Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

FINANCE

MASTER´S FINAL WORK

DISSERTATION

THE ROLE OF CLIMATE TRANSITION RISK ON THE PERFORMANCE OF EUROPEAN EQUITY MARKETS

TIAGO MIGUEL GOMES PORTUGAL DIAS PEREIRA

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SUPERVISION:

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Em homenagem ao meu falecido avô, Fernando Pereira – engenheiro químico na Siderurgia Nacional de Paio Pires, formado no Técnico – que já nos 90 estava ciente dos impactos negativos da ação humana na natureza, tanto que escreveu um livro acerca de noções gerais sobre o ambiente, o qual não chegou a terminar nem publicar.

"*Aos meus netos*

Tiago Miguel,
Ricardo Luis,
Andreia
e Mariana,

Com votos que encontrem um meio ambiente tão bom como o avô, encontrou..."

Não avô, infelizmente não encontrámos um meio ambiente tão bom como tu encontraste…

Disclaimer regarding the use of Artificial Intelligence

This master thesis was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosures regarding the use of artificial intelligence (AI) tools in the creation of this dissertation:

I disclose that AI tools were employed during the development of this thesis as follows: AI-based research tools were used to assist in literature review and to help in terms of some specific trenches of Stata code (statistical software employed) and data visualization, but all final writing, synthesis, and critical analysis are my own work.

I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information, whether traditional or AI-assisted, have been appropriately cited in accordance with academic standards. The ethical use of AI in research and writing has been a guiding principle throughout the preparation of this thesis.

Abstract

This study analyzes the relationship between climate transition risk and performance of the European equity market measured by stock total returns, using a sample of listed companies belonging to the Euro Stoxx 600 index between 2006-2022. Proxies for each of three drivers of transition risk (mitigation policies, preference change and technology) plus a series of control variables are used. Ambiguity on previous literature is perceived, thus various regression methods are applied to find a consensus regarding the effect of this risk on European stock performance.

We find that the dominant driver is mitigation policy, and the impact is significant but complex, suffering from potential endogeneity and non-linearity issues. We can see a positive association between the respective variables, which is favourable to the existence of a carbon premium required by investors, but the opposite is also found, suggesting that a firm becoming greener is increasingly being rewarded. This supports the disinvestment and carbon alpha hypotheses, given the recent greater attention to climate issues.

JEL: C33, G15, G18, Q50, Q54, Q58, Q59

Keywords: Climate change; Carbon emissions; Transition risk; European stock returns; Mitigation policies; Preference change; Technology risk

Resumo

Este estudo analisa a relação entre o risco climático de transição e o desempenho do mercado acionista europeu, medido pelos retornos totais das ações, usando dados de uma amostra de empresas cotadas pertencentes ao índice *Euro Stoxx 600* entre 2006 e 2022. São utilizados indicadores para cada um dos três *drivers* de risco de transição (políticas de mitigação, mudanças de preferência e tecnologia) e uma série de variáveis de controlo. Uma certa ambiguidade em estudos anteriores é percebida, pelo que vários métodos de regressão são aplicados para encontrar um consenso sobre o efeito deste risco na performance das ações europeias.

Concluímos que o fator dominante é a política de mitigação e que o impacto é significativo, mas complexo, sofrendo de potencial endogeneidade e não linearidade. Observa-se uma associação positiva entre as respetivas variáveis, o que é favorável à existência de um prémio exigido pelos investidores, mas o oposto também é encontrado, sugerindo que uma empresa que se torna mais sustentável é cada vez mais recompensada. Este facto defende as hipóteses do desinvestimento e do *carbon alpha*, dada a recente maior atenção às questões climáticas.

JEL: C33, G15, G18, Q50, Q54, Q58, Q59

Palavras-chave: Alterações climáticas; Emissões de carbono; Risco de transição; Retornos de ações europeias; Políticas de mitigação; Mudanças de preferência; Risco tecnológico

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Lastly, I must thank my girlfriend and some of my close friends, for their encouragement and for having recommended me to choose to do a dissertation as a master's final work, given my theoretical and analytical skills.

We can't help everyone, but everyone can help someone.

Ronald Reagan, the 40th President of the United States

Glossary

ADF – Augmented Dickey Fuller

AI – Artificial Intelligence

APT – Arbitrage Pricing Theory

(A)Rbar – (Annualized) Expected return

BETA – Market beta

B/M – Book-to-market ratio

CAPM – Capital Asset Pricing Model

CE – Carbon dioxide and equivalents emissions

CO2 – Carbon dioxide

CPU – Climate Policy Uncertainty

CRS – Carbon Risk Score

CSR – Corporate Social Responsibility

ECB – European Central Bank

EM – Emissions score

ENV – Environmental pillar score

ENVCON – Environmental controversies score

ENVIN – Environmental innovation score

ESG – Environmental, Social and Governance

ETS – Emissions Trading System

EU – European Union

FE – Fixed Effects

GDP – Gross Domestic Product

GMM – Generalized Method of Moments

GHG – Green-House Gases

h-e – High-emissions

IMF – International Monetary Fund

JEL – Journal of Economic Literature

l-e – Low-emissions

LEV – Leverage ratio

LSEG – London Stock Exchange Group

NGFS – Network for Greening the Financial System

OECD – Organization for Economic Cooperation and Development

OLS – Ordinary Least Squares

PPE/A – Property, plant and equipment over assets

R – Stock total return

Rm – STOXX market return

RIC – Reuters Instrument Code

SALESGR – Sales growth

SIZE – Size

SECT – Economic sector dummy

STOXX – Euro Stoxx 600 Index

TCFD – Task Force on Climate-Related Financial Disclosures

TEG – Technical Expert Group

US(A) – United States (of America)

VIF – Variance Inflation Factors

VOL – Volatility

WR – Weekly total return

YEAR – Year dummy

Δ – First difference operator

β – Regression coefficients associated with general independent variables

θ – Regression coefficients associated with industry-year dummy variables

γ – Regression coefficients associated with lagged dependent variables

ϕ – Regression coefficients associated with lagged independent variables

ε – Regression error terms

λ – Theoretical operator associated with the use of BETA in volatility regressions

List of Tables

List of Figures

Index

1. Introduction

The consequences of human activity on the environment and nature have been a topic of discussion for several decades, but for a long time its relationship with the capital markets has been under-investigated. Only recently, economic agents have developed a systematic concern about climate change with rising regulatory issues (Battiston et al., 2021; Weber & ElAlfy, 2019; Carè & Weber, 2023).

The existence of a stream of studies already evaluating the effects of climate change is particularly relevant for the equity market, since it is one of the most important asset classes and has a major impact on the financial sector, but the empirical evidence is ambiguous and/or contradictory (Ardia et al. 2022; Bolton & Kacperczyk, 2021; Görgen et al., 2020; Pástor et al., 2020; 2022; Reboredo & Ugolini, 2022). At the same time, most of the papers focus on the American market (Venturini, 2021), while in Europe the climate action plan seems to be being taken more rigorously (European Union Technical Expert Group (EU TEG), 2020). Moreover, there is a current common view on the sources of risk for the financial system coming from climate change – physical and transition risks (Battiston et al., 2021; Task Force on Climate-Related Financial Disclosures (TCFD), 2017) – with the latter gaining relevance due to uncertainty about future macro scenarios reliant on climate severity (Network for Greening the Financial System (NGFS), 2023).

It is aiming to find a consensus around the impact of transition risk on stock market performance, and to add investigation of the specific effect in Europe, that we decided to develop this paper, answering the following research question: *Do climate transition risk have a significant impact on stock market performance in Europe, a region where the climate action is being taken seriously? And if so, what is the dominant source?*

Literature defends the existence of three main drivers of this risk into the equity market: mitigation policies, preference change, and technology (Semieniuk et al., 2021). Furthermore, the impact found varies considerably between studies, fact justified by the presence of three lines of theoretical thought (Bolton & Kacperczyk, 2021): the carbon risk premium, disinvestment and carbon alpha hypotheses. The first one leads to an expected positive relationship between transition risk and stock returns, while the subsequent two are associated with an expected negative relationship.

Studies such as Bolton & Kacperczyk (2021) argue that investors demand compensation to be exposed to transition risk, finding a positive impact on stock performance, but others suggest the opposite, that brown stocks become unattractive or the market underprices the risk, in line instead with the disinvestment hypothesis (Reboredo & Ugolini, 2022), with the carbon alpha hypothesis (Garvey et al., 2018; In et al., 2019), with both the two theories (Ardia et al., 2022; Pástor et al., 2020; 2022) or not finding any clear evidence at all (Görgen et al., 2020).

Given the raised importance of transition risk, it is crucial to understand the transmission to the European equity market, and our study seeks a rationale behind its relationship with stock performance (measured through annualized total returns), and which driver has the most relevant impact. To this end, we use a panel data sample taken from the Refinitiv-Eikon database and composed of 393 companies listed in the Euro Stoxx 600 Index, encompassing 9 industries and 17 European countries, for the 2006-2022 period.

We can argue that this contributes substantially to the research on the topic, due to the following reasons. First, to the best of our knowledge, it is the only one that simultaneously analyses the three drivers (and not only one), solving the ambiguity in extant literature and appraising European companies. Our findings are (at least partially) consistent with most papers.

Second, it is innovative by comprising various methodologies[1] not linked to factor/asset-pricing models; by pioneering the use of the generalized method of moments (GMM) and quantile regressions in this topic; and, introducing new or adapted variables, such as the environmental controversies score and the climate policy uncertainty index. Third, it allows a clear and robust answer to the research question, with the dominant driver being effectively mitigation policies, and the impact of transition risk on stock market performance being significant but complex, suffering from potential endogeneity and non-linearity.

Fourth, unlike most empirical papers, we identify and address the mentioned biases and show that regressions are enhanced by the use of a dynamic panel data model, surpassing serial correlation issues and clarifying evidence around the dominant driver. In earlier years (notably before the Paris Agreement) the relationship was less pronounced, and a carbon premium was more noticeable given the higher returns on brown stocks and the positive impact of transition risk measures on returns, but more

[1] Mostly econometric and starting from a simple to a deeper analysis.

recently the benefits of investing in green stocks have become evident with their exponential outperformance and the negative relationship between changes in transition risk, mainly policy risk measures and returns, which is consistent with the findings favourable to disinvestment and carbon alpha hypotheses. Finally, we don't find a set of additional robustness checks, changing main variables or limiting the sample, in the extant literature, as the one presented.

Results are achieved by starting from baseline ordinary least squares (OLS) and fixed effects (FE) regressions for our five target independent variables (the natural log of carbon dioxide and equivalent gases, representing the first driver, mitigation policy risk; the environmental pillar and controversies scores, for preference change; the emissions and environmental innovation scores, for technology), then isolating the analysis to control for unobserved effects arising from heterogeneity, autocorrelation, endogeneity and non-linearity, through a two-step system GMM, quantile regressions, green-brown portfolios comparison, and a series of complementary checks to obtain a robust conclusion.

The paper proceeds as follow. Chapter 2 presents the literature review and chapter 3 shows the sample, defines the variables, and describes the models/methodology. Chapter 4 presents the baseline research results and chapter 5 comprehends deepen robustness findings. Finally, the conclusion, limitations and future research paths are in chapter 6.

2. Literature review

In recent years, there has been a growing debate on the limits of economic growth and the environmental impacts of human activities. Discussions started in the second half of the 20th century, academically with papers like Benton (1970) and Nordhaus (1977), formally with agreements such as the Montreal (1987) & Kyoto (1997) Protocols, which already highlighted the damage of green-house gases (GHG) emissions and sought mechanisms to curb global warming.

Giddens (2009) and Nordhaus (2019) argue that international cooperation in climate policy development is crucial, but, indeed, it has proved insufficient to achieve the objectives, as carbon emissions and temperatures continue to rise. The Paris Agreement (2015) gave rise to sustainable development, with actions like the 2030 Agenda, the raised promotion of Environmental, Social and Governance (ESG), and a commitment for companies and institutions to achieve carbon neutrality and limiting temperature increase to 1.5ºC by the end of the 21st century.

The role of the financial sector in the path towards a green economy has substantially grown since the Paris Agreement (Weber & ElAlfy, 2019; Carè & Weber, 2023), leading to the development of regulations like the EU Taxonomy[2], which makes the disclosure of environmental information more transparent. Despite the increasing funding of green projects, climate change raises additional risks to the financial system, categorized as physical and transition risks (Battiston et al., 2021; TCFD, 2017).

Physical risks involve the damage that climate change extreme events may have on firms' assets and on their efficiency, which can be acute (extreme weather situations, such as floods or droughts), or chronic (permanent shifts like the rise in sea level).

Contrarily, transition risks are linked to the fact that the shift to a low-carbon economy presents the possibility of sudden and unforeseen changes in prices and default rates for various asset categories (Battiston et al., 2021). These market fluctuations can have significant repercussions for the portfolios of institutional investors and for the capital requirements of banks, making it crucial for them to adapt. Moreover, these risks can arise from regulations (e.g. a company facing a penalty due to disrespect some GHG emissions targets); technology (e.g. stranded assets – assets becoming obsolete due to innovative and carbon-efficient equipment); markets (markets that may disappear, namely some commodities); and reputation (e.g. a firm can see its stock prices falling due to decreased demand associated with bad news on the compliance with sustainability goals).

These climate-related risks need to be considered in asset pricing and valuation because their possible materialization raises uncertainty, affecting future cashflows and investor expectations. Giglio et al. (2021) highlight the importance of climate change issues in finance, being capital markets a key element in the transitioning economy, since they are a primary vehicle for mitigating and transferring risk between parties and facilitate the funding of green projects (Giglio et al., 2021).

Other studies reinforce the rising relevance of considering climate-related risks when evaluating financial decisions. Alok et al. (2020) examine whether fund managers account for these risks and conclude that they adjust their portfolios in response to climate disasters. Gonçalves et al. (2023) founds a statistically significant relationship between the ESG score and firm's financial performance. Gonçalves et al. (2021) analyze the risk-

[2] A classification of environmentally and socially sustainable economic activities in compliance with some objectives, such as climate change mitigation and adaptation (EU TEG, 2020).

adjusted returns of green versus conventional funds in EU countries and reveal that the first ones outperform, namely when sustainability strongly impacts firm performance. Schober et al. (2021) found that an unfavourable transition situation could lead to major portfolio losses in equities and bonds for the German financial sector, predominantly for investment funds and insurers. Finally, Döttling & Rola-Janicka (2022) provide an analytical model that evaluates optimal carbon pricing and financial regulation in a setting with financial constraints and endogenous risk factors, showing that the relative strength of climate-related risks underlines the role of the financial system in hedging them.

Furthermore, the NGFS has developed a framework for banks, companies and other entities to assess their ability to cover unexpected losses caused by climate stress. It includes four forward-looking climate scenarios (NGFS, 2023): orderly (low physical and transition risks), that assumes prompt and efficient global implementation of climate policies, resulting in a smooth transition; disorderly (high transition risk), stating that divergent cooperation and abrupt policy changes may result in financial markets instability and shocks; "*hot house world*" (high physical risk), that assume that while certain regions have implemented climate policies, overall global efforts are not effective; and "*too little, too late*" (high physical and transition risks) defend that a delayed transition cannot cap the rise in temperature, leading to more adverse impacts.

Regarding equity markets, many authors stated the importance of the impact that climate risk factors have on investors' decisions, stock performance and valuation, since stocks are the world's second-largest asset class by total transaction value and number of securities, after fixed-income. Additionally, they are traditionally the investment type with the highest exposure to systematic risk[3] and are directly related with firms' profitability as well as profitability is linked to climate risks (Huang et al., 2018).

Faccini et al. (2023) investigate the pricing of climate-related risks in US stocks, identifying two physical risk measures (natural disasters and global warming) plus two related to transition risk (international sustainability conferences and US climate policy). They find that only the climate policy factor is reflected in stock prices, suggesting that transition risks are more likely priced in the US stock market.

[3] The risk that affects a whole market or asset class and cannot be reduced by portfolio diversification, contrary to specific risk. It can be measured using the *beta* in asset pricing models.

Zhang (2022) finds that firms globally experience negative investor reactions to perceived changes in physical and transition risks in stocks. The study highlights the market's stronger response to transition risk compared to physical risk, indicating greater attention to long-term compliance expectations and regulatory concerns. Zhang (2022) also conclude that emerging markets show a relatively low level of climate risk sensitivity, raising concerns about disorderly scenarios and divergent cooperation (NGFS, 2023).

All this helps to perceive climate risks, namely transition risk, as a major source of financial instability nowadays, with Hui-Min et al. (2021) stating that market risk is linked to climate change, deriving from the rapid emissions' growth. Transition risk can then have an important impact on stock markets, which is very pertinent for research purposes.

Moreover, while empirical studies mostly focus on the US environmental actions (Venturini, 2022), the EU has a leading position when it comes to climate policy and the promotion of environmentally aligned activities (EU TEG, 2020). For instance, in 2021 all EU Member States reported an environmental tax in percentage of taxation higher than the one reported by the USA (OECD, 2024). In 2022 the USA disclosed carbon dioxide (CO_2) emissions of 13.64 tonnes per capita (OECD, 2024), a considerably higher value than the EU average (5.93 tonnes per capita). Respectively in 2020 and 2021, the renewable to total energy ratio used in electricity generation was 19.4% and 19.8% in the USA, while the same indicator reported values of 35.5% and 35% in Europe (IMF, 2024), being this proportion particularly high in some countries, including Portugal, which represents a relevant progress in the last 20 years (IMF, 2024).

Overall, several indicators support the idea that European countries are contributing to the low-carbon transition more rigorously than other regions and the US. This may be due to more standardized legislation to achieve common goals (with systems such as the EU Taxonomy), while in the US environmental regulations are taken more diversely, at state and federal levels. Thus, we must appraise the impact of transition risk in European stock markets, since it may cause heterogeneous consequences in the behaviour of asset prices (Tedeschi et al., 2024) and hence on investment decisions.

The discussion on modelling stock performance started when Markowitz (1952) introduced the idea that investors should consider both expected values and variance of returns when allocating their wealth, pioneering the consideration of the risk-return relationship and discovering the benefits of diversification (Markowitz, 1952). Tobin

(1958) enhanced this theory stating that although there is a tendency of investors to avoid risk and to prefer liquidity, they still look for wealth growth, constrained to their risk tolerance (Ruhani et al., 2018). Sharpe (1964), Lintner (1965), Ross (1976) and other authors added more ground and developed factor models to find equilibrium (or, instead, no arbitrage) asset returns[4] and to separate the "*price of risk*" from the "*price of time*", creating the concept of risk-premium.

Despite being important for framing the risk-return relationship, the theories developed in the second half of the 20th century did not cover the effect of all sources of financial risk, particularly climate-related ones, which have only recently been incorporated and theorized (Venturini, 2022).

Semieniuk et al. (2021) says that transition risk is a function of three drivers[5] – mitigation policies[6] (policy risk), technology, and preference change – which in addition to having associated economic costs such as unemployment, can result in negative financial impacts for equity investors. First, effective mitigation policies can raise prices for high-carbon products, reduce profitability of carbon-intensive firms and contribute to creating competitive markets for greener alternatives (Semieniuk et al., 2021). Second, cost-saving technological innovation has led to a nonlinear decrease in the prices of low-carbon technologies and eventually underestimates their rate of adoption (Creutzig et al., 2017). Third, demand preferences can dictate market prices, creating exponential and network effects as an alternative is diffused (McShane et al., 2012; Pettifor et al., 2017).

The following three theories might explain how transition risk channels affect the performance of equity markets (Bolton & Kacperczyk, 2021). The carbon risk premium hypothesis says that firms with higher exposure to transition risk (e.g. firms strongly reliant on fossil energy) can see increased expected returns on their stocks through the fact that investors require to be compensated for holding equities associated with higher climate risk. Contrarily, according to the disinvestment hypothesis, stocks from high-emissions (h-e) firms can be reproved by socially responsible investors, which facilitates a decrease in demand and then a downward trend in stock prices, leading to a negative impact on returns. Lastly, the carbon alpha hypothesis suggests that the market is

[4] Such as the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT).
[5] See figure A1 in the appendices.
[6] Climate change mitigation policies can be implemented by mechanisms such as carbon taxes and green subsidies (Venturini, 2022; Metcalf, 2009).

inefficient and underprices the risk associated with carbon risk and uncertainty, enabling positive abnormal returns as was proved by a portfolio that is long stocks of low-emissions (l-e) companies and short stocks of h-e ones (In et al., 2019).

The realization of each theory relies on how market participants perceive transition risk and how much asymmetry of information is implied, thus the concept of market efficiency – the capacity of asset prices to incorporate all (or part of) available information[7] – is relevant to refer, as it traduces the effect of anticipated information (Fama, 1970).

When it comes to the shift procedure to a greener economy, Giglio et al. (2021) show two major perspectives[8] that justify the rise in climate-related risks. When uncertainty comes from the path of economic growth, a rise in consumption and output is associated with increased pollution and carbon emissions, which in turn accelerates climate change and related damages to the economy (Nordhaus, 1977; 1991; 1992). When uncertainty is about the path of climate change, climate events lead to low consumption and investment levels, which are associated with lower cashflows of high transition risk investments.

Venturini (2022) reviews a set of papers assessing the impact of climate risks on equities through two approaches, one focused on a cross-sectional analysis of stocks ("*top-down*") and the other appraising the impact on firms and investors' characteristics ("*bottom-up*").

Bolton & Kacperczyk (2021) find a positive relationship between stock returns and the total level changes of carbon emissions[9], which is consistent with the idea that investors are requesting compensation for holding stocks linked to bad environmental reputation. This defends the carbon risk premium hypothesis and contradicts the disinvestment one. The carbon alpha is also refuted by the authors, despite Garvey et al. (2018) and In et al. (2019) having found that a positive alpha is possible by creating a portfolio of stocks sorted by emissions intensity (emissions by unit of sales). Regarding the first view, Karydas & Xepapadeas (2022) also support the carbon premium as climate change

[7] The *strong* form assumes that all public and private information is reflected in a stock price; the *semi-strong* form defends that only public information is implied by the price behaviour; and the *weak* form sentences that stock prices only reflect historical information (Fama, 1970).
[8] See figure A1 in the appendices.
[9] Carbon emissions can be split into scope 1 (emissions from sources directly owned or controlled by a company), scope 2 (emissions a firm causes indirectly by the energy it consumes and used in its activity), and scope 3 (indirect emissions resulting from activities and assets not controlled by the company, but by somebody within the company's value chain or industry) (Teske et al., 2022).

deepening makes tail events more frequent and less predictable, as well as the risk-free rates drop and the equity risk premium goes up with global warming.

We can perceive carbon emissions as a good proxy for transition risk (Bolton & Kacperczyk, 2021; Hsu et al., 2022; Oestreich & Tsiakas, 2015) driven by mitigation policies, since a company reporting high levels of emissions may suffer increased future losses due to regulatory issues. Reboredo & Ugolini (2022) use a carbon risk score (CRS – a measure rating unmanaged transition risk with values between 0 and 100, being 0 considered negligible and above 50 severe) from Sustainalytics to quantify the transition risk impact on US and EU stock prices through portfolio sorts and panel regressions. The authors found that firms with lower exposure to this risk perform better in terms of profitability and stock returns, which in opposite to Bolton & Kacperczyk (2021), does not follow the carbon risk premium and defends the disinvestment hypothesis. They also observe asymmetries among US and EU: in European stock markets, investors correct underreaction by reducing (increasing) the value of companies with high (low) exposure, while in the American markets, the analysis is more ambiguous.

They are in line with Qian et al. (2020) and Chan et al. (2022), who respectively found a positive association between carbon performance and Australian stock market returns during the repeal of the carbon tax, and that increases in climate policy uncertainty led to risk-adjusted returns greater for stocks with lower exposure. Engle et al. (2020) built industry-balanced portfolios to dynamically hedge climate news, using textual analysis and ESG scores. They show a mimicking portfolio's effectiveness on hedging policy risk when environment-related variables are incorporated.

Literature tries to explain this ambiguous set of conclusions with the two major transition process drivers indicated before, and the ultimate impact of transition risk might depend on the predominant one (Reboredo & Ugolini, 2022). When the driver is uncertainty about economic growth (Giglio et al., 2021), green investments provide greater cashflows when consumption is high and therefore, we can explain a positive premium in assets with low transition risk. When the driver is uncertainty about the path of climate change, investors can accept a negative carbon risk premium for holding equities with small exposure to transition risk (Reboredo & Ugolini, 2022).

Pástor et al. (2020; 2022) propose an analytical model to check the impact of sustainability preferences on asset prices, i.e., transition risk stemming from preference change. Their findings reveal that sustainable investing can influence market outcomes, with green stocks outperforming brown ones when concerns about climate change suddenly increase. This is due to a multiplier effect caused by two channels: consumers reducing (increasing) demand for brown (green) firms, and investors adjusting discount rates on asset pricing for brown (green) firms, ultimately leading to a decrease (increase) in stock prices. This aligns with the disinvestment hypothesis as individuals shift preferences towards green firms and withdraw their investments on brown ones.

Furthermore, Ardia et al. (2022) test Pástor et al. (2020; 2022)' construction by composing a daily index with information on news articles about climate issues from important US newspapers, and comparing the performance of green against brown firms when climate change concerns unexpectedly go up. They confirm the previous argument by finding that on days of sudden increases in climate concerns, green stocks tend to go up while brown stocks may see a downward evolution. Overall, they found that sustainable firms benefit from spikes on concerns and a long-green & short-brown portfolio gives a positive abnormal return (supporting the disinvestment and carbon alpha hypotheses and rejecting the carbon premium), controlling for other risk factors.

Following the rationale, Görgen et al. (2020) created a "*brown-green score*" weighting proxies for the three transition risk factors identified by Semieniuk et al. (2021)[10]. The study took information on different ESG measures and highlighted the importance of mitigation policy risk (giving a weight of 70% to its proxy, named "*value chain*"), considering the remains as less relevant on the quantification of transition risk (15% for both "*adaptability*" and "*public perception*", the variables for technology and preferences). The authors also refuted the carbon risk premium hypothesis by not finding its evidence in global equity prices, and brown firms do not exhibit significant differences in average returns than green firms. This suggests that changes in cashflows influenced by their transition risk factor are unpriced for both types of stocks, and Görgen et al. (2020) justify that green firms are becoming more sustainable than brown firms faster.

More studies analyze transition risk dynamics with market data. Hengge et al. (2023) investigate how carbon policy "surprises" affect the stock prices of European companies in a daily basis, using information from the EU Emissions Trading System (ETS). Their

[10] Not only analyzing the mitigation policies and preference change drivers, but also the technology driver of transition risk into stock markets.

results propose that sudden regulatory changes lead to higher carbon prices and negative abnormal returns which increase with carbon emissions, indicating that investors price in transition risk stemming from mitigation policies. This negative relationship is even stronger for firms in sectors that do not participate in the ETS, which suggests that policies increasing carbon prices are effective in raising the cost of capital for brown firms.

Yang et al. (2023) innovate the literature by including machine learning algorithms to create a news-based index that measures the intensity of mitigation policies and respective market reactions. There's evidence that transition risk is considered by the market and regulations are reflected by oil and gas firms (Yang et al., 2023).

Taking this background into account, we can establish some examples of studies in favour to (or not) each hypothesis regarding the transmission of transition risk on equities[11]. There is no clear impact on stock prices and returns (Reboredo & Ugolini, 2022), as the result may depend on the major or specific transition risk drivers (Semieniuk et al., 2021) and on the conditional materialization of each theory (Bolton & Kacperczyk, 2021). Theoretically speaking, the carbon risk premium hypothesis is reasonable, since investors need to be compensated for holding an asset with higher risk, and thus the return on firms with more exposure would be greater than the ones with less exposure, respecting modern portfolio theory and equilibrium/no arbitrage models (Markowitz, 1952; Sharpe, 1964; Ross, 1976). However, from a market perspective, high-emissions stocks more potentially are seen as stranded assets and demand for them is likely to decrease, inducing a downward price trend and a decrease in long portfolio returns, as supported by the disinvestment theory.

To formulate the 1st hypothesis (H1) of this paper, we consider the ambiguous set of deductions, not defining an objective impact, but relying on the statement that the relationship among transition risk and stock performance is intrinsically important:

H1: There is a significant association between the exposure to climate transition risk and the stock returns of firms.

Venturini (2022) also discusses papers on bottom-up approaches, such as micro-econometric and event studies. Bartram et al. (2021) try to understand the change in firm-level emissions due to regulations applied in American states, appraising mitigation

[11] See table A.I in the appendices section.

policy risk. In opposite to top-down approaches, the authors found that constrained firms reallocate their emissions to other states, and this regulatory arbitrage allows them to overcome negative impacts from regulations, being no evidence that they affected their profits and so suggesting that policy risk is not priced in some markets (Venturini, 2022).

For modelling technology risk, Trinks et al. (2020) use a measure of comparative carbon efficiency to show that companies internationally disclosing higher levels are more likely to face lower systematic risk and report higher profitability, which might have a positive impact on market valuations and consequently on stock prices and returns. Concerning the preference change driver, Ricci & Banterle (2020) reinforce Pástor et al. (2020; 2022) and Ardia et al. (2022) arguments by showing that Italian consumers shifted their buying willingness to green products after the Paris Agreement.

At the investor level, Akey & Appel (2019) and Azar et al. (2021) found that some market players engage with firms to become more sustainable. The first appraises the effect of hedge funds activism campaigns on emissions reduction and concludes that these initiatives are associated with a decrease in chemical emissions and with enhanced environmental efficiency, being primarily driven by a drop in production instead of an increase in abatement activities. Azar et al. (2021) emphasize the role of large institutional investors on carbon reduction efforts, evidencing that the *Big Three* (BlackRock, Vanguard, and State Street Global Advisors) engage with carbon-intensive companies and as their ownership raises, emissions decrease.

Furthermore, Flammer et al. (2021) defend the importance of the disclosure of climate-related information by firms, revealing that environmental shareholder activism from institutional investors leads to enhanced disclosure. The paper shows that greater voluntary reporting is linked to higher market valuation, which signals a positive investor response and improved reputation, reducing transition risk (Flammer et al., 2021).

Ramelli et al. (2021) evaluates the impact of the 2016 and 2020 US elections on stock prices related to climate regulations, addressing mitigation policy risk at the investor level. It is shown that during periods of policy uncertainty, investors increase demand for green stocks. After the 2016 election, carbon-intensive US firms experienced stock price boosts due to the Trump administration's sceptical position on environmental issues. However, climate-responsible firms also performed well, influenced by the forward-looking perspectives of long-term institutional investors and their reward for firms committed to sustainable practices and improvement. Findings from the 2020 election suggest that investors anticipated stricter post-Trump environmental regulations.

There is a growing concern of economic agents with environmental issues at firm and investor levels, in their consumption (as shown by the greater demand for green products after the Paris Agreement) and investment decisions, as proved by the growing engagement towards sustainable practices and the positive relationship between voluntary disclosure and market valuation (Ricci & Banterle. 2020; Akey & Appel, 2019; Azar et al., 2021; Flammer et al., 2021). Bartram et al. (2021) findings regarding regulatory arbitrage in the US may not be easily reflected in European countries, due to stronger legislation and the existence of sovereign frontiers.

Ramelli et al. (2021) are in line with H1 showing the positive impact of mitigation policy risk (mainly) and preference changes (induced) on the returns of green stocks. On the other hand, the adverse impact from Trump's administration is not a problem in Europe, where the climate action plan is being taken more seriously, despite the recent increase in conservative right to far-right political forces.

Moreover, the technology driver is potentially linked to stock returns at a firm level as it is with profitability (Trinks et al., 2020), but the policy driver is perceived as more relevant than the others, by the higher attention given in the literature, which establishes our 2nd hypothesis (H2):

H2: Among the three specific drivers of transition risk, at least in Europe the mitigation policy risk is the one with the highest impact on the equity market.

This statement is consistent with the factor relevance order given by Görgen et al. (2020) and with the increased concerns regarding environmental regulation frameworks in Europe, as stated before. Appendices A.II and A.III summarize the essential ideas, research techniques, variables and findings of the main literature presented in this chapter.

3. Sample and Methodology

We use panel data retrieved from Refinitiv-Eikon database, encompassing European listed firms for the period between 2006 and 2022. The sample was chosen to comprise firms with different sizes and from various countries and industries, which is achieved using constituents of the Euro Stoxx 600 (STOXX), a European stock index characterized by country and industry diversification and composed with large, mid and small capitalization companies (Gonçalves et al., 2023a; Santos, 2021). Since it represents more than 80% of the most liquid trading stocks in the continent (Gonçalves et al., 2023), it is a good proxy for the European equity market (Gonçalves et al., 2022).

To identify the cross-sectional dynamics (changes in observations between firms), we gathered the Reuters Instrument Code (RIC). In terms of time series, yearly observations[12] are used. Economic sector (industry) and time specification dummies were incorporated.

Due to different regulatory settings, firms from the financial sector were removed, as well as firms under financial distress, with negative equity values (Gonçalves et al., 2023; Gonçalves et al., 2023a, 2021). Moreover, we can perceive a higher lack of ESG-related data for the first years. Some firms presenting very few observations for one or more independent variables were also dropped, ending with a sample of 393 companies, from 17 countries and 9 industries. Tables A.IV and A.V in the appendices show the firm sample composition by country and sector, respectively.

To analyze the impact of transition risk, ESG variables linked to the three drivers (Semieniuk et al., 2021) were used. The Refinitiv-Eikon database includes more than 630 company-level metrics approaching over 15 000 firms and aiming to measure ESG performance. The environmental pillar has stronger relevance in this study than the social and governance, being all the transition risk variables related to it.

Relying on previous literature, namely Bolton & Kacperczyk (2020) and Görgen et al. (2020), policy risk is often measured by the dimension of a company's carbon emissions, in this case using the natural logarithm of *total CO2 & equivalents emissions* (LN(CE)), in tonnes. Additionally, the preference change channel is addressed analyzing the *environmental pillar score* (ENV) and the *environmental controversies score* (ENVCON), since the first reflect the public opinion regarding environmental issues and can act as a decision criterion for investors (Görgen et al., 2020), and the second can be affected by negative events and news, which in turn can move consumption and investment decisions (Pástor et al., 2020; 2022). Lastly, technology risk can be derived from information on carbon efficiency, which is reflected in the *emissions score* (EM); and innovation, which is considered with the *environmental innovation score* (ENVIN).

[12] Most ESG-related information is only reported yearly, which ended up being the time step used.

A first difference component of each target variable presented was included to account for unexpected and dynamic effects (Görgen et al., 2020).

ENV, ENVCON, EM and ENVIN result from a percentile rank scoring method and they lie among 0 (the worst) and 100 (the best)[13]. Based mostly on the settings of Görgen et al. (2020), Bolton & Kacperczyk (2021) and Reboredo & Ugolini (2022), a series of control variables was employed to accurate the marginal effect of target variables, reducing the noise caused by companies' financial characteristics, such as size, valuation, and solvency (Berk & DeMarzo, 2013). Table A.VI in the appendices shows the variables used, along with their description or calculation technique, and their use in the literature.

Sales growth (SALESGR) corresponds to the unit change in annual revenues (from operating activities after deducting any sales adjustments (LSEG, 2024)) normalized by the market capitalization (Bolton & Kacperczyk, 2020). Firm *size* (SIZE) is represented by total assets in dollars and considers, on the one hand, that larger firms might benefit from economies of scale and more efficiency, and on the other that they are also more exposed to regulatory and public scrutiny to comply with certain practices (Taliento et al., 2019; Carini et al., 2017).

The *book-to-market ratio* (B/M) consists of a firm's book value of equity divided by its market capitalization (the sum of the market value for all relevant equity instruments) and lights on how under or overvalued is a company in the market. The *leverage ratio* (LEV) is computed dividing the outstanding total debt[14] by total assets, in dollars, and gives information on a firm's solvency situation, as highly levered firms are more likely to incur in debt default, agency costs and financial distress (El Ghoul et al., 2017).

Gross property, plant and equipment over total assets (PPE/A) comes from the value of a firm's fixed assets over total asset value, in dollars, serving as a proxy for the proportion of investment from the company's assets, as gross PPE includes the capital expenditures. The market *beta* (BETA) measures how much a stock price changes due to movements in the market (systematic risk), and the *volatility* (VOL) corresponds to the standard deviation of a firm' weekly returns within a year, multiplied by the square root

[13] A certain score for a firm is calculated as follows: $\frac{\text{Number of companies with a worst value} + 0.5*\text{number of companies with the same value}}{\text{Total number of companies with a value}}$ (LSEG, 2023). A score below 50 is regarded as poor and above 70 is considered very good (Investopedia, 2023).

[14] This includes the notes payable (short-term debt), the current portion of long-term debt (capital leases), and total long-term debt (LSEG, 2024).

of the number of available weekly data points for that firm-year in order to get annualized values, similarly to the computation of returns, described below.

Assuming a long portfolio perspective, stock performance can be measured by total returns, calculated from summing a period price change to any related income (usually dividends) and dividing the result by the last period price. The difficulty lies in their nature, characterized by the random behaviour of assets (Wilmott, 2007). If stocks follow a stochastic random walk, observations are independent from each other between moments of time (Neusser, 2016), meaning that values incorporate all available information. However, the time step dimension matters: it's not the same to calculate for instance daily or yearly returns, since the first implies more information than the second.

We use weekly total returns (WR) from Refinitiv terminal across the referred period, as it was the frequency with the smallest possible Δt excluding daily data. To stand with a dependent variable suitable for regressors' yearly disclosure, expected returns by year were first computed:

$$Rbar_{y,y-1} = \frac{\sum_{y-1}^{y} WR_{t,t-\Delta t}}{q}, t \in y \text{ (1)}$$

Where $Rbar$ is the expected return each year (y), relatively to the previous one (y-1), t is a weekly period during the given yearly period, Δt is the difference between the current period and the previous, and q is the number of available weekly returns within a year, which is 52 by default but for some observations it needed to be adjusted. Next, to consider the asymmetry between weekly and yearly data, $Rbar$ values were annualized assuming the number of available weeks per year:

$$ARbar_{y,y-1} = Rbar_{y,y-1} * q = \sum_{y-1}^{y} WR_{t,t-\Delta t}, t \in y \text{ (2)}$$

Where $ARbar$ is the annualized $Rbar$. When applying equations (1) and (2) to retrieved returns and merging them with remaining data, we can standardize the observations.

Some adjustments were made to the raw dataset. For instance, a substantial part of independent variables presented outliers and a strong positive skewness, problems that were appraised using the Winsor method at the usual 1% and 99% levels (Reboredo & Ugolini, 2022) to reduce anomalies and taking the natural logarithm of size to reduce the noise caused by very different scales of assets.

The models developed are based on firm-level panel regressions aiming to answer the research question of the work and to explore the hypotheses presented in the literature review. Using the variables related to each transition risk driver separately in different models, the following baseline equation intend to test H1 and H2:

$$R_{i,y} = \beta_0 + \beta_1 X_{i,y} + \beta_2 \Delta X_{i,y} + \beta_3 SALESGR_{i,y} + \beta_4 LN(SIZE)_{i,y} + \beta_5 B/M_{i,y} + \beta_6 LEV_{i,y} + \beta_7 PPE/A_{i,y} + \beta_8 BETA_{i,y} + \beta_9 VOL_{i,y} + \theta_{s,1} SECT_i + \theta_{y,2} YEAR_y + \varepsilon_{i,y} \quad (3)$$

Where i denotes each firm, y the respective year and s a certain sector.

$R_{i,y}$ is the annualized expected return (*stock return*) of firm i at year y. $\beta = [\beta_0\ \beta_1\ \beta_2\ ...\ \beta_9]$ is the vector of coefficients associated with the constant term and each independent variable; $\theta = [\theta_{s,1}\ \theta_{y,2}]$ are the coefficients associated with the industry and year dummy variables when applied; $X_{i,y}$ (and $\Delta X_{i,y}$) correspond to the target ESG variable (and its first difference between two periods, denominated by the Δ) measuring the impact of transition risk in the European stock market. The target variable is (i) LN(CE) if the driver is policy risk; (ii) ENV or ENVCON when the driver is preference change; and (iii) EM or ENVIN when the driver is technology risk. Equation (3) is intended for the use of standard and quantile fixed effects regressions.

The remaining regressors are the control variables defined before, SECT and YEAR represent economic sector and year respective dummies and ε denotes the error term, i.e., the difference between the observed value of R and the predicted one, composed by effects not internalized by the model (Wooldridge, 2010).

According to extant literature and relying on the disinvestment hypothesis, a negative relationship between each driver of transition risk and stock returns is expected. In this case, higher policy risk means higher levels of carbon emissions; higher preference change risk must be reflected by lower environmental and environmental controversies scores; and higher technology risk is linked to lower emissions and innovation scores. On the other hand, if the carbon premium hypothesis holds, the opposites are likely to occur.

From a preliminary induction, first, corporations with lower levels of carbon emissions are more likely to observe their stock prices to go up since they are less exposed to regulatory issues (Chan et al., 2022; Reboredo & Ugolini, 2022), and therefore we expect a negative relationship between LN(CE) and stock returns. Second, reputation rises when ESG metrics enhance, meaning that consumers and investors more likely spend in a firm that is becoming perceived as more sustainable (reduced preference change risk), and so a positive association between both ENV and ENVCON with stock returns is plausible (Pástor et al., 2020; 2022; Ardia et al., 2022; Ricci & Banterle, 2020). Lastly, a firm reporting higher levels of carbon efficiency, as well as investment in innovation and greener assets will tend to have decreased technology risk, which make us expect a positive association between both EM and ENVIN with stock returns.

SALESGR is employed to account for any patterns in stock returns that are purely derived from the change in revenues (Garvey et al., 2020), since the efficient market theory (Fama, 1970) and many studies already supported the positive association between firm's economic performance and stock returns[15]. This makes us expect a positive relationship between SALESGR and stock returns. On the other hand, the impact of LN(SIZE) on stock performance is not clear and depends on many factors, such as how investors perceive large vs. small firms and their risk profile (mature firms with higher total assets may be seen as less risky compared to smaller and younger firms).

According to the theory of capital structure, a rise in a firm's debt weight increases the risk for bondholders and shareholders, making the required premium going up. However, as most individuals are risk-averse, the attractiveness of related stocks is likely to decrease, reducing long returns in the equity market. Hence, a negative association between LEV and stock returns is anticipated, consistent with the findings of Bolton & Kacperczyk (2021) and Görgen et al. (2020).

At last, relationships between both BETA and VOL with returns are expected to be positive, by modern portfolio theory (Markowitz, 1952), by the CAPM and APT (Sharpe, 1964; Ross, 1976) and by previous findings (Heston et al., 1999; Morelli, 2007). The literature covering the impact of the other controls on stocks is generally ambiguous.

For robustness reasons, adaptations of the original modelling equation (3) were performed[16], which are according to the following and deeply described in chapter 5:

$$R_{i,y} = \beta_0 + \gamma_1 R_{i,y-1} + \gamma_2 R_{i,y-2} + \beta_1 X_{i,y} + \beta_2 SALESGR_{i,y} + \beta_3 LN(SIZE)_{i,y} + \beta_4 B/M_{i,y} + \beta_5 LEV_{i,y} + \beta_6 PPE/A_{i,y} + \beta_7 BETA_{i,y} + \beta_8 VOL_{i,y} + \theta_{s,1} SECT_i + \theta_{y,2} YEAR_y + \phi_1 X_{i,y-1} + \phi_2 LN(SIZE)_{i,y-1} + \varepsilon_{i,y} \quad (4)$$

[15] E.g. see Nadyayani & Suarjaya (2021).
[16] Some robustness checks still use equation 3.

$$R_{i,y} = \beta_0 + \beta_1 CPU_{i,y} + \beta_2 \Delta CPU_{i,y} + \beta_3 SALESGR_{i,y} + \beta_4 LN(SIZE)_{i,y} + \beta_5 B/M_{i,y} + \beta_6 LEV_{i,y} + \beta_7 PPE/A_{i,y} + \beta_8 BETA_{i,y} + \beta_9 VOL_{i,y} + \theta_{s,1} SECT_i + \theta_{y,2} YEAR_y + \varepsilon_{i,y} \quad (5)$$

$$V_{i,y} = \beta_0 + \gamma V_{i,y-1} + \beta_1 LN(CE)_{i,y} + \beta_2 SALESGR_{i,y} + \beta_3 LN(SIZE)_{i,y} + \beta_4 B/M_{i,y} + \beta_5 LEV_{i,y} + \beta_6 PPE/A_{i,y} + \lambda\beta_7 BETA_{i,y} + \theta_{s,1} SECT_i + \phi_1 LN(CE)_{i,y-1} + \phi_2 LN(SIZE)_{i,y-1} + \varepsilon_{i,y} \quad (6)$$

$$R - Rm_{i,y} = \beta_0 + \beta_1 X_{i,y} + \beta_2 \Delta X_{i,y} + \beta_3 SALESGR_{i,y} + \beta_4 LN(SIZE)_{i,y} + \beta_5 B/M_{i,y} + \beta_6 LEV_{i,y} + \beta_7 PPE/A_{i,y} + \beta_8 BETA_{i,y} + \beta_9 VOL_{i,y} + \theta_{s,1} SECT_i + \theta_{y,2} YEAR_y + \varepsilon_{i,y} \quad (7)$$

Where $\mathrm{y} = [\gamma_1 \; \gamma_2]$ is the vector of coefficients linked to internal instrumental variables and $\boldsymbol{\phi} = [\phi_1 \; \phi_2]$ the coefficients of lagged regressors as external instruments, with equations (4) and (6) defined for use of the system generalized method of moments (GMM). CPU stands for *climate policy uncertainty* and it's an alternative and global measure of policy risk, with equation (5) being run under OLS with dummy variables. V is a measure of volatility under CAPM and λ is a theoretical operator that assumes one if the V is total *volatility* and zero if it is *systematic* or *specific volatility*, since the *beta* is a parameter in CAPM formulas. Finally, R-Rm stands for excess returns over the market (see panel D of table A.VI in the appendices) and (7) is applied using the standard fixed effects estimator.

4. Baseline research results

4.1. Descriptive statistics and correlations

Table I shows the descriptive statistics of the variables, for the defined period (2006-2022). After the adjustments to the raw data, the total number of firm-year observations is 5934, considering the dependent variable. The asymmetry in the number of observations between variables is expected due to lower availability of data for some.

The dependent variable – *stock returns* – has a tendentially normal distribution and a positive mean, which respects the theory of economic growth (e.g. Solow (1956), Romer (1990)), as a long-term trend of output increase, capital accumulation and technological progress is linked to rising value of goods, services and assets.

With respect to the target independent variables, the log of total CO2 equivalent emissions has a mean of 12.79, a relatively high log value of emissions, but which substantially reduced through the period, as we can see in figure A2 in the appendices. The environmental pillar score, the environmental controversies score, the emissions score and the environmental innovation score present a mean (standard deviation) of 63.356 (23.349), 51.646 (9.463), 70.185 (25.69) and 42.405 (33.63), respectively. These statistics are consistent with the scoring method and balanced results of ESG metrics.

The last score has the lowest mean and the highest standard deviation, suggesting that, from one standpoint, European companies are not performing as well in terms of innovation as they are in other environmental parameters, yet from other they experienced a relatively higher evolution in terms of innovation, which is confirmed by figure A3 in the appendices, that shows the evolution of the scores through the period.

Overall, the summary statistics and appendices A2 & A3 show that a reasonable progress in terms of environmental impact has already been made by European firms (notable through the maximum ENV, EM and ENVIN scores, close to 100, and through the evolution of that metrics, in addition to LN(CE)), but on average they still face challenges in achieving good ESG ratings.

The Pearson correlation matrix is in table A.VII in the appendices, showing that most independent variables have a statistically significant correlation with stock returns. We can note an expected negative correlation between LN(CE) and stock returns (with the disinvestment hypothesis holding), but the negative correlations between both ENV and EM with returns are unanticipated. Among the ESG scores, we check relatively meaningful correlations, except for ENVIN.

In terms of control variables, we can point out that the negative coefficients between both the BETA and VOL with stock returns go against what was expected and mentioned before. Conversely, the negative relation between LEV and returns is in line with the theory and literature's findings, although being not significant. Furthermore, there is an overall statistically significant correlation among regressors.

Table I – Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
R	5934	0.119	0.261	-0.696	0.7
LN(CE)*	4918	12.79	2.516	3.706	30.125
ENV	5516	63.356	23.349	0	98.946
ENVCON	5516	51.646	9.463	0	55.713
EM	5516	70.185	25.69	0	99.906
ENVIN	5425	42.405	33.63	0	99.881
SALESGR*	5668	0.056	0.677	-7.415	14.851
LN(SIZE)*	5838	22.872	1.473	17.653	26.994
B/M*	5745	0.545	0.449	0.012	10.574
LEV*	5826	0.498	0.82	0	7.6

PPE/A*	5457	0.51	0.398	0	2
BETA	2980	0.935	0.424	-0.302	4.597
VOL	5934	0.285	0.115	0.057	1.34

Note: * means that the variable was winsorized at 1% level.

4.2. Baseline results

The baseline econometric statistics are shown in table A.VIII, from pooled ordinary least squares (OLS) estimation. Using a hierarchical comparison, the explanatory power of the models, measured by the R-squared, increases from around 0.09 to 0.30 in the five models when we add sector-year cross-sectional variables, which indicates that the individual and time-invariant effects are important to be considered. The group of regressions employed robust standard errors to avoid unequal variance or heteroskedasticity (Wooldridge, 2010), and the F test suggests that the variables are globally significant to explain stock returns.

To surpass the doubts regarding the appropriateness of OLS, due to the nature of panel data and to capture the unobserved heterogeneity, fixed and random effects estimators were considered (Arellano, 2003). The Hausman test[17] (which finds whether the difference between fixed and random effects coefficients is systematic or not) clearly proved that a fixed effects (FE) estimator is more suitable for the five models, indicating that individual-specific covariates are significant. This deduction is in line with the explanatory power added by the sector and year dummies to OLS estimation.

The results from FE regressions with robust standard errors are presented in table II. We can note that only the LN(CE) and its difference component are simultaneously significant (at 10% and 1% levels, respectively), which is favourable to H2 of policy risk being the dominant driver in the European equity market, besides the weak significance of the level component. ENVCON has a significant impact too, at 5%, but the overall R-squared associated with LN(CE) regression is the highest, which strengthens the argument in favour to H2.

The coefficients of LN(CE) and ΔLN(CE) have different effects (respectively, 0.0222 and -0.0221). The log of CO2 equivalent emissions (its changes) is positively (negatively) related with STOXX firm's returns, i.e., from one point carbon-intensive firms are more likely to get higher returns (brown firms have tended to outperform green ones, consistent with Bolton & Kacperczyk (2021) and Hengge et al. (2023)), but becoming greener is

[17] See table A.IX in the appendices section.

being rewarded by the market as a decrease in emissions is related to an increase in the dependent variable. This is in accordance with Görgen et al. (2020) panel regressions, with Karydas & Xepapadeas (2022) findings of an increase in policy risk leading to reduced participation of brown assets in portfolios, and with Ramellli et al. (2021) findings of long-term investors boosting climate-responsible companies.

ENVCON hints that the preference change driver is not benefiting stock performance of green companies, having a better score in environmental terms being related with lower returns, which conflicts with Pástor et al. (2020; 2022) and Ardia et al. (2020) theses. However, ΔEM has a 5% significant and positive coefficient, reinforcing the argument that becoming greener worths on the long-run and extending it to the technology driver via carbon efficiency, in line with Trinks et al. (2020) and indicating that reducing the environmental impact is gaining relevance.

These findings are also accordingly with H1 on the overall importance of transition risk, but with constraints, since not all the variables representing each driver proved to be statistically significant. The level components support the carbon premium hypothesis by indicating that, on average, investors are being compensated to hold stocks of browner firms (Bolton & Kacperczyk, 2021), but the positive engagement to becoming greener visible in the changes components is favourable to the disinvestment hypothesis. Regarding the controls, LN(SIZE), B/M and VOL have a reliant and strong (1%) significance across the five regressions, and their impact is negative, which in the case of volatility is not expected.

Table II – Fixed Effects (FE) Standard Regressions

Variables	(1.1) R	(1.2) R	(1.3) R	(1.4) R	(1.5) R
LN(CE)	0.0222* (0.0131)				
ΔLN(CE)	-0.0221*** (0.0083)				
ENV		-0.0002 (0.0007)			
ΔENV		0.0006 (0.0009)			
ENVCON			-0.0015** (0.0007)		
ΔENVCON			0.0006 (0.0004)		
EM				-0.0006 (0.0006)	
ΔEM				0.0012**	

				(0.0006)	
ENVIN					0.0002
					(0.0003)
ΔENVIN					-0.0005
					(0.0004)
SALESGR	0.0293	0.0275	0.0272	0.0263	0.0270
	(0.0276)	(0.0272)	(0.0275)	(0.0273)	(0.0271)
LN(SIZE)	-0.0936***	-0.0887***	-0.0881***	-0.0855***	-0.0982***
	(0.0271)	(0.0273)	(0.0270)	(0.0270)	(0.0271)
B/M	-0.3776***	-0.3843***	-0.3815***	-0.3844***	-0.3570***
	(0.0424)	(0.0417)	(0.0418)	(0.0417)	(0.0638)
LEV	-0.0214	-0.0281	-0.0275	-0.0290	-0.0239
	(0.0206)	(0.0210)	(0.0209)	(0.0209)	(0.0203)
PPE/A	-0.0695	-0.0865	-0.0802	-0.0853	-0.0721
	(0.0536)	(0.0545)	(0.0538)	(0.0540)	(0.0505)
BETA	0.0071	0.0161	0.0171	0.0169	0.0291
	(0.0209)	(0.0213)	(0.0211)	(0.0214)	(0.0204)
VOL	-0.2923***	-0.3180***	-0.3171***	-0.3155***	-0.3335***
	(0.0846)	(0.0845)	(0.0847)	(0.0849)	(0.0794)
Constant	2.0575***	2.2548***	2.3008***	2.2084***	2.4084***
	(0.6026)	(0.6176)	(0.6124)	(0.6098)	(0.6054)
Sector	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2424	2536	2536	2536	2465
Within R^2	0.380	0.378	0.379	0.380	0.377
Between R^2	0.077	0.087	0.091	0.076	0.095
Overall R^2	0.177	0.152	0.162	0.152	0.157

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses. Variables defined in table A.VI. The Within R^2 shows the proportion of variation in the dependent variable explained by the regressors within each firm, the Between R^2 focus on dynamics between firms and the Overall R^2 combines both Within and Between R^2.

To test if the results were influenced by assumption's inconsistencies, validation tests were performed. The variance inflation factors (VIF[18]), presented in table A.IX in the appendices, did not show any evidence of multicollinearity among regressors, with values always below ten. Moreover, table A.IX also exhibit the Wooldridge test[19] results, with p-values lower than 5% for all the regressions except (1.5), which strongly evidences serial correlation among the residuals. Regarding time-series, the Fischer-expanded augmented-Dickey-Fuller (ADF[20]) tests suggest that non-stationarity is not a problem.

[18] The VIF is an usual and quite straight-forward metric that evaluates multicollinearity in a regression model (Wooldridge et al., 2016). A value higher than 10 is often considered a signal of high collinearity among independent variables.
[19] This is an alternative for the usual autocorrelation tests (e.g. Breusch-Godfrey test) adapted for panel data regressions.
[20] The ADF test evaluates whether a time series is influenced by some external factor or trend that makes them non-stationary in the mean and/or variance. The Fischer expansion is an adaptation to use the test with panel data. See table A.X in the appendices.

We summarize that the models suffer from residual autocorrelation, which can affect their precision and therefore lead to inconsistent and biased estimates. On top of that, the Hausman test showing that the FE model is heavily preferred suggests that the variables may also be affected by other issues – endogeneity[21] and non-linearity – which will be appraised in the next chapter.

5. Robustness

The baseline results may suffer from endogeneity bias and non-linearity, since the explanatory power is relatively low (R-squared always below 0.4) and there may be persistent effects not captured by either the OLS or FE regressions, such as the influence of the economic cycle, future expectations about firm performance, different exposures to climate risk, or the existence of relationships depending on different magnitudes of the variables or different attention given to environmental and climate issues across the period, as we already stated the gaining relevance of this topic in the last years.

The extant literature on this paper' subject does not specifically address these problems, which reinforces the need for further evaluations. For instance, regarding different but related topics, Boubaker et al. (2017; 2020) and Gaio & Gonçalves (2022) acknowledge that omitted variables, endogeneity and reverse causality can lead to biased outcomes when appraising the relationship between Corporate Social Responsibility (CSR) and investors horizon, distress risk or board gender diversity. Moreover, Roberts & Whited (2012) and Ullah et al. (2018) strength the argument by stating that the error term is unobservable under endogeneity and there are no direct test statistics to accurately prove if it exists in a model.

We address these biases by providing an extensive and in-depth investigation, (i) trying to remove strict endogeneity by internally transforming the data, through dynamic panel data models, specifically using the generalized method of moments (GMM), proposed by Arellano & Bond (1991) and further developed by Arellano & Bover (1995) and Blundell & Bond (1998); (ii) dealing with non-linearity and the potential differentiation of unobserved sensitivity between portions of the distributions or time frames, through quantile analysis (FE quantile regressions and comparison of portfolio strategies); (iii) producing additional robustness checks, changing variables or limiting the sample.

[21] A model is considered to suffer from endogeneity when have independent variables that are highly correlated with the error term (Wooldridge et al., 2016; Ullah et al., 2017).

5.1. Appraising endogeneity

A two-step system GMM estimator was considered to deal with endogeneity (Gonçalves et al., 2023a), since the relationship between transition risk and stock performance can be dynamic over time. It requires less assumptions than previous methodologies and prevents data loss (Ullah et al., 2018). Two lags of the dependent variable used as internal instruments are sufficient to capture its persistence (Ullah et al., 2018), which is employed by Gaio & Gonçalves (2022) and Lei & Wisniewski (2018).

The results are presented in table III. The control variables are the same as before, and in addition to the internal instruments – 1^{st} and 2^{nd} lag of returns, in line with Gaio & Gonçalves (2022) and Lei & Wisniewski (2018) – the sector dummy, the lag of LN(SIZE) and the lag of each target variable are used as external instruments. First, industry-specific characteristics can influence the outcome, as various sectors can show a differential in transition risk exposure, and SECT is naturally time-invariant and exogenous. Second, the lag of LN(SIZE) is pertinent because a firm's size in previous periods can affect current situation, reflecting resource levels and growth capacity. Third, the past values of each target variable isolate persistent or delayed effects of transition risk (which is particularly relevant due to the higher reliance on long-term expectations), ultimately contributing to dynamics and reducing endogeneity.

In opposite to previous regressions, namely standard FE, the constant term goes from strongly significant to irrelevant, which reinforces the quality of system GMM appraising this issue and providing stronger outputs. Moreover, the significance of the 2^{nd} return lag across regressions proves the relevance of not using only one lag (Ullah et al., 2018).

Controlling for this bias, LN(CE) is the only statistically significant target independent variable, at 5% level. We complement the FE regressions and give more evidence of H2 by finding that, under these models, the preferences and technology drivers do not seem to influence stock performance at all, and the market movers are focusing their decisions on the transition risk through the impact of climate policies and regulations (Faccini et al., 2023).

Additionally and respecting previous arguments, as this is a dynamic model and the variables are interpreted as changes, firms need to consider that making their activities and operations more aligned with the sustainable goals and recommendations worths on the long-run, due to the negative impact of LN(CE) changes on stock returns, similar to the difference components on standard FE regressions.

The Arellano-Bond test to the persistence of second order autoregressive term (AR(2)) suggests that this set of models do not suffer from second order serial correlation in residuals, being in favour to the adequacy of the system GMM and enhancing previous estimation. In opposite and with p-values below 5%, the Hansen test to instrument validity and overidentification suggests that the external instruments are not totally valid for econometric conditions.

Table III – Two-step system GMM Regressions

Variables	(2.1) R	(2.2) R	(2.3) R	(2.4) R	(2.5) R
L.R	-0.0483	-0.0276	-0.0319	-0.0280	-0.0587
	(0.0356)	(0.0398)	(0.0389)	(0.0389)	(0.0398)
L2.R	-0.0811**	-0.0699*	-0.0741**	-0.0731**	-0.0824**
	(0.0331)	(0.0367)	(0.0361)	(0.0359)	(0.0389)
LN(CE)	-0.1146**				
	(0.0504)				
ENV		-0.0020			
		(0.0031)			
ENVCON			-0.0014		
			(0.0025)		
EM				-0.0012	
				(0.0021)	
ENVIN					-0.0007
					(0.0020)
SALESGR	-0.0265	-0.0614	-0.0671	-0.0523	-0.0659
	(0.0722)	(0.0808)	(0.0744)	(0.0779)	(0.0948)
LN(SIZE)	0.1993	0.3012**	0.2998**	0.2890**	0.3559**
	(0.1391)	(0.1406)	(0.1359)	(0.1412)	(0.1581)
B/M	-0.3799***	-0.4454***	-0.4208***	-0.4457***	-0.4254***
	(0.0651)	(0.0856)	(0.0809)	(0.0840)	(0.0916)
LEV	-0.0989**	-0.1021	-0.0965	-0.0983	-0.0539
	(0.0444)	(0.0638)	(0.0627)	(0.0614)	(0.0651)
PPE/A	0.1916	0.5562**	0.5006**	0.5333**	0.3349
	(0.2000)	(0.2491)	(0.2385)	(0.2453)	(0.2483)
BETA	0.1461**	0.1954**	0.1967**	0.1893**	0.2065**
	(0.0635)	(0.0822)	(0.0787)	(0.0814)	(0.0810)
VOL	-0.7477***	-0.8473***	-0.8660***	-0.8044***	-0.7510**
	(0.2325)	(0.2948)	(0.2927)	(0.2889)	(0.2954)
L.LN(CE)	0.0912**				
	(0.0450)				
L.ENV		0.0004			
		(0.0026)			
L.ENVCON			-0.0009		
			(0.0006)		
L.EM				0.0000	

				(0.0016)	
L.ENVIN					0.0005
					(0.0017)
L.LN(SIZE)	-0.1773	-0.2903**	-0.3079**	-0.2799**	-0.3534**
	(0.1290)	(0.1385)	(0.1355)	(0.1393)	(0.1575)
Constant	0.1763	-0.1624	0.3144	-0.1243	0.1257
	(0.4705)	(0.4252)	(0.4199)	(0.3844)	(0.3938)
Sector	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2370	2478	2478	2478	2412
F p-value	0.000	0.000	0.000	0.000	0.000
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.265	0.184	0.183	0.152	0.095
Hansen p-value	0.006	0.002	0.003	0.002	0.001

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. "L" and "L2" denote first and second lag, respectively. Robust standard errors in parentheses. Variables defined in table A.VI. The first and second lag of stock returns are used as internal (GMM-style) instruments, while the first lag of LN(SIZE), the first lag of each target independent variable and the sector dummy are used as external instruments for all the regressions. The null hypothesis of the F test is that the set of explanatory variables is not globally significant to explain the dependent variable. The null hypothesis of the Arellano-Bond tests (AR(1) and AR(2)) is that there is no first and second order autocorrelation in the residuals of the dynamic panel data model. The null hypothesis of the Hansen test stipulates that the instrumental variables are globally valid, not being correlated with the error term. A p-value lower than 5% lead to reject the null hypotheses of the F, AR(1), AR(2) and Hansen tests.

5.2. Appraising non-linear dependencies

The FE quantile regressions, in table IV, estimate the conditional impact of the set of explanatory variables by quantiles of returns rather than the average impact (Fitzenberger & Wilke, 2015), which allows us to appraise how the relationship between our transition risk metrics varies between different magnitudes of returns. For example, the impact in periods of lower returns may be different from when returns are higher, leading to the accuracy of the models depending not only on the variables defined but also on non-observed factors, such as the growth capacity of the economy and the business cycle, which consequently gives rise to non-linearity.

Indeed, the coefficients vary substantially between quantiles and different target variables, with the log of carbon emissions being again the measure with the greatest significance. On the one hand, the coefficient associated with LN(CE) is positive and relevant at least at a 10% level for quantiles 0.1, 0.3 and 0.5 (5% level in the case of 0.3), and for the same quantiles its difference component is always negative and significant at 5%. On the other hand, the impacts of the ESG scores linked to the preference changes plus technology channels are not significant except for ENVCON in quantiles 0.5 and

0.7, and the changes components are only barely meaningful for EM at the median and for ENVIN at 0.3 (at 10%).

This reinforces previous results and that becoming more sustainable is worthing at the corporate level, with lower exposure to transition risk rewarded by the investors between time periods. It gives strong insights of the presence of non-linear dependencies in the dataset since the transition risk only appears relevant when returns are relatively lower (below and around the median). Additionally, figures A4, A5, A6, A7 and A8 in the appendices show, in continuous terms, how the coefficients associated with each target regressor change over the quantiles, complementing the deductions from table IV.

Transition risk, especially mitigation policy risk, is more evident when European stock market performance is lower, and this effect decreases linearly when stock returns rise. The carbon premium hypothesis keeps plausible (Bolton & Kacperczyk, 2021), similarly to previous results, but it starts to turn meaningless as returns increase in the distribution (see figure A4). The relation between the quantile chosen and the coefficient of the ΔLN(CE) is also linear, but contrary, becoming less negative for higher quantiles, which reinforces the lower sensitivity to transition risk for higher returns. Besides not relevant enough, these opposite dynamics between level and difference variables are also visible with ENV and ENVIN (see figures A5 and A8).

Overall, we can say that a carbon premium may still hold for European equities (Bolton & Kacperczyk, 2021), but the market is increasingly compensating firms that adopt relatively more sustainable practices (Görgen et al., 2020), which in turn is aligned with the disinvestment hypothesis. Both exposures are less notable when returns are higher.

Table IV – Fixed Effects (FE) Quantile Regressions

	Percentile	10%	30%	50%	70%	90%	*N*
(3.1)	LN(CE)	0.0407*	0.0320**	0.0246*	0.0171	0.0086	2458
R		(0.0242)	(0.0160)	(0.0128)	(0.0156)	(0.0234)	
	ΔLN(CE)	-0.0374**	-0.0297**	-0.0232**	-0.0165	-0.00891	
		(0.0181)	(0.0120)	(0.00960)	(0.0117)	(0.0175)	
(3.2)	ENV	0.0002	-0.0001	-0.0003	-0.0006	-0.0008	2574
R		(0.0013)	(0.0009)	(0.0007)	(0.0008)	(0.0012)	
	ΔENV	-0.0002	0.0001	0.0004	0.0007	0.0011	
		(0.0015)	(0.0010)	(0.0007)	(0.0009)	(0.0013)	
(3.3)	ENVCON	-0.0012	-0.0013	-0.0014*	-0.0014*	-0.0015	2574
R		(0.0013)	(0.0009)	(0.0007)	(0.0009)	(0.0013)	
	ΔENVCON	0.0011	0.0008	0.0006	0.0003	0.0000	
		(0.0010)	(0.0006)	(0.0005)	(0.0006)	(0.0010)	
(3.4)	EM	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	2574
R		(0.0010)	(0.0006)	(0.0006)	(0.0007)	(0.0011)	

	ΔEM	0.0010	0.0010	0.0010*	0.0010	0.0010	
		(0.0010)	(0.0006)	(0.0006)	(0.0007)	(0.0011)	
(3.5) R	ENVIN	0.0008	0.0005	0.0002	-0.0001	-0.0004	2504
		(0.0006)	(0.0004)	(0.0004)	(0.0005)	(0.0007)	
	ΔENVIN	-0.0011	-0.0008*	-0.0006	-0.0003	0.0000	
		(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0007)	
	Sector	Yes	Yes	Yes	Yes	Yes	
	Year	Yes	Yes	Yes	Yes	Yes	
	Controls	Yes	Yes	Yes	Yes	Yes	

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors in parentheses (robust option not allowed in Stata). Variables defined in table A.VI. The controls' results were omitted because of space limitations and because they are not meaningful at this stage.

These results, together with the system GMM and standard FE regressions, suggest that the policy risk driver has the strongest impact in European stocks comparing to preference changes and technology, again in line with H2. So far, the carbon premium hypothesis is supported by the level target variables (Bolton & Kacperczyk, 2021), but it remains to be seen whether carbon emissions can really predict market performance. We can verify this by adopting a portfolio approach (Lei & Wisniewski, 2018) based on LN(CE), establishing an equally weighted green portfolio composed with shares of companies with (the log of) emissions below the 10% percentile, and a brown portfolio made up of companies above the 90%. The invested stocks are kept until the following year and the portfolios are rebalanced to maintain the investments below or above the respective percentile.

Assuming an initial investment of 1 euro in 2006 on both portfolios, the annual evolution of their values until 2022 is represented in figure A9 in the appendices, using annualized continuously compounded rates of return. The brown portfolio shows better performance until 2012, when the green portfolio starts to exponentially outperform (until 2021), ending with an approximate value of 9 euros (annual compounding rate of around 12.92%), while the brown one ended worthing around 5 euros (annual compounding rate of about 9.47%). The ending gap of 3.45% could be earned in a trading strategy with European equities considering green/brown firms as a characteristic, in absence of market imperfections such as transaction costs, which can likely be surpassed given that the rebalancing is done yearly. Nevertheless, the strategy is not riskless, besides it being low-costly.

This portfolio comparison also strengths the emergence of the carbon alpha and that the European equity market does not efficiently captures mitigation policy risk, enabling a positive abnormal return in a long-green and short-brown strategy using a climate transition risk measure, in line with Garvey et al. (2018), In et al. (2019), Pástor et al. (2020; 2022) and Ardia et al. (2020) findings.

Generally, we can clearly observe the non-linearity on the data, as brown firms showed higher cumulative returns in early years. It can justify the FE regressions giving results consistent on average with the carbon premium hypothesis. However, since 2012 the significant value increase in green investments gave support to the argument in favour to become aligned with the path towards a net zero emissions economy, being the boost from market players and long-term investors to responsible firms very reasonable to assume (Akey & Appel, 2019; Azar et al., 2021; Ramelli et al., 2021). This adds robustness to the significance of ΔLN(CE) across regressions and to both the disinvestment and carbon alpha hypotheses.

5.3. Complementary checks

Our findings show that policy risk is the driver with the most important impact on the European stock market (approving H2), and that on average investors are still compensated for holding brown stocks (favourable to the carbon premium), but that the shift towards a green economy has made green investments worth in recent years (favourable to the disinvestment and carbon alpha theories), which can explain the ambiguous set of deductions in the literature. Furthermore, the relationship between transition risk and stock performance is non-linear and depends on different market conditions and trends that change over time. Nevertheless, we ask if transition risk effectively impact European stocks under different model endowments or scenarios. This series of additional checks is in tables A.XI and A.XII in the appendices.

Looking at table A.XI, when we change LN(CE) by another commonly used policy risk measure – emissions intensity (EMINT[22]) – the results get deteriorated. Using the system GMM estimator (regression 4.1), the variable is weakly significant, but in any case, its coefficient is negative, reinforcing previous deductions from the models using LN(CE). Although, when we perform a OLS estimation (regression 4.2) with the yearly mean of the *climate policy uncertainty* index (CPU[23]) – a global and systemic measure of mitigation policy risk developed by Gavriilidis (2021) – both the level and change

[22] CE over revenue. Check panel D of table A.VI in the appendices.
[23] Check panel D of table A.VI in the appendices.

coefficients become strongly significant (at 1%), and their respective signals (positive and negative) add more reflections of the simultaneous existence of the carbon premium (probably for earlier years) and that becoming greener is being rewarded recently (Görgen et al., 2020), giving even more power to the disinvestment and carbon alpha hypotheses.

In addition to being related to returns, stock performance is also measured at a risk level (Markowitz, 1952), sustaining the decision of including volatility as a control. When we regress it as a dependent variable using the GMM[24] with the same variables and instruments (regression 4.3), we find that LN(CE) has a strong and relevant negative effect on the total risk of the equity market, complementing the baseline idea that transition risk impacts stock performance, in this case through the total risk. Furthermore, when we decompose it into *systematic* and *specific* risks using the CAPM[25] (regressions 4.4 and 4.5), the negative relationship is only significant (at 5%) for the specific one, indicating that transition risk stemming from mitigation policies is being taken as a risk factor impacting on certain companies, industries or countries. These results do not support the idea that transition risk is affecting the overall European economy and the rational impact of emissions on risk measures would be positive. Nonetheless, as the transition to decarbonization takes time, these relationships can change in the future. Also, the control variables chosen for returns might not hold consistently for volatility, but regressions 4.3, 4.4 and 4.5 are sufficient to add robustness, showing that transition risk impacts stock performance in more than one way and portfolio diversification seems effective to hedge market risk today.

When we subtract the Euro Stoxx 600 market rate of return (Rm, calculated in the same way of remaining returns) to each company-year observation, we get a measure of excess returns (R-Rm), which in regression 4.6 shows a similar result, in terms of coefficients, to the homologous baseline FE regression, further reinforcing the impact of LN(CE).

Considering appendix table A.XII, the estimation of the same baseline FE model excluding the 10% highest and the 10% lowest returns (regression 4.7) leads to a substantial reduction of the explanatory power, and mitigation policy risk becomes

[24] As financial series show a phenomenon of volatility clustering, VOL was only modelled under GMM (Bollerslev, 1986; Lei & Wisniewski, 2018).

[25] The calculation of systematic (SYVOL) and specific volatility (SPVOL) takes into account the STOXX market rate of return (Rm) and is based on the CAPM closed-form solution for volatility: $VOL^2{}_{Ri,y} = BETA^2{}_i * VOL^2{}_{Rm,y} + VOL^2{}_{si,y} \Leftrightarrow VOL^2{}_{Ri,y} = SYVOL^2{}_{Ri,y} + SPVOL^2{}_{Ri,y}$.

irrelevant, which is in accordance with the higher impact felt for lower returns in the distribution (dropping them leads to irrelevance) and, jointly with quantile regressions, suggests that this risk can act as an "*insurance effect*" in both perspectives when firm's performance is worse.

On the other hand, since most environmental regulatory actions come from EU Member States and not from all Europe itself, we excluded firms from the United Kingdom and Switzerland in regression 4.8, but the significance of coefficients and relationship between policy risk (level variable plus difference component) and stock performance maintains in the same way as previous homologous regressions, which proves, with a certain confidence, that European countries are in general paying attention to climate change.

In the last checks (regressions 4.9 and 4.10), where we split the analysis in two subperiods – one until the signing of the Paris Agreement (2006-2015) and the other afterward (2016-2022) – the support to carbon-intensive equities' disinvestment, to the existence of a potential carbon alpha and to the non-linearity of the data keeps very clear, similarly to the portfolio comparison.

Before the Paris Agreement, the impact of policy risk was negligible as the results of LN(CE) and its difference are not significant. Nevertheless, from 2016 onwards their impact turned to be strongly significant (at 1%, besides the reduction in explanatory power as showed by the R-squared metrics), and the respective coefficients are in line with regressions 1.1, 2.1, 3.1, 4.1, 4.2, 4.3, 4.6 and 4.8, which consequently makes them consistent with main findings.

At the end, despite a carbon premium still being visible (Bolton & Kacperczyk, 2021), the increasing awareness of market participants to climate regulations (Battiston et al., 2021), namely after 2015 (Weber & ElAlfy, 2019; Carè & Weber, 2023), made transition risk become very important, which supports H1 in a forward-looking perspective, even from only one driver, and makes the disinvestment hypothesis consistent (Pástor et al., 2020; 2022; Ardia et al., 2022; Reboredo & Ugolini, 2022), being brown firms condemned to observe their stocks going down as climate attention gets more and more important over time.

6. Conclusion, limitations and future research

The discussion around the impact of climate-related risks on financial markets, namely equities, has been growing as the overall environmental debate received relevance in recent times, namely after 2015 (Battiston et al., 2021; Giddens, 2009; Nordhaus, 2019; Weber & ElAlfy, 2019; Carè & Weber, 2023). Transition risk has gained an increasing role of explaining the instability on the financial system and stock market dynamics, as it raises uncertainty about future climate scenarios (Giglio et al., 2021; Hui-Min et al., 2021; NGFS, 2023) and consequently about firm's market performance. This is visible, for example, by green funds outperforming traditional ones when the sensitivity of firm performance to sustainability issues is higher, and through the evidence that an unfavorable transition scenario could induce equity fund losses (Gonçalves et al., 2021; Schober et al., 2021).

With this paper, we contributed to fulfil a notorious gap in research on the transmission of this risk to the stock market, since most studies focus on the US (Venturini, 2022), when there are more comprehensive regulations in Europe and a series of indicators suggest that in general European countries are making a greater contribution to the transition towards a green economy (EU TEG, 2020; IMF, 2024; OECD, 2024).

Transition risk is transmitted on the stock market via three drivers: mitigation policy risk, preference change and technology (Semieniuk et al., 2021). However, the literature has not found a consensual impact, with some suggesting a positive relationship, associated with a carbon premium required by investors to get greater exposure to this risk (Bolton & Kacperczyk, 2021), and others find evidence in favour of a negative relationship, which is justified by disinvestment in less sustainable companies by socially responsible investors or the presence of abnormal returns in green alternatives given that the market underprices transition risk (Ardia et al., 2022; Garvey et al., 2018; In et al., 2019; Pástor et al., 2020; 2022). There are also studies not finding a clear impact (Görgen et al., 2020), and arguing that greater transparency in the disclosure of environmental data by companies benefits their market valuation and that more recently green stocks may have received a boost from long-term institutional investors (Azar et al. 2021; Flammer et al., 2021; Ramelli et al., 2021).

We make our two hypotheses (H1 and H2) consistent and answer the research question by finding that the relationship between transition risk and stock performance is complex, but significant and that the major source of transition risk stems from mitigation policy risk, being the other drivers' proxies (ENV, ENVCON, EM and ENVIN) not relevant enough as proved by GMM (only policy risk was statistically significant) and quantile regressions (only policy risk proxy was simultaneously relevant at level and changes, for three quantiles).

Our standard fixed effects regressions suggest that, in line with Bolton & Kacperczyk (2021), a carbon premium is still reflected on stocks of European firms (with LN(CE), the variable of policy risk presenting a 10% statistically significant positive impact). Nonetheless, we also gained insights favourable to reducing carbon emissions and becoming more sustainable through the 1% significant negative impact of its change component (support of the disinvestment and carbon alpha theories, in line with Ardia et al. (2022), Garvey et al. (2018), In et al. (2019) and Pástor et al. (2020; 2022)), which in addition to a set of validation tests, suggested that the results were biased by the presence of potential endogeneity and non-linearity.

The robustness methodologies (Ullah et al., 2018; Lei & Wisniewski, 2018; Gaio & Gonçalves, 2022) further strengthened the evidence of the disinvestment and carbon alpha, as well as the presence of the mentioned problems, finding that (i) a dynamic model solves autocorrelation problems and enhance the estimation, defending H2; (ii) lower returns are more influenced by transition risk, and that the absolute coefficient decreases and becomes less important linearly as a function of quantiles, with higher returns being insensitive to risk from both the level and changes components (evidence of non-linearity in distribution); and (iii) brown firms had higher returns than greens in early years in the sample, but since around 2012 the later have exponentially grown, outperforming clearly the first (evidence of non-linearity in time).

We also find that when replacing LN(CE) by other policy risk variables, the results tend to keep consistent (with the same impact signal and deductions from baseline models), as well as substituting returns by other stock market measures clarify the importance of transition risk. Finally, when we analyze the sample by subperiods, we only get a strongly significant relationship between transition risk and stock returns for the years after the Paris Agreement, reinforcing non-linearity in time and the potential green rewarding from long-term investors (Ramelli et al., 2021).

Overall, we argue that transition risk, mainly mitigation policy risk, has a significant relation with stock performance, and the objective impact depends on unobserved effects and trends that vary among industries and time frames. We suggest that recently the disinvestment and carbon alpha hypotheses are more likely to hold, given the increasing awareness on environmental issues, mainly after 2015, and the clear boost from institutions to climate-responsible firms.

Our paper contributes to literature in the way it fulfils the gap of research in Europe and demonstrates that the relationship is not simple, supplemented by the ambiguous set of previous findings. It reduces the underuse of some methodologies in the topic such as system GMM and quantile regressions, and add several additional checks to give a comprehensive answer regarding all hypotheses. Practically, we conclude that market participants need to consider regulatory issues and policy news in equity research proving the importance of this risk and discovering that its more meaningful source comes from regulations, which is particularly important in European nations. The non-linear relationship among the two constructs is characterized by higher sensitivity of lower returns (which can suggest an *insurance effect*) and the impact decreases as returns raise in the distribution.

Lastly, limitations regarding the sample, variables and methods must be considered too. The dataset is unbalanced due to missing values for some companies, which makes the period not exactly 2006-2022 for some panels. The choice of variables was also limited, as most environmental metrics from Refinitiv-Eikon database (and others, like Moody's Orbis) do not provide enough observations. The methodologies used theoretically rely on strong assumptions, which may not be suitable under the uncertain market conditions we face nowadays.

For future research, it would be interesting to check the transition risk impact on other asset classes, such as fixed-income, derivatives or alternative investments, and their implications for the stock market; or the impact on other regions, verifying the differential with the US and EU to see if there are spillover effects (Hengge et al., 2023) or estimate the probability of divergent cooperation scenarios (NGFS, 2023).

References

Akey, P., & Appel, I. (2019). Environmental externalities of activism. Available at *SSRN 3508808*.

Almeida, J., & Gonçalves, T. C. (2024). The AI Revolution: Are Crypto Markets More Efficient after ChatGPT 3?. *Finance Research Letters*, 105608.

Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3), 1146-1183.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2020). Climate change concerns and the performance of green versus brown stocks. *Management science, forthcoming.* Available at *SSRN 3717722.*

Arellano, M. (2003). Panel data econometrics. Oxford university press.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, 68(1), 29-51.

Azar, J., Duro, M., Kadach, I., & Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics*, 142(2), 674-696.

Bartram, S. M., Hou, K., & Kim, S. (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, 143(2), 668-696.

Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. *Journal of Financial Stability*, 54, 100867.

Benton, G. S. (1970). Carbon dioxide and its role in climate change. *Proceedings of the National Academy of Sciences*, 67(2), 898-899.

Berk, J., DeMarzo, P. (2013). Corporate Finance, 3rd Edition. Pearson.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1), 115-143.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3), 307-327.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk?. *Journal of financial economics*, 142(2), 517-549.

Boubaker, S., Chourou, L., Himick, D., & Saadi, S. (2017). It's about time! The influence of institutional investment horizon on corporate social responsibility. *Thunderbird International Business Review*, 59(5), 571-594.

Boubaker, S., Cellier, A., Manita, R., & Saeed, A. (2020). Does corporate social responsibility reduce financial distress risk?. *Economic Modelling*, 91, 835-851.

Carè, R., & Weber, O. (2023). How much finance is in climate finance? A bibliometric review, critiques, and future research directions. *Research in International Business and Finance*, 64, 101886.

Carini, C., Comincioli, N., Poddi, L., & Vergalli, S. (2017). Measure the performance with the market value added: Evidence from CSR companies. *Sustainability*, 9(12), 2171.

Creutzig, F., Agoston, P., Goldschmidt, J. C., Luderer, G., Nemet, G., & Pietzcker, R. C. (2017). The underestimated potential of solar energy to mitigate climate change. *Nature Energy*, 2(9), 1-9.

Döttling, R., & Rola-Janicka, M. (2023). Too levered for Pigou: carbon pricing, financial constraints, and leverage regulation. *European Central Bank (ECB)*.

El Ghoul, S., Guedhami, O., & Kim, Y. (2017). Country-level institutions, firm value, and the role of corporate social responsibility initiatives. *Journal of International Business Studies*, 48(3), 360-385.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.

EU Technical Expert Group (TEG) (2020). Taxonomy: Final report of the Technical Expert Group on Sustainable Finance. Available in: https://finance.ec.europa.eu/system/files/2020-03/200309-sustainable-finance-teg-final-report-taxonomy_en.pdf

Faccini, R., Matin, R., & Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices?. *Journal of Banking & Finance*, 155, 106948.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383-417.

Fitzenberger, B., & Wilke, R. A. (2015). Quantile regression methods. *Emerging Trends in the Social and Behavioral Sciences: An Interdisciplinary, Searchable, and Linkable Resource*, 1-18.

Flammer, C., Toffel, M. W., & Viswanathan, K. (2021). Shareholder activism and firms' voluntary disclosure of climate change risks. *Strategic Management Journal*, 42(10), 1850-1879.

Gaio, C., & Gonçalves, T. C. (2022). Gender diversity on the board and firms' corporate social responsibility. *International Journal of Financial Studies*, 10(1), 15.

Gaio, C., Goncalves, T., & Sousa, M. V. (2022). Does corporate social responsibility mitigate earnings management?. *Management Decision*, 60(11), 2972-2989.

Garvey, G. T., Iyer, M., & Nash, J. (2018). Carbon footprint and productivity: does the "E" in ESG capture efficiency as well as environment. *Journal of Investment Management*, 16(1), 59-69.

Gavriilidis, K. (2021). Measuring climate policy uncertainty. Available at *SSRN 3847388*.

Giddens, A. (2009). Politics of climate change. Polity.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, 13, 15-36.

Gonçalves, T. C., Barros, V., & Avelar, J. V. (2023). Environmental, social and governance scores in Europe: what drives financial performance for larger firms?. *Economics and Business Letters*, 12(2), 121-131.

Gonçalves, T. C., Dias, J., & Barros, V. (2022). Sustainability performance and the cost of capital. *International Journal of Financial Studies*, 10(3), 63.

Gonçalves, T. C., & Gaio, C. (2023). Corporate sustainability disclosure and media visibility: Mixed method evidence from the tourism sector. *Journal of Business Research*, 155, 113447.

Gonçalves, T., Gaio, C., & Costa, E. (2020). Committed vs opportunistic corporate and social responsibility reporting. *Journal of Business Research*, 115, 417-427.

Gonçalves, T., Gaio, C., & Ferro, A. (2021). Corporate social responsibility and earnings management: Moderating impact of economic cycles and financial performance. *Sustainability*, 13(17), 9969.

Gonçalves, T. C., Louro, D., & Barros, V. (2023). Can corporate sustainability drive economic value added? Evidence from larger European firms. *Journal of Risk and Financial Management*, 16(4), 215.

Gonçalves, T. C., Pimentel, D., & Gaio, C. (2021). Risk and Performance of European Green and Conventional Funds. *Sustainability*, 13(8), 4226.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020). Carbon risk. Available at *SSRN 2930897*.

Hengge, M., Panizza, U., & Varghese, M. R. (2023). Carbon policy surprises and stock returns: Signals from financial markets (No. 17868). *International Monetary Fund*.

Heston, S. L., Rouwenhorst, K. G., & Wessels, R. E. (1999). The role of beta and size in the cross-section of European stock returns. *European Financial Management*, 5(1), 9-27.

Hsu, P. H., Li, K., & Tsou, C. Y. (2023). The pollution premium. *The Journal of Finance*, 78(3), 1343-1392.

Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49, 633-656.

Hui-Min, L. I., Xue-Chun, W. A. N. G., Xiao-Fan, Z. H. A. O., & Ye, Q. I. (2021). Understanding systemic risk induced by climate change. *Advances in Climate Change Research*, 12(3), 384-394.

IMF (2024). Mitigation Indicators (database). (Accessed on 31 January 2024). Available in: https://climatedata.imf.org/pages/mitigation#mi4

In, S.Y., Park, K.Y., & Monk, A. (2019). Is 'being green' Rewarded in the market? An empirical Investigation of Decarbonization and Stock Returns. Unpublished working paper. *Stanford Global Project Center*.

Investopedia (2023). How to Tell If a Company Has High ESG Scores. Available in: https://www.investopedia.com/company-esg-score-7480372#:~:text=Environmental%2C%20social%2C%20and%20governance%20(,more%20than%2070%20considered%20good.

Karydas, C., & Xepapadeas, A. (2022). Climate change financial risks: Implications for asset pricing and interest rates. *Journal of Financial Stability*, 63, 101061.

Lei, X., & Wisniewski, T. P. (2018). Democracy and stock market returns. *Journal of Financial Research*.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *Journal of Finance*, 20(4), 587-615.

LSEG (2024). Eikon Database [Database], March 2024. London.

LSEG (2023). Environmental, social and governance scores from LSEG. December 2023. Available in: https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf

Madime, E., & Gonçalves, T. C. (2022). Consequences of social and environmental corporate responsibility practices: Managers' perception in mozambique. *International Journal of Financial Studies*, 10(1), 4.

Madime, E., & Gonçalves, T. C. (2022). Determining factors for social and environmental practices of corporate responsibility in mozambique. *Revista de Gestão Social e Ambiental*, 16(2), e03002-e03002.

Markowitz, H. M. (1952). Portfolio Selection, *Journal of Finance*, 7 (1). N, 1, 71-91.

McShane, B. B., Bradlow, E. T., & Berger, J. (2012). Visual influence and social groups. *Journal of Marketing Research*, 49(6), 854-871.

Metcalf, G. E. (2009). Market-based policy options to control US greenhouse gas emissions. *Journal of Economic perspectives*, 23(2), 5-27.

Morelli, D. (2007). Beta, size, book-to-market equity and returns: A study based on UK data. *Journal of Multinational Financial Management*, 17(3), 257-272.

Nadyayani, D. A. D., & Suarjaya, A. A. G. (2021). The effect of profitability on stock return. *American Journal of Humanities and Social Sciences Research (AJHSSR)*, 5(1), 695-703.

Neusser, K. (2016). Time series econometrics. Springer.

NGFS (2023). NGFS Scenarios for central banks and supervisors. Network for Greening the Financial System Workstream on Scenario Design and Analysis. Available in: https://www.ngfs.net/sites/default/files/medias/documents/ngfs_climate_scenarios_for_central_banks_and_supervisors_phase_iv.pdf

Nordhaus, W. D. (1977). Economic growth and climate: the carbon dioxide problem. *The American Economic Review*, 67(1), 341-346.

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The economic journal*, *101*(407), 920-937.

Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science*, 258(5086), 1315-1319.

Nordhaus, W. D. (2019). Climate change: The ultimate challenge for economics. *American Economic Review*, 109(6), 1991-2014.

OECD (2024). Air and GHG emissions (indicator). doi: 10.1787/93d10cf7-en. Available in: https://data.oecd.org/air/air-and-ghg-emissions.htm

OECD (2024). Environmental tax (indicator). doi: 10.1787/5a287eac-en. Available in: https://data.oecd.org/envpolicy/environmental-tax.htm

Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking & Finance*, 58, 294-308.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2020). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2), 550-571.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns: Technical report, *National Bureau of Economic Research*.

Pettifor, H., Wilson, C., Axsen, J., Abrahamse, W., & Anable, J. (2017). Social influence in the global diffusion of alternative fuel vehicles–A meta-analysis. *Journal of Transport Geography*, 62, 247-261.

Qian, W., Suryani, A. W., & Xing, K. (2020). Does carbon performance matter to market returns during climate policy changes? Evidence from Australia. *Journal of Cleaner Production*, 259, 121040.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 US elections. *The Review of Corporate Finance Studies*, 10(4), 748-787.

Reboredo, J. C., Ugolini, A. (2022). Climate transition risk, profitability and stock prices. International Review of Financial Analysis, 83, 102271.

Ricci, E. C., & Banterle, A. (2020). Do major climate change-related public events have an impact on consumer choices?. *Renewable and Sustainable Energy Reviews*, 126, 109793.

Roberts, M. R., & Whited, T. M. (2013). Endogeneity in empirical corporate finance. In *Handbook of the Economics of Finance* (Vol. 2, pp. 493-572). Elsevier.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, 98 (5, Part 2), S71-S102.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3), 341–360.

Ruhani, F., Islam, M. A., & Ahmad, T. S. T. (2018). Theories Explaining Stock Price Behavior: A Review of the Literature. *International Journal of Islamic Banking and Finance Research*; Vol. 2, No. 2; 2018.

Santos, A. R. (2021). Market Value Relevance of Environmental, Social and Governance (ESG) Scores. Master Thesis, defended at *ISEG – Lisbon School of Economics & Management*.

Schober, D., Etzel, T., Falter, A., Frankovic, I., Gross, C., Kablau, A., Lauscher, P., Ohls, J., Strobel, L, Wilke, H. (2021). Sensitivity analysis of climate-related transition risks in the German financial sector. *Deutsche Bundesbank*.

Semieniuk, G., Campiglio, E., Mercure, J. F., Volz, U., & Edwards, N. R. (2021). Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change*, 12(1), e678.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), 425-442.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics*, 70(1), 65-94.

Taliento, M., Favino, C., & Netti, A. (2019). Impact of environmental, social, and governance information on economic performance: Evidence of a corporate 'sustainability advantage'from Europe. *Sustainability*, 11(6), 1738.

Task force on Climate-related Financial Disclosures (TCFD) (2017). Recommendations of the Task Force on Climate-related Financial Disclosures. Available in: https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11052018.pdf

Tedeschi, M., Foglia, M., Bouri, E., & Dai, P. F. (2024). How does climate policy uncertainty affect financial markets? Evidence from Europe. *Economics Letters*, 234, 111443.

Teske, S., Nagrath, K., Niklas, S., Talwar, S., Atherton, A., Orbe, J. G., ... & Giurco, D. (2022). Scopes 1, 2, and 3 Industry Emissions and Future Pathways. In Achieving the Paris Climate Agreement Goals: Part 2: Science-based Target Setting for the Finance industry—Net-Zero Sectoral 1.5˚ C Pathways for Real Economy Sectors. *Cham: Springer International Publishing*.

Tobin, J. (1958). Liquidity preference as behavior towards risk. The review of economic studies, 25(2), 65-86.

Trinks, A., Mulder, M., & Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics*, 175, 106632.

Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management*, 71, 69-78.

Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 79, 101934.

Weber, O., & ElAlfy, A. (2019). The development of green finance by sector. The rise of green finance in europe: opportunities and challenges for issuers, investors and marketplaces, 53-78.

Wilmott, P. (2007). Paul Wilmott Introduces Quantitative Finance. 2nd Ed. John Wiley & Sons, Ltd.

Wooldridge., J. M. (2010). Econometric Analysis of Cross Section and Panel Data. 2nd Ed. The MIT Press.

Wooldridge, J. M., Wadud, M., & Lye, J. (2016). Introductory econometrics: Asia pacific edition with online study tools 12 months. Cengage AU.

Yang, Y., Huang, C., & Zhang, Y. (2023). Decomposing Climate Risks in Stock Markets (No. 2023-2141). *International Monetary Fund*.

Zhang, S. Y. (2022). Are investors sensitive to climate-related transition and physical risks? Evidence from global stock markets. *Research in International Business and Finance*, 62, 101710.

Appendices

Table A.I – Hypotheses explaining the transition risk effects on the equity market

Hypothesis	Disinvestment	Carbon Premium	Carbon Alpha
Economic rationale	$\Delta Risk > 0 \Longrightarrow$ $\Longrightarrow\downarrow Q^{d}_{h-e} \Longrightarrow$ $\Longrightarrow \Delta S_{h-e} < 0$	$\Delta Risk > 0 \Longrightarrow$ $\Longrightarrow$t $Comp^{req}_{h-e} \Longrightarrow \Delta S_{h-e} > 0$	$\Delta Risk > 0 \Longrightarrow$ $\Longrightarrow$t $R^{abn}_{l-e} \Longrightarrow \Delta S_{h-e} < 0$
Literature in favour	Ardia et al. (2022); Pástor et al. (2020; 2022); Reboredo & Ugolini (2022)	Bolton & Kacperczyk (2021); Hengge et al. (2023); Karydas & Xepapadeas (2022)	Ardia et al. (2022); Engle et al. (2020); Garvey et al. (2018); Hengge et al. (2023); In et al. (2019); Pástor et al. (2020; 2022)
Literature not in favour	Bolton & Kacperczyk (2021); Görgen et al. (2020)	Ardia et al. (2022); Chan et al. (2022); Görgen et al. (2020) ; Pástor et al. (2020; 2022); Reboredo & Ugolini (2022); Qian et al. (2020)	Bolton & Kacperczyk (2021); Reboredo & Ugolini (2022)

Note: "Risk" is exposure to transition risk, Q^{d}_{h-e} is the demand for high-emissions stocks, S_{h-e} is the stock price of high-emissions firms, $Comp^{required}_{h-e}$ is the compensation required to hold high-emissions stocks and R^{abn}_{l-e} are abnormal returns of low-carbon stocks.

Table A.II – Literature Review Summary: Main Discussion Papers

Author (year)	Brief description	Main findings
Battiston, S., Dafermos, Y., Monasterolo, I. (2021)	The study states how crucial it is to tackle climate physical and transition risks within the stability of the financial sector. It delves into how these risks affect stock markets and ways to manage them using climate derivatives. It also points different papers on climate finance.	Recognition of climate change as a financial risk. Recognition of the need for mitigation strategies and the use of modelling techniques to assess potential impacts.
Giglio, S., Kelly, B., Stroebel, J. (2021)	Overview of literature on climate finance, discussing different approaches to incorporate climate risk in financial models. It explores the analysis and pricing of climate risks across asset classes and hedging portfolios.	Firms with higher (lower) carbon emissions are valued at discount (premium). Environmental policy uncertainty affects stock market valuations.
Semieniuk, G.,Campiglio, E., Mercure, J. F., Volz, U., & Edwards, N. R. (2020)	Focus on the challenges of transitioning to a low-carbon economy and the associated risks to financial stability. It emphasizes the need for a comprehensive framework to understand transition risks in both declining and emerging industries. They state the three drivers of transition risk appraised in our paper.	Transitioning to a low-carbon economy will lead to a decline in fossil fuel-related industries. Asset revaluations, debt defaults and bubbles in emerging industries can lead to financial instability.
Venturini, A. (2022)	Comprehensive review of papers appraising how climate change impacts stock returns. It compares different approaches to understand climate risk's influence on stock returns across sectors or markets, and the implications of firms and investors characteristics on asset prices.	Retail and institutional investors haven't always based their assessment of climate risks on fundamental data. However, there's been a stronger recent response in various asset classes. Increasing awareness of climate issues may facilitate an "*alpha decay*".

Table A.III – Literature Review Summary: Main Empirical/Theoretical Papers

Author (year)	Brief description and methodology	Variables	Main findings
Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2020)	Researchers investigate the impact of climate change concerns on the performance of green stocks compared to traditional ones. They create a daily Media Climate Change Concerns index to detect unexpected spikes in concerns.	Excess returns (*dep*); MCCC index; Unexpected changes in climate change concerns; GHG emissions intensity; Factors; Energy & macroeconomic variables	Unexpected increases in climate concerns help to explain the performance differences between green and brown stocks. Green firms tend to outperform brown firms when there are unexpected spikes in concerns. Discount rates are relevant to explain the relationship between stock returns and climate concerns.
Bolton, P., & Kacperczyk, M. (2021)	This study investigates if investors care about carbon risk and their impact on US stock returns. They analyze the relationship between carbon emissions and stock returns, controlling for known risk factors, industry and firm characteristics. They use cross-sectional regressions with fixed effects for firm-level differences and time-varying factors; and clustering methods to account for the correlation of errors within firms and over time.	Monthly stock returns (*dep*); Carbon emissions; Carbon intensity; GHG Impact ratios; Market cap; Book-to-market ratio; ROE; Leverage; Volatility; Capital expenditures; Betas	Positive relationship between stock returns and the carbon emissions. Contradiction of the disinvestment and carbon alpha hyphoteses, suggesting that investors are already demanding compensation for their exposure to carbon risk, reflected in asset prices. Carbon premium isn't linked to traditional risk factors.
Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020)	The paper explores the use of climate change news data extracted from textual analysis and constructing climate change hedging portfolios. Analysing the relationship between climate news and financial markets, they encompass climate risk exposure using ESG in the hedging strategy.	Climate change news sentiment indices (*dep*); Market variables; ESG scores; Climate risk exposures of firms	Climate change news can be used to construct hedging portfolios. News and regulations have a significant impact on financial markets.
Garvey, G. T., Iyer, M., & Nash, J. (2018)	The paper appraises the relation between carbon emissions, productivity, and financial performance at the corporate level. By analyzing data from the period 2011-2015 for firms in the MSCI universe, the researchers explore how changes in carbon intensity affect measures of company performance, analyzing transition risk using regression analysis.	Stock returns (*dep*); Profitability (*dep*); Sales; Total assets; Total employees; Carbon intensity	Firms can reduce carbon emissions by improving efficiency, leading to stronger future financial performance. Negative relationship between carbon intensity and financial outcomes.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020)	Focusing on measuring transition risk impact in the financial markets by merging fundamental information from various ESG databases, the authors select specific variables related to carbon issues, to analyze their impact. They explore the relationship between carbon risk and equity prices using panel regressions and asset pricing models.	Yearly stock returns (*dep*); Emissions intensity; Carbon emissions score; Innovation score; Environmental score; Other ESG metrics and controls	Brown firms (with higher carbon emissions and lower environmental friendliness scores) exhibit different return patterns compared to green firms, but there's no significant evidence of a carbon risk premium in asset pricing.
Hengge, M., Panizza, U., & Varghese, M. R. (2023)	The paper evaluates the impact of carbon policy surprises on stock returns of European firms, using data from the EU ETS and over publicly listed European companies (2011-2021 period). It addresses the relationship between carbon prices and stock returns and explores the implications for the cost of equity of brown firms. The research also examines the role of transition risk in investor behaviour and the potential global spillover effects of EU regulations on non-European firms. Regression analysis with fixed effects is implemented.	Stock returns (*dep*); Scope 1 and 2 emissions intensity; Daily change in futures prices	Higher carbon prices lead to negative abnormal returns, showing that investors consider transition risk. This effect is more pronounced for firms outside the EU ETS, indicating that policies on emissions and raising carbon prices effectively increase the cost of capital for brown firms. Potential spillover effects for firms outside the EU.
Karydas, C., & Xepapadeas, A. (2022)	The article explores the impact of climate change on financial stability, asset pricing, and interest rates using a dynamic CAPM model with rare disasters. It also considers the potential decline in real interest rates and reduced weight of carbon-intensive assets due to increasing policy risk.	Equity risk premium (*dep*); Temperature anomaly; Macroeconomic & environmental disasters; Policy stringency; Recursive preferences	As global warming decreases risk-free rates, equity risk premiums rise due to disaster vulnerability. Reduced participation of brown assets in portfolios, with rising temperatures, driven by policy risk.
Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2020; 2022)	The 2020 paper presents a theoretical model that integrates sustainable investing considerations into traditional financial frameworks. It explores how ESG characteristics of firms influence investor preferences and market outcomes. The authors analyze the relationship between sustainable investing, market efficiency, and risk. The 2022 work focuses on dissecting green asset returns (using time-series regressions and factor models), in the context of increasing environmental concerns	Equity risk premium (*dep*); Stock returns (*dep*); ESG characteristics; Climate risks; Investor preferences; Climate change concerns; Financial and regulatory factors	Sustainable investing can influence market outcomes. Climate risks affect market efficiency and risk management strategies. Incorporating ESG considerations into investment decisions lead to different asset pricing dynamics. Green assets have exhibited higher returns in recent years, driven by social and regulatory considerations. Climate policy news have a stronger association with green asset

	and climate change. Green assets are compared to brown assets, examining the factors driving the outperformance of the first ones.		returns than environmental disasters news.
Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021)	The study examines the impact of the 2016 and 2020 US elections on stock price movements of firms with varying levels of climate responsibility. It explores how investors perceive and value climate-related factors in the context of changing political and regulatory endowments, particularly focusing on post-Trump climate policy. They use investor horizon analysis.	Abnormal stock returns (*dep*); Climate scores; Carbon intensity; Investor horizon; Controls	After the 2016 election, stock prices of both carbon-intensive and climate-responsible firms rose. Long-term institutional investors notably boosted climate-responsible companies' stock prices, anticipating stricter regulations and rewarding them.
Reboredo, J. C., Ugolini, A. (2022)	This paper evaluates the impact of climate transition risk on the financial performance and stock prices of publicly traded European and US firms. The authors use a firm-level carbon risk score (CRS) to quantify transition risk and suggest that this kind of information is useful for designing portfolios and managing transition risk in a way that exploits the benefits of the transition to a low-carbon economy. They use different methodologies such as portfolio sorts and panel regressions.	ROA (*dep*); ROE (*dep*); EBITDA/Assets (*dep*); Tobin's Q (*dep*); Stock returns (*dep*); CRS; Paris Agreement dummy; Quintile dummy; Controls (size, leverage, sales/assets, etc.);	Firms with lower exposure to transition risk perform better in terms of profits and stock returns. After 2015, the spread between green and brown firms narrows. EU firms are more sensitive to transition risk than US ones: in Europe, investors more likely correct underreaction by reducing (increasing) the value of companies with high (low) transition risk exposure.

Note: "*dep*" indicates that the referred variable is a dependent variable in the respective paper.

Table A.IV – Sample composition by country

Country	Frequency	Percentage
Austria	5	1.27%
Belgium	5	1.27%
Denmark	15	3.82%
Finland	15	3.82%
France	60	15.27%
Germany	49	12.47%
Ireland	9	2.29%
Italy	19	4.83%
Luxembourg	5	1.27%
Netherlands	18	4.58%
Norway	9	2.29%
Poland	2	0.51%
Portugal	3	0.76%
Spain	18	4.58%
Sweden	32	8.14%
Switzerland	31	7.89%
United Kingdom	98	24.94%
Total	393	100%

Table A.V – Sample composition by sector

Sector	Frequency	Percentage
Basic Materials	50	12.72%
Consumer Cyclicals	64	16.28%
Consumer Non-Cyclicals	37	9.41%
Energy	20	5.09%
Healthcare	38	9.67%
Industrials	87	22.14%
Real Estate	26	6.62%
Technology	46	11.70%
Utilities	25	6.36%
Total	393	100%

Classification according to *The Refinitiv Business Classification* (TRBC)

Table A.VI – Variables definition and their use by the Literature

Panel A. Dependent variable		
Stock Returns (R)	$E(\text{Weekly returns within a year}) * q$, $q \equiv$ number of available obs. in a year (by default 52)	Ardia et al. (2020); Bolton & Kacperczyk (2021); Görgen et al. (2020); Hengge et al. (2023); Pástor et al. (2020; 2022); Reboredo & Ugolini (2022)
Panel B. Target independent variables		
CE	Total CO2 and equivalents emissions	Ardia et al. (2020)*; Bolton & Kacperczyk (2021); Garvey et al. (2018)*; Görgen et al. (2020)**; Hengge et al. (2023)*; Ramelli et al. (2021)**
ENV	ESG category score of a company's impact on natural systems and ecosystems, reflecting how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities to generate long term shareholder value (LSEG, 2024)	Engle et al. (2020); Görgen et al. (2020)
ENVCON	ESG category score of a company's exposure to environmental controversies and negative events observable in global media (LSEG, 2024)	Author
EM	ESG category score of a company's commitment and effectiveness reducing environmental emissions in its processes (LSEG, 2024)	Görgen et al. (2020)
ENVIN	ESG category score regarding the capacity to reduce the environmental costs for customers and creating new market opportunities through new environmental technologies and processes (LSEG, 2024)	Görgen et al. (2020)

ΔX	$X_y - X_{y-1}$, X is a target independent variable (CE, ENV, ENVCON, EM or ENVIN)	Görgen et al. (2020)
Panel C. Control variables		
SALESGR	$\frac{\text{Revenue}_y - \text{Revenue}_{y-1}}{\text{Market capitalization}_{y-1}}$	Bolton & Kacperczyk (2021); Garvey et al. (2018)*; Ramelli et al. (2021)*
SIZE	Total assets	Bolton & Kacperczyk (2021)**; Görgen et al. (2020); Ramelli et al. (2021)**; Reboredo & Ugolini (2022)**
B/M	$\frac{\text{Book value of equity}}{\text{Market capitalization}}$	Bolton & Kacperczyk (2021); Görgen et al. (2020); Pástor et al. (2022); Reboredo & Ugolini (2022)
LEV	$\frac{\text{Total debt}}{\text{Total assets}}$	Bolton & Kacperczyk (2021); Görgen et al. (2020); Ramelli et al. (2021); Reboredo & Ugolini (2022)
PPE/A	$\frac{\text{Gross property, plant \& equipment}}{\text{Total assets}}$	Author; Bolton & Kacperczyk (2021)*; Görgen et al. (2020)*
BETA	Market beta. Different look back periods can be used to measure it, in order of preference: 5Y monthly, 3Y weekly, 2Y weekly, 180D daily, 90D daily (LSEG, 2024)	Bolton & Kacperczyk (2021); Görgen et al. (2020); Reboredo & Ugolini (2022)
VOL	$\text{Sd(Weekly returns within a year)} * \sqrt{q}$, $q \equiv$ number of available obs. in a year (by default 52)	Bolton & Kacperczyk (2021); Görgen et al. (2020)*; Reboredo & Ugolini (2022)
Panel D. Complementary variables		
SYVOL	Systematic volatility, computed as $\sqrt{BETA^2_{i,y} * VOL^2_{Rm}}$ and represents the overall market risk affecting major aggregate outcomes	Lei & Wisniewski (2018)
SPVOL	Specific volatility, computed as $\sqrt{VOL^2_{i,y} - SYVOL^2_{i,y}}$ and representing the risk affecting a certain company or industry	Lei & Wisniewski (2018)
R-Rm	Excess return over the European stock market, subtracting the STOXX return rate from a certain firm-year return	Author; Lei & Wisniewski (2018)*
EMINT	$\frac{\text{Total CO2 and equivalents emissions}}{\text{Revenue}}$	Ardia et al. (2020); Bolton & Kacperczyk (2021); Garvey et al. (2018); Görgen et al. (2020); Hengge et al. (2023); Ramelli et al. (2021)
CPU	Annual mean of the climate policy uncertainty index, constructed by scaling the number of relevant articles per month (containing terms such as “uncertainty”, “climate”, “carbon”, etc…) with the total number of articles during the same month (Gavriilidis, 2021)	Author; Gavriilidis (2021)

Note: some papers use similar versions of the presented variables (e.g. using monthly returns instead of weekly). *The indicated literature uses the given variable but define it through a different way (e.g. some studies use the idiosyncratic volatility instead of volatility); **The indicated literature uses a different but related variable (e.g. some studies use the market cap instead of total assets as firm size).

Table A.VII – Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) R	1.000						
(2) LN(CE)	-0.062***	1.000					
(3) ENV	-0.050***	0.341***	1.000				
(4) ENVCON	0.023*	-0.256***	-0.087***	1.000			
(5) EM	-0.047***	0.296***	0.836***	-0.067***	1.000		
(6) ENVIN	-0.016	0.242***	0.683***	-0.064***	0.358***	1.000	
(7) SALESGR	-0.001	0.071***	0.048***	-0.008	0.071***	-0.001	1.000
(8) LN(SIZE)	-0.089***	0.664***	0.525***	-0.247***	0.500***	0.327***	0.101***
(9) BM	-0.260***	0.217***	0.144***	-0.123***	0.125***	0.117***	0.063***
(10) LEV	-0.015	-0.133***	-0.009	0.037***	-0.056***	0.044***	-0.032**
(11) PPE/A	-0.015	0.505***	0.168***	-0.099***	0.164***	0.109***	0.001
(12) BETA	-0.066***	0.222***	0.127***	-0.116***	0.135***	0.074***	0.098***
(13) VOL	-0.252***	0.036*	-0.012	-0.058***	-0.022	0.023*	-0.034***
Variables	(8)	(9)	(10)	(11)	(12)	(13)	
(8) LN(SIZE)	1.000						
(9) BM	0.264***	1.000					
(10) LEV	-0.074***	-0.019	1.000				
(11) PPE/A	0.159***	0.101***	-0.057***	1.000			
(12) BETA	0.173***	0.248***	-0.028	0.102***	1.000		
(13) VOL	-0.076***	0.216***	0.031*	0.021	0.451***	1.000	

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table A.VIII – Pooled OLS Regressions (general statistics)

	R	R	R	R	R
N	2424	2536	2536	2536	2465
R^2 *(sector, year)*	0.301	0.296	0.302	0.298	0.302
R^2 *(no sector, no year)*	0.086	0.087	0.093	0.091	0.089
F p-value	0.000	0.000	0.000	0.000	0.000

Note: the R^2 is a metric of the predictive and explanatory power of the model. The variables inputted are the same of those on fixed effects (FE) regressions. The variable's results were omitted because they are not relevant for research conclusions. The null hypothesis of the F test is that the set of explanatory variables is not globally significant to explain the dependent variable.

Table A.IX – Variance Inflation Factors (VIF), Hausman and Wooldridge Tests

	LN(CE)	**ENV**	**ENVCON**	**EM**	**ENVIN**
X	2.91	1.33	1.77	1.27	1.16
ΔX	1.05	1.03	1.54	1.03	1.04
SALESGR	1.05	1.04	1.04	1.04	1.05
LN(SIZE)	2.08	1.50	1.32	1.43	1.28
B/M	1.22	1.22	1.23	1.22	1.21
LEV	1.02	1.01	1.01	1.01	1.02
PPE/A	1.58	1.06	1.05	1.05	1.05
BETA	1.39	1.36	1.36	1.36	1.36
VOL	1.34	1.34	1.34	1.34	1.35
Hausman p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Wooldridge p-value	0.0197	0.0302	0.0303	0.0307	0.0919

Note: a VIF above 10 is often considered a signal of multicollinearity. A p-value below 5% leads to reject the null hypothesis of the tests. The null hypothesis of the Hausman test is that the difference in coefficients between fixed and random effects estimators are not systematic. The null hypothesis of the Wooldridge test is that there's no serial correlation among the residuals.

Table A.X – Fischer-type Augmented Dickey Fuller (ADF) Tests for one lag

Variable	χ^2 p-value	χ^2 p-value (with trend)
R	0.0000	0.0000
LN(CE)	0.0000*	0.0000
ENV	0.0000	0.0000
ENVCON	0.0000	0.0000
EM	0.0000	0.0000
ENVIN	0.0000	0.0000
SALESGR	0.0000	0.0000
LN(SIZE)	0.0000*	0.0000
B/M	0.0000	0.0000
LEV	0.0000	0.0000
PPE/A	0.0000	0.0000
BETA	0.0000*	0.0000
VOL	0.0000	0.0000

Note: * means that the p-value from Chi-squared distribution is below 5%, but the one from normal distribution is above. A p-value below 5% leads to reject the null hypothesis of the tests. The null hypothesis of the ADF test for panel data is that all panels contain unit roots, while the alternative hypothesis is that at least one panel is stationary.

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Table A.XI – Additional robustness checks: Changing target/dependent variables

Variables	**Changing LN(CE) by EMINT**	**Changing LN(CE) by CPU**	**Changing R by VOL**	**Changing R by systematic VOL**	**Changing R by specific VOL**	**Changing R by excess returns**
	(4.1) R	(4.2) R	(4.3) VOL	(4.4) SYVOL	(4.5) SPVOL	(4.6) R-Rm
EMINT	-238.3000*					
	(122.2000)					
CPU		0.0011***				
		(0.0001)				
ΔCPU		-0.0214***				
		(0.0014)				
LN(CE)			-0.1627***	-0.2365	-0.2844**	0.0222*
			(0.0565)	(0.2265)	(0.1178)	(0.0131)
ΔLN(CE)						-0.0221***
						(0.0083)
SALESGR	-0.110	0.0750**	-0.3126***	-0.1880	-0.1753*	0.0293
	(0.0862)	(0.0244)	(0.0695)	(0.2073)	(0.1001)	(0.0276)
LN(SIZE)	0.2590*	-0.0086*	0.0381	-1.2568***	-0.3235	-0.0936***
	(0.1360)	(0.0034)	(0.0851)	(0.3765)	(0.2155)	(0.0271)
B/M	-0.4470***	-0.1290***	0.1966***	0.6532***	0.4289***	-0.3780***
	(0.0879)	(0.0134)	(0.0744)	(0.1545)	(0.0986)	(0.0424)
LEV	-0.0613	-0.0059	0.0580	0.2909**	0.0880	-0.0214
	(0.0582)	(0.0049)	(0.0482)	(0.1396)	(0.0711)	(0.0206)
PPE/A	0.5100**	-0.0003	0.3089*	1.6962***	0.7067***	-0.0695
	(0.2390)	(0.0121)	(0.1660)	(0.5626)	(0.2190)	(0.0536)
BETA	0.1650**	0.0148	0.3074***			0.0071
	(0.0731)	(0.0144)	(0.0542)			(0.0209)
VOL	-0.6880**	-0.1620*				-0.2920***
	(0.2870)	(0.0703)				(0.0846)
L.R	-0.0357					

	(0.0390)					
L2.R	-0.0926***					
	(0.0340)					
L.VOL			-0.2874***			
			(0.0650)			
L.SYVOL				0.0616		
				(0.1015)		
L.SPVOL					-0.0487	
					(0.0669)	
L.EMINT	218.7000**					
	(104.2000)					
L.LN(CE)			0.0915	0.0474	0.1743	
			(0.0568)	(0.2309)	(0.1089)	
L.LN(SIZE)	-0.2530*		-0.0067	1.3324***	0.3609*	
	(0.1320)		(0.0832)	(0.3886)	(0.2134)	
Constant	-0.0678	0.2060*	-0.0250	-0.7211	0.1286	2.0070***
	(0.3730)	(0.0801)	(0.2670)	(0.6404)	(0.2831)	(0.6030)
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	No	No	Yes
N	2370	2660	2424	2136	2063	2370
Method	GMM	OLS	GMM	GMM	GMM	FE
Within R^2						0.173
Between R^2						0.065
Overall R^2		0.307				0.062
AR(1) p-value	0.000		0.015	0.033	0.061	
AR(2) p-value	0.198		0.782	0.748	0.575	
Hansen p-value	0.014		0.000	0.052	0.011	

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively; "L" and "L2" denote first and second lag, respectively. Robust standard errors in parentheses. Variables defined in table A.VI. Regression 4.1 replaces the target regressor, LN(CE), by emissions intensity (EMINT), using the two-step system GMM estimator. Regression 4.2 replaces LN(CE) by the carbon policy uncertainty index yearly mean (CPU) and uses the pooled OLS with dummy variables estimator. Regressions 4.3, 4.4 and 4.5 replace the dependent variable, R, by the volatility (VOL), the systematic volatility (SYVOL) and the specific volatility (SPVOL), respectively, using the two-step system GMM estimator with the same characteristics as previously except for the use of only one lag as internal instrument, and removing VOL as regressor (and also BETA in the case of 4.4 and 4.5 due to the fact that it is needed for calculation of SYVOL under the CAPM). Regression 4.6 replaces R by excess returns over the European stock market (R-Rm), using the FE estimator. The first and second lag of stock returns are used as internal (GMM-style) instruments, while the first lag of LN(SIZE), the first lag of each target independent variables and the sector dummy are used as external instruments for regressions 4.1, 4.3, 4.4 and 4.5. The null hypothesis of the Arellano-Bond tests (AR(1) and AR(2)) is that there is no first and second order autocorrelation in the residuals of the dynamic panel data model. The null hypothesis of the Hansen test stipulates that the instrumental variables are globally valid, not being correlated with the error term. A p-value lower than 5% lead to reject the null hypotheses of the AR(1), AR(2) and Hansen tests.

Table A.XII – Additional robustness checks: Limiting or separating the sample

Variables	**Model using 80% of the sample**	**Model excluding firms from the United Kingdom and Switzerland (outside the EU)**	**Estimation for different subperiods (2006-2015 | 2016-2022)**	
	(4.7) R	(4.8) R	(4.9) R	(4.10) R
LN(CE)	0.0153	0.0261*	0.00503	0.0327***
	(0.0128)	(0.0145)	(0.0144)	(0.0117)
ΔLN(CE)	-0.0069	-0.0248***	0.00471	-0.0328***
	(0.0136)	(0.0087)	(0.0126)	(0.00789)
SALESGR	-0.0060	0.0245	0.00772	0.0365
	(0.0176)	(0.0255)	(0.0151)	(0.0296)
LN(SIZE)	-0.0368	-0.106***	-0.0883***	-0.0780***

	(0.0241)	(0.0373)	(0.0322)	(0.0291)
B/M	-0.2210***	-0.373***	-0.409***	-0.373***
	(0.0394)	(0.0502)	(0.0387)	(0.0539)
LEV	0.0108	-0.0178	-0.0719***	-0.0269
	(0.0120)	(0.0210)	(0.0250)	(0.0239)
PPE/A	0.0089	-0.0658	-0.0720	-0.0329
	(0.0414)	(0.0541)	(0.0443)	(0.0631)
BETA	-0.0022	0.0350		
	(0.0163)	(0.0302)		
VOL	-0.2140***	-0.330***	-0.00330	-0.233***
	(0.0680)	(0.117)	(0.0894)	(0.0800)
Constant	0.6430	2.307***	2.307***	1.770***
	(0.5230)	(0.835)	(0.733)	(0.661)
Sector	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	2021	1614	1762	2164
Method	FE	FE	FE	FE
Within R^2	0.281	0.390	0.518	0.390
Between R^2	0.045	0.074	0.143	0.068
Overall R^2	0.141	0.189	0.251	0.201

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels. Robust standard errors in parentheses. Variables defined in table A.VI. Regression 4.7 uses 80% of the sample, excluding the observations below (above) the 10th (90th) percentiles. Regression 4.8 excludes firms with headquarters on the United Kingdom and Switzerland. Regressions 4.9 and 4.10 cover only parts of the period, respectively until 2015 (inclusive) and after 2015. The BETA was excluded from regressions 4.8 and 4.9 due to insufficient observations when considering it. All regressions use the FE estimator.

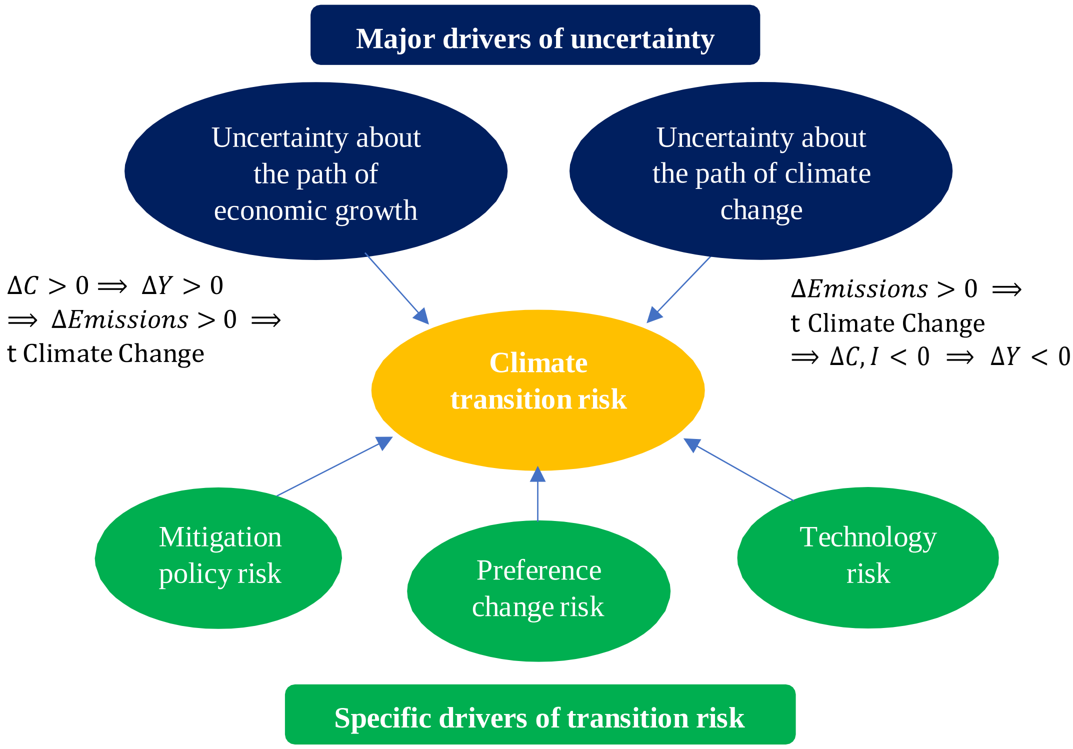

Figure A1 – Key drivers of uncertainty and climate transition risk

Note: The formulas presented below the major drivers of uncertainty are economic rationales regarding them. C is consumption, I is investment, Y is the Gross Domestic Product (GDP) and Emissions are carbon emissions.

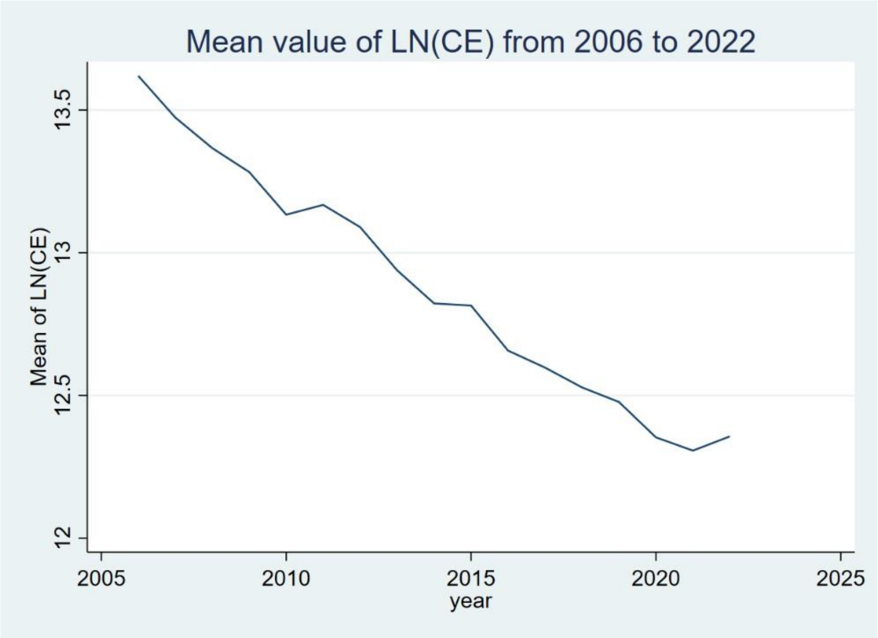

Figure A2 – Mean value of LN(CE) from 2006 to 2022

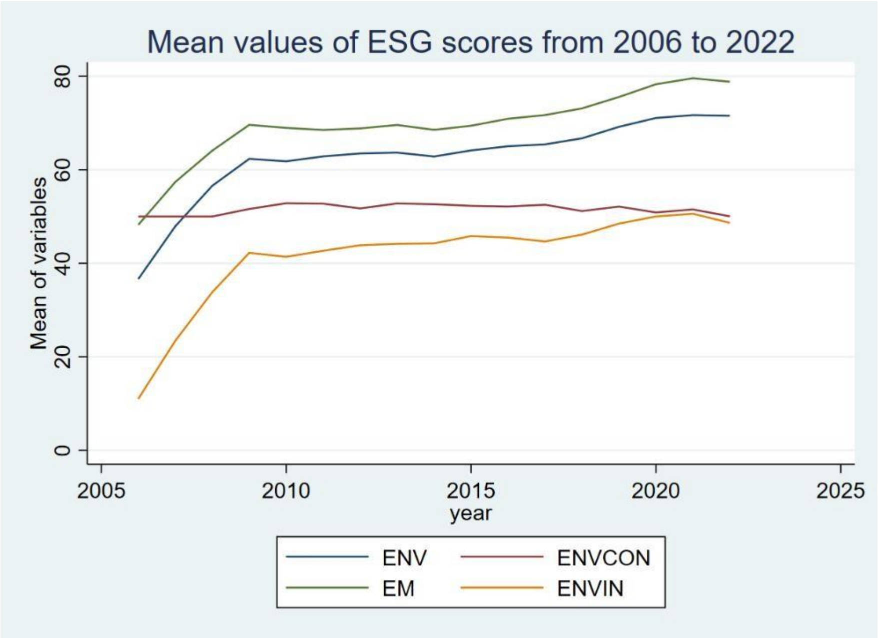

Figure A3 – Mean values of ENV, ENVCON, EM and ENVIN from 2006 to 2022

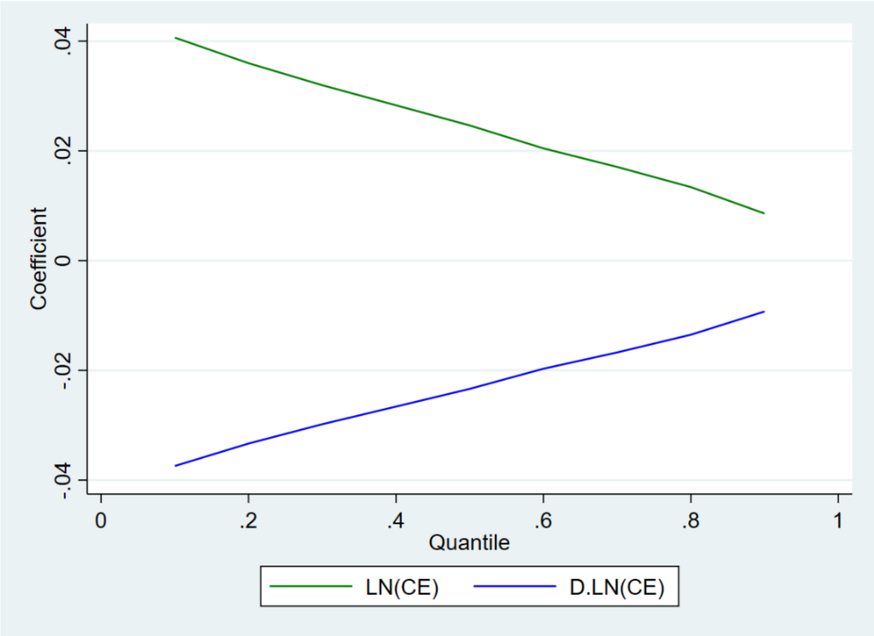

Figure A4 – Quantile regression coefficients of LN(CE) and ΔLN(CE)

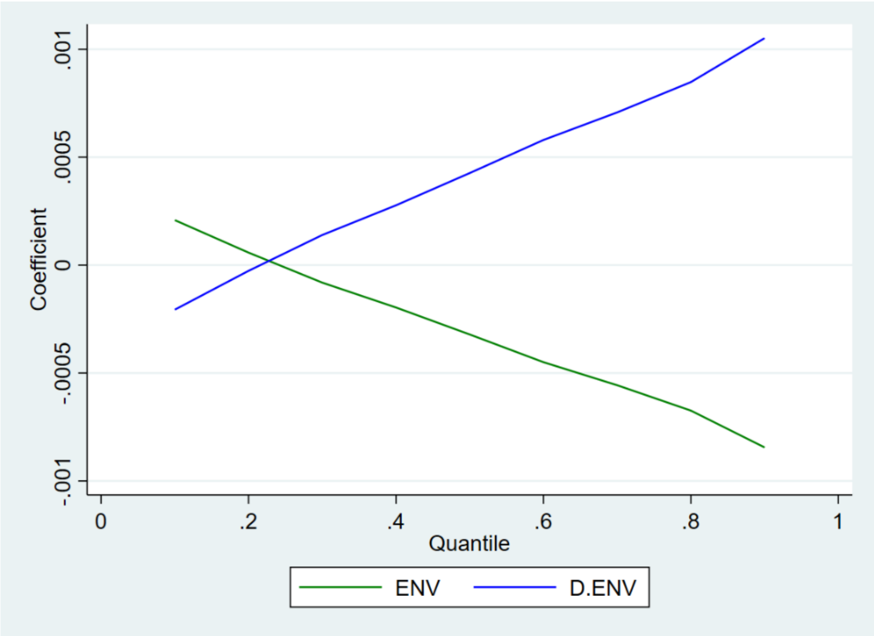

Figure A5 – Quantile regression coefficients of ENV and ΔENV

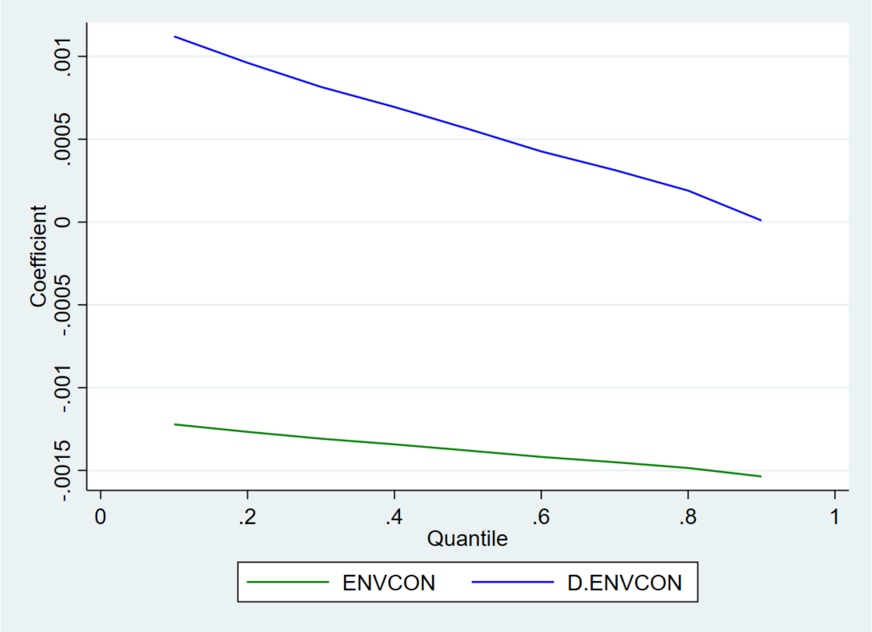

Figure A6 – Quantile regression coefficients of ENVCON and ΔENVCON

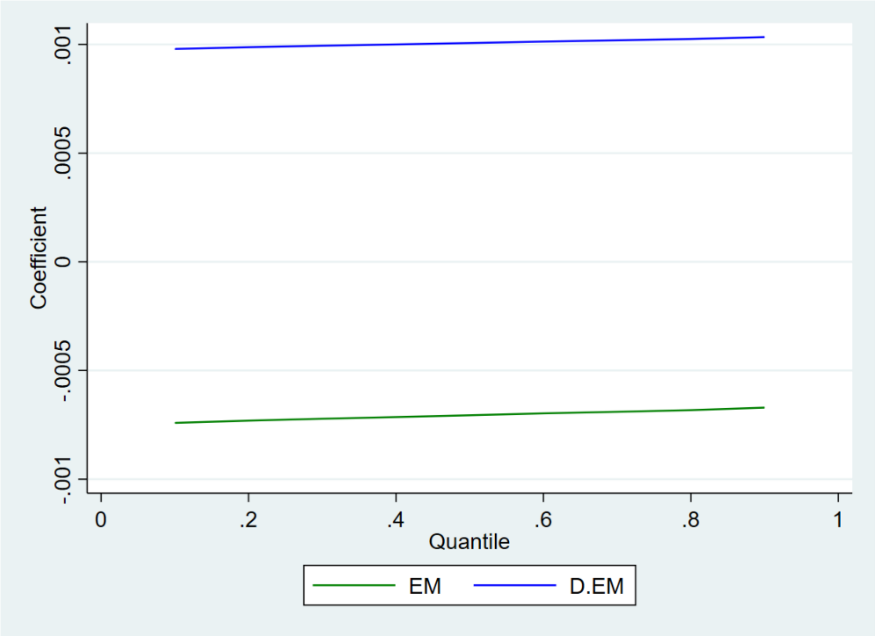

Figure A7 – Quantile regression coefficients of EM and ΔEM

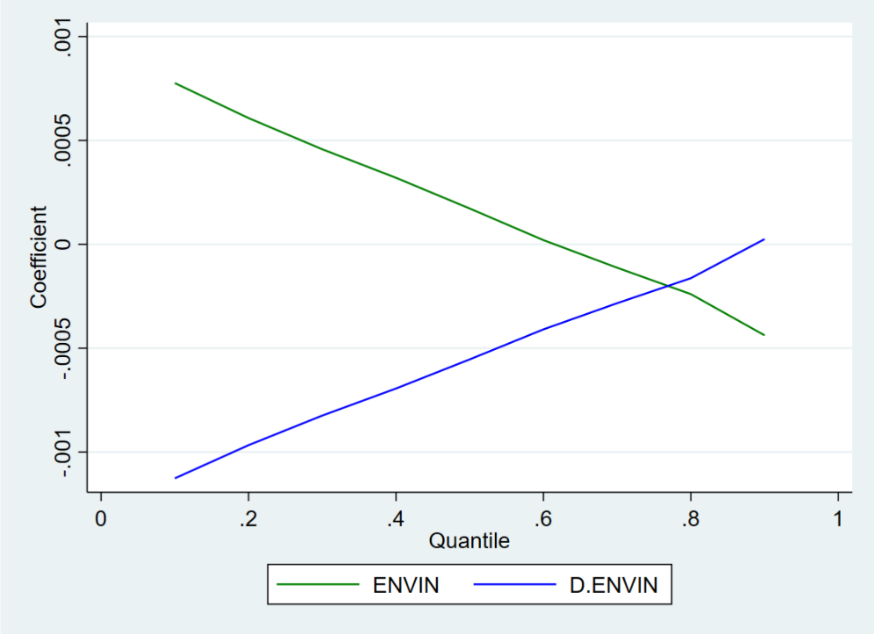

Figure A8 – Quantile regression coefficients of ENVIN and ΔENVIN

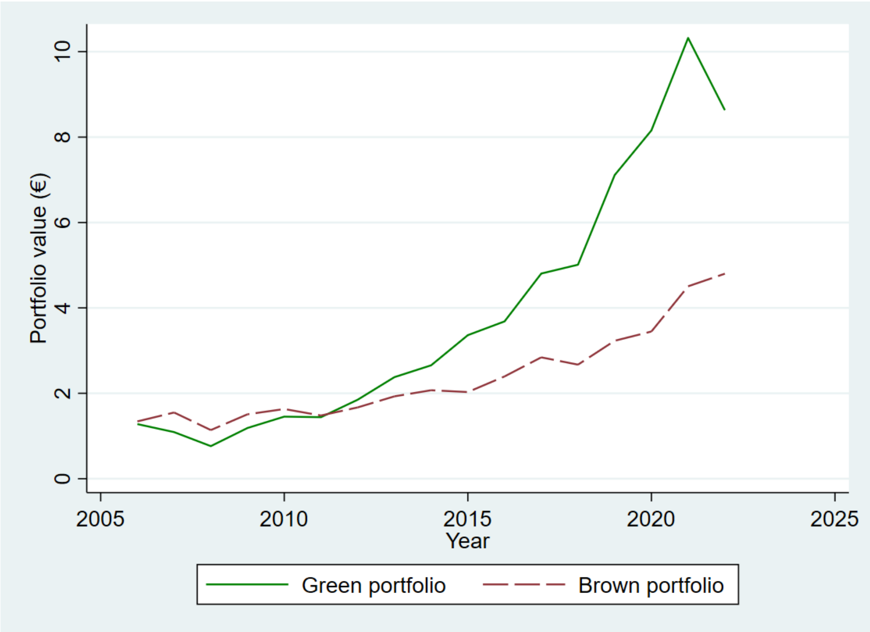

Figure A9 – Cumulative value of green versus brown portfolios from 2006 to 2022

Note: the green portfolio is composed by the 10% stocks with lower values of LN(CE), while the brown portfolio is composed by the 10% with higher figures. The portfolios are rebalanced each year to take firms with lower (or higher) emissions considering the 10% (or 90%) percentile. The cumulative returns were computed using a continuously compounding rate, and the value of 1€ is invested at the beginning: $P_0 =$ 1€; $P_y = P_{y-1} * e^{r_y} = P_0 * \ e^{(r_1 + \cdots + r_y)}$, where P is the value of the portfolio and r is the mean rate of return at period y. We use a homogeneous portfolio strategy.