carbon budget (CB). Using these targets, we build an economic model in two phases, where in the first phase firms must make a strategic decision on abating their emissions at a rate of their choice, by committing to a low-carbon target, or not making any abatement effort. The second phase of the model focuses on a group of investors with climate preferences that allocate their capital to the companies' stocks based on their commitment decisions. The choices of companies and the allocation of investors provide market-clearing conditions and equilibrium stock prices.

We consider an economy with a number M of publicly traded companies. The model is set up over the following timeline:

1. *Evaluation phase*: in this phase, between $t = 0^-$ and $t = 0^+$, companies choose whether to commit to a low-carbon target. If they choose to commit, they must decide on a decarbonization rate. A company selects its target based on its decarbonization ability and on the expected revenue payoff.

We assume that in this phase, stocks are not traded, and companies emit a negligible quantity of greenhouse gas emissions so as not to change the CB. At the end of this phase, companies publicly announce their low-carbon targets.

2. *Operational phase*: this phase starts at $t = 0^+$ when investors make their allocation decisions depending on companies' low-carbon targets and on their own financial preferences. During this phase, companies that have chosen targets abate their emissions.
3. At $t = 1$, the low-carbon targets are successfully reached if companies have continuously decreased their emissions at their chosen rate. The CB is met if all emissions have been abated at the benchmark rate. All stocks are then sold to other investors.

Low-carbon targets of companies

For a company j , we define a low-carbon target as the objective to decrease its emissions by a decarbonization rate $\tau_j \in [0, 1[$:

$$\text{For } t \in [0, T] : e_{j,t} = e_{j,0}(1 - \tau_j)^t$$

where $e_{j,0}$ is the level of emissions. The low-carbon target of a company is therefore characterized by a single parameter, τ_j .

Companies can be classified into 3 categories, based on the type of target they choose:

- **Type B** firms choose to commit to a low-carbon target and select the benchmark decarbonization rate: $\tau_j = \tau_B$.
- **Type H** firms choose to commit to a target dependent on their decarbonization ability: $\tau_j = (a_j + \kappa)^2$ with $0 < \kappa \ll 1$.
- **Type N** firms choose not to commit to a low-carbon target: in this case, investors interpret that the company will not abate its emissions at all: $\tau_j = 0$.

The decarbonization ability of a firm a_j is defined as its capacity to abate its emissions. It can be modeled as a set of parameters (such as the governance of the firm on the topic of climate change, the green technologies developed by the firm, its financial resources, and the historical trend of direct and indirect emissions) assembled under one variable.

Decisions of firms and investors

The evaluation period focuses on the companies' decision whether or not to set a low-carbon target. We assume that the expected net profit for firm j depends on the target it selects: we represent the shift in customer demand through a growth factor that diverges for type B, type H, and type N stocks:

$$E[\pi_{1,j}] = \begin{cases} \pi_{0,j}(1 + g_j^H + \lambda_j \tau_j) & \text{for type H} \\ \pi_{0,j}(1 + g_j^B + \lambda_j \tau_j) & \text{for type B} \\ \pi_{0,j}(1 + g_j^N) & \text{for type N} \end{cases} \quad (1.3)$$

$\pi_{0,j}$ and $\pi_{1,j}$ are the net profits of company j at times 0 and 1. For type H (type B) firms, g_j^H (g_j^B) is the marginal growth rate of net profit for a type H (type B) low-carbon target. As committing to a target mobilizes additional costs, we consider that the marginal growth rate can vary if the company sets a target. For type N companies, g_j^N is the marginal net profit growth rate of the company if it selects a type N target. $\lambda_j \tau_j$ is an additional growth rate reflecting the increase in customer demand for products from companies making significant efforts to reduce their emissions. It is conditional on the company achieving its target and therefore depends on the probability of success λ_j .

We show that when firms must decide on a target, there exists a threshold of ability a^* above which firms will systematically select a type H target. Companies with lower abilities, below the threshold a^* , will choose to be type B companies if the opportunity cost (loss of productivity) does not exceed the potential reward in profit (increase in sales) from achieving their target.

When focusing on the operational phase, we assume that investors will make their allocation decisions by maximizing their expected utility (Pástor et al., 2021; Avramov et al., 2022). The utility function includes an additional term that reflects the climate preference of investors:

$$U(w_i, \mathbf{x}_i) = -e^{-\gamma_i w_i - \frac{\delta_i}{\tau_B} \mathbf{x}_i' \boldsymbol{\tau}}$$

where γ_i is the relative risk aversion, w_i is the gross return of the portfolio at $t = 1$, δ_i is the climate preference, and the vector $\boldsymbol{\tau}$ is a vector with the decarbonization rates chosen by the M underlying companies of the portfolio.

We assume that the return of a stock is defined by a CAPM structure (Sharpe, 1964) to which we add a climate risk premium:

$$r_j = \beta_{mkt,j} r_{mkt} + \tilde{r}_j + \epsilon_j = r_{j,capm} + \tilde{r}_j + \epsilon_j$$

where $\beta_{mkt,j}$ is the sensitivity of asset j to the market return r_{mkt} , \tilde{r}_j is the climate risk premium, and ϵ_j is a normally distributed variable of mean 0 and variance σ_j^2 .

The climate risk premium of a stock depends on the category of target:

$$\tilde{r}_j = \begin{cases} \tilde{r}_H = (1 - \lambda(1 - \tau_B)) \rho_H^T & \text{for type H companies} \\ \tilde{r}_B = (1 - \lambda) \rho_B^T & \text{for type B companies} \\ \tilde{r}_N = \rho_N^T + \rho_N^R & \text{for type N companies} \end{cases}$$

The structure of the climate risk premium reflects the expected exposure to climate-related risks. We consider that regardless of investor preferences, all stocks are exposed to a transition and a reputational risk. In the case of type H and type B stocks, the climate risk premium is the product of two terms: the probability of failing to reach the target (which is the reputational risk) and a transition risk factor specific to each type of company: ρ_H^T and ρ_B^T . The climate risk premium for type H and type B stocks increases when the probability of success is low, as investors will ask for compensation from a higher climate risk exposure of the stock: higher returns are expected when there is a low probability of success.

If a type H or a type B firm fails to achieve its target, its climate risk exposure increases via two channels:

- Firstly, the reputational risk of the firm increases as it has failed one of its main objectives.
- Secondly, there is a shock in the transition risk estimation of the firm, which was expected to be at a certain level but is higher than expected as the firm failed to reach its target. This is reflected by the transition risk factor.

Both of these risks can have significant impact on the firm's financial performance due to possible investor rejection and decreased customer demand. For type N firms, the risk premium is associated to both types of risks (ρ_N^T and ρ_N^R), as the reputation of the company is degraded if it does not take any climate action, and its exposure to transition risk naturally increases over time as it does not make any abatement efforts.

By maximizing the expected utility, the investor's demand provides market-clearing conditions when associated with the choice of companies.

Market equilibrium

We study the market equilibrium under simplified conditions: when the economy has two companies, a type B and a type N, and when the economy has three companies, a type H, a type B, and a type N.

When there are two assets within the economy (a type B and a type N), companies have low decarbonization abilities: this means that companies are not able to easily abate their emissions (this could, for example, be the case for a polluting industry), or the CB is very small, meaning that the benchmark abatement rate is very high. We find that the number of type B stocks is concave with regard to τ_B . This means that there can be a maximum number of stocks with a given decarbonization rate. This marks the existence of a tipping point for the number of firms undertaking a low-carbon commitment: if the exogenous benchmark rate is too high, the number of firms with sufficient abilities to follow the benchmark target becomes smaller. There is a higher probability of failure, which could damage the firm's reputation: the number of companies willing to become type B instead of type N is lower and not optimal.

We also find interesting results when studying the climate risk premium of the two companies. We find that the transition risk factor for the type B company is a decreasing function of τ_B , which translates to a higher climate risk when the benchmark rate is low should the company fail to achieve its target. The climate risk premium for type N is not monotonous but convex with regard to τ_B and reaches a minimum when the number of type B stocks is highest. The convexity of the risk premium highlights the two types of risk for the type N firm: a high reputational risk when the benchmark rate is low and a high transitional risk when the benchmark rate is high.

The results are different when we introduce a third type of company (type H) in the economy (a type H, type B, and type N firm): the number of type N stocks now becomes concave with regards to τ_B , and the number of type H stocks is a decreasing function of τ_B and does not depend on investors' preferences. The climate risk premium profile also differs and is more difficult to interpret. Overall, we find a general trade-off between the climate risk exposure of a firm and the impact of investors' climate preferences.

The theoretical results provide useful insights for policymakers. First, the benchmark decarbonization rate, which serves as a reference for the economy, is scientifically determined using the carbon budget; yet as we have observed, a restrictive carbon budget can discourage firms from committing to low-carbon targets or make them unachievable. Therefore, the regulator can provide help to encourage investors to commit. This can be done through subsidies or tax cuts on transitioning activities in order for firms to minimize the cost of undertaking a target, and maximizing net profit. Another possibility could be to increase customer demand in the case of type B and type H firms: in a business-to-business setting for example, regulators could impose a more stringent reporting on the scope 3 upstream activities of companies and encourage them to select suppliers with clear transition plans. This means that suppliers which set low-carbon targets would be favored from other companies. Another possibility for policymakers could be to increase the climate preference of investors for transitioning companies in all sectors, not just simply companies that are inherently considered as green champions because they emit very little. Furthermore, increasing the transition risk exposure of firms that do not commit to low-carbon targets is another possibility to encourage them to change their strategy. This could be done with a comply-or-explain mechanism: if a company refuses to commit to targets, regulators could impose for the company to explain why it has chosen not to do so, and report the resulting increase in transition risk.

We proceed to empirical illustrations of our model: the main objective is to identify a climate risk premium associated with the alignment strategies of companies. Using the Science-Based Targets initiative database, we find limited evidence of a climate risk premium for companies that do not make target announcements, especially in sectors that are more exposed to climate risk. We also identify a premium that depends on the current alignment of their emissions to a low-carbon scenario, which we obtain with a temperature ratings database.

This chapter focuses on a nascent topic in the academic literature that is nevertheless very popular within the financial industry: low-carbon targets of companies. By approaching the issue from a theoretical standpoint, we highlight several market mechanisms that may be set in place to influence the market composition or the financial risk of firms.

1.4.3 Chapter 4: drivers and successes of low-carbon strategies

The last chapter focuses on an empirical approach to rate and to better understand the financial mechanisms behind low-carbon target strategies of firms. As low-carbon targets

have become a mainstream communication tool for companies to investors, they can become an indicator of a firm's long-term exposure to transition risk. However, an investor can encounter difficulties when assessing the ambition of a low-carbon target (its compatibility with a low-carbon macroeconomic scenario) and its credibility (whether the target is achievable by the company). The financial and extra-financial drivers behind the ambition and credibility of low-carbon targets could also be useful indicators for investors: they can anticipate whether a firm sets ambitious targets and whether the firm will be able to achieve them.

One of the main difficulties when studying the low-carbon targets of companies is the overlap between them: the company can set multiple targets, that cover different scopes of emissions, and it can also update them but with different base and target years. Thus, we start by defining a yearly decarbonization rate for each target, and then we aggregate the targets together in order to compute, for each company, a yearly decarbonization rate and a yearly abatement rate. In order to benchmark the targets, we also refer to a low-carbon scenario from the Net-Zero emissions scenario. This helps us build three datasets of emissions:

- The targeted emissions are the projected emissions of the company if it follows its targets;
- The net-zero emissions are the projected emissions of the company that are compatible with the IEA NZE scenario;
- The historical and trend emissions group the historical emissions from the company and project future emissions the company is likely to emit if it follows its past emissions trend.

We also identify fundamental metrics (both financial and extra-financial) that could have an impact on the decisions of companies to set a target and that could change once the target is announced and the company starts to abate its emissions. We select financial ratios as explanatory variables in our model, and select metrics that reflect the market and corporate performance of companies: from a financial standpoint, we select profitability, solvency, and market valuation metrics to determine the value of the company. We also look at non-financial metrics, and especially climate performance metrics, by comparing the GHG emissions of a firm within the investment universe, within its own industry, and the evolution of these emissions within the investment universe. Our aim is to identify which metrics are the main drivers for the ambitions and successes of low-carbon targets. Our data covers companies within the MSCI® World Index in the 2014-2024 period.

We provide different measures of a low-carbon target's ambition. Our first objective is to study the financial and extra-financial performance of firms before they decide to set a low-carbon target. We find that the profitability of a firm is an important parameter when committing to an ambitious target. We also observe the evolution of financial and extra-financial drivers prior to committing to a low-carbon target and find evidence that, historically, firms that increase their market capitalization are incentivized to pledge ambitious targets and that pledging to a more ambitious target is a way to continue attracting investors. When observing climate performance metrics, we find that the highest target commitments are undertaken by the least-polluting companies, a result that was already observed in previous literature but that does not align with the required efforts of low-carbon scenarios recommended by institutions.

We then go on to measure the credibility of low-carbon targets using historical and trend emissions. When comparing the target, net-zero and historical emissions of firms, we find heterogeneous results between industries: for certain sectors, staying below the net-zero scenario is easily achievable, therefore companies can overachieve their own targets, and they have a few years ahead of what is required of them in terms of a net-zero budget. On the contrary, for other sectors, the historical emissions are already above the net-zero scenario or even their own targets. This suggests that the success of a firm at achieving its target is not systematic and that this could have an impact on the firm's reputational risk.

When observing the financial and climate drivers behind the achievement of targets, we notice different results than those obtained with the ambition of targets. We now observe that firms with lower profitability achieve more of their targets and that firms that increase their leverage (Net Debt/EBITDA) also tend to achieve their targets. We also observe a positive impact of the CAPEX/Sales ratio over the target achievement, suggesting that successful firms look for ways to invest in their abatement efforts after having set their targets.

We end this chapter by building net-zero aligned portfolios: one that is built with companies whose ambitions are aligned to a net-zero scenario (using the target emissions and the net-zero emissions), and another with companies whose emissions are aligned to a net-zero scenario. We find that although the performance and risk profiles of the portfolios are similar, the composition of the portfolios is very different: by selecting companies with ambitious targets, there is no guarantee that the portfolio will continue to be net-zero aligned in the future.

This chapter contributes to the literature on the long-term transition risk exposure of firms. The ambition and credibility measures of low-carbon targets can be useful tools for investors and can help them detect greenwashing practices. Furthermore, we have been able to identify several financial and climate performance drivers that give an indication of the profile of firms that are most likely to set ambitious targets, or that will have the greatest probability of achieving them. This is a complementary approach to the literature on the relation between financial performance and climate risk, as it focuses on the fundamentals of a company (not the stock price) and the climate risk exposure. Deploying reporting metrics on the credibility of transition plans could also be interesting for policymakers, in order to increase transparency and limit the environmental impact of firms in the future.

1.5 Outline of the thesis

The rest of the thesis is structured as follows:

- In Chapter 2, we propose a new methodology for constructing a new Brown-minus-Green factor. This is done with a double purpose: to improve the measure of climate transition risk and to improve asset pricing models. We start by identifying a climate market trend from common market signals between low-carbon transition indexes. Using the sensitivity of stock prices to this climate market trend, we build a brown-minus-green factor that does not rely on fundamental climate data (Gorgen et al., 2020; Roncalli et al., 2020). We then observe the relevance of the BMG factor in asset pricing models, and its relevance for measuring climate transition risk through the sensitivity of stock prices to the BMG factor, a measure we call the climate beta. We end by measuring the climate beta for certain assets: enabler stocks.
- In Chapter 3, we use a theoretical approach to study the market mechanisms behind the decision of firms to commit to a low-carbon target and the influence of investors' preferences on this decision. We build a two-phase model, in which firms have the choice to set targets that are compatible with a low-carbon scenario and observe the conditions under which the number of firms that commit to a low-carbon target can be optimized. We also identify a climate transition risk premium and a reputational risk premium; both vary according to the urgency of climate action. We empirically identify a risk premium from not committing to ambitious low-carbon targets through a third-party verification platform, the SBTi.
- In Chapter 4, we pursue an empirical study that identifies methodologies for assessing the ambition of low-carbon targets, i.e. their compatibility with a low-carbon

macroeconomic scenario, and the credibility of low-carbon targets, or their achievability by firms. We aim to identify the financial and climate performance drivers behind the decision to set an ambitious target and the success of achieving the target. We aggregate the targets of companies and build three emissions datasets: the projected target emissions, the net-zero emissions, and the historical emissions. With these datasets, we build ambition and credibility metrics and confront them to the financial and climate performance of firms. We end this chapter by building two net-zero portfolios, that are either aligned to a net-zero scenario through the ambition of firms or that are aligned using the credibility of targets.

A PRICE SIGNAL APPROACH TO MEASURE CLIMATE TRANSITION
RISK AND IMPROVE ASSET PRICING

2.1	Introduction	40
2.2	Literature review	44
2.3	Theoretical identification of a climate market trend and isolation of green and brown assets	47
2.3.1	Theoretical identification of a climate market trend	47
2.3.2	Covariance matrix estimation of ecological indexes	48
2.3.3	Determination of the climate market trend	48
2.3.4	Construction of the Brown-minus-Green factor from the sensitivity to the climate market trend	49
2.4	Empirical construction of Brown-minus-Green factors	51
2.4.1	Empirical identification of a trend from ecological indexes	51
2.4.2	Isolation of green and brown assets using the climate mar- ket trend	57
2.5	Relevance of the Brown-minus-Green factor	61
2.5.1	Relevance for asset pricing models	61
2.5.2	Relevance within previous literature	67
2.5.3	Dynamic analysis of sensitivities to the BMG factor	74
2.6	Application: measuring the climate transition risk of enabler stocks	80
2.7	Discussion and conclusion	83
2.8	Appendix	85
2.8.1	Benchmark regulation - Sensitive sectors	85
2.8.2	Tyler-M estimator recursive algorithm	85
2.8.3	Huber loss function	86
2.8.4	List of green and brown companies	86
2.8.5	Sensitivity of Green/Brown portfolios to the Paris Agreement	86

This chapter is based on a published article and a conference in collaboration with Thibault Soler.

Green factor: Quantifying equity returns' climate risk using green active fund allocations

15th International Conference on Computational and Methodological Statistics, December 2022, King's College London, UK

Carbon data isn't the whole story: A price signal approach to measure climate transition risk and improve asset pricing

Mansoux, J. and Soler, T., Journal of Climate Finance, 7, June 2024,

<https://doi.org/10.1016/j.jclimf.2024.100042>

Abstract

The shift to a green, low-carbon economy is generating new investment strategies and impacting asset prices. In this paper, we isolate price signals related to the low-carbon transition using statistical multi-factor models and the Random Matrix Theory (RMT). This allows us to isolate green and brown stocks, and to build a Brown-minus-Green (BMG) factor which has two purposes. Firstly, the sensitivity of asset prices to this new BMG factor gives us a market measure of climate transition risk that does not involve naturally outdated fundamental climate metrics. Secondly, adding this BMG factor to asset pricing models significantly and robustly improves previous BMG factors used in the literature. We contribute to the nascent literature on climate factors by improving the climate risk measure of enabling activities: we achieve the isolation of companies that allow others to reduce their climate risk and that are challenging to capture when using only greenhouse gas (GHG) emissions or previous BMG factors, due to their high carbon intensities.

Keywords: Climate transition risk, Enabling activities, Price signals, Brown-minus-Green factor, Asset pricing, Random matrix theory

JEL: C38, G12, Q54

2.1 Introduction

Identifying and mitigating risks related to climate change has become a standard practice within the financial industry (Chatzitheodorou et al., 2019; Giglio et al., 2021). Investors play an important part in orienting companies towards the low-carbon transition, by redirecting their investments towards firms that mitigate their greenhouse gas (GHG) emissions better or that manage their climate change risks and opportunities more efficiently. This sends firms a strong signal to develop extra-financial performance practices and thus to improve agency ratings. For example, firms can take part in voluntary programs, such as the Science-Based Targets Initiative or the Carbon Disclosure Project. They can also adapt their activities to comply with investor demand and with stringent regulations.

Financial portfolios are also exposed to climate risk by investing in firms impacted by climate change. Investors have become increasingly exposed to more rigorous regulations, with an obligation to report how their portfolios are exposed to climate risk and how they impact the planet. This is known as the double materiality concept, on which investors within the European Union must report (Sustainable Finance Disclosure Regulation).

The Taskforce on Climate-related Financial Disclosure (TCFD) has identified three types of risks related to climate change to which investors are exposed (Carney, 2015): physical risks lead to financial losses from climate change impacts (natural disaster events that increase in frequency and magnitude); transition risks appear when a company does not orient its activities towards a low-carbon economy, which can involve the loss of financial value from disinvestment or the obsolescence of activities and assets; finally, a company faces liability risks when it doesn't tackle the aforementioned risks and can be subjected to financial compensations for the damages they cause.

Most of the focus is currently on transition risks and relies on fundamental climate data that provides information on how a company adapts to a rapidly evolving regulation and pressure from investors. The data is used by investors to compare the performance of companies within their investment universe and the industry. Fundamental climate data is obtained through specialist or generalist data providers in the form of metrics, such as the annual direct and indirect GHG emissions of a company (scope 1, 2, and 3 emissions), water consumption, exposure to fossil fuel energy sources, or revenue from carbon-intensive economic activities. Some metrics also identify opportunities related to climate change, such as the change in revenue from carbon-intensive to low-carbon economic activities, consumption from renewable resources, or change in providers to lower indirect emissions.

Another approach is to build a Brown-minus-Green (BMG) factor (a long/short portfo-

lio) and measure the stock price sensitivity to this factor. This serves as a market measure of climate risk (Gorgen et al., 2020; Roncalli et al., 2020) and relies on the hypothesis that climate risk generates market movements and that it is possible to isolate it. Using market data can provide additional information to fundamental climate data and has several advantages: first, isolating market movements in stock prices related to climate risks allows an investor to appreciate the market consensus on the risk when fundamental climate data is often heterogeneous and incomplete. Second, the market data is much more dynamic and up-to-date than fundamental climate data, which is often disclosed on an annual basis and only exploitable one to two years after the emission date. Finally, aggregating metrics on both risks and opportunities around climate change can be a very strenuous task, especially when building a rating that can cluster several dozens of metrics, with relative weights based on the characteristics of a company: industry, region, size, etc., whereas isolating a climate risk factor in a stock price gives a unique global rating on the climate risk exposure of a company. We find in the existing literature that the construction methodology of the BMG factor is either complex to implement as it requires a lot of databases (Gorgen et al., 2020), or is heavily correlated to the GHG emissions of companies (Roncalli et al., 2020), which as we show later hold time-lag issues and incomplete assessments of the climate risk exposure.

In this paper, we develop a new methodology to measure the systematic climate transition risk factor reflected in stock prices. We do so by isolating price signals from indexes that track leaders in the mitigation of transition risk. Based on statistical multi-factor models (Rosenberg, 1974), we isolate a climate risk mitigation trend (common risk factor) from the covariance matrix of these indexes using the Random Matrix Theory (RMT) (Wigner, 1955) and the upper bound of the Marčenko-Pastur (MP) distribution (Marčenko and Pastur, 1967). This is called the “climate market” trend, which starts overperforming the market during the post-COVID economic recovery. Computing the sensitivity of stock prices against the climate market trend, we build a long/short portfolio, the Brown-minus-Green factor. To the best of our knowledge, we are the first to use such a methodology to isolate a green portfolio and a brown portfolio.

The construction of a BMG factor has several outcomes. The first is that the BMG factor enhances the explanatory power of asset pricing models, especially the CAPM, Fama/French three-factor, and the Carhart model (Sharpe, 1964; Fama and French, 1995; Carhart, 1997; Fama and French, 2005). This result withstands robustness checks. Furthermore, the BMG factor has a relatively low correlation to factors such as size, value, and momentum; most importantly, it has a very low correlation to the market, which could be useful for diversi-

fication purposes.

The second outcome is that this BMG factor can provide a new market measure of the climate transition risk, which we call the climate beta. We calculate this risk by computing the sensitivity of asset returns to the BMG factor while controlling for market, size, value, and momentum factors (Carhart model). We aim to pursue research on market measures of climate risk as a complementary approach to using fundamental climate data. By calculating the climate beta of a stock, we provide an overview of the market consensus on its exposure to the transition risk, which has the advantage of aggregating a large volume of information into a single market signal. Furthermore, previous market measures of climate risks rely heavily on the GHG emissions of companies: brown and green portfolios are built by separating high-emitting companies from low-emitting companies, accounting for all industrial sectors, including those less exposed to the low-carbon transition. In our view, this does not solve the issues we have identified with fundamental climate data: the market measure will prove an insufficient evaluation of stocks' exposure to climate transition risk, and the measure will be outdated because it will be based on emissions from the previous or second-to-last year, making the market measure obsolete. We provide an alternative and complementary approach, by capturing price signals from the market leaders in the low-carbon transition. Therefore, the climate beta of a stock will reflect a global market consensus on its ability to follow leaders.

Finally, we show that this additional metric provides an improved measure of climate risk for a family of companies that are usually hard to accurately rate with fundamental climate data: enabling companies. We identify enabling companies, or “enablers” as firms which, through their activities, allow other companies or consumers to make positive a contribution to environmental objectives, such as the lowering of GHG emissions. Our BMG factor allows the identification of enablers as having a green sensitivity, a result that is not observed when using a BMG factor built with fundamental climate data.

To summarize, our climate betas translate into a general market consensus on the exposure of an asset to the climate transition risk. This means that the betas hold information beyond the carbon footprint, which is generally used as a measure of transition risk but which is often incomplete, especially in the case of enabling companies. This new measure of climate risk is more dynamic and up-to-date than previous market measures of climate risks within the literature.

The rest of this paper is organized as follows: Section 2 reviews the literature on the subject. Section 3 details the theoretical structure for isolating green and brown stocks.

Section 4 lays out the empirical identification of a climate market trend and the subsequent construction of a Brown-minus-Green factor. Section 5 highlights the relevance of the BMG factor within asset pricing models and recent literature. Section 6 highlights how the BMG factor can contribute to measuring climate transition risk in the case of enabler stocks. Section 7 is a discussion and conclusion of this paper's contribution.

Notations: Bold capital letters, such as \mathbf{A} , represent matrices and bold letters like \mathbf{v} represent column vectors. \mathbf{A}' is the transpose of \mathbf{A} . The trace of \mathbf{A} is denoted by $Tr(\mathbf{A})$. \mathbf{A}^{-1} is the inverse of \mathbf{A} . \mathbf{I}_m is the $m \times m$ identity matrix.

2.2 Literature review

Catering climate risk within investment portfolios falls within a more general practice: socially responsible investment (SRI), in which asset allocation strategies take more than strictly financial aspects into account. Investors play a critical role in driving the sustainability transition of companies when coordinated with complementary actions from regulators (governments) and market intermediaries, such as ESG rating providers (Crifo and Sami, 2019). In particular, institutional investors mitigate climate-related risks with both financial and non-financial motivations (Hartzmark and Sussman, 2021; Barber et al., 2021). A survey study shows that investors care most about transition risks, especially the ones emerging with a fast-changing regulation because they have already started to materialize (Krueger et al., 2020). This result is confirmed when extending the survey to various stakeholders within the financial sector: asset managers, scholars, and regulators (Stroebel and Wurgler, 2021). Moreover, funds with lower GHG emissions (which is one of the ways to mitigate climate risks) attract more investors, which shows the financial incentive of reducing climate risk exposure for asset managers (Humphrey and Yong, 2021).

Investors and fund managers measure climate risk through fundamental climate data, a common-used approach to evaluate how a company adapts to and mitigates climate change. Greenhouse gas (GHG) emissions are the most commonly-used metric, which companies can publicly report through annual or sustainability reports, or on platforms such as the Carbon Disclosure Project. Yet several issues appear when using corporate carbon performance (CCP). There is a lack of climate data, which is often only available for large listed equities. There is often a focus on the biggest firms, which are the most polluting, because investors believe that putting pressure on companies to report their carbon emissions will also make them mitigate said emissions (Matisoff, 2013): therefore targeting large firms will have the most impact on risk mitigation. Furthermore, even though there has been an effort to increase data comparability (GHG Protocol, Carbon Disclosure Project), companies adopt different approaches when they calculate their GHG emissions, both in terms of what they report on (scopes) and what methodology they use (Stanny, 2018). Inconsistencies also exist between GHG emissions reported by companies and third-party providers, especially for indirect emissions; in that regard, mandatory reporting does not improve data consistency enough (Busch et al., 2022b). The lack of consistency and commensurability impacts portfolio performance (Gibson et al., 2021; Avramov et al., 2022) by generating a negative relationship between data consistency and financial performance, as investors consider that there is a risk premium when holding an asset with more uncertainty on its carbon performance. Another problem is the absence of a relation between carbon performance data

and future stock performance. Carbon performance metrics, such as GHG emissions, are divulged many months after they have been emitted into the atmosphere. Furthermore, a lot of carbon performance metrics are passive by nature. GHG emissions are annually updated metrics and third-party data providers build datasets where severe incidents are aggregated into controversy ratings which usually last for a long time. Past environmental performances do not reflect future environmental behavior and strategies, (Chatterji et al., 2009), therefore it is hard for investors to anticipate future performance (both financial and extra-financial) with fundamental climate data.

By using fundamental climate data to measure climate risk, investors change their allocation strategies to incorporate the extra-financial performance of companies, thereby impacting asset prices. Under the efficient market hypothesis, climate change risk pricing reflects the exact value of future cash flows, taking into account the three types of risks related to climate change: physical, transition, and liability risks (Campiglio et al., 2022). Any change in the anticipation of climate risks has a proportionate impact on the asset price. The existing literature on the subject is extensive and highlights that climate change-related risks are starting to be reflected in stock returns, even if they are not necessarily priced efficiently. There is for example a divergence in the systematic risk after the Paris Agreement, but only for low-carbon assets, with no reaction for carbon-intensive assets (Monasterolo, 2020). While returns are abnormal when portfolio strategies take into account changes in corporate carbon performance, which means that risks are reflected in stock returns, financial markets seem inefficient when pricing public information on GHG emissions (Liesen et al., 2017).

The literature on Brown-minus-Green (BMG) factors has developed extensively with a double purpose: to enhance the empirical literature on the relative performance of green versus brown stocks and to improve the measure of climate risk. Green and brown firms are often separated using GHG emissions (Roncalli et al., 2020; Ardia et al., 2023), although other metrics exist such as water consumption, exposure to fossil fuel energy sources, change in revenue from carbon intensive to low carbon economic activities, or consumption from renewable resources (Gorgen et al., 2020; De Angelis and Monasterolo, 2024). BMG factors are a useful tool for isolating abnormal returns related to climate change. The empirical findings remain inconclusive, contrary to the prediction of theoretical findings on the expected returns of green stocks (Pástor et al., 2021; Pedersen et al., 2021). This is due to methodological and sampling differences (Bauer et al., 2022). Using a Media Climate Change Concerns (MCCC) index, the authors in Ardia et al. (2023) empirically confirm the findings of Pástor et al. (2021) that green firms overperform brown firms when there is a

global concern about climate change. However, in [Bauer et al. \(2022\)](#), they generalize the higher risk-adjusted returns of green stocks vs brown stocks over the past 10 years, except when there is a peak of unexpected demand from the Energy and Defense sectors, an event which happened in 2022 with the Russian invasion of Ukraine. Using a different climate change news index, they find in [Maeso and O’Kane \(2023\)](#) that only brown portfolios are affected by climate change news and drive the relative performance of green and brown stocks. Other papers have opposite findings [Alessi et al. \(2021\)](#); [Bolton and Kacperczyk \(2023\)](#), especially in the aftermath of shocks ([Agliardi et al., 2022](#)).

Studies have also shown that BMG factors improve capital asset pricing models, and contribute to improving the measure of the climate risk of a stock. We refer to the BMG factors of [Gorgen et al. \(2020\)](#) and [Roncalli et al. \(2020\)](#), which both build the factors using fundamental climate data: in [Gorgen et al. \(2020\)](#) they use four ESG databases to build 55 proxy variables, which serve as metrics for a brown-green score; in [Roncalli et al. \(2020\)](#) the authors use direct GHG emissions. However, these studies are the first to provide a market metric of carbon risk, through the sensitivity of stock returns to the BMG factor (which they call the carbon beta). This market measure of carbon risk is used to assess the exposure of climate risk within sectors that are indirectly exposed to climate change risk and are therefore hard to rate with fundamental climate data, such as Capital Goods or Materials.

Using fundamental climate data as a discriminating factor to identify green and brown stocks has its limits. Carbon metrics are not up-to-date, therefore the BMG factor will capture a past representation of climate risk. Furthermore, [Gorgen et al. \(2020\)](#) uses a very complex methodology, which is hard to implement in practice, to build a discriminating score. By simplifying the methodology, [Roncalli et al. \(2020\)](#) lose information related to climate risk: the carbon footprint of a stock is a proxy for carbon risk but does not reflect a holistic assessment of the exposure of a stock to risks related to climate change. This is especially visible for enabling companies that cannot be discriminated based solely on carbon footprint. This study aims to improve the capture of climate-related risks of stocks: the discriminating metric will be related to a price signal of stocks that have a very low exposure to carbon risk.

2.3 Theoretical identification of a climate market trend and isolation of green and brown assets

This section presents our methodology to build the Brown-minus-Green (BMG) factor. First, based on statistical multi-factor models (Rosenberg, 1974; Grinold et al., 1989), we use the Random Matrix Theory (RMT) (Wigner, 1955) and more especially the upper bound of the Marčenko-Pastur (MP) distribution (Marčenko and Pastur, 1967) to extract common features between ecological indexes that focus on the low-carbon transition and create a price signal that we call the “climate market” trend. Then, we can separate green and brown assets through the sensitivity of stock returns to the climate market trend.

2.3.1 Theoretical identification of a climate market trend

We start by selecting m ecological indexes that are composed of companies with the lowest risk exposure to climate change, which we call market leaders, with a focus on the low-carbon transition. Let us consider $\mathbf{r}_t = (r_t(1), r_t(2), \dots, r_t(m))'$ the m -dimensional daily return vector of the m ecological indexes. We also suppose that \mathbf{r}_t admits a K factors structure, where the $K < m$ common factors are unknown, but one of them is a “climate market” trend. The assumed model for \mathbf{r}_t is as follows:

$$\mathbf{r}_t = \mathbf{B}_t \mathbf{f}_t + \boldsymbol{\epsilon}_t \quad (2.1)$$

where \mathbf{r}_t is the m -vector of returns at time t , \mathbf{B}_t is the $m \times K$ -matrix of index sensitivities to each factor at time t , \mathbf{f}_t is the K -vector of factor values at t supposed to be common to all indexes, and $\boldsymbol{\epsilon}_t$ is a m -vector of Gaussian white noises with variances σ^2 uncorrelated to the factors. Given Eq. 2.1, the covariance matrix at time t is expressed as:

$$\mathbf{C}_t = \mathbf{B}_t \mathbf{C}_t^f \mathbf{B}_t' + \boldsymbol{\Omega}_t$$

where $\mathbf{C}_t^f = \mathbb{E}[\mathbf{f}_t \mathbf{f}_t']$ is the factor-related term and $\boldsymbol{\Omega}_t$ is the covariance matrix of $\boldsymbol{\epsilon}_t$. In the case where the factors are known *a priori*, we deal only with the estimation of \mathbf{B}_t and $\boldsymbol{\epsilon}_t$. In our case, however, the factors are unobservable and have to be determined from the m ecological indexes.

Determining the number of factors is a challenging task in model order selection problems. Subspace methods such as the Random Matrix Theory (RMT) (Wigner, 1955; Marčenko and Pastur, 1967) aim to identify the K highest eigenvalues of \mathbf{C}_t supposed to represent

the K -factors, especially when the power of the factors is greater than the noise power. Moreover, before determining the number of factor K , the covariance matrix of indexes \mathbf{C}_t must be estimated.

2.3.2 Covariance matrix estimation of ecological indexes

First, we estimate the covariance matrix with the widely used estimator called the Sample Covariance Matrix (SCM). For a given period in $[0, T]$, the SCM estimator is defined as:

$$\hat{\mathbf{C}}_{scm} = \frac{1}{T} \sum_{t=1}^T (\mathbf{r}_t - \bar{\mathbf{r}})(\mathbf{r}_t - \bar{\mathbf{r}})'$$

$$\text{where } \bar{\mathbf{r}} = \frac{1}{T} \sum_{t=1}^T \mathbf{r}_t$$

The SCM is the optimal estimator in the case of multivariate Gaussian samples (maximum likelihood estimator). However, in financial modeling, the returns are non-Gaussian as they are asymmetric, have fat tails and tail-dependence (Mandelbrot, 1963; Fama, 1965; Cont, 2001). There can be a better way to estimate the covariance matrix of returns, by using a robust estimator. We aim to evaluate the contribution of a robust covariance matrix estimation to the accuracy of factor extraction.

For the second covariance matrix estimator, we use the Tyler-M estimator (Tyler, 1987), as it is considered, under non-Gaussian assumptions such as elliptical distributions (Kelker, 1970; Cambanis et al., 1981), to be the “most robust” covariance matrix estimator in the sense of minimizing the maximum asymptotic variance (Tyler, 1987; Pascal et al., 2008). The Tyler-M estimator is defined as the solution of the following fixed-point equation:

$$\hat{\mathbf{C}}_{tyl} = \frac{m}{T} \sum_{t=1}^T \frac{\mathbf{r}_t \mathbf{r}_t'}{\mathbf{r}_t' \hat{\mathbf{C}}_{tyl}^{-1} \mathbf{r}_t}$$

where $Tr(\hat{\mathbf{C}}_{tyl}) = m$. The solution can be found using the recursive algorithm (Pascal et al., 2014) in Appendix 2.8.2.

2.3.3 Determination of the climate market trend

Subspace methods such as the RMT (Wigner, 1955; Marčenko and Pastur, 1967) aim to identify the K highest eigenvalues of $\hat{\mathbf{C}}$ expected to represent the K factors. Based on the RMT, it is shown that any eigenvalue above the Marčenko-Pastur (MP) threshold $\lambda^+ =$

$\sigma^2(1 + \sqrt{m/T})^2$ represents the signal space and can therefore be considered as factors of interest. The number of eigenvalues above this threshold determines the order of the model, and thus the number of information-bearing factors in the universe (Laloux et al., 2000; Bun et al., 2017; Soler, 2021).

First, we apply the spectral decomposition of the estimate covariance matrix denoted $\hat{\mathbf{C}}$, which in our case can be either $\hat{\mathbf{C}}_{scm}$ or $\hat{\mathbf{C}}_{tyl}$ as follows:

$$\lambda_j \tilde{\mathbf{v}}_j = \hat{\mathbf{C}} \tilde{\mathbf{v}}_j$$

with $1 \leq j \leq m$ and where λ_j is the associated eigenvalue to the eigenvector $\tilde{\mathbf{v}}_j$.

Then, the number of significant factors K is determined with the MP threshold¹ λ^+ , and we define the matrix \mathbf{V} as the matrix of size $m \times K$ where columns correspond to the normalized eigenvectors, sorted by significant eigenvalues ($\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_K$):

$$\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_K)'$$

$$\text{where } \mathbf{v}_j = \frac{\tilde{\mathbf{v}}_j}{\sum_{i=1}^m \tilde{v}_{i,j}}$$

Finally, the identified common factors $\hat{\mathbf{f}}_t$ (orthogonal basis) are computed in the following way:

$$\hat{\mathbf{f}}_t = \mathbf{V}' \mathbf{r}_t$$

Being that the covariance matrixes are computed by isolating indexes that focus on the low-carbon transition, we can expect that one of the factors $\hat{\mathbf{f}}_t$ will reflect a “climate market” trend, which will be decorrelated from traditional common factors (the market for example).

2.3.4 Construction of the Brown-minus-Green factor from the sensitivity to the climate market trend

We then build a Brown-minus-Green (BMG) factor. We use two different regression models to separate green stocks from brown stocks. The only difference within the models is the

¹Note when we consider the normalized-SCM or Tyler-M, σ^2 is equal to 1.

control for industry. The models are written as follows:

1. We identify green stocks from brown stocks using the stock price sensitivity to the climate market trend and market factor

$$r_i(t) = \alpha_i + \beta_{m,i}r_m(t) + \beta_{g,i}r_g(t) + \epsilon_i(t) \quad (2.2)$$

where $r_i(t)$ is the daily return of stock i at date t . $r_m(t)$ the market return and $r_g(t)$ the climate market trend return. The sensitivities to the market factor and climate market trend are β_m and β_g . $\epsilon_i(t)$ is the error term.

2. We also test whether decoupling the sensitivity to the industry in which the stock belongs is useful to better isolate the “green” or “brown” component within stock prices

$$r_i(t) = \alpha_i + \beta_{m,i}r_m(t) + \beta_{g,i}r_g(t) + \beta_{ind,i}r_{ind}(t) + \epsilon_i(t) \quad (2.3)$$

where $r_{ind}(t)$ is the industry² return in which the stocks belongs and industry sensitivity is β_{ind} .

The regressions are conducted using the Ordinary Least Squares (OLS) (Montgomery et al., 2012), but we also want to account for the non-Gaussian characteristic of stock returns and to test whether using a robust regression improves the construction of the BMG factor. We thus use the Huber loss (Huber, 1964; Rousseeuw and Leroy, 1987) to estimate the BMG factor with a robust regression. The formula for the Huber loss function can be found in Appendix 2.8.3.

²We use the first level of the Global Industry Classification Standard (GICS® Sectors).

2.4 Empirical construction of Brown-minus-Green factors

Using the methodology described in the previous section, we proceed to an empirical application and isolate a climate market trend from indexes that focus on the low-carbon transition, each with a different topic. We then compute BMG factors by identifying green and brown stocks from a restrained universe (only using sensitive sectors defined in Appendix 2.8.1 Table 2.14) with different regression methodologies.

2.4.1 Empirical identification of a trend from ecological indexes

We test the identification of a climate market trend. The main objective is to capture common features between thematic indexes that focus on ecological topics with a particular emphasis on the low-carbon transition: clean energy, water management, and compliance with low-carbon transition policies. We select four indexes from three different index providers that differ in transition themes, sectoral exposure, number of lines, and construction methodology; our purpose is to diversify the sources of index providers to avoid potential biases in the construction methodology of indexes and to collect a maximum amount of information on market signals related to the low-carbon transition. By aggregating the indexes into a common trend, we capture market movements arising from events on different topics that have an impact on the performance of a variety of industrial sectors and avoid disagreements on the “greenness” of the assets. Table 2.1 resumes the main characteristics of the indexes.

Table 2.1: Indexes for the construction of the climate market trend.

Table 2.1 summarizes the main characteristics of the indexes used for the climate market trend. “Univ.” indicates the equities universe, “Compo.” indicates the number of lines within the portfolio at the last date, “Focus” indicates the environmental focus of the fund, “Ann. Return” indicates the annual portfolio return, “Ann. Volatility” indicates the annual portfolio volatility.

Index	Univ.	Compo.	Focus	From	To	Ann. Return (%)	Ann. Volatility (%)
RENIXX® Index	World	30 lines	Renewable energy	01/09/2010	13/10/2022	8.1	26.9
S&P® Global Clean Energy Index	World	95 lines	Renewable energy	01/09/2010	13/10/2022	5.1	23.3
MSCI® Global Environment Index	World	295 lines	Environmental benefit	01/09/2010	13/10/2022	13.3	19.6
S&P® Global Eco Index	World	39 lines	Environmental benefit	01/09/2010	13/10/2022	10.9	16.3

The indexes we select have a common feature: assets are selected by measuring the ex-

posure to low-carbon transition themes, through the revenues they generate. The RENIXX[®] and S&P[®] Global Clean Energy indexes focus on clean energy: they are both exposed to low-carbon electricity utilities (production and distribution of clean electricity) and manufacturers of renewable energy equipment. Stocks within the RENIXX[®] index are weighted according to their capitalization and the index holds only 30 lines. The S&P[®] Global Clean Energy index holds a larger number of constituents, therefore decreasing the volatility compared to the RENIXX[®]; the stocks' weights slightly deviate from their market capitalization. The utility sector makes up 44% of the index, and it is less exposed to the Northern American market: the US represents 40% of the weight, while Chinese stocks make up 13% of the weight, which is much higher than traditional market indexes such as the MSCI[®] ACWI IMI, which represents the market for developed and emerging countries.

We aim not only to capture the clean energy theme but also other themes that contribute to climate change concerns. Therefore, we introduce two more indexes, the MSCI[®] Global Environment and the S&P[®] Global Eco indexes that focus on clean energy, water management, green building, clean technology, and pollution prevention. The MSCI[®] Global Environment index only holds stocks that derive 50% or more of their revenue from the above-mentioned subthemes and holds almost 300 lines from an initial developed and emerging markets universe. The consumer discretionary sector makes up 46% of the index, while the real estate sector makes up 23% of the index, diverging from the previous indexes' composition. The utilities represent only 6% of the index weight. Contrary to the RENIXX[®] index, it holds a larger weight of small stocks compared to its parent index. The S&P[®] Global Eco index holds 66% of its stocks from the industrial sector and is only exposed to two more sectors (utilities and information technology), making it less diversified than the other indexes. Overall, we introduce thematic indexes with heterogeneous sector and country weights to capture as many leaders in the transition as possible: Green Solutions, Fast Transitioning companies, Enabler stocks, etc. We only take four indexes into account, but this number could increase or instead decrease to focus on a specific low-carbon transition theme.

Following the methodology detailed in 2.3.3, we determine the common factors between these four indexes using both the SCM (non-robust method) and the Tyler-M estimator (robust method). We use index daily returns that start on 01/09/2010 until 16/09/2022 and compute the covariance matrix for each quarter from December 2010 to September 2022 (48 quarters), increasing the estimation window to include the latest index returns. Moreover, the factor's time series matrix $\hat{\mathbf{F}}$ is computed by multiplying the vector of weights \mathbf{V}_Q obtained at quarter Q by the daily index returns $\mathbf{R}_{Q-1:Q}$ from the previous quarter $Q-1$ to Q as follows: $\hat{\mathbf{F}}_{Q-1:Q} = \mathbf{V}'_Q \mathbf{R}_{Q-1:Q}$ with $Q \in [1, 48]$. Table 2.2 summarizes the eigenvalues

results from these estimations. For each quarter, we look for eigenvalues that are above the MP threshold³.

Table 2.2: Statistics of the eigenvalues.

Table 2.2 presents the main statistics from the eigenvalues from the SCM and the Tyler-M estimator. Eigenvalues are sorted by descending order, the statistics cover 48 quarters between December 2010 and September 2022 with increasing time periods, in order to include the latest index daily returns. We highlight values which are over the Marchenko-Pastur’s threshold (*).

	min	max	mean	avg. explained variance (%)
<i>Eigenvalues from the SCM</i>				
1	2.73*	3.23*	3.11*	77.8
2	0.42	0.97	0.54	13.5
3	0.15	0.29	0.23	5.78
<i>Eigenvalues from the Tyler-M estimator</i>				
1	2.76*	3.18*	3.05*	76.3
2	0.55	0.82	0.62	15.4
3	0.18	0.31	0.24	6.12

For both estimations (SCM and Tyler-M), we isolate the first eigenvalue as the only one above the MP threshold⁴. Hence the second, third, and fourth eigenvalues cannot be decoupled from noise and only the first eigenvectors from each period can be considered as holding significant information. The first eigenvectors, on average between all periods and between the robust and non-robust methods, account for more than 76% of the explained variance.

The correlation between the first common factor, the indexes, and the market factor is a first indication that can help us identify the first factor as a “climate market trend”. As can be shown in Table 2.3, over the whole period, the common factor holds a very high correlation to the indexes with which it was built: between 86% and 95% for the factor built using the SCM, and between 83% and 94% for the factor built using the Tyler-M estimator. Despite strong correlations with the S&P[®] Global Clean Energy index, the annualized tracking errors⁵ with the first factors remain significant, exceeding 8% over the period. These substantial tracking errors suggest pronounced divergence in performance at specific times, indicating their ability to capture information from other indexes. The correlation to the market factor (MSCI[®] World Index) is 77% and 73% respectively, which is lower than the

³Overall, the lowest/highest MP threshold is 1.26/1.56 (longest/shortest period).

⁴The minimum first eigenvalue is above the highest MP threshold (see section 2.3.3). The maximum second eigenvalue is below the minimum MP threshold.

⁵Tracking error measure quantify the variability in returns between two assets. It is the standard deviation of the difference between the returns of the two assets. To annualize the tracking error, we multiply it by $\sqrt{252}$.

correlation of the two ecological indexes to the market factor. This points out the fact that the first factors yield a specific trend, different from the market, which, given the transition focus of indexes, reflects what we call a “climate market” trend. Moreover, the first factors from the SCM and the Tyler-M covariance matrix show a correlation of over 99% at all periods, which suggests that the two first factors capture quite similar information.

Table 2.3: Correlation table for the indices and first factors.

Table 2.3 shows the correlations between daily returns for the two first factors (SCM and Tyler-M), the ecological indexes, and the MSCI World Index (market); the dates range from 01/09/2010 to 16/09/2022, the second part of the table shows the correlation for a specific period between 01/01/2020 and 16/09/2022. Results are shown in %. The superscript symbol * indicates the indexes that have more than 90% correlation to the two first factors.

01/09/2010 - 16/09/2022	First factor SCM	First factor Tyler-M	RENIXX® Index	S&P® Global Clean Energy Index	MSCI® Global Environment Index	S&P® Global Eco Index	MSCI® World Index
First factor - SCM	100						
First factor - Tyler-M	99.62*	100					
RENIXX® Index	87.67	91.30*	100				
S&P® Global Clean Energy Index	94.28*	93.97*	78.00	100			
MSCI® Global Environment Index	86.00	83.14	64.00	72.55	100		
S&P® Global Eco Index	87.43	83.82	60.94	83.02	75.19	100	
MSCI® World Index	77.32	73.33	50.31	68.93	80.78	84.01	100
01/01/2020 - 16/09/2022	First factor SCM	First factor Tyler-M	RENIXX® Index	S&P® Global Clean Energy Index	MSCI® Global Environment Index	S&P® Global Eco Index	MSCI® World Index
First factor - SCM	100.00						
First factor - Tyler-M	99.71*	100.00					
RENIXX® Index	89.86	92.89*	100				
S&P® Global Clean Energy Index	95.10*	94.86*	82.20	100			
MSCI® Global Environment Index	84.26	81.85	65.58	70.55	100		
S&P® Global Eco Index	87.33	84.50	65.84	86.37	66.71	100	
MSCI® World Index	70.36	66.42	45.10	64.38	69.89	80.18	100

Figure 2.1 shows the relative performance of the first factors (“First factor - SCM” and “First factor - Tyler-M”) and the climate market indexes over two different periods. The highest price variations appeared in the aftermath of the COVID crisis, as it had a deep effect on the performance of indexes. During the period between September 2010 and March 2020, all ecological indexes underperform the market. The tendency turns around during the rebound of the second half of 2020, where the majority of the ecological indexes outperform the market and have much higher volatility (Figure 2.1): this is especially the case for the RENIXX® and the S&P® Global Clean Energy Index, which cumulated performance spikes to almost 350% and 250% respectively between January 2020 and February 2021. These performance trends, which decouple the market performance from the ecological indexes performance are confirmed if we observe the correlation between these indexes and the market, that falls during the period September 2020 and September 2022. We confirm a very similar trend between the first principal factors (SCM and the Tyler-M). The only difference is that extreme values are slightly weaker when using the robust estimation. The combined correlation results and the performance trajectory confirm the identification of the first factor as our climate market trend, with which we can build a BMG factor. Moreover, to account for non-gaussian returns, we continue this study with the first factor from the robust covariance matrix (Tyler-M estimator).

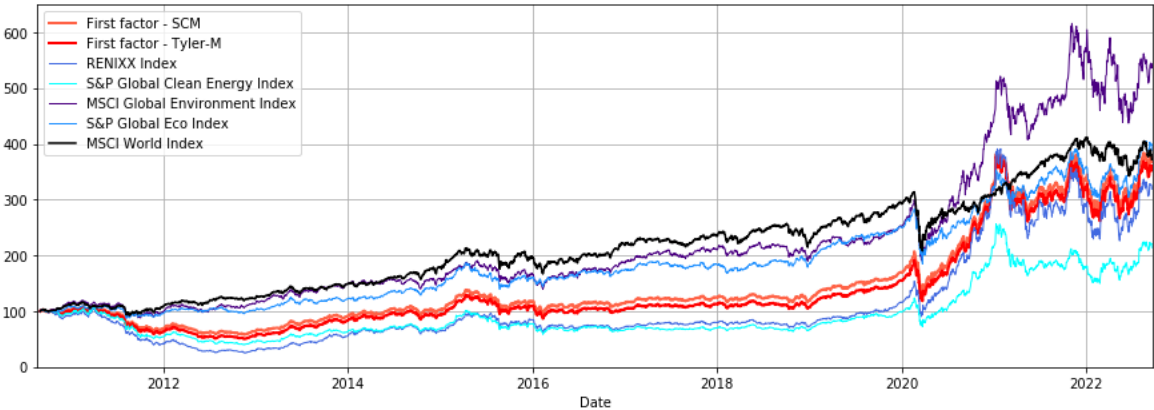


Figure 2.1: Cumulative performance of the climate market trend and indexes.

The performance is shown between September 2010 and September 2022. The climate market trends correspond to the first factors from the SCM (“First-factor - SCM”) and Tyler-M (“First-factor - Tyler-M”) covariance matrices. The indexes are the climate market indexes used for the construction of the climate market trends and the MSCI® World Index.

2.4.2 Isolation of green and brown assets using the climate market trend

With the climate market trend, we isolate green and brown assets to build BMG factors. We select asset returns from the MSCI® World Index that captures large and mid-cap stocks across Developed Markets (DM) of 23 countries. There are around 1500 companies at each rebalancing date and it covers approximately 85% of the DM free float-adjusted market capitalization. Within the MSCI® World Index, we target stocks within sensitive sectors, i.e. sectors that are the most exposed to climate risk (see Table 2.14 in Appendix 2.8.1). The sectors are selected following the European Union classification of sensitive and non-sensitive sectors, that is used for the benchmark portfolios regulation ([European Commission, 2020](#)). We heavily restrain the universe for the construction of the BMG factor, but this allows us to avoid certain biases: we take away several sectors that are less exposed to the impacts of the transition, thereby limiting the risk of not capturing a signal related to climate performance if we use stock returns from those assets. Other sectors, such as the financial sector, are indirectly exposed to climate risk, thus appearing as overperforming other industrial sectors in terms of carbon metrics. They are also very hard to rate, and can add uncertainty when searching for a green and a brown benchmark; thus we also avoid the financial sector from our green and brown portfolios universe.

We perform 47 quarterly regressions (March 2011 to September 2022) with a window of 130 past daily returns⁶. At each quarter, using coefficients from the regression, we create a green portfolio and a brown portfolio that are defined as follows:

- the green quarterly portfolio holds stocks that have a strictly positive sensitivity to the climate market trend returns at the 5% confidence interval; when there is a high number of stocks for which it is the case, we select the top 30% of stocks with the highest sensitivity.
- the brown quarterly portfolio holds stocks that have a strictly negative sensitivity to the climate market trend returns at the 5% confidence interval; when there is a high number of stocks for which it is the case, we select the bottom 30% of stocks with the lowest sensitivity.

We therefore isolate green and brown portfolios using the sensitivity of the stock return to a climate market trend over the period, and not on the fundamental climate data. To the best of our knowledge, we are the first to use such a methodology to isolate a green portfolio and a brown portfolio.

To summarize (see Table 2.4), we create four different BMG factors, labeled A, B, C, and D, that depend on what regression models we use (Eq. 2.2 or 2.3) and whether we perform the regressions with a robust methodology (Huber loss).

Table 2.4: BMG portfolio names.

Table 2.4 presents the names that are given according to the regression models and the estimation methods. In the columns, the regression models used (market factor, climate market trend, and GICS[®] Sector); the estimation methods (OLS or Huber loss) are detailed in the rows.

	Market + Climate market trend	Market + Climate market trend + GICS [®] Sector
OLS	A	B
Huber (Robust)	C	D

The cumulative performance of the different BMG factors, green and brown portfolios are shown in Figure 2.2. As an example, we also provide a list of companies identified as green and brown for the BMG D factor in Appendix 2.8.4.

⁶We also perform regressions throughout 260 past daily returns, with similar results, that are available upon request.



Figure 2.2: Cumulative performance of BMG factors, brown and green portfolios.

The performances are shown for daily prices between March 2011 and September 2022.

We notice several relevant information on the performance of the brown and green portfolios. First, the overall performance trend is similar between the different regression methodologies. There is a strong contrast between the performance of the brown and the green portfolio, with a clear outperformance of brown stocks between 2011 and 2020. The post-covid economic recovery reverses the trend for BMG A, with the green stocks outperforming the brown stocks until the beginning of 2022. This confirms the shift that we observed between the performance of the indexes and the climate market trend we use in the regressions. For BMG factors B, C, and D, the outperformance of green stocks starts even sooner at the end of 2016 and accelerates in 2020.

Second, accounting for industry bias within the regressions (see Eq. 2.3) has an impact on the performance of both portfolios, but is stronger for the brown portfolio: the annualized return is lowered by 2.4 percentage points when accounting for the industry within the robust regressions. Using the industry returns allows us to better isolate, within each industry, the green stocks from the brown stocks, much the same as a best-in-class methodology. Moreover, using a robust regression model increases the volatility of both the green and brown portfolios. The BMG factor has a lower overall performance: both the

cumulated and annualized returns are negative over the period, which means that robust regressions will have a larger effect of lowering the performance of the brown portfolio.

Finally, when studying the graphic performance of the different portfolios, it seems that global events related to climate change, such as global summits or natural disaster events have very little impact on the performance of brown/green stocks. We test whether this is the case by studying the impact of the Paris Agreement on factor returns. Adopting a similar approach as in [Monasterolo \(2020\)](#); [De Angelis and Monasterolo \(2024\)](#) that involves testing if a climate event creates a structural break on Green/Brown portfolio returns, we observe that the announcement of the Paris Agreement impacts Green portfolios more significantly than Brown portfolios. Two Green portfolios (A and C) exhibit positive abnormal mean returns, although very limited, while three show (B, C, and D) reduced systematic risk. Conversely, all four Brown portfolios display only an increase in systematic risk, without any significant abnormal mean returns. The methodology and results are reported in Appendix 2.8.5 and Table 2.16.

While the overall trends and the statistics hold slight differences between the different methodologies, this does not tell us whether accounting for industry returns and using a robust regression methodology have a statistically significant impact. Therefore, we assess the impact of accounting for industry returns and introducing robustness in the regressions by studying the relevance of the BMG factors within asset pricing models.

2.5 Relevance of the Brown-minus-Green factor

In this section, we test the relevance of our construction methodology, first by studying the impact of our BMG factors on asset pricing models (Sharpe, 1964; Fama and French, 1995; Carhart, 1997; Fama and French, 2005), and by comparing the BMG factors to common factors. We then test the relevance of a selected BMG factor over previous BMG factors within the literature Gorgen et al. (2020); Roncalli et al. (2020).

2.5.1 Relevance for asset pricing models

Improving asset pricing models

To test the relevance of the BMG factor and to assess whether the robustness within the regression and the control for industry returns are relevant, we introduce the different BMG factors in asset pricing models and observe the adjusted R^2 of the regressions.

For single stocks within the MSCI[®] World Index between September 2011 and September 2022, we run six factor models summarized in Table 2.5 (Sharpe, 1964; Fama and French, 1995; Carhart, 1997; Fama and French, 2005). We use the Kenneth French library as a source for the market, size, value, and momentum factors (Developed Markets database with daily returns). We compute quarterly OLS regressions (45 quarters) over 130 past daily returns between September 2011 and September 2022 and collect the average adjusted R^2 from the regressions from all the periods and over all the assets.

Table 2.5: Asset pricing models used to test the contribution of the BMG factor.

Table 2.5 summarizes the asset pricing models used for the regression. The Y means that the factor serves as a regressor to the stock price regression and N means that the factor is not included in the regression.

Model	Market (Mkt)	Size (SMB)	Value (HML)	Momentum (WML)	BMG
CAPM	Y				
CAPM + BMG	Y				Y
FF 3-factor	Y	Y	Y		
FF 3-factor + BMG	Y	Y	Y		Y
Carhart	Y	Y	Y	Y	
Carhart + BMG	Y	Y	Y	Y	Y

The results in Table 2.6 show that the BMG factor enhances the explanatory power of factor models: in the case of the BMG D for the CAPM model, there is an increase of 3.77

percentage points between the CAPM and the CAPM + BMG model. The result holds for the Fama/French and the Carhart model, with the BMG factor improving the average adjusted R^2 by 2.79 and 2.36 percentage points respectively. For the Carhart + BMG model, the average adjusted R^2 is at 32.90%, almost 9 percentage points above the CAPM model. When comparing the contributions of the different BMG factors, we find that the BMG D factor, built using a robust regression and controlling for industry, holds the best average adjusted R^2 for all asset pricing models. While robustness marginally improves asset pricing accuracy, it is based on a sounder theoretical background as it accounts for non-gaussian returns. However, the control for industry does make a difference within asset pricing models, whether the regressions are run with an OLS model (BMG B compared to BMG A) or a Huber model (BMG D compared to BMG C).

The results are validated by conducting bootstrap tests for the various models (CAPM, Fama-French 3 factors, and Carhart). We compute long/short portfolios by randomly selecting 30% of stocks within the MSCI[®] World Index that stands for the long portfolio and another 30% that stands for the short. We perform the same regressions as in Table 2.6, adding the random long/short portfolios to the CAPM, Fama-French 3 factors, and Carhart models. We repeat the operation for 1000 occurrences (we generate 1000 random long/short portfolios) and obtain the distributions of the average adjusted R^2 for each model. We find that the average adjusted R^2 with the BMG factor is, for each model, within the 99th percentile when replacing the Brown-minus-Green (BMG) factors with random factors. Overall, the BMG D, built using a robust methodology and controlling for industry returns holds the highest average adjusted R^2 and the highest differences between models.

Table 2.6: Explanatory power of asset pricing models.

Table 2.6 shows the effect of introducing the BMG factor within three asset pricing models: the CAPM, the Fama/French 3-factor model (“Fama/French”), and the Carhart model. Panel A shows the average adjusted R^2 from factor models, which are tested for the assets within the MSCI[®] World Index during the study period, between September 2011 and September 2022 (45 quarterly OLS regressions over 130 past daily returns for each stock). Panel B shows the relative difference between the adjusted R^2 between models. The BMG factors are labeled as A to D, their specific construction methodology is indicated below. ***, **, and * mean that the average adjusted R^2 are respectively within the 99th, 95th and 90th percentile of the bootstrap test results.

	BMG A	BMG B	BMG C	BMG D
	OLS regression	OLS regression	Robust regression	Robust regression
	Regressors: market, climate market trend	Regressors: market, climate market trend, GICS[®] Sector	Regressors: market, climate market trend	Regressors: market, climate market trend, GICS[®] Sector
<i>Panel A: average adjusted R^2 from the regressions (%)</i>				
CAPM	23.95	23.95	23.95	23.95
CAPM + BMG	27.40***	27.67***	27.50***	27.72***
Fama/French	28.43	28.43	28.43	28.43
Fama/French + BMG	30.76***	31.09***	30.88***	31.21***
Carhart	30.53	30.53	30.53	30.53
Carhart + BMG	32.42***	32.81***	32.54***	32.90***
<i>Panel B: adjusted R^2 difference between asset pricing models (percentage points)</i>				
Fama/French vs CAPM	4.48***	4.48***	4.48***	4.48***
Carhart vs Fama/French	2.11***	2.11***	2.11***	2.11***
CAPM + BMG vs CAPM	3.45***	3.72***	3.55***	3.77***
Fama/French + BMG vs Fama/French	2.33***	2.66***	2.46***	2.79***
Carhart + BMG vs Carhart	1.89***	2.28***	2.01***	2.36***

Comparison to common factors

Here, we compare the BMG factors to other factors from the Carhart model: the market (Mkt), size (SMB), value (HML), and momentum (WML) factors. In Table 2.7, we find that overall, the BMG factor is almost uncorrelated to the market factor, which can be very helpful for diversification purposes. The BMG correlation to the size and momentum factors is relatively low: there is, on average between the BMG factors, a 20% correlation for the size factor, which is lower than what was previously observed in other papers on BMG factors (Gorgen et al. (2020); Roncalli et al. (2020)). We would expect a negative correlation between the BMG factors and the SMB factor, meaning that brown stocks are typically larger than green stocks (e.g., Oil & Gas companies). However, the market structure has evolved significantly in recent years with the rise of growth stocks, especially technology stocks (e.g., the “Magnificent Seven” stocks⁷). Over the study period, the correlation between the Energy sector and the SMB factor is -4%, whereas it was -19% between 2000 and 2010. The average correlation to the momentum factor is 22.5%. The highest effect we find is for the value factor, with a 34% correlation for the entire study period; this shows that green assets also tend to be growth stocks. This higher correlation can be partially explained by the construction of the BMG factor: by only selecting stocks exclusively within sensitive sectors, we naturally induce a value bias, especially for brown stocks. This observation is reinforced during the 2020-2022 period, where there is a 46% correlation to the value factor.

Table 2.7: Correlation between factors.

Table 2.7 shows the correlation between daily returns from the market (Mkt), size (SMB), value (HML), momentum (WML), and BMG factors between September 2011 and September 2022 (daily returns). All results are in %.

	BMG A	BMG B	BMG C	BMG D	Mkt	SMB	HML	WML
BMG A	100.0							
BMG B	79.9	100.0						
BMG C	87.6	78.6	100.0					
BMG D	76.6	94.9	78.9	100.0				
Mkt	-8.5	-0.8	-3.6	0.3	100.0			
SMB	21.0	19.9	19.7	20.1	-3.9	100.0		
HML	31.7	35.2	32.8	38.1	18.1	60.1	100.0	
WML	23.4	22.2	23.1	21.1	8.5	51.4	22.0	100.0

Overall, BMG D, issued from the robust regression which controls for industry returns shows the highest regression quality with an average adjusted R^2 of 32.9% for stocks within the MSCI® World Index. It is also the least correlated factor to the market. We therefore

⁷“Magnificent Seven” stocks: Microsoft, Apple, Nvidia, Alphabet, Amazon, Meta and Tesla

pursue this study with this BMG factor.

Consistency of the model within decile portfolios

We pursue our study of the explanatory power of BMG factors by observing their contribution to decile portfolios' asset pricing using the BMG D factor. From the MSCI® World Index, we separate our universe according to the average sensitivity of stocks to the BMG D factor, a measure of their exposure to climate risk which we call the climate beta. We obtain equal-weighted decile portfolios, which are rebalanced every quarter. For each decile, we perform OLS regressions with the Carhart + BMG factor model and the Carhart model. The regressions are performed with daily returns from the decile portfolios and the factors over the whole period from September 2011 to September 2022. We report our results in Table 2.8: the mean climate beta of the stocks within decile portfolios is reported in the first column; the sensitivity of decile portfolio returns to the Carhart and BMG factors is reported on the left side of the table. The differences in sensitivities with the Carhart asset pricing model are reported on the right side of the table. The far right column reports the difference in adjusted R^2 between the Carhart + BMG asset pricing model and the Carhart model. We verify the significance of the difference in adjusted R^2 with the F-test on nested models.

Overall, adding the BMG factor significantly enhances the adjusted R^2 within each decile portfolio. The average adjusted R^2 , while highest for the first decile portfolios (which tilt toward brown stocks), has the greatest increase from the Carhart model for decile portfolios with a negative sensitivity to the BMG factor, that is decile portfolios with a green tilt. The sensitivity to the BMG factor is consistent with the mean climate betas and is significant at the 1% confidence interval for each portfolio. The market sensitivity goes from 0.75 to 1 for all portfolios. However, the size (SMB) and value (HML) sensitivities are heterogeneous across portfolios. All portfolio returns yield a negative sensitivity to the momentum factor (WML).

Table 2.8: Explanatory power for decile portfolios.

Table 2.8 shows decile portfolios sorted by their average sensitivity to the BMG factor (“Mean climate beta”) with coefficients from the Carhart + BMG factor model. The adjusted R^2 difference, in percentage points, is the difference between the adjusted R^2 from the regression with the Carhart + BMG model and the regression with the Carhart model. The OLS regressions are run for the period September 2011 to September 2022. The superscript symbols *, **, *** denote significant results at 10%, 5%, and 1% confidence intervals respectively. The superscript symbols (same confidence levels) in the last column (Δ Adj. R^2 (%)) are based on a one-sided F-Test with $H_0: \beta_i^{BMG} = 0$ with $i \in \{Q1, \dots, Q10\}$.

Decile	Mean climate beta	Coefficients							Difference in coefficients					
		Const.	Mkt	SMB	HML	WML	BMG	Adj. R^2 (%)	Δ Const.	Δ Mkt	Δ SMB	Δ HML	Δ WML	Δ Adj. R^2 (%)
Q1	0.556	8.29E-05	1.052***	0.059**	0.095***	-0.204***	0.286***	76.887	0.000	0.037***	0.101	-0.215***	-0.079***	8.091***
Q2	0.348	6.75E-05	0.985***	-0.040**	0.104***	-0.074***	0.239***	83.593	0.000	0.031***	0.085**	-0.180***	-0.074***	6.377***
Q3	0.244	2.02E-05	0.972***	-0.082***	0.099***	-0.036***	0.191***	84.990	0.000	0.025***	0.068***	-0.143***	-0.036***	4.191***
Q4	0.157	5.99E-05	0.947***	0.001	0.089***	-0.065***	0.142***	85.385	0.000	0.018***	0.050	-0.107***	-0.065***	2.464***
Q5	0.051	7.50E-06	0.857***	0.094***	0.040***	-0.073***	0.083***	84.326	0.000	0.011***	0.029***	-0.062***	-0.023***	1.048***
Q6	-0.091	-9.60E-06	0.758***	0.218***	0.012	-0.129***	-0.036***	73.325	0.000	-0.005***	-0.013***	0.077	0.010***	0.241***
Q7	-0.218	1.19E-05	0.743***	0.159***	0.064***	-0.162***	-0.102***	70.277	0.000	-0.013***	-0.036***	0.064***	0.028***	2.107***
Q8	-0.342	-9.08E-06	0.744***	0.077***	0.117***	-0.183***	-0.171***	72.240	0.000	-0.022***	-0.060***	0.117***	0.047***	5.680***
Q9	-0.486	1.15E-05	0.784***	0.029	0.190***	-0.237***	-0.251***	70.674	0.000	-0.032***	-0.089	0.190***	0.069***	10.421***
Q10	-0.759	6.14E-05	0.869***	0.003	0.237***	-0.311***	-0.344***	61.646	0.000	-0.044***	-0.122	0.237***	0.095***	15.229***

2.5.2 Relevance within previous literature

Divergence in the construction of BMG factors and their characteristics

We then focus on the contribution of our BMG factor in the recent literature on Brown-minus-Green factors. We especially want to analyze the impact of divergent construction methodologies: in our case, we do not use extra-financial performance (such as carbon intensity) as a discriminating metric to isolate green assets from brown assets, but we rather aim for market signals to identify movements related to climate information. We compare the financial characteristics of our BMG factor (BMG D) to two factors within the literature. The construction details of those two factors are summarized hereafter:

- We extract the daily BMG returns from the CARIMA methodology, developed by [Gorgen et al. \(2020\)](#). To identify brown and green stocks, a brown-green score is built by taking into account ratings from four ESG databases (55 proxy variables) to assess the current and future performance of firms, and the possible reaction of stock prices to a change in climate policy. The brown stocks are then identified as the bottom scorers, and the green stocks as the best of the brown-green scorers. The authors build 6 portfolios, following the methodology of [Fama and French \(1995\)](#): small green (SG), neutral green, and big green (BG); small brown (SB), neutral brown, and big brown (BB). The BMG factor is a long-short portfolio with the following return formula:

$$R_{bm_g}(t) = \frac{1}{2}(R_{SB}(t) + R_{BB}(t)) - \frac{1}{2}(R_{SG}(t) + R_{BG}(t)) \quad (2.4)$$

$R_{SB}(t)$, $R_{BB}(t)$, $R_{SG}(t)$, and $R_{BG}(t)$ are the daily returns of the Small Brown, Big Brown, Small Green, and Big Green portfolios respectively. We hereby call this long-short portfolio the CARIMA factor.

- We build another BMG factor: within our universe (MSCI® World Index), we identify the brown portfolio by selecting the 30th percentile with the highest carbon intensity (sum of the scopes 1, 2, and 3 upstream GHG emissions over the revenue), and the green portfolio by selecting the 30th percentile with the lowest carbon intensity. Both portfolios are weighted according to the capitalization of the stocks and are rebalanced every trimester. We hereby call it the Carbon Intensity factor. This methodology is similar to the one used by [Roncalli et al. \(2020\)](#), which aims at simplifying the construction method from the CARIMA methodology separating the green stocks from the brown stocks with only scope 1, 2, and 3 upstream emissions.

The performance and statistics of the three BMG factors are shown in Table 2.9 and

Figure 2.3. We separate the results into two periods, as the CARIMA factor returns are only available until the end of 2019. We find that overall, the performance of our BMG factor has a very different trend to the other BMG factors: its volatility is much higher, with an annual figure of 14.74% against 6.98% and 6.13% between 2011 and 2019. The volatility increases even more between 2020 and 2022 at 24.64% for the BMG factor. The cumulated and annual returns are opposed between our BMG and the other BMG factors for both periods. This is confirmed by the performance of the three factors shown in Figure 2.3. BMG factors from fundamental data, CARIMA, and the Carbon Intensity factor have a negative cumulated performance over the entire period, which means that green stocks outperform brown stocks. This is not the case for our BMG factor, which had a positive performance from 2011 to 2017, reaching almost 160% of its initial price in 2016, and then started to underperform. Our results seem more compatible with theoretical predictions in the literature (Pástor et al., 2021; Pedersen et al., 2021), which state that when there is no concern for climate change, brown stocks tend to outperform green stocks. It also appears that during the 2017-2021 period, and especially in the aftermath of the Covid crisis, green stocks started to outperform brown stocks. This is also consistent with another theoretical finding, which is that green stocks outperform brown stocks when there is a positive climate shock (Pástor et al., 2021). This 2017-2021 period corresponds to a time when discussions on the topic of climate change started to become mainstream (aftermath of the Paris Agreement), when sustainable investments soared (according to the US Sustainable Investment Forum) and, especially during the Covid crisis, where customer demand started to favor a more responsible consumption (Leal Filho et al., 2022). The start of the Ukraine war, at the beginning of 2022, reversed the situation, as there were tensions in the European energy supply chain (Chen et al., 2022). This corresponds to a negative climate shock, which triggered brown stocks to outperform green stocks again: it suggests that investors cared less about environmental sustainability and more about the costs of energy. The CARIMA factor seems to become flatter during the 2017-2019 period but the performance has a very low daily return correlation to our factor: 2.68% between 2011 and 2019. The correlation to the Carbon Intensity factor also remains low: 7.10% between 2011 and 2019, dropping to 2.13% between 2020 and 2022 (correlation based on daily returns).

Table 2.9: Statistics and correlations between factors from the literature and the BMG factor from this study.

In Table 2.9, the factors' daily returns from the literature ("CARIMA" and "Carbon Intensity factor") are compared over two time periods: between March 2011 and December 2019 and between January 2020 and September 2022 (for this period returns for the CARIMA factor are not available). All results are in %.

In %	Cumulated return	Annualized return	Annualized volatility	Correlation between daily returns		
				CARIMA (Gorgen et al., 2019)	Carbon Intensity factor	BMG D
<i>Period between March 2011 and December 2019</i>						
CARIMA (Gorgen et al., 2020)	-12.88	-1.56	6.98	100		
Carbon Intensity factor	-40.23	-5.69	6.13	30.79	100	
BMG D	25.13	2.58	14.74	2.68	7.10	100
<i>Period between January 2020 and September 2022</i>						
Carbon intensity factor	1.96	0.72	9.43		100	
BMG D	-21.04	-8.32	24.64		2.13	100



Figure 2.3: Cumulative performance of BMG factors from divergent methodologies.

The BMG factor from this study is labeled "BMG D", and is compared to the performances of two factors from the previous literature, labeled "CARIMA" and "Carbon Intensity factor". Performances are computed for daily prices between March 2011 and September 2022.

Comparing the contribution of BMG factors within asset pricing models

We also study how our BMG factor compares to the others when introduced within the Carhart asset pricing model. We perform the same OLS regressions as in Table 2.6 to study the explanatory power of the different BMG factors. To account for the period over which the CARIMA factor exists, we distinguish two periods: from September 2011 to December 2019 and from January 2020 to September 2022.

The results in Table 2.10 show that overall our BMG factor improves the asset pricing model better than the other BMG factors: following the regressions for all stocks, the average adjusted R^2 is at 32.07% for our BMG factor, while the one from Gorgen et al. is at 30.56% and the Carbon Intensity factor is at 30.52% between March 2011 and December

2019. The adjusted R^2 is closer between the Carbon Intensity factor and our BMG factor for the period between 2020 and 2022. The average sensitivity of stock returns to our BMG factor is much lower, meaning that the market has a neutral sensitivity, compared to the brown bias of the CARIMA and Carbon Intensity factors.

As in 2.5.1, we conduct bootstrap tests to compare the robustness of the average adjusted R^2 between the BMG factors. Following the same methodology, we build 1000 BMG factors and compute the distribution of the average adjusted R^2 when regressing the stocks' daily returns of the MSCI[®] World Index with a Carhart + random BMG factor model. This test is conducted at both periods, between 2011 and 2019 and between 2020 and 2022. We find that the CARIMA factor and the Carbon Intensity factor's average adjusted R^2 are below the 90th percentile of the bootstrap distribution, but our BMG D is within the 99th percentile, which means that it is more robust than the other two factors over that period. For the 2020-2022 period, the Carbon Intensity factor's average adjusted R^2 falls within the 90th percentile of the distribution, and our BMG D is within the 95th percentile of the distribution.

Table 2.10: Relevance of the BMG factor within the literature.

Table 2.10 compares the results of asset pricing models (Carhart + BMG) with three different BMG factors. OLS regressions are run daily for stocks within the MSCI[®] World Index at two time periods: 09/2011-12/2019 and 01/2020-09/2022. The results are then average values between all assets. "Mkt", "SMB", "HML", and "WML" correspond to the average sensitivity of stock prices, "BMG" corresponds to the average sensitivity of stock prices to the corresponding BMG factor (CARIMA, Carbon Intensity or our BMG D factor). For the average adjusted R^2 column ("Adj. R^2 (%)"), ***, **, and * mean that the results are respectively within the 99th, 95th, and 90th percentile of a bootstrap test.

Factor used within regression model	Const.	Adj. R^2 (%)	Average sensitivity of assets to the factors				
			Mkt	SMB	HML	WML	BMG
<i>Period between September 2011 and December 2019</i>							
CARIMA factor	0.004	30.56	0.961	0.071	-0.025	-0.041	0.088
Carbon Intensity factor	0.003	30.52	0.968	0.064	-0.017	-0.053	0.021
BMG D	0.003	32.07***	0.965	0.06	-0.013	-0.069	-0.004
<i>Period between January 2020 and September 2022</i>							
Carbon Intensity factor	0.003	31.11*	0.979	0.107	0.090	-0.134	0.083
BMG D	0.003	31.27**	0.944	0.108	0.107	-0.138	-0.008

Overall, we find that the average adjusted R^2 from the regressions of the MSCI[®] World Index stock returns (45 quarters), when using the Carhart factors and our BMG factor is at the 99th percentile of the average adjusted R^2 from the bootstrap tests, which means that there is evidence that our BMG factor is statistically significant in asset pricing models. This result is much higher than the average adjusted R^2 from the other BMG factors found in the previous literature. This result suggests that our BMG factor improves the explana-

tory power of asset pricing models better: there is evidence that using a climate market trend from stock prices to discriminate green from brown stocks has a higher statistical significance than relying on extra-financial performance data.

The ability of BMG factors to capture transition risk

Here, we investigate the ability of BMG factors to apprehend transition risk. Following the study and the methodology in [De Angelis and Monasterolo \(2024\)](#), we adopt the Media Climate Change Concern (MCCC) index proposed in [Ardia et al. \(2023\)](#) as an indicator for gauging transition risk. This index is sourced from major US newspapers, Associated Press Newswires, and Reuters News. It represents, at monthly frequency, the average of the normalized source-specific climate change concerns. These “concerns” are the product of the proportion of risk words and the degree of negativity, allowing us to differentiate between negative and positive articles. Subsequently, they established four overarching “themes” which included Business Impact, Environmental Impact, Social Debate, and Research applying the Correlated Topic Model. Furthermore, the authors highlight the Business Impact theme as particularly relevant to transition risks.

Using the Business Impact theme of the MCCC index, we investigate whether our BMG factor (BMG D) more effectively captures transition risk compared to CARIMA and Carbon Intensity factors. We explore the relationship between the Business Impact theme (BI) and BMG factor returns using a structural Vector AutoRegressive model (VAR) with classical Cholesky identification as follows:

$$\mathbf{x}(t) = \boldsymbol{\mu} + \mathbf{A}_1\mathbf{x}(t-1) + \dots + \mathbf{A}_p\mathbf{x}(t-p) + \mathbf{u}(t) \quad (2.5)$$

$$\mathbf{u}(t) = \mathbf{L}\boldsymbol{\epsilon}(t) \quad (2.6)$$

where $\mathbf{x}(t) = (BI(t), BMG_i(t))'$ with BMG_i is one of the three BMG factors, $\boldsymbol{\mu}$ is a (2×1) vector of constants, $\mathbf{A}_1, \dots, \mathbf{A}_p$ are (2×2) coefficient matrices, p is the model order, \mathbf{L} is a (2×2) lower triangular matrix representing contemporaneous effects, and $\boldsymbol{\epsilon}(t)$ is a (2×1) vector of structural innovations with $E[\boldsymbol{\epsilon}(t)\boldsymbol{\epsilon}'(t)] = \mathbf{I}_2$.

Then, to assess the effectiveness of BMG factors in capturing transition risk, we analyze the impulse response functions (IRFs) for a shock of one standard deviation of the BI theme, along with 90% confidence intervals using 1000 Monte Carlo integrated error bands,

assuming a normal distribution for IRFs [Lütkepohl \(2005\)](#).

As in the previous section, to account for the period over which the CARIMA factor exists, we distinguish two periods: the first one spans from March 2011 to December 2019, while the second extends from March 2011 to September 2022. For each period, the lag order p is determined according to the Akaike Information Criterion AIC [Akaike \(1973, 1974\)](#) and is set to the maximum lag among the three BMG factors. It is set to $p = 4$ for the first period and $p = 2$ for the second period.

The results for the first period are depicted in Figure 2.4. These findings reveal that our BMG factor and Carbon Intensity factor exhibit negative and significant responses (i.e., green portfolios outperform brown portfolios) at steps 3 and 4, respectively, while CARIMA displays a significant positive response at step 1 and a significant negative response at step 2. These results suggest that both our BMG factor and Carbon Intensity factor are better able to capture transition risk. However, regarding the second period, the results in Figure 2.5 indicate that our BMG factor better captures transition risk. Indeed, a shock in the BI theme index causes a significant negative response at step 1, whereas the Carbon Intensity factor shows significant positive responses from step 1 onwards. Overall, these outcomes indicate that our proposed BMG factor demonstrates a greater ability to capture transition risk compared to CARIMA and Carbon Intensity factors.

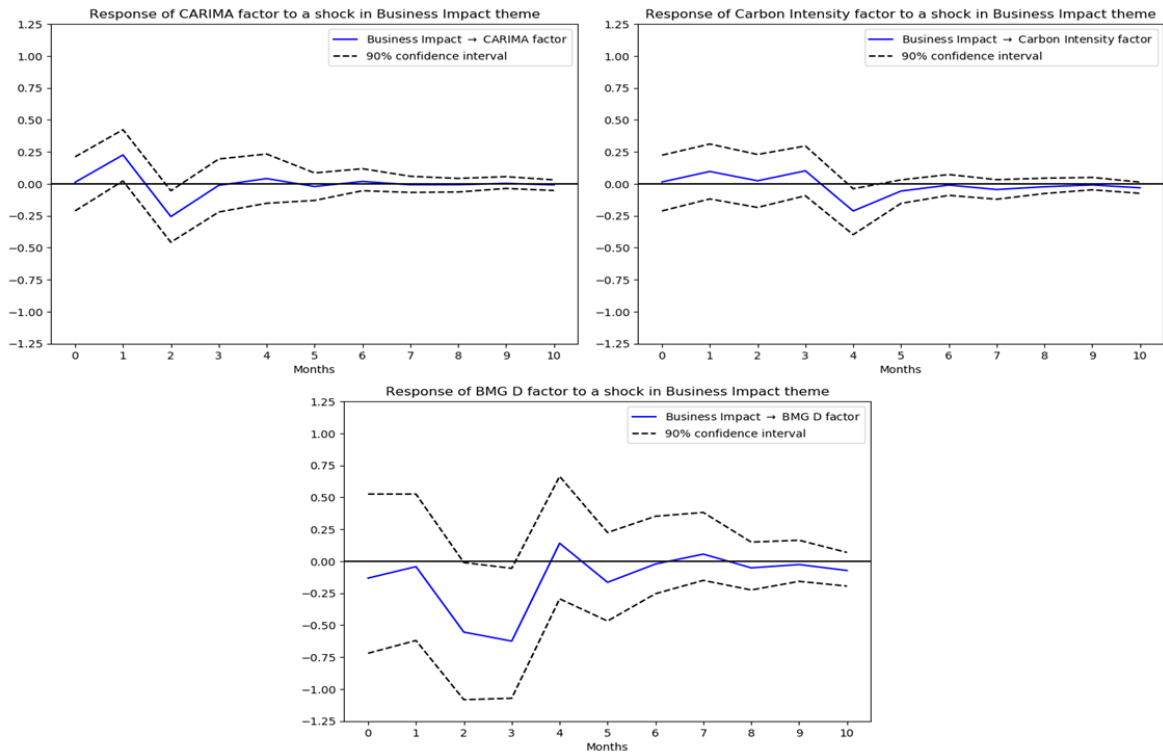


Figure 2.4: Impulse response functions for a shock of one standard deviation of the Business Impact theme in BMG factors from March 2011 to December 2019.

The impulse response functions of the three BMG factors (CARIMA, Carbon Intensity, and BMG D) are computed based on monthly returns, using lag order $p = 4$.

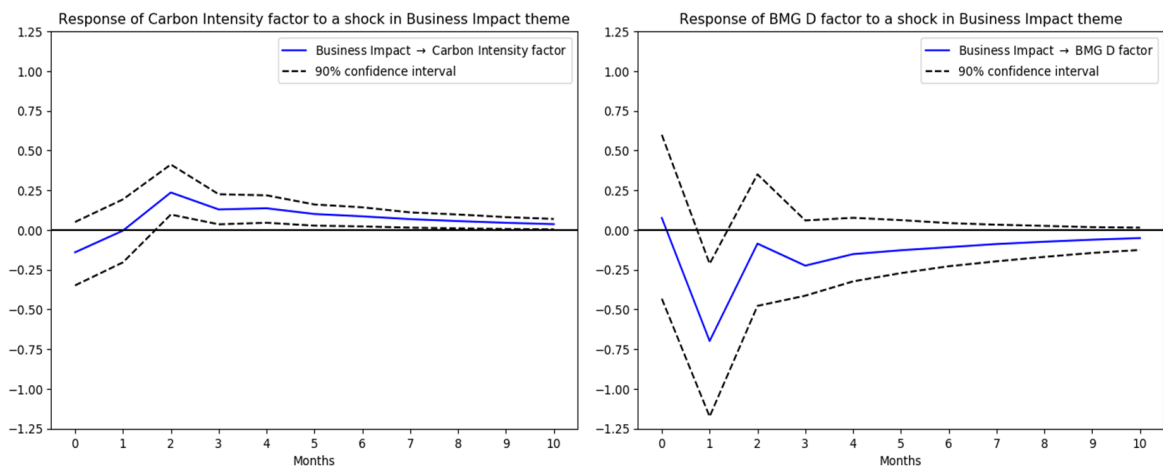


Figure 2.5: Impulse response functions for a shock of one standard deviation of the Business Impact theme in BMG factors from March 2011 to September 2022.

The impulse response functions of the two BMG factors (Carbon Intensity and BMG D) are computed based on monthly returns, using lag order $p = 2$.

2.5.3 Dynamic analysis of sensitivities to the BMG factor

We provide additional test results on the significance of the BMG factor as a climate metric. We hereby identify the climate risk exposure of a stock as the sensitivity of the return to the BMG factor, within a Carhart + BMG model (this means we control for market, size, value, and momentum returns). We call this measure the climate beta β_C . A stock that has a negative climate beta can be considered as having a low climate transition risk exposure. On the contrary, a stock will be considered exposed to climate transition risk when it has a positive climate beta⁸.

First, we study the overall significance of climate betas. Table 2.11 shows the weight distribution according to the significance of the climate sensitivity for High Climate Impact sectors (HCIS). We find that, on average, 48% of the HCIS have significant sensitivities to the BMG factor, with 27% “brown” (positive sensitivities) stocks and 20% “green” (negative sensitivities) stocks. A majority of results are not significant, which is to be expected as the climate betas come from a Carhart + BMG factor regression model: the stock price can also be explained by other factors, such as SMB or HML. However, there are significant results for several sectors which are usually hard to rate due to a lack of fundamental data: the Capital Goods sector is evenly distributed between green and brown weights, with overall weights that are higher than the insignificant results; the Materials sectors also has a significant weight of green assets, which as we show in the next section is because that it contains enabler stocks. The Energy and Utility sectors hold more brown than green stocks, which could be expected as these are the two sectors most exposed to climate risks. Overall, we find no surprising results from this distribution.

⁸This can seem counterintuitive, as we would expect a green stock to hold a positive climate beta. For consistency purposes with the previous literature, we measure the sensitivity of a stock against a BMG factor, and we call it the climate beta for simplification purposes.

Table 2.11: Significance of Climate betas.

Table 2.11 presents the average distribution of Industry Group weights relative to the significance of the sensitivities to our BMG factor (“BMG D”) from the Carhart + BMG D model. Results are presented for the High Climate impact sectors over the 45 OLS regressions (September 2011 - September 2022). The “Green”/“Brown” columns show the average weight of each Industry Group with significant positive/negative sensitivities to the BMG factor at the 95th confidence interval. The “Not significant” column sums up the average Industry Group weights where there were no significant results for the sensitivity to the BMG factor. All results are in %.

Industry Group	Brown	Green	Not significant	Total
Automobiles & Components	0.4	2.4	2.8	5.6
Capital Goods	5.6	4.9	7.9	18.4
Energy	5.1	2.3	9.3	16.6
Food, Beverage & Tobacco	2.8	2.4	4.3	9.6
Materials	1.6	3.2	7.0	11.9
Real Estate	2.6	0.9	3.7	7.2
Semiconductors & Semiconductor Equipment	1.7	1.1	3.8	6.6
Technology Hardware & Equipment	2.5	0.7	7.4	10.5
Transportation	1.5	0.8	3.1	5.4
Utilities	3.3	1.6	3.2	8.1
Total	27.1	20.4	52.5	100

We then move on to the overall distribution of the climate beta within industries and countries. Once again we focus on HCIS. Figures 2.6 and 2.7 show the distribution of significant climate betas for the whole 2011-2022 period. The results show heterogeneous distributions within industries, with the widest distribution for sectors that are usually considered the most polluting and therefore the most exposed to climate risk: Energy, Utility, and Materials. The medians have varying signs, being positive for sectors such as Energy, Food & Beverage, Utilities, or Real Estate, but negative for Semiconductors, Capital Goods, or Automobiles. We find that the dispersion of climate betas is highest for the Materials sector, which supports the idea that within this sector, which is usually hard to rate because it holds very diversified economic activities, climate beta could be used as a discriminating metric. When observing the countries’ distribution, the results are quite different: there is a clear trend separating Japan and European countries from North America. 90% of the US distribution is positive, which means that American stocks are overall most exposed to climate risk. However, we find that the United States also holds extreme values that are very negatively sensitive to the BMG factor (e.g., Tesla). Country dispersion is much smaller within countries than within industries, which suggests that the climate beta could hold signals related to national policies on climate mitigation and adaptation.

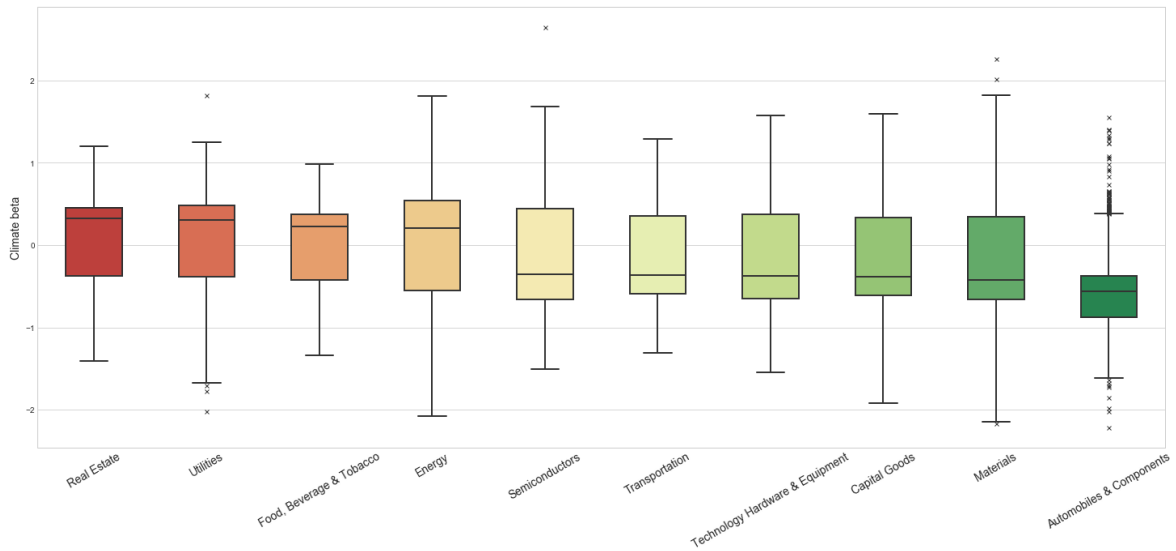


Figure 2.6: Distribution of climate betas within High Climate Impact sectors (HCIS).

The climate betas are the sensitivities of stock returns to the BMG D factor within a Carhart + BMG D factor model, run for OLS regressions for the period September 2011 to September 2022 (45 quarterly regressions over 130 daily returns).

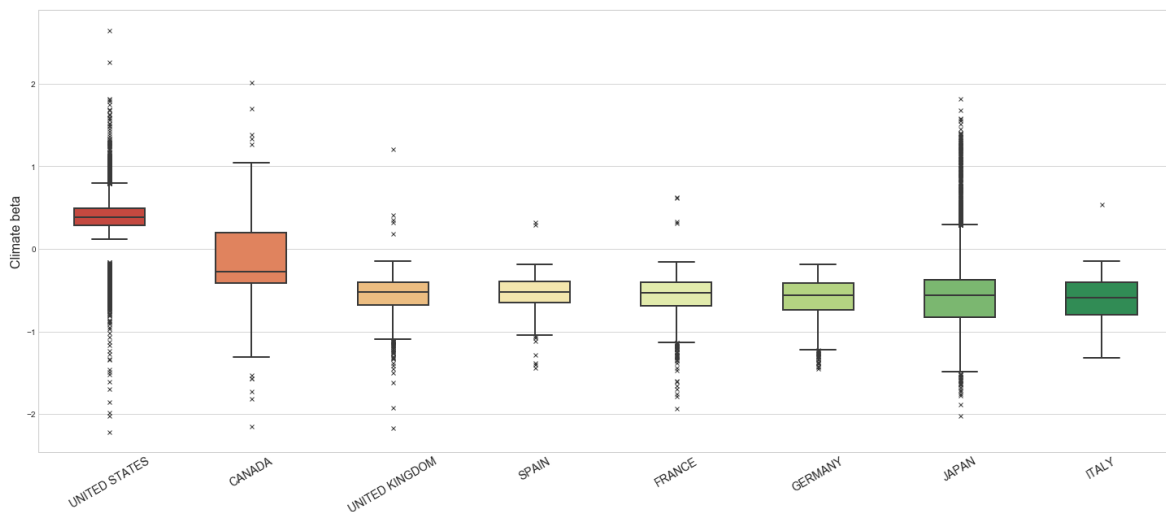


Figure 2.7: Distribution of climate betas within selected countries.

The climate betas are the sensitivities of stock returns to the BMG D factor within a Carhart + BMG D factor model, run for OLS regressions for the period September 2011 to September 2022 (45 quarterly regressions over 130 daily returns).

Finally, we also look at the dynamics of the climate beta, by observing the evolution of weighted average sensitivities within High Climate Impact sectors. Figure 2.8 highlights the overall stability of the sensitivities in all industries except for the Automobiles & Components. There are industry-specific dynamics, with more volatile sectors, such as Energy,

Utilities, or Semiconductors. The Capital Goods and Materials sectors are very stable over time, although Figure 2.6 shows a high dispersion of climate beta values within these sectors. Overall, we find an average positive sensitivity to the BMG factor: this is the case for the Utilities, Energy (up until 2017), Transportation, and Real Estate sectors, which are usually considered very polluting sectors. As in [Roncalli et al. \(2020\)](#), we find a downward trend in the weighted average climate beta of the Energy sector between 2016 and 2017, which corresponds to a period of oil price increase. The Utilities sector was heavily impacted by the Covid crisis: the climate beta significantly decreased between 2020 and 2021; this trend reversed around the start of the war in Ukraine. In the Automobile sector, we observe a downward trend that accelerates in 2020; this corresponds to the exponential increase in the stock price and capitalization of Tesla and suggests that the nascent EV market is viewed as lowering the transition risk of stocks.

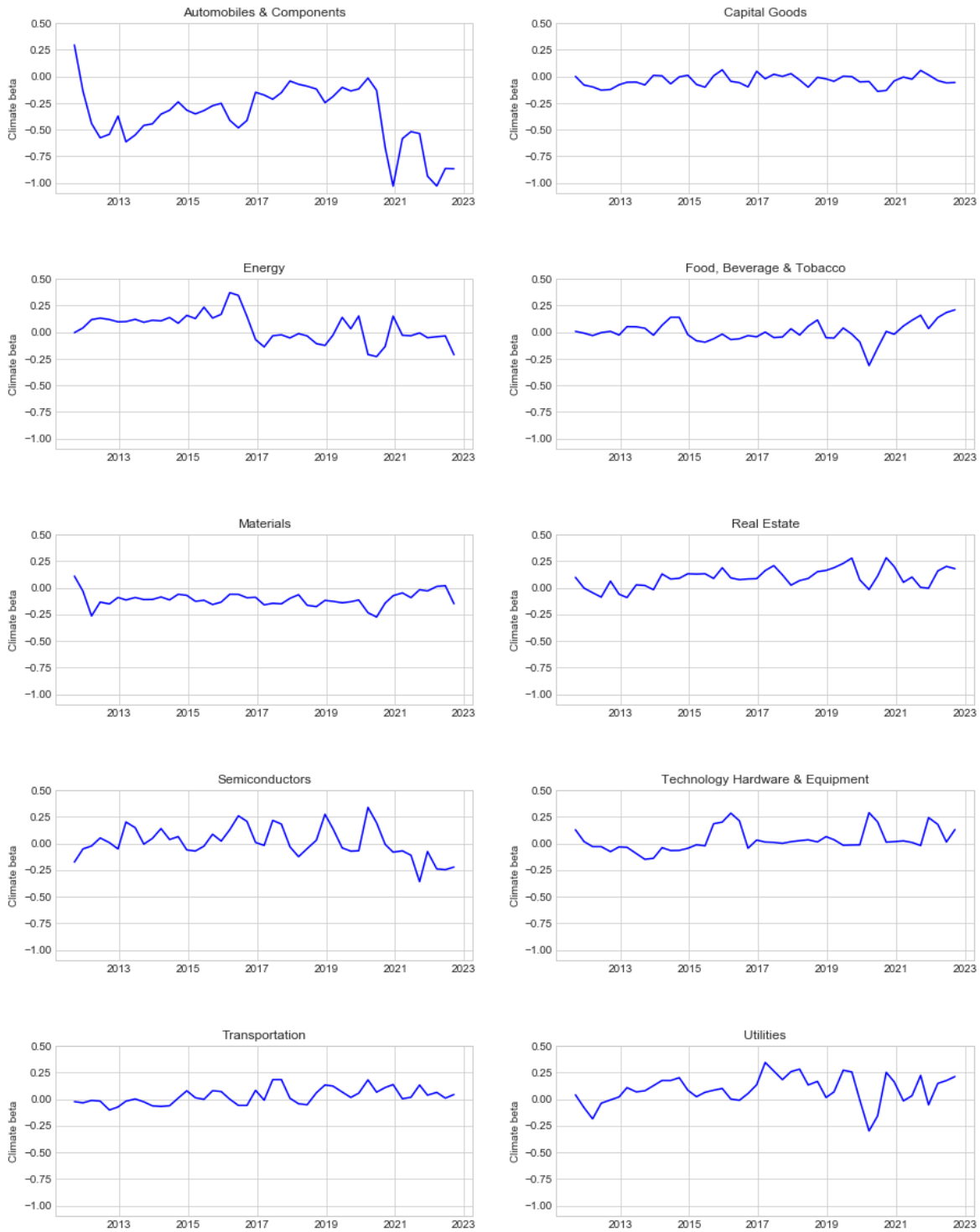


Figure 2.8: Dynamics of weighted climate betas for High Climate Impact Sectors.

The climate betas are the sensitivities of stock returns to the BMG D factor within a Carhart + BMG D factor model, run for OLS regressions for the period September 2011 to September 2022 (45 quarterly regressions over 130 daily returns). The weight of each stock is defined as the relative weight of the stock within its sector, the weighted climate beta of an industry is the weighted average of all stocks' climate betas within the industry.

All of these results suggest that the climate beta captures market signals on the transition risk exposure of stocks. The dispersion in sectors such as Capital Goods or Materials could provide additional information to fundamental climate data. While the overall volatility of industries' climate beta is low, we can detect certain events that could be the source of an increase or a decrease in transition risk exposure. Our climate beta could therefore be useful for rating companies more dynamically than with fundamental data, or capturing information on stocks that are hard to rate. This is what we propose in the next section for enabler stocks.

2.6 Application: measuring the climate transition risk of enabler stocks

In this section, we analyze how the BMG factor can contribute to the measure of climate risk in the case of enabling companies. We use the same notation as in the previous section for the climate risk exposure of a stock, which we refer to as the climate beta β_C .

We test the efficiency of our model to the identification of enabling companies. With our methodology, the capture of market signals from these enablers stocks should mean that their sensitivity to the BMG factor would tend to be negative. We extract enabling companies by using an index, the Solactive iClima[®] Global Decarbonisation Enablers Index, which identifies companies that can enable CO_2 avoidance in the following industries: Green Energy, Green Transportation, Water & Waste Improvements, Enabling Solutions, and Sustainable Products. Weights depend on companies' market capitalizations. This index starting date only goes back to the beginning of August 2017. The performance of the index can be found in Figure 2.9.



Figure 2.9: Solactive iClima[®] Enablers Index performance.

Daily prices are shown with those from the MSCI[®] World Index (September 2017 to September 2022).

From the Solactive iClima[®] Global Decarbonisation Enablers Index, we extract stocks that are within the MSCI[®] World Index (this gives us 60 stocks). For each trimester between March 2018 and September 2022, we run OLS regressions of these stock returns over a window of 130 past daily returns, using the Carhart model framework. There are 19 time periods over which we run regressions for 60 enabler stocks, this means we run 1140 regressions. The objective is to observe the β_C of enabler stocks as well as the contribution of the BMG factor in the asset pricing of these stocks. Table 2.12 presents the overall results from these regressions, and Table 2.13 shows more detailed results for certain stocks.

The average coefficients and standard deviation shown in Table 2.12 are the average results across all stocks and for all 19 time periods. We find that most of the stocks have a negative sensitivity to the BMG factor, with an average β_C of -0.34. This means that a majority of enabler stocks can be considered as green stocks. The table also shows that when considering the absolute and relative counts of significant coefficients across the regressions, the BMG factor holds a higher significance than the size, value, and momentum factors at 10%, 5%, and 1% confidence intervals. For enabler stock returns, this means that our BMG factor has the most explanatory power. Enabler stocks are thus more exposed to climate transition risk.

Table 2.12: Contribution of the BMG factors for enabler stocks.

Table 2.12 shows the overall results from OLS regressions for 60 enabler stocks, run each trimester between March 2018 and September 2022 (19 time periods, 1140 regressions in total) using the Carhart + BMG model. “Average coefficient” and “Standard deviation” are the means and standard deviations at a 1% confidence interval for coefficients from all of the regressions. On the right side of the table, the absolute (“abs.”) and relative (“rel.”) counts detail significant coefficients at 10%, 5%, and 1% confidence intervals for all of the regressions. The absolute counts correspond to an average number of stocks per regression for which the corresponding coefficient is significant.

	Average coefficient	Standard deviation	10% level		5% level		1% level	
			abs.	rel.	abs.	rel.	abs.	rel.
Mkt	1.10	0.46	54	90	52	87	48	80
SMB	-0.10	1.28	17	27	12	20	6	10
HML	0.01	0.96	17	28	13	21	6	11
WML	-0.19	0.85	24	41	20	34	12	20
BMG	-0.34	0.49	37	61	32	53	23	38

Table 2.13 compares the climate transition risk exposure for specific stocks among two BMG factors: our BMG D (the risk exposure is the β_C) and the carbon intensity factor (see previous section 2.5.2 for the construction methodology). The results are presented as means over 19 regressions run between August 2017 and October 2022. We show the results for enabler stocks with the highest β_C , as well as for the Solactive iClima® Global Decarbonisation Enablers Index itself. Several interesting results are worth mentioning. First, the 10 stocks with the most negative sensitivity to the BMG D factor do not have a negative sensitivity to the Carbon Intensity factor: not one stock can be characterized as having a low exposure to the climate transition risk when considering a factor built solely with GHG emissions performance. This is the case for companies such as Tesla Inc. (electric vehicles manufacturer), Siemens Gamesa Renewable Energy, S.A. (wind turbine manufacturer), Vestas Wind Systems A/S (wind turbine manufacturer), and Kingspan Group Plc (thermal isolation materials manufacturer) which economic activities are at the heart of

the low-carbon transition. Therefore our BMG factor is able, unlike factors built with fundamental climate data, to identify enablers as stocks that have a low-risk exposure to the transition.

Furthermore, adding the BMG D to a Carhart model significantly improves the asset pricing quality for all those enabler stocks. The average adjusted R² for regressions run every trimester between March 2018 and October 2022 is 3 percentage points higher in a Carhart + BMG D model at 83% than in a Carhart model. This result is consistent when considering the top 10 enabler stocks, and the improvement is the highest for stocks with the lowest (most negative) β_C . The adjusted R² is also better for a Carhart + BMG D model than for a Carhart + Carbon Intensity factor, for both the index and the top 10 enabler stocks. This shows that price signals related to the transition can be lost in translation when only measuring the risk of a stock through carbon intensity and that capturing price signals from transition leaders helps to measure the risk of enabler stocks. The pricing of enabler stocks is more accurate when relying on pure market analysis aggregates information, and not on fundamental climate data.

Table 2.13: Climate betas of enabler stocks.

Table 2.13 shows the average sensitivities to our BMG factor (“BMG D”), average sensitivities to the Carbon Intensity factor (“CI factor”), and average adjusted R² of the regressions for the Carhart + BMG D, Carhart + Carbon Intensity factor, and the Carhart models. Results are presented for the Solactive iClima[®] Enablers Index and for the ten stocks within the index with the highest average climate betas over the 19 OLS regressions (March 2018 - September 2022).

	BMG D	CI factor	Adj. R ² (%) Carhart + BMG D	Adj.R ² (%) Carhart + CI factor	Adj. R ² (%) Carhart
<i>Solactive iClima[®] Enablers Index</i>	-0.193	0.235	82.8	80.8	79.8
Tesla Inc	-1.388	0.865	38.9	29.0	28.0
Siemens Gamesa Renewable Energy, S.A.	-0.709	1.358	17.0	13.9	12.7
Vestas Wind Systems A/S	-0.667	1.419	16.9	14.4	12.4
Infineon Technologies AG	-0.648	0.541	43.6	38.3	37.5
Johnson Matthey Plc	-0.574	1.158	28.2	25.5	23.8
NIBE Industrier AB Class B	-0.569	1.179	35.5	30.9	29.0
DS Smith Plc	-0.563	1.005	29.8	26.7	25.2
Kingspan Group Plc	-0.560	0.996	17.4	14.2	13.5
Wacker Chemie AG	-0.557	1.282	26.2	25.4	23.1
TOMRA Systems ASA	-0.542	1.079	21.0	21.4	19.3

2.7 Discussion and conclusion

We see several instances in which our study may contribute to the evaluation of climate risk and asset pricing under climate change.

First of all, we have been able to identify a “climate market trend” with a statistical multi-factor model, from the covariance matrix of ecological indexes, using Random Matrix Theory and the upper bound of the Marčenko-Pastur distribution. To the best of our knowledge, we are the first to employ such methodology and to be able to capture a “climate market trend” from a quantitative point of view; the economic context seems to confirm that the isolated trend reflects a price tendency of market leaders in the climate transition. For example, the September 2020-September 2022 period corresponds to an overall increase in the amount of renewable electricity available on the grid (as reported by the International Energy Agency in 2021), the emergence of responsible investment practices across European financial markets (the number of signatories to the Principles for Responsible Investment has increased by more than 60% between 2019 and 2021), and general awareness for climate change impacts. This methodology can be adapted to focus on a specific issue related to climate change: the selection process of indexes can focus on themes such as water stress, adaptation to climate change, enabler companies, etc. The composition of the index is thus critical. Furthermore, it is critical to use several low-carbon transition indexes from different to limit biases related to climate information from a single database, preferably with varied allocation methodologies to capture exhaustive information across industrial sectors.

Secondly, the identification of green and brown stocks by measuring the stock price sensitivity to the climate market trend has a strong purpose: it can serve as a new methodology to build a BMG factor, which enhances the explanatory power of asset pricing models. By using the stock price sensitivity of an asset, we can capture the global market consensus of price-makers on the climate transition risk exposure of a stock. Furthermore, we can provide a more dynamic measure of the exposure of a stock to climate transition risk. This is very useful in the context of extra-financial performance data, which is not up-to-date. Building a BMG factor from market consensus can provide a new way of measuring the climate risk of an asset. We can use the sensitivity of a stock price to the BMG factor, which we call the climate beta, to provide complementary information to extra-financial performance data. This new measure of climate risk has the advantage of being comparable to other market measures of a stock, such as the size or value bias; it is a collection of aggregated analyses by financial analysts and is therefore easy to implement and use as it is a

single metric computed as a stock price sensitivity. There are no biases associated with the use of a specific climate database. It could be argued that while the market does price some risks related to climate change, it does not necessarily price them efficiently. Therefore the climate beta could reflect inaccurate information on the climate transition risk exposure of the stock. However, the climate beta should be considered as a complementary metric to capture additional information to fundamental climate data, especially regarding dynamic trends (climate strategies of companies, news on operational efforts to abate emissions, etc.).

This is especially useful when stocks are hard to rate on their climate performance based on fundamental climate data: sectors which are less exposed to transition risk for example, or which are indirectly exposed to it, such as Capital Goods or Materials. We have highlighted the case of enabler stocks, which cannot be isolated when using direct and indirect GHG emissions, but which can be isolated through price signals. We have shown that we improve the pricing of these stocks when we add our BMG factor to a classic asset pricing model, such as the Carhart model, a result that is not sustained when we add a carbon intensity factor to the Carhart model. An interesting metric for enabler stocks would be their avoided emissions, which are the emission savings from their activities (for example, generating electricity using a wind turbine rather than a coal power plant), but this metric is very difficult to apprehend and requires a methodological consensus, which is far from existing. Therefore, our climate beta can fill a lack of data availability for such stocks.

There are several ways the model could be improved. Other types of funds could be used to build a climate market trend, for example, actively managed funds which could allow a more dynamic assessment of the market consensus on the financial trend of transition leaders, under the condition that it is possible to isolate a signal related to climate transition risk. We could also use a more dynamic regression model (for example a Kalman filter) to build the BMG factor. The market measure could be further decomposed into climate change materiality metrics, that is to say, we could determine whether price signals come from changes in the activities of a company, its carbon footprint, investments in enabling or green activities, a change in its climate governance, etc. Finally, this new market measure should be seen as additional to traditional measures of climate risk, which are built using fundamental climate data. Using both measures within climate risk rating models would allow a more dynamic assessment of climate risk, but would also allow discrimination for stocks that have poor ratings in one or several categories of fundamental climate data, such as GHG emissions.

2.8 Appendix

2.8.1 Benchmark regulation - Sensitive sectors

Sensitive sectors (High Climate Impact Sectors) are defined by the European Union for the benchmark portfolios regulation ([European Commission, 2020](#)). The Industry Group Name corresponds to the second level of the Global Industry Classification Standard (GICS®) in 2022.

Table 2.14: Sensitive sectors (GICS® Industry Group Name).

GICS® Industry Group
Automobiles & Components
Capital Goods
Energy
Food, Beverage & Tobacco
Materials
Real Estate
Semiconductors & Semiconductor Equipment
Technology Hardware & Equipment
Transportation
Utilities

2.8.2 Tyler-M estimator recursive algorithm

The solution can be found using the following recursive algorithm ([Pascal et al., 2014](#)):

- Initialize $\hat{\mathbf{C}}_{tyl,(1)}$ with any full-rank matrix (e.g. $m \times m$ identity matrix),
- Iterate over $k \geq 1$:

$$\tilde{\mathbf{C}}_{tyl}^{(k+1)} = \frac{m}{T} \sum_{t=1}^T \frac{\mathbf{r}_t \mathbf{r}'_t}{\mathbf{r}'_t (\hat{\mathbf{C}}_{tyl}^{(k)})^{-1} \mathbf{r}_t}$$

$$\hat{\mathbf{C}}_{tyl}^{(k+1)} = \frac{m}{Tr(\tilde{\mathbf{C}}_{tyl}^{(k+1)})} \tilde{\mathbf{C}}_{tyl}^{(k+1)}$$

until the relative Frobenius norm between two consecutive values becomes lower than a fixed threshold $\epsilon \in \mathbb{R}^+$, i.e. until: $\frac{\|\hat{\mathbf{C}}_{tyl}^{(k+1)} - \hat{\mathbf{C}}_{tyl}^{(k)}\|_F}{\|\hat{\mathbf{C}}_{tyl}^{(k)}\|_F} < \epsilon$

2.8.3 Huber loss function

The Huber loss function [Huber \(1964\)](#) of the residuals (ϵ) is a compromise between the L_1 and L_2 losses:

$$L_\delta(\epsilon) = \begin{cases} \frac{1}{2}\epsilon^2, & \text{if } |\epsilon| \leq \delta \\ \delta|\epsilon| - \frac{1}{2}\delta^2, & \text{otherwise} \end{cases}$$

where $\delta \in \mathbb{R}^+$ is the threshold that controls the transition from L_1 to L_2 . In our case, δ is set to 1.35.

2.8.4 List of green and brown companies

The following table shows a list of companies identified as green and brown companies, related to the sensitivity of stock returns to the market climate trend.

Table 2.15: List of green and brown companies.

Twenty green and twenty brown companies are identified by running OLS regressions for the period September 2011 to September 2022 (45 quarterly regressions over 130 daily returns). The list is sorted by the decreasing number of occurrences in which companies appear in quarterly green or brown portfolios.

Green portfolio			Brown portfolio		
Name	Industry Group	Number of occurrences	Name	Industry Group	Number of occurrences
Vestas Wind Systems	Capital Goods	40	Duke Energy Corporation	Utilities	36
Infineon Technologies	Semiconductors	28	CMS Energy Corporation	Utilities	34
EDP	Utilities	27	American Electric Power	Utilities	33
Iberdrola	Utilities	27	DTE Energy Company	Utilities	33
Tesla	Automobiles & Components	26	Dominion Energy	Utilities	33
STMicroelectronics	Semiconductors	25	Southern Company	Utilities	32
Fortum	Utilities	24	Xcel Energy	Utilities	31
RWE	Utilities	24	Alliant Energy Corp	Utilities	30
ASML Holding	Semiconductors	23	Consolidated Edison	Utilities	30
Ferrovial	Capital Goods	23	Public Service Enterprise Group	Utilities	30
Atlas Copco	Capital Goods	22	Ameren Corporation	Utilities	29
First Solar	Semiconductors	22	Edison International	Utilities	26
BMW	Automobiles & Components	21	3M Company	Capital Goods	25
ENGIE	Utilities	21	Atmos Energy Corporation	Utilities	25
Eiffage	Capital Goods	21	Entergy Corporation	Utilities	25
Red Electrica Corp.	Utilities	21	Pinnacle West Capital Corporation	Utilities	25
CNOOC Limited	Energy	20	Northrop Grumman Corporation	Capital Goods	24
Prysmian	Capital Goods	19	Public Storage	Real Estate	24
Veolia Environnement	Utilities	19	Exxon Mobil Corporation	Energy	23
Enel	Utilities	19	NiSource	Utilities	23

2.8.5 Sensitivity of Green/Brown portfolios to the Paris Agreement

To evaluate the influence of a climate event (here the Paris Agreement) on Green/Brown portfolio returns, we examine significant shifts (structural breaks) in both systematic risk (market risk) and alpha (abnormal mean returns) using the following model [Monasterolo \(2020\)](#); [De Angelis and Monasterolo \(2024\)](#):

$$r_i(t) = \alpha_i + \delta_i d(t) + \beta_{m,i} r_m(t) + \gamma_i r_m(t) d(t) + \epsilon_i(t)$$

where $r_i(t)$ is the daily return of Green/Brown portfolio i at date t , $d(t)$ is a dummy variable taking value 1 after the Paris Agreement (12th December 2015) and 0 before. $r_m(t)$ is the market return (MSCI[®] World Index) and market sensitivity is $\beta_{m,i}$. The potential impact of the Paris Agreement is captured by δ_i (abnormal mean return) and γ_i (systematic risk level). $\epsilon_i(t)$ is the error term.

The findings for the four different Green and Brown portfolios (A, B, C, and D) are reported in 2.16. The results are based on daily returns over the period from March 2011 to September 2022.

Table 2.16: CAPM with Paris Agreement model results for Green and Brown portfolios.

Table 2.16 compares the results of asset pricing models (CAPM + Paris Agreement impacts) with the four (A, B, C and D) different Green and Brown portfolios. OLS regressions are based on daily returns over the period from March 2011 to September 2022. ***, **, and * denote significance levels at 1%, 5% and 10% respectively.

	$\hat{\alpha}$	$\hat{\delta}$	$\hat{\beta}_m$	$\hat{\gamma}$	Adj. R ²
Green portfolio A	-0.0004*	0.0006**	1.1119***	-0.0048	0.6554
Brown portfolio A	0.0000	0.0001	0.8211***	0.2623***	0.6196
Green portfolio B	-0.0004*	0.0004	1.0897***	-0.0922***	0.6600
Brown portfolio B	0.0000	-0.0001	0.8529***	0.2524***	0.7486
Green portfolio C	-0.0005**	0.0007**	1.1067***	-0.0551*	0.6123
Brown portfolio C	0.0000	0.0000	0.8313***	0.2838***	0.6011
Green portfolio D	-0.0004*	0.0005	1.0749***	-0.0826***	0.6144
Brown portfolio D	0.0000	-0.0002	0.8579***	0.2510***	0.7327



CLIMATE SCENARIOS AND LOW-CARBON TARGETS OF COMPANIES:
A THEORETICAL APPROACH ON ALIGNMENT STRATEGIES AND MAR-
KET EQUILIBRIUM

3.1	Introduction	92
3.2	Model set-up	96
3.2.1	General set-up	96
3.2.2	Evaluation phase: choosing a low-carbon pathway	98
3.2.3	Decision of investors: allocation of the portfolios	101
3.3	Market equilibrium	104
3.3.1	“Lemon market” structure: only one type of company within the economy	104
3.3.2	Economy with type B and type N companies	106
3.3.3	Model with three assets	109
3.3.4	General market equilibrium	112
3.4	Empirical illustration: identifying a climate risk premium from low-carbon target alignment strategies	114
3.4.1	Identification of a target announcement risk premium	114
3.4.2	Identification of a risk premium associated with the align- ment performance of a company	119
3.5	Discussion	122
3.5.1	Alignment strategies of firms	122
3.5.2	Market equilibrium	126
3.6	Conclusion	128
3.7	Appendix	129
3.7.1	Low-carbon pathways	129
3.7.2	Variables and parameters	131
3.7.3	Ability threshold	132
3.7.4	Demand for stocks	133
3.7.5	Market equilibrium with type B and type N stocks	134
3.7.6	Market equilibrium with type H, type B, and type N stocks	135
3.7.7	Portfolio allocation under a decarbonization constraint	136
3.7.8	General market equilibrium	137
3.7.9	Empirical identification of alignment risk premia	138

This chapter is based on a seminar, a conference, and an article under submission in collaboration with Patricia Crifo and Thibault Soler.

Climate scenarios and low-carbon targets of companies: A theoretical approach on alignment strategies and market equilibrium

CES Economic Theory Seminar, June 2024, Centre d’Economie de la Sorbonne, Paris 1 Panthéon Sorbonne, France

Climate scenarios and low-carbon targets of companies: A theoretical approach on alignment strategies and market equilibrium

Doctorissimes Conference (Poster session), April 2024, Paris School of Economics, France

Abstract

Firms are increasingly announcing low-carbon targets, yet there is uncertainty as to whether a company will successfully reach its target as it depends on the initial ambition of the target and the firm’s ability to abate its emissions. This paper proposes a theoretical model and empirical illustration of its main predictions to analyze low-carbon targets announced by companies, in reference to a climate scenario (NZE commitments) within an economy of publicly traded companies and investors. We show that the number of firms committing to a low-carbon target depends on the remaining carbon budget. We also identify a cost to announcing a low-carbon target in the climate risk premium of stock returns. Finally, we show that the investors’ climate preferences are essential to maximizing the number of companies committing to low-carbon targets.

Keywords: Climate scenario, Alignment, Low-carbon target, Climate risk premium, Asset pricing

JEL: D21, D53, G12, Q54

3.1 Introduction

Initially developed in climate science and macroeconomics with the Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1993), climate scenarios¹ have been adapted at the firm level through the concept of “alignment”. The alignment to a climate scenario has become a mainstream tool both for companies and for investors since the Paris Agreement (Watson et al., 2023; Black et al., 2021). Even though there is no formal definition, it is generally viewed as a set of measures to follow a certain future scenario (Cochran et al., 2019). A company can align its activities to a simple scenario: for instance, it can follow a carbon budget², which determines its contribution to a certain temperature rise of the climate system (Friedlingstein et al., 2022). More sophisticated scenarios exist to determine a projection of greenhouse gas emissions from an exhaustive set of social and economic parameters, and policies on managing greenhouse gas emissions (O’Neill et al., 2017; Lee and Romero, 2023).

Announcing an alignment to a low-carbon scenario (below 2°C global warming compared to pre-industrial levels) is one of the ways for a company to communicate to investors how it intends to manage its climate risk³ (Fernandez-Feijoo et al., 2014; Haleem et al., 2022). This information is a long-term indicator of the firm’s financial risk exposure for an investor and provides a solution to the issue of short-termism that leads to climate inaction (Slawinski et al., 2017). There are other objectives behind committing to a low-carbon target: to lessen the impact of climate change, to increase customer demand, and to attract investors (Flammer, 2012; Chen et al., 2019; Bolton and Kacperczyk, 2021b). It can also lead to greenwashing practices, where environmental disclosure does not reflect real performance (Lyon and Montgomery, 2015) and commitment targets are purely symbolic: Delmas and Burbano (2011) provide a conceptual framework for identifying the main drivers of greenwashing, while several theoretical models have been developed to review the underpinnings of corporate motives and the regulatory environment (Lyon and Maxwell, 2011; Akin and Akin, 2024; Cartellier et al., 2024; Chen, 2024). Multi-stakeholder initiatives, such as the Science-Based Targets initiative (SBTi), play an important role in accelerating the commitment of firms to low-carbon targets (de Bakker et al., 2019; Nikolaeva et al., 2023). These organizations, whose governance joins business and societal participants, have the common objec-

¹The climate scenario is defined as a “plausible representation of future climate that has been constructed for explicit use in investigating the potential consequences of anthropogenic climate change”, see Mearns et al. (2001).

²Maximum amount of cumulative net global anthropogenic greenhouse gas emissions that would result in limiting global warming to a given level with a given probability, see Friedlingstein et al. (2022).

³Climate risk is defined as the negative impact of climate change on corporations (Institute, 2021).

tive of helping firms build low-carbon targets that are achievable by firms while following specific climate scenarios (Fransen, 2012). It has been shown that a firm's participation in such initiatives contributes positively to the mitigation of its impact on climate change (Romito et al., 2023), although there is some uncertainty around the use of carbon credits within the low-carbon pledges.

The notion of alignment extends to financial portfolios. The alignment of a financial portfolio can be assessed with metrics such as Implied Temperature Ratings (Raynaud et al., 2020), or with a more straightforward approach with a carbon budget constraint: this is the case for Net-Zero portfolios, which follow a scientifically-determined decarbonization pathway (Bolton et al., 2022).

Companies are increasingly announcing low-carbon targets, but this only reflects an expected future performance. There is a given uncertainty as to whether a company will successfully reach its target. The probability of success depends on the initial ambition of the low-carbon target, and the firm's capacity to abate its emissions. If a firm fails to achieve its target, its climate risk exposure (Carney, 2015) increases via two channels: first, the reputational risk of the firm increases and can lead to accusations of greenwashing practices. Secondly, there is a shock in the transition risk estimation of the firm, which was expected to be at a certain level but is higher than expected as the firm failed to reach its target. This can have significant impact on the firm's financial performance due to possible investor rejection and decreased customer demand. Cenedese et al. (2024) show that firms with a lower likelihood of being excluded from net-zero portfolios have a higher valuation.

The impact of abatement efforts on stock returns remains empirically uncertain. It is generally recognized that a higher abatement increases customer demand (Dai et al., 2021; Meier et al., 2022) and decreases the cost of capital (Hong and Kacperczyk, 2009; Krüger, 2015; Bolton and Kacperczyk, 2021a). Several theoretical models have been developed to include the environmental preference of investors for stocks with a high climate performance (the most commonly-used metrics are greenhouse gas emissions) of companies in the allocation of portfolios (Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022; Zerbib, 2022), which tilts stock returns. However, to date, the choice of a company to commit to a low-carbon target has not been approached theoretically and the impact on the financial return of such a choice remains uncertain. To be more precise, if many theoretical models include the preference of investors, they do not include the reputational and transition risks that appear when a company sets a target. Yet this is an important issue, as it has

been shown that firms do not necessarily set ambitious enough targets, largely resorting to carbon removal technology that is not simply used for residual emissions [Arendt \(2024\)](#).

The main objective of this paper is to contribute theoretically to the literature on climate scenario alignment. We especially focus on two issues: first, the underlying mechanism in a company deciding to set a target, and the potential influence of investors behind this strategic decision; second, whether the financial risk of a company decreases (lower risk premium) when setting a target.

We start by defining low-carbon targets for companies through a decarbonization rate associated with a carbon budget. Using these targets, we build an economic model in two phases, where in the first phase firms must make a strategic decision on abating their emissions at a rate of their choice, by committing to a low-carbon target, or not making any abatement effort. We introduce the concept of decarbonization ability ([Crifo and Sami, 2008](#)) as a discriminating variable, representing the companies' capacities to abate their emissions. We show that companies choose their targets following profit opportunities from the low-carbon targets, a result consistent with corporate finance literature ([Cornell and Damodaran, 2020](#)), and that their decision depends on their decarbonization abilities and the shifts in customer demand for sustainable products.

The second phase of the model begins with the announcement of low-carbon strategies and focuses on a group of environmentally aware investors that allocate their capital in the companies' stocks based on their climate preference and on the exposure of firms to risk. This follows a strand of literature on asset pricing, where the climate preferences of investors are included in asset pricing models. The climate risk premium contains two factors: the exposure to transition risk once companies have achieved their targets and the reputational risk should they fail to do so. The climate strategy of firms serves both as an indicator of a firm's long-term exposure to transition and reputational risk, and as an indicator of climate performance. Therefore, the demand for stocks depends on their exposure to climate risk (through a climate risk premium) and on the investors' climate preferences. The choices of companies and the allocation of investors provide market-clearing conditions and equilibrium stock prices.

There are three main results to our model: first, companies with the highest abilities to abate their emissions will always have better opportunities to commit to a low-carbon target, but this is not necessarily the case for firms with lower abilities, which are more exposed to climate risks ([Bolton and Kacperczyk, 2021a](#)). Second, we show that the climate risk premium for companies that commit to low-carbon targets substantially depends on

the reputational risk they face should they fail to reach their target. Finally, we show that the number of companies committing to a low-carbon target can be optimized and that the optimization conditions depend on the average greenhouse gas abatement efforts required to stay within a carbon budget, the investors' preferences, and the level of ambitions of market leaders (with the highest decarbonization abilities) when they commit to a low-carbon target. From a policy standpoint, we provide potential insights for regulators in the discussion section of this paper, analyzing the different mechanisms that can be set in place to encourage more firms to pledge to low-carbon targets.

We empirically test one of our model's assumptions: the existence of a climate risk premium for companies that do not have low-carbon strategies. We observe the announcement effect on stock returns when firms publicly commit to a low-carbon target through the SBTi platform and the alignment effect on stock returns when the projection of future greenhouse gas emissions of firms is compatible with a low-carbon scenario. We find evidence of a climate risk premium from companies that do not announce low-carbon targets as well as companies whose greenhouse gas emissions performances do not align with low-carbon scenarios, but this result is not consistent within industries.

To resume, the main contribution of this paper is the identification of certain mechanisms behind the company/investor nexus. The market distribution is often overlooked in models studying the impact of investors' allocations on financial performance. However we show that the market distribution is determined by the carbon budget, the climate preference of investors, and the behavior of other firms. Introducing the decarbonization ability of a firm is also a novelty from a theoretical standpoint: it differs from the performance of a company as it does not predict what the company will do, but what the company should be able to do. This is especially interesting when studying the choice between setting the benchmark target (type B) and not setting any target (type N). Finally, we introduce a reputational risk alongside the transition risk in the climate risk premium of firms that reflects a cost to announcing a low-carbon target.

The rest of the paper is organized as follows: section 2 details the two-phase theoretical model and section 3 studies the market equilibrium that appears under the market clearing conditions. Section 4 provides empirical evidence of climate risk premia from the alignment strategies of firms. Section 5 provides a discussion of the model and the empirical evidence and section 6 concludes this paper.

3.2 Model set-up

Given the definition of a company's low-carbon target and the benchmark target, we propose a model to study the firm's decisions to commit to a low-carbon target, which they will communicate to investors and the subsequent investment decisions that will translate to portfolio allocations.

3.2.1 General set-up

Let us consider an economy with a number M of publicly traded companies. The model is set up over the following timeline⁴:

1. *Evaluation phase*: This phase is defined between $t = 0^-$ and $t = 0^+$, when companies choose whether to commit to a low-carbon target. If they choose to commit, they must decide on a decarbonization rate. A company selects its target based on its decarbonization ability, which we define in paragraph 3.2.1, and on the expected revenue payoff.

We assume that in this phase, stocks are not traded, and companies emit a negligible quantity of greenhouse gas emissions so as not to change the economy's carbon budget. At the end of this phase, companies publicly announce their low-carbon targets.

2. *Operational phase*: this phase starts at $t = 0^+$ when a group of investors makes their allocation decisions depending on both companies' low-carbon targets and financial preferences. During this phase, companies that have chosen targets abate their emissions.
3. At $t = 1$, the low-carbon targets are successfully reached if companies have continuously decreased their emissions at their chosen rate. The carbon budget is met if all emissions have been abated at the benchmark rate. All stocks are then sold to other investors.

Low-carbon targets

For a company j , we define a low-carbon target as the objective to decrease its emissions by a decarbonization rate $\tau_j \in [0, 1[$:

Definition 1 (Low-carbon target for a company) Emissions of company $j \in [1, M]$ must be abated by the selected decarbonization rate τ_j :

$$\text{For } t \in [0, T] : e_{j,t} = e_{j,0}(1 - \tau_j)^t$$

⁴This timeline is inspired by the entrepreneurial financing decisions sequence of [Crifo and Sami \(2008\)](#).

where $e_{j,0}$ is the level of emissions⁵ reported by company j at time $t = 0^-$.

The low-carbon target of a company is therefore characterized by a single parameter, τ_j . The company does not make any abatement efforts if it chooses a decarbonization rate equal to zero. We also define a reference target for companies, τ_B that we refer to as the benchmark target, compatible with a global low-carbon scenario. More details are provided in Appendix 3.7.1.

Companies can be classified into 3 categories, based on the type of target they choose:

- **Type B** firms choose to commit to a low-carbon target and select the benchmark decarbonization rate: $\tau_j = \tau_B$.
- **Type H** firms choose to commit to a target dependent on their decarbonization ability: $\tau_j = (a_j + \kappa)^2$ with $0 < \kappa \ll 1$.
- **Type N** firms choose not to commit to a low-carbon target: $\tau_j = 0$.

We assume that if companies choose to announce a target, it must satisfy a minimum level of ambition, that is the benchmark rate. Therefore a type H company can only select a rate above the benchmark. Companies that do not select an ambitious target are automatically considered type N firms. We discuss the implications of this hypothesis in the Discussion section of the paper.

Decarbonization ability

The decarbonization ability of a firm is its capacity to abate its emissions. It is a critical metric for investors when evaluating the credibility of a low-carbon target and can provide insight into the future climate risk the firm faces (Carney, 2015). It can be modeled as a set of parameters (such as the governance of the firm on the topic of climate change, the green technologies developed by the firm, its financial resources, and the historical trend of direct and indirect emissions) assembled under one variable.

Investors can estimate the decarbonization ability of a firm. We label this metric a_j for firm j , with $a_j \geq 0$.

⁵We do not specify the scope of these emissions, but this could be for example absolute scope 1 (direct) emissions.

Variables and parameters

The variables and parameters of the model are detailed in Appendix 3.7.2. The phases of the model are summarized in Figure 3.1.

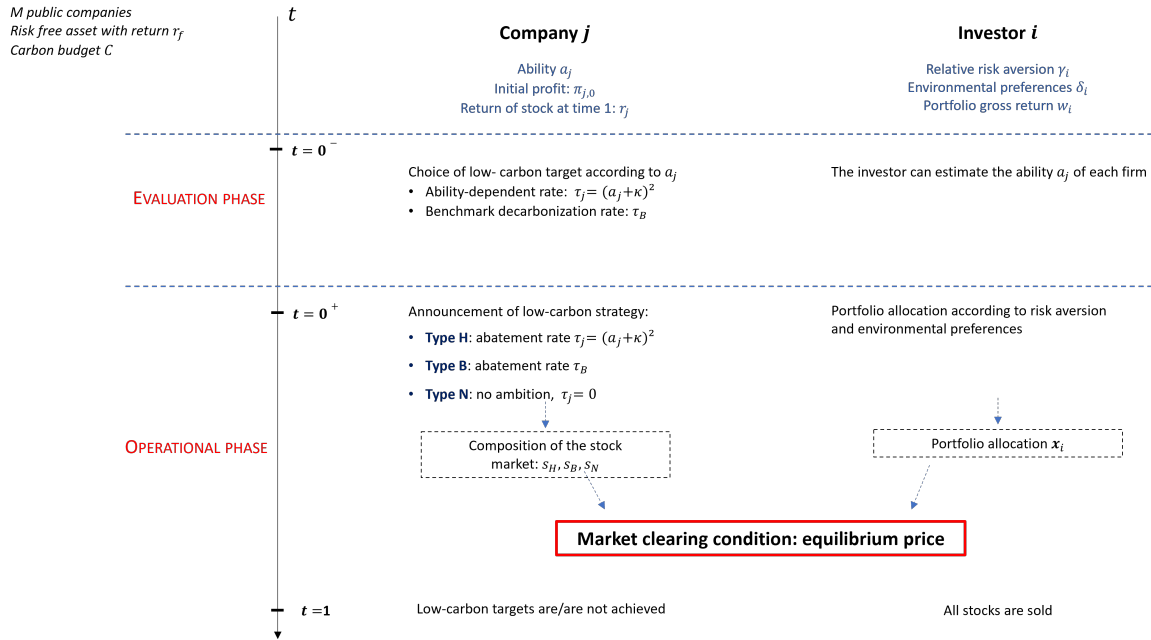


Figure 3.1: Model set-up

3.2.2 Evaluation phase: choosing a low-carbon pathway

Expected net profit of companies

The evaluation period focuses on the companies' decision whether or not to set a low-carbon target. At the beginning of the phase, company j evaluates its decarbonization ability a_j and decides whether to commit to a low-carbon target. We refer to traditional corporate finance to assume that the objective of the firms is to increase their value by maximizing their expected net profit (Robert, 2023; Cornell and Damodaran, 2020) and that this will determine their low-carbon target decision⁶.

The expected net profit for firm j depends on the target it selects: we represent the shift in customer demand through a growth factor that diverges for type B, type H, and type N stocks:

⁶There are four ways of maximizing a firm's value (Cornell and Damodaran, 2020): maximizing revenue growth, maximizing operating margins, optimizing investment efficiency, and minimizing the cost of capital. Under the efficient market hypothesis, given that companies are financed through equity, maximizing revenue is equivalent to minimizing the cost of capital.

$$E[\pi_{1,j}] = \begin{cases} \pi_{0,j}(1 + g_j^H + \lambda_j \tau_j) & \text{for type H} \\ \pi_{0,j}(1 + g_j^B + \lambda_j \tau_j) & \text{for type B} \\ \pi_{0,j}(1 + g_j^N) & \text{for type N} \end{cases} \quad (3.1)$$

$\pi_{0,j}$ and $\pi_{1,j}$ are the net profits of company j at times 0 and 1. For type H (type B) firms, g_j^H (g_j^B) is the marginal growth rate of net profit for a type H (type B) low-carbon target. As committing to a target mobilizes additional costs, we consider that the marginal growth rate can vary if the company sets a target. For type N companies, g_j^N is the marginal net profit growth rate of the company if it selects a type N target. $\lambda_j \tau_j$ is an additional growth rate reflecting the increase in customer demand for products from companies making significant efforts to reduce their emissions. It is conditional on the company achieving its target and therefore depends on the probability of success λ_j :

$$\lambda_j = \begin{cases} \lambda (1 - \tau_B) & \text{for type B} \\ \lambda & \text{for type H} \end{cases}$$

For a type B firm, the probability of success depends on the benchmark rate, while for a type H firm, the probability is constant. This implies that, for a type H firm, any changes in the macro-economic scenario (carbon budget, macroeconomic shocks, individual preferences, technological breakthroughs, etc.) will not impact the probability of success, but rather the ambitions of the target through the decarbonization rate. The situation is reversed for a type B firm, where a macroeconomic change will impact the probability of success as the decarbonization rate is constrained.

Strategies of firms

The company selects its target by maximizing its expected revenue. We show in Appendix 3.7.3 that if a firm decides to commit to a low-carbon target, there is a unique ability threshold a^* above which companies choose to be type H:

$$a^* = -\kappa + \sqrt{\tau_B (1 - \tau_B)} \quad (3.2)$$

The ability threshold increases with the benchmark decarbonization rate. This means that with a larger carbon budget, emissions can be abated on a slower rhythm: companies with lesser abilities will have the possibility of committing to the benchmark target without much effort.

We now consider the choice of setting or not setting a low-carbon target. A firm will be indifferent between choosing whether or not to commit if the expected revenues are equal:

$$\pi_{0,j}(1 + g_j^K + \lambda_j \tau_j) = \pi_{0,j}(1 + g_j^N) \quad \text{with } K \in \{H; B\}$$

This means that a firm will choose to commit to a low-carbon target if the increase in revenue from committing to a low-carbon target exceeds the potential loss of profit margin. If committing to the benchmark target incurs a high cost (which is a cost of opportunity), then the company should be willing to sacrifice a part of its margin to achieve its target.

We make an additional assumption:

Assumption 1 For firm j , if $a_j > a^*$, then $g_j^H + \lambda_j \tau_j > g_j^N$.

With this hypothesis, we assume that companies with high abilities will always choose to commit to a low-carbon target because they will always get a higher net profit from doing so.

Companies with lower abilities, below the threshold a^* , will choose to be type B companies if the increase in revenue from committing to the benchmark target compensates the loss of net profit margin.

Composition of the stock market

At the end of the evaluation phase, companies publicly announce their choice before investors allocate their assets. We determine the composition of the stock market by considering that each firm has the same number of traded stocks, and we write s_B , s_H , and s_N as the proportions of type B, H, and N stocks, respectively. The relative sum of these stocks is equal to 1. Assuming that firms' abilities are uniformly distributed, the proportion of stocks for type H, type B, and type N satisfies the conditions:

$$\begin{cases} s_B + s_N = a^* \\ s_H = 1 - a^* \end{cases} \quad (3.3)$$

The proportion of type H stocks is determined by the ability threshold a^* , as type H companies will never decide not to commit. The choice to be a type B or a type N company partly depends on the cost of opportunity, which can be reduced if the company receives sufficient capital from investors. We, therefore, turn towards the investors' decisions and their portfolio allocation to determine the conditions for increasing investments towards

firms that commit to low-carbon targets.

3.2.3 Decision of investors: allocation of the portfolios

We now focus on the operational phase, when investors make their portfolio allocation decisions according to the expected performance of companies at $t = 1$ and to their own climate preferences. Let us consider investor i , with relative risk aversion γ_i , constant over time, and climate preference coefficient δ_i . We assume she wishes to invest in M risky assets and a risk-free asset with return r_f . The returns of the risky assets are grouped within vector \mathbf{r} , where r_j is the return of asset j .

Climate risk premium

We assume that the return of a stock is defined by a CAPM (Capital Asset Pricing Model) structure (Sharpe, 1964) to which we add a climate risk premium:

$$r_j = \beta_{mkt,j} r_{mkt} + \tilde{r}_j + \epsilon_j = r_{j,capm} + \tilde{r}_j + \epsilon_j \quad (3.4)$$

where $\beta_{mkt,j}$ is the sensitivity of asset j to the market return r_{mkt} , \tilde{r}_j is the climate risk premium, and ϵ_j is a normally distributed variable of mean 0 and variance σ_j^2 .

Previous theoretical and empirical literature supports the presence of a climate risk premium as a component of stock return (Bauer et al., 2022; Enders et al., 2024). In our case, it represents a diversifiable risk and reflects the exposure of a stock to climate-related risks⁷. For all companies, the climate risk can be decomposed into a reputational risk and a transition risk:

$$\tilde{r}_j = \begin{cases} \tilde{r}_H = (1 - \lambda(1 - \tau_B)) \rho_H^T & \text{for type H companies} \\ \tilde{r}_B = (1 - \lambda) \rho_B^T & \text{for type B companies} \\ \tilde{r}_N = \rho_N^T + \rho_N^R & \text{for type N companies} \end{cases}$$

The structure of the climate risk premium reflects the expected exposure to climate-related risks. In the case of type H and type B stocks, the climate risk premium is the product of two terms: the reputational risk factor, represented by the probability of failing to reach the target, and the transition risk factor specific to each type of company: ρ_H^T and

⁷Climate-related risks, which we defined as the negative impact of climate change on corporations, are decomposed into physical risks, transition risks and reputational risks, see Carney (2015). In this case, we focus on transition risks, resulting from the lack of adjustment towards a lower-carbon economy, and reputational risks that originate in the possibility of legal proceedings if the company is identified as largely contributing to global warming.

ρ_B^T . The climate risk premium for type H and type B stocks increases when the probability of success is low, as investors will ask for compensation from a higher climate risk exposure of the stock: higher returns are expected when there is a low probability of success. If firms achieve their targets, then they will not be exposed to transition risk as they have respected the boundaries of the carbon budget, therefore the climate risk premium will be null. However for a type N firm, no matter its reputational risk exposure, it will always be exposed to a transition risk factor.

Investors' portfolio allocation

The investor's portfolio allocation decision is made by maximizing her expected utility. Drawing from previous literature (Pedersen et al., 2021; Avramov et al., 2022), the utility function depends on her relative risk aversion γ_i , the gross return of the portfolio w_i at $t = 1$, her climate preferences δ_i , and the decarbonization rates chosen by the M underlying companies of the portfolio, gathered under the vector $\boldsymbol{\tau}$:

$$U(w_i, \mathbf{x}_i) = -e^{-\gamma_i w_i - \frac{\delta_i}{\tau_B} \mathbf{x}_i' \boldsymbol{\tau}} \quad (3.5)$$

The gross return of the portfolio depends on returns from the risk-free and risky assets and on the portfolio weights gathered under an M -vector \mathbf{x}_i , where $x_{i,j}$ is the weight of asset j within the portfolio of investor i :

$$w_i = (1 + r_f + \mathbf{x}_i' \mathbf{r})$$

with $\sum_{j=1}^M x_{i,j} = 1$ and $\mathbf{r} = (r_1, \dots, r_M)'$.

The investor's risk aversion parameter reflects her appetite for financial risks that include climate-related risks. We also assume, following a growing strand of literature (Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022), that investors can have preferences for stocks that abate their carbon emissions. This is the climate preference, which in our case reflects the investor's taste for companies that make low-carbon targets; it is, therefore, not a preference for the firm's current low-carbon performance, but future low-carbon performance.

Demand of investors for type H, B, and N stocks

We assume that investors have the same relative risk aversion for simplification: $\gamma_i = \gamma$. The allocation decision of investor i follows the maximization objective: $\max_{x_i} \mathbb{E}[U(w_i, \mathbf{x}_i)]$. The first-order conditions, detailed in Appendix 3.7.4, give the following risky assets' allocation for investor i :

$$\mathbf{x}_i = \frac{1}{\gamma} \Sigma^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\delta_i}{\gamma \tau_B} \boldsymbol{\tau}) \quad (3.6)$$

This allocation of risky assets serves as a demand for those assets, that depends on the investor's relative risk aversion, the covariance matrix of assets Σ^{-1} , the expected return of the asset, and the investor's additional demand due to her preference for companies with ambitious transition plans.

3.3 Market equilibrium

In this section, we study the market equilibrium that appears under the market clearing conditions: the composition of the stock market provides a supply of stocks while investors, through their portfolio allocation decisions, determine the demand for stocks. For simplification purposes and to identify the underlying mechanism behind the strategies undertaken by firms, we reduce the economy and study the market equilibrium under three instances:

- when the market holds a single type of company ("lemon market" structure)
- when the economy only has two types of companies: type B and type N;
- when the economy has three types of companies: type H, B and N with close climate-risk profiles.

In these simplified models, we assume that investors' allocation depends solely on diversifiable risk. The underlying hypothesis is that investors will only consider diversifiable risk within their allocation decisions and will not concern themselves with the systematic risk $r_{j,capm}$. Each time, we proceed to a numerical application of the market composition and the climate risk premium of firms.

This section ends by detailing the general market equilibrium when the economy has M companies.

3.3.1 "Lemon market" structure: only one type of company within the economy

We start by considering a market with only one company. We consider a company j , with variance σ_j , climate risk premium \tilde{r}_j , and targeted decarbonization rate τ_j .

The portfolio allocation of an investor i can thus be simplified:

$$1 = \frac{1}{\gamma \sigma_j^2} (\tilde{r}_j + \frac{\delta}{\gamma \tau_B} \tau_j)$$

Therefore the climate risk premium is determined as:

$$\tilde{r}_j = \gamma \sigma_j^2 - \frac{\delta}{\gamma} \frac{\tau_j}{\tau_B} \quad (3.7)$$

If the company does not choose to make any announcement, the climate risk premium is a product of its volatility and of the aversion to risk: $\tilde{r}_N = \gamma \sigma_N^2$.

The climate risk premium does not hold information regarding its exposure to climate transition risk, nor on its exposure to reputational risk, nor does it depend upon the investors' preferences. In this layout, the investors cannot mitigate their exposure to climate-related risks, no matter their climate preferences.

However if the company selects a type B target then the climate risk premium does not depend on the benchmark decarbonization rate:

$$\tilde{r}_B = (1 - \lambda)\rho_B^T = \gamma \sigma_B^2 - \frac{\delta}{\gamma}$$

This means that the transition risk factor itself does not depend on τ_B :

$$\rho_B^T = \frac{\gamma \sigma_B^2 - \frac{\delta}{\gamma}}{(1 - \lambda)}$$

Unlike the type N case, \tilde{r}_B can be impacted by investor preferences, through the weighted-average climate preference δ . We find that if the average is high (the majority of investors desire to hold portfolios with low exposure to climate risks), the climate risk premium deviates from its original structure: this means that investors expect less excess return from stocks that mitigate their transition risk exposure by committing to a low-carbon target. This also applies to the transition risk factor and suggests that if investors have, on average, higher environmental preferences, then they price the transition risk of a type B firm lower than climate-neutral investors. This means that if investors care about climate risk, then announcing a low-carbon target via the settlement of a low-carbon target is already an indicator that the firm decreases its transition risk of a firm.

If the company has a high decarbonization ability and selects a type H target, then this time the climate risk premium depends on the benchmark decarbonization rate τ_B and also on the decarbonization rate the company has chosen, τ_H :

$$\tilde{r}_H = (1 - \lambda(1 - \tau_B)) \rho_H^T = \gamma \sigma_H^2 - \frac{\delta \tau_H}{\gamma \tau_B}$$

If we stabilize the ratio τ_H/τ_B to a constant, then the climate risk premium of a type H company only depends on the average preference of investors δ . However, the transition risk factor is a decreasing function of the benchmark decarbonization rate:

$$\rho_H^T = \frac{\gamma \sigma_H^2 - \frac{\delta \tau_H}{\gamma \tau_B}}{(1 - \lambda(1 - \tau_B))}$$

This means that the transition risk factor of a company that pledges to ambitious climate action decreases with a carbon budget that becomes more constrained. This is the case even if investors are, on average, climate-neutral ($\delta = 0$).

We illustrate the transition risk factors of type H and type B companies with a numerical application by taking simple parameters relevant to the results. We assume that investors are risk averse: $\gamma = 3$ and that stocks have a volatility close to the market's historical volatility level: $\sigma_B = \sigma_H = 0.2$. The results are presented in Figure 3.2.

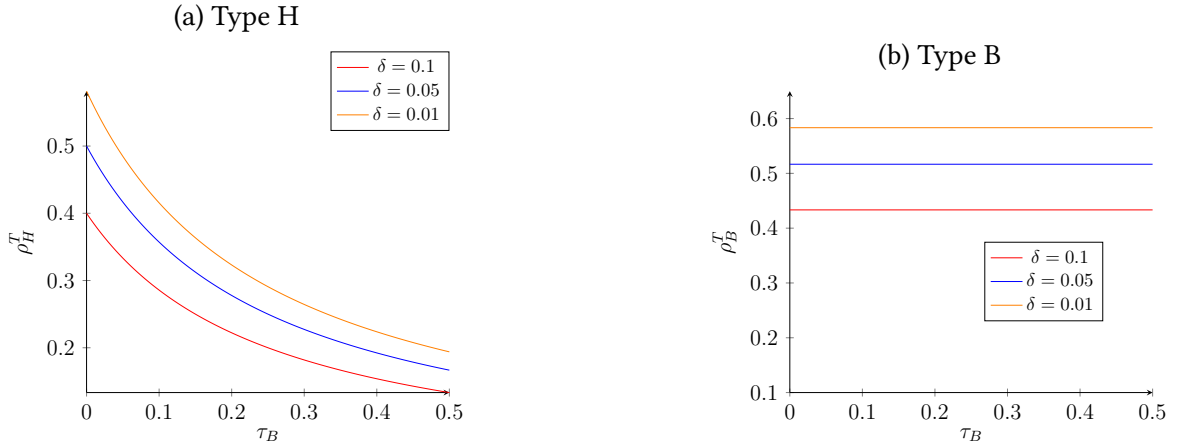


Figure 3.2: Climate risk factor for type H and type B stocks in a lemon market.

If we consider the climate risk premia of type H, type B, and type N stocks, we find that if the market holds, on average, a positive environmental preference ($\delta > 0$), then the premium is highest for type N stocks and lowest for type H stocks. This suggests the existence of a climate risk premium for firms that do not commit to low-carbon targets.

3.3.2 Economy with type B and type N companies

We consider that the economy has two types of companies, a type B and a type N with relative stock proportions: $s_B + s_N = 1$. All investors have an identical positive climate preference $\delta > 0$, which means that they will favor companies with low-carbon targets, in this case, type B stocks. We assume that the assets are independent and within each type of company, have identical volatilities: the covariance matrix is diagonal with asset variances σ_B^2 and σ_N^2 .

The hypothesis that investors will solely care about their diversifiable risk means that for investor i , the portfolio's allocation can be simplified:

$$\mathbf{x}_i = \frac{1}{\gamma} \Sigma^{-1} \left(\tilde{\mathbf{r}} + \frac{\delta}{\gamma \tau_B} \boldsymbol{\tau} \right)$$

Under these hypotheses, the market-clearing condition yields:

$$\mathbf{s} = \frac{1}{\gamma} \Sigma^{-1} \left(\tilde{\mathbf{r}} + \frac{\delta}{\gamma \tau_B} \boldsymbol{\tau} \right)$$

The market-clearing conditions for type B and type N stocks are detailed in Appendix 3.7.5. We find that the relative supply of stocks for each type of company:

$$s_B = 1 - s_N = \frac{\frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B) + \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.8)$$

We find that with $\tau_B \in]0, 0.5]$ and the parameters used in our numerical application, the number of type B companies is concave with regard to τ_B . This means that there can be a maximum number of firms for a given decarbonization rate. For very high values of τ_B , the number of type B stocks falls: this can be interpreted as a withdrawal from investors because the probability of success becomes very low for firms with low abilities that set up transition plans. Therefore, the financial profile of type N firms becomes more attractive for investors when the carbon budget is very small.

This marks the existence of a tipping point for the number of firms undertaking a low-carbon commitment: if the exogenous benchmark rate is too high, the number of firms with sufficient abilities to follow the benchmark target becomes smaller. There is a higher probability of failure, which could damage the firm's reputation: the number of companies willing to become type B instead of type N is lower and not optimal. A less ambitious benchmark decarbonization rate is also suboptimal for the proportion of type B stocks: there is a lower climate risk premium compared to the type N stocks (see Appendix 3.7.5) which makes the profile of type B less interesting to investors. In a context where the carbon budget remains high, this means that type B stocks will not be attractive to investors, therefore fewer companies will commit.

This latest observation also highlights the existence of an important mechanism: the role of companies on motivating others to commit to low-carbon targets. We see that the

market distribution of firms (not just the expected return) depends on both the carbon budget (through the reference decarbonization benchmark τ_B) and on the average climate preference of investors that impacts the allocation of portfolios. This is a new result compared to previous models, where investor preferences only impacted the risk premium of firms. It suggests that the behavior of firms, via their strategic decision to set a target, serves as an externality for the decisions of other firms: in an economy where a majority of investors have a strong climate preference, if firms set targets (this means that there are type B companies within the economy), then more firms will be encouraged to set targets as well, otherwise they risk being divested from the portfolios of investors.

We illustrate our results through a numerical application by taking simple parameters relevant to the results. We assume that investors are risk averse: $\gamma = 3$ and that type B and type N stocks have the same volatilities, close to the market's historical volatility: $\sigma_B = \sigma_N = 0.2$. Furthermore, we assume that $\lambda = 0.8$. We compute the number of type B and type N stocks according to the benchmark decarbonization rate in Figure 3.3 and their climate risk factor in Figure 3.4. We identify the tipping point for $\tau_B = 0.4$.

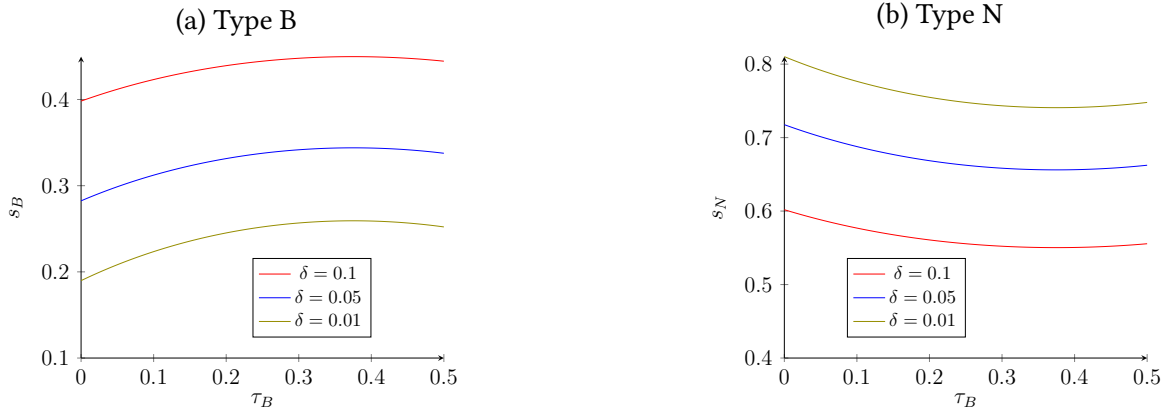


Figure 3.3: Number of type B and type N stocks in an economy with 2 companies.

We also compute the climate risk premium for both types of companies (see Appendix 3.7.5 for further details):

$$\tilde{r}_B = (1 - \tau_B) \tilde{r}_N = \frac{\gamma \sigma_N^2 (1 - \frac{\delta}{\gamma \sigma_B^2}) (1 - \tau_B)}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.9)$$

The climate risk premium for the type B company is a decreasing function of τ_B . In the case of a company committing to a low-carbon target, the climate risk premium could be interpreted as a cost-to-announcement. For a less ambitious target (if τ_B is low), the

cost of failing would be very high because the company would have failed to achieve an easier target, its reputation suffering even more than when the target was difficult to attain. Surprisingly, we find that for the type N company, the climate risk premium is not monotonous but convex with regard to τ_B and reaches a minimum when the number of type B stocks is highest. This is not very intuitive and warrants an interpretation for extreme values of τ_B . When the benchmark decarbonization rate is low, there is a higher risk for type N companies because the target is easier to reach for any company with low abilities: the reputational risk of type N companies is high. For high values of τ_B , the climate risk increases once again as the company is identified as having the highest transition risk, by being, in the eyes of investors, the biggest future polluter from not making efforts to decrease its emissions.

For both type B and type N companies, the climate risk premium also depends on the environmental preference of the investor. In both cases, it is higher for lower values of δ , which means that the climate risk assessment of companies depends on the investors' interest in the low-carbon transition.

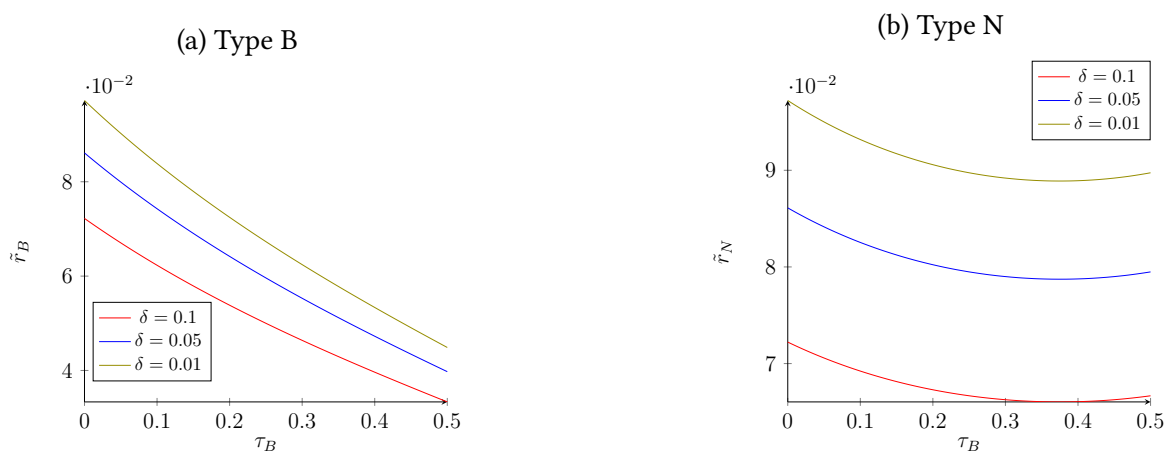


Figure 3.4: Climate risk premium for type B and type N stocks in an economy with 2 companies.

3.3.3 Model with three assets

We extend our model by adding type H companies with high decarbonization abilities. The proportion of type B, H, and N stocks are labeled s_H , s_B , and s_N , respectively, and follow the conditions that we detailed in the previous section:

$$\begin{cases} s_H = 1 - a^* \\ s_B + s_N = a^* \end{cases}$$

We label τ_H the decarbonization rate of firm H. As in the previous paragraph, all investors have the climate preference $\delta > 0$, and the assets are independent with asset variances σ_B , σ_H , and σ_N .

The market-clearing conditions for type B and type N stocks are detailed in Appendix 3.7.6. We find that the relative supply of stocks for type B and type N companies:

$$s_B = a^* - s_N = \frac{\frac{\sigma_B^2}{\sigma_N^2} a^* (1 - \lambda(1 - \tau_B)) (1 - \tau_B) + \frac{\delta}{\sigma_B^2} \gamma^2}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.10)$$

The number of type H assets is only determined by the ability threshold a^* , other parameters related to investors do not interfere with the relative supply of those stocks. As in the previous section, the numbers of type B and type N stocks depend on parameters related to type B and type N stocks, and the benchmark decarbonization rate plays a determining role in determining the proportion of companies that will choose a type B target. However, introducing a type H company in the model has an impact on the number of type N stocks, which is now concave with regard to τ_B . For small values of τ_B the ability threshold a^* will be low, therefore the offer of type H stocks will be greater. However, as τ_B increases, the numbers of type H and type N stocks simultaneously increase because companies cannot commit to type H targets and must decide between choosing the benchmark decarbonization rate or not making any commitment because it is unachievable (the cost of opportunity exceeds the additional profit from committing to a target).

This is illustrated in Figure 3.5, where we take the same parameter values as in the previous paragraph (we consider that type H assets have a higher variance: $\sigma_H = 0.3$ and that $\frac{\tau_H}{\tau_B} = 1.1$). Once again, the climate preferences of investors are a determining factor in optimizing the number of type B and type N stocks: when climate preferences are low, type N stocks prevail. The situation is reversed when the climate preference is high: companies will attract more investors by committing to a low-carbon target, therefore the number of type B companies increases with δ . This is an important result: the climate preferences of investors are a determining driver in optimizing the number of stocks that commit to low-carbon targets for an exogenous benchmark decarbonization rate τ_B .

We also determine the climate risk premia for the type B, H, and N stocks, which are de-

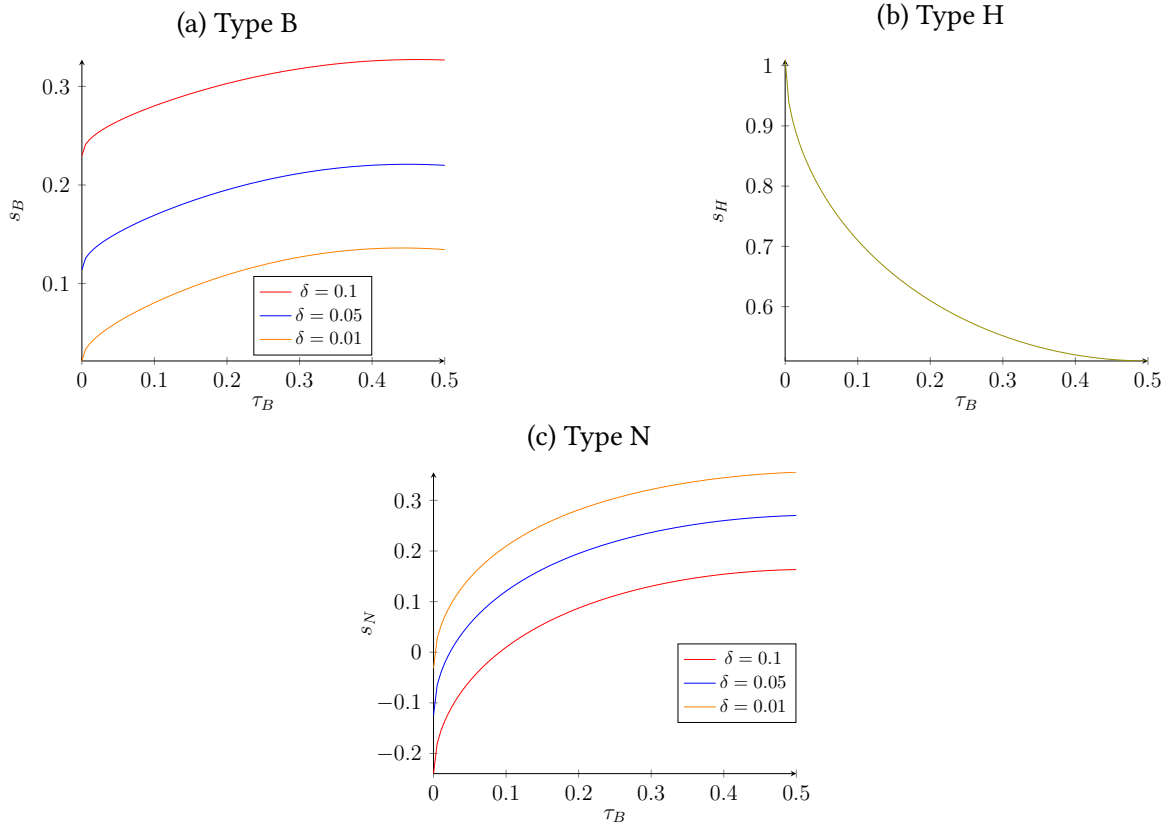


Figure 3.5: Number of type B, type H, and type N stocks in an economy with 3 companies.

tailed in Appendix 3.7.6. The volatility of the type H stock has a direct impact on the climate risk premium and is empirically higher than type B or type N stocks: market leaders in the low-carbon transition are often companies with a high volatility⁸. The risk premium also decreases when the company takes an ambitious target: $\frac{\tau_H}{\tau_B} \gg 1$, which signifies that announcing an ambitious target, when a company can fulfill it, decreases the reputational risk exposure. The climate risk premium for a type N company increases with τ_B , which means that the company faces greater exposure to reputational and transition risk if it does not make any effort in a world with an urgency to decrease greenhouse gas emissions. This is consistent with theoretical and empirical evidence found in [Bolton and Kacperczyk \(2021b\)](#). The climate risk premium for a type B company is concave with regard to τ_B , which is a different result than in the previous paragraph. The maximum is reached at different values of τ_B , depending on the investors' climate preference: the risk premium quickly decreases when the climate preference is high.

⁸Companies within the RENIXX Index are representative of the high volatility of low-carbon transition market leaders.

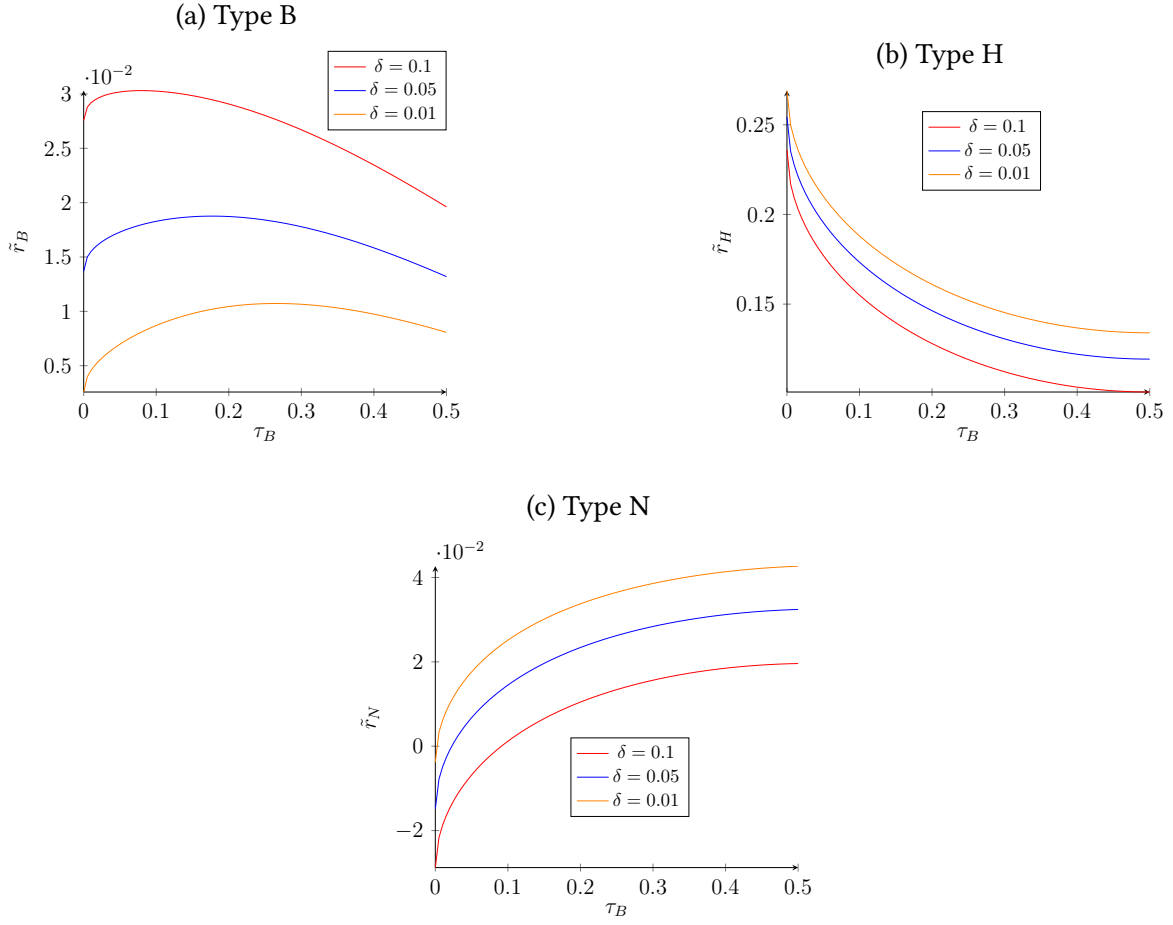


Figure 3.6: Climate risk premium for type B, type H, and type N stocks in an economy with 3 companies.

3.3.4 General market equilibrium

We now turn towards the general market equilibrium, by removing constraints that we used in the previous sections. We now consider that investors have heterogeneous preferences and risk aversions and that they also take into account systemic (market) risk. Assets are no longer independent and type H companies can select heterogeneous targets. Considering the M vector supply of stocks \mathbf{s} , the market-clearing condition states that the supply of stocks meets the demand, therefore:

$$\mathbf{s} = \int_i w_{i,0} \mathbf{x}_i \, di$$

$w_{i,0} = W_{i,0} / \int_i W_{i,0} \, di$ is the relative wealth of investor i at time $t = 0^+$.

This gives us the following market equilibrium (see Appendix 3.7.8):

$$\mathbf{s} = \frac{1}{\bar{\gamma}} \Sigma^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\bar{\delta}}{\bar{\gamma}^2} \Sigma^{-1} \boldsymbol{\tau})$$

where $\bar{\gamma}$ and $\bar{\delta}$ are the average risk aversion and climate preferences of investors respectively.

This means that the climate risk premium can be determined by the supply and risk of stocks as well as the average demand of investors for sustainable assets:

$$\tilde{\mathbf{r}} = \bar{\gamma} \Sigma \mathbf{s} - \mathbf{r}_{capm} - \frac{\bar{\delta}}{\bar{\gamma}} \boldsymbol{\tau} \quad (3.11)$$

Unsurprisingly, a positive average demand from investors $\bar{\delta}$ reduces the climate risk premium for type B and type H firms. The general market equilibrium is very close in its form to [Pástor et al. \(2021\)](#). However, an additional term, the climate risk premium $\tilde{\mathbf{r}}$, further increases the deviation from the CAPM return model. Furthermore, the terms reflect the long-term exposure to climate risk of the stocks within the climate risk premium and the ambition of firms, additionally to their current climate performance through carbon emissions.

3.4 Empirical illustration: identifying a climate risk premium from low-carbon target alignment strategies

In this section, we perform an empirical analysis to assess the existence of a climate risk premium associated with the alignment strategies of companies. Our aim is therefore to highlight the existence of a non-diversifiable risk premium (see Equation 3.4) linked to the alignment strategies of companies. Using the Science-Based Targets initiative database, we find limited evidence of a climate risk premium for companies that do not make target announcements, especially in sectors that are more exposed to climate risk. We also identify a premium that depends on the current alignment of their emissions to a low-carbon scenario.

3.4.1 Identification of a target announcement risk premium

We start by analyzing the possible premiums when a company makes a low-carbon target announcement. We compare stock returns using a staggered difference-in-difference approach. We estimate the following model:

$$r_i(t) = \delta d_{i,t} + \gamma_i + \gamma_t + \epsilon_i(t)$$

where $r_i(t)$ is the return of stock i at time t , $d_{i,t}$ is the treatment indicator, which equals 1 if company i has a low-carbon target within the SBTi platform at time t , and 0 otherwise. δ is the average treatment effect. γ_i and γ_t are firm and time fixed effects, and $\epsilon_i(t)$ is the error term, assumed to be uncorrelated with the regressors.

We consider the null hypothesis (H_0) of no change in the residual returns of a company that has set a target, compared to the returns of a company that has not set any target before and after having announced the target, against the following hypotheses:

- H_{1A} : after the publication date, returns from companies that have set a target are lower than returns from companies that have not made any target announcements: $\delta < 0$.
- H_{1B} : after the publication date, returns from companies that have set a target are higher than returns from companies that have not made any target announcements: $\delta > 0$.

We perform this test for stock returns as well as residual returns $r_{res,i}(t)$ to control for other determinants of stock returns and test the hypotheses on the stocks' alphas. We therefore take out the market, size, and book-to-market factors following the Fama-French

3-factor model Fama and French (1995):

$$r_{res,i}(t) = r_i(t) - \beta_{m,i} r_m(t) - \beta_{SMB,i} r_{SMB}(t) - \beta_{HML,i} r_{HML}(t) \quad (3.12)$$

$r_{res,i}(t)$ is the residual return of stock i at time t , $r_m(t)$, $r_{SMB}(t)$, $r_{HML}(t)$ are the returns of the market, size and value factors at time t and $\beta_{m,i}(t)$, $\beta_{SMB,i}$ and $\beta_{HML,i}$ are the sensitivities of stock i to the factors.⁹

We select companies from the MSCI[®] World Index, which captures large and mid-cap stocks across Developed Markets (DM) of 23 countries. We use the SBTi platform to isolate companies with low-carbon targets, with a Target Set status. We consider all levels of ambitions and all emissions coverage within the SBTi platform as companies are required to audit their strategy. Therefore any target that is published on the platform can be considered credible and compatible with climate scenarios that limit global warming to well below 2°C. We observe the results by Industry Group, using the Global Industry Classification Standard (GICS). Time fixed effects are set up using quarters for time periods. Results are observed between June 2015 and June 2023.

Table 3.1 reports the results for the sectors that are the most exposed to climate risk (sensitive sectors defined by the European Commission). We do not find differences above 15 base points (bps), which suggests that the market does little to price the commitment decisions of companies. We find heterogeneous results between industries, with significant results for the Energy sector: controlling for firm and time fixed effects, as well as market, size, and market-to-book biases, we find a negative premium of -2.71 bps behind the commitment to a low-carbon target. The Financial Services sector also presents a negative risk premium of almost -3 bps. For several industries, such as Automotive & Components, Consumer Discretionary Distribution & Retail, or Transportation, results are less clear and depend on the control for firm and time fixed effects.

⁹We extract market, size, and value returns from the Kenneth R. French library, using the developed markets database with daily returns.

Table 3.1: Identification of industrial climate risk premia from staggered difference-in-difference regressions.

Table 3.1 presents the coefficients from the staggered difference-in-difference regressions. Columns (1) to (6) report coefficient δ in bps for each industry group (committed vs not committed). Regressions are run for stock returns in columns (1) to (3) and for residual returns (taking away the market, size and book-to-market factor sensitivities) in columns (4) to (6). Columns (2), (3), (5), and (6) include firm fixed effects. Columns (3) and (6) also include time fixed effects (controls are defined for every quarter). We cluster standard errors at the firm and time dimensions. ***1% significance; **5% significance; *10% significance.

INDUSTRIES	(1)	(2)	(3)	(4)	(5)	(6)
	δ (in bp)					
Automobiles & Components	-3.99 (3.10)	-2.11 (1.48)	0.10 (2.39)	-2.81 (2.61)	0.18 (1.31)	0.11 (2.09)
Capital Goods	-3.69*** (1.24)	-3.48*** (1.06)	-2.20** (1.09)	-1.50 (1.02)	-0.78 (0.85)	-0.76 (0.95)
Consumer Discretionary Distribution & Retail	-8.47** (3.49)	-9.25** (3.82)	-3.53 (3.52)	-4.39 (3.09)	-3.68 (2.41)	-0.97 (2.78)
Consumer Staples Distribution	-1.62 (2.26)	-0.43 (2.63)	1.32 (2.67)	-1.73 (2.09)	-1.00 (2.39)	0.55 (2.47)
Energy	-1.18 (9.12)	-0.27*** (0.00)	-4.73*** (0.79)	1.53 (7.78)	5.34*** (0.00)	-2.71*** (0.83)
Equity Real Estate Investment	-3.73*** (1.47)	-4.61** (1.78)	-1.54 (1.43)	-3.88*** (1.24)	-4.60*** (1.36)	-1.76 (1.30)
Financial Services	-5.34** (2.78)	-11.53*** (2.98)	-6.03** (2.59)	-2.12 (2.27)	-6.96*** (2.09)	-2.97 (2.17)
Food, Beverage & Tobacco	-1.15 (1.18)	-0.73 (0.79)	2.74* (1.45)	-0.88 (1.07)	-0.47 (0.69)	1.98 (1.27)
Materials	-3.79** (1.61)	-2.91** (1.32)	-0.97 (1.21)	-3.37** (1.39)	-2.02** (1.03)	-0.85 (1.08)
Real Estate Management & Development	-2.94 (2.73)	-4.30*** (1.62)	2.23 (2.41)	-1.28 (2.42)	-2.57* (1.47)	2.62 (2.08)
Semiconductors & Semiconductor Equipment	5.45 (4.60)	-0.42 (3.64)	6.57* (4.05)	8.01** (3.90)	4.33 (3.75)	4.61 (4.91)
Technology Hardware & Equipment	-3.43** (1.68)	-1.74 (1.36)	2.60* (1.53)	-0.72 (1.40)	1.81 (1.24)	2.63* (1.48)
Transportation	1.94 (2.43)	0.71 (2.17)	1.20 (2.30)	3.30 (2.12)	2.61 (2.53)	0.85 (2.58)
Utilities	-2.49 (1.70)	-3.66*** (1.06)	-1.21 (1.19)	-0.94 (1.53)	-1.14 (1.11)	0.71 (1.22)
Residuals	N	N	N	Y	Y	Y
Firm FE	N	Y	Y	N	Y	Y
Time FE	N	N	Y	N	N	Y
Observations	6,118,405	6,118,405	6,118,405	6,118,405	6,118,405	6,118,405

To provide an additional illustration of the climate risk premium, we search for significant changes in stock prices by confronting specific company returns: we perform a difference-in-difference regression between the residual returns of two companies within the same industry. We test the following model:

$$r_{res,i}(t) = \delta_{i,g} d_g + \delta_{i,p} d_p + \delta_{i,gp} d_g d_p + \epsilon_i(t)$$

d_g is a dummy variable that differentiates the treatment group from the control group: the treatment group holds the stock returns of the company that sets a target at a certain Publication Date and for which $d_g = 1$; the control group holds the stock returns of the company that does not set a target. d_p is a dummy variable that takes the value 1 when $t > PublicationDate$ and 0 otherwise. $\delta_{i,g}$, $\delta_{i,p}$, and $\delta_{i,gp}$ are the treatment effects of the dummy variables.

For simplification purposes, we consider a sample of companies from 4 different industry groups from the Global Industry Standard Classification: Automobile & Components, Materials, Transportation, and Utilities¹⁰. We perform multiple regressions for each company that has set a target, using different control groups from the stock returns of each company within the same Industry Group that has not set a target. The regressions are performed over 130 business days and 65 business days before and after publication. We present results from several companies in Table 3.2.

¹⁰These sectors are among the sensitive sectors concerning the European Union's classification of sensitive and non-sensitive sectors (European Commission, 2020), which means that they are heavily exposed to climate change-related risks

Table 3.2: Identification of a climate risk premium.

Table 3.2 presents the coefficients from the difference-in-difference regressions. Each treatment group is specified in the ‘Company’ column, with residual returns spanning 130 business days before and after the Science-Based Target announcement, which date is specified in the ‘Publication Date’ column. The ‘Control Group’ column specifies the company whose residual returns were taken over the same period as the treatment group and serve as the control group. Coefficients from the time and group dummy variables are specified in the columns ‘ δ_p ’ and ‘ δ_g ’. Coefficients from the composite variable ‘ δ_{pg} ’ give an indication of the existence of a climate premium. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively. All results are in base points.

Company	Control Group	Industry	Publication Date	Coefficients (in bp)		
				δ_p	δ_g	δ_{pg}
Electricite de France SA	Exelon Corporation	Utilities	10/12/2020	-5.4	43.4*	-101.0**
Electricite de France SA	Pinnacle West Capital Corporation	Utilities	10/12/2020	-13.9	43.4*	-92.5**
Electricite de France SA	Fortum Oyj	Utilities	10/12/2020	2.4	43.4*	-108.8***
ENGIE	National Fuel Gas Company	Utilities	27/02/2020	44.8*	19.3	100.1**
ENGIE	Osaka Gas Co., Ltd.	Utilities	27/02/2020	33.4	19.3	-88.7**
SSE	Fortum Oyj	Utilities	16/12/2021	-59.3***	-7.9	73.6*
Continental AG	Goodyear Tire & Rubber Company	Automobile & Components	03/12/2020	61.2*	14.2	-98.1*
Continental AG	Magna International Inc.	Automobile & Components	03/12/2020	33.1	14.2	-70.0*
Air Liquide SA	Air Products and Chemicals, Inc.	Materials	19/05/2022	13.2	20.0	-57.7**
Stora Enso Oyj Class R	Avery Dennison Corporation	Materials	21/10/2021	-11.4	-22.8	58.7**
Stora Enso Oyj Class R	International Paper Company	Materials	21/10/2021	-26.7	-22.8	74.0**
Stora Enso Oyj Class R	Packaging Corporation of America	Materials	21/10/2021	-8.6	-22.8	55.9*
Stora Enso Oyj Class R	Sonoco Products Company	Materials	21/10/2021	-16.6	-22.8	63.8**
Wheaton Precious Metals Corp	Sonoco Products Company	Materials	12/05/2022	23.8	10.0	-73.2**
Wheaton Precious Metals Corp	Avery Dennison Corporation	Materials	12/05/2022	26.1	10.0	-75.5**
ANA Holdings Inc.	Deutsche Lufthansa AG	Transportation	08/12/2022	45.8**	24.3	-80.5**
Kuehne & Nagel International AG	Copa Holdings, S.A. Class A	Transportation	15/07/2021	28.7	19.9	-59.7*
Kuehne & Nagel International AG	Old Dominion Freight Line, Inc.	Transportation	15/07/2021	15.9	19.9	-46.9*
Kuehne & Nagel International AG	AerCap Holdings NV	Transportation	15/07/2021	20.2	19.9	-51.1*
Norfolk Southern Corporation	Aurizon Holdings Ltd.	Transportation	29/07/2021	-14.6	-21.5	45.2*

We obtained significant results for a few companies within the four industries. We notice a negative coefficient for most companies from the difference-in-difference regression, highlighting a risk premium for companies that do not commit to low-carbon targets. For example, Fortum Oyj has a 92 bp premium over Electricite de France, both companies being heavy producers of electricity from nuclear power plants. ENGIE is a good example of a company that turned its strategy around and aimed at reducing its exposure to climate risk; the National Fuel Gas Company and Osaka Gas Company hold a premium of 100 and 89 bp from the SBTi target announcement effect. We notice that companies investing in low-carbon technologies, such as Air Liquide with hydrogen production, have had lower returns since setting targets with the SBTi than other companies in the same industrial segment, such as Air Products and Chemicals. The Stora Enso company, which published its targets in October of 2021, paradoxically holds a premium over companies that did not set targets. This may suggest that the climate risk premium is not systematized and that other market mechanisms can overtake the existence of a risk premium for companies that do not cover their climate risk exposure. Furthermore, we obtained very few significant results when considering the entirety of the companies; this suggests that during the study period, the market did not price the future exposure to climate risk efficiently.

3.4.2 Identification of a risk premium associated with the alignment performance of a company

We now turn towards the performance of companies, regardless of their commitment to a low-carbon target. Our aim is to analyze whether the market recognizes a company's alignment to a low-carbon scenario as a driver for financial performance. Using the Trucost Paris Alignment metrics database (see Appendix 3.7.9 for details on the database construction methodology), we build two portfolios from the MSCI World Index, separating assets on their alignment to different scenarios. We set the 'Aligned' status for companies that are evaluated below 2°C, and 'Not Aligned' otherwise.

We analyze the performance of both portfolios during the period between March 2019 and May 2024, bearing in mind that there is, on average, a two-year gap between the greenhouse gas emissions metrics, necessary to build the Alignment Metrics database, and the current date (for example, the alignment information used to build the portfolio in September 2020 uses greenhouse gas emissions performance from 2018). We observe the difference in performance on residual returns, following equation 3.12, and we break down the performance by Industry Group. Figure 3.7 shows the cumulative performance of residual returns

for the ‘Aligned’ and ‘Not Aligned’ portfolios and Table 3.3 shows the cumulative and annual returns, as well as the annual volatility of each Industry Group.



Figure 3.7: Cumulative performance of residual returns (alphas) of ‘Aligned’ and ‘Not Aligned’ portfolios.

The performance is shown between March 2019 and May 2024. Residual returns are determined after having taken the market, size, and book-to-market factor components of the stock returns. According to the Fama-French 3-factor model, residual returns correspond to the alphas of the stocks.

Overall, Figure 3.7 shows that the relative performance of the ‘Aligned’ and ‘Not Aligned’ portfolios are similar until the beginning of 2022 when the aligned portfolio begins to underperform. We find two interpretations for this result: first, this performance stall corresponds to a time when the market rallye of 2020-2021 for stocks considered as market leaders in the climate transition ended, and in a context of greater inflation, stocks with a poor climate performance tended to outperform ‘green’ stocks. Second, the figure can also suggest that investors are beginning to price the climate risk of not aligning to a low-carbon scenario and are currently demanding a greater return for stocks that do not align in the medium term (2025-2030).

When considering the performance of the portfolios within each Industry Group of the GICS classification, we find heterogeneous results within industries. It is worth noting that within certain industries, there is a high imbalance between aligned and not aligned weights that can bias the difference in performance as portfolios have a difference in concentration. This is the case for sectors where emissions are difficult to abate, such as Energy or Materials. The utility sector reports results suggesting the existence of a premium for companies that do not align to a low-carbon scenario: there is a 1.61 bp difference in the average α between the not aligned and the aligned portfolio, and the cumulated return also shows a higher performance for the portfolio that is not aligned. This is also the case for

the Consumer Discretionary Distribution Retail (418 bp difference), the Food & Beverage (131 bps), and the Materials sector (624 bps difference) sectors. This suggests the market prices current and future climate risk and explains the requirement for higher returns from firms that have higher exposure to this risk. However, this is not the case for sectors such as Automobiles & Components, Capital Goods, Real Estate, or Transportation, where aligned firms tend to outperform not aligned firms. This suggests that different mechanisms may be in place, for example the existence of a rallye for market leaders in the low-carbon transition in the 2020-2021 period. These heterogeneous results are not new and confirm the uncertainty of the environmental impact on stock returns (Alareeni and Hamdan, 2020).

Table 3.3: Identification of a climate risk premium from alignment performance.

Table 3.3 presents the difference in portfolio performance per industry from companies that are aligned to low-carbon scenarios to companies that are not. We compute the portfolio performance using residual returns after controlling for market, size, and book-to-market biases. All results cover the period March 2019 - May 2024.

Industry Group	Average portfolio weight (%)		Annualized Residual Return (average yearly α , in %)		Cumulated Residual Return (%)		Annualized Residual Volatility (%)	
	Aligned	Not Aligned	Aligned	Not Aligned	Aligned	Not Aligned	Aligned	Not Aligned
Automobiles & Components	0.90	1.46	-5.39	-5.97	-25.08	-27.45	23.42	20.97
Capital Goods	2.22	4.86	0.68	-1.19	3.59	-6.04	8.71	7.55
Consumer Discretionary Distribution Retail	2.63	1.02	-3.99	0.19	-19.11	0.98	16.64	12.60
Consumer Staples Distribution	0.20	1.70	-11.33	3.14	-46.57	17.51	17.67	11.74
Energy	0.47	3.77	-6.27	-7.02	-28.64	-31.58	18.87	17.37
Equity Real Estate Investment	0.87	1.17	-12.14	-12.64	-49.07	-50.57	13.51	15.81
Financial Services	4.37	1.64	-5.28	-6.29	-24.63	-28.74	7.94	10.40
Food, Beverage & Tobacco	1.38	3.31	-7.12	-5.81	-31.95	-26.80	11.11	9.32
Materials	1.11	2.89	-5.98	-0.26	-27.48	-1.35	9.82	9.01
Real Estate Management & Development	0.16	0.29	-3.43	-11.73	-16.65	-47.81	15.63	14.32
Semiconductors & Semiconductor Equipment	2.98	1.71	23.55	1.13	201.09	6.05	19.68	17.86
Technology Hardware & Equipment	0.53	5.91	0.64	6.09	3.38	36.07	12.54	14.16
Transportation	1.04	1.22	-2.68	-8.03	-13.23	-35.36	12.13	9.09
Utilities	1.78	1.38	-7.11	-5.50	-31.94	-25.56	12.92	13.54
Banks	4.35	2.35	-9.01	-5.74	-38.87	-26.50	11.11	10.35
Commercial & Professional Services	0.96	0.59	0.10	-0.81	0.51	-4.17	10.18	9.84
Consumer Durables & Apparel	1.12	1.06	1.02	0.44	5.45	2.34	13.23	13.85
Consumer Services	0.83	0.97	-9.48	-5.66	-40.49	-26.20	13.20	13.37
Health Care Equipment & Services	2.37	2.22	-5.94	-4.15	-27.34	-19.83	14.16	11.29
Household & Personal Products	0.27	1.67	-9.50	-3.34	-40.57	-16.22	16.23	11.95
Insurance	1.72	1.62	-2.29	-1.43	-11.38	-7.22	8.57	9.01
Media & Entertainment	4.07	1.35	0.44	-12.38	2.30	-49.79	15.88	16.98
Pharmaceuticals, Biotechnology	5.71	3.19	-1.40	0.09	-7.07	0.46	10.39	11.20
Software & Services	1.67	6.59	-5.80	2.35	-26.75	12.86	11.45	10.37
Telecommunication Services	0.36	2.04	-10.72	-9.43	-44.63	-40.33	23.49	9.26

3.5 Discussion

We see several contributions that our model brings to the current literature on alignment strategies and portfolio allocation.

3.5.1 Alignment strategies of firms

Low-carbon targets

We define climate scenarios by a simple approach using a carbon budget, corresponding to cumulative net global anthropogenic greenhouse gas emissions that result in a global warming limitation to a given level at a given probability. In other words, we define a climate scenario as an average temperature rise resulting from a determined quantity of greenhouse gas emissions (SBTi, 2015). The global decarbonization rate becomes a parameter that translates the emissions abatement effort the entire economy requires. The carbon budget is overshoot when emissions are not sufficiently reduced. This simple model allows us to formalize a climate scenario characterized by a single parameter, the decarbonization rate τ_B . In this form, the climate scenario itself is straightforward: there is a constant abatement of emissions within the economy, which limits cumulative emissions to the carbon budget C and global warming to 2°C above the pre-industrial level.

This simplified approach also applies to low-carbon targets, determined by a decarbonization rate τ_j , and has several implications. The abatement effort follows a constant rhythm: year on year, emissions must be decreased at the same rate. If two companies decide to set the same low-carbon target, the abatement efforts will be consistent in terms of flow, as they have both chosen an identical decarbonization rate. However, if companies have different levels of initial emissions, choosing the same carbon target means that the company with the higher initial emissions will abate a greater volume of greenhouse gas emissions. The definition of the low-carbon target is, therefore, heterogeneous in terms of stock. This is consistent with the convergence approach detailed in Raynaud et al. (2020). This is illustrated in Appendix 3.7.1.

The benchmark target definition requires that the greenhouse gas emissions data from all companies be accessible and defined for the same perimeter (direct and/or indirect emissions) to ensure consistency and comparability. The benchmark target is set using historical emissions at a single date for all companies and does not consider any future macroeconomic, technological, or regulatory trends that could alter the carbon budget.

Classification of firms

We introduce the concept of decarbonization ability (or capabilities) as a discriminating variable for setting a low-carbon target. The decarbonization ability serves as a way to measure the capacities of firms to mitigate their environmental impact. For an investor, this has two useful purposes: to be able to anticipate the trajectory of a firm's emissions and to evaluate the credibility of communication around low-carbon targets.

Recent literature has begun to focus on this topic and examines the determinants of a firm's ability to decarbonize. In particular, several papers study the relationship of a firm's extra-financial performance (a more general framework than the greenhouse gas emissions of the firm) to financial metrics such as the return on equity, the cost of debt and credit rating, the dividend policy or the valuation of the company (Coqueret, 2022; Gianfrate et al., 2023). Another strand of the literature examines whether and how firms reduce their carbon footprints under financial resource constraints (see, e.g., (Ng et al., 2023)). In this model, we build upon this literature by considering the decarbonization ability of a firm as an endogenous variable upon which companies make their choices.

We build a classified economy by separating companies based on their level of decarbonization ability. We assume a uniform distribution for the ability of firms in the paper for simplification purposes. A more representative way would be to consider a Gaussian distribution, although the theoretical results remain the same. Type N or type B firms have low capabilities to decarbonize their emissions and therefore less adaptive capacities to succeed in a low-carbon society. Type B companies must make significant efforts to abate their emissions if their ability is low. This can involve investing in new technologies, changing the firm's governance or business plan, etc. Type B or N firms are representative of companies that are heavily exposed to climate-related risks and for which the set-up of a low-carbon strategy is costly. In the model, we assume that a type B firm has a probability of success that depends on the benchmark decarbonization rate; an extension to the model could be to consider heterogeneous levels for the probability of success, that would depend on the ability of firms. This could reflect the idea that firms with very low abilities that set a type B target (they could be made to do so by a stringent regulation or if investors have a very strong preference for green stocks) will have a high climate risk premium as they have a very low chance of achieving their targets, which increases the expected transition risk premium and the reputational risk premium.

Type N firms are unwilling to sacrifice revenue and/or profit margin to adapt to a low-carbon economy. In the model, we assume that investors consider that these companies

will not abate any of their emissions. We could also consider that type N firms could abate their emissions by a low rate (lower than the benchmark rate), but their alignment strategy would still not be enough to consider them as aligning to a low-carbon scenario. However, type N companies still hold climate-related risks in their returns that are higher than the climate risks of type H and type B companies, as previous theoretical literature states (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021a). They can therefore be of interest to investors for financial return, however, the portfolios that hold a lot of type N stocks will be very risky.

On the contrary, type H firms have high decarbonization abilities and a competitive advantage by selecting ambitious low-carbon targets. These companies can be considered market leaders in carbon emissions mitigation performance. Unlike a type B firm, the rate chosen by a type H firm is a quadratic function of its ability a_j . A type H firm can adapt easily to stringent regulations requiring companies to abate their emissions or to low values of carbon budgets that imply a high benchmark decarbonization rate. This also explains why the higher revenue growth factor is higher for a type H firm than for a type B firm.

To some extent, this approach follows the methodology developed by initiatives such as the Science-Based Targets Initiative (Weber and Faria, 2019) with the GEVA (Greenhouse Gas Emissions per unit of Value added) approach. Only targets compatible with stringent carbon budgets are allowed to ensure that the targets are consistent with scientific recommendations and are comparable across industries (Friedlingstein et al., 2022)¹¹.

Overall, this model design and the resulting ability threshold that determines the market composition reflects the call for global decarbonization action sooner rather than later, as a dwindling carbon budget only increases the difficulty of low-carbon targets (Nikolaeva et al., 2023).

Greenwashing opportunities

In constructing the model and defining low-carbon targets using firms' decarbonization ability, we have made a strong assumption ruling out greenwashing practices by firms. Following the definition of Lyon and Montgomery (2015), greenwashing arises when a company misleads stakeholders, especially customers and investors, into "overly positive

¹¹This approach also has a simplification purpose when, at the beginning of the operational phase, the investor makes her allocation. The absence of low-carbon targets less ambitious than the benchmark validates the credibility of the low-carbon targets undertaken by type H and type B firms. If the investor sets a decarbonization constraint on her portfolio (see the next section of this paper), then unlike the set-up within Bolton et al. (2022), she can rely on the targets set by companies to ensure that the emissions of her portfolio will be abated.

beliefs" about its environmental practices or products. In our model, such a behavior could arise in two instances:

1. When a company with abilities below the ability threshold a^* declares itself a type H company;
2. When a company announces the benchmark target, although it has no chance of success.

There are two ways to overcome those issues: first, we have assumed that investors can evaluate companies' decarbonization abilities. This means that they can detect unrealistic targets. The capacity of investors to assess the abilities of companies means that there is no information asymmetry between investors and companies regarding their ability to abate their emissions¹². This rules out the first greenwashing opportunity, although there still could be a discussion around the use of carbon offset when setting targets: [Arendt \(2024\)](#) empirically highlighted that carbon removal technologies are an important part of company targets, and that they do not necessarily favor reducing emissions to a residual level and then use carbon removal as a last resort.

Second, per the probability of success, there is always a chance of success in reaching the benchmark target for a company with low decarbonization ability. However, the company can lose profit growth opportunities if it decides to make a benchmark target, even though the increase in market share does not sufficiently compensate for the opportunity cost. We assume that companies will make rational decisions and choose the target (or absence of target) according to the most significant revenue growth opportunities.

For type H and B firms, the cost of making an announcement is often overlooked in the literature, especially since today's objective is to encourage companies to commit to ambitious low-carbon targets [Nikolaeva et al. \(2023\)](#); [Romito et al. \(2023\)](#). We can predict that the climate risk premium of a type N stock will depend on the choices made by type H and type B companies: the transition risk can increase if most of the companies within the economy follow ambitious targets, representing a rapid shift to a low-carbon economy. Companies that are not making any efforts can be identified as contributing to most of the negative impacts of climate change, which further increases their reputational risk.

¹²In reality, there is information asymmetry on the market regarding environmental communication, but it can be mitigated through punishment practices of investors with environmental preferences, see [Cartellier et al. \(2024\)](#).

3.5.2 Market equilibrium

When observing the general market equilibrium, we find, like [Pástor et al. \(2021\)](#), [Pedersen et al. \(2021\)](#), or [Avramov et al. \(2022\)](#), that the stocks' returns deviate from their CAPM values if investors care about climate risk. However, in our model, we add an additional term, the climate risk premium of stocks, which is determined by the supply of stocks, risk aversion, and investors' climate preference. The climate risk premium's existence is not dependent on a positive average climate preference from investors: it still exists even if $\delta = 0$.

The market composition in the 2-stock and 3-stock cases highlights the existence of tipping points. These support the implementation of transition plans when there is a sufficient remaining amount of carbon budget and, therefore, a lower benchmark decarbonization rate. The investors' environmental preferences also significantly push the number of companies to commit to decreasing their emissions.

The risk premium also depends on the market climate preference. For the 2-stock model, it is a decreasing function of the ability threshold and a concave function in the 3-stock model. This reflects the idea that in the eyes of a climate-aware investor (with a high climate preference), a company that fails to reach its target represents a double threat to her portfolio, especially when the benchmark decarbonization rate is low. The first threat is the possibility of a massive divestment, as it becomes clear that the company is failing its target, which can cause a fall in the return of the stock. The second threat is if the portfolio itself is under a constraint of abating its emissions (which is a growing practice), the failure of a company increases the investor's own reputational risk.

The market equilibrium also reveals that policies can be set in place to influence the market composition or the financial risk of firms. We see three mechanisms that can be set in place:

- Carbon budget: if the carbon budget is first and foremost a scientific concept, As the 2-stock and 3-stock model show, a stringent policy imposing very high benchmark rates can decrease the number of firms committing to low-carbon targets. Yet policymakers can encourage more firms to choose a type B or type H target through subsidies or tax cuts on transitioning activities in order for firms to minimize the cost of undertaking a target, and maximizing net profit. Another possibility could be to increase customer demand in the case of type B and type H firms: in a business-to-business setting for example, regulators could impose a more stringent reporting on the scope 3 upstream

activities of companies and encourage them to select suppliers with clear transition plans. This means that suppliers that set low-carbon targets would be favored from other companies.

- Tax on revenue for non-committing firms: in the model, the model of type N and type B firms is determined by the investors' preference. It could be determined during the evaluation phase by adding a tax on revenue for firms that do not decide to commit to a target: this would lower the relative cost of commitment and could directly determine the market composition based on the ability of firms and the cost of not committing to a low-carbon target. At the moment, regulations are beginning to emerge in the European Union on reporting the commitment of firms (through the Corporate Sustainability Reporting Directive), but taxes are only set for current greenhouse gas emissions performance. This tax could be viewed as internalizing the negative externality that is future greenhouse gas emissions.
- Climate preference of investors: as we observed in the market equilibrium, the climate preference of investors plays an important part in the market composition and in the climate risk premium of stocks. We also show in Appendix 3.7.7 that the climate preference of investors can be determined when their portfolios are under decarbonization constraints. Regulators could also intervene in the financial sector to set carbon budgets or decarbonization constraints on portfolios: this would determine risk profiles for firms and push investors to reallocate their portfolios to stocks with underlying low-carbon target commitments.

3.6 Conclusion

This paper contributes to the theoretical literature on risks and opportunities associated with climate change.

First, defining a climate scenario under a carbon budget constraint is a straightforward method of defining low-carbon emission targets for companies. Yet, it remains consistent from a scientific point of view. Our model best applies when emissions from companies are initially similar, for example, the case within an industry. By separating the model into two phases, we also isolate the decisions taken by the companies on one side and the investors on the other. The ability of firms to abate their emissions is a crucial but overlooked determinant of the decarbonization strategies of companies. It is essential when investors and regulators aim to encourage a maximum of companies to commit to low-carbon targets. Through our model, we show that firms' ability determines the ambition of their carbon targets, the climate risk premium of assets, and the availability of stocks on the market, aiming to transition to a low-carbon target. We also show that a maximum number of stocks with lower abilities can be reached if investors have climate preferences. This means they will have a higher demand for stocks that commit to low-carbon targets, regardless of the potential impact on expected returns. Finally, to the best of our knowledge, we are the first to identify a cost to making a low-carbon target announcement under the condition that greenwashing practices do not exist, especially if the low-carbon target is not very ambitious. This can serve as an explaining factor for the reluctance of companies to commit to low-carbon targets. We illustrate this cost empirically by identifying a premium for companies that do not commit in key sectors for the low-carbon transition.

Further theoretical and empirical work could be done to go deeper into companies' alignment strategies and investors' choices. First, the definition of low-carbon targets could be made more complex by introducing more metrics than companies' greenhouse gas emissions to set low-carbon targets. Furthermore, the model applies well to companies with similar initial greenhouse gas emissions, such as companies within the same industry. The case of companies with already low emissions within an industry or an investment universe should be addressed. Identifying high and low-ability companies could be empirically set, and investors' supply and demand mechanisms for companies announcing low-carbon targets could be further studied empirically. This topic is becoming important overall, as many companies have now committed to low-carbon targets, and investors should evaluate the credibility of those targets and their achievability.

3.7 Appendix

3.7.1 Low-carbon pathways

Carbon budget and decarbonization rate

We formalize variables that are used in the model to define the low-carbon targets of companies.

We consider an economy with emissions E_t at time t . We assume that an external party defines an exogenous parameter, the remaining carbon budget $C > 0$ that allows the limitation of global warming to a determined excess temperature, which we assume is 2°C above the pre-industrial level¹³. The carbon budget is the amount of cumulated emissions that the entire economy can emit in the future:

$$\int_0^{\infty} E_t dt = C$$

Unless the carbon budget is infinite, there must be a global reduction of the current level of emissions to abide by this carbon budget constraint. We apply the continuous decarbonization rate τ to the emissions at time t :

$$E_0 \int_0^{\infty} (1 - \tau)^t dt = E_0 \int_0^{\infty} e^{t \ln(1-\tau)} dt = C$$

Computing the primitives from the previous equation gives us:

$$C = -\frac{E_0}{\ln(1 - \tau)}$$

given that

$$\lim_{t \rightarrow \infty} \frac{(1 - \tau)^t}{\ln(1 - \tau)} = 0$$

Therefore we have:

$$\ln(1 - \tau) = -\frac{E_0}{C}$$

We obtain the following decarbonization rate:

¹³As of 2023, the global carbon budget for the entirety of emitters has been evaluated at 380 GtCO₂, for a temperature rise of 1.5°C with a 50% likelihood (Friedlingstein et al., 2022).

$$\tau = 1 - e^{-E_0/C}$$

This simple model allows us to formalize a climate scenario characterized by a single parameter, the decarbonization rate τ .

Targets for companies

For a company j , we define a low-carbon target as the objective to decrease its emissions by a rate $\tau_j \in [0, 1[$, which represents the company's decarbonization rate:

Definition 2 (Target for company) Emissions of company $j \in [1, M]$ must be abated by the selected decarbonization rate:

$$\text{For } t \in [0, T]: e_{j,t} = e_{j,0}(1 - \tau_j)^t$$

where $e_{j,0}$ is the level of emissions reported by company j at time $t = 0$.

The benchmark target, compatible with the carbon budget C is the overall low-carbon target for the economy, defined between time $t = 0$ and time $t = T$ with a benchmark decarbonization rate τ_B :

Definition 3 (Benchmark low-carbon target) Cumulative emissions must be equal to the carbon budget:

$$\sum_{j=1}^M \sum_{t=0}^T e_{j,0} \cdot (1 - \tau_B)^t = C$$

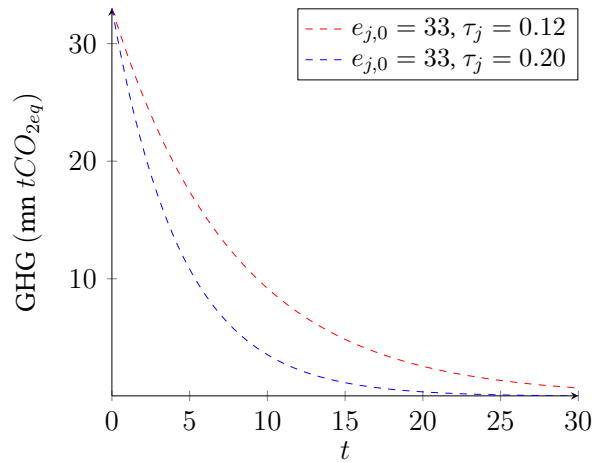


Figure 3.8: Carbon emission pathways for companies: heterogeneous efforts with homogeneous initial levels of emissions

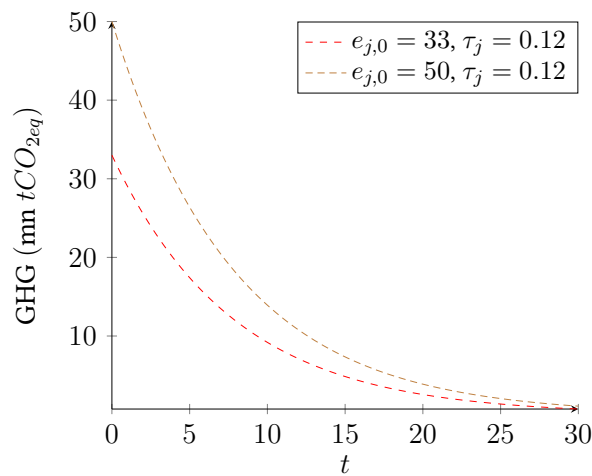


Figure 3.9: Carbon emission pathways for companies: homogeneous efforts with heterogeneous initial level of emissions

3.7.2 Variables and parameters

The table below gathers all the variables and parameters to the model, during the evaluation and operational phases.

Definition	
Company j	
a_j	Decarbonization ability
τ_j	Decarbonization rate chosen by the company
λ_j	Probability of achieving the low-carbon target
Evaluation phase	
$\pi_{j,t}$	Revenue at time t
g_j	Revenue growth factor resulting from the cost of opportunity for type H and type B companies
g_N	Revenue growth factor for type N companies
Operational phase	
r_j	Return of the stock associated to company j at $t = 1$
$r_{j, capm}$	Market risk premium of the stock at $t = 1$
$\beta_{j, mkt}$	Sensitivity of the stock to the market factor
\tilde{r}_j	Climate risk premium of the stock at $t = 1$
σ_j^2	Variance of the stock
Investor i	
Operational phase	
γ_i	Relative risk aversion
δ_i	Climate preference
w_i	Gross return of the investor's portfolio at $t = 1$
$x_{i,j}$	Weight of stock j within the portfolio of investor i
General parameters	
M	Number of companies within the economy
Evaluation phase	
τ_B	Benchmark decarbonization rate
s_H, s_B, s_N	Proportion of type H, B and N stocks
Operational phase	
r_f	Return of the risk-free asset

3.7.3 Ability threshold

Company j will choose to be of type H if the expected profit is higher than the expected profit of type B:

$$\pi_{0,j}(1 + g_j^H + \lambda (a_j + \kappa)^2) \geq \pi_{0,j}(1 + g_j^B + \lambda \tau_B (1 - \tau_B))$$

Given that $a_j > 0$ and $0 < \tau_B < 1$, the previous inequality implies that there is a unique threshold of ability $a^* \geq 0$ above which companies will choose to be type H:

$$a^* = -\kappa + \sqrt{\tau_B (1 - \tau_B)}$$

The ability threshold is illustrated below for $0 \leq \tau_B \leq 0.5$.

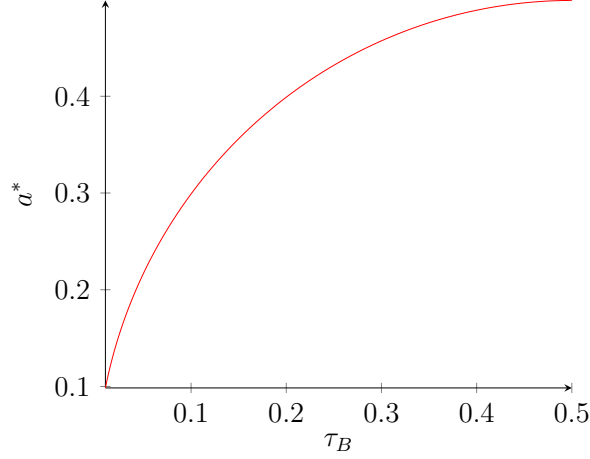


Figure 3.10: Benchmark decarbonization rate constraint on ability of firms

3.7.4 Demand for stocks

We consider investor i , with portfolio weights \mathbf{x}_i , aversion to risk γ , and climate preferences δ_i . The investor seeks to maximize the following utility function:

$$\begin{aligned} U(w_i, \mathbf{x}_i) &= \mathbb{E}[-e^{-\gamma w_i - \delta_i \mathbf{x}_i' \boldsymbol{\tau}}] \\ &= \mathbb{E}[-e^{-\gamma(1+r_f + \mathbf{x}_i' \mathbf{r}) - \delta_i \mathbf{x}_i' \boldsymbol{\tau}}] \\ &= -e^{-\gamma(1+r_f)} \mathbb{E}[e^{-\gamma \mathbf{x}_i' \mathbf{r} - \delta_i \mathbf{x}_i' \boldsymbol{\tau}}] \\ &= -e^{-\gamma(1+r_f)} \mathbb{E}[e^{-\gamma \mathbf{x}_i' (\mathbf{r} + \frac{\delta_i}{\gamma} \boldsymbol{\tau})}] \end{aligned}$$

Following the structure of asset returns, we have, with $\boldsymbol{\Sigma}$ the covariance matrix of returns:

$$\mathbb{E}[e^{-\gamma \mathbf{x}_i' (\mathbf{r} + \frac{\delta_i}{\gamma} \boldsymbol{\tau})}] = e^{-\gamma \mathbf{x}_i' (\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\delta_i}{\gamma} \boldsymbol{\tau}) + \frac{1}{2} \gamma^2 \mathbf{x}_i' \boldsymbol{\Sigma} \mathbf{x}_i}$$

The first-order condition, related to the investor's portfolio weights, gives the following

equation:

$$-\gamma(\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\delta_i}{\gamma} \boldsymbol{\tau}) + \frac{1}{2} \gamma^2 2 \boldsymbol{\Sigma} \mathbf{x}_i = 0$$

This means that the investor's portfolio weights are:

$$\mathbf{x}_i = \frac{1}{\gamma} \boldsymbol{\Sigma}^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\delta_i}{\gamma} \boldsymbol{\tau})$$

3.7.5 Market equilibrium with type B and type N stocks

The market-clearing condition for type B stocks is as follows:

$$s_B = \frac{1}{\gamma \sigma_B^2} (1 - \lambda(1 - \tau_B)) \tilde{r}_B + \frac{1}{\gamma \sigma_B^2} \frac{\delta}{\gamma}$$

The market-clearing condition for type N stocks is:

$$s_N = 1 - s_B = \frac{1}{\gamma \sigma_N^2} \tilde{r}_N$$

We make the following assumption:

$$\tilde{r}_B = (1 - \tau_B) \tilde{r}_N$$

The climate risk premium for a type B asset will be smaller than the climate risk premium for a type N asset, as the absence of any plan to decrease emissions represents the highest exposure to climate risk. By reporting this into the previous equations, we find the relative supply for each stock:

$$s_B = 1 - s_N = \frac{\frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B) + \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)}$$

$$s_N = \frac{1 - \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)}$$

The climate risk premia of the stocks is determined using the previous equations:

$$\tilde{r}_N = \gamma \sigma_N^2 s_N = \frac{\gamma \sigma_N^2 - \frac{\sigma_N^2 \delta}{\sigma_B^2 \gamma}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)}$$

$$\tilde{r}_B = (1 - \tau_B) \tilde{r}_N = \gamma \sigma_N^2 s_N = \frac{(1 - \tau_B) (\gamma \sigma_N^2 - \frac{\sigma_N^2 \delta}{\sigma_B^2 \gamma})}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)}$$

3.7.6 Market equilibrium with type H, type B, and type N stocks

The market clearing conditions are the same as in the previous paragraph:

$$\mathbf{s} = \frac{1}{\gamma} \Sigma^{-1} (\tilde{\mathbf{r}} + \frac{\delta}{\gamma} \boldsymbol{\tau})$$

For each asset, the market equilibrium writes:

$$\begin{aligned} s_B &= \frac{1}{\gamma \sigma_B^2} (1 - \lambda(1 - \tau_B)) \tilde{r}_B + \frac{\delta}{\gamma^2 \sigma_B^2} \\ s_H &= 1 - a^* = \frac{1}{\gamma \sigma_H^2} (1 - \lambda) \tilde{r}_H + \frac{\delta}{\gamma^2 \sigma_H^2} \frac{\tau_H}{\tau_B} \\ s_N &= \frac{\tilde{r}_N}{\gamma \sigma_N^2} \end{aligned} \quad (3.13)$$

From the market-clearing condition, we can compute several variables. First, we determine the number of type B and type N assets by making the same assumption as in Appendix 3.7.5: $\tilde{r}_B = (1 - \tau_B) \tilde{r}_N$.

$$s_B = a^* - s_N = \frac{\frac{\sigma_B^2}{\sigma_N^2} a^* (1 - \lambda(1 - \tau_B)) (1 - \tau_B) + \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.14)$$

$$s_N = a^* - s_B = \frac{a^* - \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.15)$$

We then determine the risk premia for each type of stock:

$$\tilde{r}_H = \frac{\gamma \sigma_H^2 (1 - a^*) - \frac{\delta}{\gamma} \frac{\tau_H}{\tau_B}}{1 - \lambda} \quad (3.16)$$

$$\tilde{r}_N = \frac{\gamma \sigma_N^2 a^* - \frac{\delta}{\gamma}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} \quad (3.17)$$

$$\tilde{r}_B = (1 - \tau_B) \tilde{r}_N \quad (3.18)$$

3.7.7 Portfolio allocation under a decarbonization constraint

We consider the case where the portfolio of investor i is subjected to a carbon budget constraint at time $t = 1$:

$$\sum_{j=1}^M x_{i,j} e_{j,1} = (1 - \tau_B) \sum_{j=1}^M x_{i,j} e_{j,0}$$

The weighted-average portfolio emissions must follow the benchmark decarbonization rate and must have decreased by rate τ_B at $t = 1$. In the case of a 3-asset universe, with initial emissions of type H, B, and N stocks being respectively $e_{0,H}$, $e_{0,B}$, and $e_{0,N}$ we have:

$$x_{i,H} e_{0,H} (1 - \tau_H) + x_{i,B} e_{0,B} (1 - \tau_B) = (x_{i,H} e_{0,H} + x_{i,B} e_{0,B} + x_{i,N} e_{0,N}) (1 - \tau_B)$$

We simplify this equation:

$$x_{i,H} e_{0,H} (\tau_B - \tau_H) = x_{i,N} e_{0,N} (1 - \tau_B) \quad (3.19)$$

We maintain the assumption that the market equity risk premium is not considered in the allocation of the portfolio, meaning that the demand for type H and type N stocks following climate preference δ is:

$$x_{i,H} = 1 - a^*$$

$$x_{i,N} = \frac{a^* - \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)}$$

We rewrite equation 3.19 with the demands for type H and type N stocks:

$$(1 - a^*) e_{0,H} (\tau_B - \tau_H) = \frac{a^* - \frac{\delta}{\sigma_B^2 \gamma^2}}{1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B)} e_{0,N} (1 - \tau_B)$$

From this, we can deduce the investor's climate preference:

$$\delta = \gamma^2 \sigma_B^2 \left(a^* + (1 - a^*) \frac{e_{0,H}}{e_{0,N}} \frac{\tau_H - \tau_B}{1 - \tau_B} \left(1 + \frac{\sigma_B^2}{\sigma_N^2} (1 - \lambda(1 - \tau_B)) (1 - \tau_B) \right) \right) \quad (3.20)$$

The investor's climate preference will be determined by the relative balance of the initial emissions between type H and type N companies and by the general level of the benchmark decarbonization rate.

3.7.8 General market equilibrium

The market clearing condition, where supply meets demand, gives the following equations:

$$\begin{aligned} \mathbf{s} &= \int_i w_{i,0} \mathbf{x}_i \, di \\ &= \int_i w_{i,0} \frac{1}{\gamma} \boldsymbol{\Sigma}^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}} + \frac{\delta_i}{\gamma} \boldsymbol{\tau}) \, di \\ &= \frac{1}{\gamma} \boldsymbol{\Sigma}^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}}) \int_i w_{i,0} \, di + \frac{1}{\gamma^2} \boldsymbol{\Sigma}^{-1} \boldsymbol{\tau} \int_i w_{i,0} \delta_i \, di \\ &= \frac{1}{\gamma} \boldsymbol{\Sigma}^{-1} (\mathbf{r}_{capm} + \tilde{\mathbf{r}}) + \frac{\bar{\delta}}{\gamma^2} \boldsymbol{\Sigma}^{-1} \boldsymbol{\tau} \end{aligned}$$

with $\bar{\delta} = \int_i w_{i,0} \delta_i \, di$ is the weighted average environmental preference of the investors.

3.7.9 Empirical identification of alignment risk premia

Staggered difference-in-difference for other sectors

Table 3.4: Identification of industrial climate risk premia from staggered difference-in-difference regressions for non-sensitive sectors.

Table 3.4 presents the coefficients from the staggered difference-in-difference regressions for non-sensitive groups. Columns (1) to (6) report coefficient δ in bps for each industry group (committed vs not committed). Regressions are run for stock returns in columns (1) to (3) and for residual returns (taking away the market, size and book-to-market factor sensitivities) in columns (4) to (6). Columns (2), (3), (5), and (6) include firm fixed effects. Columns (3) and (6) also include time fixed effects (controls are defined for every quarter). We cluster standard errors at the firm and time dimensions. ***1% significance; **5% significance; *10% significance.

INDUSTRIES	(1)	(2)	(3)	(4)	(5)	(6)
	δ (in bp)					
Banks	-0.57 (6.83)	-2.99 (8.48)	4.32 (8.73)	3.71 (5.42)	2.03 (8.33)	7.64 (8.57)
Commercial & Professional Services	-3.79 (1.61)	-2.99 (3.03)	2.26 (2.80)	-0.22 (2.31)	0.75 (2.77)	3.18 (2.70)
Consumer Durables & Apparel	-5.08** (2.44)	-7.62** (3.70)	-4.76 (4.51)	-2.58 (2.27)	-5.07 (3.62)	-4.42 (4.39)
Consumer Services	-0.69 (3.28)	1.13 (2.04)	5.06*** (1.79)	0.76 (2.80)	1.81 (1.94)	2.35 (2.09)
Health Care Equipment & Services	-7.10** (3.24)	-6.60*** (1.33)	-1.07 (2.52)	-5.10* (2.86)	-5.34*** (1.28)	-1.89 (1.66)
Household & Personal Products	-2.45 (1.94)	-3.67* (1.99)	1.53 (2.88)	-1.20 (1.77)	-2.53 (1.68)	1.89 (2.59)
Insurance	-18.71* (10.01)	-16.00*** (0.00)	-13.72*** (0.70)	-13.79* (7.93)	-10.96*** (0.00)	-11.05*** (0.73)
Media & Entertainment	-4.24 (3.37)	-2.96 (3.56)	6.29** (2.86)	-0.80 (3.02)	1.65 (2.08)	7.38*** (2.20)
Pharmaceuticals, Biotechnology	-5.41 (5.76)	-0.67 (1.27)	12.61*** (3.52)	-2.15 (5.67)	1.03 (1.01)	9.91*** (3.37)
Software & Services	-5.03** (2.27)	-4.99*** (1.52)	4.04** (1.76)	-1.25 (1.87)	-0.49 (1.02)	3.04** (1.38)
Telecommunication Services	-1.41 (1.91)	-3.60*** (1.11)	-0.97 (1.72)	-0.66 (1.79)	-2.78*** (1.02)	-1.56 (1.70)
Residuals	N	N	N	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	N	N	Y	N	N	Y
Observations	6,118,405	6,118,405	6,118,405	6,118,405	6,118,405	6,118,405

Trucost Paris Alignment metrics methodology and data description

Trucost methodology for identifying alignment of companies.

Table 3.5: Data description: Paris-aligned dataset from Trucost - cross-section

The sample period to build the 2 degrees alignment database is 2017 - 2022 for Trucost. This table reports the distribution of average yearly observations (weights and number of companies) by Industry Group (from the Global Industry Classification Standard). The “N (align.)” column refers to the following categories: <1.5°C,<1.75°C,1.5-2°C, and 1.75-2°C.

INDUSTRY GROUP	Weighted average alignment breakdown (%)										N(tot.)	N(align.)
	1.5-2°C	1.75-2°C	2-2.7°C	2-3°C	3-4°C	4-5°C	<1.5°C	<1.75°C	>2.7°C	>5°C		
Automobiles & Components	0.23	0	0	0.20	0.08	0.08	0.63	0	0	1.07	29	7
Banks	2.20	0	0	0.77	0.21	0.36	1.96	0	0	0.97	68	37
Capital Goods	0.75	0	0	1.24	0.31	0.19	1.38	0	0	2.90	129	40
Commercial & Professional Services	0.41	0	0	0.16	0.05	0.04	0.50	0	0	0.35	36	16
Consumer Discretionary Distribution & Retail	0.39	0	0	0.71	0.08	0.05	2.12	0	0	0.40	29	14
Consumer Durables & Apparel	0.59	0	0	0.54	0.03	0.11	0.48	0	0	0.41	41	22
Consumer Services	0.17	0	0	0.13	0.03	0.06	0.65	0	0	0.75	32	10
Consumer Staples Distribution	0.12	0	0	0.63	0.48	0.15	0.07	0	0	0.47	24	6
Energy	0.20	0	0	0.21	0.12	0.04	0.35	0	0	3.30	47	6
Equity Real Estate Investment	0.19	0	0	0.20	0.11	0.06	0.68	0	0	0.81	55	22
Financial Services	1.48	0	0	0.43	0.09	0.25	2.69	0	1.37	0.78	64	39
Food, Beverage & Tobacco	0.56	0	0	0.78	0.21	0.18	0.76	0	0	2.05	54	15
Health Care Equipment & Services	1.16	0	0	0.60	0.12	0.05	1.11	0	0	1.38	53	23
Household & Personal Products	0.15	0	0	0.22	0.13		0.11	0	0	1.35	14	4
Insurance	0.59	0	0	0.32	0.19	0.04	1.05	0	0	1.09	62	32
Materials	0.59	0	0.03	0.37	0.10	0.14	0.44	0.04	0.13	2.05	91	29
Media & Entertainment	1.05	0	0	0.17	0.05	0.02	2.84	0	0	1.10	30	15
Pharmaceuticals, Biotechnology	2.70	0	0	1.44	0.05	0.21	2.76	0	0	1.38	62	33
Real Estate Management & Development	0.09	0	0	0.08	0.04	0.03	0.13	0	0	0.17	19	8
Semiconductors & Semiconductor Equipment	0.92	0	0	0.17	0.23	0.03	1.93	0	0	1.23	31	14
Software & Services	0.49	0	0	0.88	0.10	0.25	1.11	0	0	5.21	53	21
Technology Hardware & Equipment	0.26	0	0	2.20	1.05	0.07	0.29	0	0	2.64	40	12
Telecommunication Services	0.33	0	0	0.42	0.14	0.36	0.13	0	0	1.28	26	3
Transportation	0.64	0.03	0.11	0.34	0.11	0.12	0.35	0.02	0.05	0.51	41	15
Utilities	0.47	0.17	0.55	0.12	0.02	0.03	0.41	1.25	0.24	0.39	65	33
TOTAL	16.72	0.19	0.69	13.32	4.14	2.90	24.91	1.30	1.79	34.03	1194	478

Table 3.6: Data description: Paris-aligned dataset from Trucost - time series

The sample period to build the 2 degrees alignment database is 2017 - 2022 for Trucost. This table reports the distribution of weights and numbers of companies by reported year. The “N (align.)” column refers to the following categories: <1.5°C,<1.75°C,1.5-2°C, and 1.75-2°C.

Year	Weighted average alignment breakdown (%)										N (tot.)	N (align.)
	<1.5°C	<1.75°C	1.5-2°C	1.75-2°C	2-2.7°C	>2.7°C	2-3°C	3-4°C	4-5°C	>5°C		
2017	14.67	1.82	19.09	0.00	0.74	0.79	10.52	2.62	3.15	46.60	827	141
2018	16.77	1.48	18.78	0.23	0.92	0.65	16.87	2.38	2.32	39.61	914	160
2019	23.09	0.91	17.29	0.16	0.69	0.33	15.90	4.70	2.16	34.77	1347	263
2020	28.65	0.25	23.17	0.06	0.58	0.27	14.95	4.36	1.19	26.51	1437	340
2021	40.92	0.01	10.89	0.00	0.59	0.92	11.06	2.65	1.67	31.29	1400	507
2022	46.08	0.01	6.01	0.00	0.50	1.58	9.14	2.51	1.93	32.23	1372	555
Avg.	28.36	0.75	15.87	0.08	0.67	0.76	13.07	3.20	2.07	35.17		

Company alignment performance: difference in returns for ‘Aligned’ and ‘Not Aligned’

Table 3.7: Identification of a climate risk premium from alignment performance.

Table 3.7 presents the difference in portfolio performance per industry from companies that are aligned to low-carbon scenarios to companies that are not. We compute the portfolio performance using raw stock returns. All returns cover the period March 2019 - May 2024.

Industry Group	Average portfolio weight (%)		Cumulated Return (%)		Annualized Return (%)		Annualized Vol (%)	
	Aligned	Not Aligned	Aligned	Not Aligned	Aligned	Not Aligned	Aligned	Not Aligned
Automobiles & Components	0.90	1.46	-3.86	22.53	-0.75	3.97	28.47	30.75
Capital Goods	2.22	4.86	79.40	64.27	11.86	9.99	19.97	20.60
Consumer Discretionary Distribution Retail	2.63	1.02	76.20	61.17	11.48	9.59	28.87	21.09
Consumer Staples Distribution	0.20	1.70	-10.34	83.86	-2.07	12.39	22.65	16.47
Energy	0.47	3.77	44.64	26.88	7.34	4.67	31.70	30.67
Equity Real Estate Investment	0.87	1.17	-7.96	-8.59	-1.58	-1.71	23.92	23.64
Financial Services	4.37	1.64	66.76	22.51	10.31	3.97	23.93	21.64
Food, Beverage & Tobacco	1.38	3.31	12.83	8.34	2.34	1.55	16.82	14.04
Materials	1.11	2.89	16.78	62.03	3.02	9.70	19.97	19.94
Real Estate Management & Development	0.16	0.29	4.06	-35.95	0.77	-8.19	19.53	19.98
Semiconductors & Semiconductor Equipment	2.98	1.71	608.18	124.11	45.57	16.74	36.32	30.88
Technology Hardware & Equipment	0.53	5.91	71.39	190.01	10.89	22.66	21.30	26.75
Transportation	1.04	1.22	66.82	5.43	10.31	1.02	22.30	19.05
Utilities	1.78	1.38	12.45	19.50	2.28	3.48	18.81	18.48
Banks	4.35	2.35	32.19	14.96	5.50	2.71	27.92	21.41
Commercial & Professional Services	0.96	0.59	72.08	40.89	10.97	6.80	18.35	17.02
Consumer Durables & Apparel	1.12	1.06	49.94	69.37	8.08	10.64	21.66	23.77
Consumer Services	0.83	0.97	12.45	37.00	2.28	6.23	22.56	24.76
Health Care Equipment & Services	2.37	2.22	37.69	40.28	6.33	6.71	21.76	19.72
Household & Personal Products	0.27	1.67	-18.96	29.83	-3.95	5.14	19.28	15.87
Insurance	1.72	1.62	53.35	60.29	8.55	9.47	19.70	19.45
Media & Entertainment	4.07	1.35	121.94	-7.24	16.52	-1.43	28.12	24.60
Pharmaceuticals, Biotechnology	5.71	3.19	45.11	40.30	7.40	6.71	15.32	16.25
Software & Services	1.67	6.59	45.93	148.24	7.52	19.06	26.67	26.49
Telecommunication Services	0.36	2.04	-21.55	-14.85	-4.55	-3.04	27.00	13.80

FINANCIAL AND CLIMATE PERFORMANCE DRIVERS FOR LOW-CARBON STRATEGIES

4.1	Introduction	144
4.2	Low-carbon target metrics	149
4.2.1	Low-carbon target metrics	149
4.2.2	Financial and environmental metrics	153
4.2.3	Dataset description	155
4.3	Drivers behind the ambition of targets	157
4.3.1	Ex-ante approach: identifying drivers for setting a target .	157
4.3.2	Net-zero ambition of targets: binary approach	163
4.3.3	Predicting the ambition of a company	169
4.4	Drivers behind the credibility of target	172
4.4.1	Achieving a target: industry breakdown	172
4.4.2	Credibility of targets: binary approach	175
4.4.3	Predicting the success of targets	179
4.4.4	Comparative analysis: does ambition signify success? . .	181
4.5	Net-Zero portfolio construction	183
4.6	Discussion and conclusion	189
4.7	Appendix	192
4.7.1	CDP target breakdown by GICS Industry Group and country	192
4.7.2	Addition and merging of targets	193
4.7.3	IEA Net Zero emissions abatement	193
4.7.4	IEA sector match	193
4.7.5	High Climate Impact Sectors (HCIS)	194
4.7.6	Support Vector Machine model	194
5.1	Motivations	223
5.1.1	Scénarios climatiques et budget carbone	224
5.1.2	Implication du secteur financier	226
5.2	Objectifs de la thèse	228
5.3	Contributions principales	229
5.3.1	Chapitre 2 : identification d'un facteur brown-minus-green	229
5.3.2	Chapitre 3 : scénarios climatiques et stratégies d'alignement des entreprises	234
5.3.3	Chapitre 4 : moteurs et succès des stratégies bas-carbone .	239
5.4	Conclusion	241

Abstract

The commitment of firms to low-carbon targets has largely increased these past years, with reference climate scenarios serving as benchmarks. In this paper, we build low-carbon target metrics that allow us to evaluate the quality of those targets on two factors: their ambition (whether the targets are aligned to a net-zero scenario) and credibility (whether companies are capable of achieving them). We then use these target metrics and observe the financial and extra-financial drivers behind them. We identify strong signals as to the impact of profitability before setting a target, the investments a company makes in order to achieve its targets, as well as environmental impacts related to the level of emissions of the companies. We end this paper by applying our target metrics to the construction of low-carbon portfolios, and we observe their impacts on the risk-return profile as well as the sector distribution.

Keywords: Low-carbon targets, Financial performance, Climate transition risk, Net-zero alignment

JEL: G11, Q54, Q56

4.1 Introduction

Since 2015 and the signature of the Paris Agreement, many countries have set targets to reduce their greenhouse gas (GHG) emissions. These low-carbon targets are either voluntary or imposed by the legislation. A majority of these objectives involve the private sector, the design of many low-carbon climate scenarios putting forward decarbonization pathways for industries. These pathways, or benchmarks, serve as a reference for measuring the efforts companies have to undertake in order to be “aligned” to a low-carbon scenario. Among the many climate scenarios that have been designed, the Intergovernmental Panel on Climate Change (IPCC) provides the 1.5°C alignment scenario (IPCC, 2018) and the Shared Socio-Economic Pathways (Lee and Romero, 2023): these scenarios cover a range of macro-economic projections and associate average surface temperature warming to them. Another example is the International Energy Agency (IEA) and its Net-Zero Pathway scenario (Bouckaert et al., 2021), which is aligned to a limit of +1.5°C in surface temperature above pre-industrial levels. This scenario provides specific pathways for sectors that are heavily exposed to climate risk as they depend on fossil fuels: industry, transportation, utility, and real estate. This is useful for companies, as they can benchmark their own objectives against recommendations that are specific to their own industry.

Low-carbon targets have become a mainstream communication tool for companies to investors, as they reflect the orientation of the company’s strategy on mitigating its climate risk (Fernandez-Feijoo et al., 2014; Haleem et al., 2022) and are also a way to attract more investments: companies that announce ambitious targets are building a positive image, and this can orient investors’ decisions (Bolton and Kacperczyk, 2021a). Moreover, announcing a target can provide a solution to the issue of short-termism, when firms tend to avoid making decisions that have an uncertain long-term impact (Wang and Bansal, 2012), which can increase their exposure to long-term climate risk. However, taking into account the target of a company within an investment decision can prove to be hard for an investor, as three types of problems arise: firstly, gathering data on targets can be difficult. Among the most common issues, companies can set multiple targets that overlap in scopes: two targets can be announced, one for scope 1 emissions¹ and another for scope 1 and scope 2 emissions². Targets can also evolve in time and be updated: the difficulty lies with the fact that the update can impact the target’s time horizon and either extend or restrain the scope of emissions. Secondly, it can be difficult to ascertain that a target is compatible with the macro-scenarios previously mentioned, in other words, the target’s ambition can be

¹Scope 1 emissions are the direct emissions of a company, that are emitted during the production process.

²Scope 2 emissions are indirect emissions from the use of electricity and heat.

difficult to obtain. Finally, although the target announcement of a firm can be interpreted as a signal of its future exposure to climate risk, there is no guarantee that the target will be achieved; the investor ignores the scale of necessary financial and operational changes the company should make to be successful.

Some work has been done to overcome these issues. Many data providers have developed “temperature ratings” to help investors assess the alignment of a company to a scenario. Most low-carbon scenarios are based on a carbon budget³ that is associated to a given temperature rise of the climate system. Temperature ratings assess whether a company’s GHG emissions are compatible with an overall carbon budget: the company is evaluated as “aligned” to the temperature scenario if this is the case. Very often, scenarios are built for a global warming of +1.5°C, +2°C, or a business-as-usual scenario (the latter would result in a global warming of over 4°C by the end of the century). The CDP has also used similar methodologies, coordinating with the WWF, to develop temperature ratings on their database, in which companies can report their absolute and intensity carbon targets (SBTi, 2015). Temperature ratings extend to the portfolio level: the Alignment Cookbook (Raynaud et al., 2020) summarizes and compares the various existing methodologies to assess the alignment of financial portfolios to a temperature scenario.

More recently, work has been done not only to gather targets but also to measure their ambition and their credibility. Multi-stakeholder initiatives (Fransen, 2012), such as the Science-Based Targets initiative, have also helped investors validate the targets as aligned to specific temperature scenarios: +1.5°C, well-below 2°C, 2°C, etc (Watson et al., 2023). Companies applying for a target validation must also ensure that the targets are achievable. The compatibility of targets with macroeconomic scenarios is the ambition of targets, and their achievability is their credibility. Recent literature has shown that initiatives such as the SBTi lead to an improved environmental performance from participating firms (Bolton and Kacperczyk, 2021b; Romito et al., 2023). The work of Le Guenedal et al. (2022) contributed to developing several net-zero carbon metrics to measure the ambition and credibility of targets by aggregating targets and comparing GHG emission projections to a benchmark low-carbon scenario.

While recent papers on the low-carbon targets of companies focus on the impact of setting a target, the motivations of companies for setting such a target have been less studied. One notable exception is the study conducted by Bolton and Kacperczyk (2021b), which highlights the motivations for setting a target: they find that firms with smaller greenhouse

³The carbon budget is defined as the remaining amount of greenhouse gases that human activities can emit in the future while limiting global warming to a certain temperature with a given level of probability.

gas emissions are more likely to commit to low-carbon targets in the first place. However, there is still little knowledge of the existence of financial and extra-financial drivers that incite companies to set and achieve low-carbon targets. This could nevertheless be useful for the investor: using financial and environmental indicators to predict whether a firm will successfully set and reach a target compatible with a net-zero carbon scenario allows her to protect her investments from firms with higher exposure to climate risk. An extensive part of the literature studies how climate risks and financial metrics are related, especially the financial return of stocks (Campiglio et al., 2022). A lack of climate risk mitigation can hinder the market valuation of a company (Hong and Kacperczyk, 2009; De Villiers et al., 2023). The climate risk reporting efforts of companies are also positively correlated with dividend payouts (De Villiers et al., 2023). When considering other types of financial metrics that measure the operational performance of firms, Alareeni and Hamdan (2020) find a contradictory result: the climate performance of firms has a negative impact on the return-on-assets (ROA) of firms, meaning that a company less exposed to climate risks will have a lower operational performance. When considering the cost of equity, Matsumara et al. (2022) highlights a negative correlation between the cost of capital and the reporting efforts of companies. Yet most of this literature focuses on the impact of current climate risk exposure on financial performance but does not consider the impact of financial performance on the decisions of companies regarding their future exposure to climate risk, especially when building a low-carbon strategy using targets.

In this paper, we identify financial and extra-financial drivers behind the ambition and the credibility of net-zero carbon targets. Based on the work of Le Guenedal et al. (2022), we use the CDP database to collect all individual targets from companies and aggregate the targets for each company so that we obtain a unique annual abatement rate between 2015 and 2050. We then create metrics that evaluate the ambition and credibility of those targets. We formally define the ambition of a low-carbon target as the level of abatement that the company announces. It can be measured as an absolute metric, or it can be a comparative metric: whether the announced rate is enough to abate emissions to a level compatible with the IEA net-zero scenario. We also define credibility as whether the company has either achieved its target or if the target is easily achievable. In this regard, we adopt a simplified approach from the work of Le Guenedal et al. (2022) in order to allow investors to build simple ambition and credibility⁴ variables.

We go on to identify the financial and environmental performance drivers behind the

⁴The credibility of a target is very new in the literature and should be interpreted with caution: in our case, we consider that a target is credible if the company's carbon performance shows that it should be able to achieve it

ambition and credibility of targets, drawing from [Bolton and Kacperczyk \(2021b\)](#), in order to understand what differentiates a firm that decides to commit to an ambitious target (one that is for example aligned to a net-zero emissions scenario) from a company with lesser objectives and to identify key parameters behind the success at achieving a low-carbon target. While financial variables are often approached in the literature as control variables to determine the impact of setting targets or the motivations for doing so, we consider that they are key parameters when a company sets its low-carbon strategy, which reflects its future exposure to climate transition risk. We also define a more sophisticated approach to measure the climate performance of a company, by comparing the company's behavior not only within the investment universe but also within its own industry and by constructing a metric that measures the efforts it makes to abate its greenhouse gas emissions.

We apply different measures of ambition and credibility in order to identify the financial and climate performance drivers behind firms' low-carbon strategies. When focusing on the ambition of firms, we find that while a majority of industrial sectors have ambitions that can be considered compatible with a net-zero macro-economic scenario in the 2015-2023 period, the 2030 horizon is much more concerning: a majority of companies do not have net-zero aligned ambitions. We find that the profitability of companies is a significant driver for deciding to set ambitious targets, and maintaining that ambition over time. The market capitalization is also an important parameter: smaller firms tend to be more ambitious in their pledges. When observing the climate performance of companies, we find evidence that supports the result predicted by [Bolton and Kacperczyk \(2021b\)](#): firms with lower emissions set more ambitious targets. We also notice that the overall extra-financial risk exposure of a firm has an impact on its ambition level.

When considering the success, or credibility, of companies, we find that the majority of companies do not have aligned emissions in the medium and long term, and evidence from the 2015-2023 period shows mixed results in success achievements between industries, especially in industries that are most exposed to climate risks. The 2030 perspective is also concerning, as a majority of companies are neither on track to meet the targets they have set, but they are also not on track to be aligned to a net-zero scenario. When observing the financial and climate performance drivers behind the credibility of companies, we find that the profitability, investments, and size of firms are important parameters: we identify signals indicating that firms are willing to sacrifice some of their margins and are making significant investments after having set targets. We also find, unlike ambition, that bigger firms are more likely to achieve their targets. For both the ambition and credibility of targets, we perform a predictive model using Support Vector Machines that determines whether a firm will be ambitious in the target it has set and whether it will actually achieve

its target. This can be a useful tool for an investor who seeks to mitigate her portfolio exposure to climate transition risk. It also raises a new issue for policymakers: what reporting requirements can be set in place to evaluate the credibility of a target and go beyond the "simple" ambition?

Finally, we apply our metrics to the construction of a portfolio where we select companies based on the ambition level of their targets and another portfolio where we select net-zero-aligned companies. We show that the ambition portfolio holds a better risk/return profile than the net-zero-aligned portfolio and that both portfolios differ in their structure. However, only the net-zero-aligned companies portfolio guarantees the investor that the climate risk is mitigated. There is therefore a trade-off between the financial and climate performance when selecting net-zero-aligned portfolios.

The rest of this paper is organized as follows: section 2 details the data, target metrics, financial, and environmental metrics we use. Section 3 presents the results from the identification of financial and environmental drivers for the targets' ambition and credibility. Section 4 is an application of the target metrics to portfolio construction, and section 5 concludes this paper.

4.2 Low-carbon target metrics

In this section, we develop low-carbon target metrics we use for testing our hypotheses. We start by aggregating the various targets reported on the CDP platform by companies, and we build several metrics that serve as a basis for measuring the ambition and credibility of firms' targets. We also report the financial and extra-financial metrics we use as drivers.

4.2.1 Low-carbon target metrics

We build several metrics that characterize the targets and serve as a basis for our study, drawing from the work of [Le Guenedal et al. \(2022\)](#). We begin by computing single yearly rates of abatement for each company. Indeed, each company can have several targets that overlap over time and over emissions scopes. Each target is announced at a set year, starts at a base year and ends at a target year, concerns a certain scope of emissions, and aims at a total abatement level. For example, here are three targets that overlap:

- *Target 1*: the target is set in 2017, and aims at a global abatement of 50% of scope 1 and scope 2 emissions between the years 2016 (base year) and 2030 (target year);
- *Target 2*: the target is set in 2019, and aims at a global abatement of 35% of scope 1 and scope 2 emissions between the years 2019 (base year) and 2025 (target year);
- *Target 3*: the target is set in 2021, and aims at a global abatement of 40% of scope 3 emissions between the years 2019 (base year) and 2030 (target year).

In this example, targets 1 and 2 overlap in time and in scopes: target 2 is a revision of target 1 over a shorter period. Target 3 is independent of targets 1 and 2, as it defines an ambition for scope 3 emissions. We therefore defined aggregated metrics for each company that allow us to merge targets and to compute annual abatement rates.

Aggregating the low-carbon targets: annual abatement rate and annual aggregated abatement

Let us consider a company i , with a number N of targets. We focus on target $k \in [1, \dots, N]$, defined between the base year t_0^k and the target year t_f^k for a scope s . The total targeted abatement is defined as $\tilde{A}_{i,s}^k$. The yearly decarbonization rate of a target k is defined as follows:

$$\tilde{R}_{i,s}^k(t) = \mathbf{1}_{\left\{t \in [t_0^k, t_f^k]\right\}} \left(1 - \left(1 - \tilde{A}_{i,s}^k \frac{1}{t_f^k - t_0^k} \right) \right)$$

The target database may have overlapping targets, as companies are not limited by

the number of targets or the scope coverage. We proceed using a similar approach to [Le Guenedal et al. \(2022\)](#) detailed in Appendix 4.7.2 to treat the cases where targets overlap in scopes.

This allows us to compute a single annual target rate for each scope of emissions that we label $R_{i,s}^{target}(t)$ with $s \in \{1, 2, 3\}$. In other words, at a given year t during a time period defined between t_0 and t_f , company i will aim at abating its scope s emissions by rate $R_{i,s}^{target}(t)$.

Using the annual target rate, we can compute the aggregated abatement for each scope at time $t \in [t_0, t_f]$:

$$A_{i,s}^{target}(t) = 100 \times \left(1 - \prod_{p=t_0}^t R_{i,s}^{target}(p) \right)$$

The annual rates and the aggregated abatement allow us to compare the aggregated abatement that companies target to a benchmark aggregated abatement, defined by a net-zero emissions (NZE) scenario. We label the net-zero aggregated abatement for company i as $A_{i,s}^{nze}(t)$, and we compute the annual net-zero rate between 2015 and 2050, assuming that $A_{i,s}^{nze}(t_0 - 1) = 100$:

$$R_{i,s}^{nze}(t) = 1 - \frac{A_{i,s}^{nze}(t)}{A_{i,s}^{nze}(t_0 - 1)}$$

For each company, there are therefore targeted annual rates $R_{i,s}^{target}(t)$ and corresponding targeted aggregated abatement $A_{i,s}^{target}(t)$, and reference NZE annual rates $R_{i,s}^{nze}(t)$ and corresponding NZE aggregated abatement $A_{i,s}^{nze}(t)$.

Building historical, target and net-zero emissions datasets

We then build several greenhouse gas emissions datasets to allow an easier comparison between the targets, the reference net-zero scenario, and the historical performance of companies in terms of emissions. Using the previous target and net-zero annual aggregated abatements, we can compute the targeted emissions as well as the net-zero emissions of a company i for a scope s at $t \in [t_0, t_f]$:

$$E_{i,s}^{target}(t) = E_{i,s}^{hist}(t_0 - 1) * (1 - A_{i,s}(t))$$

These are the projected scope s emissions that company i should emit if it follows its

targets. $E_{i,s}^{hist}(t_0 - 1)$ are the historical scope s emissions of company i at time $t_0 - 1$. Targeted emissions are therefore projections of the company's low-carbon objectives. The net-zero emissions are computed in a similar manner:

$$E_{i,s}^{nze}(t) = E_{i,s}^{hist}(t_0) * (1 - A_{i,s}^{nze}(t))$$

to compare these projected emissions to the historical performance of companies, we also collect the historical greenhouse gas emissions during the $[t_0, t_f]$ and we label these emissions $E_{i,s}^{hist}(t)$ for company i and scope s . The targeted emissions and net-zero emissions can be projections of emissions in the future, whereas historical emissions can only partially cover the $[t_0, t_f]$ period. To bring a complementary approach to what the company might achieve based on its past behavior, we estimate future emissions using past trends. We use the following regression model:

$$E(t) = \alpha + \beta * (t - t_{latest}) + \epsilon(t)$$

where t_{latest} is the latest historical emission datapoint we have.

We then rescale the trend so that the latest datapoint matches β . Therefore we can define the trend emissions:

$$E_{i,s}^{trend}(t) = \begin{cases} E_{i,s}^{hist}(t) & \text{if } t \leq t_{latest} \\ E_{i,s}^{hist}(t_{latest}) + \beta_{i,s} (t - t_{latest}) & \text{if } t > t_{latest} \end{cases} \quad (4.1)$$

where $\beta_{i,s}$ is the coefficient from the regression of historical scope s emissions for company i . For simplification purposes, we assume that t_{latest} is uniform for all companies.

For each company, we therefore have three emissions data points: the targeted emissions $E_{i,s}^{target}(t)$, the net-zero emissions $E_{i,s}^{nze}(t)$, and the trend emissions $E_{i,s}^{trend}(t)$ for scope 1, 2, and 3 emissions.

Illustrated example

We illustrate the metrics with a concrete example. We take the case of a company with the following historical emissions:

Table 4.1: Historical emissions - example

Year	Scope 1 (tCO ₂ eq)	Scope 2 (tCO ₂ eq)	Scope 3 upstream (tCO ₂ eq)
2015	29,548	74,207	52,253
2016	30,284	61,154	49,734
2017	27,573	83,220	51,705
2018	30,366	83,179	51,406
2019	23,293	48,880	31,487
2020	20,995	42,984	30,967
2021	16,437	28,158	38,994
2022	18,668	24,767	27,131
2023	19,036	23,709	33,892

The company has set multiple targets over the years:

Table 4.2: CDP targets - example

Target ID k	SBTI approved	Set year	Base year t_0	Target year t_f	Scope s	Base year emissions	Targeted abatement $\tilde{A}_{i,s}^k$	Targeted emissions
0	Yes	2019	2019	2022	Scope 2	20630.0	100.0	0.00
1	Yes	2020	2019	2029	Scope 1; Scope 2; Scope 3	180805.0	70.0	54241.50
2	Yes	2020	2019	2029	Scope 1; Scope 2	48290.0	80.0	9658.00
3	Yes	2020	2019	2029	Scope 3	132515.0	67.0	43729.95
4	Yes	2020	2019	2025	Scope 1; Scope 2; Scope 3	180805.0	60.0	72322.00
5	Yes	2020	2019	2025	Scope 1; Scope 2	48290.0	62.0	18350.20
6	Yes	2020	2019	2025	Scope 3	132515.0	60.0	53006.00

We compute the annual target rates for scope 1, 2 and 3 emissions as well as the aggregated abatement that we show in the graphs below. We also represent historical, targeted, net-zero and trend emissions.

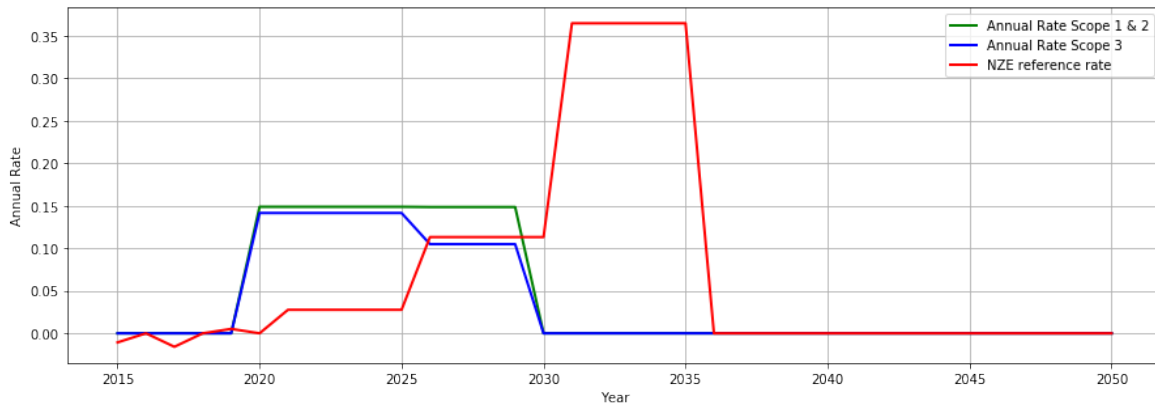


Figure 4.1: Example - Annual target ($R_{i,s}^{target}$ with $s \in \{1; 2; 3\}$) and net-zero ($R_{i,s}^{nze}$) rates

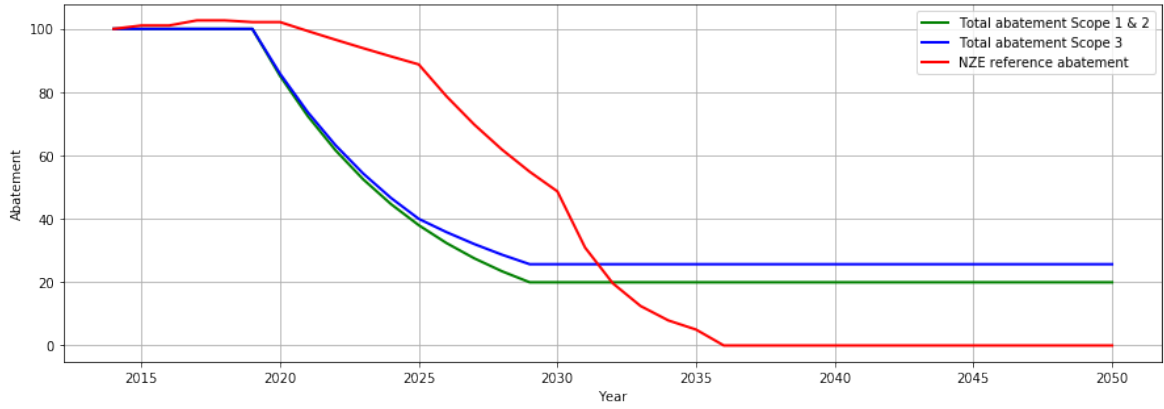


Figure 4.2: Example - Aggregated targeted abatement ($A_{i,s}^{target}$ with $s \in \{1; 2; 3\}$) and net-zero abatement ($R_{i,s}^{nze}$)

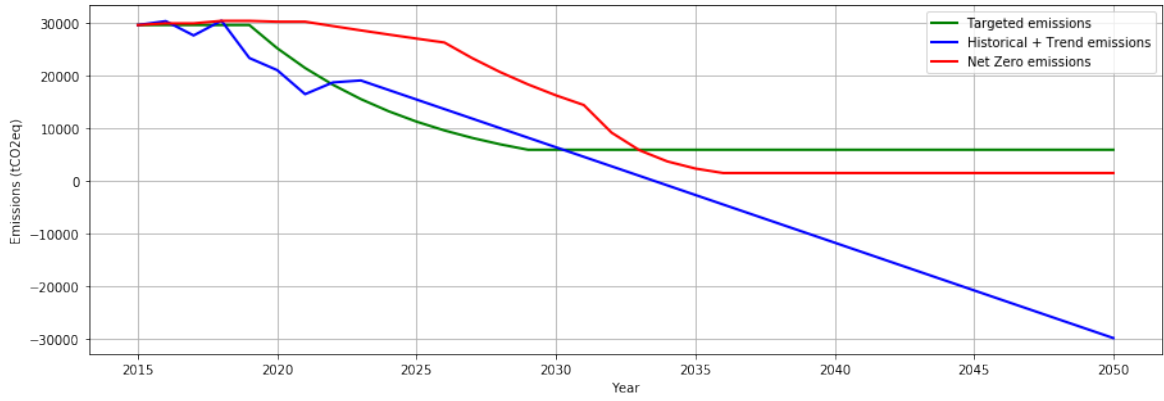


Figure 4.3: Example - historical ($E_{i,1}^{hist}$), trend ($E_{i,1}^{trend}$), targeted ($E_{i,1}^{target}$), and net-zero ($E_{i,1}^{nze}$) scope 1 emissions

4.2.2 Financial and environmental metrics

As we previously mentioned, we use the Factset database for the financial metrics, the Trucost S&P Global database for carbon emissions data, and the Sustainalytics database for other ESG ratings. We select several financial ratios as explanatory variables in our model that reflect the main characteristics of a firm's financial performance (Ross et al., 2016; Kaplan and Norton, 1992):

- Profitability: we use the gross profit margin, the 3-year earnings-per-share (EPS) growth rate, and the 2-year average return on equity (ROE) as measures of the firm's capacity to generate profit from its operations;
- Solvency: we use the Net Debt/ Earnings Before Interests, Taxes, Depreciation, and Amortization (EBITDA) ratio to measure the company's ability to control its long-term debt;

- Valuation metrics: for metrics related to the market's valuation of the company, we use the total capitalization as well as the price-to-book (PB) ratio;
- Growth metrics: finally, we use the CAPEX/Sales ratio as a proxy for measuring the growth perspectives of the company and its investment strategy.

These financial metrics have previously been used in the literature as observation variables to measure the impact of climate risk on a firm's value (Campiglio et al., 2022). While the literature has mainly focused on the impact of climate risk on the price of companies, several studies have also highlighted the impact of climate risks on other financial characteristics of a firm, such as solvency or profitability (Coqueret, 2022).

We also consider the climate performance of a company to study its impact on the decision to set ambitious targets and to achieve them. We use several climate performance metrics, mainly using carbon data: scope 1 emissions are the amount of emissions from a company's own operations, scope 2 emissions are the emissions associated with the use of electricity and heat, and scope 3 are all other indirect emissions. From these, we compute the carbon intensity scope 1, 2, and 3 emissions, which are the ratios between the emissions and the company's revenue. Using the carbon intensity measures, we build 3 additional carbon ratios: the best-in-universe z-score, the best-in-class z-score, and the best-effort z-score:

$$best-in-universe = \frac{CI_{1,2,3} - \mu_{univ}(CI_{1,2,3})}{\sigma_{univ}(CI_{1,2,3})}$$

$$best-in-class = \frac{CI_{1,2,3} - \mu_{industry}(CI_{1,2,3})}{\sigma_{industry}(CI_{1,2,3})}$$

$$best-effort = \frac{\Delta CI_{1,2,3} - \mu_{industry}(\Delta CI_{1,2,3})}{\sigma_{industry}(\Delta CI_{1,2,3})}$$

$$\text{with } \Delta CI_{1,2,3} = \frac{CI_{1,2,3}(t)}{CI_{1,2,3}(t-5)}$$

$CI_{1,2,3}$ is the total carbon intensity (scope 1, 2, and 3 upstream⁵), $\mu_x(CI_{1,2,3})$ and $\sigma_{industry}(CI_{1,2,3})$ are the mean and standard deviation of the universe for the best-in-universe score or the Industry Group of the GICS® classification for the best-in-class score, and $\Delta CI_{1,2,3}$ is the variation of the carbon intensity within the last five years⁶. The best-in-universe, best-in-

⁵Due to insufficient data, we do not include the scope 3 downstream carbon intensity.

⁶when the data does not go back to five years, we observe the variation over the past four years or the past three years in case the data is not available for the past four years.

class, and best-effort metrics are therefore normally distributed variables that reflect the carbon performance of a company and allow an easy comparison to its peers. We also use the ESG Risk Ratings database from Sustainalytics[®], which serves as an indicator of the overall extra-financial performance of companies on several ESG topics. The risk rating of a company is rated between 0 and 100; it is considered high when it is above 30, and low when it is below 10.

4.2.3 Dataset description

We restrict the universe to the MSCI[®] World Index, which serves as a reference for the biggest capitalizations of the developed markets. The universe includes, on average, 1,900 companies.

The data covers the 2014-2024 period. We collect company low-carbon targets from the CDP database via the Climate Change questionnaire. The CDP platform is an important initiative for the environmental impact disclosure of corporations and cities. It serves as a global basis for data providers, investors, and institutions. The target database covers information from almost 3,000 companies in 2023. Each CDP target has the following parameters: the year the target is set, the base and target years that determine the period that the target covers, the scopes of emissions (direct scope 1 or indirect scope 2 or 3), the amount of emissions covered (for example 50% of scope 1 emissions) and the targeted total abatement. A column also specifies whether the target has been approved by the Science-Based Targets initiative (SBTi).

A description of low-carbon targets is provided in Appendix 4.7.1. We notice that within all industries, a majority of companies report their scope 1 & 2 emissions, while there are fewer companies reporting scope 3; sectors such as Transportation, Materials, or Food & Beverage are among the best in terms of reporting efforts. When considering the overall targets of companies, we notice that Real Estate and Materials hold the highest proportion of companies: these are two critical sectors in terms of climate change impact and among the most exposed to climate risk. It is therefore consistent with the idea that companies within these sectors aim at reducing their impact. When considering countries, we observe that European countries have the highest relative numbers of reporting companies as well as companies that set targets. Japan also has high numbers. This suggests, at least for European countries where the legislation is more stringent, that there are more efforts to mitigate the impact on the climate system.

We use the Factset[®] database for the financial metrics of firms, which are available for our universe in the 2010-2024 period. Finally, we rely on the CDP platform to collect carbon data from companies (greenhouse gas emissions). When the data is not available, Trucost[®] S&P Global serves as a secondary database for collecting greenhouse gas emissions. We use the Sustainalytics[®] Risk Ratings database for another metric: a global environmental, social, and governance (ESG) rating that captures the exposure to overall extra-financial risk.

We refer to the IEA Net Zero by 2050 scenario to obtain benchmark emissions for companies. The scenario defines the aggregated abatement between 2015 and 2050 that serves as a reference in five categories: Utilities, Buildings, Transport, Industry, and Other. Using the Global Industry Classification Standard[®], we match the subindustry in which the company belongs with the corresponding sector for the NZE scenario (the matching methodology is detailed in Appendix 4.7.4). The scenario makes no distinction between the emissions' scopes.

4.3 Drivers behind the ambition of targets

In this section, we focus on identifying the key drivers behind the commitment decisions of companies to set low-carbon targets. Our objective is to identify whether there are financial and extra-financial drivers behind the decision to commit to a low-carbon target. We adopt two types of approaches. The first approach is to identify ex-ante drivers: we study whether the value or variation of financial or climate metrics prior to setting a target can impact its ambition level. The second approach is to use aggregated data to determine an annual ambition for each company: we confront this annual ambition with financial and climate performance metrics. With this approach, the annual ambition of targets serves as an indicator of the willingness of a company to mitigate its climate risk in a given year; we identify the impact of performance metrics behind the annual ambition level of companies.

For the remainder of this section, measures of ambition are labeled with the symbol Z .

4.3.1 Ex-ante approach: identifying drivers for setting a target

We start by identifying the financial and climate drivers behind the decision to commit to a low-carbon target. Let us consider an individual target set by a company. Following the notations we used in the previous section, we defined the total targeted abatement $A_{i,s}^k$ that the company aimed between the base year t_0^k and the target year t_f^k . We define the first measure of ambition as the annualized abatement rate for each individual target:

Definition 4 (Annual abatement rate for a target) *At the target level, the ambition $Z_{i,s}^k$ is interpreted as the annual abatement rate:*

$$Z_{i,s}^k = \frac{A_{i,s}^k}{t_{k,f} - t_{k,0}}$$

We label the ambition measure of the k -th target $Z_{i,s}^k$, defined for the scope s emissions of company i . In this case, the ambition is defined at the target level, but not at the company level. We defined an annualized abatement rate because targets are not set at similar time horizons. With this definition, an ambitious target corresponds to a high annual level of emissions abatement: this means that the company is planning to make a lot of abatement efforts to reduce its climate impact. We want to study whether several financial or climate performance drivers can be at the source of the ambition level of an individual target. This is why we observe the values of financial and climate metrics (described in the last section) in different time periods prior to the date the target was set: first, we observe the average financial and climate values in the 5 years prior to the year the target is set. Second, we

observe the values in the last year before the target is set. In order to identify whether the variation of financial performance or climate performance has an impact on the decision to set a target, we also observe the average year-on-year variation of metrics over the 5 years prior to setting the target. In order to identify a potential impact, we conduct Ordinary-Least-Squares and robust (using the Huber M-estimator) regressions for the ambition of targets within the 2015 to 2023 period. This means that we use financial and climate data performance metrics over the 2010 to 2022 period as explanatory variables. We perform the regressions on normalized variables.

The regression model we use for measuring the impact of financial performance is as follows:

$$\begin{aligned}\hat{Z}_{i,s}^k(t) = & \beta_{GM}^p GM_i^p(t) + \beta_{EPS}^p EPS_i^p(t) \\ & + \beta_{ROE}^p ROE_i^p(t) + \beta_{Debt}^p Debt_i^p(t) + \beta_{cap}^p logCap_i^p(t) \\ & + \beta_{PB}^p PB_i^p(t) + \beta_{invest}^p Invest_i^p(t) + \epsilon_i(t)\end{aligned}$$

where *GM* is the gross margin, *EPS* the 3-year earnings-per-share growth rate, *ROE* is the 2-year average return on equity, *Debt* is the Net Debt/EBITDA ratio, *logCap* is the logarithm of capitalization, *PB* is the price-to-book ratio, and *Invest* is the CAPEX to sales ratio. *p* is the period over which the values are computed: we either take the 5-year average value prior to the year the target is set, or we take the latest value from the year before the target is set. $\epsilon_i(t)$ is the error term.

Table 4.3 shows the results for the financial metrics. Panel A presents the coefficients from the regressions using the average value of the 5 previous years (first 3 columns) and the average value of the year prior to the commitment only (3 last columns). Panel B presents the results when the ambition is measured against the average variation of financial metrics over the 5 years prior to the commitment. We observe significant and positive impacts of the gross margin and EPS growth rate on the level of ambition of the firms' targets, although the impact of the EPS growth rate is much smaller. This suggests that the profitability of a firm is an important parameter when committing to an ambitious target: higher profitability will have a positive impact on the ambition level of a target. While the average values of Net Debt/EBITDA or ROE have no significant impact on the ambition of a target, their variation levels in the previous years seem more important: firms that decrease their leverage are able to announce more ambitious targets. This seems consistent with the idea

that firms anticipate the idea that abating their emissions will require further investments, therefore reducing their relative level of debt may retain and attract investors. Turning toward the valuation metrics, the variation of the price-to-book ratio has a positive impact on the level of abatement: firms with a higher market outperformance potential are more ambitious in their low-carbon target pledges. This would suggest that firms with an increasing "growth" bias are incentivized to pledge ambitious targets and that pledging to a more ambitious target is a way to continue attracting investors. We notice a significant negative effect of the size of the firm on its ambition: smaller firms tend to make more ambitious targets, however, we notice that the variation of capitalization has a positive impact on the ambition level of targets. This leads us to conclude that smaller firms tend to make more ambitious targets, but that firms that increase capital prior to making a commitment will make a more ambitious one. However, we notice that the investment efforts of a company have little impact on its ambition level. We also conduct the test using robust regression methods, using the Huber M-estimator and we obtain similar results.

Table 4.3: Financial drivers for setting a target.

Table 4.3 shows the results from the OLS regressions of the target ambition $Z_{i,s}^k$ against financial metrics. In Panel A, the regressors are either the 5-year average value prior to the target commitment or the value of the latest year prior to the commitment. In Panel B, the regressors are the 5-year average variation of the metric. We control for fixed effects detailed at the bottom of the table. All results cover the period January 2015 - December 2022 with 1,621 observations. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

<i>PANEL A: Average or latest values</i>						
	Coefficients					
	Previous 5 years (average value)			Previous year		
Gross margin	0.181*** (0.027)	0.181*** (0.027)	0.189*** (0.027)	0.168*** (0.027)	0.168*** (0.027)	0.175*** (0.027)
EPS growth rate	0.057*** (0.026)	0.057*** (0.026)	0.055*** (0.027)	0.046* (0.026)	0.046* (0.026)	0.045* (0.027)
2-year average ROE	0.018 (0.043)	0.019 (0.043)	0.019 (0.043)	-0.018 (0.027)	-0.018* (0.039)	-0.016 (0.039)
Net Debt/EBITDA	-0.026 (0.026)	-0.026 (0.026)	-0.025 (0.026)	0.001 (0.027)	0.001 (0.027)	0.003 (0.027)
Capitalization (log)	-0.070** (0.032)	-0.069** (0.032)	-0.066** (0.033)	-0.053 (0.033)	-0.053 (0.032)	-0.050 (0.032)
Price-to-Book	-0.049 (0.044)	-0.049 (0.044)	-0.049 (0.044)	0.000 (0.040)	0.001 (0.040)	-0.002 (0.040)
CAPEX/Sales	0.012 (0.027)	0.012 (0.027)	0.017 (0.027)	0.033 (0.027)	0.034 (0.027)	0.040 (0.026)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	N	Y	Y	N
Country FE	Y	N	Y	Y	N	Y
Company FE	Y	Y	Y	Y	Y	Y

<i>PANEL B: Variation of metrics</i>			
	Coefficients		
	Previous 5 years (average variation)		
Δ Gross margin	-0.012 (0.031)	-0.010 (0.031)	-0.012 (0.031)
Δ EPS growth rate	-0.012 (0.029)	-0.012 (0.029)	-0.011 (0.029)
Δ 2-year average ROE	-0.010 (0.033)	-0.012 (0.033)	-0.005*** (0.033)
Δ Net Debt/EBITDA	-0.073** (0.029)	-0.073** (0.029)	-0.072** (0.029)
Δ Capitalization (log)	0.066** (0.030)	0.066** (0.030)	0.070** (0.030)
Δ Price-to-Book	0.058* (0.032)	0.062** (0.032)	0.055* (0.032)
Δ CAPEX/Sales	0.019 (0.030)	0.017 (0.030)	0.028 (0.030)
Year FE	Y	Y	Y
Industry FE	Y	Y	N
Country FE	Y	N	Y
Company FE	Y	Y	Y

The model when observing the impact of climate performance prior to setting the target is as follows:

$$\begin{aligned}\hat{Z}_{i,s}^k(t) = & \beta_{GHG}^p GHG_i^p(t) + \beta_{int}^p Intensity_i^p(t) \\ & + \beta_{class}^p bclass_i^p(t) + \beta_{effort}^p beffort_i^p(t) + \\ & \beta_{univ}^p buniverse_i^p(t) + \beta_{ESG}^p ESG_i^p(t) + \epsilon_i(t) \\ & + \delta_{company} + \delta_{year} + \delta_{industry} + \delta_{country}\end{aligned}$$

where *GHG* is the total amount of greenhouse gas emissions, *Intensity* is the GHG emissions intensity (GHG emissions to revenue ratio), *bclass* is the best-in-class score of the company, *beffort* is the best-effort score, *buniverse* is the best-in-universe score, and *ESG* is the ESG Risk Rating. *p* is the period over which the values are computed: we either take the 5-year average value prior to the year the target is set, or we take the latest value from the year before the target is set. $\epsilon_i(t)$ is the error term. We also control for firm, year, industry, and country fixed effects.

Table 4.4 shows a much lower impact of climate performance metrics on the ambition of targets than financial performance metrics, both for the average values as well as the variation of metrics. There are significant results for the best-in-universe score values and 5-year average variation, with a negative effect on the values of the scores and a positive effect on the variation of the scores: this means that firms with a lower best-in-universe score, or higher emissions prior to setting a target will tend to announce a more ambitious target. It also means that firms that tend to increase their best-in-universe score, and therefore to decrease their emissions prior to announcing a target, will be more ambitious. This results slightly differs from what was found by (Bolton et al., 2022): firms with lower emissions will set more low-carbon targets. We also notice a negative impact of the ESG Risk Rating variation on the ambition level of targets: this means that firms that lower their ESG Risk Rating score and therefore reduce their overall exposure to extra-financial risk will tend to undertake more ambitious targets. Surprisingly, we do not find significant results for the best-in-class or best-efforts scores: this suggests that setting better low-carbon targets may not be a way for firms to increase their competitive advantage within their industry. It could also mean that the level of ambition within industries may not be extensive: firms will commit to similar low-carbon targets, a practice encouraged by institutions such as the SBTi.

While this first approach focuses on the individual targets set by companies, it does not take into account whether a target is compatible with a global macroeconomic scenario. We therefore take another approach, at the company level, and interpret the ambition of a firm as the compatibility of its objectives with a low-carbon scenario.

Table 4.4: Environmental drivers for setting a target

Table 4.4 shows the results from the OLS regressions of the target ambition $Z_{i,s}^k$ against ESG metrics. In Panel A, the regressors are either the 5-year average value prior to the target commitment or the value of the latest year prior to the commitment. In Panel B, the regressors are the 5-year average variation of the metric. We always control for firm and year fixed effects. We also control for industry and country fixed effects although not systematically. All results cover the period January 2015 - December 2022 with 1,686 observations. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

PANEL A: Average or latest environmental values						
	Coefficients					
	Previous 5 years (average value)			Previous year		
Total GHG emissions	0.000	0.003	0.000	-0.001	0.000	-0.001
(tCO2eq)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Total GHG emissions intensity	-0.282	-0.250	-0.308	-0.217	-0.195	-0.225
(tCO2eq/mn USD)	(0.185)	(0.184)	(0.183)	(0.115)	(0.115)	(0.114)
Best-in-class z-score	0.014	0.015	-0.013	0.021	0.022	0.021
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Best-effort z-score	0.019	0.017	0.019	0.028	0.028	0.027
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Best-in-universe z-score	-0.128**	-0.135**	-0.120**	-0.100	-0.109*	-0.097
	(0.061)	(0.060)	(0.060)	(0.062)	(0.062)	(0.062)
ESG Risk Rating	0.038	0.035	0.035	0.011	0.010	0.010
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	N	Y	Y	N
Country FE	Y	N	Y	Y	N	Y
Company FE	Y	Y	Y	Y	Y	Y

PANEL B: Variation of environmental metrics			
	Coefficients		
	Previous 5 years (average variation)		
Δ Total GHG emissions	0.002	0-0.003	0.004
(tCO2eq)	(0.035)	(0.035)	(0.035)
Δ Total GHG emissions intensity	0.071*	0.072*	0.069*
(tCO2eq/mn USD)	(0.040)	(0.040)	(0.040)
Δ Best-in-class z-score	-0.016	-0.013	-0.016
	(0.035)	(0.035)	(0.035)
Δ Best-effort z-score	0.019	0.022	0.019
	(0.035)	(0.035)	(0.035)
Δ Best-in-universe z-score	0.056*	0.059*	0.055*
	(0.035)	(0.035)	(0.035)
Δ ESG Risk Rating	-0.061*	-0.057	-0.061*
	(0.036)	(0.035)	(0.036)
Year FE	Y	Y	Y
Industry FE	Y	Y	N
Country FE	Y	N	Y
Company FE	Y	Y	Y

4.3.2 Net-zero ambition of targets: binary approach

We now turn to a firm-level approach, by studying the year-on-year impact of financial and environmental metrics on other measures of target ambition. We define the ambition of a company by using the emissions databases we have built: the historical and trend emissions, the projected emissions, and the net-zero emissions (see the previous section).

We adopt a simple approach and consider that an annual target rate can be considered ambitious if it is equal to or higher than the rate required by the Net-Zero emissions scenario of the corresponding industry and year. To put it in other words, if the projected emissions of a company from its targets are below the net-zero emissions, then the targets can be evaluated as sufficient, and the ambition is aligned to a net-zero ambition. Therefore, we build a binary variable, the target ambition $Z_{i,s}^B$ of firm i for scope s targets, taking the value 1 if the projected target emissions are below the net-zero emissions and the value 0 otherwise:

Definition 5 (Binary approach at the company level) *The ambition $Z_{i,s}^B(t)$ of a firm depends on its alignment to a low-carbon scenario:*

$$Z_{i,s}^B(t) = \begin{cases} 1 & \text{if } E_{i,s}^{target}(t) \leq E_{i,s}^{nze}(t) \\ 0 & \text{otherwise} \end{cases} \quad (4.2)$$

We obtain, for each company, an annual binary variable that states whether the company's ambitions (with the targets it may have set in place at the time) are aligned with what is required by the net-zero emissions scenario. The target ambition can be set for the period 2015 to 2050.

Figures 4.4 and 4.5 show the capitalization weighted-average distribution of net-zero aligned and non-aligned companies within industry groups at two different horizons: from 2015 to 2023 and in the medium term 2030 for scope 1 (direct) emissions. We observe a clear shift in terms of net-zero ambitions, with firms becoming less ambitious over time. Between 2015 and 2023, the financial services, banking, and telecommunication services sectors have the highest relative share of net-zero aligned targets, while the most polluting sectors, such as utilities, energy, transportation, and automotive sectors do not have net-zero aligned ambitions. This is not a surprising result, given that setting ambitious targets in sectors that heavily rely on fossil fuel energy requires more efforts in terms of investments, innovation, and even business model changes. Using this definition of a firm's ambition, we find that the least-polluting sectors (in terms of direct emissions) have had

a tendency to set the most ambitious targets and that heavy polluters have been laggards in the low-carbon transition. However, the 2030 target ambition shows that apart from the Food & Beverage sector, most of the capitalization does not have net-zero aligned ambitions, including the least-polluting sectors. An investor may therefore consider that its portfolio holds a medium and long-term climate transition risk, as a majority of the market capitalization has not set ambitious enough targets.

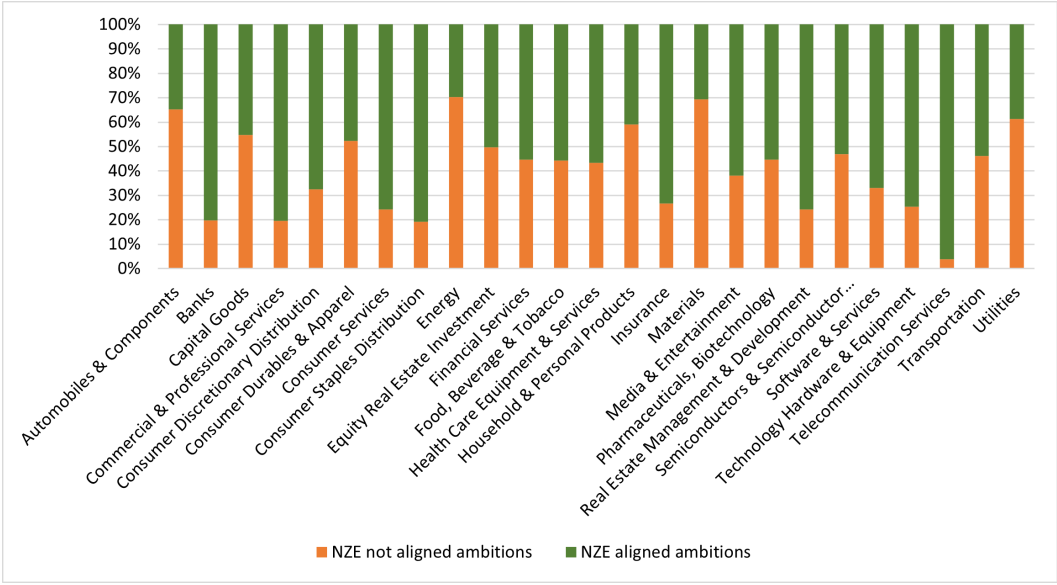


Figure 4.4: Breakdown by industry group.

NZE alignment for targets between 2015 and 2023.

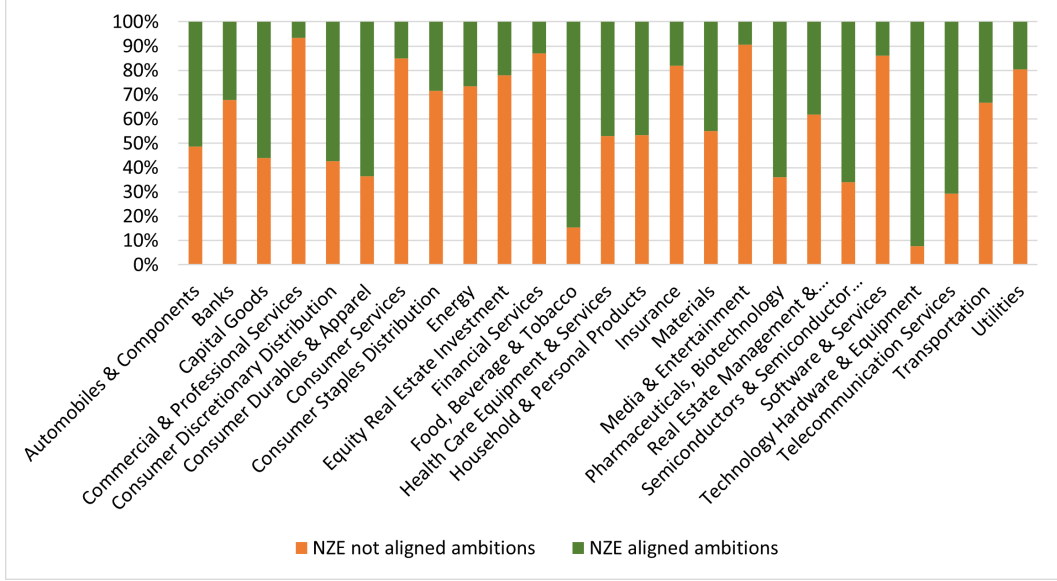


Figure 4.5: Breakdown by industry group.

NZE alignment for 2030 targets.

With this new approach, where the ambition is an annual variable for each company, we aim to identify financial and climate performance drivers behind the annual ambition level of companies. Because the ambition variable is binary, we perform logistic regressions to understand the impact of financial and climate performance behind the low-carbon ambition $Z_{i,s}^B(t)$. We perform this logistic regression at two time periods:

- During the 2015-2023 period: we compute the annual value of the ambition against the corresponding annual value of the financial and climate performance of companies;
- At the 2030 horizon: we consider the values of firms' ambition in 2030 and we observe the impact of the average values of financial and climate performance metrics over the 2015-2030 period.

The logistic regression model (Hosmer and Lemeshow, 2000) writes as follows:

$$P(Z_{i,s}^B(t) = 1|V_i(t)) = \frac{1}{1 + e^{-(\beta_{const} + \beta_{GM}GM_i(t) + \beta_{EPS}EPS_i(t) + \dots + \beta_{invest}Invest_i(t))}} \quad (4.3)$$

where $V_i(t)$ is the vector of financial metrics for firm i : the gross margin $GM_i(t)$, earnings-per-share growth rate $EPS_i(t)$, the 2-year average ROE $ROE_i(t)$, the Net Debt to EBITDA ratio $Debt_i(t)$, the logarithm of the firm's capitalization $logCap_i(t)$, the price-to-book ratio $PB_i(t)$, and the CAPEX to sales ratio $Invest_i(t)$. β_{const} is the intercept. All

variables are normalized.

Table 4.5 shows the results for the financial drivers at the two different time periods: the results for the 2015-2023 period are presented in Panel A, and the results for the 2030 horizon are presented in Panel B for each scope of emissions. We do not extend the study beyond 2050, as the ambition variable is not discriminatory (an overwhelming majority of companies do not have net-zero aligned ambitions) and therefore there would be a lack of accuracy. As in the previous paragraph, Panel A shows a clear positive impact of the gross margin on the target ambition of firms: firms with higher margins, and therefore higher profitability, hold more ambitious targets. Therefore the profitability of a firm seems to be an important parameter before setting a target, but also for keeping and updating its level of ambition. Another important result is the negative relationship with the CAPEX to sales ratio, which may suggest that firms with ambitious targets might reduce investments in new assets and possibly divest or close operations due to the reduction of their climate impact. We find significant results for the size of the company, which has a negative impact on the ambition of a firm, a result already observed: over the 2015-2023 period, smaller firms seem to announce climate action plans that are more in line with low-carbon scenarios. We find limited significance for other financial performance metrics. In Panel B, the CAPEX to sales ratio continues to have a negative impact on the medium-term ambition of firms. However, we find a contradictory result when observing the profitability profile of companies: firms with lower margins tend to announce more ambitious targets in the medium term. This suggests a discrepancy in the role of profitability when announcing a low-carbon target: in the short term, firms that are not profitable will not make ambitious targets, as this may mean sacrificing an even greater margin due to the investment requirements from committing to a low-carbon target. Only firms with appealing profitability perspectives for investors will undertake short-term ambitious climate action. In the medium term, announcing an ambitious climate action presents less risk of losing profitability as there are more years to successfully reach the objectives: this may explain why firms with lesser profitability take the risk of announcing a longer-term climate action plan.

Table 4.5: Impact of financial performance on the target ambition success of firms.

Table 4.5 summarizes the results from the logistics regressions of the target ambition success or failure $TA_{i,s}^B(t)$ with $s \in \{1, 2, 3\}$ against financial performance metrics. In Panel A, the regressions are run over the historical period 2015-2022. In Panel B, the regressions are run using the target ambition success in the medium term (year 2030), using the average values of performance metrics between 2015 and 2022 as regressors. We systematically control for firm, year, industry, and country fixed effects. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

	Scope 1 ambition success	Scope 2 ambition success	Scope 3 ambition success
<i>Panel A: Target aligned to the NZE scenario between 2015 and 2023</i>			
Gross margin	0.09*** (0.02)	0.14*** (0.02)	0.18*** (0.02)
EPS growth rate	-0.02 (0.02)	-0.02 (0.02)	-0.03 (0.02)
2-year average Return on Equity (ROE)	-0.03 (0.02)	-0.03 (0.02)	0.02 (0.03)
Net Debt/EBITDA	0.04 (0.03)	0.03 (0.03)	0.05* (0.03)
Capitalization (log)	-0.11*** (0.02)	-0.13*** (0.02)	-0.10*** (0.02)
Price-to-Book	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)
CAPEX/Sales	-0.11*** (0.02)	-0.13*** (0.02)	-0.10*** (0.02)

	Scope 1 ambition success	Scope 2 ambition success	Scope 3 ambition success
<i>Panel B: Medium-term (2030) target alignment to the NZE scenario</i>			
Gross margin	-0.20*** (0.05)	-0.15*** (0.05)	-0.11* (0.07)
EPS growth rate	-0.01 (0.05)	-0.01 (0.05)	-0.06 (0.05)
2-year average Return on Equity (ROE)	0.00 (0.05)	0.00 (0.05)	0.03 (0.05)
Net Debt/EBITDA	0.06 (0.05)	0.03 (0.05)	0.13*** (0.06)
Capitalization (log)	0.54*** (0.03)	0.49*** (0.06)	0.65*** (0.08)
Price-to-Book	-0.08 (0.09)	-0.07 (0.09)	-0.05 (0.11)
CAPEX/Sales	-0.46*** (0.13)	-0.52*** (0.14)	-0.37** (0.17)
Year FE	Y	Y	Y
Country FE	Y	Y	Y
Industry FE	Y	Y	Y
Company FE	Y	Y	Y

We turn towards identifying climate performance drivers. We undertake the same logistic regression model as in Equation 4.3, but change the observatory variables: we now observe the effect of the best-in-universe, best-in-class, and best-effort z-scores as well as the ESG Risk Rating. The results are presented in Table 4.6. Panel A highlights important climate performance impacts: firms with a higher best-in-universe score, or lower emissions, have more ambitious targets. The best-in-class score also plays an important role in scope 3 targets, where companies with higher emissions within their industry will tend to be more ambitious. The ESG Risk Rating has a negative impact on ambition in the short term, meaning that firms with lower exposure to extra-financial risk are able to announce more ambitious low-carbon targets. Panel B shows an interesting result: the best-in-universe score has a negative impact on target ambition, meaning that the most polluting firms are making ambitious targets by 2030. There are two possible explanations for this: they are either incentivized to set up ambitious targets or are able to submit to ambitious targets at a later date (2030). The second possibility could however highlight the existence of greenwashing practices: firms announce longer-term targets so as not to take any reputational or legal risks in the short term, all the while signaling to investors that they have intentions of mitigating their climate risk exposure at a later date. While this binary approach gives useful indicators as to the financial and climate drivers behind

a firm's ambition, it may not illustrate an exhaustive description of a firm's ambition. This is why we turn to an intensive measure of ambition at the firm level.

Table 4.6: Impact of climate performance on the target ambition success of firms.

Table 4.6 summarizes the results from the logistics regressions of the target ambition success or failure $TA_{i,s}^B(t)$ with $s \in \{1, 2, 3\}$ against climate performance metrics. In Panel A, the regressions are run over the historical period 2015-2022. In Panel B, the regressions are run using the target ambition success in the medium term (year 2030), using the average values of performance metrics between 2015 and 2022 as regressors. We systematically control for firm, year, industry, and country fixed effects. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

	Scope 1 ambition success	Scope 2 ambition success	Scope 3 ambition success
<i>Panel A: Target aligned to the NZE scenario between 2015 and 2023</i>			
Best-in-universe z-score	0.32*** (0.03)	0.35*** (0.03)	0.36*** (0.03)
Best-in-class z-score	-0.04* (0.03)	-0.05* (0.03)	-0.07*** (0.03)
Best-effort z-score	0.01 (0.02)	0.00 (0.02)	-0.02 (0.02)
ESG Risk Rating	-0.43*** (0.03)	-0.44*** (0.03)	-0.43*** (0.03)
<i>Panel B: Medium-term (2030) target alignment to the NZE scenario</i>			
Best-in-universe z-score	-0.35*** (0.18)	-0.19*** (0.07)	-0.35*** (0.09)
Best-in-class z-score	0.10* (0.06)	0.10* (0.06)	0.14* (0.07)
Best-effort z-score	-0.07 (0.05)	-0.08 (0.05)	-0.07 (0.07)
ESG Risk Rating	-0.31*** (0.06)	-0.31*** (0.06)	-0.57*** (0.09)
Year FE	Y	Y	Y
Country FE	Y	Y	Y
Industry FE	Y	Y	Y
Company FE	Y	Y	Y

4.3.3 Predicting the ambition of a company

We end this section by considering an out-of-sample approach in order to determine whether a firm's ambition $Z_{i,s}^B(t)$ can be predicted using data from previous years. We conduct our test by considering both the financial and climate performance of firms and using a support vector machine (SVM) approach (Cortes and Vapnik, 1995) to classify the net-zero ambition

of companies during the 2015-2021 period and predict the ambition for the year 2022.

The model for the SVM classification is detailed in Appendix 4.7.6. Firstly, we select classification variables according to their level of significance in the previous logistic regression model:

- Financial metrics: gross margin, capitalization, and the CAPEX to sales ratio
- Climate performance metrics: best-in-universe, best-in-class, and ESG Risk Rating scores

We also include industry, country, firm, and year fixed effects in the classification variables (we introduce them as dummy variables). The training dataset covers the 2015-2021 period and includes 6,298 data points. We use a Radial Basis Function (RBF) kernel approach for the optimization function, with a regularization parameter of 10. The testing variable is binary and corresponds to the companies' ambition in 2022, with 1,208 data points. We perform the prediction test separately for financial performance and climate performance variables. The results for the prediction using financial performance variables are presented in Tables 4.7 and 4.8, and Figure 4.6.

Table 4.7: Classification report - financial performance variables.

Table 4.7 summarizes the results for the prediction of the ambition of companies using financial performance variables. The classification and prediction are run using an RBF kernel approach of the SVM model. Training data covers the 2015-2021 period and testing data covers the year 2022. We include firm, year, industry, and country dummy variables in the classification process. The 'Precision' score is the proportion of positive identifications that were actually correct, the 'Recall' score is the proportion of actual positives that were identified correctly, and the 'F1-Score' is the harmonic mean of precision and recall.

Classification report - financial performance variables

Class	Precision	Recall	F1-score	Support
0	0.87	0.89	0.88	564
1	0.90	0.89	0.90	644

Table 4.8: Classification report - climate performance variables.

Table 4.8 summarizes the results for the prediction of the ambition of companies using climate performance variables. The classification and prediction are run using an RBF kernel approach of the SVM model. Training data covers the 2015-2021 period and testing data covers the year 2022. We include firm, year, industry, and country dummy variables in the classification process.

Classification report - climate performance variables

Class	Precision	Recall	F1-score	Support
0	0.87	0.89	0.88	564
1	0.90	0.89	0.89	644

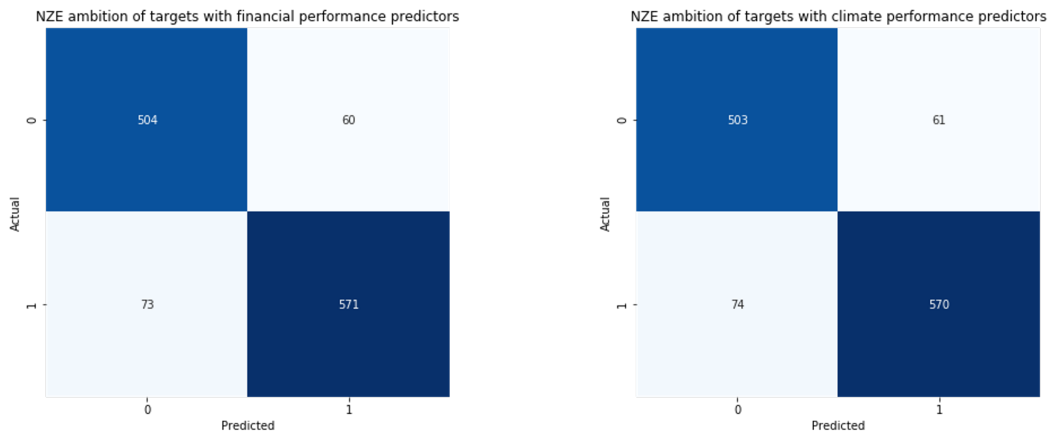


Figure 4.6: Confusion matrix for financial and climate performance variables.

SVM model with RBF kernel, $C=10$.

We obtain significant results for both the financial and climate performance predictors. The F1 scores are very high for companies with net-zero-aligned ambitions and for ambitions that fail to be net-zero aligned. The confusion matrixes support this idea, with very few false positives and false negatives. We observe that including the firm, year, industry, and country fixed effects is essential in order to obtain satisfactory results. This can be a useful approach for an investor if he wants to predict whether a firm will hold an ambitious strategy in the future.

4.4 Drivers behind the credibility of target

In this section, we pursue the identification process behind the low-carbon strategies of firms, but this time we focus on the achievement of the targets that companies have set. Beyond the ambition of companies when considering low-carbon targets, the achievement of those targets is an important issue, as it gives the real exposure of firms to climate risks, not future projections. This is an important indicator for an investor as he is then able to measure the climate risk exposure of his portfolio. The ability for an investor to predict whether a firm will achieve its target is therefore an important challenge. The achievement of a target gives an indication of the credibility of a company's target announcement, per the definition used by [Le Guenedal et al. \(2022\)](#). We investigate whether financial and climate performance could have an impact on the credibility of the target.

For the remainder of this section, measures of success, or credibility, are labeled with the symbol S .

4.4.1 Achieving a target: industry breakdown

We start by focusing on several industries and study the evolution of historical, targeted, and net-zero emissions using the databases built with the low-carbon targets of companies and the net-zero scenario. We show the weighted-average emissions (the weights follow the capitalization of companies) for several High Climate Impact Sectors (HCIS, see Appendix 4.7.5) which are industries that are the most exposed to climate risks. The results are presented in Figure 4.7. We observe different patterns in the evolution of emissions between 2015 and 2023: sectors such as the Utilities or Food & Beverage have much lower historical emissions than the projected target or NZE scenario emissions, which indicates that these companies are easily able to overachieve their own targets and that they have a few years ahead of what is required of them in terms of a net-zero budget. It also means that they can improve their own reputation by staying close in their ambitions to the NZE scenario, but being able to largely improve their targets and communicate their success to investors.

For sectors such as Energy, Materials or the Automobile, historical emissions closely match what is required from a Net-Zero scenario perspective, with a slight stall after 2021 for the automobile sector. This suggests that companies may make different choices between selecting a target and actually achieving it. We therefore observe the drivers behind the target achievements to better understand the innovations companies put in place to

achieve their targets.

When considering trend emissions, we see that a majority of industries are not on a net-zero track in the medium (by 2030) or long term (by 2050). For industries such as Capital Goods, Real Estate, or Semiconductors, there is a clear upward trend in the scope 1 emissions while targets and net-zero emissions follow a similar pathway that reaches net-zero emissions by 2050. For sectors such as the Automobile, Energy, or Materials, emissions follow a constant pathway just as the target emissions. In the case of the Energy and Materials sectors, trend emissions are, in the medium and long term, below target emissions, but highly above the net-zero pathway. The case of the utilities sector is the exception, where emissions follow a downward trend, but the net-zero scenario requires emissions to be at 0 by 2040, which is not the case for the sector. However in the medium term, trend emissions are below both target and net-zero emissions, the sector is therefore successful until 2033 and unsuccessful after.

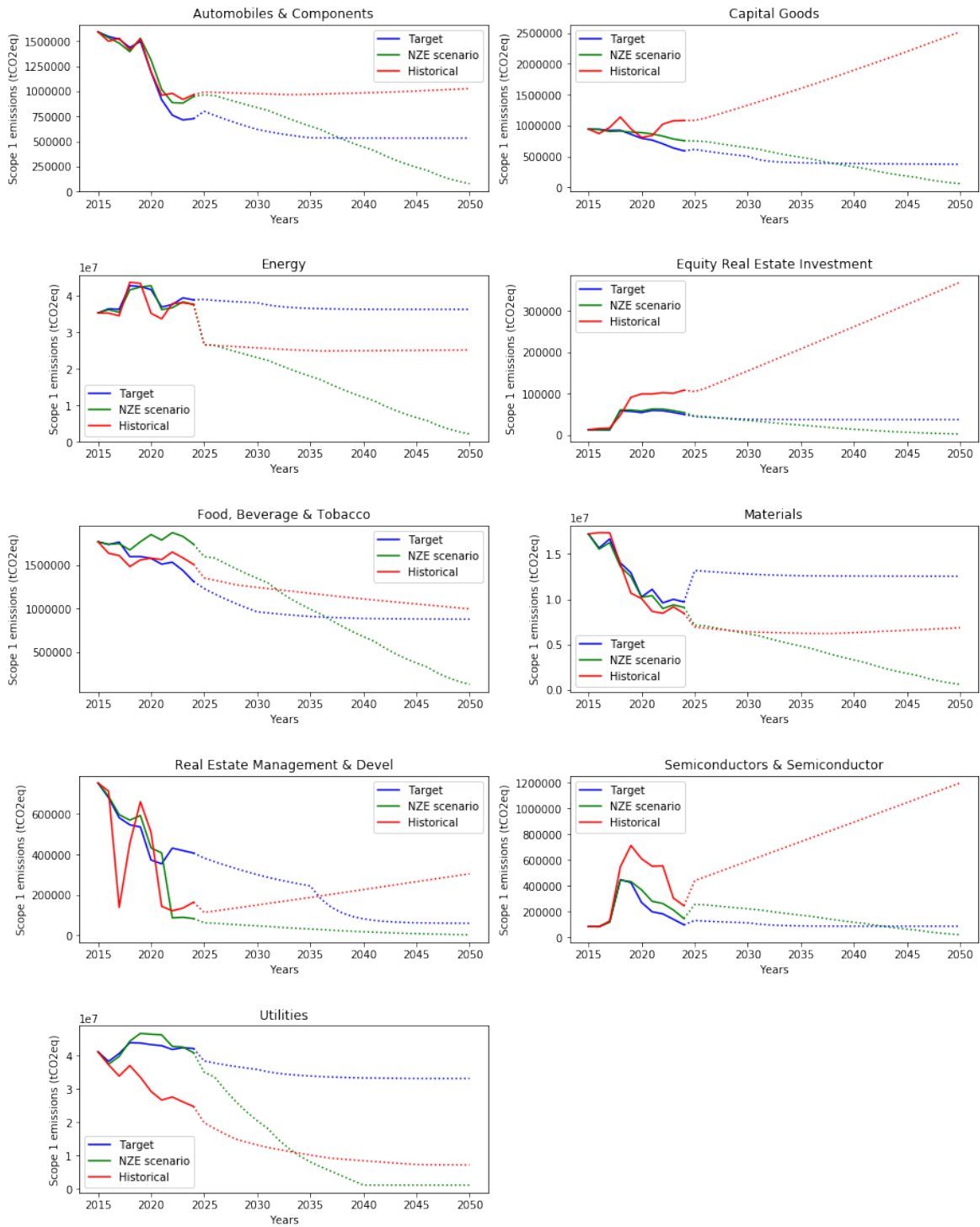


Figure 4.7: Historical, target projections and NZE scenario scope 1 emissions of industry groups between 2015 and 2023.

In order to understand the impact of financial and climate performance on the historical emissions of firms, we adopt a similar approach as for the ambition of targets.

4.4.2 Credibility of targets: binary approach

We measure the credibility of a target using a binary approach. There are two possible measures: a target can be evaluated as credible if the historical or trend emissions are below the projected emissions from the target the company has set. A harder approach is to consider a target to be credible if the historical or trend emissions are below the corresponding net-zero emissions. Therefore, we build two binary metrics, the target credibility and the net-zero credibility:

$$S_{i,s}^T(t) = \begin{cases} 1 & \text{if } E_{i,s}^{hist}(t) \leq E_{i,s}^{target}(t) \\ 0 & \text{otherwise} \end{cases}$$

$$S_{i,s}^{NZE}(t) = \begin{cases} 1 & \text{if } E_{i,s}^{hist}(t) \leq E_{i,s}^{nze}(t) \\ 0 & \text{otherwise} \end{cases}$$

In the 2015-2023 period, the credibility of a target is measured using historical emissions of companies: the target credibility corresponds to the achievement of reaching the annual target that is set by a company. For the 2024-2050 period, the credibility of the target does not correspond to the achievement of the target per se, but to the likelihood that the target will be achieved, based on the trend emissions.

In order to obtain significant results as to the impact of financial and climate performance on the credibility of companies' low-carbon strategies, we hereby focus on the historical period, between 2015 and 2023. Figures 4.8 and 4.9 highlight the weighted average value of the target credibility and the net-zero credibility for scope 1 emissions respectively. We find results consistent with Figure 4.7: in a majority of sectors that include industries that are less exposed to climate risk and less polluting, targets are not achieved in a majority of cases. Companies therefore tend to make ambitious targets that are not followed through. However, the results are mixed when observing the distribution of the net-zero credibility of firms: a majority of stocks within the Utilities, Food & Beverage, or Banking sectors are net-zero aligned, which means that within these sectors, companies announce targets that are more ambitious than what is required by a net-zero scenario, all the while able to reach the net-zero scenario but not what they had announced.

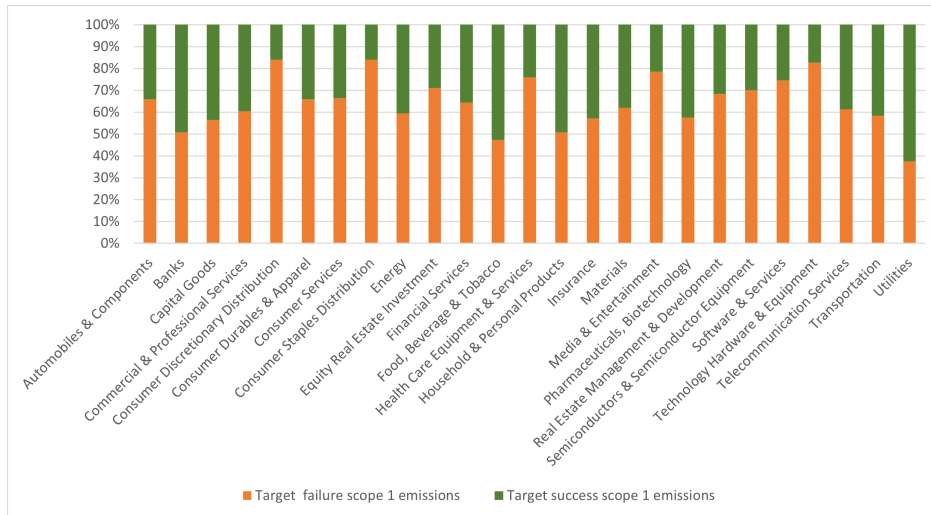


Figure 4.8: Breakdown by industry group.
Target achievement of firms between 2015 and 2023.

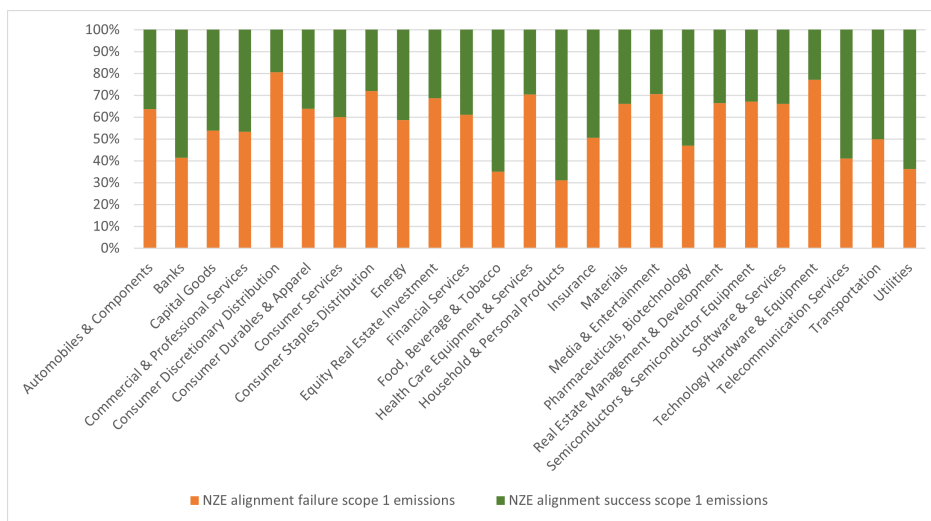


Figure 4.9: Breakdown by industry group.
Alignment of emissions to the NZE scenario between 2015 and 2023.

The target and net-zero credibility metrics are indicators of a firm’s annual capacity at reaching its target and be aligned to a net-zero scenario. Similarly to the previous section, we perform logistic regressions to understand the impact of financial and climate performance behind both of these metrics in the historical period between 2015 and 2023.

The logistic regression model for financial performance metrics writes as follows:

$$P(S_{i,s}^\gamma(t) = 1|V_i(t)) = \frac{1}{1 + e^{-(\beta_{const} + \beta_{GM}GM_i(t) + \beta_{EPS}EPS_i(t) + \dots + \beta_{invest}Invest_i(t))}} \quad (4.4)$$

where $\gamma \in \{T, NZ\}$, $V_i(t)$ is the vector of financial metrics for firm i : the gross margin $GM_i(t)$, earnings-per-share growth rate $EPS_i(t)$, the 2-year average ROE $ROE_i(t)$, the Net Debt to EBITDA ratio $Debt_i(t)$, the logarithm of the firm's capitalization $logCap_i(t)$, the price-to-book ratio $PB_i(t)$, and the CAPEX to sales ratio $Invest_i(t)$. β_{const} is the intercept. All variables are normalized.

The impact of a firm's financial performance are presented in Table 4.9. The results differ from what we observed with the ambition success of firms. Firstly, there are many more significant impacts of financial metrics. The orientation of certain metrics is also different. We now observe that firms with lower profitability achieve more of their targets and have a better likelihood of being aligned to a net-zero scenario. Several interpretations could be possible for this result, one could be that firms are willing to sacrifice margins in order to reach their targets, through the sacrifice of part of their revenue by the divestment of some of their activities for example. We also observe a positive relationship between the target credibility and the leverage (Net Debt/EBITDA) of firms. This result remains consistent regardless of the scope of emissions. Both this result and the positive impact of the CAPEX/Sales ratio over the target achievement suggest that after having committed to targets, firms look for ways to invest in their abatement efforts. The EPS growth rate and ROE continue to have little impact on the credibility of firms, much like the ambition. The market valuation metrics also have a significant impact on the credibility metrics: the size of firms has a positive impact on their target success rate and on their net-zero alignment, and the price-to-book ratio has a negative impact on the credibility of companies. This suggest that bigger firms have a higher success rate, an explanation for this could be that they have more resources at hand, therefore it is easier for them to reorient investment towards the achievement of targets. They also tend to be under much higher scrutiny from investors, their exposure to reputational risk should they fail on their announcements is also higher.

Table 4.9: Impact of financial performance on the target and net-zero credibility of firms.

Table 4.9 summarizes the results from the logistics regressions of the target credibility $S_{i,s}^T(t)$ and net-zero credibility $S_{i,s}^{NZ}(t)$ with $s \in \{1, 2, 3\}$ against financial performance metrics. The regressions are run over the historical period 2015-2023. We systematically control for firm, year, industry, and country fixed effects. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

	Scope 1 target credibility	Scope 2 target credibility	Scope 3 target credibility	Scope 1 NZE credibility	Scope 2 NZE credibility	Scope 3 NZE credibility
Gross margin	-0.07*** (0.03)	-0.21*** (0.03)	-0.13*** (0.03)	-0.05* (0.03)	-0.11*** (0.03)	-0.15*** (0.04)
EPS growth rate	0.01 (0.02)	0.01 (0.02)	-0.03 (0.02)	0.01 (0.02)	0.01 (0.02)	-0.03 (0.02)
2-year average ROE	0.07 (0.05)	0.85*** (0.23)	0.02 (0.03)	0.04 (0.04)	0.92*** (0.32)	0.01 (0.04)
Net Debt/EBITDA	0.14*** (0.05)	0.06** (0.03)	0.05** (0.02)	0.13*** (0.06)	0.03 (0.02)	0.05** (0.03)
Capitalization (log)	0.34*** (0.03)	0.18*** (0.03)	0.21*** (0.03)	0.45*** (0.03)	0.25*** (0.03)	0.24*** (0.03)
Price-to-book	-0.03 (0.03)	-0.10*** (0.04)	-0.04 (0.04)	0.00 (0.03)	-0.11*** (0.05)	-0.08 (0.06)
CAPEX/Sales	0.02 (0.05)	0.12** (0.05)	0.21*** (0.06)	-0.01 (0.07)	0.03 (0.07)	0.06 (0.07)
FE Year	Y	Y	Y	Y	Y	Y
FE Industry	Y	Y	Y	Y	Y	Y
FE Country	Y	Y	Y	Y	Y	Y
FE Company	Y	Y	Y	Y	Y	Y

We also conduct the study on the impact of climate performance metrics, using the same regression model but with the following variables: the best-in-universe, best-in-class, and best-effort scores, as well as the ESG Risk Rating. The results for the climate performance metrics are presented in Table 4.10. Similarly to the financial performance metrics, they are all significant and clearly oriented for all scopes, although different from the logistic regression results for the ambition of targets. The best-in-universe score has a negative impact on the success of targets as well as the net-zero emissions alignment: the most polluting firms that have set targets have a higher probability of achieving their targets and being net-zero aligned. This can suggest that firms setting less ambitious targets have a higher chance of achieving them, however the net-zero alignment results are surprising, given that it may be more difficult for firms to align to net-zero emissions if they are heavy polluters. A possible explanation is that the net-zero abatement between 2015 and 2023 is limited (see Appendix 4.7.3), and therefore it can be easy to achieve. The best-in-class z-score and best-effort z-score have a positive impact on the success probability of targets: the best-effort z-score is straightforward, as companies that make the most efforts to abate their emissions will have a higher chance of achieving their targets. The best performing companies (in terms of carbon intensity) within their industries also have a higher chance

of reaching their targets, although this effect is small. The best-effort score has a positive impact on the success of companies: this is consistent due to the fact that firms with the highest best-effort score are the ones that most abate their emissions. The ESG Risk Rating holds a negative impact, a result that is consistent with the ambition metrics: firms with the highest exposure to other extra-financial risk have the lowest success rate.

Table 4.10: Impact of climate performance on the target and net-zero credibility of firms.

Table 4.10 summarizes the results from the logistics regressions of the target credibility $S_{i,s}^T(t)$ and net-zero credibility $S_{i,s}^{NZ}(t)$ with $s \in \{1, 2, 3\}$ against climate performance metrics. The regressions are run over the historical period 2015-2023. We systematically control for firm, year, industry, and country fixed effects. The superscript symbols *, **, and *** denote significant results at the 10%, 5%, and 1% confidence intervals respectively.

	Scope 1 target credibility	Scope 2 target credibility	Scope 3 target credibility	Scope 1 NZE credibility	Scope 2 NZE credibility	Scope 3 NZE credibility
Best-in-universe z-score	-0.11*** (0.03)	-0.28*** (0.03)	-0.14** (0.04)	-0.07*** (0.03)	-0.22*** (0.03)	-0.12*** (0.04)
Best-in-class z-score	0.02*** (0.03)	0.09*** (0.03)	0.00 (0.03)	0.01 (0.03)	0.07*** (0.03)	0.01*** (0.03)
Best-effort z-score	0.24*** (0.02)	0.21*** (0.02)	0.08*** (0.02)	0.25*** (0.02)	0.19*** (0.02)	0.07*** (0.02)
ESG Risk Rating	-0.06** (0.03)	-0.08*** (0.03)	0.01 (0.03)	-0.12*** (0.03)	-0.14*** (0.03)	-0.02*** (0.03)
FE Year	Y	Y	Y	Y	Y	Y
FE Industry	Y	Y	Y	Y	Y	Y
FE Country	Y	Y	Y	Y	Y	Y
FE Company	Y	Y	Y	Y	Y	Y

Both the ambition and the credibility of companies regarding their low-carbon strategies depend on their financial and climate performance. By being able to isolate the metrics that have the most impact, we provide investors the solutions to anticipate their future exposure to climate risk through the possible success or failure of firms to announce ambitious targets and to achieve them.

4.4.3 Predicting the success of targets

Similarly to the section on the ambition of companies, we end by considering an out-of-sample approach in order to predict a firm's success $S_{i,s}^T(t)$ at achieving their targets using data from previous years. We observe the influence of financial and climate performance on the SVM classification between 2015-2021 (training data) and study the prediction results for the year 2022.

We select classification variables based on the significance in the previous logistic regression model:

- Financial metrics: gross margin, net debt/EBITDA ratio, and capitalization
- Climate performance metrics: best-in-universe, best-in-class, best-effort, and ESG Risk Rating scores

We also include industry, country, firm, and year dummy variables in the classification variables. We use a Radial Basis Function (RBF) kernel approach for the optimization function, with a regularization parameter of 1. The testing variable is binary and corresponds to the companies' target success $S_{i,s}^T(t)$ in 2022. We perform the prediction test separately for financial performance and climate performance variables. The results for the predictions are presented in Tables 4.11 and 4.12, and Figure 4.10.

Table 4.11: Classification report - financial performance variables for the target success of companies.

Table 4.11 summarizes the results for the prediction of the target success of companies using financial performance variables. The classification and prediction is run using an RBF kernel approach of the SVM model. Training data covers the 2015-2021 period, testing data covers the year 2022. We include firm, year, industry, and country dummy variable in the classification process.

Classification report - financial performance variables

Class	Precision	Recall	F1-score	Support
0	0.93	0.91	0.92	957
1	0.79	0.82	0.81	383

Table 4.12: Classification report - climate performance variables for the target success of companies.

Table 4.12 summarizes the results for the prediction of the target success of companies using climate performance variables. The classification and prediction is run using an RBF kernel approach of the SVM model. Training data covers the 2015-2021 period, testing data covers the year 2022. We include firm, year, industry, and country dummy variable in the classification process.

Classification report - climate performance variables

Class	Precision	Recall	F1-score	Support
0	0.91	0.92	0.91	1019
1	0.81	0.80	0.80	462

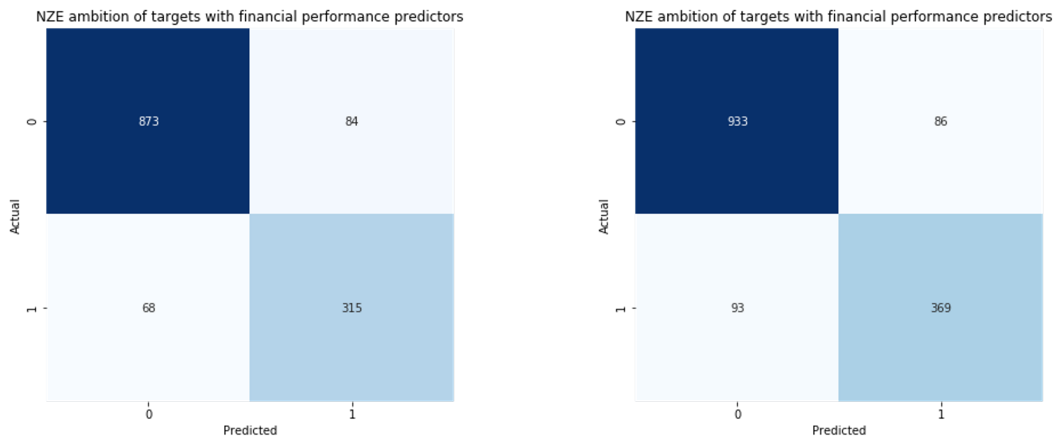


Figure 4.10: Confusion matrix for the target success of companies using financial and climate performance variables.

SVM model with RBF kernel, $C=1$.

Much like the ambition of companies, we obtain satisfactory results for both the financial and climate performance predictors. The F1 scores are especially very high for companies that fail their targets, an important information for an investor if he wants to protect his portfolio from climate risk. Once again, we observe that including the firm, year, industry, and country fixed effects is essential in order to obtain satisfactory results. Investors may therefore be able to predict whether firms will be able to sustain their ambition and achieve or fail their targets: this can serve as an indicator as to the exposure of a financial portfolio to transition and liability climate risks.

4.4.4 Comparative analysis: does ambition signify success?

After identifying drivers for ambition and success, we study the common features between drivers for ambition and credibility. The definition of ambition and credibility is to be interpreted cautiously as these measures are beginning to be developed both in the academic literature as well as within the financial industry. While the ambition reflects the compatibility of the target with the net-zero scenario, the credibility reflects the capacity of firms to achieve their targets.

Table 4.13 below recaps the significant financial and financial drivers for measures of ambition and credibility. Overall, we find that gross margin, capitalization, the best-in-universe score, and the ESG Risk Rating are the most significant drivers for both ambition and credibility, but their orientation differs: a higher gross margin means that, until now, firms are more likely to set ambitious targets, but this is not the case in the medium term, and it is not the case if a firm is aiming to make a credible target. We find an interesting

mechanism behind this topic: in order to announce more credible targets, firms should be ready to sacrifice margin, but also to increase their Net Debt/EBITDA ratio, which suggests that setting a target that is achievable implies sacrificing net profit. The capitalization of a firm follows the same trend: smaller firms have historically made more ambitious targets, but this reverses in the medium term, and bigger firms make more credible targets. This may suggest that historically, bigger firms are under more scrutiny from investors and have had to make targets that they could achieve; this could have been done by setting less ambitious targets, thereby increasing the chance of success. The lack of ambition could also be explained by the higher inertia in larger firms. Finally, the environmental drivers are (mainly) oriented in the same way for ambition and credibility: the least-polluting firms within the universe (lowest best-in-universe score) are more likely to set ambitious targets and also achieve them; this is the same for ESG risk exposure: the least-exposed companies (lowest ESG Risk Rating score) are the most likely to set ambitious and credible targets. This highlights a potential impact issue: the most polluting companies should be the ones making the most efforts, but struggle the most to abate their emissions. This could be corrected by policymakers via mechanisms of subsidies or support to help the most polluting firms commit to ambitious targets.

Table 4.13: Summary table - significant financial and extra-financial drivers for measures of target ambition and target credibility

Table 4.13 recaps the results for the main (significant) financial and extra-financial drivers behind ambition and credibility. The sign ‘+’ means that there is a positive relationship between variables, ‘-’ means that the driver negatively impacts the ambition or credibility measure, and ‘NS’ means that the variable is not significant.

	AMBITION			CREDIBILITY
	Intensity approach	Binary approach (historical)	Binary approach (medium term)	Binary approach (historical)
<i>Financial drivers</i>				
Gross margin	+	+	-	-
EPS Growth rate	+	NS	NS	NS
Capitalization	-	-	+	+
CAPEX/Sales	NS	-	-	+
Net Debt/EBITDA	NS	NS	NS	+
<i>Extra-financial drivers</i>				
Best-in-universe score	-	+	-	-
Best-in-class score	NS	NS	NS	+
Best-effort score	NS	NS	NS	+
ESG Risk Rating	NS	-	-	-

4.5 Net-Zero portfolio construction

In the last section of this paper, we build several portfolios that aim an alignment to a net-zero emissions scenario, either through the ambition of companies or through their achievement. We start by selecting companies with target ambitions aligned to the reference NZE scenario and companies with historical net-zero aligned emissions. With these two selection processes, we build portfolios that we compare with the market and another portfolio built using by selecting companies with the lowest carbon emissions. We compare portfolios based on their financial and climate performances, as well as their diversification perspectives.

We start by building a portfolio where companies' ambitions are aligned to the NZE scenario: each year, the annual abatement of emissions must be equal or greater than the required level of abatement from the NZE scenario. If we take the former binary target ambition variable defined in the previous section, we only select companies where: $Z_{i,s}^B(t) = 1$. We create the portfolio between September 2015 and August 2024 by reweighting the stocks according to their market capitalization each trimester. This is the ambition aligned portfolio.

We also build a portfolio by selecting companies with emissions that are net-zero aligned. This means that by using the net-zero credibility variable (see previous section), we select companies for which: $S_{i,s}^{NZ}(t) = 1$. The portfolio is also created between September 2015 and August 2024, with stocks reweighted according to their market capitalization each trimester. This portfolio is called the NZE emissions aligned portfolio.

We compare the portfolio to two reference portfolios: the first one is the MSCI® World Index that serves as the market portfolio, and the second is the best-in-universe portfolio: from the market portfolio, we select the top 20% of companies with the lowest values of scope 1, scope 2 and scope 3 upstream carbon intensities. Each portfolio is rebalanced each trimester to match the two net-zero portfolios we built.

Firstly, the performance of portfolios is shown in Figure 4.11, and the statistics of the portfolios in Table 4.14. The performance of the target ambition aligned portfolio improves the performance of the best-in-universe portfolio (10.3% vs 9.3% in annual return) and has a similar trend, although it does not outperform the market, with a 11.8% annual return. The maximum drawdown is also controlled and close to the market value at 33.7%. If the

portfolio itself holds net-zero aligned ambitions, this does not guarantee that the portfolio will be net-zero aligned in the future, as companies may not achieve their targets. We find a lower performance for the NZE aligned portfolio, with a 7.4% annual return. The portfolio underperforms both the target ambition aligned portfolio and the best-in-universe portfolio while maintaining a close volatility level. Furthermore, its maximum drawdown is higher than the market index and the best-in-universe portfolio, which suggests that the portfolio can be riskier. Overall, the portfolio is riskier and more volatile than the target ambition aligned portfolio.

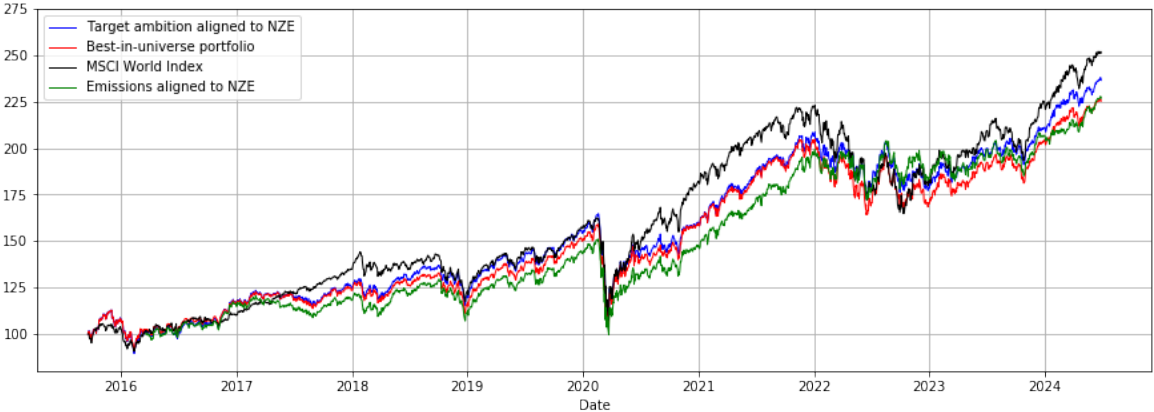


Figure 4.11: Portfolio performance with targets aligned to net-zero ambitions.

Table 4.14: Financial performance statistics for portfolios.

	Cumulated Return (%)	Annualized Return (%)	Annualized volatility (%)	Maximum Drawdown (%)
Target ambition aligned portfolio	136.5	10.3	15.1	33.7
NZE emissions aligned portfolio	87.3	7.40	14.1	34.3
Best-in-universe portfolio	118.5	9.3	14.7	32.9
MSCI® World Index	166.6	11.8	15.4	33.8

Turning to the climate performance of portfolios, we show the weighted-average scope 1 emissions over the 2015-2050 period. Up until 2023, emissions correspond to historical emissions, and we use the carbon trend methodology to compute the emissions over the 2024-2050 period. We observe that the net-zero aligned emissions portfolio is effectively net-zero aligned in terms of trend, with emissions becoming negative around 2042. The target ambition aligned portfolio is, however, not net-zero aligned, as the trend has a positive slope, much like the best-in-universe portfolio. However, emissions are still below the market portfolio’s weighted average emissions. This suggests that while the ambition-aligned portfolio is more stable and holds a better performance than the net-zero emis-

sions aligned portfolio, there is no guarantee that the portfolio will be net-zero aligned if investors select companies with net-zero aligned targets. The climate performance metrics support the strong performance of the net-zero emissions aligned portfolio. Table 4.15 shows the weighted-average scores for each portfolio. It overperforms every other portfolio in the best-in-universe score, including the best-in-universe portfolio. The target ambition aligned portfolio has a strong best effort score, although holding scope 1, 2, and 3 emissions intensity closer to the market portfolio. This climate performance seems to support the idea that there can be a tradeoff between financial and climate performance for the investor.

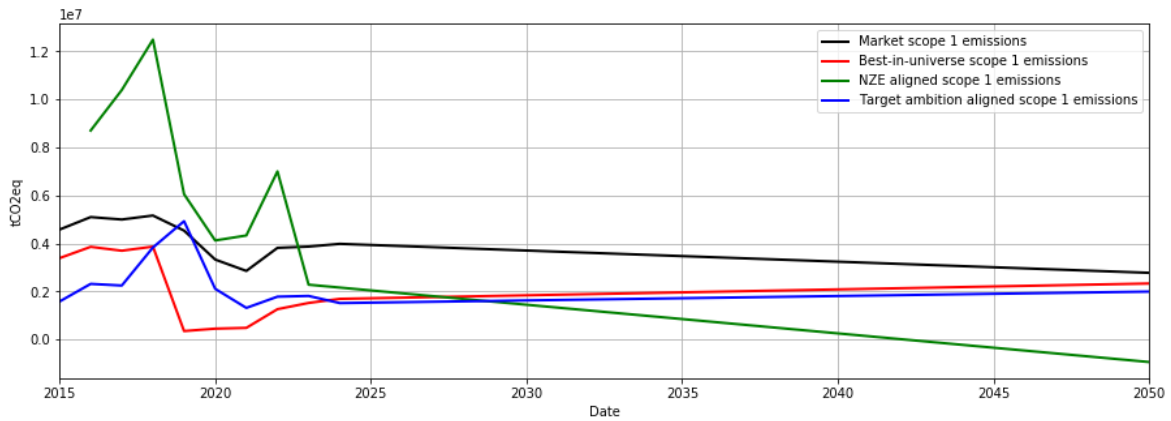


Figure 4.12: Weighted-average emissions of portfolios

Table 4.15: Climate performance of portfolios.

	ESG Risk Rating	Best-in-universe zscore	Best-in-class zscore	Best-effort zscore	Scope 1-2-3 emissions intensity
Target ambition aligned portfolio	17.33	0.202	-0.034	0.035	176.9
NZE emissions aligned portfolio	18.80	0.046	-0.019	0.136	292.2
Best-in-universe portfolio	19.00	0.067	-0.044	0.022	260.9
MSCI® World Index	18.86	-0.016	-0.162	0.006	291.9

We now consider the diversification perspectives of the portfolios. Holding portfolios that are either net-zero aligned in their ambition or their credibility can indeed be of interest for the investor, as he seeks to maximize the diversification of his assets in order to minimize risk.

We start by showing the weighted average portfolio emissions and breakdown by industry. We observe important differences in the sector weight distributions between the target ambition and the net-zero aligned portfolios: this is especially the case for the Energy, Utilities as well as the Materials sectors, where the NZE portfolio holds much less weight. These are the most polluting sectors, therefore the most difficult to decarbonize.

Both portfolios also hold a very different composition to the market portfolio, especially for HCIS industries that are overweighted.

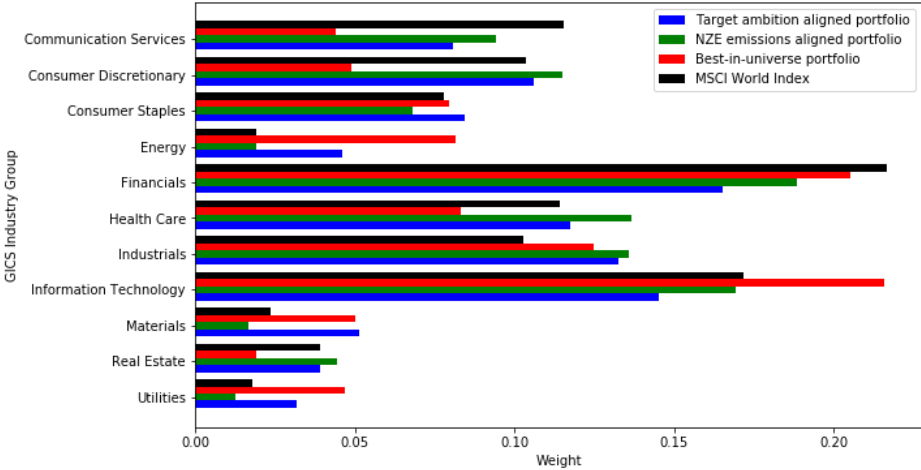


Figure 4.13: Breakdown of GICS Sector weights

Next, when considering the top 10 lines for each portfolio at the last rebalancing date, we notice that the portfolio composition is very different: while the target ambition portfolio holds megacap stocks, which are also the top lines for the market portfolio, the NZE emissions aligned portfolio is less concentrated on the first line. In each case, the majority of the top 10 lines are stocks that do not come from polluting industries, or sectors that are the most at risk in terms of the climate transition. One notable exception is the presence of Exxon Mobil Corporation within the NZE emissions aligned portfolio, an oil & gas major that is very exposed to climate transition risk. However, when further looking into the trend emissions for that company, the emissions do have a downward trend, but one that is not sufficient to remain net-zero aligned: by 2030, the company should be out of the portfolio.

Target ambition aligned portfolio			NZE emissions aligned portfolio		
Name	Weight (%)	Market weight (%)	Name	Weight (%)	Market weight (%)
Microsoft Corporation	6.53	3.95	Broadcom Inc.	2.36	0.70
Apple Inc.	6.31	3.81	Eli Lilly and Company	2.21	0.65
Alphabet Inc. Class A	4.09	2.47	Visa Inc. Class A	1.85	0.55
Amazon.com, Inc.	3.47	2.10	Exxon Mobil Corporation	1.84	0.54
Meta Platforms Inc Class A	2.15	1.30	Procter & Gamble Company	1.54	0.46
Broadcom Inc.	1.50	0.91	ASML Holding NV	1.38	0.41
Eli Lilly and Company	1.49	0.90	Nestle S.A.	1.33	0.39
JPMorgan Chase & Co.	1.11	0.67	Merck & Co., Inc.	1.21	0.36
Novo Nordisk A/S Class B	0.88	0.53	Bank of America Corp	1.21	0.36
UnitedHealth Group Incorporated	0.88	0.53	Adobe Incorporated	1.20	0.36

Table 4.16: Top 10 lines for the target aligned and the NZE emissions aligned portfolios.

Finally, we observe the various biases that can exist within both portfolios by studying the correlation between the financial performance and factors from the Carhart model (Fama and French, 1995, 2005; Carhart, 1997): the market, size, value, and momentum factors. We notice a very high correlation between the portfolio returns and the market factor, which suggests that the portfolios may serve less a purpose of diversification from the market, but can be a solution if the aim is to remain close to the market portfolio while mitigating climate risk. Both portfolios have a negative correlation to the size factor, which means that they are more exposed to companies with the largest capitalizations. The correlation with the value and momentum factors is very small: it is positively correlated to the behavior of value firms (firms that are undervalued by the market) and negatively correlated to the momentum factor.

	Target ambition aligned	NZE emissions aligned	Market	SMB	HML	WML
Target ambition aligned	100.0					
NZE emissions aligned	97.2*	100.0				
Market	98.6*	96.9*	100.0			
SMB	-19.2	-15.9	-14.2	100.0		
HML	4.3	17.4	6.5	54.4	100.0	
WML	-2.1	-6.5	-2.8	33.0	12.0	100.0

Table 4.17: Correlation table the portfolios and the Carhart factors.

Table 4.17 shows the correlations between daily returns for the target aligned portfolio, the NZE emissions aligned portfolio, and factors from the Carhart model: market, size ('SMB'), value ('HML'), and momentum ('WML'). The dates range from 01/01/2016 to 31/12/2023. Results are shown in %. The superscript symbol * indicates the indexes that have more than 90% correlation to the two first factors.

From their financial performance and high correlation to the market factor, both the target ambition aligned and the NZE emissions aligned portfolios are very similar to the

market portfolio, although the market outperforms both portfolios during certain periods of time. These portfolios cannot be used for diversification purposes by investors. Instead, they can serve as replacements of the market portfolio while mitigating the investor's exposure to climate transition risk. Indeed, the climate performance of the NZE emissions aligned portfolios is much higher than the market over the 2015-2023 period, and the projection of emissions by 2050 protect the investor from climate risk as it is the only portfolio that is net-zero aligned.

4.6 Discussion and conclusion

This study contributes to a growing literature on the low-carbon strategies of firms, especially carbon transition plans that are becoming an essential topic when analyzing the performance of companies for investors.

First, building comparative metrics that allow the evaluation of a low-carbon target of a company is an essential tool for investors. Evaluating targets can allow them to get a better insight at the ambition and credibility. We have achieved this by building several GHG emissions databases that translate the ambition of companies when they announce low-carbon targets, as well as the reference net-zero scenario that we adapt to each company. This makes the construction of evaluation metrics easier and comparable between companies and between industries. They could also be applied at the portfolio level and provide an evaluation of the ambition and credibility of a portfolio at different time horizons.

The ambition of firms has already been studied in previous literature. Papers such as [Bolton and Kacperczyk \(2021b\)](#) gave priority to databases such as the Science-Based Targets initiative commitment database to identify companies that have net-zero aligned ambitions. Our purpose was to generalize the methodology to all firms, as the SBTi mainly focuses on the largest capitalized companies. By extracting and aggregating individual targets, we are able to project the ambition of any firm into emissions and check whether they are aligned to a reference scenario. While the number of firms that have set targets has grown between 2015 and 2023, the ambition of those targets remains heterogeneous within industries. The medium-term ambition has a negative trend with regards to a net-zero alignment, although we find that the most polluting firms tend to set more ambitious target by 2030. For several industries, companies announce targets that are more ambitious than what is required by a net-zero scenario; as we show later in the paper, they are not necessarily able to reach the target they announced, but are still capable of being net-zero aligned. These mixed results can be a source of confusion for investors and lead to uncertainty as to the real climate performance of a company.

While [Bolton and Kacperczyk \(2021b\)](#) consider financial performance metrics as control variables, our purpose is to identify whether any of these variables are actual drivers for the ambition of a company. This is why we separate our study in two categories throughout most of the paper: on the one hand, we identify financial performance drivers that impact

the ambition and credibility level of a firm, and on the other hand we study the climate performance of firms prior to setting a target. The climate performance corresponds to the current level of climate risk to which a company is exposed, and we study its influence on indicators of future exposure to climate risk, via the ambition and credibility of targets.

We have observed that the profitability and size of firms are important parameters on the decision to set a target. Firms that are more profitable are more likely to set ambitious targets. The profitability of a firm is an essential parameter when measuring the firm's value: therefore firms that announce ambitious targets are firms with a better financial profile, an interesting result as investors will likely analyze the financial impact of committing to an ambitious target. Performance metrics that measure the solvency do not have a significant impact. However, smaller firms tend to make more ambitious targets. This is another interesting result, as smaller firms can be considered more agile and therefore more likely to set up operational change to abate their emissions. However, we should interpret this result with caution, given that our investment universe is made with companies with a capitalization of at least 1 to 2 billion euros. When observing the ambition of a target year after year, we find that the impact of financial and environmental drivers becomes less clear in the medium and long term. To our knowledge, we are the first to conduct a study on prospective data and by using financial performance as explanatory variables.

We pursue our study by not just considering the ambition, but also the credibility of targets, using the work of [Le Guenedal et al. \(2022\)](#) to build a simple evaluation metric and identifying the financial and climate drivers behind the heterogeneous levels we find. The credibility of a target may be an even more important parameter than the ambition, as it reveals the real exposure of a firm to climate risk, which has become an essential parameter for investors ([Coqueret, 2022](#)). We observe that the historical emissions of industries are aligned in several polluting sectors, such as Materials and Utilities in the 2015-2023 period, but other sectors are lagging. The weight of stocks with target failures increases over time, which is not a good signal for the future. The financial drivers behind the achievement of a target are important but indicate that many firms are willing to sacrifice profit margin and must invest in order to achieve their targets, thereby taking the risks to attract less investors. We also observe that the most polluting firms have the most chance of success, a surprising result that is to be interpreted cautiously as these firms might not set the most ambitious low-carbon targets, therefore their objectives might be easier to achieve. We also use a predictive approach to confirm that profitability, investment, size, and climate performance are essential parameters to predict whether a firm will achieve its target.

From a policy perspective, deploying reporting metrics on the credibility of transition plans could also be interesting for policymakers, in order to increase transparency and limit the environmental impact of firms in the future. Indeed, failing to achieve a target represents a risk both for the company, but also for the investors. The differentiation between credible and unfeasible targets should be assessable at the earliest stage: when a firm announces a target to avoid an increased exposure to reputational risk (for example, a company could be accused of greenwashing practices).

Finally, the portfolio construction of ambition-aligned and net-zero aligned portfolios indicate that the risk-return profile of such low-carbon portfolios may be controlled, however the portfolios cannot be used for diversification purposes as their performance closely resembles the market.

We suggest several research questions that could be investigated on this topic. The target data obtained through the CDP could be confronted to the communication undertaken by companies to announce their low-carbon strategy plans: complementary information could be obtained with methods such as Natural Language Processing to improve the measure of ambition and credibility. Some work could also be done to study the relationship between firms and identify the impact of a company that provides goods or services to another company. This would be useful when measuring the ambition and credibility of scope 3 targets, that largely depend on the behavior of providers and consumers. Finally, construction methodologies to identify net-zero portfolios could be improved by using a more robust approach for diversification purposes: it could be interesting to build a net-zero aligned portfolio (either aligned through the ambition or through the credibility) that does not resemble the market and focuses on a smaller number of firms. This could be done by building more sophisticated ambition and credibility target evaluation metrics.

4.7 Appendix

4.7.1 CDP target breakdown by GICS Industry Group and country

Table 4.18: CDP Dataset description.

Table 4.18 presents the industry and country breakdown of the CDP target dataset. All targets cover the 2014-2022 period.

Panel A - Industry breakdown

GICS Industry Group	All	Scope 1 & 2 disclosure	Scope 3 disclosure	Companies with targets	Companies with scope 1 or 2 targets	Companies with scope 3 targets	Companies with science-based approved targets
Automobiles & Components	56	43	40	30	29	16	22
Banks	112	77	75	59	59	29	31
Capital Goods	259	189	162	137	137	70	94
Commercial & Professional Services	76	53	53	40	40	24	24
Consumer Discretionary Distribution	72	46	42	35	35	15	24
Consumer Durables & Apparel	78	54	50	47	47	30	39
Consumer Services	86	40	39	29	28	16	22
Consumer Staples Distribution	48	32	32	26	25	19	21
Energy	136	74	48	30	29	11	13
Equity Real Estate Investment	115	68	56	34	34	21	32
Financial Services	152	82	79	51	51	29	33
Food, Beverage & Tobacco	89	79	72	62	62	44	51
Health Care Equipment & Services	120	59	49	40	40	10	26
Household & Personal Products	28	19	19	21	20	16	17
Insurance	100	65	63	44	44	27	27
Materials	190	146	130	93	92	42	67
Media & Entertainment	94	48	46	26	26	17	20
Pharmaceuticals, Biotechnology	150	75	66	61	61	30	38
Real Estate Management & Development	50	26	23	17	17	10	13
Semiconductors & Semiconductor Equipment	66	52	43	37	37	10	21
Software & Services	139	72	65	48	47	30	38
Technology Hardware & Equipment	83	72	68	56	54	40	41
Telecommunication Services	49	37	35	34	33	27	29
Transportation	87	68	63	32	31	20	18
Utilities	115	79	78	49	45	27	26
Total	2550	1655	1496	1138	1123	630	787

Panel B - Country breakdown

Country	All	Scope 1 & 2 disclosure	Scope 3 disclosure	Companies with targets	Companies with scope 1 or 2 targets	Companies with scope 3 targets	Companies with science-based approved targets
AUSTRALIA	82	62	57	28	28	12	25
AUSTRIA	6	5	5	5	5	3	3
BELGIUM	13	10	10	10	10	7	8
CANADA	119	82	71	44	44	18	22
DENMARK	20	18	16	16	15	11	11
FINLAND	17	13	12	13	13	8	11
FRANCE	87	73	71	62	62	46	51
GERMANY	76	58	55	48	46	28	32
HONG KONG	64	28	20	24	23	4	12
IRELAND	8	6	6	6	6	2	5
ISRAEL	8	5	5	5	5	2	2
ITALY	29	23	22	18	18	13	14
JAPAN	272	225	211	192	190	119	127
NETHERLANDS	36	28	26	17	17	12	11
NEW ZEALAND	6	6	6	4	4	1	3
NORWAY	12	10	10	9	9	4	8
PORTUGAL	4	3	3	3	3	1	2
SINGAPORE	25	14	11	8	8	5	6
SPAIN	27	25	25	21	21	14	13
SWEDEN	52	38	38	30	30	26	22
SWITZERLAND	49	42	42	30	30	20	24
UNITED KINGDOM	176	146	139	103	100	68	79
UNITED STATES	1362	735	635	442	436	206	296
Total	2550	1655	1496	1138	1123	630	787

4.7.2 Addition and merging of targets

We detail the methodology for determining the yearly targeted abatement rates with overlapping targets. We sort the targets by the years in which they were set in an ascending order. When two targets have been set the same year and have overlapping scopes (for example a scope 1 and a scope 1+scope 2 target), we prioritize the target with a unique scope coverage. If a target is updated, we replace the old target with the newer target.

Below is an example of the algorithm for a company:

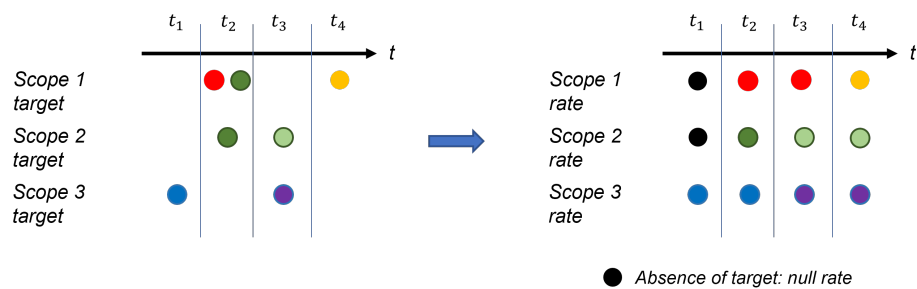


Figure 4.14: Example of the target algorithm.

4.7.3 IEA Net Zero emissions abatement

Below is the aggregated abatement computed from the Net-Zero scenario rates for several sectors: Utilities, Transport, Industry, and Buildings.

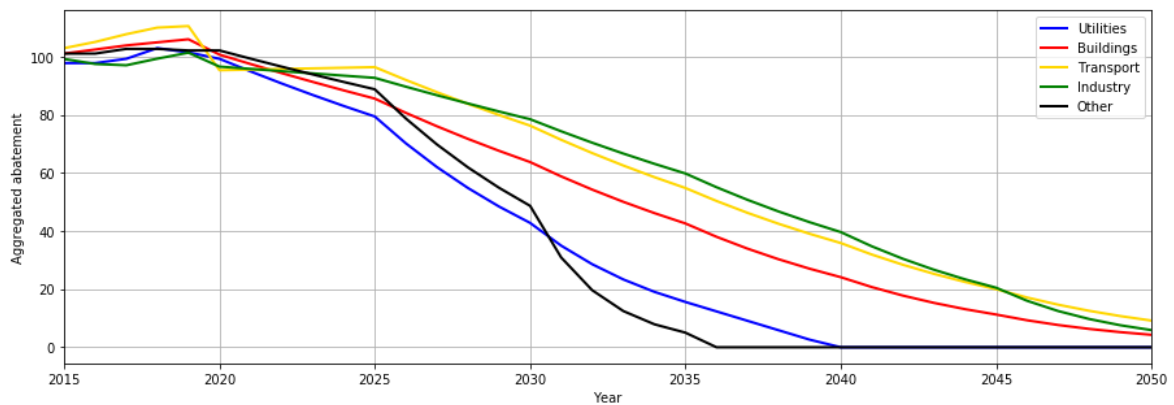


Figure 4.15: Aggregated abatement for the IEA net-zero scenario.

4.7.4 IEA sector match

We use a similar matching methodology to [Le Guenedal et al. \(2022\)](#):

1. We match each company to a NACE code (4-digit code) from the statistical classification of economic activities in the European Community, using the Global Industry

Classification Standard (GICS).

2. We match the NACE codes to the International Standard Industrial Classification (ISIC).
3. We are then able to match the ISIC codes to the IEA sectors used in the scenario using different mapping methodologies in the literature:
 - For the energy sector, we use the IRES mapping from the United Nations ([United Nations, 2018](#));
 - For the industrial sector, we rely on the work of Carvalho and Guyon to make a mapping of the industrial sector, making our own calculations at times due to a lack of details;
 - We assume that the Utilities sector is the same as the Utilities Industry Group of the GICS Classification, therefore we match all subindustries to the corresponding sector
 - We also identify the Transportation sector of the IEA to the Transportation Industry Group of the GICS classification;
 - Finally, we merge the ‘Real Estate’ and the ‘Other’ sectors together, and appoint the remaining unmatched companies to this category.

4.7.5 High Climate Impact Sectors (HCIS)

Table 4.19: Sensitive sectors (GICS[®] Industry Group Name).

GICS [®] Industry Group
Automobiles & Components
Capital Goods
Energy
Equity Real Estate Investment Food, Beverage & Tobacco
Materials
Real Estate Management & Development
Semiconductors & Semiconductor Equipment
Utilities

4.7.6 Support Vector Machine model

In the Support Vector Machine (SVM) model with a Radial Basis Function (RBF) kernel, the objective is to map the data into a higher-dimensional space and find a hyperplane that

maximally separates the two classes. The RBF kernel has the advantage of allowing for non-linear decision boundaries. First, the objective of the classification is to maximize the margin and minimize the classification error. The optimization problem for SVM classification with the RBF kernel is:

$$\min_{\mathbf{w}, b, \xi} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n \xi_i$$

under the following constraints:

$$y_i \left(\sum_{j=1}^n \alpha_j y_j \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2) + b \right) \geq 1 - \xi_i, \quad \forall i$$

where:

- $y_i \in \{-1, +1\}$ are the true labels of the data points;
- \mathbf{x}_i and \mathbf{x}_j are feature vectors;
- α_i are the Lagrange multipliers;
- γ is a hyperparameter that controls the influence of each support vector (the spread of the kernel);
- ξ_i are slack variables that allow misclassification: $\xi_i \geq 0 \quad \forall i$;
- C is a regularization parameter that balances the trade-off between maximizing the margin and minimizing classification errors.

The constraint ensures that the SVM with the RBF kernel finds a non-linear decision boundary in the original space, while maximizing the margin and allowing for controlled misclassification.

Once the SVM is trained, the prediction for a new input sample \mathbf{x} is made using the decision function:

$$f(\mathbf{x}) = \sum_{i=1}^n \alpha_i y_i \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}\|^2) + b$$

where :

- \mathbf{x} is the input feature vector.
- \mathbf{x}_i are the support vectors, the points that define the decision boundary found using

the classification.

- $y_i \in \{-1, +1\}$ are the class labels of the support vectors.
- α_i are the Lagrange multipliers, non-zero only for the support vectors.
- γ is a hyperparameter that controls the influence of each support vector (the spread of the kernel).
- b is the intercept.

$\exp(-\gamma\|\mathbf{x}_i - \mathbf{x}\|^2)$ is the RBF kernel function that computes the similarity between \mathbf{x}_i and \mathbf{x} .

The prediction is determined by the sign of the prediction function:

$$\hat{y} = \text{sign}\left(\sum_{i=1}^n \alpha_i y_i \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}\|^2) + b\right)$$

- if $\hat{y} = +1$, the input sample is classified into class +1.
- if $\hat{y} = -1$, the input sample is classified into class -1.

CONCLUSION

The objective of this thesis was to improve the measure of climate transition risk. We focused on using alternate metrics than fundamental climate performance data, which has been largely used as a proxy for climate risk in past literature and within the financial industry. The market measure of climate transition risk provides an alternate metric for the current transition risk exposure of stocks, while the low-carbon strategies of companies can be used as indicators of the future exposure to transition risk. Both of these approaches allow the development of portfolio allocation methodologies, with various diversification or financial performance purposes.

Chapter 2 contributes to a rising literature on the capture of climate risk through market signals. We were able to capture a climate market trend using Random Matrix Theory (RMT) that captures a price pattern of leader companies in the low-carbon transition. The isolation of a market signal using RMT can be adapted to other environmental themes and does not require an extensive analysis using fundamental climate performance data, which is often a strenuous task. Using this climate market trend, we built a Brown-minus-Green factor (BMG) with a double purpose: to improve asset pricing models and to develop a new methodology to measure the exposure of a stock to transition risk through the price sensitivity of an asset to this BMG factor. We were also able to show that the BMG factor is structurally different from other conventional factors (Fama and French, 1995; Carhart, 1997), therefore it can be useful to an investor for diversification purposes. The new measure of climate risk provides the market sentiment of price makers on the risk exposure of a stock, and is more dynamic and up-to-date than traditional measures (greenhouse gas emissions for example) that are only updated annually and can have a one to two-year lag. Finally, the market measure of climate transition risk is useful when companies are difficult to evaluate using fundamental data: this is the case for enabler stocks, which hold an essential role in the low-carbon transition but are hard to isolate as transition stocks. We were

able to isolate and identify them as highly sensitive to the BMG factor, which translates their role in the transition.

Chapter 3 provides a more theoretical contribution to the literature on climate change risks. First, we provided a simple approach to design a low-carbon scenario, to which we can associate low-carbon targets that are a reflection of a company's strategy on mitigating its exposure to risk. We then built a model to identify several mechanisms behind the motivations of firms to commit to low-carbon targets and the role of investors in encouraging them to do so. We introduce a key variable, the decarbonization ability of firms, which has become a topic in recent empirical literature. Our model, which develops a market equilibrium between companies and investors, highlights the call for global decarbonization action sooner rather than later, as a dwindling carbon budget only increases the difficulty of low-carbon targets. The market equilibrium reflects the existence of tipping points beyond which the carbon budget becomes too stringent and companies are not encouraged to commit to low-carbon targets. Investors, through their preference for "greener" firms, also play an important part in the market composition and in the quantification of climate risk for all companies. Our model design approaches the important question of low-carbon strategies, and identifies a cost to making a low-carbon target announcement. This can serve as an explaining factor for the reluctance of companies to commit to low-carbon targets. We illustrate this cost empirically by identifying a premium for companies that do not commit in key sectors for the low-carbon transition.

In Chapter 4, we pursue our study of the low-carbon strategies of companies through an empirical study on the ambition and credibility of low-carbon targets. We start by building simple metrics to evaluate the strategy of a company when setting a low-carbon target. We evaluate two aspects of targets: their ambition, especially their alignment to a low-carbon reference scenario, and their credibility, less studied in the literature, which reflects the actual capacity of a company to achieve its carbon target. This allows an easy comparison of the low-carbon strategies of firms and gives investors more information on the pathway the company has chosen to mitigate its exposure to climate risk. We also contribute to bridging the gap between financial performance and climate risk: we argue that when a company sets a target, its motivations are both financial and extra-financial. Our objective was therefore to identify financial and climate performance drivers behind the decision to commit to ambitious targets, and behind the success at achieving those targets. While a strand of literature studied the relationship between current climate risk and financial performance, we isolated several interesting results on the relation between future climate risk and financial performance: profitability and market size are important parameters for

setting an ambitious target and achieving it: more profitable firms are more likely to set ambitious targets, however the dynamic changes when the objective is to achieve the target. The financial drivers indicate that firms are willing to sacrifice profit margin and must invest in order to achieve their targets, thereby taking the risk to attract less investors. We apply our new methodology to the development of net-zero aligned portfolios that can be used to improve the climate risk exposure of an investor.

We see several extensions to this thesis. When considering the BMG factor, although we were able to provide a new measure of climate transition risk, further work could be done to decompose this risk and improve its comprehension. In other, what is the market information behind the dynamics of the market transition risk (climate event, change of policy, subtheme of the low-carbon transition, etc.)? This could be done by using a more precise approach when building the climate market trend, for example by using open funds that focus on a particular topic of the low-carbon transition.

The question of low-carbon transition plans is essential to measure the future exposure to climate risk, therefore the work undertaken in chapters 3 and 4 should be continued to improve the evaluation of companies' performance on the topic. This is also useful for investors, as a growing number of financial analysts seek evaluation tools to measure the diligence of low-carbon strategies. Other theoretical approaches could be considered to define a climate scenario, as well as the mechanisms between companies and investors as to the question of low-carbon strategies. One example could be to design a theoretical model on individual and collaborative engagement of investors on firms. Empirical studies should also be pursued to improve the evaluation of low-carbon transition plans, which are not only reflected by targets. Many companies communicate using press releases when they announce projects to abate their emissions. Methodologies such as Natural Language Processing could therefore be considered to provide complementary information to low-carbon targets.

Finally, the reputational risk of a company is becoming an important matter: there is a cost to announcing a low-carbon transition plan, especially if the company, due to internal or macroeconomic factors, has a low probability of achieving it. This translates into a financial risk that should be separated from transition risk and evaluated more precisely. This could help investors better protect their portfolios.



LIST OF FIGURES

1.1	Global CO_2 emissions from the Shared Socio-economic Pathways database.	3
1.2	Contraction-based and convergence-based methodologies for aligning the company to a low-carbon scenario	15
1.3	Cumulative performance of the BMG factor, brown and green portfolios. .	25
2.1	Cumulative performance of the climate market trend and indexes	56
2.2	Cumulative performance of BMG factors, brown and green portfolios . . .	59
2.3	Cumulative performance of BMG factors from divergent methodologies . .	69
2.4	Impulse response functions for a shock of one standard deviation of the Business Impact theme in BMG factors from March 2011 to December 2019	73
2.5	Impulse response functions for a shock of one standard deviation of the Business Impact theme in BMG factors from March 2011 to September 2022	73
2.6	Distribution of climate betas within High Climate Impact sectors (HCIS) .	76
2.7	Distribution of climate betas within selected countries	76
2.8	Dynamics of weighted climate betas for High Climate Impact Sectors . . .	78
2.9	Solactive iClima [®] Enablers Index performance	80
3.1	Model set-up	98
3.2	Climate risk factor for type H and type B stocks in a lemon market.	106
3.3	Number of type B and type N stocks in an economy with 2 companies. . .	108
3.4	Climate risk premium for type B and type N stocks in an economy with 2 companies.	109
3.5	Number of type B, type H, and type N stocks in an economy with 3 companies.	111
3.6	Climate risk premium for type B, type H, and type N stocks in an economy with 3 companies.	112
3.7	Cumulative performance of residual returns (alphas) of ‘Aligned’ and ‘Not Aligned’ portfolios	120
3.8	Carbon emission pathways for companies: heterogeneous efforts with homogeneous initial levels of emissions	131
3.9	Carbon emission pathways for companies: homogeneous efforts with heterogeneous initial level of emissions	131
3.10	Benchmark decarbonization rate constraint on ability of firms	133
4.1	Example - Annual target ($R_{i,s}^{target}$ with $s \in \{1; 2; 3\}$) and net-zero ($R_{i,s}^{nze}$) rates	152
4.2	Example - Aggregated targeted abatement ($A_{i,s}^{target}$ with $s \in \{1; 2; 3\}$) and net-zero abatement ($R_{i,s}^{nze}$)	153

4.3	Example - historical ($E_{i,1}^{hist}$), trend ($E_{i,1}^{trend}$), targeted ($E_{i,1}^{target}$), and net-zero ($E_{i,1}^{nze}$) scope 1 emissions	153
4.4	Breakdown by industry group - NZE alignment for targets between 2015 and 2023	164
4.5	Breakdown by industry group - NZE alignment for 2030 targets	165
4.6	Confusion matrix for financial and climate performance variables: ambition of firms	171
4.7	Historical, target projections and NZE scenario scope 1 emissions of industry groups between 2015 and 2023	174
4.8	Breakdown by industry group - Target achievement of firms between 2015 and 2023	176
4.9	Breakdown by industry group - Alignment of emissions to the NZE scenario between 2015 and 2023	176
4.10	Confusion matrix for the target success of companies using financial and climate performance variables	181
4.11	Portfolio performance with targets aligned to net-zero ambitions.	184
4.12	Weighted-average emissions of portfolios	185
4.13	Breakdown of GICS Sector weights	186
4.14	Example of the target algorithm.	193
4.15	Aggregated abatement for the IEA net-zero scenario.	193
5.1	Émissions mondiales de CO_2 de la base de données des trajectoires socio-économiques partagées. Source : Global Carbon Project	225
5.2	Performance cumulée du facteur BMG, portefeuilles brun et vert. performances sont montrées pour les prix quotidiens entre mars 2011 et septembre 2022.	232

LIST OF TABLES

2.1	Indexes for the construction of the climate market trend	51
2.2	Statistics of the eigenvalues	53
2.3	Correlation table for the indices and first factors	55
2.4	BMG portfolio names	58
2.5	Asset pricing models used to test the contribution of the BMG factor	61
2.6	Explanatory power of asset pricing models	63
2.7	Correlation between factors	64
2.8	Explanatory power for decile portfolios	66
2.9	Statistics and correlations between factors from the literature and the BMG factor from this study	69
2.10	Relevance of the BMG factor within the literature	70
2.11	Significance of Climate betas	75
2.12	Contribution of the BMG factors for enabler stocks	81
2.13	Climate betas of enabler stocks	82
2.14	Sensitive sectors (GICS® Industry Group Name).	85
2.15	List of green and brown companies	86
2.16	CAPM with Paris Agreement model results for Green and Brown portfolios	87
3.1	Identification of industrial climate risk premia from staggered difference-in-difference regressions.	116
3.2	Identification of a climate risk premium: difference-in-difference approach	118
3.3	Identification of a climate risk premium from alignment performance	121
3.4	Identification of industrial climate risk premia from staggered difference-in-difference regressions for non-sensitive sectors.	138
3.5	Alignment breakdown by industry	139
3.6	Alignment breakdown by year	139
3.7	Identification of a climate risk premium from alignment performance	140
4.1	Historical emissions - example	152
4.2	CDP targets - example	152
4.3	Financial drivers for setting a target	160
4.4	Environmental drivers for setting a target	162
4.5	Impact of financial performance on the target ambition success of firms	167
4.6	Impact of climate performance on the target ambition success of firms	169
4.7	Classification report - financial performance variables	170
4.8	Classification report - climate performance variables	170

4.9	Impact of financial performance on the target and net-zero credibility of firms	178
4.10	Impact of climate performance on the target and net-zero credibility of firms	179
4.11	Classification report - financial performance variables for the target success of companies	180
4.12	Classification report - climate performance variables for the target success of companies	180
4.13	Comparison table - significant drivers for ambition and credibility	182
4.14	Financial performance statistics for portfolios.	184
4.15	Climate performance of portfolios.	185
4.16	Top 10 lines for the target aligned and the NZE emissions aligned portfolios.	187
4.17	Correlation table the portfolios and the Carhart factors	187
4.18	CDP Dataset description	192
4.19	Sensitive sectors (GICS® Industry Group Name).	194

BIBLIOGRAPHY

- E. Agliardi, T. Alexopoulos, and K. Karvelas. The environmental pillar of esg and financial performance: A portfolio analysis. *Energy Economics*, 120(106598), 2022. doi: <https://doi.org/10.1016/j.eneco.2023.106598>.
- H. Akaike. *Information Theory and an Extension of the Maximum Likelihood Principle*, pages 199–213. Springer New York, 1973.
- H. Akaike. A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6):716–723, 1974.
- I. Akin and M. Akin. Behavioral finance impacts on us stock market volatility: an analysis of market anomalies. *Behavioural Public Policy*, 2024. doi: [doi:10.1017/bpp.2024.13](https://doi.org/10.1017/bpp.2024.13).
- A. B. Alareeni and A. Hamdan. Esg impact on performance of us s&p 500-listed firms. *Corporate Governance*, 20(7):1409–1428, 2020. doi: <https://doi.org/10.1108/CG-06-2020-0258>.
- L. Alessi, E. Ossola, and R. Panzica. What greenium matters in the stock market? the role of greenhouse gas emissions and environmental disclosures. *Journal of Financial Stability*, 54:100869, 2021. doi: <https://doi.org/10.1016/j.jfs.2021.100869>.
- A. Amel-Zadeh and G. Serafeim. Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal*, 74(3):87–103, 2018. doi: <https://doi.org/10.2469/faj.v74.n3.2>.
- Y. Antoniuk and T. Leirvik. Climate change events and stock market returns. *Journal of Sustainable Finance & Investment*, 14(1), 2024. doi: <https://doi.org/10.1080/20430795.2021.1929804>.
- D. Ardia, K. Bluteau, K. Boudt, and K. Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632, 2023. doi: [10.1287/mnsc.2022.4636](https://doi.org/10.1287/mnsc.2022.4636).
- R. Arendt. Residual carbon emissions in companies' climate pledges: who has to reduce and who gets to remove? *Climate Policy*, 24(9):1195–1210, 2024. doi: <https://doi.org/10.1080/14693062.2024.2358989>.
- K. J. Arrow. *Essays in the theory of risk-bearing*. North-Holland Pub. Co., 1971.
- D. Avramov, S. Cheng, A. Lioui, and A. Tarelli. Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145(2):642–664, 2022. doi: <https://doi.org/10.1016/j.jfineco.2021.09.009>.
- B. M. Barber, A. Morse, and A. Yasuda. Impact investing. *Journal of Financial Economics*, 139(1):162–185, 2021.

-
- T. Barko, M. Cremers, and L. Renneboog. Shareholder engagement on environmental, social, and governance performance. *Journal of Business Ethics*, 180:777–812, 2022. doi: <https://doi.org/10.1007/s10551-021-04850-z>.
- M. Barnett, W. Brock, and L. P. Hansen. Climate change uncertainty spillover in the macroeconomy. NBER Working Paper 29064, 2021.
- S. Battiston, M. Mandel, I. Monasterolo, F. Schutze, and G. Visentin. A climate stress-test of the financial system. *Nature Climate Change*, 7(4):283–288, 2017. doi: <https://doi.org/10.1038/nclimate3255>.
- M. D. Bauer, D. Huber, G.D. Rudebusch, and O. Wilms. Where is the carbon premium? Global performance of green and brown stocks. *Journal of Climate Finance*, 1(100006): 1–15, 2022. doi: <https://doi.org/10.1016/j.jclimf.2023.100006>.
- J. Baumüller and K. Sopp. Double materiality and the shift from non-financial to european sustainability reporting: review, outlook and implications. *Journal of Applied Accounting Research*, 23(1):8–28, 2022. doi: <https://doi.org/10.1108/JAAR-04-2021-0114>.
- E. Bernardini, J. Di Giampaolo, I. Faiella, and R. Poli. The impact of carbon risk on stock returns: Evidence from the european electric utilities. *Journal of Sustainable Finance and Investment*, 0(0):1–26, 2021. doi: <https://doi.org/10.1080/20430795.2019.1569445>.
- R. Black, K. Cullen, B. Fay, T. Hale, J. Lang, S. Mahmood, and S.M. Smith. Taking stock: A global assessment of net zero targets. Technical report, Energy & Climate Intelligence Unit and Oxford Net Zero, 2021.
- P. Bolton and M. Kacperczyk. Do investors care about carbon risk? *Journal of financial economics*, 142(2):517–549, 2021a. doi: <https://doi.org/10.1016/j.jfineco.2021.05.008>.
- P. Bolton and M. Kacperczyk. Firm commitments. SSRN Working Paper, 2021b.
- P. Bolton and M.T. Kacperczyk. Global pricing of carbon-transition risk. *Journal of Finance*, forthcoming, 2023.
- P. Bolton, M. Despres, L. A. Pereira da Silva, F. Samama, and R. Svartzman. The green swan. *BIS Books*, 2020. doi: <https://EconPapers.repec.org/RePEc:bis:bisbks:31>.
- P. Bolton, M. Kacperczyk, and F. Samama. Net-zero carbon portfolio alignment. *Financial Analysts Journal*, 78(2), 2022. doi: <https://doi.org/10.1080/0015198X.2022.2033105>.
- S. Bouckaert, A. Fernandez Pales, C. McGlade, U. Remme, B. Wanner, L. Varro, D. D’Ambrosio, and T. Spencer. Net zero by 2050: A roadmap for the global energy sector. Technical report, International Energy Agency, 2021.
- G. Bressan, A. Duranović, I. Monasterolo, and S. Battiston. Asset-level assessment of climate

-
- physical risk matters for adaptation finance. *Nature Communications*, 15(5371):1–13, 2024. doi: <https://doi.org/10.1038/s41467-024-48820-1>.
- E. Broccardo, A. Trevisiol, and S. Paterlini. Climate risk in finance: unveiling transition risk exposure in green vs. brown companies. *Journal of Sustainable Finance & Investment*, 14(2):237–257, 2024. doi: <https://doi.org/10.1080/20430795.2024.2315151>.
- B. Buchner, B. Naran, R. Padmanabhi, S. Stout, C. Strinati, D. Wignarajah, G. Miao, J. Connolly, and N. Marini. Global landscape of climate finance 2023. Technical report, Climate Policy Initiative, 2023.
- J. Bun, J. P. Bouchaud, and M. Potters. Cleaning large correlation matrices: tools from random matrix theory. *Physics Reports*, 666:1–165, 2017.
- T. Busch, A. Bassen, S. Lewandowski, and F. Sump. Corporate carbon and financial performance revisited. *Organization & Environment*, 35(1):154–171, 2022a. doi: <https://doi.org/10.1177/1086026620935638>.
- T. Busch, M. Johnson, and T. Pioch. Corporate carbon performance data: Quovadis? *Journal of Industrial Ecology*, 26(1):350–363, 2022b. doi: <https://doi.org/10.1111/jiec.13008>.
- T. Busch, V. van Hoorn, M. Stapelfeldt, and E. Pruessne. Classification scheme for sustainable investments. Technical report, Eurosif & University of Hamburg, 2022c. Available at: <https://www.eurosif.org/news/white-paper-from-eurosif-and-the-university-of-hambourg/>.
- B. Caldecott. Introduction to special issue: stranded assets and the environment. *Review of Environmental Economics and Policy*, 7(1):1–13, 2017. doi: <https://doi.org/10.1080/20430795.2016.1266748>.
- B. Caldecott, E. Harnett, T. Cojoianu, T. Kok, and A. Pfeiffer. Stranded assets: A climate risk challenge. Technical report, Inter-American Development Bank, 2016.
- S. Cambanis, S. Huang, and G. Simons. On the theory of elliptically contoured distributions. *Journal of Multivariate Analysis*, 11(3):368–385, 1981. doi: [https://doi.org/10.1016/0047-259X\(81\)90082-8](https://doi.org/10.1016/0047-259X(81)90082-8).
- E. Campiglio and F. van der Ploeg. Macrofinancial risks of the transition to a low-carbon. *Review of Environmental Economics and Policy*, 16(2):173–195, 2022. doi: <https://www.journals.uchicago.edu/doi/pdf/10.1086/721016>.
- E. Campiglio, L. Daumas, P. Monnin, and A. von Jagow. Climate-related risks in financial assets. *Journal of Economic Surveys*, 37(3):950–992, 2022. doi: <https://doi.org/10.1111/joes.12525>.

-
- E. Campiglio, F. Lamperti, and R. Terranova. Believe me when i say green! heterogeneous expectations and climate policy uncertainty. Centre for Climate Change Economics and Policy Working Paper, 2023.
- M. Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52(1): 57–82, 1997. doi: <https://doi.org/10.1111/j.1540-6261.1997.tb03808.x>.
- M. Carney. Breaking the tragedy of the horizon—climate change and financial stability, 2015. Speech given at Lloyd’s of London.
- F. Cartellier, P. Tankov, and O. D. Zerbib. Can investors curb greenwashing? SSRN Working paper 4644741, 2024.
- N. Cassola, C. Morana, and E. Ossola. Climate change risk pricing in the european stock market. *Applied Economics*, pages 1–20, 2024. doi: <https://doi.org/10.1111/fire.12414>.
- M. Ceccarelli and S. Ramelli. Climate transition beliefs. Swiss Finance Institute Research Paper, 2024.
- M. Ceccarelli, S. Ramelli, and A. F. Wagner. Low carbon mutual funds. *Review of Finance*, 28(1):45–74, 2024. doi: <https://doi.org/10.1093/rof/rfad015>.
- G. Cenedese, S. Han, and M. Kacperczyk. Carbon-transition risk and net-zero portfolios. SSRN Working Paper, 2024.
- A.K. Chatterji, D.I. Levine, and M.W. Toffel. How well do social ratings actually measure corporate social responsibility? *Journal of Economic Management and Strategy*, 18(4): 125–169, 2009. doi: <https://doi.org/10.1111/j.1530-9134.2009.00210.x>.
- K. Chatzitheodorou, A. Skouloudis, K. Evangelinos, and I. Nikolaou. Exploring socially responsible investment perspectives: A literature mapping and an investor classification. *Sustainable Consumption and Production*, 19:117–129, 2019. doi: <https://doi.org/10.1016/j.spc.2019.03.006>.
- S. Chava. Environmental externalities and cost of capital. *Management Science*, 60(9): 2223–2247, 2014. doi: <https://www.jstor.org/stable/24550583>.
- A. Cheema-Fox, B. R. LaPerla, G. Serafeim, D. Turkington, and H. Wang. Decarbonization factors. Harvard Business School Working Paper 20037, 2019.
- L. Chen, Y. Chen, A. Kumar, and W. S. Leung. Firm-level ESG news and active fund management. SSRN Working Paper 3747085, 2020.
- L. Chen, Y. Chen, and C. Zhang. Sustainable investing during the war in ukraine. Available at SSRN: <https://ssrn.com/abstract=4183829>, 2022.
- S. Chen. Green investors and green transition efforts: Talk the talk or walk the walk?

Working Paper, 2024.

- Y. Chen, A. Kumar, and C. Zhang. Social sentiment and asset prices. SSRN Working paper 3331866, 2019.
- I. Cochran, A. Pauthier, A. Clark, J. Choi, B. Tonkonogy, V. Micale, and C. Wetherbee. Aligning with the paris agreement. Technical report, Institute for Climate Economics and Climate Policy Initiative, 2019.
- UN Global Compact. Annual report 2022. Technical report, United Nations Global Compact, 2022. Available at: <https://unglobalcompact.org/library/5221>.
- R. Cont. Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, 1(2):223–236, 2001. doi: 10.1088/1469-7688/1/2/304.
- G. Coqueret. *Perspectives in sustainable equity investing*. CRC Focus Series. Routledge, London, UK, 2022.
- B. Cornell and A. Damodaran. Valuing ESG: doing good or sounding good? *Journal of Impact and ESG Investing*, 1(1):76–93, 2020. doi: 10.3905/jesg.2020.1.1.076.
- C. Cortes and V. Vapnik. Support-vector networks. *Machine Learning*, 20(3), 1995. doi: <https://doi.org/10.1007/BF00994018>.
- P. Crifo and H. Sami. Entrepreneurship turnover and endogenous returns to ability. *Economic Modelling*, 25:585–604, 2008. doi: 10.1016/j.econmod.2007.10.005.
- P. Crifo and H Sami. Encouraging Investors to enable corporate sustainability transitions: the case of responsible investment in France. *Organization & Environment*, 32(2):125–144, 2019. doi: <https://doi.org/10.1177/1086026619848145>.
- R. Dai, H. Liang, and L. Ng. Socially responsible corporate customer. *Journal of Financial Economics*, 142(2):598–626, 2021.
- K. D. Daniel, R. B. Litterman, and W. Gernot. Applying asset pricing theory to calibrate the price of climate risk. NBER Working Paper 22795, 2018.
- L. De Angelis and I. Monasterolo. Greenness Confusion and the Greenium. SSRN Working Paper, 2024.
- F. G. A. de Bakker, A. Rasche, and S. Ponte. Multi-stakeholder initiatives on sustainability: A cross-disciplinary review and research agenda for business ethics. *Business Ethics Quarterly*, 29(3):343–383, 2019. doi: 10.1017/beq.2019.10.
- C. De Villiers, D. Ma, and A. Marques. Csr disclosure, dividend pay-outs and firm value: Relations and mediating effects. *Accounting & Finance*, 64(1):185–219, 2023. doi: <https://doi.org/10.1111/acfi.13140>.

-
- M. A. Delmas and V. C. Burbano. The drivers of greenwashing. *California Management Review*, 54(1):5–165, 2011. doi: <https://doi.org/10.1525/cmr.2011.54.1.64>.
- S. Dietz, A. Bowen, C. Dixon, and P. Gradwell. ‘climate value at risk’ of global financial assets. *Nature Climate Change*, 6:676–679, 2016. doi: <https://doi.org/10.1038/nclimate2972>.
- E. Dimson, Z. Karakas, and X. Li. Active ownership. *Review of Financial Studies*, 28(12):3225–3268, 2015. doi: <https://doi.org/10.1093/rfs/hhv044>.
- E. Dimson, Z. Karakas, and X. Li. Coordinated engagement. European Corporate Governance Institute – Finance Working Paper No. 721/2021, 2018.
- E. Dimson, P. Marsh, and M. Staunton. Exclusionary screening. *The Journal of Impact and ESG investing*, 1(1):66–75, 2020. doi: 10.3905/jesg.2020.1.1.066.
- T. Duan, F. W. Li, and Q. Wen. Is carbon risk priced in the cross section of corporate bond returns? *Journal of Financial and Quantitative Analysis*, page 1–35, 2023. doi: <https://doi.org/10.1017/S0022109023000832>.
- A. Enders, T. Lontzek, K. Schmedders, and M. Thalhammer. Carbon risk and equity prices. *The Financial Review*, pages 1–20, 2024. doi: <https://doi.org/10.1111/fire.12414>.
- R. F. Engle, S. Giglio, B. Kelly, H. Lee, and J. Stroebel. Hedging climate change news. *Review of Financial Studies*, 33(3):1184–1216, 2020. doi: <https://doi.org/10.1093/rfs/hhz072>.
- European Commission. Commission delegated regulation (eu) 2020/1818 of 17 july 2020 supplementing regulation (eu) 2016/1011 as regards minimum standards for eu climate transition benchmarks and eu paris-aligned benchmarks, 2020.
- E. F. Fama. The behavior of stock-market prices. *The Journal of Business*, 38(1):34–105, 1965. doi: <http://www.jstor.org/stable/2350752?origin=JSTOR-pdf>.
- E. F. Fama and K. R. French. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22, 2005. doi: <https://doi.org/10.1016/j.jfineco.2014.10.010>.
- E.F. Fama and K.R. French. Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance*, 50(1):131–155, 1995. doi: <https://doi.org/10.1111/j.1540-6261.1995.tb05169.x>.
- B. Fernandez-Feijoo, S. Romero, and S. Ruiz. Effect of stakeholders’ pressure on transparency of sustainability reports within the gri framework. 2013, 122:53–63, 2014. doi: <https://link.springer.com/article/10.1007/s10551-013-1748-5>.
- C. Flammer. Corporate social responsibility and shareholder reaction: The environmental awareness of investors. *Academy of Management Journal*, 56(3):758–781, 2012. doi:

<https://doi.org/10.5465/amj.2011.0744>.

Network for Greening the Financial System. Annual report 2023. Technical report, Network for Greening the Financial System, 2024.

- L. Fransen. Multi-stakeholder governance and voluntary programme interactions: legitimation politics in the institutional design of corporate social responsibility. *Socio-Economic Review*, 10(1):163–192, 2012. doi: <https://doi.org/10.1093/ser/mwr029>.
- P. Friedlingstein, M. O’Sullivan, M. W. Jones, R. M. Andrew, L. Gregor, J. Hauck, C. Le Quéré, I. T. Lujckx, A. Olsen, G. P. Peters, W. Peters, J. Pongratz, C. Schwingshackl, S. Sitch, J. G. Canadell, P. Ciais, R. B. Jackson, S. R. Alin, R. Alkama, A. Arneeth, V. K. Arora, N. R. Bates, M. Becker, N. Bellouin, H. C. Bittig, L. Bopp, F. Chevallier, L. P. Chini, M. Cronin, W. Evans, S. Falk, R. A. Feely, T. Gasser, M. Gehlen, T. Gkritzalis, L. Gloege, G. Grassi, N. Gruber, O. Gurses, I. Harris, M. Hefner, R. A. Houghton, G. C. Hurtt, Y. Iida, T. Ilyina, A. K. Jain, A. Jersild, K. Kadono, E. Kato, D. Kennedy, K. Klein Goldewijk, J. Knauer, J. I. Korsbakken, P. Landschützer, N. Lefèvre, K. Lindsay, J. Liu, Z. Liu, G. Marland, N. Mayot, M. J. McGrath, N. Metzl, N. M. Monacci, D. R. Munro, S.-I. Nakaoka, Y. Niwa, K. O’Brien, T. Ono, P. I. Palmer, N. Pan, D. Pierrot, K. Pockock, B. Poulter, L. Resplandy, E. Robertson, C. Rödenbeck, C. Rodriguez, T. M. Rosan, J. Schwinger, R. Séférian, J. D. Shutler, I. Skjelvan, T. Steinhoff, Q. Sun, A. J. Sutton, C. Sweeney, S. Takao, T. Tanhua, P. P. Tans, X. Tian, H. Tian, B. Tilbrook, H. Tsujino, F. Tubiello, G. R. van der Werf, A. P. Walker, R. Wanninkhof, C. Whitehead, A. Willstrand Wranne, R. Wright, W. Yuan, C. Yue, X. Yue, S. Zaehle, J. Zeng, , and B. Zheng. Global carbon budget 2022. *Earth Syst. Sci. Data*, 14:4811–4900, 2022. doi: <https://doi.org/10.5194/essd-14-4811-2022>.
- P. Friedlingstein, M. O’Sullivan, M. W. Jones, R. M. Andrew, D. C. E. Bakker, J. Hauck, P. Landschützer, C. Le Quéré, I. T. Lujckx, G. P. Peters, W. Peters, J. Pongratz, C. Schwingshackl, S. Sitch, J. G. Canadell, P. Ciais, R. B. Jackson, S. R. Alin, P. Anthoni, L. Barbero, N. R. Bates, M. Becker, N. Bellouin, B. Decharme, L. Bopp, I. B. M. Brasika, P. Cadule, M. A. Chamberlain, N. Chandra, T.-T.-T. Chau, F. Chevallier, L. P. Chini, M. Cronin, X. Dou, K. Enyo, W. Evans, S. Falk, R. A. Feely, L. Feng, D. J. Ford, T. Gasser, J. Ghattas, T. Gkritzalis, G. Grassi, L. Gregor, N. Gruber, O. Gurses, I. Harris, M. Hefner, J. Heinke, R. A. Houghton, G. C. Hurtt, Y. Iida, T. Ilyina, A. R. Jacobson, A. Jain, T. Jarníková, A. Jersild, F. Jiang, Z. Jin, F. Joos, E. Kato, R. F. Keeling, D. Kennedy, K. Klein Goldewijk, J. Knauer, J. I. Korsbakken, A. Kortzinger, X. Lan, N. Lefèvre, H. Li, J. Liu, Z. Liu, L. Ma, G. Marland, N. Mayot, P. C. McGuire, G. A. McKinley, G. Meyer, E. J. Morgan, D. R. Munro, S.-I. Nakaoka, Y. Niwa, K. M. O’Brien, A. Olsen, A. M. Omar, T. Ono, M. Paulsen, D. Pierrot, K. Pockock, B. Poulter, C. M. Powis, G. Rehder, L. Resplandy, E. Robertson, C. Rödenbeck, T. M. Rosan, J. Schwinger, R. Séférian, T. L.

-
- Smallman, S. M. Smith, R. Sospedra-Alfonso, Q. Sun, A. J. Sutton, C. Sweeney, S. Takao, P. P. Tans, H. Tian, B. Tilbrook, H. Tsujino, F. Tubiello, G. R. van der Werf, E. van Ooijen, R. Wanninkhof, M. Watanabe, C. Wimart-Rousseau, D. Yang, X. Yang, W. Yuan, X. Yue, S. Zaehle, J. Zeng, and B. Zheng. Global carbon budget 2023. *Earth System Science Data*, pages 5301–2369, 2023. doi: <https://doi.org/10.5194/essd-15-5301-2023>.
- A. Garg, P. Goel, A. Sharma, and N. P. Rana. As you sow, so shall you reap: Assessing drivers of socially responsible investment attitude and intention. *Technological Forecasting and Social Change*, 184:1–14, 2024. doi: <https://doi.org/10.1016/j.techfore.2022.122030>.
- G. T. Garvey, M. Iyer, and J. Nash. Carbon footprint and productivity: Does the “e” in esg capture efficiency as well as environment. *Journal of Investment Management*, 16(1):59–69, 2018. doi: <https://joim.com/downloads/carbon-footprint-and-productivity-does-the-e-in-esg-capture-efficiency-as-well-as-environment/>.
- G. Gianfrate, D. Schoenmaker, and S. Wasama. Cost of capital and climate risks. In A. Sundaram and R. Hansen, editors, *Handbook of Business and Climate Change*, pages 480–502. Edward Elgar Publishing, Cheltenham, UK, 2023.
- R. Gibson, P. Krueger, and P. Schmidt. ESG rating disagreement and stock returns. *Financial Analysts Journal*, 77(4):104–127, 2021. doi: <https://doi.org/10.1080/0015198X.2021.1963186>.
- G. Giese, Z. Nagy, and C. Cote. Net-zero alignment: Objectives and strategic approaches for investors. Technical report, MSCI, 2021.
- S. Giglio, B. T. Kelly, and J. Stroebel. Climate finance. *Annual Reviews of Financial Economics*, 13:15–36, 2021. doi: <https://doi.org/10.1146/annurev-financial-102620-103311>.
- I. Goldstein, A. Kopytov, L. Shen, and H. Xiang. On ESG investing: Heterogeneous preferences, information, and asset prices. Available at: <http://dx.doi.org/10.2139/ssrn.3823042>, 2022.
- C. Gollier. *Pricing the planet’s future: the economics of discounting in an uncertain world*. Princeton University Press, 2013.
- M. Gorgen, A. Jacob, M. Nerlinger, R. Riordan, M. Rohleder, and M. Wilkens. Carbon Risk. SSRN Working Paper, 2020.
- R. Grinold, A. Rudd, and D. Stefek. Global factors: Fact or fiction? *Journal of Portfolio Management*, pages 79–88, Fall 1989.
- F. Haleem, S. Farooq, Y. Cheng, and B. V. Waehrens. Sustainable management practices and stakeholder pressure: A systematic literature review. *Sustainability*, 14(4), 2022. doi: <https://doi.org/10.3390/su14041967>.

-
- S. Hartzmark and A. Sussman. Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance*, 74(6):2789–2837, 2021. doi: <https://doi.org/10.1111/jofi.12841>.
- H. Hong and M. Kacperczyk. The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36, 2009. doi: <https://doi.org/10.1016/j.jfineco.2008.09.001>.
- H. Hong, F. W. Li, and J. Xu. Climate risks and market efficiency. *Journal of Econometrics*, 208(1):265–281, 2019. doi: <https://doi.org/10.1016/j.jeconom.2018.09.015>.
- D. W. Hosmer and S. Lemeshow. *Applied Logistic Regression (2nd ed.)*. John Wiley & Sons, 2000.
- A. W.-h. Hsu and T. Wang. Does the market value corporate response to climate change? *Omega*, 41(2):195–206, 2013. doi: <https://doi.org/10.1016/j.omega.2011.07.009>.
- P.-H. Hsu, K. Li, and C.-Y. Tsou. The pollution premium. *The Journal of Finance*, 78(3):1343–1392, 2023. doi: <https://doi.org/10.1111/jofi.13217>.
- P. J. Huber. Robust estimation of a location parameter. *The Annals of Mathematical Statistics*, 35(1):73–101, 1964.
- J. E. Humphrey and L. Yong. Who goes green: Reducing mutual fund emissions and its consequences. *Journal of Banking and Finance*, 126:1–17, 2021. doi: <https://doi.org/10.1016/j.jbankfin.2021.106098>.
- S. Y. In, K. Y. Park, and A. Monk. Is “being green” rewarded in the market? an empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics*, 46(48), 2017.
- EDHEC Risk Climate Institute. Climate risk, 2021.
- IPCC. Global warming of 1.5°C, special report. Technical report, Intergovernmental Panel on Climate Change, 2018.
- B. Jongman, P. J. Ward, and J. C. Aerts. Global exposure to river and coastal flooding: Long term trends and changes. *Global Environmental Change*, 22(4):823–835, 2012. doi: <https://doi.org/10.1016/j.gloenvcha.2012.07.004>.
- R. S. Kaplan and D. P. Norton. The balanced scorecard: Measures that drive performance. *Harvard Business Review*, 70(1):71–79, 1992.
- E. Kashefi Pour. Climate change risk, investor sentiment, and the performance of new entrant firms, 2024. CGF Seminar, University of London.
- Charles D. Keeling. Is carbon dioxide from fossil fuel changing man’s environment? *Pro-*

-
- ceedings of the American Philosophical Society*, 114(1):10–17, 1970.
- D. Kelker. Distribution theory of spherical distributions and a location- scale parameter generalization. *Sankhyā: The Indian Journal of Statistics, Series A*, 32(4):419–430, 1970.
- K. Kempa, U. Moslener, and O. Schenker. The cost of debt of renewable and non-renewable energy firms. *Nature Energy*, 6(2):135–142, 2021. doi: <https://doi.org/10.1038/s41560-020-00745-x>.
- P. Krueger, Z. Sautner, and L. T. Starks. The importance of climate risks for institutional investors. *Review of Financial Studies*, 33(3):1067–1111, 2020. doi: <https://doi.org/10.1093/rfs/hhz137>.
- P. Krüger. Corporate goodness and shareholder wealth. *Journal of Financial Economics*, 115(2):304–329, 2015.
- L. Laloux, P. Cizeau, M. Potters, and J.-P. Bouchaud. Random Matrix Theory and financial correlations. *International Journal of Theoretical and Applied Finance*, 3(03):391–397, 2000.
- T. Le Guenedal, F. Lombard, T. Roncalli, and T. Sekine. Net Zero Carbon Metrics. Available at: http://www.thierry-roncalli.com/download/Net_Zero_Carbon_Metrics.pdf, 2022.
- W.L. Leal Filho, A.L. Salvia, A. Paco, M.A.P. Dinis, D.G. Vidal, D.A. Da Cunha, C.R. de Vasconcelos, R.J. Baumgartner, I. Rampasso, R. Anholon, F. Doni, G. Sonetti, U. Azeiteiro, S. Carvalho, and F. J. Montoro Rios. The influences of the covid-19 pandemic on sustainable consumption: An international study. *Environmental Sciences Europe*, 34(54): 1–17, 2022. doi: 10.1186/s12302-022-00626-y.
- H. Lee and J. Romero. Climate change 2023: Synthesis report. contribution of working groups i, ii and iii to the sixth assessment report of the intergovernmental panel on climate change. Technical report, IPCC, 2023.
- S. Li, H. Ruan, S. Titman, and H. Xiang. ESG Spillovers. NBER Working Paper 31248, 2023.
- A. Liesen, F. Figge, A. G. F. Hoepner, and D. M. Patten. Climate change and asset prices: Are corporate carbon disclosure and performance priced appropriately? *Journal of Business Finance & Accounting*, 44(1):35–62, 2017. doi: <https://doi.org/10.1111/jbfa.12217>.
- A. Lioui and A. Tarelli. Chasing the esg factor. *Journal of Banking & Finance*, 139(106498): 1–24, 2022. doi: <https://doi.org/10.1016/j.jbankfin.2022.106498>.
- T. P. Lyon and J. W. Maxwell. Greenwash: Corporate environmental disclosure under threat of audit. *Journal of Economics and Management Strategy*, 20(1):3–41, 2011. doi: <https://doi.org/10.1111/j.1530-9134.2010.00282.x>.

-
- T. P. Lyon and A. W. Montgomery. The means and end of greenwash. *Organization & Environment*, 28(2):223–249, 2015. doi: <https://doi.org/10.1177/1086026615575332>.
- H. Lütkepohl. *New Introduction to multiple time series analysis*. Springer Verlag, 2005.
- J.M. Maeso and D. O’Kane. Investigating the influence of news sources and language models on climate beta estimates. *Journal of Portfolio Management*, 50(2):1–25, 2023. doi: 10.3905/jpm.2023.1.550.
- A. Mandel, T. Tiggeloven, D. Lincke, E. Koks, P. Ward, and J. Hinkel. Risks on global financial stability induced by climate change: the case of flood risks. *Climatic Change*, 166(4):1–24, 2021. doi: <https://doi.org/10.1007/s10584-021-03092-2>.
- B. Mandelbrot. The variation of certain speculative prices. *The Journal of Business*, 36(4):394–419, 1963. doi: <http://www.jstor.org/stable/2350970?origin=JSTOR-pdf>.
- H. Markowitz. Portfolio selection. *Journal of Finance*, 7(1):77–91, 1952. doi: <https://doi.org/10.2307/2975974>.
- H. Markowitz. The optimization of a quadratic function subject to linear constraints. *Naval Research Logistics Quarterly*, 3:111–133, 1956.
- P. R. Martin and D. V. Moser. Managers’ green investment disclosures and investors’ reaction. *Journal of Accounting and Economics*, 61(1):239–254, 2016. doi: <https://doi.org/10.1016/j.jacceco.2015.08.004>.
- V. A. Marčenko and L. A. Pastur. Distribution of eigenvalues for some sets of random matrices. *Math. USSR-Sbornik*, 1(4):457–483, 1967.
- D. Matisoff. Different rays of sunlight: Understanding information disclosure and carbon transparency. *Energy Policy*, 55(1):579–592, 2013. doi: <https://doi.org/10.1016/j.enpol.2012.12.049>.
- E. M. Matsumara, R. Prakash, and S. C. Vera-Munoz. Climate risk materiality and firm risk. Working Paper, 2022.
- L.O. Mearns, M. Hulme, T. R. Carter, R. Leemans, M. Lal, P. Whetton, L. Hay, R.N. Jones, R. Katz, T. Kittel, J. Smith, and R. Wilby. Climate scenario development. Technical report, Intergovernmental Panel on Climate Change, 2001.
- J. M. Meier, H. Servaes, J. Wei, and S. C. Xiao. Do consumers care about ESG? evidence from barcode-level sales data. SSRN Working paper 3331866, 2022.
- JF. Mercure, H. Pollitt, J.E. Viñuales, N.R. Edwards, P. B. Holden, U. Chewpreecha, P. Salas, I. Sognaes, A. Lam, and F. Knobloch. Macroeconomic impact of stranded fossil fuel assets. *Nature Climate Change*, 8:588–593, 2018. doi: <https://doi.org/10.1038/>

s41558-018-0182-1.

- I. Monasterolo. Climate change and the financial system. *Annual Review of Resource Economics*, 12:299–320, 2020. doi: <https://doi.org/10.1146/annurev-resource-110119-031134>.
- I. Monasterolo and L. de Angelis. Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics*, 170:106571, 2020. doi: <https://doi.org/10.1016/j.ecolecon.2019.106571>.
- I. Monasterolo and M. Raberto. The impact of phasing out fossil fuel subsidies on the low-carbon transition. *Energy Policy*, 123:175–184, 2018. doi: [10.1016/j.enpol.2018.08.050](https://doi.org/10.1016/j.enpol.2018.08.050).
- D. C. Montgomery, E. A. Peck, and G. Geoffrey Vining. *Introduction to Linear Regression Analysis: 5th Edition*. Wiley Series in Probability and Statistics. Wiley, 2012.
- Lilian Ng, Xiaoqiong Wang, and Jing Yu. Corporate decarbonization under financial constraints: International evidence. European Corporate Governance Institute–Finance Working Paper number 877, 2023.
- L. Niamir, T. Filatova, A. Voinov, and H. Bressers. Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. *Energy Policy*, 118(1): 325–345, 2018. doi: <https://doi.org/10.1016/j.enpol.2018.03.045>.
- A. Nikolaeva, A. Lanre-Oyebola, A. Clapper, A. Kruip, A. Sepulveda, B. Mendes-Jorge, E. Malysheva, E. Castro, E. Borjigin Wang, I. Ait Aissa, J. Roberts, L. Levitina, L. Buchhass, L. Du, L. Pastora, M. Meixner, M. Smith, M. Ozulu, O. Ajimati, R. Modi, R. Maher, R. Doroteo, R. Williams, T. Valeev, and T. Hopwood. SBTi monitoring report 2022. Technical report, Science Based Targets initiative, 2023.
- J. Nilsson. Investment with a conscience: Examining the impact of pro-social attitudes and perceived financial performance on socially responsible investment behavior. *Journal of Business Ethics*, 83:307–325, 2008. doi: <https://doi.org/10.1007/s10551-007-9621-z>.
- J. Noailly, L. Nowzohour, and M. van Den Heuvel. Heard the news? environmental policy and clean investments. Centre for International Environmental Studies, The Graduate Institute working paper No. 70–2021, 2021.
- W. D. Nordhaus. The ‘DICE’ Model: Background and structure of a dynamic integrated climate-economy model of the economics of global warming. Cowles Foundation Discussion Papers no 1252, 1992.
- W. D. Nordhaus. Optimal greenhouse-gas reductions and tax policy in the ‘DICE’ Model. *The American Economic Review*, 83(2):313–317, 1993. doi: <https://www.jstor.org/stable/2117683>.

-
- W. D. Nordhaus. Evolution of modeling of the economics of global warming: changes in the DICE model. *Climatic Change*, 148(4):623–640, 2018. doi: <https://doi.org/10.1007/s10584-018-2218-y>.
- OECD. Guidelines for multinational enterprises on responsible business conduct. Technical report, Organisation for Economic Co-operation and Development, 2011. <https://doi.org/10.1787/81f92357-en>.
- B. C. O’Neill, E. Kriegler, K. L. Ebi, E. Kemp-Benedict, K. Riahi, D. S. Rothman, B. S. van Ruijven, D. F. van Vuuren, J. Birkmann, K. Kok, M. Levy, and W. Solecki. The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, 42(1):169–180, 2017. doi: <https://doi.org/10.1016/j.gloenvcha.2015.01.004>.
- R.K. Pachauri and L.A. Meyer. Climate change 2014: Synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change. Technical report, IPCC, 2014.
- F. Pascal, Y. Chitour, J. P. Ovarlez, P. Forster, and P. Larzabal. Covariance structure maximum-likelihood estimates in compound Gaussian noise: Existence and algorithm analysis. *IEEE Transactions on Signal Processing*, 56(1):34–48, 2008. doi: 10.1109/TSP.2007.901652.
- F. Pascal, Y. Chitour, and Y. Quek. Generalized robust shrinkage estimator and its application to STAP detection problem. *IEEE Transactions on Signal Processing*, 62(21), 2014.
- L. Pástor and M. B. Vorsatz. Mutual fund performance and flows during the COVID-19 crisis. *The Review of Asset Pricing Studies*, 10(4):791–833, 2020. doi: <https://doi.org/10.1093/rapstu/raaa015>.
- L. Pástor, R. F. Stambaugh, and L. A. Taylor. Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571, 2021. doi: <https://doi.org/10.1016/j.jfineco.2020.12.011>.
- L. Pástor, R. F. Stambaugh, and L. A. Taylor. Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424, 2022. doi: <https://doi.org/10.1016/j.jfineco.2022.07.007>.
- L. H. Pedersen, S. Fitzgibbons, and L. Pomorski. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2):572–597, 2021. doi: <https://doi.org/10.1016/j.jfineco.2020.11.001>.
- J. W. Pratt. Risk aversion in the small and in the large. *Econometrica*, 32(1-2):122–136, 1964. doi: 10.2307/1913738.
- The Greenhouse Gas Protocol. A corporate accounting and reporting standard. Technical

-
- report, World Business Council for Sustainable Development, 2005.
- N. Pérez-Zanón, L.-P. Caron, S. Terzago, B. Van Schaeybroeck, L. Lledó, N. Manubens, E. Roulin, M. C. Alvarez-Castro, L. Batté, C. Delgado-Torres, M. Domínguez, F. Fabiano, I. Giuntoli, J. von Hardenberg, E. Sánchez-García, V. Torralba, and D. Verfaillie. The cstoos (v4. 0) toolbox: from climate forecasts to climate forecast information. *Geoscientific Model Development*, 15(15):6115–6142, 2022. doi: <https://doi.org/10.5194/gmd-15-6115-2022>.
- S. Ramelli, E. Ossola, and M. Rancan. Stock price effects of climate activism: Evidence from the first global climate strike. *Journal of Corporate Finance*, 69:1–14, 2021. doi: <https://doi.org/10.1016/j.jcorpfin.2021.102018>.
- N. Ranger, O. Mahul, and I. Monasterolo. Assessing financial risks from physical climate shocks: a framework for scenario generation. Technical report, World Bank Open Knowledge Repository, 2022.
- P. Rankin. Under pressure: exploring pressures for corporate social responsibility in mutual funds. *Qualitative Research in Organizations and Management*, 16(3):594–613, 2021. doi: <https://doi.org/10.1108/QROM-07-2020-2000>.
- A. Ravina and R. Hentati-Kaffel. The impact of low-carbon policy on stock returns. Working Paper, 2020.
- J. Raynaud, S. Voisin, P. Tankov, A. Hilke, and A. Pauthier. The alignment cookbook - a technical review of methodologies assessing a portfolio’s alignment with low-carbon trajectories or temperature goal. Technical report, Institut Louis Bachelier, 2020.
- H. J. Reinders, D. Schoenmaker, and M. van Dijk. A finance approach to climate stress testing. *Journal of International Money and Finance*, 131(1):1–19, 2023. doi: <https://doi.org/10.1016/j.jimonfin.2022.102797>.
- A. Riedl and P. Smeets. Why do investors hold socially responsible mutual funds? *Journal of Finance*, 72(6):2505–2550, 2017. doi: <https://doi.org/10.1111/jofi.12547>.
- M. Robert. Corporate finance: Maximizing value for companies. *Business Studies Journal*, 15(S2):1–2, 2023. doi: <https://www.abacademies.org/articles/corporate-finance-maximizing-value-for-companies-15972.html>.
- S. Romito, C. Vurro, and S. Pogutz. Joining multi-stakeholder initiatives to fight climate change: The environmental impact of corporate participation in the science based targets initiative. Forthcoming, 2023.
- T. Roncalli, T. Le Guenedal, Th. Roncalli, F. Lepetit, and T. Sekine. Measuring and managing carbon risk in investment portfolios. SSRN Working Paper, 2020.

-
- T. Roncalli, T. Le Guenedal, F. Lepetit, Th. Roncalli, and T. Sekine. The market measure of carbon risk and its impact on the minimum variance portfolio. SSRN Working Paper, 2021.
- B. Rosenberg. Extra-Market components of covariance in security markets. *Journal of Financial and Quantitative Analysis*, 9(2):263–274, 1974.
- S. A. Ross, R. Westerfield, and J. Jaffe. *Corporate finance (11th ed.)*. McGraw-Hill Education, 2016.
- P. J. Rousseeuw and A. M. Leroy. *Robust Regression and Outlier Detection*. Wiley Series in Probability and Statistics. Wiley, 1987. doi: DOI:10.1002/0471725382.
- C. Santi. Investor climate sentiment and financial markets. *International Review of Financial Analysis*, 86(102490), 2023. doi: <https://doi.org/10.1016/j.irfa.2023.102490>.
- Z. Sautner, L. Van Lent, G. Vilkov, and R. Zhang. Firm-level climate change exposure. *The Journal of Finance*, 78(3), 2023. doi: <https://doi.org/10.1111/jofi.13219>.
- SBTi. Sectoral decarbonization approach (sda): A method for setting corporate emission reduction targets in line with climate science. Technical report, CDP, WRI, WWF, 2015.
- G. Semieniuk, E. Campiglio, J.-F. Mercure, U. Volz, and N. R. Edwards. Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change*, 12(1), 2021. doi: <https://doi.org/10.1002/wcc.678>.
- G. Semieniuk, P. B. Holden, J.-F. Mercure, P. Salas, H. Pollitt, K. Jobson, P. Vercoulen, U. Chewprecha, N. E. Edwards, and J. E. Viñuales. Stranded fossil-fuel assets translate to major losses for investors in advanced economies. *Nature Climate Change*, 12: 532–538, 2022. doi: <https://doi.org/10.1038/s41558-022-01356-y>.
- S. Sen and M.-T. von Schickfus. Climate policy, stranded assets, and investors’ expectations. *Journal of Environmental Economics and Management*, 100:1–43, 2020. doi: <https://doi.org/10.1016/j.jeem.2019.102277>.
- W. F. Sharpe. Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3):425–442, 1964. doi: <https://doi.org/10.1111/j.1540-6261.1964.tb02865.x>.
- N. Slawinski, J. Pinkse, T. Busch, and S. B. Banerjee. The role of short-termism and uncertainty avoidance in organizational inaction on climate change: A multi-level framework. *Business & Society*, 56(2):253–282, 2017. doi: <https://doi.org/10.1177/0007650315576136>.
- B. Soh, Y. In, K. Y. Park, and A. Monk. Is ‘being green’ rewarded in the market?: An empirical

-
- investigation of carbon emission intensity and stock returns. Stanford Global Project Center Working Paper, 2017.
- T. Soler. *Combining robust covariance estimates and new dependency measures : an innovative approach to portfolio allocation*. PhD thesis, University Paris 1 Panthéon-Sorbonne, 2021.
- E. Stanny. Reliability and Comparability of GHG Disclosures to the CDP by US Electric Utilities. *Social and Environmental Accountability Journal*, 38(2):111–130, 2018. doi: <https://doi.org/10.1080/0969160X.2018.1456949>.
- J. Stroebel and J. Wurgler. What do you think about climate finance? *Journal of Financial Economics*, 142(2):487–498, 2021. doi: <https://doi.org/10.1016/j.jfineco.2021.08.004>.
- D. E. Tyler. A distribution-free M -estimator of multivariate scatter. *The annals of Statistics*, 15(1):234–251, 1987. doi: DOI:10.1214/aos/1176350263.
- United Nations. International Recommendations for Energy Statistics, Department of Economic and Social Affairs, Statistical Papers, Series M, 93, 2018.
- R. Vermeulen, E. Schets, M. Lohuis, B. Kölbl, D.-J. Jansen, and W. Heeringa. The heat is on: A framework for measuring financial stress under disruptive energy transition scenarios. *Ecological Economics*, 190(1–11), 2021. doi: <https://doi.org/10.1016/j.ecolecon.2021.107205>.
- T. Wang and P. Bansal. Social responsibility in new ventures: Profiting from a long-term orientation. *Strategic Management Journal*, 33(10):1135–1153, 2012. doi: <https://doi.org/10.1002/smj.1962>.
- E. Watson, A. Chang, A. Carrillo Pineda, C. Anderson, C. Cummis, and M. Stevenson. SBTi corporate Net Zero standard. Technical report, Science Based Targets Initiative, 2023.
- C. Weber and P. Faria. Foundations of science-based target setting. Technical report, SBTi, 2019.
- M. L. Weitzman. Fat-tailed uncertainty in the economics of catastrophic climate change. *Review of Environmental Economics and Policy*, 5(2):275–292, 2011.
- D. Welsby, J. Price, S. Pye, and P. Ekins. Unextractable fossil fuels in a 1.5°C world. *Nature Climate Change*, 597:230–234, 2021. doi: <https://doi.org/10.1038/s41586-021-03821-8>.
- E. Wigner. Characteristic vectors of bordered matrices with infinite dimensions. *Annals of Mathematics*, 62(3):548–564, 1955. doi: <https://doi.org/10.2307/1970079>.
- O. D. Zerbib. A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. *Review of Finance*, 26(6):1345–1388, 2022.

doi: <https://doi.org/10.1093/rof/rfac045>.

S. Zhang. Carbon returns across the globe. *Journal of Finance*, pages 1–32, 2024. doi: <https://doi.org/10.1111/jofi.13402>.



RÉSUMÉ

Cette synthèse est organisée de la manière suivante : dans un premier temps, je présente les motivations de ce travail en mettant en avant l'urgence du changement climatique au XXI^e siècle et le rôle critique du secteur financier pour relever ce défi. Après avoir détaillé les principaux objectifs de ce travail, je présenterai ensuite les contributions des trois chapitres qui constituent la thèse.

5.1 Motivations

En 1958, l'américain Charles David Keeling a commencé à mesurer quotidiennement la concentration en dioxyde de carbone atmosphérique (CO_2) depuis l'observatoire de Mauna Loa ; en plus d'identifier une variabilité saisonnière du CO_2 atmosphérique, il a observé que cette concentration augmentait en raison des activités humaines. En 1969, lors d'un symposium sur la pollution atmosphérique (Keeling, 1970), il a présenté ses découvertes et conclu par l'avertissement suivant :

« Si l'humanité survit jusqu'au XXI^e siècle, avec l'augmentation de la population qui semble maintenant inévitable, les gens de cette époque devront probablement faire face, en plus d'autres troubles, à la menace d'un changement climatique provoqué par une augmentation incontrôlée du CO_2 atmosphérique issu des combustibles fossiles. »

Soixante ans plus tard, le consensus scientifique selon lequel le changement climatique est principalement dû aux activités humaines est bien établi. Bien que Charles D. Keeling ait prédit que la plupart des gens ne verraient pas les conséquences du changement climatique de leur vivant, nous avons depuis identifié des impacts importants qui deviennent de plus en plus graves et fréquents. Il est maintenant urgent d'accélérer les efforts pour atténuer le changement climatique et s'adapter à ses effets. Dans le dernier rapport d'évaluation du Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC), plusieurs impacts potentiels menacent l'économie à moyen et long terme (Lee and Romero, 2023). Par exemple, les rendements agricoles pourraient diminuer jusqu'à 20% d'ici 2050, et entre 1 et 3 milliards de personnes pourraient faire face chaque année à des températures extrêmes (épisodes de canicule) si la température moyenne à la surface de la planète augmente de 2°C.

La mise en place de politiques d'adaptation et d'atténuation requiert une transformation importante de l'économie mondiale. L'objectif principal est de réduire drastiquement la consommation de énergies fossiles, qui représente actuellement 75% du mix énergétique

mondial. Cette transition vers une économie bas-carbone implique une métamorphose des modèles économiques et des systèmes de production. L'intensité et la vitesse de cette transition joueront un rôle crucial pour déterminer les risques et opportunités auxquels les entreprises seront confrontées. Dans ce contexte, les scénarios climatiques sont des outils précieux, reliant les facteurs socio-économiques aux émissions de gaz à effet de serre (GES) et, par conséquent, à l'ampleur du réchauffement climatique.

5.1.1 Scénarios climatiques et budget carbone

Les scénarios climatiques sont des outils essentiels qui aident les décideurs à projeter des futurs possibles en fonction de leurs décisions économiques. Depuis le début du XXI^e siècle, les chercheurs ont développé des modèles avancés pour projeter l'évolution du système climatique à partir d'un ensemble de paramètres. Les modèles du GIEC adoptent une double approche : d'abord, les Representative Concentration Pathways (RCPs, [Pachauri and Meyer \(2014\)](#)) utilisent des modèles climatiques pour prévoir les données climatiques (changement de température de surface, schémas de précipitations, etc.) à partir du forçage radiatif¹, qui provient lui-même de l'augmentation des émissions de GES. Les trajectoires socio-économiques partagées (SSPs) fournissent une approche complémentaire en projetant l'évolution de paramètres socio-économiques, comme la population, la croissance économique, le commerce international, les conflits, l'innovation technologique, etc., tout au long du XXI^e siècle et prédisent ainsi le niveau d'émissions de GES. Ensemble, les RCPs et les SSPs déterminent l'évolution du système climatique selon les choix sociaux, économiques et politiques que nous faisons.

¹Le forçage radiatif est défini comme le changement du flux radiatif (en $W.m^2$) dû à une modification d'un facteur externe du changement climatique, tel qu'un changement de la concentration de dioxyde de carbone (CO_2), de la concentration d'aérosols volcaniques ou de la production solaire (voir la définition du GIEC dans le glossaire).

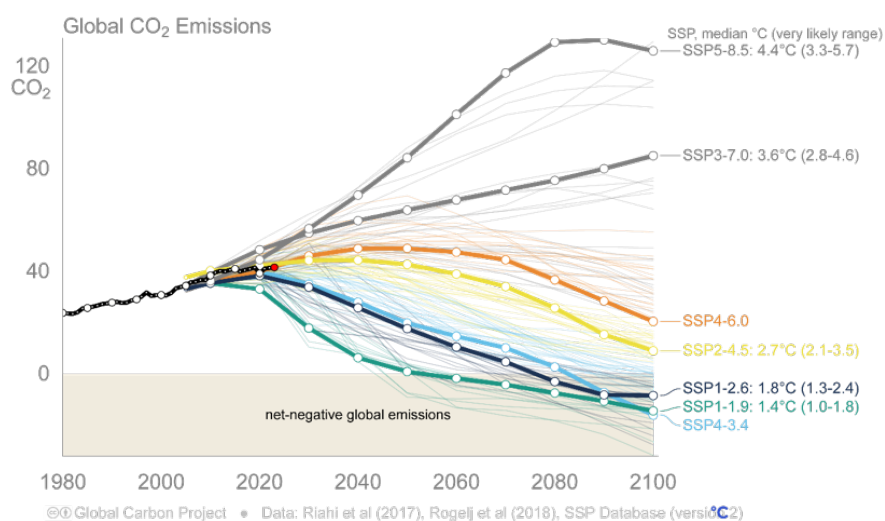


Figure 5.1: Émissions mondiales de CO_2 de la base de données des trajectoires socio-économiques partagées. Source : Global Carbon Project

La Figure 5.1 montre une gamme de futurs possibles en fonction de différentes combinaisons de SSPs et de RCPs. Certains SSP, comme le SSP 5 ou le scénario de "développement des énergies fossiles", conduisent à une forte augmentation des émissions mondiales de GES et à un réchauffement global de 3°C à 5°C d'ici 2100, selon le RCP. D'autres scénarios, tels que le SSP 1 avec des RCP correspondants de 2,6 W.m² ou 1,9 W.m², entraînent une forte baisse des émissions de GES dès 2020, avec des émissions nettes négatives dès 2080 ou plus tôt. Le scénario du statu quo est le SSP 2-4.5 où les émissions suivent la tendance passée, entraînant probablement un réchauffement global de 4°C d'ici la fin du XXIe siècle.

Depuis la seconde moitié du XXe siècle, les scientifiques alertent sur les impacts du changement climatique et la nécessité de mettre en place des politiques ambitieuses d'atténuation et d'adaptation. Les coalitions internationales n'ont cependant commencé à aborder ce sujet qu'à la fin du XXe siècle, avec la création du GIEC et des Conférences des Parties (COPs). En 2015, l'Accord de Paris ou COP 21 a été une étape majeure dans la lutte contre le changement climatique : 195 pays se sont engagés à limiter le réchauffement climatique bien en dessous de +2°C d'ici la fin du XXIe siècle. Cela implique des efforts continus et importants pour réduire les émissions de gaz à effet de serre couvertes par le Protocole de Kyoto : dioxyde de carbone, méthane, protoxyde d'azote (N_2O), hydrofluorocarbones, perfluorocarbones, hexafluorure de soufre, et trifluorure d'azote. Dans le sillage de l'Accord de Paris est apparue la notion de budget carbone, popularisée par des institutions telles que le Global Carbon Project ou le Mercator Research Institute on Global Commons and Climate Change. Le budget carbone est utile pour définir une trajectoire de transition bas-carbone qui limite le réchauffement climatique à moins de 2°C. Le terme « budget carbone » fait référence à

deux concepts dans la littérature [Lee and Romero \(2023\)](#) :

- *Le budget carbone global* : Somme de toutes les sources et puits de carbone au niveau mondial. La production des énergies fossiles et le changement d'utilisation des terres sont les deux principales sources de carbone, tandis que les océans et la végétation constituent les deux principaux puits de carbone naturels. Lorsqu'il y a un déséquilibre entre les sources et les puits de carbone, la concentration atmosphérique de CO_2 augmente : c'est ce qu'on appelle le déséquilibre du budget carbone. Le Global Carbon Project évalue le budget carbone global chaque année.
- *Le budget carbone restant* : À partir d'une date spécifiée, la quantité cumulative restante d'émissions nettes mondiales anthropiques de CO_2 permettant de limiter le réchauffement climatique à un certain niveau avec une probabilité donnée. En d'autres termes, le budget carbone restant représente la quantité restante que les activités humaines peuvent émettre dans le futur tout en limitant le réchauffement climatique à une certaine température. Dans le reste de cette thèse, lorsque nous mentionnons le terme « budget carbone », nous faisons référence à ce second concept : le budget carbone restant.

Le Global Carbon Project [Friedlingstein et al. \(2023\)](#) a estimé qu'à partir de 2024, « le budget carbone restant pour limiter le réchauffement climatique à 1,5°C, 1,7°C et 2°C est de 275 GtCO₂, 625 GtCO₂ et 1150 GtCO₂ respectivement, soit l'équivalent de 7, 15 et 28 ans à partir de 2024 ». Cela laisse une fenêtre de temps réduite et nécessite l'implication des secteurs public et privé pour accélérer la transition vers une économie bas-carbone.

5.1.2 Implication du secteur financier

La transition vers une économie bas-carbone est cruciale pour atténuer les impacts du changement climatique et nécessite des efforts importants du secteur privé. Cette transition affecte le secteur financier par le biais d'un concept appelé double matérialité [Baumüller and Sopp \(2022\)](#) : le système financier fait face à des risques liés à la fois aux impacts du changement climatique et à la transformation de l'économie dans le cadre de la transition bas-carbone ([Battiston et al. \(2017\)](#); [Mercure et al. \(2018\)](#), voir section 1.2.2); mais le secteur financier a aussi un impact sur le système climatique par la destination des flux de capitaux. En conséquence, les investisseurs font face à un double devoir fiduciaire : ils doivent limiter l'exposition de leurs actifs aux risques climatiques tout en orientant leurs investissements vers des entreprises à faible impact sur le climat, ou des entreprises en transition vers des activités économiques à faible impact ([Campiglio and van der Ploeg, 2022](#)). Les investissements dans l'énergie et les technologies bas-carbone et les solutions d'économie d'énergie sont souvent regroupés sous le terme “finance verte” et représentent des opportunités sig-

nificatives. Ainsi, les décisions prises par les entreprises pour réduire leur exposition aux risques climatiques et poursuivre la transition bas-carbone deviennent des facteurs cruciaux pour les investisseurs lorsqu'ils déterminent leurs allocations.

Depuis l'Accord de Paris de 2015, qui a souligné la nécessité de diriger les flux de capitaux vers la réduction des émissions de GHG, le secteur financier s'adapte de plus en plus à la transition bas-carbone. Des progrès significatifs ont été réalisés en finance verte : les flux financiers ont augmenté, et les canaux par lesquels les investissements sont réalisés se sont diversifiés (Lee and Romero, 2023). Selon l'Agence Internationale de l'Énergie, les investissements dans les énergies bas-carbone se sont élevés à 1,74 trillion de dollars en 2023, tandis que les investissements dans les énergies fossiles diminuent lentement depuis 2015, bien qu'ils restent élevés à 1,05 trillion de dollars. La plupart des investissements sont axés sur l'atténuation du changement climatique. L'écart d'investissement entre les énergies bas-carbone et les énergies fossiles augmente constamment, en raison d'une forte baisse des coûts des énergies bas-carbone (notamment les énergies renouvelables comme l'éolien ou le solaire) entre 2014 et 2020. Le secteur financier privé joue un rôle important dans le financement de la transition (625 milliards USD en 2023), cependant, les flux financiers sont très concentrés géographiquement (Asie de l'Est, Amérique du Nord et Europe) et restent insuffisants pour permettre la transition vers un scénario bien en-dessous de 2°C (Buchner et al., 2023).

Il est essentiel de guider les investisseurs vers des solutions bas-carbone tout en éliminant progressivement les activités économiques à fortes émissions. En parallèle, il est crucial de maintenir la stabilité du système financier. La déstabilisation de ce dernier peut survenir en cas de progrès insuffisants ou d'ajustements trop brutaux : si les agents économiques ne prennent pas des mesures suffisantes d'atténuation et d'adaptation aux impacts du changement climatique, les risques de pertes financières sont considérables (Battiston et al. (2017)). Cependant, si les régulateurs contraignent les investisseurs à réorienter leurs investissements de manière trop brutale, cela crée des actifs échoués (Semieniuk et al., 2022) et menace la stabilité financière et économique mondiale. Les actifs échoués sont des ressources et infrastructures qui, à l'avenir, pourraient ne plus être utilisées et devenir des passifs avant la fin de leur durée de vie économique prévue (Welsby et al., 2021).

Depuis 2015, plusieurs organisations ont été créées pour aider les investisseurs à aligner leurs investissements avec la transition bas-carbone : premièrement, une coalition de banques centrales a créé le Network for Greening the Financial System (NGFS) en 2017, qui

publie des rapports réguliers soulignant l'impact du risque climatique sur la stabilité du système financier (for [Greening the Financial System, 2024](#)). Le Task Force on Climate-related Financial Disclosures (TCFD) a été créé par le Conseil de Stabilité Financière en 2015, dans le but de fournir des indicateurs normalisés pour le reporting des données liées au climat pour les institutions financières. Le TCFD a depuis fusionné avec l'International Sustainability Standards Board, avec pour objectif de d'amener le reporting des indicateurs de durabilité au même niveau que le reporting financier traditionnel. Le secteur privé a également mobilisé des ressources pour orienter les investissements vers la transition bas-carbone : la Glasgow Financial Alliance for Net Zero (GFANZ), créée en 2023, est une coalition de PDG du secteur financier qui partagent les meilleures pratiques et connaissances technologiques pour accélérer la transition. En effet, certains des principaux défis pour les investisseurs sont l'identification et la mesure du risque climatique, de ses impacts sur les portefeuilles financiers, et l'évaluation de l'ampleur des réponses des entreprises en matière d'atténuation et d'adaptation climatique. Les préférences climatiques des investisseurs sont également un facteur important dans l'allocation de capital. La littérature académique sur ces sujets a donc fortement augmenté au cours des dix dernières années.

5.2 Objectifs de la thèse

Dans cette thèse, nous cherchons à améliorer la mesure des risques de transition climatique en utilisant des approches à la fois théoriques et empiriques.

Le premier objectif est d'améliorer la mesure du risque de transition en construisant un facteur Brown-minus-Green (BMG) qui s'appuie sur le sentiment des investisseurs, lui-même reflété dans les prix des actifs. Par nature, ce facteur sera plus dynamique qu'un facteur construit à partir de données climatiques fondamentales. La création de ce facteur BMG permettra de construire un portefeuille couvert contre les risques de transition.

Le deuxième objectif est de contribuer à l'amélioration des modèles d'évaluation d'actifs en intégrant des primes de risque climatique (risque de transition et risque de responsabilité) dans ces modèles et en vérifiant empiriquement l'existence de risques de transition climatique idiosyncratiques et systémiques dans les prix des actions.

Le troisième objectif se concentre sur la notion de trajectoires ou objectifs bas-carbone, en l'abordant d'un point de vue théorique et empirique. Nous souhaitons apporter une contribution théorique à la question des ambitions climatiques des entreprises, et nous cher-

chons à clarifier le rôle des investisseurs dans leur rôle d’incitateurs pour les entreprises à atténuer leurs risques futurs. En outre, nous cherchons à développer des notations qui évaluent la qualité, l’ambition et la crédibilité des objectifs bas-carbone ; l’impact des indicateurs de performance financière et climatique fondamentaux d’une entreprise sur l’ambition et la crédibilité d’un objectif bas-carbone (avant et après l’annonce d’un objectif) doit être explorée. Cela pourrait fournir aux investisseurs une indication de la stratégie d’atténuation réelle des entreprises et les aider à identifier les entreprises susceptibles de réaliser des objectifs bas-carbone ambitieux.

Notre dernier objectif est d’aider les investisseurs à construire des portefeuilles couverts contre les risques de transition climatique actuels et futurs : en utilisant différentes méthodologies pour mesurer le risque de transition climatique, nous souhaitons construire des portefeuilles à la fois diversifiés et thématiques, centrés sur les entreprises les mieux adaptées à la transition bas-carbone.

5.3 Contributions principales

5.3.1 Chapitre 2 : identification d’un facteur brown-minus-green

Dans ce chapitre, nous cherchons à améliorer la mesure du risque de transition systématique en construisant un facteur brown-minus-green à partir de signaux de prix. Nous isolons les signaux de prix d’indices qui suivent les leaders en matière de réduction du risque de transition. En utilisant des modèles statistiques multifactoriels (Rosenberg, 1974), nous construisons une tendance de prix qui isole les signaux de marché d’atténuation du risque climatique : nous utilisons la matrice de covariance de ces indices avec la théorie des matrices aléatoires (RMT) (Wigner, 1955). Le facteur brown-minus-green est construit à partir des sensibilités des prix des actions par rapport à cette tendance d’atténuation du risque climatique.

Identification d’une tendance de marché climatique

Nous considérons un nombre m d’indices écologiques composés d’entreprises ayant la plus faible exposition au changement climatique. Soit $\mathbf{r}_t = (r_t(1), r_t(2), \dots, r_t(m))'$ le vecteur de rendements quotidiens à m dimensions des m indices écologiques. Nous supposons également que \mathbf{r}_t admet une structure de K facteurs, où les $K < m$ facteurs communs sont inconnus, mais l’un d’eux est une “tendance de marché climatique”. Le modèle proposé

pour \mathbf{r}_t est le suivant :

$$\mathbf{r}_t = \mathbf{B}_t \mathbf{f}_t + \boldsymbol{\epsilon}_t \quad (5.1)$$

où \mathbf{r}_t est le vecteur des rendements à l'instant t , \mathbf{B}_t est la matrice $m \times K$ des sensibilités des indices à chaque facteur au moment t , \mathbf{f}_t est le vecteur K de facteurs supposées communes à tous les indices, et $\boldsymbol{\epsilon}_t$ est un vecteur de bruits blancs gaussiens avec des variances σ^2 , non corrélés aux facteurs.

D'après l'équation (2.1), la matrice de covariance à l'instant t s'exprime par :

$$\mathbf{C}_t = \mathbf{B}_t \mathbf{C}_t^f \mathbf{B}_t' + \boldsymbol{\Omega}_t$$

où $\mathbf{C}_t^f = \mathbb{E}[\mathbf{f}_t \mathbf{f}_t']$ est le terme lié aux facteurs et $\boldsymbol{\Omega}_t$ est la matrice de covariance de $\boldsymbol{\epsilon}_t$. Dans le cas où les facteurs sont connus *a priori*, nous nous intéressons uniquement à l'estimation de \mathbf{B}_t et $\boldsymbol{\epsilon}_t$. Dans notre cas, cependant, les facteurs sont inobservables et doivent être déterminés à partir des m indices écologiques.

Nous utilisons deux estimateurs de la matrice de covariance : la matrice de covariance empirique (SCM), optimale pour des échantillons gaussiens multivariés. Cependant, en modélisation financière, les rendements sont non gaussiens : ils sont asymétriques, avec queues épaisses et dépendance de queue (Mandelbrot, 1963; Fama, 1965; Cont, 2001). Nous utilisons donc aussi un estimateur de matrice de covariance robuste, l'estimateur de Tyler-M (Tyler, 1987) :

$$\widehat{\mathbf{C}}_{tyl} = \frac{m}{T} \sum_{t=1}^T \frac{\mathbf{r}_t \mathbf{r}_t'}{\mathbf{r}_t' \widehat{\mathbf{C}}_{tyl}^{-1} \mathbf{r}_t}$$

où $Tr(\widehat{\mathbf{C}}_{tyl}) = m$.

En utilisant la théorie des matrices aléatoires (RMT) (Wigner, 1955), nous identifions les K plus grandes valeurs propres de $\widehat{\mathbf{C}}_{tyl}$, supposées représenter les K facteurs. Nous utilisons les valeurs propres au-dessus du seuil de Marčenko-Pastur (MP) (Marčenko and Pastur, 1967) pour isoler les facteurs d'intérêt.

Nous testons empiriquement l'existence d'une tendance de marché climatique en sélectionnant des indices thématiques centrés sur des thèmes écologiques et, en particulier, sur

la transition bas-carbone : énergie propre, gestion de l'eau, et conformité aux politiques de transition bas-carbone. Pour les deux estimations de la matrice de covariance des rendements de ces indices (SCM et Tyler-M), nous isolons la première valeur propre comme la seule au-dessus du seuil MP. Nous cherchons ensuite à confirmer que le vecteur propre (ou facteur) associé représente bien une tendance de marché climatique. Nous observons que la tendance est fortement corrélée aux indices utilisés pour la construire, avec une corrélation beaucoup plus faible par rapport au facteur de marché, ce qui montre que les premiers facteurs reflètent une tendance spécifique, différente du marché, que nous appelons "tendance de marché climatique". De plus, les premiers facteurs des matrices de covariance SCM et Tyler-M présentent une corrélation de plus de 99% en toutes périodes, ce qui suggère que les deux premiers facteurs capturent une information similaire. Nous sélectionnons le facteur construit à partir de la matrice de covariance Tyler-M pour construire un facteur BMG. La tendance de marché climatique couvre la période de septembre 2010 à septembre 2022.

Construction des facteurs Brown-minus-Green

Nous passons ensuite à la construction d'un facteur BMG en mesurant la sensibilité des prix des actions à la tendance de marché climatique. Nous utilisons le modèle de régression suivant pour séparer les actions vertes des actions brunes :

$$r_i(t) = \alpha_i + \beta_{m,i}r_m(t) + \beta_{g,i}r_g(t) + \beta_{ind,i}r_{ind}(t) + \epsilon_i(t)$$

où $r_i(t)$ est le rendement quotidien de l'action i à la date t , $r_m(t)$ le rendement de marché, $r_g(t)$ le rendement de la tendance de marché climatique, et $r_{ind}(t)$ est le rendement sectoriel². Les sensibilités aux facteurs de marché, de tendance climatique et de secteur sont notées respectivement β_m , β_g , et β_{ind} . $\epsilon_i(t)$ est le terme d'erreur. Les régressions sont effectuées en utilisant la fonction de perte de Huber (Huber, 1964; Rousseeuw and Leroy, 1987) pour estimer le facteur BMG avec une régression robuste, afin de prendre en compte le caractère non gaussien des rendements d'actions.

Nous réalisons 47 régressions trimestrielles (de mars 2011 à septembre 2022) avec une fenêtre de 130 rendements quotidiens passés pour les actions de l'indice MSCI® World qui appartiennent aux secteurs les plus exposés à la transition bas-carbone (secteurs à fort impact climatique). À chaque trimestre, en utilisant les coefficients de la régression, nous créons un portefeuille vert et un portefeuille brun définis comme suit :

²Nous utilisons le premier niveau de la Global Industry Classification Standard (GICS® Sectors).

- Le portefeuille trimestriel vert détient les actions ayant une sensibilité strictement positive aux rendements de la tendance de marché climatique, avec un intervalle de confiance de 5% ; s'il y a un nombre élevé d'actions dans ce cas, nous sélectionnons les 30% des actions ayant la plus haute sensibilité.
- Le portefeuille trimestriel brun détient les actions ayant une sensibilité strictement négative aux rendements de la tendance de marché climatique, avec un intervalle de confiance de 5% ; s'il y a un nombre élevé d'actions dans ce cas, nous sélectionnons les 30% des actions ayant la plus faible sensibilité.

La performance du facteur BMG est présentée dans le graphique 5.2.

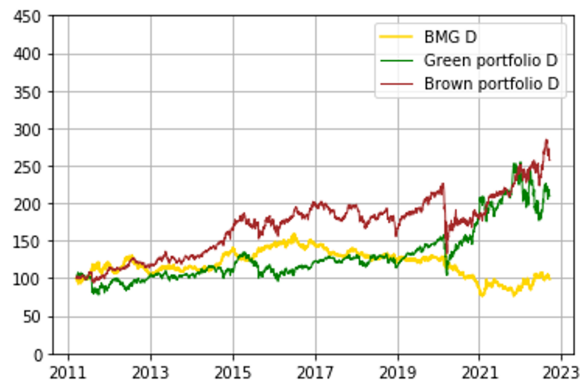


Figure 5.2: Performance cumulée du facteur BMG, portefeuilles brun et vert. Les performances sont montrées pour les prix quotidiens entre mars 2011 et septembre 2022.

Pertinence du facteur Brown-minus-Green

Pour tester la pertinence du facteur BMG, nous introduisons les différents facteurs BMG dans les modèles d'évaluation d'actifs et observons le R^2 ajusté des régressions. Les résultats montrent que le facteur BMG améliore significativement le pouvoir explicatif des modèles factoriels : on observe une augmentation de 3,77 points de pourcentage entre le CAPM (Markowitz, 1956) et le modèle CAPM + BMG. Ce résultat se confirme pour le modèle à trois facteurs de Fama-French (Fama and French, 1995) et le modèle de Carhart (Carhart, 1997), le facteur BMG augmentant le R^2 ajusté moyen de 2,79 et 2,36 points de pourcentage respectivement.

Nous observons également la corrélation entre le facteur BMG et les autres facteurs du modèle de Carhart : le marché (Mkt), le facteur size (SMB), le facteur value (HML) et le momentum (WML). Nous constatons que le facteur BMG est quasiment décorrélié du

facteur de marché, ce qui peut être très utile pour des objectifs de diversification. La corrélation du facteur BMG avec les facteurs size et momentum est relativement faible : il y a, en moyenne, une corrélation de 20% entre le facteur BMG et le facteur size, ce qui est inférieur à ce qui a été observé dans d'autres études sur les facteurs BMG (Gorgen et al., 2020; Roncalli et al., 2020). L'effet le plus élevé que nous trouvons concerne le facteur value, ce qui peut s'expliquer en partie par la méthodologie de construction du facteur BMG, qui se concentre sur les secteurs à fort impact climatique.

Nous comparons ensuite notre facteur BMG à d'autres facteurs construits précédemment dans la littérature. Nous observons une faible corrélation avec les facteurs BMG construits en utilisant la performance en matière d'émissions de GES (Roncalli et al., 2020) ou les notations climatiques des fournisseurs de données (Gorgen et al., 2020). Globalement, le profil de performance et de volatilité de notre facteur est très différent et plus cohérent avec les prédictions théoriques (Pástor et al., 2021; Pedersen et al., 2021), qui stipulent qu'en l'absence de préoccupation pour le changement climatique, les actions brunes tendent à surperformer les actions vertes. Il apparaît également que sur la période 2017-2021, et surtout après la crise de Covid, les actions vertes ont commencé à surperformer les actions brunes. Cela est également en accord avec une autre conclusion théorique, selon laquelle les actions vertes surperforment les actions brunes en cas de choc climatique positif (Pástor et al., 2021). Nous montrons également que, globalement, notre facteur BMG améliore davantage le modèle d'évaluation d'actifs que les autres facteurs BMG.

Enfin, nous calculons une nouvelle mesure du risque de transition climatique des actions, en utilisant la sensibilité des prix au facteur BMG, que nous appelons le bêta climat β_C . Une action ayant un bêta climat négatif peut être considérée comme ayant une faible exposition au risque de transition climatique. Nous constatons que le bêta climat est significatif dans des secteurs qui sont habituellement difficiles à noter en raison d'un manque de données fondamentales : les secteurs des biens d'équipement, des matériaux, de l'énergie ou des services publics. Nous analysons également la dynamique des bêtas climat au sein des secteurs industriels et trouvons que, malgré la faible volatilité du bêta climat des industries, certains événements peuvent être à l'origine d'une augmentation ou d'une diminution de l'exposition au risque de transition. Notre bêta climat pourrait donc être utile pour noter les entreprises de manière plus dynamique que les données fondamentales, ou pour capturer des informations sur les actions difficiles à noter. Cela est particulièrement pertinent pour les entreprises habilitantes qui, par leurs activités, permettent à d'autres entreprises ou consommateurs de contribuer positivement aux objectifs environnementaux, tels que la réduction des émissions de GES. Nous trouvons que la plupart des entreprises habilitantes

ont une sensibilité négative au facteur BMG, ce qui signifie qu'une majorité de ces actions peuvent être considérées comme vertes. Contrairement aux autres facteurs BMG présentés dans la littérature, notre facteur BMG a le pouvoir explicatif le plus élevé. Les entreprises habilitantes sont donc plus exposées au risque de transition climatique que ce qui avait été observé précédemment.

En construisant un facteur BMG à partir d'une tendance de marché climatique, nous sommes donc en mesure de capturer le sentiment global des acteurs de marché quant à l'exposition au risque de transition climatique d'une action. De plus, nous pouvons fournir une mesure plus dynamique de l'exposition d'une action au risque de transition climatique. Ceci est particulièrement utile dans le contexte des données de performance extra-financières, qui ne sont pas à jour. La nouvelle mesure du risque climatique, le bêta climat, est accessible pour toute action et facilement comparable aux autres facteurs de marché tels que la taille ou la valeur. Le bêta climat devrait être considéré comme une métrique complémentaire permettant de capturer des informations supplémentaires par rapport aux données climatiques fondamentales, notamment en ce qui concerne les tendances dynamiques.

5.3.2 Chapitre 3 : scénarios climatiques et stratégies d'alignement des entreprises

Dans ce chapitre, nous apportons une contribution théorique à la littérature sur l'alignement des scénarios climatiques. Nous commençons par définir des objectifs bas-carbone pour les entreprises définis par un taux de décarbonation, lui-même associé à un budget carbone. En utilisant ces objectifs, nous construisons un modèle économique en deux phases, où, dans la première phase, les entreprises doivent prendre une décision stratégique quant à la réduction de leurs émissions, en s'engageant ou non à établir un objectif bas-carbone au taux de décarbonation de leur choix. La deuxième phase du modèle se concentre sur un groupe d'investisseurs soucieux de l'environnement qui font leurs allocations en fonction de leurs engagements. Les choix des entreprises et l'allocation des investisseurs fournissent des conditions d'équilibre de marché et des prix d'équilibre.

Considérons une économie avec un nombre M d'entreprises cotées en bourse. Le modèle se déroule selon la chronologie suivante :

1. *Phase d'évaluation* : dans cette phase, les entreprises choisissent de s'engager ou non à la mise en place d'un objectif bas-carbone. Si elles choisissent de s'engager, elles doivent décider d'un taux de décarbonation. Une entreprise choisit son objectif en fonction de sa capacité de décarbonation et du rendement escompté.

Nous supposons que, durant cette phase, les actions ne sont pas échangées et que les entreprises émettent une quantité négligeable de gaz à effet de serre afin de ne pas modifier le budget carbone de l'économie. À la fin de cette phase, les entreprises annoncent publiquement leurs objectifs bas-carbone.

2. *Phase opérationnelle* : cette phase commence à $t = 0$ lorsque les investisseurs prennent leurs décisions d'allocation en fonction des objectifs bas-carbone et de leurs préférences financières. Pendant cette phase, les entreprises ayant choisi des objectifs réduisent leurs émissions.
3. À $t = 1$, les objectifs bas-carbone sont atteints si les entreprises ont réduit leurs émissions de manière continue au taux choisi. Le budget carbone est respecté si toutes les émissions ont été réduites au taux de référence. Toutes les actions sont alors vendues à d'autres investisseurs.

Objectifs bas-carbone des entreprises

Pour une entreprise j , nous définissons un objectif bas-carbone comme l'objectif de réduction de ses émissions selon un taux de décarbonation $\tau_j \in [0, 1[$:

$$\text{Pour } t \in [0, T] : e_{j,t} = e_{j,0}(1 - \tau_j)^t$$

où $e_{j,0}$ est le niveau d'émissions initial. L'objectif bas-carbone d'une entreprise est donc caractérisé par un seul paramètre, τ_j .

Les entreprises peuvent être classées en trois catégories selon le type d'objectif qu'elles choisissent :

- **Type B** : les entreprises choisissent de s'engager à un objectif bas-carbone en sélectionnant le taux de décarbonation de référence : $\tau_j = \tau_B$.
- **Type H** : les entreprises choisissent un objectif dépendant de leur capacité de décarbonation : $\tau_j = (a_j + \kappa)^2$ avec $0 < \kappa \ll 1$.
- **Type N** : les entreprises choisissent de ne pas s'engager à un objectif bas-carbone : $\tau_j = 0$.

La capacité de décarbonation d'une entreprise, a_j , représente sa capacité à réduire ses émissions. Elle peut être modélisée par un ensemble de paramètres (tels que la gouvernance de l'entreprise en matière de stratégie climatique, les technologies vertes développées par l'entreprise, ses ressources financières, et la tendance historique des émissions directes et indirectes) réunis sous une seule variable.

Décisions des entreprises et des investisseurs

La phase d'évaluation se concentre sur la décision des entreprises quant à la mise en place d'un objectif bas-carbone. Nous supposons que le chiffre d'affaires attendu pour l'entreprise j dépend de l'objectif choisi : nous représentons le changement de demande client par un facteur de croissance qui diffère pour les actions de type B, type H et type N :

$$E[\pi_{1,j}] = \begin{cases} \pi_{0,j}(1 + g_j^H + \lambda_j \tau_j) & \text{pour les types H} \\ \pi_{0,j}(1 + g_j^B + \lambda_j \tau_j) & \text{pour les types B} \\ \pi_{0,j}(1 + g_j^N) & \text{pour les types N} \end{cases} \quad (5.2)$$

$\pi_{0,j}$ et $\pi_{1,j}$ sont les chiffres d'affaires de l'entreprise j aux temps 0 et 1. Pour toutes les entreprises, g_j^K avec $K \in \{H; B; N\}$ est le taux de croissance marginal des bénéfices et peut être positif ou négatif. $\lambda_j \tau_j$ est un taux de croissance supplémentaire reflétant l'augmentation de la demande client pour des produits d'entreprises ayant réduit significativement leurs émissions ; il dépend de la probabilité de réussite λ_j .

Nous montrons que lorsqu'une entreprise doit décider d'un objectif, il existe un seuil de capacité a^* au-delà duquel les entreprises sélectionnent systématiquement un objectif de type H. Les entreprises de capacité inférieure à ce seuil a^* choisiront d'être de type B si le coût d'opportunité (perte de productivité) n'excède pas la récompense potentielle en profit (augmentation des ventes) obtenue en atteignant leur objectif.

Dans la phase opérationnelle, nous supposons que les investisseurs effectuent leurs décisions d'allocation en maximisant leur utilité espérée (Pástor et al., 2021; Avramov et al., 2022) :

$$U(w_i, \mathbf{x}_i) = -e^{-\gamma_i w_i - \frac{\delta_i}{\tau_B} \mathbf{x}_i' \boldsymbol{\tau}}$$

où γ_i est l'aversion relative au risque, w_i est le rendement brut du portefeuille à $t = 1$, δ_i est la préférence climatique, et le vecteur $\boldsymbol{\tau}$ est un vecteur contenant les taux de décarbonation choisis par les M entreprises sous-jacentes du portefeuille.

Nous supposons que le rendement d'une action suit une structure de type CAPM (Capital Asset Pricing Model) à laquelle nous ajoutons une prime de risque climatique :

$$r_j = \beta_{mkt,j} r_{mkt} + \tilde{r}_j + \epsilon_j = r_{j,capm} + \tilde{r}_j + \epsilon_j$$

où $\beta_{mkt,j}$ est la sensibilité de l'actif j au rendement du marché r_{mkt} , \tilde{r}_j est la prime de risque climatique, et ϵ_j est une variable suivant une distribution normale de moyenne 0 et de variance σ_j^2 .

La prime de risque climatique d'une action dépend du type d'objectif choisi :

$$\tilde{r}_j = \begin{cases} \tilde{r}_H = (1 - \lambda(1 - \tau_B)) \rho_H^T & \text{pour les entreprises de type H} \\ \tilde{r}_B = (1 - \lambda) \rho_B^T & \text{pour les entreprises de type B} \\ \tilde{r}_N = \rho_N^T + \rho_N^R & \text{pour les entreprises de type N} \end{cases}$$

La structure de la prime de risque climatique reflète l'exposition future attendue aux risques liés au climat. Dans le cas des actions de type H et B, la prime de risque climatique est le produit de deux termes : la probabilité d'échec dans l'atteinte de l'objectif et un facteur de risque de transition spécifique à chaque type d'entreprise : ρ_H^T et ρ_B^T . La prime de risque climatique pour les actions de type H et B augmente lorsque la probabilité de succès est faible, les investisseurs exigeant une compensation pour une exposition plus élevée au risque climatique : des rendements plus élevés sont attendus quand la probabilité de succès est faible.

En maximisant l'utilité espérée, la demande de l'investisseur fournit les conditions d'équilibre de marché en association avec le choix des entreprises.

Équilibre de marché

Nous étudions l'équilibre de marché dans des conditions simplifiées : quand l'économie a deux entreprises, une de type B et une de type N, et quand l'économie compte trois entreprises, une de type H, une de type B et une de type N.

Lorsqu'il y a deux types d'actions dans l'économie (une entreprise de type B et une de type N), les entreprises ont de faibles capacités de décarbonation : cela signifie que les entreprises ne sont pas capables de réduire facilement leurs émissions (ce qui pourrait être le cas pour une industrie polluante) ou que le budget carbone est très limité, ce qui signifie que le taux de réduction de référence est très élevé. Nous trouvons que le nombre d'actions de type B est concave par rapport à τ_B , ce qui signifie qu'il peut y avoir un nombre maximum d'actions pour un taux de décarbonation donné. Cela marque l'existence d'un point de basculement pour le nombre d'entreprises engagées dans une démarche bas-carbone : si le taux de référence exogène est trop élevé, le nombre d'entreprises ayant les capacités suffisantes

pour atteindre l'objectif de référence diminue. La probabilité d'échec est plus élevée, ce qui pourrait nuire à la réputation de l'entreprise ; le nombre d'entreprises souhaitant devenir de type B plutôt que de type N est plus faible et n'est pas optimal.

Nous trouvons également des résultats intéressants en étudiant la prime de risque climatique des deux entreprises. Nous constatons que le facteur de risque climatique pour l'entreprise de type B est une fonction décroissante de τ_B , ce qui se traduit par un risque réputationnel plus élevé lorsque le taux de référence est faible si l'entreprise échoue à atteindre son objectif. Le facteur de risque climatique pour le type N n'est pas monotone mais convexe par rapport à τ_B et atteint un minimum lorsque le nombre d'actions de type B est le plus élevé. Cela marque l'existence de deux types de risque pour l'entreprise de type N : un risque réputationnel élevé lorsque le taux de référence est faible et un risque de transition élevé lorsque le taux de référence est élevé.

Les résultats diffèrent lorsque nous introduisons une troisième entreprise de type H dans l'économie (une entreprise de type H, une de type B et une de type N) : le nombre d'actions de type N devient concave par rapport à τ_B , et le nombre d'actions de type H est une fonction décroissante de τ_B et ne dépend pas des préférences des investisseurs. Le profil de la prime de risque climatique diffère également et est plus difficile à interpréter. Globalement, nous trouvons un compromis entre le risque de transition et le risque réputationnel d'une entreprise.

Nous procédons à des illustrations empiriques de notre modèle : l'objectif principal est d'identifier une prime de risque climatique associée aux stratégies d'alignement des entreprises. À l'aide de la base de données Science-Based Targets Initiative, nous trouvons des preuves limitées d'une prime de risque climatique pour les entreprises qui n'annoncent pas d'objectifs, en particulier dans les secteurs les plus exposés au risque climatique. Nous identifions également une prime qui dépend de l'alignement actuel de leurs émissions par rapport à un scénario bas-carbone, que nous obtenons via une base de données de notation de température.

Ce chapitre se concentre sur un sujet émergent dans la littérature académique, mais qui est néanmoins très populaire dans le secteur financier : les objectifs bas-carbone des entreprises. En abordant la question sous un angle théorique, nous mettons en lumière plusieurs mécanismes de marché qui pourraient influencer la composition du marché ou le risque financier des entreprises.

5.3.3 Chapitre 4 : moteurs et succès des stratégies bas-carbone

Ce dernier chapitre adopte une approche empirique pour comprendre et évaluer les mécanismes financiers sous-jacents liés aux stratégies bas-carbone des entreprises. Les objectifs bas-carbone étant devenus un outil de communication courant pour attirer les investisseurs, ils peuvent servir d'indicateur de l'exposition future d'une entreprise aux risques de transition. Toutefois, les investisseurs peuvent rencontrer des difficultés pour évaluer l'ambition d'un objectif bas-carbone (sa compatibilité avec un scénario macroéconomique bas-carbone) ainsi que sa crédibilité (si l'objectif est réalisable par l'entreprise). Identifier les moteurs financiers et extra-financiers derrière l'ambition et la crédibilité des objectifs bas-carbone pourrait également fournir des informations précieuses aux investisseurs, leur permettant d'anticiper si une entreprise fixe des objectifs ambitieux et si elle dispose de la capacité de les atteindre.

Une des principales difficultés dans l'analyse des objectifs bas-carbone des entreprises est leur superposition : une entreprise peut fixer plusieurs objectifs couvrant différents périmètres d'émissions, et elle peut également les actualiser avec différentes années de référence et années cibles. Nous commençons par définir un taux de décarbonation annuel pour chaque objectif, puis nous les agrégeons pour calculer un taux de décarbonation et un taux de réduction annuel pour chaque entreprise. Pour comparer ces objectifs, nous faisons référence à un scénario bas-carbone de l'Agence Internationale de l'Énergie (AIE), le Net-Zero Emissions (NZE) scenario. Nous construisons trois jeux de données sur les émissions :

- Les données "émissions ciblées" regroupe les émissions projetées si l'entreprise respecte ses objectifs ;
- Les données "émissions net-zéro" regroupe les émissions projetées compatibles avec le scénario NZE de l'AIE ;
- Les données "émissions historiques et tendanciennes" regroupe les émissions historiques de l'entreprise et projette les émissions futures si l'entreprise suit sa tendance passée.

Nous identifions également des facteurs fondamentaux qui peuvent influencer la décision d'une entreprise de fixer un objectif, lesquels peuvent changer une fois l'objectif annoncé et que l'entreprise commence à réduire ses émissions. Nous sélectionnons des ratios financiers comme variables explicatives dans notre modèle, et nous nous concentrons sur des mesures reflétant la performance de marché et la performance fondamentale des entreprises. Sur le plan financier, nous considérons la rentabilité, la solvabilité, et la valorisation pour mesurer la valeur d'une entreprise. Les mesures non-financières, en particulier

les mesures de performance climatique, sont également incluses en examinant les émissions de GES d'une entreprise par rapport à son secteur d'activité et à l'univers d'investissement, ainsi que la tendance de ces émissions. Notre objectif est d'identifier quelles mesures sont les principaux moteurs de l'ambition et du succès des objectifs bas-carbone. Nos données couvrent les entreprises de l'indice MSCI® World Index sur la période 2014-2024.

Nous proposons diverses mesures de l'ambition d'un objectif bas-carbone. Notre premier objectif est d'étudier la performance financière et extra-financière des entreprises avant leur engagement envers un objectif bas-carbone. Nous constatons que la rentabilité joue un rôle essentiel dans la décision d'une entreprise de s'engager sur un objectif ambitieux. En analysant l'évolution des facteurs financiers et extra-financiers avant l'engagement, nous trouvons des preuves que les entreprises en croissance de capitalisation boursière sont incitées à s'engager sur des objectifs ambitieux, et que cet engagement peut être une stratégie pour continuer d'attirer des investisseurs. En ce qui concerne les mesures de performance climatique, nous observons que les engagements les plus ambitieux sont généralement réalisés par les entreprises les moins polluantes, une observation cohérente avec la littérature précédente, mais qui n'est pas totalement alignée avec les efforts requis par les scénarios bas-carbone recommandés par les institutions.

Nous mesurons ensuite la crédibilité des objectifs bas-carbone en comparant les émissions historiques et les tendances d'émissions. Notre analyse révèle une hétérogénéité entre les secteurs d'activité : dans certains secteurs, rester en dessous du scénario NZE est plus facilement réalisable, ce qui permet aux entreprises de dépasser leurs propres objectifs et de rester en avance en termes de budget net-zéro. Dans d'autres secteurs, les émissions historiques dépassent déjà le scénario NZE ou même les objectifs de l'entreprise, ce qui suggère que la réussite d'une entreprise à atteindre son objectif n'est pas uniforme et peut affecter son risque réputationnel.

En examinant les moteurs financiers et climatiques influençant la réalisation des objectifs, nous constatons des résultats différents de ceux observés pour l'ambition des objectifs. Plus précisément, nous observons que les entreprises ayant une rentabilité plus faible sont plus susceptibles d'atteindre leurs objectifs, et les entreprises qui augmentent leur levier (Dette Nette/EBITDA) tendent également à réaliser leurs objectifs. Nous notons également un impact positif du ratio CAPEX/Ventes sur la réalisation des objectifs, suggérant que les entreprises performantes cherchent activement à investir dans leurs efforts de réduction après s'être fixées des objectifs.

Ce chapitre conclut par la construction de portefeuilles alignés sur le net-zéro : un portefeuille constitué d'entreprises dont les ambitions sont alignées sur un scénario net-zéro (basé sur les émissions ciblées et les émissions net-zéro), et un autre constitué d'entreprises dont les émissions sont alignées sur un scénario net-zéro. Bien que les profils de performance et de risque des portefeuilles soient similaires, leur composition diffère considérablement : sélectionner des entreprises avec des objectifs ambitieux ne garantit pas que le portefeuille restera aligné sur le net-zéro à l'avenir.

Ce chapitre contribue à la littérature sur l'exposition future au risque de transition des entreprises. Les mesures d'ambition et de crédibilité des objectifs bas-carbone peuvent être des outils utiles pour les investisseurs, les aidant à détecter les pratiques de greenwashing. De plus, nous identifions divers moteurs de performance financière et climatique qui indiquent quelles entreprises sont les plus susceptibles de fixer des objectifs ambitieux ou ont une plus grande probabilité de les atteindre. Cette approche complète la littérature sur la relation entre performance financière et risque climatique, en se concentrant sur les fondamentaux d'une entreprise (plutôt que sur le prix de l'action) et sur son exposition future au risque climatique.

5.4 Conclusion

L'objectif de cette thèse était d'améliorer la mesure du risque de transition climatique. Nous nous sommes concentrés sur l'utilisation de métriques alternatives aux données fondamentales de performance climatique, largement utilisées comme indicateurs de risque climatique dans la littérature et au sein de l'industrie financière. La mesure du risque de transition climatique par les signaux-prix fournit une métrique alternative de l'exposition actuelle des actions au risque de transition, tandis que les stratégies bas-carbone des entreprises peuvent être utilisées comme indicateurs de l'exposition future au risque de transition. Ces deux approches permettent de développer des méthodologies d'allocation de portefeuille, avec divers objectifs de diversification ou de performance financière.

Nous envisageons plusieurs prolongements à cette thèse. En ce qui concerne le facteur BMG, bien que nous ayons pu fournir une nouvelle mesure du risque de transition climatique, des travaux supplémentaires pourraient être menés pour décomposer ce risque et en améliorer la compréhension. En d'autres termes, quelles sont les informations de marché derrière les dynamiques du risque de transition (événement climatique, changement de poli-

tique, sous-thème de la transition bas-carbone, etc.) ? Cela pourrait être réalisé en utilisant une approche plus précise pour construire la tendance de marché climatique, par exemple en utilisant des fonds spécialisés dans un sujet particulier de la transition bas-carbone.

La question des plans de transition bas-carbone est essentielle pour mesurer l'exposition future au risque climatique, et les travaux entrepris dans les chapitres 3 et 4 devraient se poursuivre pour améliorer l'évaluation des performances des entreprises sur ce sujet. Cela est également utile pour les investisseurs, car un nombre croissant d'analystes financiers recherchent des outils d'évaluation pour mieux évaluer les stratégies bas-carbone. D'autres approches théoriques pourraient être envisagées pour définir un scénario climatique, ainsi que les mécanismes entre entreprises et investisseurs sur la question des stratégies bas-carbone. Par exemple, il serait possible de concevoir un modèle théorique sur l'engagement individuel et collaboratif des investisseurs envers les entreprises. Des études empiriques devraient également être poursuivies pour améliorer l'évaluation des plans de transition bas-carbone, qui ne se reflètent pas uniquement dans les objectifs. De nombreuses entreprises communiquent via des communiqués de presse lorsqu'elles annoncent des projets de réduction d'émissions. Des méthodologies telles que le Traitement Automatique du Langage Naturel (NLP) pourraient donc être envisagées pour fournir des informations complémentaires aux objectifs bas-carbone.

Enfin, le risque de réputation d'une entreprise devient un enjeu important : il existe un coût à l'annonce d'un plan de transition bas-carbone, surtout si l'entreprise, en raison de facteurs internes ou macroéconomiques, a peu de chances de l'atteindre. Cela se traduit par un risque financier qui devrait être séparé du risque de transition et évalué plus précisément, ce qui pourrait aider les investisseurs à mieux protéger leurs portefeuilles.